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Adaptation, Beliefs, and Impacts: Essays on the Economics of Climate

Guglielmo Zappala

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Guglielmo Zappala. Adaptation, Beliefs, and Impacts: Essays on the Economics of Climate. Economics and Finance. Université Panthéon-Sorbonne - Paris I, 2023. English. NNT : 2023PA01E037 . tel-04777447

HAL Id: tel-04777447

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UFR02 Économie - Paris Jourdan Sciences Économiques
DOCTORAL SCHOOL: ED 465 – Économie Panthéon Sorbonne

Dissertation

Submitted for the degree of Doctor of Philosophy in Economics

Prepared and defended on September 11, 2023 by

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ADAPTATION, BELIEFS, AND IMPACTS:
ESSAYS ON THE ECONOMICS OF CLIMATE

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ÉCOLE DOCTORALE: ED 465 – Économie Panthéon Sorbonne

Thèse

Pour l'obtention du grade de Docteur en Sciences Économiques

Présentée et soutenue publiquement le 11 Septembre 2023 par

Guglielmo ZAPPALÀ

ADAPTATION, CROYANCES, ET IMPACTS :
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Acknowledgements

Colleagues, mentors, friends, and family have all meaningfully contributed to this dissertation in their own way in these three years. Although a few lines will not do justice to their contribution, the convention of devoting a section to acknowledge them is extremely useful. First and foremost, I am hugely grateful to my advisor, Katrin Millock. Her patience, availability, guidance, wise advice, and attention to detail from our first meeting for my master's thesis to the final submission of this dissertation are things I will always be thankful for.

I am grateful to Lint Barrage and Wolfram Schlenker for accepting to be the referees and Leonie Wenz for accepting to be the examiner of this dissertation. It was an honor to have researchers I have always admired reading my research and I thank them for taking the time and providing precious feedback. I am thankful to Andrew Clark and H el ene Ollivier for serving on my jury as internal members and on my thesis committee. I will always carry with me Andrew's meticulousness in reading my drafts since the first year and H el ene's detailed and accurate feedback. During my time at PSE, I had the opportunity to learn and have helpful conversations with Geoffrey Barrows, Nicolas Jacquemet, Fran ois Libois, Casey Maue, Benjamin Michallet, Hillel Rapoport, Claudia Senik, and Thierry Verdier.

Although the first year was mostly spent working from home in lockdown and with curfews, two research visits hugely contributed to my research progress and marked my second and third years. For this, I gratefully acknowledge funding from the Paris School of Economics, Universit  Paris 1 Panth on-Sorbonne, and the  le-de-France region.

I would like to deeply thank Tamma Carleton for hosting me at UC Santa Barbara. Her valuable and insightful comments and precious advice have had a fundamental role in shaping my critical thinking as an aspiring researcher and in spurring my deep interest in climate economics. I am humbled to have the opportunity to work with her in the future and learn more. Many more people have contributed to making my time at UCSB extremely pleasant and productive, among others, I thank Kathy Baylis, Olivier Deschenes, Kyle Meng, and the whole emLab community, and fellow graduate students Flavio Malagutti, Roberto Santos, Ravi Vora.

I also thank the people I met during my second research stay at the LSE. In particular, I am very grateful to Simon Dietz for hosting me after several iterations and failed attempts due to external circumstances. Many people have made this stay memorable and useful, and I would like to thank all the faculty and graduate students at the Grantham Research Institute on Climate Change and the Environment and the Department of Geography and Environment for their warm hospitality.

I attended and presented my work at various conferences and seminars over the three years. These experiences helped me to learn about novel research, meet new

colleagues and friends, and receive valuable feedback. In particular, I would like to thank the many researchers I met, including Cevat Aksoy, Joe Aldy, Cristoph Albert, Roberto Bonfatti, Valentina Bosetti, Giulia Brancaccio, Fiona Burlig, Maria Coto-fan, Davide Cerruti, Tatyana Deryugina, Ludovica Gazzè, Namrata Kala, Christian Krekel, Giovanni Marin, Matto Mildenberger, Gregor Singer, Rob Stavins, and Rich Sweeney for helpful conversations, and my fellow conference friends Gustav Fredriksson, Daniel Haerle, Dylan Hogan, Manuel Linsenmeier, Oda Nedregård, Filippo Pavanello, Francesco Pintus, Romano Tarsia, Vincent Thivierge. Moreover, I thank Tom Bearpark and Alex Marbler for hours of stimulating conversations on climate and econometrics.

I am grateful to colleagues that I met at the IMF during the Fund Internship Program, in particular, I would like to thank Valerie Cerra and Emanuele Massetti for insightful conversations and advice.

I also thank my office mates in R4-73, Nicolas, David, Alice, Damien, and Pierre for the helpful exchanges, and my former office mate Benjamin for the many talks. Thanks also to the fellow PSE PhD and master's mates, Bayram, Raphaël, Claire, Daniel, and Manpreet.

Special thanks to Armon Rezai. His support, advice, and mentorship have been crucial in the last miles of this marathon. His passion and enthusiasm for research are virtues I am aspiring to for the rest of my career. I am also deeply grateful to Marco Tabellini. His infinite patience, availability, and enthusiasm first made me passionate about research. I am thankful to Ruben Durante, Paola Giuliano, and Giovanni Peri for stimulating conversations on political economy and migration that influenced my curiosity about this research area. I also thank my undergraduate mentor Cesare Dosi for encouraging and supporting me in the application process to master's degrees abroad and inviting me to present and teach at my alma mater.

Dulcis in fundo, my parents and my sister have been essential landmarks without whom nothing would have been possible. For constant support, encouragement, brainstorming, advice, and much more, Camilla, thank you.

Summary

As global greenhouse gas emissions exacerbate the climate change challenge, there is growing urgency to understand the socio-economic impacts of climate change and the role of human ability to adapt to it. This dissertation comprises four essays on the economics of climate, studying a new channel of climate impacts through production networks and sectoral interlinkages, the determinants of individual climate beliefs, and their role, together with cognitive biases, in adaptive behavior, and the drivers of individual climate concern and pro-environment voting behavior.

In the first chapter, *Sectoral impact and propagation of weather shocks*, I examine the heterogeneous effect of weather shocks on sectoral economic production across the world and then trace their propagation across sectors, countries, and over time. In contrast with previous studies that study the response of local economic activity to local weather shocks, this chapter introduces the role of input-output sectoral interlinkages as a transmission mechanism of weather shocks in a production network model. Using a six-sector global dataset from 1975 to 2020, I document that agriculture is the most harmed sector by a range of weather shocks. Most importantly, I find that sectors at later stages of the supply chain, though non-responsive to local weather, suffer from substantial and persistent losses over time due to domestic and foreign heat shocks in agriculture that propagate downstream. Using counterfactual scenarios, I show a substantial underestimation of the economic cost of temperature increases accounting for shocks across trade partners since 2000 and I characterize global losses depending on the sectoral centrality in the production network.

In the second chapter, *Adapting to climate change accounting for individual beliefs*, I use a longitudinal survey of rural households in Bangladesh combined with weather data and I formalize a theoretical framework to examine how climate beliefs differentially influence individuals' responsiveness to dryness in the use of irrigation. The empirical analysis shows that farmers' inaccurate priors asymmetrically drive irrigation response to dryness shocks and farmers respond to changes in beliefs by irrigating more only in drier areas. I also explore different mechanisms through which cognitive factors may affect adaptive decisions, by comparing the severity, timing, and frequency of self-reported droughts with recorded meteorological events. In a counterfactual analysis with beliefs based on meteorological conditions, I quantify the *belief gap* derived in the theoretical framework and monetize the losses induced by inaccurate beliefs, documenting the welfare implications.

The third chapter, *Drought exposure and accuracy: Motivated reasoning in climate change beliefs*¹, is based on the rural household survey in Bangladesh combined with a meteorological measure of dryness to examine the belief formation process

¹Published in Zappalà, G. (2023). *Environmental and Resource Economics*, 85, 649–672. Online version accessible here: <https://doi.org/10.1007/s10640-023-00779-1>

of individuals about droughts and test whether individuals exhibit directional motivated reasoning when interpreting them. First, I analyze how long-term averages and short-term deviations in dryness exposure determine belief formation and the recollection of drought events. Then, using exposure to meteorological dryness as an instrumental variable, I document that individual prior beliefs lead to a distorted interpretation of droughts that is biased towards their priors, providing suggestive evidence of the presence of confirmation bias as a directional motivated reasoning mechanism.

The fourth chapter, *Climate-induced migration and environmental values*, explores a new determinant of individual climate concern, examining whether the upsurge in weather-driven migration flows has spurred a greater concern for climate change in the European Union host countries between 2000 and 2019. I find that weather-induced asylum demands raise individual concern about climate change among citizens in the destination countries, in particular among young generations and right-wing individuals. These changes in stated preferences, however, do not translate into changes in voting behavior, as there is no effect of climate-induced migration flows on Green party votes in the European Parliament elections. A set of co-existing alternative mechanisms behind these findings suggest that the results are driven by the drop-out of traditional Green voters, changes in preferences for individuals below the voting age, as well as no changes in the pro-environmental policy manifesto of political parties.

DISCIPLINE: Economics

KEYWORDS: Adaptation; Beliefs; Climate change; Climate concern; Climate damages; Climate impacts; Weather shocks

Résumé

Alors que les émissions mondiales de gaz à effet de serre exacerbent le défi du changement climatique, il est de plus en plus urgent de comprendre les effets socio-économiques du changement climatique et le rôle de la capacité humaine à s’y adapter. Cette thèse comprend quatre essais sur l’économie du climat, étudiant un nouveau canal des effets climatiques à travers les interconnexions sectorielles, les déterminants des croyances climatiques individuelles et leur rôle, ainsi que les biais cognitifs, dans le comportement adaptatif, et les moteurs des préoccupations climatiques individuelles et du comportement de vote en faveur de l’environnement.

Dans le premier chapitre, *Sectoral impact and propagation of weather shocks*, j’examine l’effet hétérogène des chocs météorologiques sur la production économique sectorielle à travers le monde, puis je retrace leur propagation entre les secteurs, les pays et dans le temps. Contrairement aux études précédentes qui étudient la réaction de l’activité économique locale aux chocs météorologiques locaux, ce chapitre introduit le rôle des liens sectoriels d’entrée-sortie en tant que mécanisme de transmission des chocs météorologiques dans un modèle de réseau de production. À l’aide d’un ensemble de données mondiales portant sur six secteurs, de 1975 à 2020, je montre que l’agriculture est le secteur le plus touché par une série de chocs météorologiques. Plus important encore, je constate que les secteurs situés à des stades ultérieurs de la chaîne d’approvisionnement, bien qu’ils ne réagissent pas aux conditions météorologiques locales, subissent des pertes substantielles et persistantes au fil du temps en raison des chocs thermiques dans l’agriculture qui se propagent en aval. En utilisant des scénarios contrefactuels, je montre une sous-estimation substantielle du coût économique des augmentations de température en tenant compte des chocs sur les partenaires commerciaux depuis 2000 et je caractérise les pertes globales en fonction de l’importance sectorielle dans le réseau de production.

Dans le deuxième chapitre, *Adapting to climate change accounting for individual beliefs*, j’utilise une enquête longitudinale sur les ménages ruraux au Bangladesh combinée à des données météorologiques et je formalise un cadre théorique pour examiner comment les croyances climatiques influencent de manière différentielle la réactivité des individus à la sécheresse dans l’utilisation de l’irrigation. L’analyse empirique montre que les croyances influencent l’irrigation uniquement dans les zones plus sèches, avec des réponses hétérogènes selon les saisons de croissance et les types d’irrigation. J’explore également les différents mécanismes par lesquels les facteurs cognitifs peuvent affecter les décisions d’adaptation, en comparant l’intensité, le moment et la fréquence des sécheresses autodéclarées avec les événements météorologiques enregistrés. Dans une analyse contrefactuelle avec des croyances basées sur les conditions météorologiques, je montre que les agriculteurs sous-utilisent l’irrigation et

subissent des pertes monétaires substantielles en raison des croyances inexacts observées, générant un *belief gap*.

Le troisième chapitre, *Drought exposure and accuracy: Motivated reasoning in climate change beliefs*¹, est basée sur la même enquête auprès des ménages ruraux combinée à une mesure météorologique de la sécheresse afin d'examiner le processus de formation des croyances des individus sur les sécheresses et de tester si les individus font preuve d'un raisonnement directionnel motivé lorsqu'ils les interprètent. Tout d'abord, j'analyse comment les moyennes à long terme et les écarts à court terme dans l'exposition à la sécheresse déterminent la formation des croyances et le souvenir des événements de sécheresse. Ensuite, en utilisant l'exposition à la sécheresse météorologique comme variable instrumentale, je démontre que les croyances des individus conduisent à une interprétation déformée des sécheresses qui est biaisée par rapport à leurs croyances antérieures, suggérant la présence d'un biais de confirmation en tant que mécanisme de raisonnement motivé.

Le quatrième chapitre, *Climate-induced migration and environmental values*, explore un nouveau déterminant de l'inquiétude individuelle face au climat, en examinant si les flux migratoires induits par les conditions météorologiques a suscité une plus grande préoccupation climatique dans les pays d'accueil de l'Union européenne entre 2000 et 2019. Je constate que les demandes d'asile liées aux conditions météorologiques augmentent les préoccupations individuelles concernant le changement climatique parmi les citoyens des pays de destination, en particulier parmi les jeunes générations et les individus de droite. Ces changements dans les préférences déclarées ne se traduisent cependant pas par des changements dans le comportement électoral, car il n'y a pas d'effet des flux migratoires induits par le climat sur les votes du parti des Verts aux élections du Parlement européen. Une série de mécanismes alternatifs coexistants derrière ces résultats suggèrent que les résultats sont dus à l'abandon des électeurs verts traditionnels, aux changements dans les préférences des personnes n'ayant pas l'âge de voter, ainsi qu'à l'absence de changements dans les manifestes politiques pro-environnementaux des partis politiques.

DISCIPLINE: Sciences Économiques

MOTS-CLEFS: Adaptation ; Croyances ; Changement climatique ; Préoccupations climatiques ; Dommages climatiques ; Impacts climatiques ; Chocs météorologiques

¹Publié dans Zappalà, G. (2023). *Environmental and Resource Economics*, 85, 649–672. Version en ligne accessible ici: <https://doi.org/10.1007/s10640-023-00779-1>

General Introduction

Climate and Society

Climate and society have shared an indissoluble relationship since ancient times. The interplay between climate and human societies has shaped the course of history, influencing the beliefs and actions of individuals and communities across the globe. Global environmental changes have characterized various historical eras, as exogenous historical processes to which societies were exposed and were forced to rethink their livelihoods and lifestyle.

The main structural transformations of society followed epochal climatic changes. Humans are children of the Ice Age: it was only when the intense cold of the last ice age began to ease, more than 10,000 years ago, that cultivation began, and urbanization followed (Behringer, 2010). As paradoxical as it may seem, the warming of the climate contributed to the creation of humankind. Similar major transformations followed, emphasizing the innate human ability to adapt: from a nomadic to a sedentary life; from hunting to agriculture and animal husbandry; from barter and material exchanges to an interconnected world with fragmented global supply chains comprising trade and financial interlinkages.

In the short run, global greenhouse gas emissions continue to rise as world per capita income increases. In light of this tight intricate relationship, anthropogenic climate change and the increasingly rapid pace of changes in weather fluctuations and in the frequency, intensity, duration, timing, and spatial distribution of extreme weather events pose one of the most urgent and cumbersome challenges for human society and ecosystems (IPCC, 2021). If, on the one hand, income increases will be beneficial for billions of people in the developing world, on the other hand, given the current technologies, emissions will exacerbate the climate change challenge, which will make adaptation even more important to guarantee future improvements in people's standard of living.

While a number of efforts are being made to reach international environmental agreements and reduce greenhouse gas emissions, given that the repercussions of extreme weather events on society are already tangible, attention is turning from mitigation to adaptation and coping strategies for individuals, firms, governments, and, in general, human society, to understand how we can change our lives as the climate change challenge becomes more severe.

The connection between environmental change and human well-being has long intrigued economists and other social scientists. However, it is only in recent times that research on this relationship has grown exponentially. This can be attributed to the growing significance of climate change as a major policy concern, advancements in statistical and econometric tools for causal inference for non-experimental studies, and progress in computer science and climatology, which have enhanced our ability to parameterize the elements associated with climatic variations that are most pertinent to the socio-economic outcomes under scrutiny. Answering these questions takes on an extremely policy-relevant connotation to design more stringent and targeted mitigation and adaptation policies and garner public climate awareness and support for climate policies.

Integrating Climate into Economics

To price the global climate externality, climate economists have directed their efforts toward estimating the external damages. Traditionally, climate damages have been calculated using theoretical-numerical Integrated Assessment Models (IAMs). The original efforts in the development of a climate-economy model incorporating the economy's greenhouse gas emissions, the carbon cycle, and a climate change damage function into an economic growth model led to the recognition of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel in 2018 (Nordhaus, 1992). The results of these models are then converted into policy-relevant monetary figures using the Social Cost of Carbon (SCC), which represents the net present value of the future marginal damages caused by emitting one additional tonne of carbon today (Waldhoff et al., 2014; Nordhaus, 1993a,b). To bridge the economic and the natural systems, these models use theoretical “damage functions” that describe how global mean temperature translates into economic and social costs (Revesz et al., 2014). Although serving the purpose of combining the economic and natural domains into a single framework, the results of the calculations from these models heavily rely on modeling assumptions that often do not reflect well the dynamics of climate change (Pindyck, 2013; Weitzman, 2010). Despite efforts in advancing climate dynamics and embedding state-of-the-art climate science into economic models (Dietz et al., 2021), recent models still hinge on simplified climate damage functions that assume increases in global mean surface temperature from pre-industrial levels as a reasonable sufficient statistic for damages through a non-linear (quadratic)

relationship and omitting any other weather variation, cumulative effects or effects depending on the speed of changes (Barrage and Nordhaus, 2023). These models - and the resulting SCC estimates - assume that the temperature increases always have the same effect, thus assuming adaptation does not take place. Moreover, they do not account for heterogeneous unequal impacts across space.

As opposed to theoretical and numerical exercises, there has been more recent interest in statistical approaches that use historical data and estimate the relationship in real-world settings. Climate science has enormously progressed in refining our understanding of long-run historical climate variations, short-run weather forecasts, and climate prediction models. Such data and models can help answer a variety of questions with important implications for the economy, both in terms of our understanding of the historical relationship between society and climate, and of how it can help shape the future. The combination of data sets from the physical and social sciences combined with recent methodological advancements in causal inference has contributed to providing data-driven estimates of highly policy-relevant relationships between human well-being and climatic changes.

Measuring Climate Impacts

Early studies estimating the economic damages associated with climate change used cross-sectional variation in climate (occurring at one point in time) to estimate the marginal economic effect of long-run changes in the distribution of temperature and rainfall (Mendelsohn et al., 1994). Nevertheless, the “credibility revolution” in empirical economics (Angrist and Pischke, 2010) has rapidly permeated the research field of environmental economics and spurred the birth of a research area on its own often defined as “climate econometrics” (Hsiang, 2016). This emerging literature uses weather data, that vary over both space and time, to estimate the effects of interannual variation on economic and social outcomes while accounting for cross-sectional unobserved omitted variables, for which it is not possible to control for using cross-sectional data (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). This plethora of new studies driven by the credibility revolution has made use of better-quality data and econometric techniques to uncover causal links between changes in the climate and a wide range of social outcomes (see Dell et al. (2014) and Carleton and Hsiang (2016) for reviews). Such studies rely on observational data to obtain climate damage functions and fill the methodological gap left by the impossibility of randomly allocating climate to two sample populations identical in every other way.

A comprehensive description of the potential channels of climate impacts is crucial for formulating an optimal climate policy. The empirical estimation of the social and economic impacts of climate can be broadly grouped into two main strands. On the one hand, bottom-up approaches focus on sector-specific market and non-market

damages representing different sectors of the economy, including human health, economic conditions, and social interactions. In this strand of the literature, there is evidence of the impact of temperature variations on many domains, including mortality (Heutel et al., 2021; Barreca et al., 2015), agriculture and crop yields (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009), electricity consumption (Wenz et al., 2017; Auffhammer et al., 2017), labor productivity (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018), human capital (Fishman et al., 2019), conflicts (Hsiang et al., 2011; Hsiang and Jina, 2014), crime (Ranson, 2014), mental health (Obradovich et al., 2018), sleep (Minor et al., 2022; Obradovich et al., 2017), profanity and hatred (Stechemesser et al., 2021; Baylis, 2020). On the other hand, top-down approaches consider aggregate measures of economic production, such as GDP or regional economic production, and their response to temperature variations (Dell et al., 2012; Burke et al., 2015b; Kalkuhl and Wenz, 2020; Acevedo et al., 2020; Kahn et al., 2021). While the former approach has the advantage of providing accurate sector-specific response functions to weather fluctuations, the latter should theoretically capture all market impacts of climate change. Both approaches, however, share certain limitations, which I detail below.

First and foremost, empirical climate impact studies rely on a well-defined framework to study the effect of climate with restrictive assumptions (Hsiang, 2016; Deryugina and Hsiang, 2017). This dissertation (in Chapters 1, 2 and 3) provides some theoretical and empirical arguments on the restrictiveness of certain assumptions, that rely on perfect information, and complete rationality (Arrow and Debreu, 1954). Most importantly, there have long been concerns that the effect of interannual weather variation on economic outcomes cannot be used to identify the effect of climate change. The response to short-run weather fluctuations is fundamentally different from the response to permanent changes in climate. Individuals and firms may respond differently to permanent changes in the expected distribution of weather (i.e., the climate) than to short-term unexpected variations in weather. The impact of weather fluctuations would be a good proxy for the effect of a permanent change in the climate only if adaptation was not important.

Second, the number of fields on which climate has an effect is very large, and any aggregation of sector-specific estimates may be incomplete and only provide partial measures of the SCC. A variety of market and non-market responses are yet unexplored. Likewise, although the empirical designs and novel data sources allow researchers to explore various weather shocks, most of the literature has so far focused on the impact of temperature and recent work has started investigating more in-depth the effect of rainfall (Kotz et al., 2022), cyclones (Hsiang and Jina, 2014), floods (Gandhi et al., 2022; Kocornik-Mina et al., 2020), water runoff (Russ, 2020), and wildfires (Heft-Neal et al., 2023). Yet, climate change affects the moments of the distribution of several weather events, whose impact on many social and economic outcomes is still understudied.

Third, partial estimates do not account for interactions between sectors and regions. Spatial and sectoral interactions can cause double-counting when aggregating sectors and one should account for the covariance of impacts across sectors to obtain the distribution of aggregate damages. More importantly, these interactions may distort the efficient allocation of resources for sector-specific government intervention policies. As opposed to theoretical and numerical models for climate damages, empirical sector-specific studies do not address the feedback between the economy and climate. Such limitation applies to population and goods flows (Cruz and Rossi-Hansberg, 2023; Costinot et al., 2016) and endogenous sectoral reallocation (Nath, 2020), which are not usually accounted for in reduced-form empirical studies and are studied only in spatial general equilibrium settings. Chapter 1 of this dissertation provides empirical evidence of the importance to account for sectoral interlinkages even in a reduced-form top-down approach.

Last, climate impact studies leverage short-run variations in weather variables to identify the effect on economic and social outcomes. It is yet unclear how the welfare economics of climate change would change as a function of unprecedented physical events and potential climatic irreversibilities, such as tipping points.

More recently, in an effort to reconstruct dose-response functions with global coverage, in a number of studies, the Climate Impact Lab empirically estimates partial market and non-market climate damages allowing for local non-linearities and accounting for adaptation costs and benefits in various sectors, including mortality (Carleton et al., 2022), energy and electricity demand (Rode et al., 2021), labor supply and disamenity (Rode et al., 2022), agriculture and crop yields (Hultgren et al., 2022). Combining these sector-specific estimates can inform a more accurate and data-driven derivation of the SCC (Nath et al., 2022).

While all these studies have strong internal validity given the rigorous attention to the identification strategy in the empirical design, there are questions regarding how suitable the impacts of idiosyncratic weather shocks are for informing the future impacts of changes in climate which, among other things, are spatially correlated, and not always perfectly observable by individuals. The chapters comprising this dissertation extensively rely on this recent empirical literature. Nevertheless, this research deviates from previous work both in the types of questions addressed as well as along several methodological dimensions.

Understanding Climate and Forming Expectations

An ongoing debate in economics explores how people understand and interpret past events and how they form expectations over the likelihood of future events. The neo-classical rational expectations school hypothesizes that individuals use all available information in forming their beliefs and converge to a true posterior. Such assumptions have been widely disputed in the field of behavioral economics arguing

that people are prone to cognitive mistakes. These innovations have been so important that they led to the recognition of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel in 2002 (Kahneman and Tversky, 1979) and in 2017 (Thaler, 2015). Blending economics with psychology, more realistic models of human behavior have integrated new psychological traits, including behavioral anomalies, bounded rationality, and cognitive biases (Kahneman and Tversky, 1973, 1982).

While theoretical and empirical work in psychology and behavioral economics suggests that these assumptions are often unjustified, implicit economic models in climate economics still assume that agents are perfectly informed and have unbiased beliefs that meteorological conditions can fully account for. To clarify the role of beliefs and expectations, I summarize the underlying conceptual framework that guides the climate impact and adaptation models (Hsiang, 2016).

Climate \mathbf{C} is defined as the high-dimensional vector of parameters that describe the joint probability distribution of possible weather conditions that can be expected to occur over a specific interval of time. Weather realizations \mathbf{c} are a random vector drawn from the climate distribution. A social or economic outcome of interest Y is affected by climate in two ways. First, the climate directly influences what realizations of weather \mathbf{c} actually occur, affecting the population. Second, individuals' beliefs over the structure of \mathbf{C} may be altered by a change in climate, affecting their actions and resulting outcomes. Respectively, these two channels are defined as the *direct* and *belief* effects. Individuals take actions \mathbf{b} based on their beliefs, such that the relationship between the outcome and climate can be modeled as

$$Y = f(\mathbf{b}(\mathbf{C}); \mathbf{c}(\mathbf{C})) \quad (1)$$

This framework assumes that agents have perfect information about the climate they inhabit and thus the belief effect captures adaptation as the optimizing behavior of the agent. If one considers a simple maximization problem of a representative individual (or firm), for instance on expected profits π , this would be written as

$$\max_{\mathbf{b}} \mathbb{E}(\pi) = \mathbb{E}[f(\mathbf{b}, \mathbf{c}) - g(\mathbf{b})] \quad (2)$$

where \mathbf{b} is the vector of actions that the individual can take, and \mathbf{c} is the vector of stochastic weather conditions, given a well-behaved twice continuously differentiable and concave function $f(\cdot)$, normalized output price to one, and a cost function $g(\cdot)$ convex in actions. From the solution of this optimization problem, it follows that adaptation is the behavioral response of individuals in actions to expected changes in weather conditions $\mathbb{E}[\mathbf{c}]$. Expectations about the long-run climate inform costly investments to protect against increasing exposure to adverse conditions. This sketched framework shows how important it is to understand how individuals form expectations about climate to measure adaptation and thus accurately quantify

climate impacts. Lack of awareness about changing climate conditions hinders our ability to adapt accordingly.

A few recent studies have advanced our understanding of individuals' and firms' expectations regarding the impact of weather and climate on their adaptation decisions. Weather realizations only provide a noisy signal of the climate state. Observing repeated evidence in the form of repeated weather realizations can lead the individual to update their beliefs about the underlying climate distribution, which then leads them to reoptimize investments and actions to maximize welfare under the new climate distribution. The adjustment rate of individuals through adaptive responses is thus constrained by inferring changes in the underlying climate distribution through weather signals (Kelly et al., 2005) and the cost and the rate of adjustment depend on the accuracy of beliefs about the state of the climate distribution. Adjustment costs do not depend on the learning process only as long as agents acquire knowledge from weather conditions and adjust their expectations regarding the climate distribution (Moore, 2017).

A smaller number still of studies rely on observational data on individual climate beliefs. One of the few exceptions finds that Indian farmers are averse to ambiguity and change planting dates in response to changes in the onset of the monsoon, particularly so in villages that have experienced greater changes to the rainfall distribution recently (Kala, 2017). Shrader (2023) finds large benefits of forecasts in adaptation to El Niño-Southern Oscillation (ENSO) variation for albacore tuna harvesters in the North Pacific US. Chapter 3 in this dissertation explores individual-level changes in beliefs over time to understand the climate belief formation process and cognitive biases in a setting where timely adaptation is extremely important.

Lastly, other work has looked at how expectations about climate change are priced in the market, in particular, real estate markets and municipal bonds capitalize sea level rise (Bernstein et al., 2019), while temperatures are capitalized in weather derivatives (Schlenker and Taylor, 2021) and land markets (Severen et al., 2018). These studies suggest that individuals - at least partially - recognize the non-stationarity of climate. Using past observations of weather to estimate the climate distribution may result in a biased estimate of climate change impacts since these forward-looking outcomes already capture expectations of future climate damages. Ideally, one would use individuals' beliefs about the weather distribution to measure climate impacts (Kolstad and Moore, 2020). Chapter 2 demonstrates the importance to account for individual beliefs. Moving forward, climate economics can benefit immensely from leveraging the progress made in the design of surveys to elicit otherwise invisible factors such as perceptions, knowledge and beliefs, attitudes, and reasoning (Stantcheva, 2022).

Adapting to Climate Change

Climate losses could be avoided, in theory, if populations fully adapted to the changing dimensions of their climate. Individual choice, markets, and technological innovation can help shield us from climate risk (see Kahn (2016) for a review). Yet, climate conditions continue to play an important role in shaping modern society due to persistent *adaptation gaps* (Carleton and Hsiang, 2016). A number of different dimensions of adaptation gaps have been examined to understand why populations differ so much in adaptive behavior across geographical and temporal contexts. The adaptation gaps include weak incentives to adapt (Annan and Schlenker, 2015), limited access to credit (Burgess et al., 2014), limited market competition (Kochhar and Song, 2023), limited information about benefits (Hornbeck, 2012), access to technologies (Olmstead and Rhode, 2011), trade barriers (Nath, 2020), and institutional constraints (Ospital, 2023). An approach to detect adaptation is the explicit measurement of outcomes that are themselves thought to be adaptations, such as investing in irrigation after a drought, as studied in Chapter 2. An alternative approach measuring adaptation implicitly can be obtained by observing the response functions that link climate to social and economic outcomes. Populations that adapt more will have a flatter damage function.

Different methodologies exist to implicitly measure climate change adaptation, each with its own advantages and disadvantages (Massetti and Mendelsohn, 2018). Studying climate adaptation requires confronting the “frequency-identification” trade-off (Hsiang and Burke, 2014). On the one hand, using high-dimensional fixed effects to account for unobserved omitted variables enhances the internal validity and allays concerns about the endogeneity of the residual short-run variation in weather. On the other hand, using cross-sectional variation allows to estimate the long-run equilibrium response to climate change which accounts for adaptation. High-frequency shocks used in the first case are more likely to be unexpected and exogenous and thus measure impacts *net* of adaptation, whereas low-frequency shocks are more likely to shift beliefs and expectations and account for adaptive responses. Short-run and long-run elasticities are equal only under certain assumptions (Lemoine, 2021). In between these two extremes of approaches, a few recent methodological advancements have proposed the combination of both short- and long-run variation in panel data in order to improve estimates of climate change damages (see Kolstad and Moore (2020) for a review).

The first approach entails the estimation of the heterogeneous marginal effect of weather as a function of climate, which implies a nonlinear response function. Two co-existing methods have been adopted to estimate these heterogeneous marginal effects. Both methods require panel data to exploit both interannual weather variability across multiple locations and climate differences across locations. The first methodology uses non-linear panel models and conditions the marginal effect of weather to vary with climate across locations (Heutel et al., 2021). If adaptation

changes the marginal response to short-run weather variations, then these adaptation margins are captured in the panel estimates. Other relevant dimensions of adaptation, such as income, can be used in a symmetric manner (Carleton et al., 2022). The second methodology is a multistage model that first estimates the short-run elasticity to weather for each location and then models the coefficient on weather as a function of climate (Auffhammer, 2022).

A second approach uses long-run changes in weather conditions - so-called “long differences” - to exploit variation in long-term temperature and precipitation trends. Exploiting longer-term climate fluctuations provides a better estimate of how agents will respond to climate change (Burke and Emerick, 2016; Liu et al., 2023) and comparing long-term with short-term elasticities to weather can provide evidence on adaptation. An attenuated impact of extreme temperatures when moving from an annual panel specification to a long difference would provide suggestive evidence of adaptation. While partially accounting for adaptation, this approach relies on across-location variation in weather conditions and locations warming more may be systematically different from locations that warm less.

A third approach is to use the differences in the impacts between slow-moving changes in temperature and short-run shocks estimated in the same equation to quantify the extent of adaptation, as recently shown to quantify the impact of temperature changes on atmospheric ozone concentration to detect adaptation (Bento et al., 2023). This approach, similar in spirit to partitioning variation exercises (Mérel and Gammans, 2021), which jointly estimate the effects of both long- and short-run variation, shares typical problems on the ability to measure long-term climate and differentiate it from unexpected exogenous shorter-run variation. Given the non-stationarity of climate, this is particularly difficult when individuals’ beliefs are not observed as usually is the case. Chapter 2 discusses this issue more in detail and showcases the consequences of not accounting for beliefs.

In a fourth and last approach, climate economics has applied recent advances in machine learning techniques to identify which weather variables are quantitatively important in determining economic outcomes, rather than relying on particular functional forms or weather variables. This approach has already been implemented to estimate how weather shocks impact crop yields (Hultgren et al., 2022) and GDP (Akyapi et al., 2022). The methodology has the benefit of not relying on the researcher to specify ex-ante the correct functional form of the relationship between weather and the outcomes and could be applied in the future to many other settings.

Climate Concern and Support for Climate Policies

Accurate quantification of climate impacts plays a crucial role in formulating today’s policies and facilitating an effective approach to adaptation, which necessitates strategic planning and timely investments. In order for the markets to internalize

these costs and potential benefits through public policy measures and traditional policy instruments, such as carbon taxes or tradable emission allowances, it is essential to accurately estimate them.

Many young people are deeply concerned about climate change. Inspired by environmental activists and global climate demonstrations, they seek to hold elected officials accountable for their slow carbon mitigation efforts. One optimistic scenario is that as new generations continue to emphasize more and more the climate change challenge, a political shift could occur over time (Kahn, 2021).

Despite this growing concern in numerous countries regarding climate change and people's willingness to take action (Dechezleprêtre et al., 2022; Douenne and Fabre, 2020), the climate policy agenda is struggling to move forward and disagreements regarding the methods to address the issue continue to exist. Only a limited number of governments worldwide have implemented a carbon price. The difficulty lies in designing a policy proposal that effectively prices carbon emissions while also protecting the real incomes of individuals working in the fossil fuel sector, those with assets tied to fossil fuel use, and those who rely on fossil fuels for their daily lives. These individuals would experience short-term losses from the introduction of carbon pricing incentives and have thus resisted the implementation of these policies (Douenne and Fabre, 2022).

Advancing climate policy agendas requires public awareness and support for parties proposing pro-environment policy platforms. For this reason, it is crucial to understand the drivers of climate concern and attitudes. In spite of a growing literature that examines the role of socio-demographic correlates, such as gender, age, education, or political orientation (Dechezleprêtre et al., 2022; Czarnek et al., 2021; Duijndam and van Beukering, 2021) and the role of personal experience of local extreme events (Hazlett and Mildemberger, 2020; Hoffmann et al., 2022), the effect of socio-economic climate impacts on climate concern is still unexplored. Chapter 4 provides new evidence in this regard testing for the role of climate-induced migration.

Outline of the dissertation

The four essays in this dissertation propose new perspectives to advance our understanding of climate impacts on economic and social outcomes. Instead of estimating the reduced-form impact of weather variations, the essays focus on understanding the channels and mechanisms through which climate change could have an effect so as to better inform and implement policy to mitigate and adapt to future impacts. The dissertation focuses on the channels through which weather affects economic outcomes (through global supply chains, inaccurate beliefs, and cognitive biases) to provide insights into how climate change could affect economic outcomes in the future. Furthermore, this dissertation turns the attention towards the role that the

social and economic consequences of climate change have on individual climate concern and public support for climate policies, diverting from previous research that only focuses on the role of individual socio-demographic characteristics or climate-related hazards.

To address the research questions in the chapters, the dissertation applies various reduced-form econometric methods guided by economic theory and combines multiple sources of variation to a wide range of observational data sets, including individual small- and large-scale surveys, national accounts, input-output matrices, gridded climate data, structured text data, and geolocalized satellite data.

Below, I provide a brief summary of each essay and the particular data settings and methodologies which allow me to explore questions on climate change adaptation, beliefs, impacts, and concern.

Chapter 1: Sectoral impact and propagation of weather shocks

The first chapter, *Sectoral impact and propagation of weather shocks*, introduces the importance of global supply chains and the role of input-output sectoral interlinkages as a transmission mechanism of weather shocks in a production network model. The chapter sets out to explore how sectoral economic activity over the world is heterogeneously affected by local weather shocks, as well as indirectly by distant weather shocks through supply chain networks. Exploiting input-output sectoral interlinkages, I construct a measure of domestic and foreign exposure to weather shocks, distinguishing between upstream and downstream propagation, and estimate both the effect of local direct and linkage indirect effect of weather on the economic activity of sectors all over the world between 1975 and 2020. First, I find that agriculture is the most harmed sector by a range of weather shocks, including hot and cold days, droughts, and cyclones. Second, I document that production in sectors at later stages of the supply chain (construction; mining and manufacturing; wholesale and retail trade; transport; other activities), although not significantly affected by local weather fluctuations, is strongly damaged by hot-temperature shocks that hit the agricultural sector and propagate downstream through the supply chain, inducing persistent losses over time. Using counterfactual scenarios, I show that the average global annual economic cost of temperature increases accounting for shocks across trade partners since 2000 is 0.33% of GVA, much larger than the 0.1% loss obtained by omitting sectoral interlinkages. I also characterize global losses in different scenarios and document a strong positive gradient with the importance of the countries in the production network. These results suggest that localized weather-related productivity shocks can have significant economic effects across countries and over time, and if we fail to account for the interconnectedness of sectors we may substantially underestimate the consequences of short-run weather and future climate change on economic activity.

Contributions

The main contribution of this chapter is to unveil a new channel of the impact of weather shocks on the economy. The growing climate impact literature has so far only studied the effect of local weather shocks on local economic activity (Dell et al., 2012; Kalkuhl and Wenz, 2020; Burke et al., 2015b). This paper sets out a simple conceptual framework for the importance of accounting for sectoral interlinkages. Neglecting the interconnections among sectors while weather shocks are spatially correlated leads to violations of common identifying assumptions, by violating the stable unit treatment value assumption. In contrast to previous papers examining the transmission of shocks on the economy (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Boehm et al., 2019), the empirical analysis conducted in this chapter has a global coverage of sectors over 45 years instead of using firm-level micro-data and exploits interannual variations in the number of days above country-specific percentiles of temperature and precipitation distributions instead of natural disaster events. This chapter also adds to the climate impact literature with a top-down approach using measures of economic activity, by providing new evidence on the heterogeneous impacts of a variety of weather shocks on sectoral economic activity, using the most sectorally disaggregated comprehensive data.

Chapter 2: Adapting to climate change accounting for individual beliefs

The second chapter, *Adapting to climate change accounting for individual beliefs*, relaxes one of the key assumptions in the climate impact and adaptation literature that relies on perfect information and optimal beliefs. I introduce a theoretical framework of inattention to characterize a behavioral friction driving the wedge between expected profits for a rational farmer and a behavioral farmer with inaccurate beliefs, deriving the conditions under which beliefs differentially influence the responsiveness to meteorological changes. Using a panel survey of rural households in Bangladesh combined with a meteorological measure of dryness, I empirically test the implications and find heterogeneous responses in the use of irrigation as a function of beliefs, which drive more irrigation only in drier locations. Farmers' inaccurate priors asymmetrically drive irrigation response to dryness shocks. I also explore various alternative cognitive channels and provide evidence of salience, recall errors, and overreaction driving irrigation decisions. In a counterfactual analysis where I compare observed beliefs with beliefs based on meteorological conditions, I document that farmers underuse irrigation and incur substantial financial losses as a result of inaccurate beliefs, generating a *belief gap*.

Contributions

This chapter contributes to the climate impact and adaptation literature in several ways. It theoretically shows the importance of accounting for individual beliefs and allowing for inaccuracy in beliefs. There is a large number of *adaptation gaps* (Carleton and Hsiang, 2016), including financial and technological constraints, that may prevent individuals from optimally adjusting their input use in response to changes in weather. The conventional climate impact and adaptation models, however, assume that agents are rational and hold beliefs that optimally adjust in response to weather signals (Hsiang, 2016; Deryugina and Hsiang, 2017). This chapter for the first time uses panel data on individual-level beliefs about climate to explore the differential effect of exposure to dryness on irrigation use by individual beliefs. By focusing on Bangladesh, one of the countries most exposed to climate risk, this chapter sheds light on a critical new angle of determinants of climate adaptation that has never been studied before.

Chapter 3: Drought exposure and accuracy: Motivated reasoning in climate change beliefs

The third chapter, *Drought exposure and accuracy: Motivated reasoning in climate change beliefs*, uses the same panel data of rural households in Bangladesh to study more closely the determinants and the climate belief formation process. Once the importance of climate beliefs for adaptation is demonstrated, this chapter further investigates the determinants of them and whether individuals exhibit cognitive biases. Studying the effect of long-term average drought exposure and short-term deviations on drought beliefs, I find that beliefs are based on long-run exposure and do not systematically differ by short-run deviations. To explore how individuals interpret past droughts, I adopt an instrumental variable approach and investigate whether individual beliefs lead to asymmetric distortion of objective information. The results show that individuals recollect and overweight evidence tilted towards their prior beliefs. Holding beliefs that droughts have increased has a strong positive effect on the probability and extent of overestimating the number of droughts. These results provide evidence of confirmation bias as a directional motivated reasoning mechanism.

Contributions

This chapter makes several contributions to the climate impacts and adaptation literature. It is the first paper that provides empirical evidence on the determinants of climate beliefs in a developing country, focusing on slow-onset environmental changes. This is particularly important in Bangladesh, where climate change awareness has been low (Rzepa and Ray, 2020). The only other paper that studies climate belief formation does not exploit within-individual variation in beliefs and is set in

the US (Deryugina, 2013). The chapter also contributes to the understanding of cognitive biases associated with climate change beliefs, previously only theoretically formulated (Druckman and McGrath, 2019), and specifically, it tests the confirmation bias hypothesis in a developing country context. By employing an instrumental variable approach to address endogeneity concerns, the chapter establishes a causal relationship between beliefs and the distortion of information from weather events. The findings of this chapter emphasize the need to account for behavioral factors and cognitive biases in climate change belief formation to design effective adaptation policies.

Chapter 4: Climate-induced migration and environmental values

The fourth chapter, *Climate-induced migration and environmental values*, is devoted to studying the determinants of climate concern and pro-environment voting behavior. The paper investigates the relationship between weather-induced asylum applications, individual climate concern, and voting behavior for Green parties in the European Union. It introduces weather-induced migration from non-OECD countries as a novel determinant of climate concern and examines its impact on public attitudes and electoral choices. Using data from 2000 to 2019, the chapter employs an instrumental variable approach exploiting exogenous variations in weather to estimate the causal effect of weather-induced asylum demands. The results reveal that weather-induced asylum applications heighten concern about climate change as a political priority among individuals. However, these changes in climate concern do not translate into changes in voting behavior for Green parties in the European Parliament elections, indicating a disconnect between stated preferences and actual electoral choices.

Contributions

The main contribution of this chapter relates to the analysis of the determinants of climate concerns. There is a growing literature that examines the role of socio-economic drivers, such as gender, education, political orientation (see Drews and van den Bergh (2016) for a review), and the impact of direct experiencing extreme events (Hazlett and Mildenerger, 2020; Hoffmann et al., 2022). This chapter expands the understanding of climate concern by considering weather-induced migration as an influential factor. This novel determinant highlights the role of distant weather anomalies through exposure to migration inflows in shaping climate concern. The chapter demonstrates that weather-induced asylum applications increase individual climate concern, particularly among right-wing voters. This finding underscores the complex relationship between climate change, migration, and political ideologies, in contrast with previous findings on right-wing ideology, that for instance moderates the effects of education on climate beliefs (Czarnek et al., 2021).

The chapter examines the gap between climate concern and voting behavior, revealing that the increased concern does not lead to changes in support for Green parties in European Parliament elections. This highlights the importance of considering other factors, such as the dropout of traditional Green voters and preferences among individuals below the voting age. By estimating the impact of weather variations on asylum demands in the European Union, this chapter contributes to the understanding of the relationship between climate and migration (Missirian and Schlenker, 2017b; Abel et al., 2019; Cai et al., 2016; Cattaneo and Peri, 2016). Overall, the paper enhances our understanding of the drivers of climate concern and sheds light on the complexities of translating concern into meaningful political climate action.

Introduction Générale

Climat et société

Le climat et la société partagent une relation indissoluble depuis l'Antiquité. L'interaction entre le climat et les sociétés humaines a façonné le cours de l'histoire, influençant les croyances et les actions des individus et des communautés à travers le monde. Les changements environnementaux mondiaux ont caractérisé diverses époques, en tant que processus historiques exogènes auxquels les sociétés ont été exposées et ont été forcées de repenser leurs moyens de subsistance et leur mode de vie.

Les principales transformations structurelles de la société ont suivi les changements climatiques de l'époque. L'homme est l'enfant de la période glaciaire: ce n'est que lorsque le froid intense de la dernière période glaciaire a commencé à s'atténuer que l'agriculture a débuté, et l'urbanisation a suivi (Behringer, 2010). Aussi paradoxal que cela puisse paraître, le réchauffement du climat a contribué à la création de l'humanité. Des transformations majeures similaires ont suivi, soulignant la capacité innée de l'homme à s'adapter: d'une vie nomade à une vie sédentaire ; de la chasse à l'agriculture et à l'élevage; de trocs et échanges matériels à un monde interconnecté avec des chaînes d'approvisionnement mondiales fragmentées comprenant des liens commerciaux et financiers.

À court terme, les émissions mondiales de gaz à effet de serre continuent d'augmenter à mesure que le revenu mondial par habitant s'accroît. À la lumière de cette relation étroite et complexe, le changement climatique anthropique et le rythme de plus en plus rapide des changements dans les fluctuations météorologiques et dans la fréquence, l'intensité, la durée, la temporalité et la distribution spatiale des événements météorologiques extrêmes constituent l'un des défis les plus urgents et les plus difficiles à relever pour la société humaine et les écosystèmes (IPCC, 2021). Si, d'une part, l'augmentation des revenus sera bénéfique pour des milliards de personnes dans les pays en développement, d'autre part, compte tenu des technologies actuelles, les émissions exacerberont le défi du changement climatique, ce qui rendra l'adaptation encore plus importante pour garantir les améliorations futures du niveau de vie des populations.

Alors qu'un certain nombre d'efforts sont déployés pour parvenir à des accords internationaux sur l'environnement et réduire les émissions de gaz à effet de serre, étant donné que les répercussions des phénomènes météorologiques extrêmes sur la société sont déjà tangibles, l'attention se tourne de l'atténuation vers l'adaptation et les stratégies de survie pour les individus, les entreprises, les gouvernements et, en général, la société humaine, afin de comprendre comment nous pouvons changer nos vies à mesure que le défi du changement climatique s'aggrave.

Le lien entre les changements environnementaux et le bien-être humain intrigue depuis longtemps les économistes et autres chercheurs en sciences sociales. Toutefois, ce n'est que récemment que la recherche a connu une croissance exponentielle dans l'étude de cette relation. Cela peut être attribué à l'importance croissante du changement climatique en tant que préoccupation politique majeure, aux progrès des outils statistiques et économétriques pour l'inférence causale dans les études non expérimentales, et aux progrès de l'informatique et de la climatologie, qui ont amélioré notre capacité à attribuer les dommages aux variations climatiques. La réponse à ces questions revêt une connotation extrêmement pertinente pour concevoir des politiques d'atténuation et d'adaptation plus strictes et plus ciblées et pour sensibiliser le public au changement climatique et obtenir son soutien pour les politiques climatiques.

Intégrer le climat dans l'économie

Pour évaluer l'externalité climatique mondiale, les économistes du climat ont concentré leurs efforts sur l'estimation des dommages de cette externalité. Traditionnellement, les dommages climatiques ont été calculés de modèles théoriques et numériques d'évaluation intégrée (IAMs). Les efforts initiaux de développement d'un modèle climat-économie incorporant les émissions de gaz à effet de serre de l'économie, le cycle du carbone et une fonction de dommages liés au changement climatique dans un modèle de croissance économique ont conduit à la reconnaissance du prix de la Banque de Suède en sciences économiques en mémoire d'Alfred Nobel en 2018 (Nordhaus, 1992). Les résultats de ces modèles sont ensuite convertis en chiffres monétaires pertinents pour les politiques à l'aide du coût social du carbone (SCC), qui représente la valeur actuelle nette des dommages futurs causés par l'émission d'une tonne supplémentaire de CO₂ (Waldhoff et al., 2014; Nordhaus, 1993a,b). Pour faire le lien entre les systèmes économiques et naturels, ces modèles utilisent des fonctions de dommages théoriques qui décrivent comment la température moyenne mondiale se traduit en coûts économiques et sociaux (Revesz et al., 2014). Bien qu'ils servent à combiner les domaines économiques et naturels dans un cadre unique, les résultats des calculs de ces modèles reposent fortement sur des hypothèses de modélisation qui ne reflètent souvent pas bien la dynamique du changement climatique (Pindyck, 2013; Weitzman, 2010). Malgré les efforts déployés pour faire progresser la

dynamique du climat et intégrer la science climatique dans les modèles économiques (Dietz et al., 2021), les modèles récents s'appuient toujours sur des fonctions simplifiées de dommages climatiques qui supposent que l'augmentation de la température moyenne à la surface du globe par rapport aux niveaux préindustriels est une statistique suffisante raisonnable pour les dommages par une relation non linéaire (quadratique) et en omettant toute autre variante météorologique, les effets cumulatifs ou les effets dépendant de la vitesse des changements (Barrage and Nordhaus, 2023). Ces modèles - et les estimations du SCC qui en résultent - supposent que les augmentations de température ont toujours le même effet, ce qui suppose qu'il n'y a pas d'adaptation. En outre, ils ne tiennent pas compte des impacts hétérogènes et inégaux dans l'espace.

Par opposition aux exercices théoriques et numériques, l'intérêt s'est porté plus récemment sur les approches statistiques qui utilisent des données historiques et estiment la relation dans des contextes réels. La science du climat a énormément progressé dans la compréhension des variations climatiques historiques à long terme, des prévisions météorologiques à court terme et des modèles de prévision climatique. Ces données et modèles peuvent aider à répondre à toute une série de questions ayant des implications importantes pour l'économie, à la fois en termes de compréhension de la relation historique entre la société et le climat, et de la manière dont cette relation peut évoluer à l'avenir. La combinaison d'ensembles de données provenant des sciences physiques et sociales et des progrès méthodologiques récents en matière d'inference causale a contribué à fournir des estimations basées sur des données de relations hautement pertinentes pour les politiques entre le bien-être humain et les changements climatiques.

Mesurer les impacts climatiques

Les premières études estimant les dommages économiques associés au changement climatique ont utilisé la variation transversale du climat (se produisant à un moment donné) pour estimer l'effet économique marginal des changements à long terme dans la distribution des températures et des précipitations (Mendelsohn et al., 1994). Néanmoins, la "credibility revolution" en économie empirique (Angrist and Pischke, 2010) a rapidement imprégné le domaine de recherche de l'économie de l'environnement et stimulé la naissance d'un domaine de recherche à part entière souvent défini comme "climate econometrics" (Hsiang, 2016). Cette littérature émergente utilise des données météorologiques, qui varient dans l'espace et dans le temps, pour estimer les effets de la variation interannuelle des conditions météorologiques sur les résultats économiques et sociaux tout en tenant compte des variables omises, pour lesquelles il n'est pas possible de contrôler à l'aide de données transversales (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). De nombreuses études entraînées par la "credibility revolution" ont utilisé des données de meilleure

qualité et des techniques économétriques pour découvrir des liens de causalité entre les changements climatiques et un large éventail de résultats sociaux (voir Dell et al. (2014) et Carleton and Hsiang (2016) pour des revues de cette littérature). Ces études s'appuient sur des données observationnelles pour obtenir des fonctions de dommages climatiques et combler le vide méthodologique laissé par l'impossibilité d'attribuer d'une façon aléatoire le climat à deux échantillons de population identiques en tous points.

Une description complète des canaux potentiels des effets climatiques est cruciale pour formuler une politique climatique optimale. L'estimation empirique des effets socio-économiques du climat peut être divisée en deux grandes catégories. D'une part, les approches "bottom-up" se concentrent sur les dommages marchands et non marchands spécifiques à un secteur, représentant différents secteurs de l'économie, y compris la santé humaine, les conditions économiques et les interactions sociales. Dans ce contexte, il existe des quantifications de l'impact des variations de température dans de nombreux domaines, notamment la mortalité (Heutel et al., 2021; Barreca et al., 2015), l'agriculture et le rendement des cultures (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009), la consommation d'électricité (Wenz et al., 2017; Auffhammer et al., 2017), la productivité du travail (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018), le capital humain (Fishman et al., 2019), les conflits (Hsiang et al., 2011; Hsiang and Jina, 2014), la criminalité (Ranson, 2014), la santé mentale (Obradovich et al., 2018), le sommeil (Minor et al., 2022; Obradovich et al., 2017), la profanité et la haine (Stechemesser et al., 2021; Baylis, 2020). D'autre part, les approches "top-down" considèrent des mesures agrégées de la production économique, telles que le PIB ou la production économique régionale, et leur réponse aux variations de température (Dell et al., 2012; Burke et al., 2015b; Kalkuhl and Wenz, 2020; Acevedo et al., 2020; Kahn et al., 2021). Si la première approche présente l'avantage de fournir des fonctions de réponse précises et spécifiques au secteur aux fluctuations météorologiques, la seconde devrait théoriquement rendre compte de tous les effets du changement climatique sur le marché. Les deux approches présentent toutefois certaines limites, que je détaille ci-dessous.

Tout d'abord, les études empiriques sur les effets du climat s'appuient sur un cadre bien défini pour étudier ces effets avec des hypothèses restrictives (Hsiang, 2016; Deryugina and Hsiang, 2017). Cette thèse (dans les chapitres 1, 2 and 3) fournit des arguments théoriques et empiriques sur le caractère restrictif de certaines hypothèses, qui reposent sur une information parfaite et une rationalité complète (Arrow and Debreu, 1954). Plus important encore, on craint depuis longtemps que l'effet des variations météorologiques interannuelles sur les résultats économiques ne puisse être utilisé pour identifier l'effet du changement climatique. La réaction aux fluctuations météorologiques à court terme est fondamentalement différente de la réaction aux changements climatiques permanents. Les individus et les entreprises

réagiraient différemment à des changements permanents dans la distribution attendue des conditions météorologiques (c'est-à-dire le climat) qu'à des variations météorologiques inattendues à court terme. Ce n'est que si l'adaptation n'était pas importante que l'effet des fluctuations météorologiques serait une bonne approximation de l'effet d'un changement permanent du climat.

Deuxièmement, de nombreux domaines sont touchés par les effets du climat, et toute agrégation d'estimations sectorielles peut être incomplète et ne fournir que des mesures partielles du SCC. Différentes réponses marchandes et non marchandes n'ont pas encore été étudiées. De même, bien que les modèles empiriques et les nouvelles sources de données permettent aux chercheurs d'explorer divers chocs météorologiques, la plupart des études ont jusqu'à présent été axées sur les effets de la température et des travaux récents ont commencé à étudier plus en profondeur l'effet des précipitations (Kotz et al., 2022), des cyclones (Hsiang and Jina, 2014), des inondations (Gandhi et al., 2022; Kocornik-Mina et al., 2020), du ruissellement de l'eau (Russ, 2020), et les incendies de forêt (Heft-Neal et al., 2023). Le changement climatique affecte les moments de la distribution de plusieurs événements météorologiques, dont l'impact sur de nombreux autres résultats sociaux et économiques est encore peu étudié.

Troisièmement, les estimations partielles ne tiennent pas compte des interactions entre les secteurs et les régions. Les interactions spatiales et sectorielles peuvent entraîner un double comptage lors de l'agrégation des secteurs et il faut tenir compte de la covariance des impacts entre les secteurs pour obtenir la distribution des dommages agrégés. Plus important encore, ces interactions peuvent fausser l'allocation efficace des ressources pour les politiques d'intervention gouvernementale spécifiques au secteur. Contrairement aux modèles théoriques et numériques des dommages climatiques, les études empiriques sectorielles n'abordent pas le "feedback" entre l'économie et le climat. Cette limitation s'applique aux flux de population et de marchandises (Cruz and Rossi-Hansberg, 2023; Costinot et al., 2016) et à la réallocation sectorielle endogène (Nath, 2020), qui ne sont généralement pas pris en compte dans les études empiriques de forme réduite et qui ne sont étudiées que dans le cadre de l'équilibre général spatial. Le chapitre 1 de cette thèse fournit une estimation empirique de l'importance de prendre en compte les liens sectoriels même dans une approche descendante de forme réduite.

Enfin, les études des effets socio-économiques du climat exploitent les variations à court terme des variables météorologiques pour identifier l'effet sur les résultats économiques et sociaux. On ne sait pas encore très bien comment l'économie du bien-être liée au changement climatique évoluerait en fonction d'événements physiques sans précédent et d'irréversibilités climatiques potentielles, telles que les points de basculement.

Plus récemment, dans un effort pour reconstruire les fonctions dose-réponse avec une couverture mondiale, dans un certain nombre d'études, le Climate Impact Lab

fait des estimations des dommages climatiques partiels marchands et non marchands en tenant compte des non-linéarités locales et en comptabilisant les coûts et avantages de l'adaptation dans divers domaines, y compris la mortalité (Carleton et al., 2022), la demande d'énergie et d'électricité (Rode et al., 2021), l'offre de travail (Rode et al., 2022), l'agriculture et les rendements des cultures (Hultgren et al., 2022). La combinaison de ces estimations sectorielles peut permettre d'obtenir une dérivée plus précise et fondée sur des données du SCC (Nath et al., 2022).

Bien que toutes ces études aient une forte validité interne en raison de l'attention rigoureuse portée à la stratégie d'identification dans l'analyse empirique, des questions se posent quant à la pertinence des effets des chocs météorologiques idiosyncrasiques pour informer des impacts futurs des changements climatiques qui, entre autres, sont corrélés dans l'espace et ne sont pas toujours parfaitement observables par les individus. Les chapitres de cette thèse s'appuient largement sur cette littérature empirique récente. Néanmoins, la thèse s'écarte des travaux antérieurs à la fois par le type de questions abordées et par plusieurs dimensions méthodologiques.

Comprendre le climat et former des espérances

Un débat permanent en économie porte sur la manière dont les gens comprennent et interprètent les événements passés et sur la manière dont ils forment des attentes quant à la probabilité d'événements futurs. L'école néoclassique des anticipations rationnelles émet l'hypothèse que les individus utilisent toutes les informations dont ils disposent pour évaluer la probabilité d'un événement futur. Les gens ont tendance à utiliser les informations dont ils disposent pour former leurs croyances et à converger vers un vrai postérieur. Ces hypothèses ont été largement contestées dans le domaine de l'économie comportementale, qui soutient que les gens sont enclins à commettre des erreurs cognitives. Ces innovations ont été si importantes qu'elles ont conduit à l'attribution du prix de la Banque de Suède en sciences économiques en mémoire d'Alfred Nobel en 2002 (Kahneman and Tversky, 1979) et en 2017 (Thaler, 2015). En associant l'économie à la psychologie, des modèles plus réalistes du comportement humain ont intégré de nouveaux traits psychologiques, notamment les anomalies comportementales, la rationalité limitée et les biais cognitifs (Kahneman and Tversky, 1973, 1982).

Alors que les travaux théoriques et empiriques en psychologie et en économie comportementale suggèrent que ces hypothèses sont souvent injustifiées, les modèles économiques en économie du climat supposent toujours que les agents sont parfaitement informés et ont des croyances impartiales expliquées entièrement par les conditions météorologiques. Pour clarifier le rôle des croyances et des attentes, je résume le cadre conceptuel sous-jacent qui guide les modèles d'impact et d'adaptation climatiques (Hsiang, 2016).

Le climat \mathbf{C} est défini comme le vecteur à haute dimension des paramètres qui décrivent la distribution de probabilité conjointe des conditions météorologiques possibles susceptibles de se produire au cours d’un intervalle de temps spécifique. Les réalisations météorologiques \mathbf{c} sont un vecteur aléatoire tiré de la distribution climatique. Un “outcome” socio-économique d’intérêt Y est influencé par le climat de deux manières. Premièrement, le climat influe directement sur les conditions météorologiques \mathbf{c} qui se produisent réellement et qui affectent la population. Deuxièmement, les croyances des individus sur la structure du \mathbf{C} peuvent être modifiées par un changement du climat, affectant leurs actions et les résultats qui en découlent. Ces deux canaux sont respectivement définis comme l’effet *direct* et l’effet des *croyances*. Les individus agissent en fonction de leurs croyances \mathbf{b} , de sorte que la relation entre le résultat et le climat peut être modélisée comme suit

$$Y = f(\mathbf{b}(\mathbf{C}); \mathbf{c}(\mathbf{C})) \quad (3)$$

Ce cadre suppose que les agents disposent d’informations parfaites sur le climat dans lequel ils vivent et que l’effet de croyance reflète l’adaptation en tant que comportement d’optimisation de l’agent. Si l’on considère un simple problème de maximisation d’un individu (ou d’une entreprise) représentatif, par exemple les bénéfices attendus π , cela s’écrirait comme suit

$$\max_{\mathbf{b}} \mathbb{E}(\pi) = \mathbb{E}[f(\mathbf{b}, \mathbf{c}) - g(\mathbf{b})] \quad (4)$$

où \mathbf{b} est le vecteur des actions que l’individu peut entreprendre, et \mathbf{c} est le vecteur des conditions météorologiques stochastiques, compte tenu d’une fonction $f(\cdot)$ deux fois continuellement différentiable et concave, d’un prix de production normalisé à un, et d’une fonction de coût $g(\cdot)$ convexe dans les actions. De la solution de ce problème d’optimisation, il découle que l’adaptation est la réponse comportementale des individus aux changements attendus des conditions météorologiques $\mathbb{E}[\mathbf{c}]$. Les attentes concernant le climat à long terme sont à l’origine d’investissements coûteux visant à se protéger contre une exposition croissante à des conditions défavorables. Ce cadre théorique montre à quel point il est important de comprendre comment les individus forment leurs attentes à l’égard du climat pour mesurer l’adaptation et donc quantifier avec précision les effets du climat. La méconnaissance de l’évolution des conditions climatiques entrave notre capacité à nous adapter en conséquence.

Seules quelques études ont permis de mieux comprendre les attentes des individus et des entreprises concernant les effets des conditions météorologiques et climatiques sur leurs décisions d’adaptation. Les réalisations météorologiques ne fournissent qu’un signal bruyant de l’état du climat. L’observation de preuves répétées sous la forme de réalisations météorologiques répétées peut conduire l’individu à mettre à jour ses croyances sur la distribution climatique sous-jacente, ce qui l’amène ensuite à réoptimiser ses investissements et ses actions afin de maximiser le bien-être dans

le cadre de la nouvelle distribution climatique. Le taux d'ajustement des individus par le biais de réponses adaptatives est donc limité par l'inférence de changements dans la distribution climatique sous-jacente par le biais de signaux météorologiques (Kelly et al., 2005) le coût et le taux d'ajustement dépendent de l'exactitude des croyances sur l'état de la distribution climatique. Les coûts d'ajustement ne dépendent pas uniquement du processus d'apprentissage tant que les agents acquièrent des connaissances à partir des conditions météorologiques et ajustent leurs attentes concernant la distribution du climat (Moore, 2017).

Un nombre encore plus restreint d'études s'appuient sur des données d'observation concernant les croyances individuelles en matière de climat. Kala (2017), notamment, montre que les agriculteurs indiens sont réticents à l'ambiguïté et modifient les dates de plantation en réponse aux changements dans l'arrivée de la mousson, en particulier dans les villages qui ont connu récemment des changements plus importants dans la répartition des précipitations. Shrader (2023) constate que les prévisions sont très bénéfiques pour l'adaptation aux variations d'El Niño et de l'oscillation australe (ENSO) des pêcheurs de thon blanc dans le Pacifique Nord des États-Unis. Le chapitre 3 de cette thèse explore les changements de croyances au niveau individuel au fil du temps afin de comprendre le processus de formation des croyances climatiques et les biais cognitifs dans un contexte où l'adaptation en temps opportun est extrêmement importante.

Enfin, d'autres travaux ont examiné la manière dont les attentes concernant les changements climatiques sont intégrées dans les prix du marché, en particulier, le marché immobilier et les obligations municipales capitalisent l'élévation du niveau de la mer (Bernstein et al., 2019), tandis que les températures sont intégrées dans les produits dérivés météorologiques (Schlenker and Taylor, 2021) et les marchés fonciers (Severen et al., 2018). Ces études suggèrent que les individus reconnaissent - au moins partiellement - le caractère non stationnaire du climat et que l'utilisation des observations météorologiques passées pour estimer la distribution du climat peut entraîner une estimation biaisée des impacts du changement climatique, car ces résultats prospectifs reflètent déjà les attentes concernant les dommages climatiques futurs. L'idéal serait d'utiliser les croyances des individus sur la distribution des conditions météorologiques pour mesurer le climat (Kolstad and Moore, 2020). Le chapitre 2 montre qu'il est important de les prendre en compte. Pour aller de l'avant, l'économie du climat peut bénéficier des progrès réalisés dans la conception des enquêtes afin de mesurer des facteurs autrement invisibles tels que les perceptions, les connaissances et les croyances, les attitudes et le raisonnement (Stantcheva, 2022).

Adaptation au changement climatique

Les pertes climatiques pourraient être évitées, en théorie, si les populations s'adaptaient pleinement aux dimensions changeantes de leur climat. Les choix individuels, les

marchés et l'innovation technologique peuvent contribuer à nous protéger des risques climatiques (voir Kahn (2016) pour une revue de la littérature). Pourtant, les conditions climatiques continuent de jouer un rôle important dans le façonnement de la société moderne en raison des *adaptation gaps* (Carleton and Hsiang, 2016). Un certain nombre de dimensions différentes des écarts d'adaptation ont été examinées pour comprendre pourquoi les populations ont des comportements d'adaptation si différents selon les contextes géographiques et temporels. Les *adaptation gaps* comprennent de faibles incitations à s'adapter (Annan and Schlenker, 2015), un accès limité au crédit (Burgess et al., 2014), une concurrence limitée sur le marché (Kochhar and Song, 2023), des informations limitées sur les avantages (Hornbeck, 2012), l'accès aux technologies (Olmstead and Rhode, 2011), des barrières commerciales (Nath, 2020), et des contraintes institutionnelles (Ospital, 2023). Une approche pour détecter l'adaptation est la mesure explicite des résultats qui sont eux-mêmes considérés comme des adaptations, tels que l'investissement dans l'irrigation après une sécheresse, comme étudié au chapitre 2. Une autre approche pour mesurer l'adaptation de manière implicite peut être obtenue en observant les fonctions de réponse qui relient le climat aux résultats socio-économiques. Les populations les mieux adaptées auront une fonction de dommage "plus plate".

Il existe différentes méthodologies pour mesurer implicitement l'adaptation au changement climatique, chacune ayant ses propres avantages et inconvénients (Masseti and Mendelsohn, 2018). L'étude de l'adaptation au climat nécessite de faire face à l'arbitrage "fréquence-identification" (Hsiang and Burke, 2014). D'une part, l'utilisation d'effets fixes à haute dimension pour tenir compte des variables omises non observées renforce la validité interne et dissipe les inquiétudes concernant l'endogénéité de la variation résiduelle à court terme des conditions météorologiques. D'autre part, l'utilisation de la variation transversale permet d'estimer la réaction d'équilibre à long terme au changement climatique, qui tient compte de l'adaptation. Les chocs à haute fréquence utilisés dans le premier cas sont plus susceptibles d'être inattendus et exogènes et mesurent donc les effets *nets* de l'adaptation, tandis que les chocs à basse fréquence sont plus susceptibles de modifier les croyances et les attentes et de tenir compte des réactions d'adaptation. Les élasticités à court et à long terme ne sont égales que sous certaines hypothèses (Lemoine, 2021). Entre ces deux extrêmes des approches, quelques avancées méthodologiques récentes ont proposé de combiner les variations à court et à long terme dans les données de panel afin d'améliorer les estimations des dommages liés au changement climatique (voir Kolstad and Moore (2020) pour une revue de la littérature).

La première approche implique l'estimation de l'effet marginal hétérogène des conditions météorologiques en fonction du climat, ce qui implique une fonction de réponse non linéaire. Deux méthodes coexistantes ont été adoptées pour estimer ces effets marginaux hétérogènes. Les deux méthodes nécessitent des données de panel pour exploiter à la fois la variabilité météorologique interannuelle sur plusieurs

sites et les différences climatiques entre les sites. La première méthode utilise des modèles de panel non linéaires et conditionne l'effet marginal des conditions météorologiques à une variation du climat entre les différents sites (Heutel et al., 2021). Si l'adaptation modifie la réponse marginale aux variations météorologiques à court terme, alors ces marges d'adaptation sont prises en compte dans les estimations du panel. D'autres dimensions pertinentes de l'adaptation, telles que le revenu, peuvent être utilisées de manière symétrique (Carleton et al., 2022). La seconde méthodologie est un modèle à plusieurs étapes qui estime d'abord l'élasticité à court terme aux conditions météorologiques pour chaque lieu, puis modélise le coefficient des conditions météorologiques en fonction du climat (Auffhammer, 2022).

Une deuxième approche utilise les changements à long terme des conditions météorologiques - ce que l'on appelle les "long differences" - pour exploiter les variations des tendances à long terme des températures et des précipitations. L'exploitation des fluctuations climatiques à long terme permet de mieux estimer la manière dont les agents réagiront au changement climatique (Burke and Emerick, 2016; Liu et al., 2023) et la comparaison des élasticités à long terme et à court terme par rapport aux conditions météorologiques peut fournir des preuves de l'adaptation. Un impact atténué des températures extrêmes lorsque l'on passe d'une spécification de panel annuel à une différence longue fournirait des preuves suggestives de l'adaptation. Bien qu'elle prenne partiellement en compte l'adaptation, cette approche repose sur la variation des conditions météorologiques d'un lieu à l'autre et les lieux qui se réchauffent plus peuvent être systématiquement différents des lieux qui se réchauffent moins.

Une troisième approche consiste à utiliser les différences d'effet entre les changements de température à évolution lente et les chocs à court terme estimés dans la même équation pour quantifier l'ampleur de l'adaptation, comme cela a été démontré récemment pour quantifier l'impact des changements de température sur la concentration d'ozone atmosphérique afin de détecter l'adaptation (Bento et al., 2023). Cette approche, similaire dans l'esprit aux exercices de partitionnement de variation (Mérel and Gammans, 2021), qui estiment conjointement les effets des variations à long et à court terme, partagent des problèmes typiques liés à la capacité de mesurer le climat à long terme et de le différencier des variations exogènes inattendues à court terme. Étant donné la non-stationnarité du climat, cela est particulièrement difficile lorsque les croyances des individus ne sont pas observées, comme c'est généralement le cas. Le chapitre 2 aborde cette question plus en détail et montre les conséquences de l'omission des croyances.

Dans une quatrième et dernière approche, l'économie du climat a emprunté les progrès récents des techniques d'apprentissage automatique (*machine learning*) pour identifier les variables météorologiques qui sont quantitativement importantes pour déterminer les résultats économiques, plutôt que de s'appuyer sur des formes fonctionnelles ou des variables météorologiques particulières. Cette approche a déjà été

mise en œuvre pour estimer l'impact des chocs météorologiques sur les rendements des cultures (Hultgren et al., 2022) et le PIB (Akyapi et al., 2022). La méthodologie a l'avantage de ne pas dépendre du chercheur pour spécifier ex ante la forme fonctionnelle correcte de la relation entre les conditions météorologiques et les résultats et pourrait être appliquée à l'avenir à de nombreux autres contextes.

Préoccupations climatiques et soutien aux politiques climatiques

La quantification précise des effets climatiques joue un rôle crucial dans la formulation des politiques actuelles et facilite une approche efficace de l'adaptation, qui nécessite une planification stratégique et des investissements opportuns. Pour que les marchés internalisent ces coûts et avantages potentiels par le biais de mesures de politique publique et d'instruments économiques traditionnels, tels que les taxes sur le carbone ou les systèmes de permis d'émissions négociables, il est essentiel de les estimer avec précision.

De nombreux jeunes sont profondément préoccupés par le changement climatique. Inspirés par les militants écologistes et les manifestations mondiales en faveur du climat, ils cherchent à responsabiliser les élus quant à la lenteur de leurs efforts de réduction des émissions de carbone. Un scénario optimiste veut que les nouvelles générations continuent à mettre de plus en plus l'accent sur le défi du changement climatique et qu'un changement politique se produise au fil du temps (Kahn, 2021).

Malgré la préoccupation croissante de nombreux pays à l'égard du changement climatique et leur volonté d'agir (Dechezleprêtre et al., 2022; Douenne and Fabre, 2020), l'agenda de la politique climatique peine à avancer et les désaccords sur les méthodes à employer pour résoudre le problème persistent. Seul un nombre limité de gouvernements dans le monde a mis en place un prix sur le carbone. La difficulté réside dans la conception d'une proposition politique qui fixe efficacement le prix des émissions de carbone tout en protégeant les revenus réels des personnes travaillant dans le secteur des combustibles fossiles, de celles dont les actifs sont liés à l'utilisation des combustibles fossiles et de celles qui dépendent des combustibles fossiles pour leur vie quotidienne. Ces personnes subiraient des pertes à court terme suite à l'introduction d'incitations à la tarification du carbone et se sont donc opposées à la mise en œuvre de ces politiques (Douenne and Fabre, 2022).

Pour faire avancer les programmes de politique climatique, il faut sensibiliser le public et soutenir les partis qui proposent des plates-formes politiques favorables à l'environnement. C'est pourquoi il est essentiel de comprendre les facteurs qui déterminent les préoccupations et les attitudes à l'égard du climat. Malgré une littérature de plus en plus abondante qui examine le rôle des corrélats sociodémographiques, tels que le sexe, l'âge, l'éducation ou l'orientation politique (Dechezleprêtre et al., 2022; Czarnek et al., 2021; Duijndam and van Beukering, 2021) et le rôle de l'expérience

personnelle des événements extrêmes locaux (Hazlett and Mildenerger, 2020; Hoffmann et al., 2022), l'effet des impacts socio-économiques du climat sur les préoccupations climatiques est encore inexploré. Le chapitre 4 apporte de nouvelles preuves à cet égard en testant le rôle des migrations induites par le climat.

L'objet de cette thèse

Les quatre chapitres de cette thèse proposent de nouvelles perspectives pour faire progresser notre compréhension des effets du climat sur les résultats socio-économiques. Au lieu d'estimer l'impact de forme réduite des variations météorologiques, les chapitres se concentrent sur la compréhension des canaux et des mécanismes par lesquels le changement climatique pourrait avoir un effet afin de mieux informer et mettre en œuvre des politiques visant à atténuer les effets futurs et à s'y adapter. Cette thèse se concentre sur les canaux par lesquels les conditions météorologiques affectent les résultats économiques (par les chaînes d'approvisionnement mondiales, des croyances inexactes et des biais cognitifs) afin de donner un aperçu de la manière dont le changement climatique pourrait affecter les résultats économiques à l'avenir. En outre, cette thèse s'intéresse au rôle que les conséquences socio-économiques du changement climatique ont sur les préoccupations climatiques individuelles et le soutien du public aux politiques climatiques, contrairement aux recherches précédentes qui se concentrent uniquement sur le rôle des caractéristiques sociodémographiques individuelles ou des conditions météorologiques liés au climat.

Pour répondre aux questions de recherche posées dans les chapitres, la thèse applique diverses méthodes économétriques à forme réduite guidées par la théorie économique et combine de multiples sources de variation à un large éventail d'ensembles de données d'observation, y compris des enquêtes individuelles à petite et grande échelle, des comptes nationaux, des matrices d'entrées-sorties, des données climatiques maillées, des données textuelles structurées et des données satellitaires géolocalisées.

Ci-dessous, je présente un bref résumé de chaque article et des paramètres de données et méthodologies particuliers qui me permettent d'explorer les questions relatives à l'adaptation, aux croyances, aux impacts et aux préoccupations concernant le changement climatique.

Chapitre 1: Sectoral impact and propagation of weather shocks

Le premier chapitre, *Sectoral impact and propagation of weather shocks*, présente l'importance des chaînes d'approvisionnement mondiales et le rôle des interconnexions sectorielles entrées-sorties en tant que mécanisme de transmission des chocs météorologiques dans un modèle de réseau de production. Le chapitre vise à explorer la manière dont la production économique sectorielle dans le monde est affectée de manière hétérogène par les chocs météorologiques locaux, ainsi qu'indirectement par

les chocs météorologiques lointains à travers les réseaux de chaînes d’approvisionnement. En exploitant les liens sectoriels entrée-sortie, je construis une mesure de l’exposition nationale et étrangère aux chocs météorologiques, en distinguant la propagation en amont et en aval, et je quantifie l’effet direct local et l’effet indirect des liens entrée-sortie des chocs météorologiques sur l’activité économique des secteurs dans le monde entier entre 1975 et 2020. Premièrement, je constate que l’agriculture est le secteur le plus touché par une série de chocs météorologiques, notamment les journées chaudes et froides, les sécheresses et les cyclones. Deuxièmement, je constate que la production des secteurs situés en aval de la chaîne d’approvisionnement (construction, industrie minière et manufacturière, commerce de gros et de détail, transports, autres activités), bien qu’elle ne soit pas affectée de manière significative par les fluctuations météorologiques locales, est fortement endommagée par les chocs thermiques qui frappent le secteur agricole et se propagent en aval de la chaîne d’approvisionnement, entraînant des pertes persistantes au fil du temps. À l’aide de scénarios contrefactuels, je montre que le coût économique annuel mondial moyen des hausses de température tenant compte des chocs entre partenaires commerciaux depuis 2000 est de 0.33% de la valeur ajoutée brute, soit beaucoup plus que la perte de 0.1% obtenue en omettant les liens sectoriels. Je caractérise également les pertes globales dans différents scénarios et documente un fort gradient positif avec l’importance des secteurs dans le réseau de production. Ces résultats suggèrent que les chocs de productivité localisés liés aux conditions météorologiques peuvent se propager avec des effets économiques significatifs dans les pays et dans le temps, et que si nous ne tenons pas compte de l’interconnexion des secteurs, nous risquons de sous-estimer considérablement les conséquences des conditions météorologiques à court terme et du changement climatique futur de la production économique.

Contributions

La principale contribution de ce chapitre est de dévoiler un nouveau canal de l’impact des chocs météorologiques sur l’économie. La littérature croissante sur l’impact du climat n’a jusqu’à présent étudié que l’effet des chocs météorologiques locaux sur l’activité économique locale (Dell et al., 2012; Kalkuhl and Wenz, 2020; Burke et al., 2015b). Le chapitre définit un cadre conceptuel simple pour démontrer l’importance de la prise en compte des interconnexions sectorielles. Négliger les interconnexions entre les secteurs alors que les chocs météorologiques sont corrélés dans l’espace conduit à des violations des hypothèses d’identification courantes, en violant l’hypothèse d’une valeur de traitement unitaire stable. Contrairement aux articles précédents qui examinent la transmission des chocs sur l’économie (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Boehm et al., 2019), l’analyse empirique menée dans ce chapitre a une couverture mondiale des secteurs sur 45 ans au lieu d’utiliser des micro-données au niveau de l’entreprise et exploite les variations interannuelles du

nombre de jours au-dessus des percentiles spécifiques au pays des distributions de température et de précipitations au lieu des événements de catastrophe naturelle. Ce chapitre enrichit également la littérature sur l'impact du climat avec une approche descendante utilisant des mesures de l'activité économique, en fournissant de nouvelles preuves sur les impacts hétérogènes d'une variété de chocs météorologiques sur la production économique sectorielle, en utilisant les données complètes les plus désagrégées au niveau sectoriel sur la production économique.

Chapitre 2: Adapting to climate change accounting for individual beliefs

Le deuxième chapitre, *Adapting to climate change accounting for individual beliefs*, assouplit l'une des hypothèses clés de la littérature sur l'impact du climat et l'adaptation, qui repose sur une information parfaite et des croyances optimales. J'introduis un cadre théorique d'inattention pour caractériser une friction comportementale qui creuse un fossé entre les bénéfices attendus pour un agriculteur rationnel et un agriculteur comportemental ayant des croyances inexactes, en dérivant les conditions dans lesquelles les croyances influencent de manière différentielle la réactivité aux changements météorologiques. À l'aide d'une enquête sur les ménages ruraux au Bangladesh et d'une mesure météorologique de la sécheresse, je teste empiriquement les implications et trouve des réponses hétérogènes dans l'utilisation de l'irrigation en fonction des croyances, qui conduisent à une irrigation plus importante uniquement dans les endroits les plus secs. Les agriculteurs ayant des croyances inexactes réagissent différemment au même choc de sécheresse en fonction de leurs croyances antérieures. J'explore également divers canaux cognitifs alternatifs et apporte la preuve que la saillance, les erreurs de mémoire et les réactions excessives influencent les décisions en matière d'irrigation. Dans une analyse contrefactuelle où je compare les croyances observées avec les croyances basées sur les conditions météorologiques, je montre que les agriculteurs sous-utilisent l'irrigation et subissent des pertes financières substantielles en raison de croyances inexactes, générant un *belief gap*.

Contributions

Ce chapitre contribue à la littérature sur l'impact du climat et l'adaptation à plusieurs égards. Il montre théoriquement l'importance de prendre en compte les croyances individuelles et de permettre l'inexactitude des croyances. Il existe un grand nombre de *adaptation gaps* (Carleton and Hsiang, 2016), notamment des contraintes financières et technologiques, qui peuvent empêcher les individus de s'ajuster de manière optimale en réponse aux changements météorologiques. Les modèles classiques d'impact et d'adaptation au climat supposent toutefois que les agents sont rationnels et ont des croyances qui s'ajustent de manière optimale en réponse aux signaux météorologiques (Hsiang, 2016; Deryugina and Hsiang, 2017). Ce chapitre

utilise pour la première fois des données de panel sur les croyances individuelles concernant le climat pour explorer l'effet différentiel de l'exposition à la sécheresse sur l'utilisation de l'irrigation en fonction des croyances individuelles. En se concentrant sur le Bangladesh, l'un des pays les plus exposés au risque climatique, ce chapitre met en lumière un nouvel angle critique des déterminants de l'adaptation au climat qui n'a jamais été étudié auparavant.

Chapitre 3: Drought exposure and accuracy: Motivated reasoning in climate change beliefs

Le troisième chapitre, intitulé *Drought exposure and accuracy: Motivated reasoning in climate change beliefs*, utilise les mêmes données de panel de ménages ruraux au Bangladesh pour étudier les déterminants et le processus de formation des croyances climatiques. Une fois démontrée l'importance des croyances climatiques pour l'adaptation, ce chapitre étudie en profondeur les déterminants de ces croyances et cherche à savoir si les individus présentent des biais cognitifs. En étudiant l'effet de l'exposition moyenne à la sécheresse sur le long terme et des écarts à court terme sur les croyances relatives à la sécheresse, je constate que les croyances sont basées sur l'exposition à long terme et ne diffèrent pas systématiquement en fonction des écarts à court terme. Pour étudier la manière dont les individus interprètent les sécheresses passées, j'adopte une approche de variable instrumentale et j'étudie si les croyances individuelles conduisent à une distorsion asymétrique de l'information objective. Les résultats montrent que les individus se souviennent et surpondèrent les preuves qui penchent en faveur de leurs croyances antérieures. Le fait de croire que les sécheresses ont augmenté a un effet positif important sur la probabilité et l'ampleur de la surestimation du nombre de sécheresses. Ces résultats prouvent que les individus présentent le biais de confirmation comme mécanisme de raisonnement motivé.

Contributions

Ce chapitre apporte plusieurs contributions à la littérature sur les impacts climatiques et l'adaptation. Il s'agit de la première étude sur données empiriques des déterminants des croyances climatiques dans un pays en développement, en se concentrant sur les sécheresses. Cet aspect est particulièrement important au Bangladesh, où la sensibilisation au changement climatique est faible (Rzepa and Ray, 2020). Le seul autre article qui étudie la formation des croyances climatiques n'exploite pas la variation intra-individuelle des croyances et utilise des données des Etats-Unis (Deryugina, 2013). Ce chapitre contribue également à la compréhension des biais cognitifs associés aux croyances en matière de changement climatique, qui n'étaient jusqu'à présent formulés que de manière théorique (Druckman and McGrath, 2019), et plus particulièrement, il teste l'hypothèse du biais de confirmation

dans le contexte d'un pays en voie de développement. En utilisant une approche de variable instrumentale pour répondre aux problèmes d'endogénéité, le chapitre établit une relation de cause à effet entre les croyances et la distorsion des informations provenant des événements météorologiques. Les résultats de ce chapitre soulignent la nécessité de prendre en compte les facteurs comportementaux et les biais cognitifs dans la formation des croyances sur le changement climatique afin d'élaborer des politiques d'adaptation efficaces.

Chapitre 4: Climate-induced migration and environmental values

Le quatrième chapitre, *Climate-induced migration and environmental values*, porte sur l'étude des déterminants des préoccupations climatiques et du comportement électoral en faveur de l'environnement. L'article étudie la relation entre les demandes d'asile induites par les conditions météorologiques, les préoccupations climatiques individuelles et le comportement de vote pour les partis verts dans l'Union européenne. Il présente la migration induite par les conditions météorologiques en provenance de pays non membres de l'OCDE comme un nouveau déterminant des préoccupations climatiques et examine son impact sur les attitudes du public et les choix électoraux. Sur la base de données allant de 2000 à 2019, l'étude utilise une approche de variable instrumentale exploitant les variations exogènes du climat pour estimer l'effet causal des demandes d'asile induites par les conditions météorologiques. Les résultats suggèrent que les demandes d'asile induites par les conditions météorologiques renforcent la préoccupation des individus à l'égard du changement climatique en tant que priorité politique. Cependant, ces changements dans les préoccupations climatiques ne se traduisent pas par des changements dans le comportement électoral des partis verts aux élections du Parlement européen, ce qui indique une déconnexion entre les préférences déclarées et les choix électoraux réels.

Contributions

La principale contribution de ce chapitre concerne l'analyse des déterminants des préoccupations climatiques. Une littérature de plus en plus abondante examine le rôle des facteurs socio-économiques, tels que le sexe, l'éducation, l'orientation politique (voir Drews and van den Bergh (2016) pour une revue de la littérature), et l'impact de l'expérience directe d'événements extrêmes (Hazlett and Mildemberger, 2020; Hoffmann et al., 2022). Le présent chapitre élargit la compréhension des préoccupations climatiques en considérant la migration induite par les conditions météorologiques comme un facteur influent. Ce nouveau déterminant met en évidence le rôle des anomalies météorologiques à distance, par le biais de l'exposition aux flux migratoires, dans la formation de la préoccupation climatique. Le chapitre démontre que les demandes d'asile induites par les conditions météorologiques augmentent la préoccupation individuelle à l'égard du climat, en particulier chez les

électeurs de droite. Ce résultat met en évidence la relation complexe entre le changement climatique, la migration et les idéologies politiques, contrairement aux résultats précédents sur l'idéologie de droite, qui modèrent par exemple les effets de l'éducation sur les convictions climatiques (Czarnek et al., 2021). Le chapitre examine l'écart entre les préoccupations climatiques et le comportement électoral, révélant que les préoccupations accrues n'entraînent pas de changements dans le soutien aux partis verts lors des élections au Parlement européen. Cela souligne l'importance de prendre en compte d'autres facteurs, tels que l'abandon des électeurs verts traditionnels et les préférences des personnes n'ayant pas atteint l'âge de voter. En estimant l'impact des variations météorologiques sur les demandes d'asile dans l'Union européenne, ce chapitre contribue à la compréhension de la relation entre le climat et la migration (Missirian and Schlenker, 2017b; Abel et al., 2019; Cai et al., 2016; Cattaneo and Peri, 2016). Dans l'ensemble, ce chapitre nous permet de mieux comprendre les moteurs des préoccupations climatiques et met en lumière la complexité de la traduction de la préoccupation climatique en actions politiques significatives en faveur du climat.

Chapter 1

Sectoral impact and propagation of weather shocks

Despite the intensification of international trade and the fragmentation of production processes, local weather shocks have only been shown to damage local economic activity. This paper introduces the role of input-output sectoral interlinkages as a transmission mechanism of weather shocks in a production network model and tests the empirical implications using a six-sector global dataset from 1975 to 2020. First, I document that agriculture is the most harmed sector by a range of weather shocks, including hot and cold days, droughts, and cyclones. Second, I find that sectors at later stages of the supply chain, though non-responsive to local weather, suffer from substantial and persistent losses over time due to domestic and foreign heat shocks in agriculture that propagate downstream. Using counterfactual scenarios, I show a substantial underestimation of the economic cost of temperature increases accounting for shocks across trade partners since 2000 and I characterize global losses depending on the sectoral centrality in the production network.

Keywords: Climate change, sectoral shocks, spillovers, weather shocks

JEL Classification: E23, E32, L14, O11, Q54, R15

I am grateful to Emanuele Massetti for his invaluable advice and helpful discussions. I also thank Geoffrey Barrows, Lint Barrage, Tom Bearpark, Roberto Bonfatti, Giulia Brancaccio, Valerie Cerra, Simon Dietz, Xavier Jaravel, Giacomo Magistretti, Casey Maue, Katrin Millock, H el ene Ollivier, Ariell Reshef, Armon Rezai, Wolfram Schlenker, Leonie Wenz and participants at the IMF Fiscal Affairs Seminar, the PSE-CREST Informal Workshop in Empirical Environmental Economics, the GSIE Seminar (PSE), ADRES Doctoral Conference 2023, the 11th IAERE Annual Conference, the IPWSD 2023, LSE Environment Day, the 11th Mannheim Conference on Energy and the Environment, the LSE Environmental Economics seminar, the EDP Jamboree, the HKS Climate Economics Workshop, and the EAERE 2023 for useful comments. I also thank Giovanni Marin for kindly sharing the EORA26 data and Phyo Ba Kyu for clarifications on the UNSD data. Part of this research was conducted during my stays at the International Monetary Fund and Grantham Research Institute at LSE, whose support and hospitality are gratefully acknowledged. All remaining errors are mine.

1.1 Introduction

There is a large and urgent demand for data-driven estimates of climate damages to properly account for the benefits of additional climate change mitigation efforts (Newell et al., 2021). Despite recent methodological advancements to estimate the relationship between climatic conditions and economic outcomes (Hsiang, 2016; Auffhammer, 2018), previous empirical studies investigate the responses of local aggregate measures of economic activity to isolated local weather shocks (see Kolstad and Moore (2020) for a review). In an increasingly interconnected world with international trade and supply-chain relations in production networks, the potential transmission of non-local weather shocks is a crucial mechanism for accurate quantification of climate damages. On the one hand, the openness to international trade and the fragmentation of production processes can help increase diversification in the supply chain and lower volatility (Caselli et al., 2020; Nath, 2020), on the other hand, however, it can increase exposure to shocks with effects rippling through the supply chain (di Giovanni and Levchenko, 2009).

This paper examines how weather shocks heterogeneously affect annual sectoral economic activity and traces their propagation in international production networks over time by using cross-country global sector-level data combined with high-resolution weather data and input-output sectoral interlinkages. To show the importance of weather shocks hitting other sectors and affecting sectoral production through sectoral interlinkages, I formalize a model of production networks (Carvalho and Tahbaz-Salehi, 2019; Acemoglu et al., 2016a), which provides intuition behind the potential bias of estimates based on local response function estimations to local weather shocks. Neglecting the interconnections among sectors while weather shocks are spatially correlated leads to contraventions of common identifying assumptions, by violating the stable unit treatment value assumption. Consequently, partial equilibrium estimates of the relationship between weather and economic outcomes become biased. In this paper, I highlight a new mechanism in the climate impact literature adding real-world features omitted in previous reduced-form attempts to quantify the economic cost of climate change.

The empirical analysis is conducted in two steps. First, I estimate the sector-specific response in the growth rate of per capita gross value added to weather shocks in a pooled multi-country sample of sectoral production across 183 countries between 1975 and 2020 for six sectors.¹ The effect of weather shocks on production is identified using plausibly exogenous year-to-year variation in the distribution of daily temperature and precipitation (Deschênes and Greenstone, 2011; Carleton et al., 2022), or in monthly dryness and wind speed to measure respectively droughts

¹Agriculture, hunting, forestry, and fishing; Mining, manufacturing and utilities; Construction; Wholesale, retail trade, restaurants, and hotels; Transport, storage, and communication; Other activities (including government and financial sector).

and cyclones. Second, I analyze how weather shocks hitting customer/supplier sectors domestically and abroad propagate through input-output interlinkages and affect sectoral economic production. I construct downstream and upstream, domestic and foreign network shocks using the global input-output tables from EORA26 (Kanemoto et al., 2011) combined with a vector of weather shocks.

In line with previous findings (Dell et al., 2012; Acevedo et al., 2020), I document that agriculture is the most harmed sector. In particular, using daily average temperature, I find that heat shocks, defined as an additional day above the 95th percentile of the country-specific daily temperature distribution, reduce the agricultural growth rate by 16% of its sample mean. Using a measure of dryness from the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), I document a negative and substantial effect of droughts and dryness conditions on agricultural production. In contrast, drier weather, measured as the number of days below the 5th percentile of the country-specific daily precipitation distribution or dryness conditions, exhibits a positive influence on productivity within the construction sector, and the transport, storage, and communication sectors. These sectors encompass operational tasks conducted in exposed “interface” areas (Cachon et al., 2012), which exhibit heightened responsiveness to variations in precipitation.

In the second part of the paper, I investigate whether sectors are affected by shocks on trade partners due to their propagation via supply chain interlinkages. I document that domestic and foreign heat shocks, respectively measured as weather shocks weighted by the relative importance of sectoral interlinkages within the same country and abroad, have a strong negative effect on several sectors’ output, notably construction; other activities; transport, storage, and communication; wholesale, retail trade, restaurants and hotels. The magnitude of the indirect effect is substantial and comparable to the direct effect of weather shocks on agricultural production. I further examine the mechanisms of the propagation effect and detect heat shocks in the agricultural sector as the main channel of downstream propagation to customer sectors. Results are stronger when accounting for the full propagation using the Leontief inverse matrix. Using local projections (Jordà, 2005), I find that the effect of network shocks is persistent over time, dampening sectoral growth up to five years after the shock.

Finally, I use the estimated parameters from the reduced-form specification as the basis of two counterfactual analyses. First, I quantify the contribution of input-output interlinkages between sectors to the average annual output loss due to recent warming from 2000 onwards. I consider a counterfactual world with no input-output linkages and with linearly trended daily temperatures from their baseline climate in 1970-2000. Accounting for network shocks, recent warming is responsible for an average annual output loss of 0.33%, compared to a 0.1% average loss when omitting spillovers. In a second exercise, I obtain the average annual cost conditional on an

additional hot day in a specific sub-region or a country. Average annual global costs are at their highest when heat shocks occur in countries with many supply chain interlinkages in the production networks, such as China, Brazil, France, India, and the United States.

Altogether, these findings provide evidence of the role of input-output sectoral interlinkages as an important mechanism for the propagation and amplification of weather shocks. They also highlight a substantial underestimation when omitting sectoral linkages and underline the importance of this channel as a component of the total economic impact of climate change.²

This paper contributes to the climate economics literature by providing jointly estimated sector-specific response functions to weather shocks across the world from 1975 through 2020. Several cross-country studies have employed aggregate measures of economic activity such as national or regional GDP per capita (Akyapi et al., 2022; Burke et al., 2015b; Kalkuhl and Wenz, 2020; Kahn et al., 2021; Burke and Tanutama, 2019; Kotz et al., 2021) to measure the impact of temperature fluctuations. Previous articles often use a coarse sectoral tripartition of the economy into agriculture, manufacturing, and services to study the channels of the impact, finding that agricultural production is the most damaged and industrial and service output are sheltered (Dell et al., 2012; Acevedo et al., 2020). At a finer level of sector disaggregation, previous work has focused on the impact of tropical cyclones in the Caribbean and Central America area (Hsiang, 2010), worldwide (Kunze, 2021), and of seasonal temperature variations in Europe (Linsenmeier, 2021).

Furthermore, this paper introduces a new mechanism in the climate impact literature. Previous studies examine economic losses as a function of local weather shocks, assuming that production depends only on local weather and holding conditions in other locations fixed (Miller et al., 2021). Besides spatial correlation as a channel for the global nature of climate change (Dingel et al., 2021), shocks can also propagate through production networks across geographically distant countries (Wenz and Willner, 2022). The existing literature has investigated how input-output interlinkages amplify and propagate economic shocks across US firms (Giroud and Mueller, 2019; Cravino and Levchenko, 2017) or sectors (Acemoglu et al., 2016b,a), and across countries (Das et al., 2022). Theoretical studies and simulations show how natural disasters can spread depending on the network structure (Henriet et al., 2012; Shughrue et al., 2020). Recent empirical studies examine the propagation of natural disasters within the US (Barrot and Sauvagnat, 2016) or after a localized single natural disaster such as the 2011 Japan earthquake or Hurricane Sandy in the US (Carvalho et al., 2021; Boehm et al., 2019; Kashiwagi et al., 2021). Pankratz and Schiller (2021) show that temperature shocks and flood events in supplier locations reduce customer firms' performance. Studies at the firm level do not justify whether

²For example, Kahn et al. (2021) show that an average increase in temperature by 0.01°C is associated with a 0.02% decrease in the annual growth rate of global economic output (see Tol (2022) for a complete meta-analysis of the economic impact of climate change).

idiosyncratic weather shocks have an important role in explaining macroeconomic fluctuations, which should wash out once aggregated across units (Lucas, 1977). Feng and Li (2021) study international spillovers of climate damage and risks on stock market valuation but use natural disaster data based on reported damages, while Kunze (2021) considers endogenous network sectoral interlinkages and finds limited indirect effects of tropical cyclones due to stickiness in the production processes. This paper contributes to the macroeconomic literature on the propagation of shocks by studying weather shocks in the supply chain through sectoral interlinkages. The findings can have substantial implications to quantify the economic damages of climate and compute the social cost of carbon, exploring a new channel of transmission of weather shocks that can amplify their effects on the economy.

The remainder of the paper is structured as follows. Section 1.2 lays out a conceptual framework of the importance of input-output sectoral interlinkages for the empirical estimation of weather shocks. Section 4.2 describes the data used in the empirical analysis. Section 1.4 introduces the empirical approach. Section 1.5 shows and summarizes the sectoral impact of weather shocks. Section 1.6 contains the main empirical results of the propagation of weather shocks through the economy, which I then use as the basis of counterfactual analyses in Section 1.7. Section 2.8 concludes.

1.2 Conceptual framework

1.2.1 Local economic response to local weather shocks

This section briefly discusses the conceptual framework underlying the estimates based on local economic response functions to local weather shocks. The majority of the reduced-form climate impact literature motivates productivity specifications with a partial equilibrium model of production (Burke et al., 2015b; Kahn et al., 2021; Dell et al., 2012; Kalkuhl and Wenz, 2020). Regardless of the level of spatial disaggregation of the analysis - firm, grid cell, region, or country - production possibilities for each unit $i = 1, \dots, n$ are usually described by the following neoclassical homogeneous of degree one production function:

$$Y_{it} = \mathcal{F}(Z_{it}, L_{it}, K_i) \tag{1.1}$$

I consider each unit i to be a sector-country and define it as a market. Each market has aggregate total factor productivity $Z_{it} = \bar{z}_i \cdot \exp(f(T_{it}, \beta_i))$ that comprises unit-specific exogenous non-weather base productivity determinants and a vector of market-specific temperature effects³, L_{it} is labor (inelastically supplied by workers

³For illustrative simplicity, here I consider a simplified example with univariate climate, where productivity only depends on temperature without loss of generality, but one can include a matrix of weather variables and study Jacobian matrices instead of first-order derivatives.

so that total population can be used as synonym), and K_i is capital.⁴ At each time t , in a simple constant returns-to-scale Cobb-Douglas version of the model with $\lambda \in [0, 1]$ the output elasticity of capital, the production function is written as

$$Y_{it} = \bar{z}_i \exp(f(T_{it}, \beta_i)) K_i^\lambda L_{it}^{1-\lambda} \quad (1.2)$$

Taking the log of both sides and rearranging in terms of output per worker, one obtains:

$$\log \frac{Y_{it}}{L_{it}} = \frac{1}{1-\lambda} [\log \bar{z}_i + f(T_{it}, \beta_i)] + \frac{\lambda}{1-\lambda} \log \left(\frac{K_i}{Y_{it}} \right) \quad (1.3)$$

In a reduced-form fixed effects econometric specification, regressing output per capita on a function of temperature and the unit- and period-specific fixed effects that absorb \bar{z}_i would estimate the effect of temperature $\hat{\beta}$ under the assumption that the residual variation in temperature is not correlated with the error term and unit-specific capital-to-output ratio is constant. Without spatially correlated patterns in temperature shocks and where production linkages between sectors and countries are negligible, $\hat{\beta}$ would then identify the effect of temperature on production.

1.2.2 Weather shocks in a production network model

Idiosyncratic micro shocks can propagate through input-output production networks and impose substantial fluctuations at the aggregate level (Carvalho et al., 2021; Acemoglu et al., 2012). In this section, I present a simple model of production networks based on Carvalho and Tahbaz-Salehi (2019); Acemoglu et al. (2016a) and originally introduced by Leontief (1941) to theoretically found the empirical analysis of heat shocks propagating through the economy by altering input prices/quantities or demand for intermediate inputs. This approach captures additional real-world features missing in previous reduced-form attempts to quantify the economic costs of climate change.

Sectors intensively use intermediate inputs produced by other domestic and foreign sectors. I consider a two-tier Cobb-Douglas model of production networks with each sector's production function with constant returns to scale ($\omega_i + \sum_j^n \omega_{ij} = 1$), such that:

$$Y_{it} = Z_{it} [K_i^\lambda, L_{it}^{1-\lambda}]^{\omega_i} \prod_j^n x_{ijt}^{\omega_{ij}} \quad (1.4)$$

where x_{ijt} is the quantity of intermediate inputs produced by market j used by market i . As before, I assume that, for each i , $\omega_i \in (0, 1]$, and $\omega_{ij} \in [0, 1]$ for all j ,

⁴In this framework, I consider Hicks-neutral productivity shocks and abstract from other potential channels of the impact of temperature on production, which could affect effective units of labor input (Nath, 2020) and capital equipment and its effective utilization (Zhang et al., 2018). In this case, estimates of Equation 1.1 would compound these three channels which cannot be further disentangled.

where ω_{ij} can be equal to zero if the output of market j is not used as an input by market i . The larger ω_{ij} , the more important sector j is as a supplier of intermediate inputs to sector i . Equation (1.1) is a simplified case in which input-output loops are removed and the shares of intermediate inputs in production are set equal to zero across all markets, such that $\omega_{ij} = 0$, for each i, j . Equation (1.4) allows for a rich input-output structure, since the intensity with which each sector's output is used as an intermediate input by other sectors varies across all sector pairs. In particular, input-output linkages between various markets can be summarized by the matrix $\mathbf{\Omega} = [\omega_{ij}]$, the direct requirements matrix defined as the first-degree input-output matrix, with some abuse of terminology (Carvalho and Tahbaz-Salehi, 2019). From the sectoral input-output interlinkages, one can also compute the Leontief inverse matrix as $\mathbf{L} = (\mathbf{I} - \mathbf{\Omega})^{-1}$, whose (i, j) elements are the importance of sector j as a direct and indirect input supplier to sector i .

Accounting for intermediate inputs sourced from multiple sectors introduces the concept of market access. This is a multilateral term, in which production in market i is a function of all market j 's productivities, and therefore all markets' temperature distributions (Rudik et al., 2022). Since inputs are sourced from various markets, temperature shocks to other markets can propagate across sectors and national borders and affect production in market i . From the Cobb-Douglas production technology assumed, it follows that a sector's expenditure on various inputs as a fraction of its output is invariant to the shocks and is thus exogenous in the model (Carvalho and Tahbaz-Salehi, 2019).⁵

1.3 Data

This section provides a summary of the main data sources used to empirically test the hypothesis that weather shocks affect sectoral production and propagate through input-output interlinkages. To do so, the three major data sets are sector-level economic production (Section 1.3.1), weather data (Section 1.3.2), and sectoral interlinkages (Section 1.3.3).

1.3.1 Sectoral production data

The sectoral economic production data come from the Economic Statistics Branch of the United Nations Statistical Division (UNSD, 2022). The National Accounts Main Aggregates database provides the Gross Value Added (GVA) by type of economic activity following the International Standard Industrial Classification (ISIC

⁵Carvalho et al. (2021) study a more complex case with production functions with a nested constant elasticity of substitution (CES) structure and show the propagation of shocks through two distinct channels using a first-order approximation in the elasticities of substitution between various intermediate inputs or between the intermediates and primary factors of production different from one.

rev. 3.1). It contains information from 1970 through 2020 for 205 countries.⁶ GVA is measured in constant 2015 USD. The data set categorizes sectors into six broad groups (with the respective ISIC code in parentheses), which provides the most comprehensive data set of global economic production disaggregated by sector with the longest time horizon: agriculture, hunting, forestry, and fishing (A-B); mining, manufacturing and utilities (C-E); construction (F); wholesale, retail trade, restaurants, and hotels (G-H); transport, storage, and communication (I); other activities (J-P).⁷ The latter encompasses, among others, the financial sector, real estate, public administration, education and health. Table A1 presents summary statistics for sectoral production. Although unbalanced, the sector-country panel dataset covers all countries in the world for most of the 46 years in the analysis.⁸

1.3.2 Weather data

I combine three main sources of weather data that use geophysical climatic information to construct measures of weather fluctuations and extreme weather events. Section 1.3.2 describes temperature and precipitation data. Appendix A.3 describes additional weather data used to construct measures of dryness, wetness and cyclones.

Temperature and precipitation

I use temperature and precipitation data from the global reanalysis ERA-5 dataset compiled by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service, 2023). Reanalysis data combine model data with observations from across the world into a globally complete and consistent dataset using the laws of physics and rely on information from weather stations, satellites and sondes, removing biases in measurement and creating a coherent, long-term record of past weather (see Auffhammer et al. (2013) for a discussion of reanalysis weather data). ERA-5 is available on a $0.25^\circ \times 0.25^\circ$ resolution grid ($\approx 28\text{km}$ at the Equator) from 1950 to the present. The original temporal frequency is hourly, but I aggregate it into daily data for the empirical analysis.

Following the standard methodology in the climate impact literature (Hsiang, 2016), I compute any nonlinear transformation of temperature and precipitation at the grid cell level before averaging values across space using grid-level weights

⁶The sample of countries is larger than the number of recognized sovereign states since it also includes quasi-autonomous countries such as Curaçao or Puerto Rico. Since the input-output data used as part of the analysis do not contain information on these countries, the final sample does not consider these countries. The final sample of countries and their frequency is reported in Table A2.

⁷The original data are available for seven sectors, since GVA in manufacturing (ISIC D) is also provided standalone. I depart from previous articles using these data (Kunze, 2021; Hsiang, 2010) and consider mining, manufacturing and utilities (ISIC C-E) as one single sector, since it is not possible to obtain a separate measure of GVA sectoral production in mining and utilities (ISIC C & E) from manufacturing (ISIC D) because value added across sectors is not additive.

⁸On average, information for each sector-country tuple is available for 44 years. Most of the sectors are covered for the entire time period except for recent geopolitical changes.

and accounting for fractional grid cells that partially fall within a country, and lastly summing or averaging days in coarser time intervals. This procedure maintains weather variability that would be otherwise lost when averaging over an entire country. To have a measure of weather exposure for the average individual in a country and to avoid giving excessive importance to weather in areas with little economic contribution to sectoral production, I aggregate grid-cell level information using time-invariant population weights from the 2000 Landscan dataset (Bright and Coleman, 2001). When constructing measures for the agricultural sector, I weigh grid-cell data by the proportion of each grid cell under cropland in 2000, using the Global Agricultural Lands dataset (Ramankutty et al., 2010). To construct sector-specific weather shocks for certain countries, I rely on Eurostat data on GVA by industry (NACE Rev. 2) at the sub-national level for 34 European countries⁹ and take a weighted average of grid cell-level weather shocks by the average sectoral economic production in the first available five years (no earlier than 1995) for each sub-national administrative unit.

1.3.3 Sectoral interlinkages

Crucial to the analysis is the identification of domestic and foreign sectoral interlinkages. I use Input-Output (IO) data from EORA26 (Lenzen et al., 2012; Kanemoto et al., 2011) to analyze how idiosyncratic weather shocks propagate through the economy. This data set contains information on 26 sectors for 189 countries from 1970 to 2021 and has the widest geographic coverage in terms of intersectoral linkages.¹⁰ I retain information on the first available five years of the IO matrix (1970-1974) and examine the propagation of weather shocks through a pre-determined constant input-output network that does not endogenously respond to the shock itself.¹¹ I aggregate the 26 sectors to match the six sectors described in Section 1.3.1 as reported in Table A3.

Construction of network shocks

To account for propagation, I construct a measure of *network* shocks that hit other sectors and propagate through input-output interlinkages. I use sector-country level

⁹I use NUTS-3 level information from 31 countries (Albania, Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, Netherland, Norway, Poland, Portugal, Republic of North Macedonia, Romania, Serbia, Slovakia, Slovenia, Sweden, Türkiye, Serbia, Spain) and NUTS-2 level for three other countries (Cyprus, Luxembourg, Montenegro).

¹⁰This data set contains, to the best of my knowledge, the richest information in terms of geographic, temporal and sectoral information on input-output interlinkages. However, the data set presents a few limitations since some data are estimated and not measured and it is slightly less accurate than the full EORA MRIO due to the aggregation of sectors from the higher sectoral detail of Eora to the lower detail of EORA26, and to the conversion of Supply/Use tables to IO tables, which involves both a net information loss and the introduction of some new assumptions.

¹¹Kunze (2021) shows a small and negligible shift of sectoral interlinkages after tropical cyclones. I also test for this assumption in Appendix Section A.4 and find little and no statistically significant effect of heat shocks on sectoral interlinkages.

information in the first available five years of the IO matrix (1970-1974) to smooth annual variation and construct a weighting scheme that accounts for the importance of a sector depending on its geographic location and position in the supply chain. In robustness checks, I consider the propagation of weather shocks in a time-varying production network constructed using the first five-year average input-output inter-linkages for each decade (see Appendix Section A.5 for details).

First, I distinguish between shocks originating in the same country, domestic, and those originating in others, foreign. Second, I classify network shocks into downstream and upstream depending on whether they hit sectors that are respectively suppliers or customers of the sector of interest. From the perspective of the sector of interest, downstream shocks originate in supplier sectors and propagate downstream. In contrast, upstream shocks hit customer sectors and travel upstream to the sector of interest. A prediction of the conceptual framework in Section 1.2 is that the supply-side shocks propagate downstream, whereas demand-side shocks propagate upstream (Carvalho and Tahbaz-Salehi, 2019; Acemoglu et al., 2016a). Given the level of aggregation of sectors, all six sectors are included in both upstream and downstream weights. Figure A1 shows the average upstream and downstream weights of each sector across countries.

In addition to the local own shock hitting sector i in country c , there are four different types of network shocks depending on the supply chain position and geographic location: downstream domestic (DnD), upstream domestic (UpD), downstream foreign (DnF), and upstream foreign (UpF), constructed as follows:

$$\text{Shock}_{i,c,t}^{DnD} = \sum_{j \neq i} \omega_{i,c,j,c} \text{Shock}_{j,c,t}^{Own} \quad (1.5)$$

$$\text{Shock}_{i,c,t}^{UpD} = \sum_{j \neq i} \hat{\omega}_{i,c,j,c} \text{Shock}_{j,c,t}^{Own} \quad (1.6)$$

$$\text{Shock}_{i,c,t}^{DnF} = \sum_j \sum_{k \neq c} \omega_{i,c,j,k} \text{Shock}_{j,k,t}^{Own} \quad (1.7)$$

$$\text{Shock}_{i,c,t}^{UpF} = \sum_j \sum_{k \neq c} \hat{\omega}_{i,c,j,k} \text{Shock}_{j,k,t}^{Own} \quad (1.8)$$

where $\text{Shock}_{j,k,t}^{Own}$ is a weather shock hitting sector j in country k in year t .¹² I take a weighted average of the shocks hitting all sectors that sector i has a linkage with by constructing the weights from the inter-country IO tables described in Section 1.3.3. Based on previous approaches to model network shocks (Acemoglu et al., 2016a,b; Das et al., 2022), I construct weights differently for upstream and downstream shocks. From the perspective of sector i in country c , for downstream shocks, I construct weights as

¹²Except for the agricultural sector all over the world and for all sectors in 33 European countries, weather shocks are not sector-specific, as detailed in Section 1.3.2.

$$\omega_{i,c,j,k} = \frac{\overline{input}_{jk \rightarrow ic}}{\sum_{lf \in \Theta_{ic}} \overline{input}_{ic \rightarrow lf}} \quad (1.9)$$

i.e., the ratio of the inputs that sector i (in country c) uses that are produced by sector j (in country k) over the total inputs supplied to its set of customer sector-countries Θ_{ic} . These weights represent downstream propagation since they reflect how much input from sector-country jk is needed to produce one unit of output of sector-country ic (Acemoglu et al., 2016a). In a similar manner, the weights associated with measures of upstream shocks are constructed as

$$\widehat{\omega}_{i,c,j,k} = \frac{\overline{input}_{ic \rightarrow jk}}{\sum_{lf \in \Theta_{ic}} \overline{input}_{ic \rightarrow lf}} \quad (1.10)$$

i.e., the ratio of the inputs of sector i (in country c) to each sector j (in country k) over the total inputs supplied to its set of customers Θ_{ic} . These represent upstream weights since they reflect the importance of each customer for the sector-country of interest ic .

As a first step in the analysis, I consider network shocks only based on the geographic location (domestic or foreign) of partners. In this case, I take an unweighted average of upstream and downstream weights to obtain a measure of the average relative importance of each sector-country ($\bar{\omega}_{icjk}$).

1.4 Empirical Approach

The empirical analysis is conducted in two steps. First, I estimate the sector-specific response in per capita GVA growth rate to weather shocks. Second, I analyze how weather shocks hitting customer/supplier sectors domestically and abroad affect sectoral economic production.

1.4.1 Local economic sector-specific response to local weather shocks

I estimate the sector-specific output-weather relationship using a pooled sample of sectoral GVA per capita growth rates across 183 countries over 45 years. The effect of temperature and precipitation on production is identified using year-to-year variation in the distribution of daily weather, following, *inter alia*, Deschênes and Greenstone (2011); Carleton et al. (2022). Specifically, the baseline specification is written as

$$\Delta \log(GVA)_{ict} = f_i(\mathbf{W}_{(i)ct}) + \alpha_{ic} + \mu_{it} + \varepsilon_{ict} \quad (1.11)$$

where I regress the growth rate of GVA per capita in sector i in country c in year t (approximated by the first difference in logarithms) on a sector-specific function of weather variables \mathbf{W} in country c in year t . I include country-sector fixed

effects to account for unobserved heterogeneity that influences countries' average sectoral growth rates, such as history, culture, or topography and time-invariant sectoral compositions of national output (Burke et al., 2015b), and sector-year fixed effect to capture year-specific worldwide shocks, such as El Niño events or global recessions, and to specific sectors (e.g. agricultural commodity price shocks). For instance, differences in country sizes do not pose a problem in the identification strategy. I do not include any other traditional time-varying determinants of sectoral production - such as investments or capital stocks - since they are endogenous to weather variations and may thus introduce bias in the estimates (Dell et al., 2014). Standard errors are clustered at the country level to account for spatial correlation of the error terms across sectors in the same country over time.

Equation (1.11) relies on usual identifying assumptions in the climate impact literature (Hsiang, 2016), by exploiting plausibly exogenous within-country variation in changes in weather fluctuations, orthogonal to changes in sectoral economic production and to weather in spatial units different than i . This approach uses random weather shocks as identifying variation, which differ from climate change (Mendelsohn and Massetti, 2017). Short-run and long-run elasticities to weather fluctuations are the same only under certain assumptions (Lemoine, 2021), therefore one should be cautious in extrapolating long-term impacts from the estimated short-term responses.

From the beginning of the reduced-form approaches to the output-weather relation (Dell et al., 2012), temperature has been used in levels to estimate its impact on economic growth (Burke et al., 2015b; Henseler and Schumacher, 2019; Acevedo et al., 2020). Since the GVA growth rate is stationary and temperature fluctuations in levels are non-stationary, studying the relationship between these two variables would reintroduce trends in the specification (for a deeper discussion, see Tol (2022) and Appendix Section A.6). For this reason, when I use temperature in levels, I consider it in first-differenced changes (see Appendix Section A.7) (Akyapi et al., 2022; Newell et al., 2021; Letta and Tol, 2019).¹³ Although the use of changes in weather variables already de-trends the variables in the model, I test for the robustness of the model in alternative specifications including country-specific linear (and quadratic) time trends to allow for non-linear evolution of underlying country characteristics, such as demographic transitions and institutional changes. In additional robustness checks, I also account for dynamics and serial correlation in the dependent variable by including the lagged dependent variable among the regressors.

Using first-differenced weather changes, however, does not inform how atypical the weather realization was with respect to individual expectations since it neglects any information provided by the levels and assumes that individuals rationally update their beliefs annually, implicitly assuming an instantaneous model

¹³I reject the null hypothesis of non-stationary series for all first-differenced economic and weather variables performing the Im-Pesaran-Shin (Im et al., 2003) panel unit root test. Results are reported in Table A5.

of adaptation. On the one hand, introducing both temperature levels and changes simultaneously would not resolve the trend problem surrounding the output growth specifications adopted in the literature (Kalkuhl and Wenz, 2020). On the other hand, weather realizations above or below certain absolute thresholds (e.g., 30°C) and binned response functions may not be globally informative since only a subset of countries experiences such levels, driving the variation and raising concerns on potential endogeneity (Osberghaus and Schenker, 2022).

For this reason, I rely on the fact that people’s climate beliefs reflect long-run climatic conditions (Zappalà, 2023b), and adaptive responses could reduce the impact of weather fluctuations on production if societies can anticipate them based on their expectations (Shrader, 2023). I consider country-specific temperature and precipitation distributions and compute the annual number of days that belongs to the p^{th} -percentile of the country-specific temperature and precipitation daily distribution over the fifty-year period (where $p \in \{1; 5; 10; 90; 95; 99\}$). These events should be interpreted as abnormally cold and hot, or dry and wet, respectively, for the bottom and top percentile of the distribution of temperature and precipitation. Using this methodology, the measure is evenly distributed across countries, and any abnormal realization is compared to the country-specific climatic norm. Country-specific time-invariant thresholds account for the influence of long-run adaptation to climatic conditions on the effects of certain weather realizations. This approach considers an implicit model of adaptation assuming that societies adapt using as a baseline a fifty-year time-invariant climate norm. This methodology is consistent with previous results that condition the temperature-production response function on long-run average temperature (Rode et al., 2021; Carleton et al., 2022).

1.4.2 Propagation of weather shocks

Sectoral output can incur losses from climate change through different channels (Carleton and Hsiang, 2016). For instance, weather is an input in crop production and can directly harm agriculture (Schlenker and Roberts, 2009; Acevedo et al., 2020; Hultgren et al., 2022). Other sectors can experience losses due to reductions in labor supply and productivity (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018; Rode et al., 2022), total factor productivity (Zhang et al., 2018; Letta and Tol, 2019), or damages to assets and infrastructure (Hsiang and Jina, 2014; Bakkensen and Barrage, 2018; Fankhauser and Tol, 2005). In this section, I design an econometric specification that examines a new impact channel of weather shocks rippling through the supply chain via sectoral interlinkages. To examine the importance of *network shocks* relative to own shocks on sectoral activity, I estimate the following econometric specification

$$\Delta \log(GVA)_{ict} = \gamma_i Shock_{ct}^{Own} + \sum_J \gamma_i^J Shock_{ct}^J + \alpha_{ic} + \mu_{it} + \eta_{ict} \quad (1.12)$$

where I expand Equation (1.11) with shocks in partner sectors J by geographic location and supply chain position. I begin by including domestic and foreign weather shocks weighted by the average interdependence of sector i with other sectors in the same country c and other countries (i.e., $J \in \{D; F\}$). Then, I also disentangle upstream and downstream weather shocks (i.e., $J \in \{DnD; UpD; DnF; UpF\}$).

This approach aims at quantifying the impact on sectoral production of trade-induced exposure to weather shocks in other sectors. Weather shocks elsewhere affect sectoral market access which could improve or deteriorate depending on market forces and trade relationships with other sectors. Although this paper does not formally pin down the channel through which weather shocks affect supplier production functions and customer demand (e.g., infrastructure or facility damages, labor productivity losses, capital equipment efficiency), this approach uncovers the role of the propagation channel for quantifying sectoral weather shocks. By only considering the *direct* impact of weather shocks on a given sector, one is omitting the amplification and transmission of such shocks due to the intersectoral reliance. A negligible or null direct effect of weather shocks on a given sector may be amplified by weather shocks hitting other sectors with strong commercial interlinkages.

A typical panel fixed effects model would study the effect of weather variations in a given location while weather elsewhere is fixed. Climate change, however, is expected to alter atmospheric conditions across the world (Dingel et al., 2021). For this reason, the estimates obtained in Equation (1.11) of the effect of local weather variations on local economic production may be biased when omitting trade linkages across observational units while weather shocks are spatially correlated by violating the stable unit treatment value assumption (SUTVA). Spatial considerations are of first-order relevance because the economy and climate are linked across space, which results in violations of common identifying assumptions with first-order effects. One approach to address this concern is to use economic primitives as the outcome of the regression, such as productivity or the share of expenditure on goods from other markets over own expenditures. This approach eliminates the multilateral trade effects and correlated spatial patterns in temperature shocks (Rudik et al., 2022). By comparison, the use of local economic production measures such as GDP, value added in productivity, or other proxies including nighttime lights suffers from bias induced by spatial considerations through the multilateral trade effects and correlated spatial patterns in temperature.

The direction of the bias is ex-ante ambiguous since it depends on market forces, the network structure of the trade relationship and on the supply chain position of the treated trade partners (Acemoglu et al., 2016a). Most importantly, differently from other sectoral shocks previously studied (Atalay, 2017), weather shocks can a priori be either demand- or supply-side shocks. On the one hand, they can induce changes in input demands by customer sectors. In this case, weather-induced demand shocks would propagate upstream and affect suppliers of the sectors hit.

At the same time, network weather shocks can have a positive effect on sectoral production through improvements in market access, due to the lower productivity of its competitors. On the other hand, an adverse weather shock can reduce the production of a sector (Nath, 2020; Graff Zivin et al., 2018), and induce an increase in the price. This effect would ripple down to downstream customer sectors to use the input less intensively and thus reduce their own production. Through these two mechanisms, non-local weather shocks can impact sectoral production creating powerful propagation. Omitting market access from the estimating equation will bias the estimate of the effect of own temperature which will also capture the market access effect. The simplified conceptual framework with a Cobb-Douglas production function facilitates the study of the two mechanisms at play where downstream effects emerge only in the case of supply-side shocks and upstream effects from demand-side shocks.

1.5 Sectoral impact of weather shocks

I first explore the extent to which local abnormal temperature and precipitation realizations affect sectoral economic production. In Appendix Section A.7, I present the results using alternative measures of temperature and precipitation and in Appendix Section A.8, I discuss the sector-specific impact of droughts and cyclones.

1.5.1 Abnormal weather realizations

I exploit within-sector year-to-year fluctuations in changes in temperature and precipitation to identify their causal effect on economic sectoral production. Differently than previous cross-country empirical evidence on the channels of the impact of weather shocks on sectoral outcomes (Acevedo et al., 2020; Dell et al., 2012; Kunze, 2021), I estimate a pooled, multi-country, sector-specific response function as detailed in Equation (1.11). This model allows me to jointly estimate responses of sectoral economic production to weather shocks and compare the different response functions. I estimate the effect of an increase in the number of days of abnormal weather realizations in a year both for temperature and precipitations. The identification strategy relies on the estimation of the impact of increases in the number of abnormally cold and hot, dry and wet days using days in the rest of the distribution as the baseline category.

Figure 1.1 shows the (standardized) coefficients associated with the number of days above the 95th and below the 5th percentile of the fifty-year daily temperature and precipitation distribution. Figure 1.1a confirms findings consistent with the prior literature that agriculture is the sector that is most harmed by heat shocks. An additional day above the 95th percentile of the daily temperature distribution in the sample reduces the agricultural growth rate by 0.03 percentage points (16% of its sample mean). Cold temperature shocks have a similar effects on agriculture,

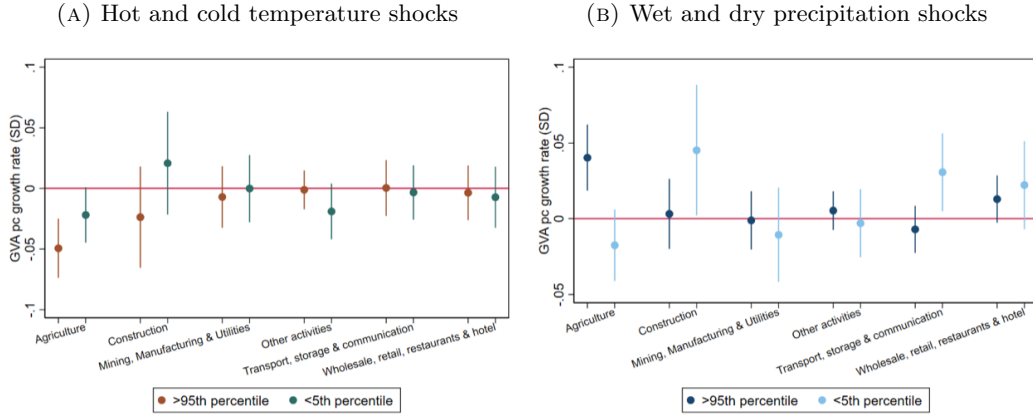
harming crops that cannot grow below a certain temperature. An additional day below the 5th percentile reduces the agricultural growth rate by 8% of its sample mean. Most of the other sectors seem not to respond to temperature shocks, neither hot nor cold, and estimates are very similar in magnitude, providing little evidence of asymmetry in the relationship between sectoral production and abnormal realizations of temperature from its historical norm.

Conversely, wet precipitation shocks do not affect sectoral production (Figure 1.1b) except for a positive effect of an additional day of precipitations above the 95th percentile on agricultural production. There are two potential explanations behind these findings, coherent with prior literature. First, excessive and insufficient precipitation may not be adequate indicators of water availability (Russ, 2020; Proctor et al., 2022). Second, precipitation as a weather phenomenon exhibits considerable spatial variation and aggregation at the country level may mask too much meaningful variation that could explain the null and noisy estimates associated with precipitation variables. To partially address the first concern, in Section A.8, I further explore sector-specific responses to a measure of dryness that accounts for potential evapotranspiration and provides a more complete picture of the water availability cycle. The second concern cannot be overcome due to the lack of data availability of sectoral production at finer administrative levels across the whole world. Previous sub-national studies show for aggregate measures of economic activity in Europe (Holtermann, 2020) and across the world (Damania et al., 2020; Kotz et al., 2022) that precipitation anomalies reduce economic growth. Future data collection efforts should be steered towards globally comprehensive measures of disaggregated sectoral production at finer geographic levels.

The baseline results are robust to how “abnormal” is defined, whether I use the top/bottom first or tenth percentile of the daily distribution (Figures A7 and A8 replicate the same exercise using the 1st and 99th, and 10th and 90th percentile). Results are also robust to estimating the baseline equation in a balanced panel (Figure A9a), excluding large countries (i.e., Brazil, China, India, Russia, US) that may suffer from aggregation bias in cross-country analysis (Figure A9b) and controlling for lagged growth rate and including linear and quadratic country-specific time trends or sub-region by year fixed effects (Figure A9c).

Time-varying climate norms. Instead of fixing the weather distribution to the fifty-year period, one can construct measures of temperature and precipitation relative to their time-varying historical norms. Following Kahn et al. (2021), I construct time-varying country-specific distributions over the preceding m years for each t , where $m \in \{20; 30; 40\}$. I exploit the temporal horizon of the weather data that start from 1950. The official World Meteorological Organization definition of climate (i.e., norm) corresponds to thirty years (Arguez et al., 2012), but I check for robustness considering other time spans. Different lengths of historical norms imply different belief formation and adaptation processes (the longer the time span of the

FIGURE 1.1: Abnormal weather realizations on sectoral production



Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95th and below the 5th percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

historical norm, the slower individuals update their beliefs and treat the new distribution as the new norm). Smaller climate damage for shorter time spans over which the distribution is computed would provide suggestive evidence on the rate of speed of adaptation (Kahn et al., 2021). In all three cases, I consider data starting from 1990 to compare estimates across time-varying historical norms with different time spans from the same sample.

Figure A10 shows the coefficients associated with abnormal temperature and precipitation realizations with respect to a time-varying country-specific daily distribution. Results are very similar to baseline estimates, showing that agriculture is negatively affected by hot temperature shocks. Assuming different speeds of change for the historical climate distribution (20-, 30- or 40-year) does not significantly alter the point estimates. The negative effect of heat shocks on agricultural production is persistent, suggesting that adaptation has not entirely offset climate damages. There is some suggestive evidence of adaptation to abnormally cold shocks with the point estimate that is not significant using a 40-year climate norm and increases in magnitude and becomes statistically significant as one increases the speed of adaptation and belief formation up to 20 years. One cannot reject the hypothesis that adaptation has not taken place in other sectors (transport, storage and communication; other activities), where output losses are mitigated, and sometimes become gains, for faster time-varying climate norms. Results are similar and robust to the use of the 1st and 99th, and 10th and 90th percentile (Figures A11 and A12).

1.6 Propagation of weather shocks

In this section, I investigate the propagation of weather shocks across the economy through input-output networks. I focus on abnormal weather realizations as a shock. Appendix Section A.9 discusses the propagation of extreme drought prevalence and tropical cyclones as two additional weather shocks.

1.6.1 Abnormal weather realizations

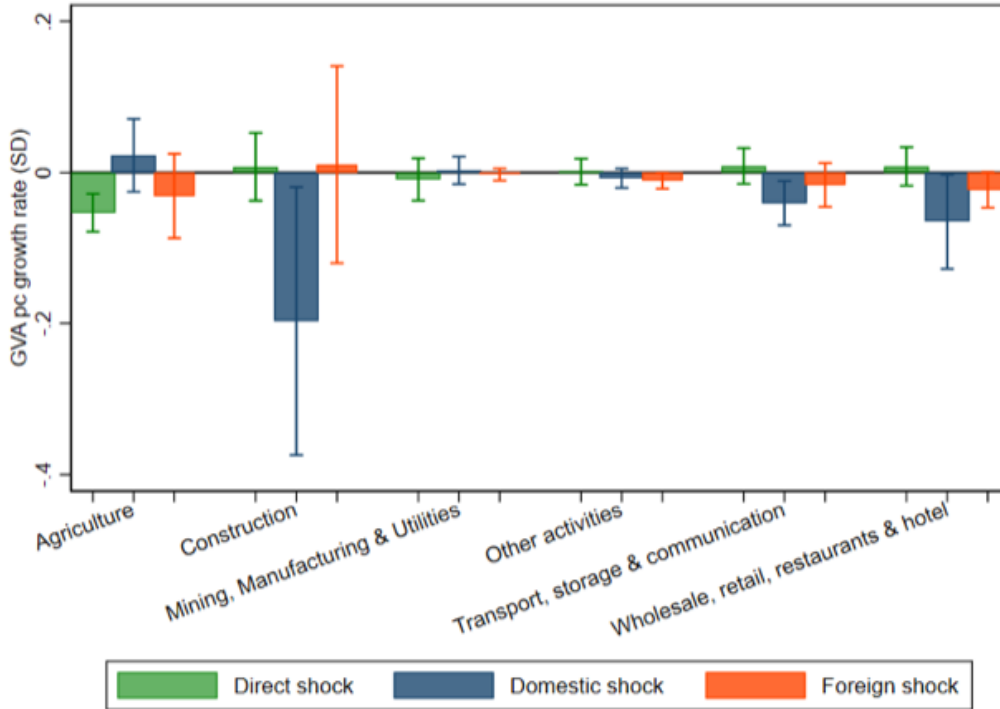
I consider the number of days above the 95th percentile of the country-specific temperature daily distribution and estimate Equation (1.12) including an average of the heat shocks in domestic and foreign trade partners weighted by the input-output interlinkages at the baseline with each specific sector.

Domestic and foreign shocks. Figure 1.2 displays the standardized estimated coefficients associated with own and *network* heat shocks decomposed into domestic and foreign with the vertical error bars indicating 95% confidence intervals based on clustered standard errors at the level of the country. The coefficient on the direct heat shock is negative and significant only for agriculture, replicating the results in Section 1.5. Domestic shocks have a significant negative and sizable effect on economic production in the sectors of construction, transport, storage and communication, and wholesale, retail trade, restaurants, and hotels. The effect of domestic heat shocks on mining, manufacturing and utilities, and other activities is also negatively but imprecisely estimated. In particular, the magnitude of the effect of domestic network shocks is substantially large for the construction sector, which relies heavily on various inputs from agriculture (e.g., timber, bamboo, straw and hay, natural fibers, plant-based binders, soil and gravel, biofuels, geotextiles) and produces investment goods, more vulnerable to climate change than e.g. the retail sector, which primarily produces consumption services (Casey et al., 2021). Foreign shocks also have a negative significant effect on sectoral production of other activities and wholesale, retail, restaurants and hotels. These results indicate that heat shocks propagate to other sectors which are usually non-responsive to direct weather shocks.

These findings have two consequences in the interpretation of previous results. First, sector-specific estimates that account only for the direct impact of weather shocks may be biased since shocks propagating from other sectors are omitted. This result underlines the importance of separately capturing direct and indirect effects and the statistical significance of coefficients on *foreign* network weather shocks suggests that also geographically distant weather realizations matter through trade interlinkages. Second, until now, the climate impact literature has focused on sector-specific impacts (Carleton and Hsiang, 2016) and identified agriculture as the most affected sector. Nevertheless, accounting for input-output interlinkages shows that weather shocks are amplified in the economy and *indirectly* affect other sectors,

too. In terms of magnitude, the effect of domestic network shocks on the other sectors is comparable with the direct damage estimated on agriculture. This implies that recent estimates on the economy have been largely underestimated due to the propagation of shocks across sectors.¹⁴

FIGURE 1.2: Domestic and foreign heat shocks on sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

Dry network shocks. An additional result from the sectoral analysis in Section 1.5 shows that sectors mostly relying on “interface” areas benefit from extremely drier conditions. I further explore the robustness of these results when accounting

¹⁴A potential worry about firms within a sector endogenously selecting trade partners based on their location and their exposure to weather shocks would not be a threat to the identification of the transmission of shocks, since it would bias the results against finding any effect.

for days below the 5th percentile of the precipitation distribution for each country-sector in the trade network. Figure A14 shows the estimates associated with dry direct, domestic and foreign shocks. When accounting for drier conditions elsewhere in the production network, the sectors of construction and transport, storage and communication show a net overall negative effect, raising further concerns about the validity of naive local weather-local output regressions.

Agricultural channel. To explore the consequences of sector-specific heat shocks and test the hypothesis that shocks in agriculture ripple through the supply chain, I estimate Equation 1.12 accounting only for heat shocks in the agricultural sector. Figure A16 reports the estimated coefficients. The coefficients on domestic heat shocks in all sectors (except mining, manufacturing and utilities) are largely negative and significant suggesting that heat shocks affecting the agricultural sector lower economic output in other sectors within the same country. Estimates of foreign agricultural heat shocks are negative but often imprecisely estimated.

Although the analysis underlines the importance of trade interlinkages as a transmission channel of weather shocks, identifying this mechanism is still subject to a fundamental challenge posed by spatial correlation due to the global nature of the phenomenon altering weather conditions everywhere (Dingel et al., 2021). To address this potential concern, I estimate a more conservative specification accounting for fixed effects at time-varying coarser spatial levels than the unit of observation (Deschênes and Meng, 2018). Figure A17 shows the estimated coefficients in a regression that additionally controls for subregion-by-year and continent-by-year fixed effects.¹⁵ This approach identifies weather variation that is local to the unit of observation and uncorrelated with weather elsewhere within the same subregion/-continent, suggesting that network effects persist and are due to trade interlinkages and not spatially correlated shocks. The strong negative effect of domestic shocks is robust to the inclusion of these additional fixed effects.

Exposure shares do not account for own trade, therefore the total sum of trade interlinkages varies across observations. To account for incomplete shares, I interact period fixed effects with the sum of exposure shares (Borusyak et al., 2022). The effects are robust to this specification (Figure A18a). Results are also robust to estimating the equation in a balanced panel (Figure A18b), excluding large countries (i.e., Brazil, China, India, Russia, US) (Figure A18c), using different cut-offs to compute percentiles of abnormal weather realizations (Figures A18d and A18e) and using a decadal time-varying production network (Figure A18f).

Upstream and downstream shocks. Shocks in trade partner locations can propagate differently from different stages of the supply chain (Acemoglu et al., 2016a; Das et al., 2022). I decompose domestic and foreign agricultural shocks into

¹⁵Subregions divide the world into 17 zones: Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Melanesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, Western Europe.

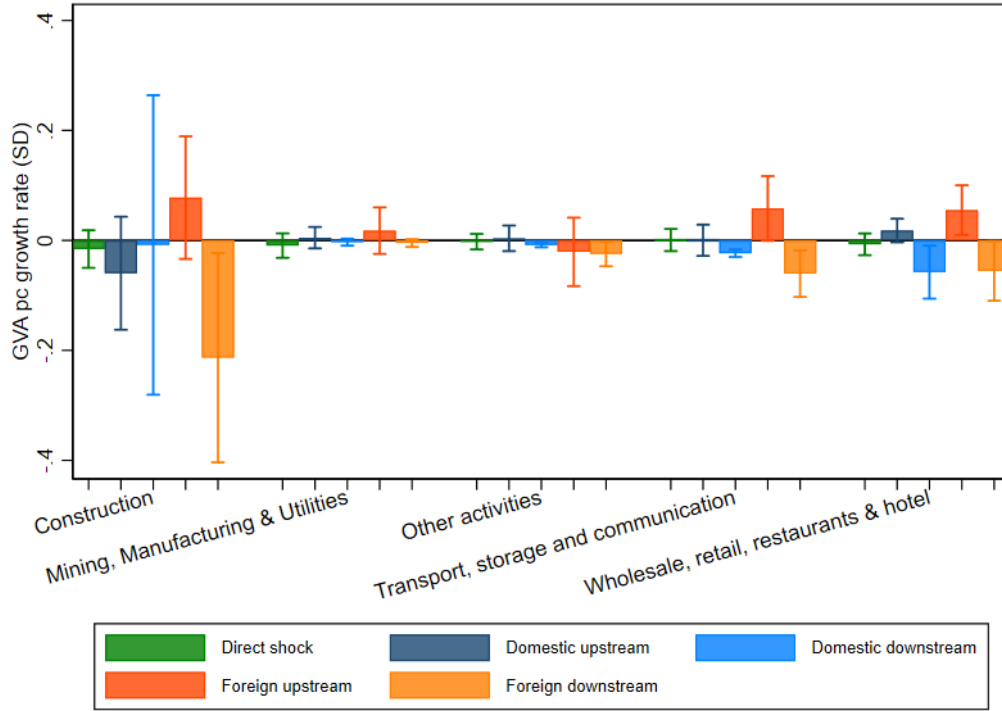
upstream and downstream as detailed in Section 1.3.3. Since temperature and precipitation are direct inputs to crop production and thus agricultural output, heat shocks can be interpreted as weather-induced supply shocks, and from the conceptual framework, it follows that such shocks should propagate downstream to customer sectors. Figure 1.3 displays the five coefficients on network shocks and local shocks for each sector. All five sectors have negative coefficients associated with both foreign and domestic downstream, indicating that heat shocks in the agricultural sector are amplified by market reactions that slow down downstream production (Wenz and Levermann, 2016).

Beyond first-degree sectoral interlinkages. The analysis so far has relied on the transmission of weather shocks from first-degree sectoral interlinkages in the production network. To account for the full transmission of shocks over the network, one can use the input-output analysis, initiated by Leontief (1941). From the input-output coefficients ω , I obtain the Leontief inverse matrix, which summarizes the sector-specific technical coefficients of the shock propagation through a power series representation of the Leontief inverse (Leontief, 1970). By taking the inner product of agricultural heat shocks and the Leontief inverse matrix, I obtain a sector-specific shock that takes full inter-sectoral relations into account. I estimate a specification including the agricultural heat shocks weighted by the Leontief-derived downstream coefficients and report the coefficients in Figure 1.4. Both domestic and foreign agricultural heat shocks are strongly negative and statistically significant, with domestic shocks larger in magnitude. The results suggest that downstream propagation of heat-induced productivity shocks in the agricultural sector has quantitatively sizable effects on the rest of the economy.

Time persistence of network shocks. While the results show that domestic and foreign shocks, particularly those originating from agriculture, matter for sectoral economic output, the estimates focus only on short-run, contemporaneous impacts. It remains an open question whether the shocks have persistent effects on the level or on the growth rate of GVA per capita. There is a long-standing debate on the “growth-vs-level” effect of weather shocks and extreme weather events (see Tol (2022) for a review). With the exception of persistent growth effects on aggregate output in Kahn et al. (2021), recent evidence has consistently documented level effects of temperature (Akyapi et al., 2022; Newell et al., 2021; Kalkuhl and Wenz, 2020). I examine longer-run effects of local and network agricultural heat shocks estimating a set of local projections (Jordà, 2005) to obtain impulse response functions. Local projections are more robust to misspecification of the data-generating process and to lag length by not imposing dynamic restrictions as in autoregressive distributed lag models. The set of estimating equations is written as

$$\Delta \log (\text{GVA})_{ict+h} = \gamma_{i,h} \text{Shock}_{ict}^{\text{Own}} + \gamma_{i,h}^D \text{Shock}^D + \gamma_{i,h}^F \text{Shock}^F + \alpha_{ic} + \mu_{ct} + \varepsilon_{ict}^h \quad (1.13)$$

FIGURE 1.3: Network abnormally hot temperature shocks and sectoral production

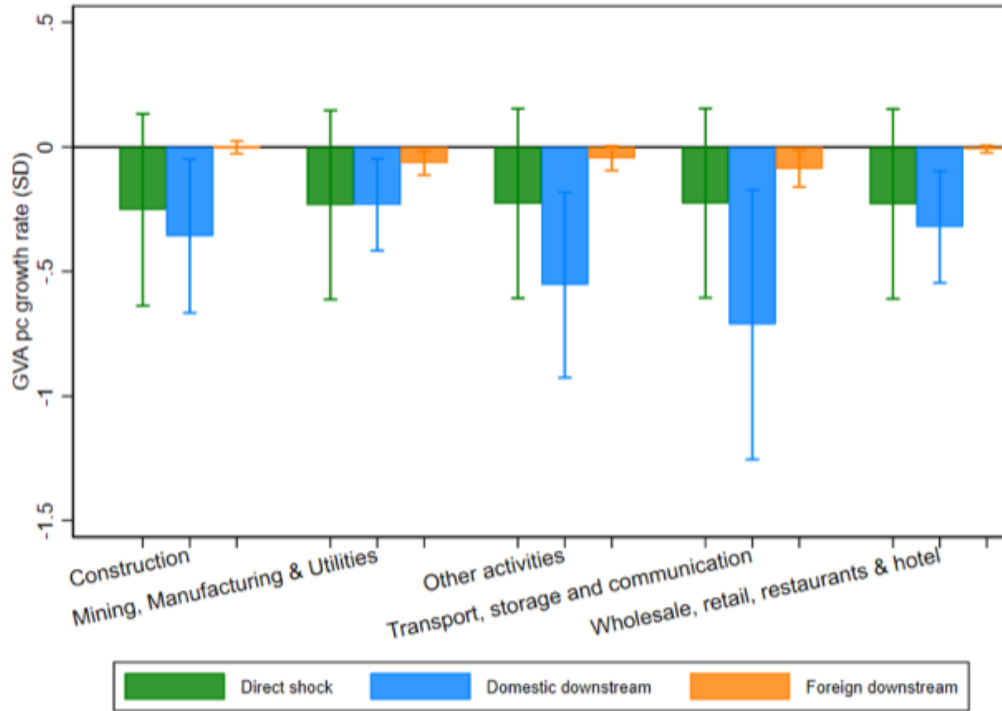


Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks distinguished between upstream and downstream, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic upstream (resp. downstream) shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the upstream (resp. downstream) interdependence with each sector. Symmetrically, foreign upstream (resp. downstream) shocks are constructed as the average weather shock in other sectors abroad weighted by the upstream (resp. downstream) interdependence with each sector. The figure reports only the coefficients associated with agriculture, other activities and wholesale, retail trade, restaurants and hotel, the specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country level.

where I project the cumulative growth rate of sectoral per capita GVA between horizons $t - 1$ and $t + h$ ($h \in \{0; 5\}$ indexes the time horizon measured in intervals of up to five years) on direct and network shocks accounting for dynamics.

First, I estimate local projections on the total gross value added at the country level. Figure A19 shows the impulse response functions for a standardized domestic (Panel a) and foreign (Panel b) heat shock. Both domestic and foreign heat shocks

FIGURE 1.4: Sector-specific response to agriculture heat shock in a Leontief matrix



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign downstream shocks in the agricultural sector, using the average number of days above the 95th percentile of the daily temperature distribution weighted by the Leontief inverse matrix obtained from the downstream sectoral interlinkages obtained as in Section 1.3.3. The specification jointly estimates all sector-specific coefficients in a stacked regression model fully saturated with country-sector, country-year, sector-year, and region-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country level.

have a small, noisy effect on total value-added levels that is statistically not distinguishable from zero. Using aggregate measures of country-level value added shows that the effect of network heat shock is not persistent.

Figure 1.5 displays the sector-specific impulse response functions for a standardized domestic heat shock obtained from the estimation of a stacked, multi-country, sector-specific regression that also includes direct and foreign shocks. Results show that the sectoral aggregation masks substantially heterogeneous effects. Domestic agricultural heat shocks have negative persistent effects in the sectors of construction; other activities; transport, storage and communication; and wholesale, retail trade, restaurants and hotels.

Figures A20 and A21 display the impulse response functions using own direct and foreign shocks. First, direct shocks do not have a persistent effect on sectoral

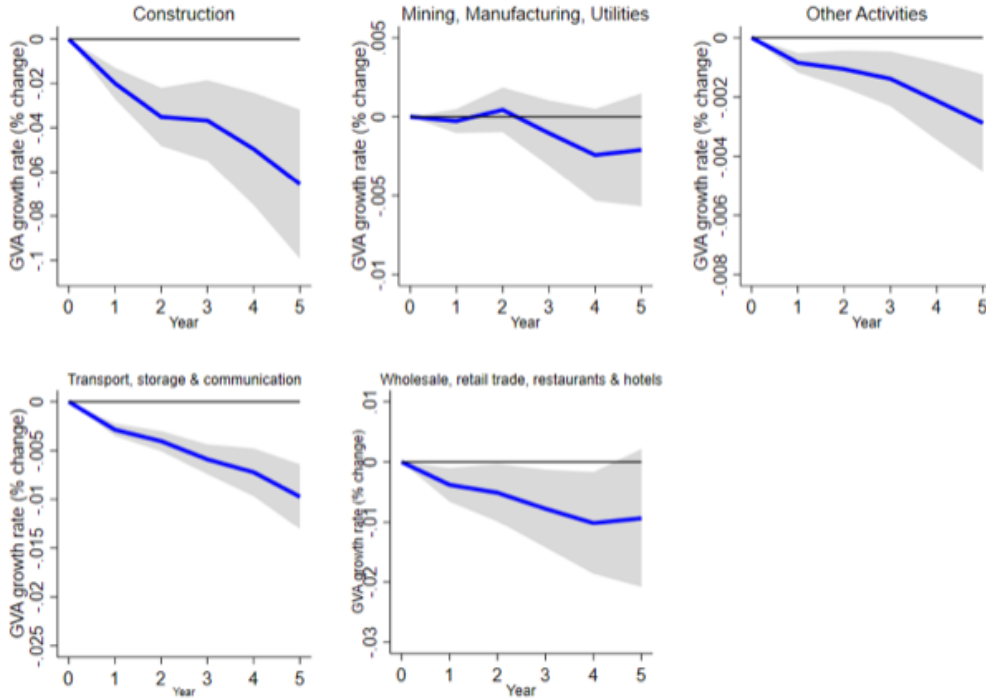
production. Agriculture is the only sector that is harmed, whereas the others appear relatively inelastic to abnormally hot temperature shocks (with the exception of transport, storage and communication, in which the negative effect of weather shocks manifests only after four years). The negative significant effect on agriculture lasts only one year and dissipates thereafter, confirming no visible long-run growth effects, but only a temporary effect on agricultural GVA levels. Second, the estimates on foreign shocks are small in magnitude and not distinguishable from zero, except in the case of other activities, which is strongly negatively affected by foreign agricultural heat shocks. The stickiness of the production processes at the sectoral and geographic level of aggregation of the analysis may explain the persistence of network heat shocks (Kunze (2021) and Appendix Section A.4). Allowing for a decadal time-varying production network shows robust persistent growth effect of domestic and foreign agricultural heat shocks (Figure A22). Agricultural heat shocks spill over other sectors also when accounting for continent-sector-year fixed effects (Figure A23) and for continent-sector linear trends (Figure A24), to control for spurious correlation between differential regional trends in warming and sectoral economic performance.

1.7 Counterfactual analysis: Cost of recent warming

To assess the economic importance of the propagation of weather shocks through production networks, I perform two counterfactual analyses. First, I compare the differential sectoral output losses/benefits as a result of recent historical warming. Prior research quantifies and projects the impact of temperature increases assuming a counterfactual with no further warming (e.g., Burke et al., 2015b; Burke and Tanutama, 2019; Kalkuhl and Wenz, 2020). To account for adaptive adjustments to changes in climate, I simulate how much slower or faster each sector would have grown over the 2001-2020 period, compared to a counterfactual in which daily temperature linearly evolves from its 1970-2000 long-run average, omitting and accounting for temperature shocks in a slowly evolving production network (see Appendix Section A.10 for additional details).

Omitting shocks in sector partners substantially underestimates the losses due to recent warming (Figure A27). The average annual GVA per capita loss across sectors considering only sector-specific local shocks is 0.02% (-0.08% median, IQR [-0.29, 0.09]), whereas accounting for network shocks it is 0.32% (0.15% median, IQR [-0.13, 0.73]). Damages are particularly larger in those sectors that appear sheltered from local shocks (other activities; transport, storage and communications), while there is larger heterogeneity in relative losses in construction and wholesale, retail, hotel and restaurants: larger damages in Sub-Saharan Africa, Latin America and South-East Asia are offset by modest benefits in Northern Europe and the Middle East. Using each country's baseline average sectoral breakdown of total GVA between 1996 and 2000, I aggregate sector-specific damages to obtain the total national average relative

FIGURE 1.5: Local projections of domestic agricultural heat shocks on sectoral production

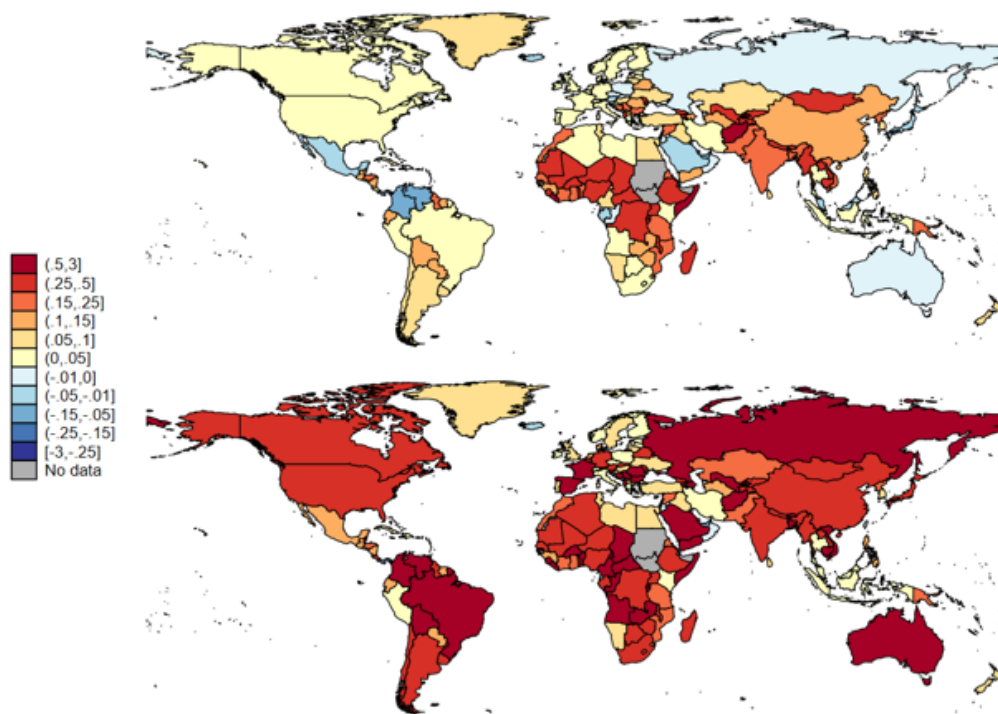


Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the domestic agricultural heat shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to direct and foreign abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country level.

losses. Accounting for indirect heat shocks, country-level damages are substantial (0.33% mean, 0.26% median, IQR [0.06, 0.53]) and largely underestimated when omitting heat shock propagation (0.10% mean, 0.05% median, IQR [0.00, 0.17]) (Figure 1.6).

In a second exercise, I quantify the macroeconomic impact of an increase in one abnormally hot day in a specific sub-region or country from 2000 onwards. Figure 1.7 reports the average annual global losses. The highest average loss (\approx 185 million 2015US\$) is recorded if each agricultural sector in the world experiences an additional hot day. Large losses are also recorded if Sub-Saharan Africa, Eastern Europe, Eastern Asia or Latin America and the Caribbean suffer an additional hot day. These regions, if experiencing additional heat, induce larger losses on average due to larger relative damages on local economic production. An alternative mechanism could be explained by a scale effect since these regions have the largest number of countries contemporaneously shocked. For this reason, on the right-hand

FIGURE 1.6: Average annual per capita GVA losses (%) due to recent warming

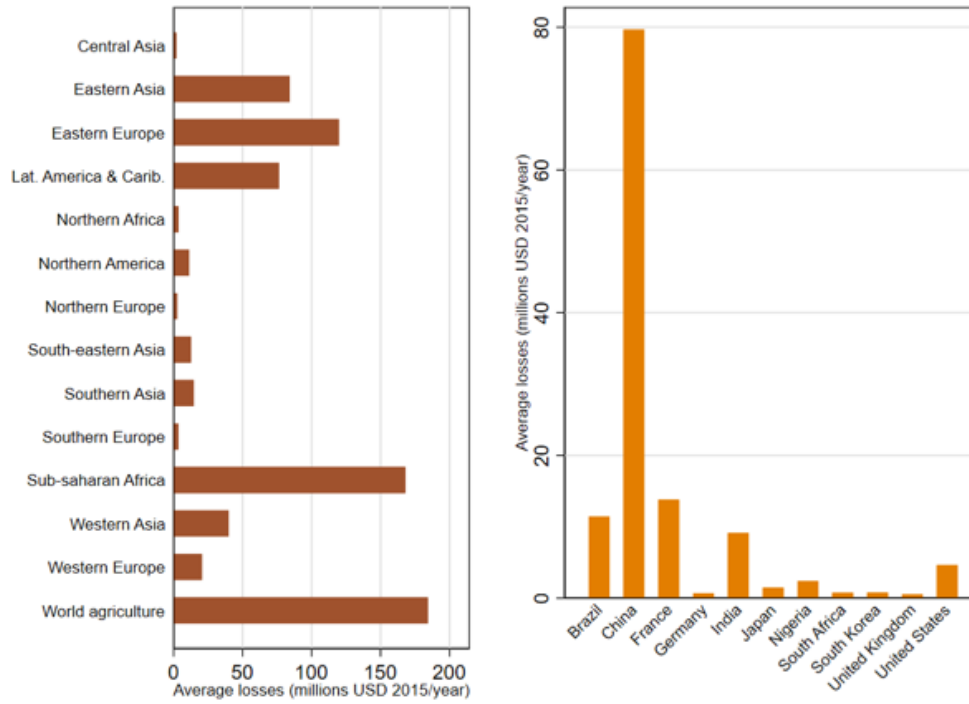


Notes: The figure shows the average annual losses (in red) and gains (in blue) in per capita GVA (%) compared to a counterfactual daily temperature evolved linearly from the trend estimated over the period 1970-2000. Sector-specific damages are weighted by the average sectoral share of total GVA between 1996 and 2000. The world map above only accounts for sector-specific direct heat and cold shocks defined as the number of days above the 95th and below the 5th percentile of the temperature distribution. The world map below accounts for shocks in other partner sectors using sector-specific semi-elasticities from bootstrapping 1000 times the underlying panel estimates of Equation (1.12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. Sector-specific losses are reported in Figure A27, Table A13 reports the sector-specific losses significant at 95% level estimated with 1000 bootstrap replications with replacement.

side of the Figure, I also report average annual global losses if one single country experiences an additional hot day. Results show that the importance of the country in the production networks substantially matters for losses induced by heat shocks. On average, global losses are at the highest for an additional hot day in China (≈ 80 million 2015US\$) and in other countries such as Brazil (≈ 12 million 2015US\$), France (≈ 14 million 2015US\$), India (≈ 10 million 2015US\$), and the United States (≈ 5 million 2015US\$). These losses are sizable considering they represent global averages for one abnormally hot day in each of these countries, where hot days have substantially increased over the sample period. For example, the decadal average

number of hot days in China in the 1970s was 11.8 and reached 29.5 in the 2010s. Similarly, the number of hot days in Brazil increased from 6.3 to 42.4 and from 7.9 to 30.3 in the US in the same time period.

FIGURE 1.7: Average annual global losses due to an additional abnormally hot day in a specific sub-region (left) or country (right)



Notes: The figure shows the average annual global losses in 2015\$ million by perturbing the production network with an additional abnormally hot day in the sub-region (resp. country) reported in the x-axis (y-axis), using sector-specific semi-elasticities from Equation (1.12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. Global averages only consider country-specific losses significant at the 95% level using 1000 bootstrap replications with replacement.

1.8 Conclusion

Recent studies in the climate impact literature have pushed forward the frontier for a timely, accurate and local measure of climate damages across sectors. The findings can have substantial implications for an adequate quantification of the total economic impact of climate change. This paper contributes to this effort by shedding light on a new potential component of climate damages, arising from the propagation of weather shocks through production networks across sectors and countries, and over time. Complementing firm-level evidence on the spillover effects of natural disaster shocks, I find that the amplification mechanism persists when aggregating units at the sector level and generates substantial fluctuations in sectoral production.

Accounting for the local effect of weather shocks on sectoral economic output is not sufficient for an accurate measure of total economic damages.

Sectors unresponsive to local weather suffer economic losses due to the interdependence of their production process with other domestic or foreign sectors that are hit by weather shocks. In particular, sectors at later stages of the supply chain, such as construction; transport, storage and communication; wholesale, retail trade, restaurants and hotels and other activities are negatively impacted by heat shocks in other sectors, with a loss comparable in magnitude to the direct impact on agriculture. I also find a strong negative persistent effect of domestic agricultural heat shocks in certain sectors' output (construction; other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotels) up to five years after the shock. In light of the negative and persistent impact of network shocks, these findings suggest that climate damages may be larger than indicated by standard empirical approaches and integrated assessment models.

The findings point to the structure of sectoral production network linkages as a key driver of aggregate fluctuations induced by weather shocks. In particular, they indicate that even if most sectors with the exception of agriculture are sheltered from weather fluctuations, the potential propagation of shocks over the economy's production network can impact them, thus resulting in movements in macroeconomic aggregates. In particular, using counterfactual simulations based on my empirical estimates, I show that the omission of input-output linkages as a mechanism for the propagation and amplification of shocks may lead to substantial underestimation of the effect of recent warming around the world and global losses are sizable even for just a single country being shocked in isolation, suggesting that countries that are more central in the production network can induce larger global losses if hit by heat shocks.

Several important issues remain open to future research. First, the analysis provides modest but suggestive evidence on the role of adaptation of countries to enhance their resilience to climate damages, in particular, that the effect of weather shocks depends on income. However, the analysis does not explicitly model adaptive investments, technological change, or other sector-specific adaptive responses (e.g. irrigation, sea-walls...) that may heterogeneously affect the response functions and lower climate damage. Accounting for other adaptive margins may also differentially drive the propagation of shocks in countries that are more sheltered from weather shocks.

Second, the analysis is conducted at a spatial level that may yet mask substantial variation both in economic responses and local weather fluctuations. High spatial resolution particularly matters for estimating the effect of precipitation on economic output (Kotz et al., 2022). Replicating the analysis on disaggregated sector-level sub-national data could show new estimates on sector-specific elasticities to weather fluctuations and shed new light on within-country regional propagation of weather

shocks across sectors.

Third, the transmission of weather shocks is studied through the relative importance of trade partners in input-output interlinkages. As previously shown (Barrot and Sauvagnat, 2016), the input specificity and elasticity of substitution are key drivers of the transmission of firm-level shocks. Weather shocks can differentially propagate in supply chains that differ by industry supplier competitiveness, input concentration, and supplier diversification (Pankratz and Schiller, 2021). These channels have only been documented at the firm level and such additional layers of heterogeneity could shed light on the exact channel of transmission of weather shocks through the economy.

Fourth, sectoral reallocation is increasingly acknowledged and studied as a potential adaptive margin to climate change (Nath, 2020; Desmet and Rossi-Hansberg, 2015). The analysis has focused on the propagation of weather shocks in a predetermined or slowly evolving production network. Adjustments in trade patterns from the substitution of affected sectors with sectors in unaffected places as a response to idiosyncratic weather shocks seem a promising avenue for future research.

Last, the analysis is mostly silent about decision-makers' climate beliefs and expectation formation processes. Despite the use of implicit models of adaptation accounting for climate as the most important factor, adaptive behavior reflects individual perceptions of climate change more than actual meteorological conditions, with inaccurate beliefs explaining substantial economic losses due to inadequate adaptation (Zappalà, 2023a). Similarly, expectations also matter in accounting for adaptation costs and benefits (Carleton et al., 2022; Shrader, 2023). Future research should focus on accounting for heterogeneous beliefs and expectations in production networks and supply-chain relationships.

Chapter 2

Adapting to climate change accounting for individual beliefs

Mounting evidence that the climate is changing requires a better understanding of how individuals adapt. Despite extensive research on various adaptation gaps, including financial and technological constraints, the adaptive decision-making process still relies on perfect information and optimal climate beliefs assumptions. Combining a survey of rural households in Bangladesh with a meteorological measure of dryness, this paper studies the role of individual beliefs about droughts on irrigation use. A theoretical framework introduces how beliefs differentially influence responsiveness to dryness. The empirical analysis reveals an asymmetric response to dryness shocks conditional on prior belief accuracy and a reinforcing effect of beliefs in drier areas, with heterogeneous responses by growing season and irrigation technique. I explore three cognitive mechanisms, exploiting the intensity and frequency of drought events and comparing self-reported and objective records. A counterfactual analysis with beliefs based on meteorological records shows that farmers underuse irrigation and incur substantial monetary losses as a result of inaccurate beliefs, generating a belief gap.

Keywords: Adaptation, agriculture, beliefs, climate change, drought, irrigation

JEL Classification: D83, O13, Q12, Q15, Q51, Q54

I am grateful to Katrin Millock for her constant support throughout the development of this paper and to Tamma Carleton for her guidance and hospitality during my stay at UCSB. I also thank Kathy Baylis, Valentina Bosetti, Andrew Clark, Olivier Deschenes, Kelsey Jack, Alexander Marbler, Emanuele Massetti, and Kyle Meng, as well as seminar participants at the Paris School of Economics and OSWEET, and participants and discussants at the 2021 BYEM, the 8th FAERE, the 2021 SEEDS Workshop, the 2021 IPECE Workshop, the 9th WICK PhD Workshop, the 13th IPWSD, the 10th IAERE, the 2022 UCSB Occasional Workshop, the 2022 AERE, the EAERE 2022, and the EEA 2022. I am also grateful to Claudia Ringler and Timothy Thomas for further clarifications on the BCCAS data. A previous version of the paper circulated with the title "Do subjective perceptions shape adaptation to climate change? Evidence from Bangladesh". All remaining errors are mine.

2.1 Introduction

Human-induced warming and climate-related extremes have slowed the growth of agricultural productivity over the past decades in mid- and low-latitudes (IPCC, 2022). The projected changes in climate threaten agricultural productivity and the communities whose economic livelihood depends on it (Ortiz-Bobea et al., 2021). Despite ongoing efforts, current adaptive measures in crop production have proven insufficient in mitigating the adverse consequences of climate change (IPCC, 2022). To address this challenge, recent studies emphasize the critical importance of quantifying and evaluating adaptation responses in light of changing climatic conditions (Auffhammer and Schlenker, 2014; Auffhammer, 2018; Carleton et al., 2022; Auffhammer, 2022; Hultgren et al., 2022). Nevertheless, prevailing implicit models of adaptation assume that agents adjust their practices based on unobserved optimal beliefs, accounted for using meteorological conditions (Hsiang, 2016; Deryugina and Hsiang, 2017). Misconceptions about climate change and inaccurate assessment of weather events can prevent individuals from responding to changes in the environment, leading to inadequate or counterproductive adaptation measures that exacerbate the impacts of climate change. Unobserved differences in beliefs can influence adaptive behavior and their omission may lead to biased estimates of the effect of weather fluctuations (Bento et al., 2023).

This paper provides evidence on farmers' heterogeneous adaptive responses to dryness exposure in Bangladesh accounting for individual beliefs of increase in droughts and sheds light on other cognitive mechanisms underpinning their adaptive decisions. Bangladesh is one of the most vulnerable least developed countries and was ranked 7th on the Global Climate Risk Index 2021 of the most affected countries since 2000 (Eckstein et al., 2021). I combine a two-wave rural household survey that contains information on individual beliefs and on their recall of the intensity and frequency of drought events with a meteorological local measure of exposure to dryness, the Standardized Precipitation Evapotranspiration Index (SPEI).

To introduce the role of individual beliefs as opposed to meteorological conditions in the individual decision-making process, I formalize a theoretical framework of behavioral inattention and action (Gabaix, 2019). I consider a profit-maximizing farmer and relax the perfect information assumption by which agents observe long-run climate and year-to-year fluctuations and make decisions based on them. Drawing on suggestive evidence of inaccurate beliefs about past climatic conditions in the sample, I introduce a behavioral friction driving the wedge between expected profits for a rational farmer and a behavioral farmer with inaccurate beliefs and characterize the conditions under which beliefs differentially influence farmers' responsiveness to dryness exposure. When testing the model empirically, adaptation refers to farmers' use of irrigation, where I exploit *within*-farmer variation in irrigation use and beliefs of increase in droughts to estimate the irrigation-belief relationship allowing the response function to vary with long-run dryness exposure.

The baseline results show that farmers' drought beliefs differentially influence responsiveness to dryness exposure in the use of irrigation. The effect is positive in drier areas and is heterogeneous across growing seasons, driving responses only in the monsoon season. For instance, for a farmer exposed to conditions one-half standard deviation drier than the historical average, beliefs are associated with an increase of around 28 percentage points in the share of irrigated land ($\approx 57\%$ at the mean). In contrast, in villages that are not drier in the period considered with respect to the historical average, beliefs are associated with a reduction in irrigated land. I rule out potential concerns about reverse causality and farmer responses through other coping mechanisms explaining this result and also show that inaccurate priors asymmetrically drive irrigation response to dryness shocks. When individuals assume a fixed climate distribution although meteorological records indicate drier conditions, they reduce irrigation use, consistent with the hypothesis of lack of adaptation to a bad random realization from a fixed distribution. Moreover, the baseline findings are driven by older farmers and farmers with formal education, which proxy for the importance of learning about agricultural technologies, the effectiveness of adaptive behavioral responses, and knowledge of the relationship between dryness and irrigation.

The results do not rule out alternative channels, such as salience and recall errors, that may affect irrigation decisions. I test for such mechanisms by exploiting the intensity and frequency of droughts and comparing self-reported experiences and meteorological records. First, I examine whether the timing of past droughts influences irrigation decisions. I use the self-reported year of the most severe drought to test whether more recent shocks have a stronger effect on adaptive decisions. I find that only self-reported one-year lagged drought events have a strong effect, providing suggestive evidence about salient events (Gallagher, 2014). Second, I compare the self-reported year with the meteorological record of the most severe drought. Inaccurate farmers who misjudge the year make potentially sub-optimal irrigation decisions, reducing the share of irrigated land. Third, I examine the role of accurate recollection in the frequency of past drought events, comparing the number of self-reported and meteorological droughts. I document that the adaptive response depends on the accuracy of recollection: overestimating droughts is associated with a higher share of irrigated land.

The main findings indicate that beliefs differentially drive individual adaptive responses to dryness conditions, but do not shed light on the welfare consequences. Using estimates from the literature on the returns to irrigation, I compute the welfare cost as a result of the *belief gap* generated by observed and accurate beliefs constructed from meteorological records. The median monetary loss amounts to \$102 in the monsoon and \$23 in the winter season, respectively around 26% and 4% of the total production value. Farmers are more accurate in the winter dry season and thus incur lower losses. The reason for this may be attributed to the climatic

conditions during winter, which require higher use of irrigation. The projected increase in the frequency and intensity of droughts and in the variability of rainfall in the monsoon season due to climate change may thus exacerbate farmer losses in that season as a result of misperceived climatic changes (Alamgir et al., 2015; Habiba et al., 2011).

This paper firstly relates to the climate adaptation literature in the agricultural sector (Burke and Emerick, 2016; Moore et al., 2017; Blakeslee et al., 2020; Chen and Gong, 2021). Various adaptive responses have been studied in developing countries, including crop diversity (Auffhammer and Carleton, 2018), crop insurance (Falco et al., 2014), land adjustments (Aragón et al., 2021), irrigation investment (Taraz, 2017; Taylor, 2021), pesticide and fertilizer use (Jagnani et al., 2021) and soil and water conservation practices (Tambet and Stopnitzky, 2021). Climate impact studies assume perfect information and full rationality of the agents and abstract from any heterogeneity in individual beliefs and understanding of climatic changes (Hultgren et al., 2022). Among the various “adaptation gaps” studied (Carleton and Hsiang, 2016), farmers may not adapt because they do not realize that the climate is changing. Limited adaptation has thus far only been conjectured to be affected by a difficulty in learning about climate change and cognitive factors (Bento et al., 2023; Burke and Emerick, 2016).¹ Previous studies have focused on beliefs about other agricultural inputs (Michelson et al., 2021; Gars and Ward, 2019; Maertens, 2017; Campenhout, 2021). The sole exception introducing climate beliefs is Kala (2017), who studies farmers’ learning models in India, however, inferring beliefs from actions. To the best of my knowledge, this is the first paper that accounts for observable individual climate beliefs in an analysis of on-farm adaptive actions to weather changes.

The paper also relates to a number of studies on the relationship between farmers’ perceptions of climate change and adaptation strategies (Ricart et al., 2022). The articles cover restricted geographical zones and provide results based on cross-sectional surveys.² This strand of literature does not unravel perceptions of different aspects of climatic changes nor it compares self-reported experiences with weather

¹Bento et al. (2023) document a higher degree of adaptation in US counties with higher beliefs in climate change, whereas Burke and Emerick (2016) find in the same context that expectations about climate change, proxied by political beliefs, have a minimal effect on farmers’ responsiveness to extreme heat.

²Studies are mainly based in Africa (Elum et al., 2017; Debela et al., 2015; Mertz et al., 2009b; Martey and Kuwornu, 2021; Ado et al., 2019; Silvestri et al., 2012; Fosu-Mensah et al., 2012; Brüssow et al., 2019) and in South-Asia (Aftab et al., 2021; Khanal et al., 2018; Waibel et al., 2018; Le Dang et al., 2014; Singh et al., 2018).

data.³ Here, I isolate the role of cognitive factors by comparing beliefs with meteorological measures of dryness. By exploiting the intensive margin in irrigation use, I quantify the role of beliefs, accounting for time-invariant individual-specific unobserved heterogeneity such as risk attitudes, that may otherwise confound the effect on behavioral responses.

Lastly, the paper is related to the role of subjective expectations in developing countries (Delavande et al., 2011). A growing literature studies expectations about climate change and their impact on various outcomes (Alem and Colmer, 2022; Giné et al., 2015; Shrader, 2023; Bakkensen and Barrage, 2022). Expectations about climate are inconsistent with the predictions from rational expectations (Cameron, 2005) and individuals over-adjust their expectations of climate in response to recent, local, and extreme weather events, indicating that more attention should be paid to availability heuristics⁴ (Marx et al., 2007; Konisky et al., 2016; Lee et al., 2018). Through expectations, agents make decisions requiring forward-looking inference on climate based on past weather fluctuations (Ji and Cobourn, 2021) and information shocks (Gibson and Mullins, 2020). Inaccuracy and mistakes in the expectation formation process may cause short-run economic losses due to sub-optimal decisions based on misjudgment and the disproportionate influence of recent realizations of drought events.

The remainder of the paper is organized as follows. Section 2.2 defines the background and the context. Section 2.3 describes the data used in the empirical analysis. Section 2.4 defines the conceptual framework and the empirical approach used to test the implications. Section 2.5 presents and discusses the main results. Section 2.6 quantifies the monetized losses due to inaccurate beliefs. Section 2.7 investigates three key mechanisms of the role of cognitive factors and section 2.8 concludes.

2.2 Background

Context. Bangladesh has a tropical monsoon climate with considerable variations in rainfall and temperatures across the country and over the year. The growing season extends over twelve months and can be divided into three overlapping seasons. These seasons are articulated following the production of three different types of rice,

³Some articles study perceptions as drivers of adaptation in a two-step approach implementing Heckman’s selection model (Deressa et al., 2011) since surveys often ask adaptation questions conditional on respondents perceiving a change in climate, assuming that perception is a necessary condition for adaptation. This approach is criticized in Munro (2020, p.1099): “[...] it might be sensible in surveys dealing with perception and adaptation to always ask the adaptation question even when respondents do not report [...] changes in climate”. In the survey used here, adaptation is measured from the land management module, which is not conditional on the perception module. Furthermore, all the studies use binary self-reported adaptation decisions, potentially subject to recall bias or “yeah saying” (Choi and Pak, 2005).

⁴The availability bias emerges when “[...] people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind” (Kahneman and Tversky, 1982).

which is the staple and main crop both in terms of cropped area and production in Bangladesh (FAO, 2014). The crop rice calendar determines three different growing seasons with different weather characteristics. During *Kharif 1*, the pre-monsoon season that goes from April to July with variable rainfall and high temperatures, the *Aus* rice is grown. *Kharif 2* is the monsoon season spanning from July to November and it is characterized by heavy rain and floods. About 80% of the total rainfall occurs during this season and *Aman* rice is the major crop. *Boro* rice is cultivated during *Rabi*, the winter dry season from December to April, with low or minimal rainfall and low temperatures (Paul and Rashid, 2016). Hereinafter, growing seasons are defined by the variety of rice that is grown.

Water resources and irrigation. In Bangladesh, rural households are subject to a considerable disparity in water availability between the monsoon and the dry season and across the country. The spatial and temporal heterogeneity is going to be exacerbated by projected climatic changes. For this reason, irrigation is a precondition for enhancing agricultural production and buffering the risk created by climate variability (Bell et al., 2015).

The main sources of irrigation in Bangladesh are surface water and groundwater. The latter has a predominant role since farmers can irrigate on demand rather than wait for their turn to access surface water (Bryan et al., 2018), and, in particular in the winter dry season, during which surface water is practically unavailable (Shahid and Hazarika, 2010). The most widely adopted irrigation technologies in Bangladesh include shallow tube wells (STWs), deep tube wells (DTWs), and low lift pumps (LLPs) (FAO, 2014). The first two use groundwater and operate either with electricity or diesel. The STWs operate with a pumping unit that has a motorized suction mode with centrifugal pumps and are generally 40-60 meters deep and have a relatively small command area (Mondal and Saleh, 2003). The DTWs operate on power force mode with submersible pumps in the wells, have a larger command area, can reach 100 meters in depth and water is supplied through buried pipes (Zahid and Ahmed, 2006). The LLPs use surface water and have centrifugal pumps mounted on a floating platform drawing water from rivers, creeks, and ponds (Majumder and Rahman, 2011).

Adequate irrigation application and operation mode of irrigation wells can increase rice yields and productivity in Bangladesh (Bell et al., 2015; Mainuddin et al., 2020). Although irrigation pump types are not found to significantly impact the average rice yield, except when the groundwater level falls below the suction limit preventing farmers from using the STW (Mainuddin et al., 2021), timely application of adequate irrigation water is extremely important since rice is very sensitive to water deficits (Doorenbos and Kassam, 1979). In 2008, the national irrigation coverage amounted to more than 5 million hectares, with groundwater covering almost 80% of the total irrigated area. In particular, STWs and DTWs comprised more than 78% of the total irrigated area (FAO, 2014). There are more than 165,000

DTWs in Bangladesh, most often government-owned due to high installation costs, with connection costs borne by farmers (Winston et al., 2013). Focusing on STW and DTW groundwater irrigation technologies guarantees a comprehensive coverage of the adaptive responses related to irrigation in Bangladesh.

Irrigation price. There are different water pricing systems in Bangladesh. The most widely implemented include a share of the crop as water charge, a land area-based fixed water charge, and a two-part tariff comprising diesel/electricity charge paid by farmer plus a land area-based fixed charge. The main energy source for lifting water is electricity, followed by diesel (Zahid and Ahmed, 2006). Many small farmers do not own their pumps and they can either rent from pump owners or buy water from the pump owners to irrigate their crops using a seasonal contract and not paying labor costs (Chowdhury, 2013). Nevertheless, pump ownership does not have a significant effect on production, and farmers who rent irrigation water do not perform worse than pump owners, suggesting that informal markets in groundwater irrigation may facilitate access and equity for irrigating farmers in Bangladesh (Bell et al., 2015).

2.3 Data

This paper explores the determinants of adaptive behavior accounting for individual beliefs. Ideally, this would require eliciting subjective probabilistic beliefs (Delavande, 2014) of weather realizations and comparing them to meteorological measures to examine consequences on individual behavioral responses and welfare over time. Future data collection efforts should head in this direction. In this paper, I rely on a survey designed by the International Food Policy Research Institute, with information on individual beliefs and I combine it with a unidimensional meteorological measure of dryness using the SPEI. This section (with complementary information in the Data Appendix D.2) describes the relevant variables for the empirical analysis and presents summary statistics.

2.3.1 Rural Household Data

Rural household data are obtained from the Bangladesh Climate Change Adaptation Survey (BCCAS), which consists of a two-wave survey designed by the International Food Policy Research Institute (2014a). Data are collected for 800 households in 40 randomly selected unions in Bangladesh.⁵ For each union, 20 agricultural households were randomly drawn from a single village in each union.

⁵Unions are the smallest rural administrative and local government unit in Bangladesh. The administrative structure is: Division \supset District (*Zila*) \supset Sub-district (*Upazila*) \supset Union. There are 5,158 unions with an average size of approximately 10–20 km². The 40 unions are selected to represent proportionally the seven agro-ecological zones (Barind Tract, *Beel* and *Haor* Basins, Floodplain, Himalayan Piedmont Plain, Modhupur Tract, Northern and Eastern Hills and Tidal Floodplains) as reported in Table B1.

The first wave of the survey was conducted in January 2011, and it covers data from the production year between December 2009 and December 2010. The first wave has been previously used to examine the impact of climatic shocks on agricultural income and adaptation strategies, although omitting individual beliefs (Delaporte and Maurel, 2018). A follow-up second wave of the survey was conducted in September 2012, and it covers data from the production year between September 2011 and August 2012 (International Food Policy Research Institute, 2014b). A timeline of the survey waves with respect to the three growing seasons in Bangladesh is reported in Figure B1.

Descriptive statistics. Table B5 presents key descriptive statistics of the households and their agricultural characteristics by survey wave. There is only one respondent for each household interviewed, who is the head of the household.⁶ Around 96% of the households (766 out of 800) were reinterviewed in the second wave.⁷ Since the focus is on self-reported individual beliefs, the final sample includes only those households who have been surveyed in both waves, did not move between the two waves and whose respondent was the same in both waves. Using this approach, I account for unobserved heterogeneity at the respondent level, allaying concerns about any bias in the coefficients associated with self-reported subjective measures. The resulting final estimation sample is a balanced panel of 714 individuals. The geographical distributions of the households in the final estimation sample across agro-ecological zones (AEZs) and by union are reported respectively in Tables B2 and C1. To further ascertain the absence of selection bias due to attrition in the second wave, I compare means for major outcomes and control variables in the first wave for attriters and non-attriters. Table C3 displays the differences in means, that are never statistically significant, except for the head of the household being a farmer.⁸ To allay concerns about attrition, I also reproduce the baseline results using inverse probability weighting (IPW) and find comparable estimates (Table B28).

Agricultural production. Households mainly rely on the production and cultivation of rice. Table B7 provides descriptive statistics on the average share of cultivated land for each crop. The three types of rice, *Aus*, *Aman* and *Boro* make up around 80% of the total cropped area for each household, with *Aman* and *Boro* corresponding to more than 70% of cultivated land. Similar figures are obtained when weighting the crop shares by the total agricultural production, as reported in

⁶A household is a group of people who live together and take food from the same pot. It counts as a member anyone who has lived in the household for at least six months, and at least half of each week. People who do not share blood relations with the head of the household are considered members if they “have stayed in the household at least 3 months of the past 6 months and take food from the same pot” (International Food Policy Research Institute, 2014a).

⁷The remaining 34 households could not be interviewed because they migrated (15 households) or nobody was at home at the time of the survey.

⁸Key results are robust to the exclusion of the variable that is used as a control in the main specifications.

Table B8.⁹ Given substantial differences in climatic conditions, rice varieties, and water needs across seasons, in the empirical analysis I distinguish irrigation decisions in the monsoon and in the winter seasons, respectively *Aman* and *Boro* (Taraz, 2017; Carleton, 2017; Chakravorty et al., 2023).

Irrigation use. To study how cultivated land is allocated to irrigation status, I use the survey module on land use. This module provides information on the irrigation status of each plot by growing season, and by irrigation technique. First, I pool all plots of own operated cultivated land in *Aman* and *Boro* and distinguish between the average share of land left rainfed and under irrigation over the agricultural production year. Then, I consider the most largely implemented irrigation types in the survey, which correspond to the most widely adopted in Bangladesh, namely STW and DTW (see Section 2.2).¹⁰ Table B9 reports descriptive statistics for irrigation use over the production year.

There is considerable variation in the irrigation use within plots across seasons, where around 56% of the plots change irrigation status between the monsoon and non-monsoon seasons (Bell et al., 2015). Table B10 displays the summary statistics for all available irrigation methods by growing season. In the *Aman* season, most of the cultivated land is left rainfed (on average more than 75%), and the most largely adopted irrigation technology is STW which covers more than 15% of the cultivated land. In the *Boro* season, households rely much less on surface water: on average, the share of rainfed cultivated land plummets to 26%, the STW covers on average more than 40% of the cultivated land and DTW covers more than 10%. Table B11 reports summary statistics on the five most widely adopted methods: rainfed and STW irrigated land in *Aman*, and rainfed, STW and DTW irrigated land in *Boro*.

Individual beliefs. Most importantly, the survey contains questions on individual beliefs about different aspects of climate change over the previous twenty years: increases in droughts, increases in erratic rainfall, and decreases in precipitations. For each question, I construct a dichotomous variable (Table B12). Since it is not possible to ascertain that changes in beliefs are driven by quasi-random variation, I compare the two sub-samples of respondents about increases in droughts by observable characteristics (Table B13, Panel A). Significant differences exist between the two groups in agricultural advisory services (receiving advice from extension agents) and in beliefs of increases in erratic rainfall and decreases in precipitation. Although differences in levels are not problematic for estimation since I include individual fixed effects in every specification, differences in beliefs persist also in the average changes between waves (Table B13, Panel B). I thus control for these variables in every specification in the empirical analysis. Despite the relatively short time span between the two waves (less than two years), there is considerable heterogeneity across waves in respondents' beliefs. In Appendix Section B.3, I examine

⁹This information is available only for the first wave.

¹⁰The share of cultivated land is constructed from the sum of all own operated cultivated plots' surfaces divided by the total own operated cultivated land of a household.

whether changes in individual beliefs are explained by an information channel or a social learning channel, ruling out both mechanisms.

Self-reported experience of droughts. Individuals are also asked a series of questions about their memories of weather events in recent years. They report the number of droughts that adversely affected their properties and productivity in the five years before the first wave and between the first and second waves. I construct the variable *self-reported # droughts*, used to compute a measure of accuracy of recollection of droughts, explained below. Individuals are also asked to report the year, over the same period as in the previous question, in which they were most badly affected by droughts. To maintain symmetry between the two waves, I construct two non-mutually exclusive dichotomous variables, $Drought_{t-1}$ and $Drought_{t-2}$, that take value one if the worst drought event has occurred respectively one and two years before the irrigation decision recorded in the survey. Table D1 reports the exact wording and formulation of each question used to construct the main variables.

2.3.2 Dryness and Drought Event Measures

Dryness exposure. To compare individual beliefs and objective exposure to dryness, I use a meteorological measure, the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), which provides information about drought conditions at the global scale, with a 0.5° spatial resolution ($\approx 55\text{km}$ at the Equator), at a monthly time resolution.¹¹ The SPEI is a measure of dryness based on water balance derived as the difference between precipitation and potential evapotranspiration. It is based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia (CRU TS version 4.03). This index captures deviation in dryness relative to the average observed between 1901 and 2018. A value of zero indicates the median amount (half of the historical amounts are below the median, and half are above the median), and the index is negative for dry conditions, and positive for wet conditions. For instance, a value of SPEI equal to -1 can be interpreted as the difference between precipitation and potential evapotranspiration one standard deviation lower than the historical average for a given grid cell. Since the analysis exploits inter-seasonal variation in dryness conditions and to avoid accounting for water balance accumulation in other seasons, I use the SPEI-1, which is based on the accumulating deficit of water balance over one month.

The SPEI presents specific advantages. It provides a unidimensional measure of climatic conditions considering the joint effects of precipitation, potential evapotranspiration and temperature. The SPEI has been used in the conflict (Harari and

¹¹I construct union-level measures overlaying the gridded SPEI database to the map of Bangladesh. The raster is aggregated spatially to the monthly union means. In the computation of the union-level averages, the grid cells' values are weighted by the fraction of the surface covered by the union. Figure B2 displays the surveyed unions (in purple) and overlays the raster data of the SPEI database in September 2012.

La Ferrara, 2018; Almer et al., 2017) and agricultural (Albert et al., 2021) literature, and specifically in Bangladesh (Miah et al., 2017; Abdullah and Rahman, 2015; Mohsenipour et al., 2018). Despite the recurrent and devastating nature of droughts (Mondol et al., 2021; Shahid and Hazarika, 2010; Shahid and Behrawan, 2008), previous research has mainly focused on the effect of floods in Bangladesh (Guiteras et al., 2015; Gray and Mueller, 2012; Chen et al., 2017). Nevertheless, droughts are the most frequent and widespread extreme weather event in Bangladesh (Alamgir et al., 2015).

I derive continuous measures of exposure to dryness at the union level over the entire production year and by growing season for the two types of rice (*Aman* and *Boro*), defined as the time interval between the planting and harvesting dates (Sacks et al., 2010). To facilitate the interpretation, all the continuous measures constructed from the SPEI are taken in the additive inverse form, $\text{SPEI} \times (-1)$, such that higher values are associated with higher dryness.

As common in the climate impact literature, I account for both the long-run average and the short-term deviation in exposure (Hsiang, 2016; Auffhammer, 2022; Albert et al., 2021). Considering long-run exposure is essential in situations that consider expectation formation and adaptation decision-making. Agents infer deviations from the average exposure, used as a reference point and upon which beliefs are built. I build a long-run exposure to dryness by taking the average of the monthly SPEI realizations over the previous 20 years for the production year and within each growing season. These measures should be interpreted as the “objective counterfactual” of beliefs of increases in droughts in the past 20 years. In an OLS regression of beliefs on long-run average exposure to dryness and short-term deviation, the coefficient on long-run exposure is 16.23 (s.e.=2.47, p-value<0.001). Using seasonal measures, the coefficient on *Aman* long-run dryness is 6.38 (s.e.=0.91, p-value<0.001) and on *Boro* is -1.69 (s.e.=2.74) (Full results reported in Table B19). Households that are differently exposed to severe droughts may consider droughts of the same magnitude in different ways (Guiteras et al., 2015). To account for this, I also consider short-term deviation as the difference between the average SPEI in the year or growing season preceding the production year and the long-run average SPEI.

Drought events. To obtain a measure of farmers’ interpretation of droughts, I compare the self-reported to the meteorological number of drought events. The climatology literature defines a drought event as the period of consecutive time points in which the SPEI index is below certain thresholds (Spinoni et al., 2014). The SPEI values can be categorized in 5 classes of droughts: i) non-drought ($\text{SPEI} > -0.5$); ii) mild droughts ($-1 < \text{SPEI} \leq -0.5$); iii) moderate droughts ($-1.5 < \text{SPEI} \leq -1$); iv) severe droughts ($-2 < \text{SPEI} \leq -1.5$); v) extreme droughts ($\text{SPEI} \leq -2$) (Paulo et al., 2012; McKee et al., 1993). Since the SPEI is normally distributed, each of

the five classes respectively accounts for about 69.1%, 15%, 9.2%, 4.4%, and 2.3% of the set of historical available values for each grid cell.

Overestimation. Following this classification, I match all the households in each union with the number of extreme droughts in the five years before the first wave of the survey (between 2006 and 2010) and between the first and the second wave (2011 and 2012).¹² Droughts have substantial impacts on agriculture when the SPEI is below -1.5, i.e., if the drought is at least severe (Zargar et al., 2011). Following this approach, I create an individual-specific measure of overestimation of past drought events:

$$\Delta_{it}^{type} = \text{self-reported \# droughts}_{it} - \text{objective \# droughts}_{ut}^{type} \quad (2.1)$$

that compares the self-reported number of drought events by individual i in union u in survey wave t and the objective number of drought events in union u over the same time period (where $type \in \{\text{moderate}; \text{severe}; \text{extreme}\}$). These wave-specific measures of accuracy infer whether respondents overestimate or underestimate the number of drought events that they have experienced. A positive value indicates that individuals overestimated the number of drought events (Zappalà, 2023b). Table B15 displays summary statistics of the measures of exposure to dryness and of the number of drought events recorded using the SPEI. Table B16 provides descriptive statistics of the main regressors used in the empirical analysis combining self-reported information from the BCCAS and meteorological measures. I also conduct a test in the balance of the covariates included in the main specification by regressing each of them on long-run dryness conditions. Table B17 shows that dryness does not affect any other characteristics of farmers in the sample such as cultivated land, household size, asset ownership. This suggests that changes in climatic conditions are driving changes in adaptive actions only through changes in the individual understanding of these events and beliefs.

2.4 Research design

2.4.1 Theoretical Framework

Climate influences outcomes through two pathways: actual weather realizations and beliefs about climate. Hsiang (2016) defines these channels respectively as “direct” and “belief” effect and shows that the marginal effects of climate and weather are locally equivalent for optimal beliefs (Deryugina and Hsiang, 2017). Most of the literature studying adaptation only includes measures of climatic conditions and weather fluctuations (Aragón et al., 2021; Taraz, 2017; Auffhammer and Carleton, 2018), assuming perfect information and abstracting from any heterogeneity in individual beliefs and understanding of climatic changes (Bento et al., 2023; Burke and

¹²I also employ other cutoffs to define the number of droughts, including moderate and severe drought events, to test for the robustness of the results.

Emerick, 2016). In this section, I consider a model of adaptation and extend it with new insights from a behavioral perspective where individual climate beliefs do not necessarily coincide with meteorological records.

Consider a farmer who maximizes expected profits by producing a univariate output at time t with output price normalized to one and choosing a single input, irrigation use a , with an associated price c .¹³ The input enters a production function, $F(a, w)$, twice continuously differentiable and concave, where the other input is weather, w , drawn from a Gaussian distribution $\mathcal{N}(\mu_t, \sigma^2)$. I consider a unidimensional weather measure summarized by dryness, that embeds the relevant climatic aspects for farmers (temperature, precipitation, potential evapotranspiration).¹⁴ Following Shrader (2023), the production function is multiplicatively separable in terms of weather and input. At the beginning of each period, a rational farmer chooses the optimal level of input $a^r = \operatorname{argmax}_a \mathbb{E}_{t-1}(\pi_t)$ that maximizes expected profits¹⁵:

$$\max_a \mathbb{E}(\pi) = \mathbb{E}(w)F(a) - c(a) \quad (2.2)$$

Because of the presence of costs associated with the use of irrigation (e.g. maintenance and pumping costs, digging channels to reach other plots, renting tubewells, contractual arrangements with equipment owners), the farmer chooses input a before weather in period t is realized and commits to the choice ex-ante, so that current weather does not affect the decision.¹⁶ This canonical setting assumes that private individual beliefs are always equal to or sufficient for the public information about the weather (Kelly et al., 2005; Moore, 2017).

I relax this assumption by considering a simple model of deterministic behavioral inattention and action (Gabaix, 2019). A farmer has been exposed to a sequence of weather realizations over the previous twenty years $\{w_{t-20}, \dots, w_{t-1}\}$ and forms beliefs $\mathbb{E}^b(w)$ about the underlying climate distribution from which weather realizations are randomly drawn. Beliefs can either be accurate - and coincide with $\mathbb{E}(w)$ - or inaccurate.

A behavioral farmer replaces the maximization problem in (2.2) with an “attention-augmented” production function (Gabaix, 2019) that is characterized by the degree of attention, i.e., the farmer’s subjective model of the world. The behavioral farmer selects the input level, a_b , that maximizes expected profit:

¹³This setting can be generalized to a farmer using k different irrigation techniques, such that $\mathbf{a} = \{a_1, \dots, a_k\}$, each of them with an associated price $\mathbf{c} = \{c_1, \dots, c_k\}$. For simplicity, I ignore credit constraints.

¹⁴One could include a vector of weather variables where derivatives would be replaced by Jacobian matrices.

¹⁵Subscripts on an expectation operator denote the information set on which the expectation is conditioned (showcased here and then omitted for brevity).

¹⁶This assumption is empirically tested in Table B20, where I consider the baseline specification and regress the share of irrigated land on contemporaneous seasonal deviations in the SPEI and find a null effect.

$$\max_a \mathbb{E}^s(\pi) = \mathbb{E}^s(w)F(a) - c(a) \quad (2.3)$$

where subjectively perceived $\mathbb{E}^s(w)$ is a convex combination of the expected weather realization using the history of past weather conditions and the farmer's beliefs about the climate distribution, parametrized by the weight γ :

$$\mathbb{E}^s(w) := \gamma \mathbb{E}(w) + (1 - \gamma) \mathbb{E}^b(w) \quad (2.4)$$

The chosen input of the behavioral farmer a_b is affected by the degree of inaccuracy of beliefs with respect to expected weather realizations and by the extent to which she weighs beliefs. In other words, farmers are making a decision based on a combination weighted by γ of what has happened and their interpretation of that. Equation (2.4) allows for individuals exposed to the same weather realizations to have different beliefs, considering realizations drawn from different climate distributions, and thus react differently.

Although the data used in the empirical analysis do not contain information on forward-looking beliefs about changes in droughts, previous studies find a strong significant correlation between past- and forward-looking beliefs about the weather and climatic events (Bakkensen and Barrage, 2022). In a non-stationary climate with scientific uncertainty, accurate expectations of future weather are not necessarily formed from long-run averages. Nevertheless, those that believe that droughts have increased take weather realizations as a signal of the future path of weather - which differs from those believing that the climate distribution is fixed.

The behavioral friction in the model drives the wedge between expected profits for a rational farmer and for a behavioral farmer with inaccurate beliefs, allowing for agents' subjective state of the world and objective meteorological conditions to differ. When $\gamma = 1$, the farmer behaves as a rational agent ($\mathbb{E}^s(w) = \mathbb{E}(w)$) and beliefs do not differentially influence inputs use. When $\gamma \in [0, 1)$, beliefs matter and the farmer may be losing profit by ignoring information up to the point $\gamma = 0$, where the farmer "does not think about" $\mathbb{E}(w)$ and replaces the subjective model of the world only with her beliefs (Gabaix, 2019).

To fix ideas, take $F(a) = a^\alpha$, where $\alpha \in (0, 1)$ and a linear cost function. Assuming interior solutions for the non-negativity constraint in the input choice, the behavioral farmer maximizes expected profits and chooses a_b :

$$a_b = \left[\frac{\alpha \mathbb{E}^s(w)}{c} \right]^{\frac{1}{1-\alpha}} \quad (2.5)$$

Using the implicit function theorem, it follows that, if $\gamma \neq 0$, for a shift to drier conditions (increase in $\mathbb{E}(w)$), the farmer uses more irrigation. A similar result follows from the comparative statics with respect to individual beliefs. Beliefs that

droughts have increased are associated with an increase in irrigation use. Nevertheless, when there are no changes in climatic conditions, a farmer who believes droughts have increased may substitute irrigation through other adaptive margins, whose subjective opportunity costs have decreased. Which of the two forces prevails is an empirical question that is discussed in Section 2.5.

The parameter of interest is the differential role of beliefs for changes in weather conditions. Adaptive decisions depend not only on meteorological changes but also on changes in their beliefs. The differential effect of beliefs $\mathbb{E}^b(w)$ on a_b is

$$\frac{\partial^2 a_b}{\partial \mathbb{E}^b(w) \partial \mathbb{E}(w)} [c, \mathbb{E}^b(w), \mathbb{E}(w), \alpha, \gamma] = \frac{\left(\frac{\alpha}{1-\alpha}\right) \cdot \left(\frac{\alpha}{c}\right)^{\frac{1}{1-\alpha}} \cdot (1-\gamma) \cdot \gamma \cdot (\mathbb{E}^s(w))^{\frac{2\alpha-1}{1-\alpha}}}{1-\alpha} > 0 \quad (2.6)$$

The testable implication that follows from this model is that beliefs matter for the adaptive decision, i.e., Equation (2.6) is different from zero. The sign is unambiguous: farmers differentially respond to changes in weather conditions depending on their beliefs by increasing their use of irrigation, as long as $\gamma \in (0, 1)$. The intuition behind this result is that in places where weather conditions are becoming drier, changes in beliefs are associated with increases in the use of irrigation.

The parameter γ relates to farmers' behavioral preferences (and to some extent heuristics/biases), attention, confidence in their own beliefs, and information sharing. This causes departure from the neoclassical setting that only considers expected weather and convergence to a correct adjusted posterior, from any prior inaccurate belief. Considering comparative statics with γ , I obtain:

$$\frac{\partial a_b}{\partial \gamma} [c, \mathbb{E}^b(w), \mathbb{E}(w), \alpha, \gamma] = \frac{\left(\frac{\alpha}{c}\right)^{\frac{1}{1-\alpha}} \left(\mathbb{E}(w) - \mathbb{E}^b(w)\right) [\mathbb{E}^s(w)]^{\frac{\alpha}{1-\alpha}}}{1-\alpha} \quad (2.7)$$

The direction of changes in input adjustment is ambiguous as it depends on $\mathbb{E}(w) - \mathbb{E}^b(w)$, i.e., the inaccuracy of beliefs with respect to the average weather realization. If $\mathbb{E}(w) - \mathbb{E}^b(w) > 0$, i.e., weather conditions have been on average drier than the farmer believes, then $\frac{\partial a_b}{\partial \gamma} > 0$. For inaccurate farmers who underestimate shifts in the climate distribution, giving more weight to the objective meteorological conditions (increasing γ) would increase the input use. If the farmer is accurate, $\mathbb{E}(w) = \mathbb{E}^b(w)$, then the inattention parameter γ does not affect irrigation decisions.

Why do beliefs about climate matter for short-run behavioral responses?

Climate change is imperfectly observed by individuals, resulting in differences between beliefs about climate and its true state. Belief-related adjustment costs arise if the observer would have acted differently in response to the actual climate distribution relative to the climate distribution that they believe (Moore, 2017). These adjustment costs are the difference in expected profits given the irrigation options that would have been chosen with full information about the climate state ($\mathbb{E}(w) = \mathbb{E}^b(w)$). A necessary and sufficient condition for the existence of

belief-related adjustment costs is that beliefs about the climate are inaccurate (i.e., $\mathbb{E}^b(w) \neq \mathbb{E}(w)$). This assumption appears to empirically hold in Table B14, where I compare observed beliefs with changes to dryness conditions in a two-way frequency table. I categorize the continuous measure of long-run dryness conditions into a binary variable, whose values correspond to the beliefs that individuals would have had based on meteorological conditions.

Consider a farmer with beliefs that droughts have increased over the past twenty years and another farmer who does not perceive droughts to have increased. The former interprets weather realizations in the past twenty years as a shift in the distribution. In contrast, the latter interprets weather realizations as draws from a fixed climate distribution. For this reason, unlike short-run weather fluctuations and associated beliefs, which only allow for marginal behavior adjustments, different climate beliefs will drive different behavioral responses which can also lead to non-marginal changes in input use.¹⁷

Although beliefs shape heterogeneously individual responses to changes in weather conditions (Bento et al., 2023), identifying their effect is challenging since they are seldom observed. Previous research has so far assumed that agents are rational and have beliefs that optimally adjust (Hsiang, 2016; Deryugina and Hsiang, 2017). In Section 2.4.2, I develop an empirical model to quantify the differential role of beliefs for changes in weather conditions, consistent with Equation (2.6).

Profit loss due to inaccurate beliefs. A rational farmer and a behavioral farmer with inaccurate beliefs with respect to climatic conditions will make different irrigation decisions. If the farmer is not accurate, the optimal irrigation choice is Equation (2.5). If the farmer has accurate beliefs, the optimal use of irrigation is

$$a^r(\mathbb{E}(w), \alpha, c) = \left[\frac{\alpha \mathbb{E}(w)}{c} \right]^{\frac{1}{1-\alpha}} \quad (2.8)$$

The expected profit loss due to inaccurate beliefs is

$$\mathbb{E}(\pi(a^r)) - \mathbb{E}(\pi(a_b)) = \left[\mathbb{E}(w)^{\frac{1}{1-\alpha}} - \mathbb{E}^s(w)^{\frac{1}{1-\alpha}} \right] \cdot \left[\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}} \right] \cdot c^{-\frac{\alpha}{1-\alpha}} \quad (2.9)$$

In Section 2.6, I provide a back-of-the-envelope calculation of the monetary loss due to inaccurate beliefs combining estimates from the literature with the results obtained in the empirical analysis.

¹⁷To draw a parallel to another adaptive response outside of agriculture, consider two individuals exposed to the same meteorological conditions and who have observed extremely hot summers. One believes that these are a consequence of a shift in climate distribution, and the other does not. In this setting, the former will ex-ante commit to investing in coping mechanisms for the next summer, e.g. air conditioning, whereas the latter will not.

2.4.2 Empirical Approach

Following the theoretical framework, the baseline empirical approach explores the differential role of beliefs on irrigation, accounting for exposure to dryness. The econometric specification is

$$a_{it}^{(k)} = \beta_1 b_{it} + \beta_2 b_{it} \times \bar{w}_u + \beta_3 \tilde{w}_{ut-1} + X'_{it} \boldsymbol{\theta} + \lambda_i + \mu_t + \varepsilon_{it} \quad (2.10)$$

where $a_{it}^{(k)}$ is the share of irrigated land for individual i in year t . I initially pool the average share of irrigated land under any irrigation method across the *Aman* and *Boro* seasons and consider the most widely adopted irrigation techniques k ($\in \{\text{STW}, \text{DTW}\}$). In Section 2.5.2, I explore the effect for season-specific irrigation decisions.

I estimate the belief-adaptation relationship allowing the response function to vary with long-run exposure to dryness \bar{w}_u . The main explanatory variables are b_{it} , a binary variable indicating whether the individual believes droughts increased over the previous twenty years, \bar{w}_u , the average long-run excess dryness over the twenty years before the first wave of the survey relative to the historical average, \tilde{w}_{ut-1} , the one-year lagged deviation.

The direction of the association between beliefs and irrigation measured by β_1 is ambiguous: on the one hand, irrigation may increase if farmers perceive an increase in dryness and enhance their input use to mitigate the economic consequences of future dryness conditions; on the other hand, irrigation may decrease if farmers exhibit decreasing absolute risk aversion and by perceiving an increase in dryness they decide to engage in precautionary savings, e.g. decrease consumption expenditure (Alem and Colmer, 2022), reduce input use or engage in other adaptive margins.

The main coefficient of interest is β_2 , which accounts for heterogeneous short-run behavioral responses to exposure to dryness accounting for individual beliefs. The estimation of this coefficient represents a testable hypothesis of a behavioral farmer who responds differently depending on individual beliefs, against the null hypothesis that beliefs do not matter for adaptive responsiveness. An estimated coefficient that is not statistically different from zero would suggest that the second-order cross partial derivative in Equation (2.6) is equal to zero, i.e., $\gamma = 1$, and adaptation is only a function of objective weather conditions, as previously assumed in the literature (Shrader, 2023).

Many factors may compromise the identification of β_1 and β_2 in Equation (2.10). Those factors can be grouped into three potential sources of endogeneity, respectively reverse causality, unobserved heterogeneity, and measurement error. Below, I discuss my primary identification strategy and discuss each of these potential sources of bias.

Equation (2.10) includes a vector λ of individual fixed effects, accounting for all time-invariant factors that differ between individuals, including unobservable characteristics that could not be accounted for in a cross-sectional empirical design,

such as risk preferences and household-specific irrigation costs. I also include a vector μ of year fixed effects, which control for unobserved shocks common to all individuals in a given year. Therefore, identification comes from within-individual variation, conditional on the year fixed effects.¹⁸ Since I cannot completely rule out the possibility that there is unobserved heterogeneity in Equation (2.10) that varies systematically across individuals and over time, I also include in the specification time-varying individual-specific covariates that may contemporaneously change as a result of climatic changes and affect irrigation, and test for their balance between farmers who differ by drought beliefs (Table B13) and examine whether dryness affects any characteristics of farmers (Table B17).¹⁹ Any threats to identification applies to the coefficients β_1 and β_2 . The β_3 coefficient on short-run deviations \tilde{w}_{ut-1} can be interpreted causally as within-union weather realizations are plausibly exogenous (Hsiang, 2016).

Equation (2.10) includes an interaction term between drought beliefs b_{it} with cross-sectional variation in long-run excess dryness conditions \bar{w}_u to estimate the differential responsiveness to beliefs. The estimated model does not include the uninteracted term for long-run dryness, \bar{w}_u , because it is collinear with the fixed effects, which shuts down the possibility to influence irrigation decisions regardless of individual beliefs. In a robustness test, I exploit time-series variation in long-run dryness strengthening the plausibility of exogeneity of the interaction term, once the main effect of the endogenous variable is accounted for (Angrist and Krueger, 1999; Nizalova and Murtazashvili, 2016; Bun and Harrison, 2019).²⁰

Another potential concern may be reverse causality. Farmers who do not perceive changes in droughts and did not increase their share of irrigated land may suffer greater damage to their agricultural production as a result of changes in weather conditions. Consequently, they change their drought beliefs as a result of larger damages. Reverse causality may also occur if increasing the use of irrigation prevents individuals from updating drought beliefs. In both cases, the estimated coefficient associated with beliefs would be negative. I empirically test for reverse causality in Section 2.5.2.

Lastly, in the case of measurement error, it may be that drought beliefs are over-reported. Although systematic measurement error is a threat to the identification

¹⁸Union fixed effects are superfluous in this setting since all individuals in the estimation sample never change place of residence.

¹⁹Most importantly, information plays a prominent role in technology adoption decisions (Suri, 2011). I include controls for the primary occupation of the respondent is a farmer and if the respondent receives extension advice as proxy variables that determine the farmer's human capital (Koundouri et al., 2006). Additional covariates include if the household has access to electricity, ownership status of STW or DTW pumps, shares of soil type of cultivated land and total hectares of land holdings as a measure of the wealth of the household, beliefs of erratic rainfall and decreases in precipitation.

²⁰For an empirical application with exogenous weather variables interacted with potentially endogenous fractions of area insured, see Annan and Schlenker (2015).

of β_1 and β_2 , the estimated relationship between the beliefs and use of irrigation would suffer from attenuation bias, biasing the estimates toward zero.

I estimate standard errors allowing for both cross-sectional spatial correlation and location-specific serial correlation. Using clustered standard errors at the union level would underestimate the standard errors since in five cases the boundaries of more than one sampled union fall within the same grid cell of the meteorological data and unions' borders lay across different grid cells (Figure B2). I impose a two-year constraint, compatible with the temporal distance between the two survey waves, on the temporal decay for the Newey-West/Bartlett kernel. In the spatial dimension, I retain a radius of 200 km with a Bartlett (triangular) kernel: close to the average distance between union centroids and around four times the spatial resolution of the SPEI to allow for correlated shocks across grid cells. The estimates are robust when changing either the spatial or temporal cutoff, or both.²¹ Inference is also largely unchanged when standard errors are clustered at the grid cell level.^{22,23}

2.5 Results

This section presents and discusses the key findings from estimating Equation (2.10). First, I consider the average share of irrigated cultivated land and then I decompose the share of irrigated cultivated land between the most adopted irrigation techniques (STWs and DTWs) averaged over the two growing seasons. In Section 2.5.2, I investigate season-specific irrigation decisions distinguishing between irrigated land in *Aman* and in *Boro* separately and using season-specific exposure measures. In Section 2.5.3, I explore heterogeneity along socio-demographic characteristics.

2.5.1 Individual beliefs and irrigation use

Table 2.1 displays the estimates of the coefficients on beliefs and the interaction with long-run exposure to dryness on the average share of land irrigated over the two main growing seasons.²⁴ In column (1), I estimate Equation (2.10) excluding the interaction term between beliefs and long-run dryness. The partial correlation

²¹Tables B29 and B30 display the baseline results when changing the spatial cutoff to 100, 400 or 800 km and the temporal autocorrelation cutoff to 5, 10, and 999 years.

²²Baseline results clustering standard errors at the grid cell-level are displayed in Tables B31 and B32. Seemingly Unrelated Regressions (SUR) (Zellner, 1962) does not suit the setting since each equation contains exactly the same set of regressors (Kruskal, 1960). The correction using bootstrap iteration, which would provide robust estimates of standard errors to heteroskedasticity and cluster-correlation structures (Freedman and Peters, 1984), is not feasible due to the small size of the estimation sample.

²³The estimation of Driscoll and Kraay standard errors, adjusted for heteroskedasticity and autocorrelation and robust to general forms of spatial and temporal dependence, is based on large T asymptotics (Driscoll and Kraay, 1998). With T fixed and N large, as it is the case here, there is not sufficient information in the time dimension relative to the cross-section dimension for this approach to work (Vogelsang, 2012; Hoechle, 2007)

²⁴Results are robust and estimates more precise when including the irrigation and meteorological records in *Aus*.

between the share of irrigated land and drought beliefs conditional on individual and year-fixed effects and individual controls is negative and statistically significant at conventional levels.

When I also include the interaction term (column 2), beliefs are still negatively associated with the share of irrigated cultivated land, with the effect larger in size. For a farmer exposed to dryness conditions that do not differ from the historical average, drought beliefs reduce irrigated land. This case never occurs in the data. In all unions in the sample (except for Khalilnagar, Laskar and Rudaghara) the environment was drier than the historical average in the twenty years before the first wave. There are four potential interpretations behind this finding. First, irrigation is a costly action, and farmers, although they believe in a change in the climate distribution, reduce the use of irrigation in non-dry periods. Second, the result may be explained by a depletion of groundwater supplies. Although it cannot be fully ruled out, behavioral responses as a result of short-run changes in beliefs between the two waves are unlikely to be explained by groundwater resources depletion which occurs over a longer time horizon (Taraz, 2017; Scanlon et al., 2012). Third, it may lend support to the hypothesis of substitution between irrigation and other coping mechanisms, whose opportunity cost may be lower for a perceived change in dryness conditions. Finally, it may raise concerns about reverse causality between behavioral responses and beliefs. The two last hypotheses are discussed in detail and empirically tested below.

The interaction term between beliefs and long-run dryness is positive, statistically significant, and around ten-fold larger than the uninteracted coefficient. For instance, under a long-run exposure to meteorological conditions one standard deviation drier than the historical average, beliefs are associated with an increase by around 65 percentage points (p.p.) in the share of irrigated land. This effect, which may seem extremely large in magnitude, is computed for a twenty-year average exposure much larger than the mean in the sample (0.07). The effect of beliefs on the share of irrigated cultivated land is positive for households exposed to at least a long-term average one-tenth of SD drier than the historical average, roughly the seventieth percentile across unions.

The key finding is that two individuals exposed to the same conditions of dryness, but with heterogeneous beliefs, choose different levels of irrigation, *ceteris paribus*. People's responsiveness to a change in climate depends on their underlying beliefs, questioning previous assumptions on rational agents and internalized information set to form beliefs on climatic conditions (Deryugina and Hsiang, 2017). There are two potential sources that explain the heterogeneity in beliefs for given climatic conditions. On the one hand, people may have different definitions of droughts and behaviorally respond in an internally consistent way regardless of meteorological conditions. On the other hand, heterogeneity may be in farmers' beliefs about a

definition of drought. Since the empirical approach exploits within-individual variation in beliefs over two years, it is unlikely, although not impossible, that individuals change their mental definitions of droughts. Moreover, the negative sign associated with the uninteracted term seems to rule out the hypothesis of an internally consistent behavior of farmers for an individual-specific definition of droughts.

Columns (3) and (4) display the estimates of Equation (2.10) for the share of cultivated land under the most widely adopted irrigation techniques across growing seasons, respectively STW and DTW. The estimates show that irrigation decisions are driven by changes in the use of STWs, that account for around 60% of the irrigated land, with noisy and imprecisely estimated association between beliefs and share of cultivated land irrigated with DTW (column 4). DTWs are mainly used in the *Boro* dry season when stored water in shallow aquifers does not meet farmers' needs, whereas the average share of land equipped with this technology is negligible in the *Aman* monsoon season. In this period of the year, precipitation is abundant and replenishes shallow aquifers so farmers prefer using STWs.

TABLE 2.1: Individual beliefs and irrigation use. OLS estimates.

<i>Dependent variable:</i> Share of cultivated land	Irrigated		STW	DTW
	(1)	(2)	(3)	(4)
Belief increase in drought (β_1)	-0.0340** (0.0145)	-0.0470*** (0.0146)	-0.0340* (0.0178)	0.00386 (0.0117)
Belief increase in drought \times Long-run dryness (β_2)		0.649** (0.291)	0.725** (0.359)	-0.377 (0.238)
Controls	X	X	X	X
Fixed Effects	X	X	X	X
Mean Outcome	0.489	0.489	0.299	0.068
SD Outcome	0.327	0.327	0.354	0.191
<i>N</i>	1428	1428	1428	1428

Notes: Table reports the OLS estimates of a regression where the outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (columns 1-2), irrigated with STW (column 3) and with DTW (column 4). Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, the share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Additional results. In Table B21, I provide results for the belief-adaptation relationship using alternative samples. In columns (1) and (2), I address the fact that changes in irrigation may be explained by investment, which could have been limited by financial constraints. Although informal markets in groundwater irrigation in Bangladesh are equitable and accessible (Bell et al., 2015), farmers who believe droughts increased may not respond differently under drier conditions because of liquidity constraints. To rule out this channel, I exclude those farmers who did not irrigate any plot in the first wave and thus may have had to invest in irrigation in the second wave (column 1) and find similar estimates to the baseline results, with the interaction term larger in magnitude. The results are similar also when

excluding farmers who may have not irrigated in any of the two waves because of other constraints than changes in beliefs or weather conditions (column 2).

I also estimate the baseline specification excluding farmers who did not harvest *Aman* or *Boro* rice in the first wave (column 3). Although I cannot entirely rule out the potential adaptive margin of changes in crop choice, this channel would underestimate the belief-adaptation relationship, assuming that farmers exposed to drier conditions and perceiving an increase in drought would grow more drought-tolerant crops that need less irrigation. I also test that the effect does not depend on ownership of the irrigation system, excluding the small share of farmers who own either STW or DTW pumps (column 4). Results are very close in magnitude to the baseline estimates, providing suggestive evidence that ownership does not play a role and informal markets for irrigation are easily accessible and efficient in Bangladesh (Bell et al., 2015). Finally, I also exclude farmers in the sole union (Piprul) in which no extreme drought event over the previous twenty years was recorded (column 5). The absence of such events does not rule out the occurrence of milder drought events or periods of drier conditions which may be used as climatic conditions for farmers to form their beliefs about droughts.

Irrigation can also be a function of increased uncertainty in production due to more erratic rainfall patterns (Koundouri et al., 2006; Falco et al., 2014), with risk-averse farmers having a higher probability of technology adoption (Groom et al., 2008; Bozzola, 2014). To account for this mechanism, I construct measures of seasonal and interannual variability in water balance using the average seasonal intra-annual standard deviation in monthly water balance and the interannual standard deviation of seasonal average monthly water balance. The interaction term between a meteorological measure of water balance variability and drought beliefs on irrigation use is positive but imprecisely estimated. The magnitude of the effect is smaller than the interaction term between beliefs and average dryness, whose magnitude is not impacted by the additional regressor and is slightly larger than the baseline estimates (Table B22).

Other adaptive margins. Farmers adjust their use of irrigation as a result of their beliefs of increases in droughts if they have been exposed historically to drier conditions. The negative coefficient of the uninteracted term of beliefs may suggest that farmers respond to their beliefs through other coping mechanisms that have become relatively cheaper compared to adjusting irrigation use. For this reason, I study other adaptive margins previously documented in the literature, in particular sales and consumption of livestock²⁵ (Rosenzweig and Wolpin, 1993) and working in non-agricultural activities or changing use of labor both hired or self-employed in agricultural activities (Colmer, 2021; Aragón et al., 2021). In Table B23, I report the estimates from the baseline specification with other coping mechanisms as outcome variables. The first set of outcomes focuses on livestock as a buffer and I find

²⁵The definition of livestock adopted here includes cattle, chicken, pigs, and sheep.

no evidence that farmers' beliefs differentially change farmers' sale or consumption behavior as a response to the long-run dryness conditions. Similar results hold when focusing on a binary indicator of the head of the household having an off-farm job²⁶ and when looking at the number of agricultural workers, crop farmers or members of the households self-employed in agricultural activities. These results seem to rule out the hypothesis that farmers use more than one adaptation strategy and only adjust their use of irrigation in response to dry conditions.

Heterogenous prior beliefs. To avoid relying on potentially endogenous changes in beliefs between the two waves, I design an alternative specification that considers baseline prior beliefs in the first wave. I compare these to a dichotomous measure that distinguishes long-run dryness conditions between drier and wetter than the historical average and construct a binary variable (*Inaccurate priors*) that is equal to one if stated beliefs on drought increase differ from meteorological conditions. I interact this variable with short-run variations in dryness conditions to estimate heterogeneous responses in irrigation to dryness shocks conditional on the inaccuracy of prior beliefs. The expected response in irrigation use may differ by the direction of inaccuracy. In a second exercise, I distinguish between individuals who believe that droughts increased when meteorological records do not support such a hypothesis (*Positive inaccurate priors*) and individuals who do not believe in such change in the distribution of droughts when records indicate drier conditions (*Negative inaccurate priors*).

Table 2.2 displays the results. Columns (1) and (2) show that a shock in dryness conditions increases irrigation use, however, much less so for individuals who have inaccurate prior beliefs about changes in climatic conditions. The response is asymmetric in the type of inaccuracy. Compared to accurate individuals, individuals who do not believe in drought increase although records indicate drier conditions reduce the share of irrigated land (columns 3-4), consistent with the hypothesis that they interpret the shock as a random realization from a fixed climate distribution and thus do not adapt. Conversely, drought beliefs when meteorological records do not record an increase do not substantially alter the irrigation response to a dryness shock, although the point estimate is positive.

2.5.2 Unbundling the effect by growing season

Since prior work has shown the differential effect of climatic conditions in the wet and dry seasons on irrigation and other adaptation strategies (Taraz, 2017; Auffhammer and Carleton, 2018), I test for heterogeneity across the two main growing seasons, *Aman* and *Boro*. The results are reported in Table 2.3. In columns (1) and (2), I show the estimates in the *Aman* monsoon season, respectively for the share of

²⁶The definition of off-farm occupation includes business/trading, rickshaw/van puller, tailor, potter, cobbler, handcrafts, small and cottage industry, mechanic, plumber, doctor, engineer, lawyer, religious.

TABLE 2.2: Heterogeneous response in irrigation use to short-run shocks by inaccurate beliefs. OLS estimates.

<i>Dependent variable:</i> Share of cultivated land	Irrigated	STW	Irrigated	STW
	(1)	(2)	(3)	(4)
Short-run dryness shock	0.136** (0.0578)	0.298** (0.122)	0.141*** (0.0543)	0.309** (0.135)
Inaccurate priors \times Short-run dryness	-0.0750** (0.0331)	-0.0836** (0.0411)		
Positive inaccurate priors \times Short-run dryness			0.0110 (0.0908)	0.101* (0.0602)
Negative inaccurate priors \times Short-run dryness			-0.0935** (0.0382)	-0.124** (0.0517)
Controls	X	X	X	X
Fixed Effects	X	X	X	X
Mean Outcome	0.489	0.299	0.489	0.299
SD Outcome	0.327	0.354	0.327	0.354
<i>N</i>	1428	1428	1428	1428

Notes: Table reports the OLS estimates of a regression where the outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (columns 1-3), irrigated with STW (column 2-4). “Inaccurate priors” is a binary variable equal to one if “Belief increase in drought” and the binary version of “Long-run dryness” differ and equal to zero when they are equal. “Negative inaccuracy” is a binary variable equal to one if “Belief increase in drought” is equal to zero and the binary version of “Long-run dryness” is equal to one, and zero otherwise. “Positive inaccuracy” is a binary variable equal to one if “Belief increase in drought” is equal to one and the binary version of “Long-run dryness” is equal to zero, and zero otherwise. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzner (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. *Controls:* main occupation of the respondent is farmer, the household receives extension advice, access to electricity, hectares of total land holdings; ownership status of STW and DTW, the share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

rained cultivated land and the share of cultivated land irrigated with STW. In columns (3)-(5), I consider the share of rainfed, STW irrigated and DTW irrigated land in the *Boro* season.²⁷

In the *Aman* season, drought beliefs are positively and statistically significantly associated with the share of rainfed cultivated land, but the marginal effect of beliefs is moderated by the coefficient of the interaction term between beliefs and long-run exposure (column 1). Likewise, the coefficient on beliefs on the share of STW-irrigated land is negative and statistically significant (column 2). The coefficient of the interaction term is positive, statistically significant, and around ten times larger than the uninteracted term. During the *Aman* season, for a long-run dryness one standard deviation drier than the historical average, beliefs are associated with a decrease by around 46 p.p. in the share of rainfed land and an increase in the share of land under STW irrigation by around 39 p.p..

Beliefs are never statistically different from zero when considering irrigation decisions in *Boro* (columns 3 to 5). These findings uncover substantial heterogeneity across growing seasons behind the results in Table 2.1. Without excessive speculation

²⁷The use of DTW irrigation in the monsoon season is negligible (the average fraction of land irrigated with DTW is 0.01), explaining the asymmetry in the outcomes of interest across the two main growing seasons.

over these results, the *Boro* season is dry and irrigation is already often implemented (the average share of cultivated land left rainfed is around 50 p.p. lower than in the *Aman* season and the average total share of irrigated land is more than 50%). For this reason, changes in beliefs may play a minor role in the adaptive decision. The lack of information on growing season-specific beliefs hinders further investigation of this result, which is left for future research. Moreover, the heterogeneity in the results across growing seasons is not driven by systematic differences in financial liquidity constraints across seasons (Bell et al., 2015).

TABLE 2.3: Individual beliefs and irrigation use by growing season. OLS estimates.

Growing Season:	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
<i>Dependent variable:</i> Share of cultivated land					
Belief increase in drought (β_1)	0.0871** (0.0361)	-0.0498* (0.0246)	0.0229 (0.0233)	-0.0234 (0.0298)	0.0188 (0.0287)
Belief increase in drought \times Long-run dryness (β_2)	-0.545* (0.279)	0.437* (0.233)	0.275 (0.338)	0.0254 (0.391)	-0.296 (0.290)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

Time-varying long-run dryness. I test for the robustness of the annual and seasonal results using a different source of variation, constructing a time-varying measure of long-run dryness as the average monthly SPEI in the twenty years preceding the survey wave. I exploit wave-to-wave within-union fluctuations in the SPEI realizations and include both the uninteracted term and its interaction with beliefs. Given the two-year time interval between the two waves, the variation in this approach relies on climate changes that occurred over shorter time periods than twenty years. The use of 20-year averages may thus introduce attenuation bias (Bareille and Chakir, 2023). Tables B33 and B34 report the results with the coefficients on beliefs and the interaction term close, but smaller, in magnitude to the main results both for annual and seasonal estimates.

Outcome variable. I also test that the results are robust to the use of a different outcome variable for the irrigation status. This alternative outcome measures the total hectares of cultivated land under each irrigation status by growing season. Results are reported in Table B35. The interaction term is negative and statistically significant on the rainfed cultivated land in both *Aman* and *Boro* seasons (columns 1 and 3). Consistent with the baseline results, the effect of the interaction term on the surface of land under STW irrigation in *Aman* is positive, although not

precisely estimated. Since the distribution of the share of cultivated land under each irrigation status has two mass points at zero and one (Figure B4), I also estimate a linear probability model using a binary version of the outcome variable taking value one if the share of cultivated land rainfed or irrigated is strictly positive, and zero otherwise and find comparable estimates (Table B36).

Reverse causality. Past irrigation decisions may determine the future beliefs of droughts (Niles and Mueller, 2016). Leaving more land rainfed may increase the probability of experiencing damages induced by drought. By attributing the cause of the damage to droughts, individuals may be more likely to report having perceived an increase in these weather events as a result of their past actions. Symmetrically, irrigating a larger share of cultivated land would decrease drought damages and lower the probability of updating drought beliefs. To allay the concerns on reverse causality, I regress drought beliefs in the second wave of the survey and the change in beliefs between the two waves on the share of irrigated cultivated land in the first wave, in a cross-sectional setting. Reassuringly, the estimates of the irrigation statuses are never statistically significant and very close to zero in magnitude (Table B37).

2.5.3 Unbundling the effect by socio-demographic characteristics

Tables 2.1 and 2.3 show that the farmers' responsiveness on average differs by beliefs over the agricultural production year and by growing season. The estimates may be heterogeneous across different characteristics of the respondents. I split the sample between individuals below and above the median age, respectively 18-44 and 45+, and using the median number of years of education, distinguishing between those with no formal education and those with at least one year.

Starting from annual-level analysis, the coefficients associated with beliefs and with the interaction term are statistically significant only among individuals above the median age (Table B25). A similar result holds also when considering the STW irrigation technique (columns 3-4). This result indicates a learning channel through which older individuals with a larger information set of weather realizations undertake adaptation strategies aligned with their beliefs depending on the degree of exposure to meteorological conditions and provide suggestive evidence against the presence of "status quo bias" (Samuelson and Zeckhauser, 1988).

The sub-sample analysis by years of education yields similar findings. Higher education attainment may explain learning about agricultural technologies, effectiveness of the adaptation strategies and knowledge of the relationship between dryness and irrigation use (Feder et al., 1985). Unfortunately, this information is not directly observed. The heterogeneous effect in the educated and non-educated sub-samples provides some evidence that educational attainment affects subsequent adaptation (Table B26). Beliefs are not statistically significant in any specification in the sub-sample of individuals with no formal education. In the sample of individuals with

at least one year of formal education, the marginal effect of beliefs on irrigated land is positive for a lower average level of long-run exposure to dryness. Overall, these findings may be indicative of the importance of formal education among farmers.

I replicate the same analysis for the irrigation decisions in *Aman*. Table B27 shows the results of the sub-sample analysis by age and education. On the one hand, there is no substantial heterogeneity by age with estimates that are qualitatively similar both in the sample below and above the median age. On the other hand, the learning channel through educational attainment persists also in the growing season results, providing further evidence of the importance of formal education among farmers.

2.6 Welfare loss due to inaccurate beliefs

In this section, I use the season-specific baseline results to monetize the loss in profits generated by inaccurate beliefs using estimates of returns to irrigation. Given seasonal heterogeneity in the use of irrigation, I consider the predicted hectares of cultivated land under STW irrigation in each growing season as a function of observed beliefs²⁸ and compare them with predicted hectares as a function of accurate beliefs, b^* , defined as a binary variable equal to one if the seasonal long-run exposure to dryness is strictly above zero (indicating a drier environment than historical averages), and zero otherwise.²⁹ Table B14 shows the two-way frequency distribution between observed and accurate beliefs in the two growing seasons, where around 54% of the respondents have accurate beliefs over the years, 44% in *Aman* and around 68% in *Boro*. These results seem to indicate that dryness conditions during the winter season most closely match droughts belief formations. I compute a difference-in-difference counterfactual in irrigation use between the two survey waves and between observed and accurate beliefs based on meteorological records:

$$\Delta \hat{a}_i^{season} = \sum_{t=1}^2 [\hat{a}_{it}^{season}(b^*, w, X) - \hat{a}_{it}^{season}(b, w, X)] \quad (2.11)$$

where $season \in \{Aman; Boro\}$. $\Delta \hat{a}^{Aman}$ is centered at -0.086 ha (SD = 0.047, interquartile range is [-0.097, -0.08]) and $\Delta \hat{a}^{Boro}$ is centered at -0.014 ha (SD = 0.015, IQR is [-0.025, -0.007]). These results indicate that farmers irrigate less land than they would have, had their beliefs been based on meteorological records, particularly in the *Aman* monsoon season.

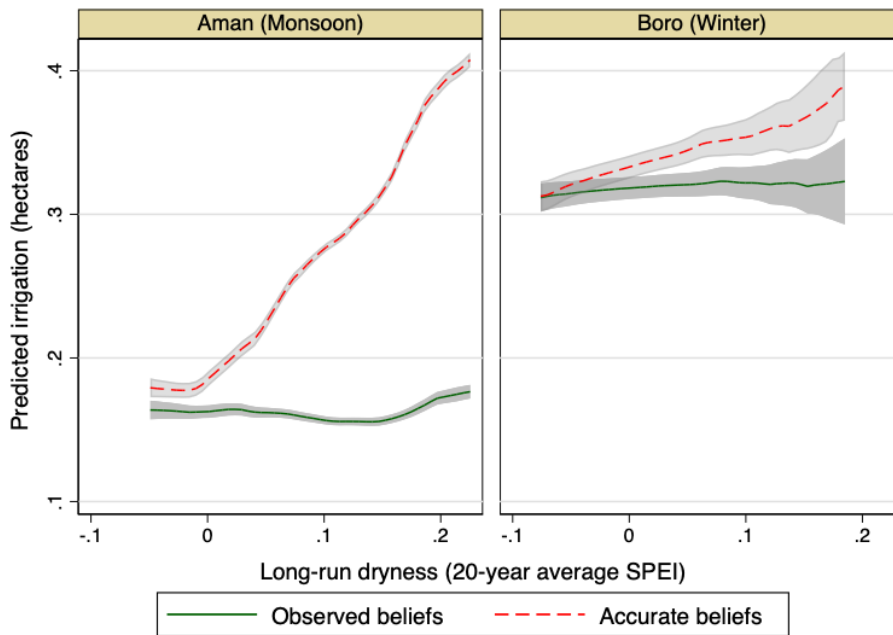
Figure 2.1 shows the semiparametric relationship between irrigation and long-run dryness, plotting a local smooth regression line of the predicted hectares of land

²⁸Estimates refer to columns 2 and 4 in Table B35.

²⁹I refer to beliefs constructed from meteorological records as “accurate” without any normative implication on how beliefs ought to be formed. I adopt this approach to translate farmer beliefs into hydro-meteorological physically based metrics matching the wording and time horizon of the survey questions.

irrigated in each growing season using accurate and observed beliefs on long-run exposure to dryness. Irrigation as predicted by observed beliefs is underutilized, with a *belief gap* that widens for drier conditions. During *Boro*, there are no statistically significant differences in the predicted use of irrigation for accurate and observed beliefs under wet conditions. Nevertheless, a *belief gap* emerges as *Boro* winter becomes drier. Below, I monetize the difference in the use of irrigation due to the *belief gap*, using estimates of returns to irrigation in similar contexts in the literature.

FIGURE 2.1: Semiparametric relationship between irrigation and long-run dryness for observed and accurate beliefs



Notes: Each line shows a local linear regression (Epanechnikov kernel) of hectares of land irrigated with STW predicted from estimating Equation (2.10) and long-run exposure to dryness. The green solid line uses observed self-reported farmer beliefs b . The red, dashed line uses accurate beliefs b^* , where accurate beliefs are equal to one if the seasonal long-run dryness exposure is strictly above zero, and zero otherwise. Shaded areas show 95% confidence intervals.

There is growing evidence on the returns to irrigation that uses quasi-experimental variation in groundwater irrigation, exploiting variation in slope characteristics of river basins (Dufflo and Pande, 2007), aquifer characteristics (Sekhri, 2014), or well-failures (Jacoby, 2017) in South Asia; and spatial discontinuities in Rwanda (Jones et al., 2022). Irrigation has substantially contributed to increases in agricultural productivity in Bangladesh (Hossain et al., 2005; Ahmed and Sampath, 1992; Haque, 1975) and has been shown as a determining factor in agricultural success (Bell et al., 2015). To the best of my knowledge, there is no systematic estimate of the returns to tube well irrigation on agricultural outcomes in Bangladesh. I provide an estimate

of the monetary loss due to inaccurate beliefs using different estimates that consider settings plausibly similar to the one adopted in my analysis. Table B24 summarizes the estimates found in the literature reporting the geographical and temporal context, the crop production, and the irrigation technology considered.

As a baseline, I use the findings in Haque (1975), which provides quantitative estimates of the effect of using STW irrigation compared to non-irrigated farms in Bangladesh by growing seasons. Using Equation (2.11), the median loss due to inaccurate beliefs is 214.16kg in Aman rice production and 49.07kg in Boro rice production. To monetize the value loss due to inaccurate beliefs, I use the most recent price at which the government procures Aman and Boro rice, equal to 40 Taka/kg³⁰ (Daily Sun, 2021; The Business Standard, 2022). The median monetized value loss is \$102.80 in Aman (IQR [\$95.63, \$115.98]) and \$23.55 in Boro (IQR [\$12.11, \$42.06]).³¹ To understand the magnitude of this loss, the median household production in the first wave of the survey was 800kg of Aman rice and 1260kg of Boro rice. The difference in average net cost per cropped hectare between STW-irrigated and non-irrigated crops is 121.08 Taka/ha (Haque, 1975). The median monetized net loss due to inaccurate beliefs is around 26.5% of the total production value of Aman rice and 3.9% of the total production of Boro.

Using returns to irrigation from other geographical contexts and for other crops, I obtain lower monetary losses, but comparable (Bhandari, 2001; Mandal and Singh, 2004). Such differences underline some potential caveats to these welfare calculations. First, I assume that rice productivity has remained constant over time, in spite of evidence showing increasing long-term production trends for *Aman* and *Boro* rice (Parvin and Rahman, 2009; Al Mamun et al., 2021). Second, the welfare calculations only account for an average measure of net costs between STW-irrigated and non-irrigated crops, rather old (Haque, 1975), and that therefore does not account for technological change and improvements that may have increased the irrigation technology efficiency. Third, returns to irrigation estimates are not conditional on increases in dryness, suggesting that the estimates may represent a lower bound (Mohsenipour et al., 2018).³²

³⁰In 2022 USD, 1 Taka \approx 0.012 \$.

³¹Similar monetary losses in *Boro* are obtained using the returns to irrigation in Parvin and Rahman (2009).

³²Other estimates from recent studies of returns to irrigation that identify plausibly causal effects provide monetized losses smaller in magnitude, however, they present substantially different geographical settings, crops produced and irrigation technology (Sekhri, 2014; Jones et al., 2022). More recent estimates on the returns to irrigation (Duflo and Pande, 2007; Fishman, 2018) cannot be used for this exercise, respectively due to a lack of information on summary statistics of the sample and since the direct effect of irrigation is not reported.

2.7 Cognitive mechanisms

Individual heterogeneity in beliefs explains different short-run behavioral responses to the same exposure to droughts. These findings are consistent with a model of behavioral inattention and action with individual asymmetric interpretation of weather conditions. This underlines the importance of accounting for both the average level of exposure and most importantly individual knowledge about it. There are other potential channels, however, that may explain short-run behavioral responses. In this section, I address three potential cognitive mechanisms consistent with the baseline results that may play a role in individual behavioral responses.

Agents adopt cognitive heuristics when assessing future uncertain events, exhibiting availability bias (Gallagher, 2014), recall errors (Guiteras et al., 2015) or motivated reasoning (Druckman and McGrath, 2019; Zappalà, 2023b). Here, I exploit the intensity and frequency of drought events, comparing self-reported and meteorological records. In Section 2.7.1, I investigate whether the timing of self-reported drought events affects irrigation decisions. Overweighting recent weather realizations could result in potentially sub-optimal irrigation decisions, when evaluated ex-post because of imperfect foresight (Ji and Cobourn, 2021). In Section 2.7.2, I test if recall errors in the timing of droughts leads to potentially sub-optimal irrigation decisions. The third mechanism in Section 2.7.3 explores whether the respondents' recollection of the frequency of droughts matters for irrigation.

2.7.1 Salience

This section investigates whether the timing of past drought events shapes individual behavioral responses. The literature on cognitive heuristics and expectation formation has introduced the “recency bias” in models of agents' learning (Kala, 2017). According to this heuristic, individuals assign higher probabilities to events that have happened recently, compared to remembering events that occurred a long time ago, and react to them (Kunreuther and Slovic, 1978; Kahneman and Tversky, 1973; Camerer and Loewenstein, 2011).

This phenomenon has been documented using different empirical evidence, in particular with respect to flood risks (Gallagher, 2014; Bakkensen et al., 2019), climate change through temperature anomalies (Deryugina, 2013; Li et al., 2011), short-term weather fluctuations (Ji and Cobourn, 2021), and financial markets (Malmendier and Nagel, 2011). In my context, experiencing a particularly harmful drought may lead agents to overreact and make adaptive decisions, without necessarily changing their long-lasting underlying beliefs on the frequency of these events. I consider the self-reported year of the most harmful drought and include in Equation (2.10) two non-mutually exclusive event time indicators described in Section 2.3.1 (“Self-reported experience of drought”).

Table 2.4 displays the results. The coefficient associated with the self-reported measure of the most harmful drought in the year before the irrigation decision is negative and statistically significant for the share of rainfed cultivated land (column 1) and positive for the share of cultivated land under STW irrigation status (column 2) in the *Aman* season. These results are consistent with the hypothesis of overreaction to salient drought events in adaptive decisions.

Similar results are obtained for *Boro*. One-year lagged drought has a positive and statistically significant effect on the share of cultivated land with DTW (column 5). $Drought_{t-1}$ has a negative and statistically significant effect on the share of cultivated land irrigated with STW (column 4). This result is specific to the winter dry season. Groundwater droughts occur when groundwater recharge or discharge deviate from normal, and the groundwater heads in an aquifer fall below a critical level over a certain period of time resulting in several adverse effects. During the peak water demand in the months of March and April, groundwater levels can fall below the suction limit making it difficult for the farmers to pump water using the STW (Mainuddin et al., 2021; Shahid and Hazarika, 2010). Groundwater droughts usually affect shallow aquifers and are caused by low precipitation in combination with high evapotranspiration, which leads to low groundwater recharge of underground aquifers (Adhikary et al., 2013). Unfortunately, the survey does not disentangle which type of droughts (whether meteorological or groundwater) is reported by the respondent, but the occurrence of a groundwater drought affecting the water recharge of shallow aquifers may explain the negative effect of one-year lagged droughts on the share of land irrigated with STW.

The behavioral response to being hit by drought does not last more than one year. $Drought_{t-2}$ is never statistically different from zero in any of the estimated equations, strengthening the hypothesis that agents respond by changing adaptive behavior in the year after they experienced the most harmful drought, without adjusting permanently.

I also test for salience using an objective measure of drought events obtained from the SPEI. I construct two different measures, respectively whether an extreme drought event occurred during the previous growing season and whether this event was the most harmful (i.e., the lowest value of SPEI) over the same time interval covered by the survey questions.³³ These results provide further evidence on the effect of salient drought events driving reactions in irrigation in the following year (Table B38). An individual in a union hit by an extreme drought event in the previous year increases the share of land under DTW irrigation by 6.1 p.p. (column 3) and decreases the share of rainfed land by 9.4 p.p. (column 1) during *Boro*, *ceteris paribus*. As previously found, a drought event in the *Boro* season negatively drives the allocation of land irrigated using STWs. When considering the most harmful

³³Since all the drought events recorded have occurred during the *Boro* season, I run the regressions only considering the outcomes and weather variables in this growing season.

objective drought events, results are qualitatively similar and the estimates larger in magnitude (columns 4-6).

TABLE 2.4: Self-reported timing of the most harmful drought and irrigation use

Growing Season: <i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Drought _{t-1}	-0.0804** (0.0355)	0.0507* (0.0273)	0.0174 (0.0250)	-0.0829** (0.0328)	0.0462 (0.0282)
Drought _{t-2}	0.0284 (0.0955)	-0.100 (0.0681)	-0.0318 (0.0945)	-0.00403 (0.152)	0.0243 (0.0285)
Belief increase in drought	0.0960*** (0.0275)	-0.0563*** (0.0187)	0.0284 (0.0174)	-0.0134 (0.0238)	0.00398 (0.0175)
Belief increase in drought × Long-run dryness	-0.666*** (0.251)	0.536*** (0.206)	0.253 (0.263)	0.114 (0.312)	-0.346 (0.211)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.562	0.574	0.749	0.671	0.584

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzter (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: **p* < 0.1, ** *p* < 0.05, *** *p* < 0.01. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

2.7.2 Recall error

The use of self-reported measures might cast some doubts due to recall errors and reference dependence (Guiteras et al., 2015). A subjective measure of salient events may not shed light on the mechanisms underlying overreaction to such events. Results in the previous section show that behavioral responses are qualitatively similar using self-reported and meteorological records for drought events, but do not compare the two.

This section proposes an empirical test of recall error, by comparing the self-reported and objectively recorded years of the most extreme drought event. I construct an indicator variable that takes value one if individuals do not self-report the most harmful drought event in $t-1$ when the minimum SPEI was recorded, and zero otherwise to test whether inaccuracy about previous year's droughts leads farmers to reduce irrigated cultivated land.

Recall errors appear to affect farmers' behavioral responses in a potentially sub-optimal manner (Table 2.5). Being inaccurate is associated with a 8.5 p.p. increase in the share of rainfed cultivated land in the *Aman* season (column 1) and with a 5.4 p.p. decrease in the share of cultivated land under STW irrigation (column 2). In the *Boro* season, inaccuracy is associated with a 6.2 p.p. decrease in the share of cultivated land under DTW irrigation (column 5), a 4.4 p.p. decrease in the share of

rained cultivated land (column 3), and a 11.3 p.p. increase in the share of land under STW irrigation (column 4). The rationale behind the effects in the *Boro* season can be explained by a groundwater drought in the winter season that prevents shallow aquifers to be recharged. Under these conditions, increasing the share of irrigated land with STWs and reducing the use of DTWs would be potentially sub-optimal.

TABLE 2.5: Recall error in the timing of harmful droughts and irrigation status

Growing Season: <i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rained (1)	STW (2)	Rained (3)	STW (4)	DTW (5)
Inaccuracy	0.0847** (0.0421)	-0.0535** (0.0239)	-0.0439* (0.0231)	0.113*** (0.0399)	-0.0618* (0.0340)
Belief increase in drought	0.101*** (0.0283)	-0.0588*** (0.0200)	0.0155 (0.0171)	-0.0111 (0.0249)	-0.00605 (0.0172)
Belief increase in drought \times Long-run dryness	-0.670*** (0.249)	0.555** (0.224)	0.00692 (0.328)	0.558 (0.404)	-0.639** (0.290)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.760	0.166	0.256	0.441	0.113
SD Outcome	0.406	0.351	0.409	0.470	0.301
N	1392	1392	1392	1392	1392
adj. R^2	0.562	0.573	0.751	0.673	0.587

Notes: The sample includes individuals whose self-reported year of the most harmful drought coincides with the meteorological drought recorded the year before the irrigation decision is taken and those that did not self-report a drought event objectively recorded. I exclude the sample of individuals who self-reported a drought event when it did not occur. The outcome variable is the share of land under each irrigation status or left rained in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

2.7.3 Overestimation

I now explore whether their frequency drives adaptive behavior (Spinoni et al., 2014) and test how the accuracy in the recollection of the number of droughts may drive irrigation decisions. I use the measure of overestimation Δ (Equation (3.1)) that considers the distance between the self-reported and the meteorological number of extreme drought events. Due to its left-skewed distribution for objective extreme drought events (Figure C3), I limit the analysis to the subsample of individuals who are either accurate ($\Delta = 0$) or overestimate the number of drought events ($\Delta > 0$). I expand the baseline specification in Equation (2.10) with either a binary variable, *Overestimation*, distinguishing accurate farmers from those who overestimate droughts, or the count variable Δ , measuring the extent of overestimation.

Table 2.6 shows that overestimating the number of drought events is associated with an increase in the share of irrigated land and a decrease in the share of rained cultivated land. Panel A reports the coefficient associated with a binary variable of overestimation. Overestimating droughts is associated with a 6 p.p. decrease in the share of rained cultivated land (column 1) and with a 4.3 p.p. increase in the share

of cultivated land under STW irrigation (column 2) in the *Aman* season. Similarly to previous findings, in the *Boro* season, the experience of drought events has a negative effect on the share of cultivated land under STW irrigation (column 4) and a positive effect on the share of cultivated land under DTW (column 5). Individuals reduce land irrigated with STWs since droughts in the winter dry season also affect water recharge of shallow aquifers and rely on water extraction from deep aquifers using DTWs.

Results in Panel B show the results when exploiting the extent to which farmers overestimate and lend further support to the argument that the accuracy of recollecting drought events drives irrigation decisions, although imprecisely estimated in *Aman*. During *Boro*, an increase in the difference between self-reported and objective droughts by one event reduces the share of cultivated land irrigated with STW by 2.6 p.p. (column 4) and increases the share of land irrigated with DTW by 3.2 p.p. (column 5). This result suggests that farmers tend to substitute land left rain-fed and irrigated with STW with irrigation using DTW, lending further support to the hypothesis of groundwater drought events.

TABLE 2.6: Overestimating drought frequency and irrigation status

Growing Season:	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
<i>Dependent variable:</i> Share of cultivated land					
<i>Panel A: Binary variable</i>					
Overestimation	-0.0599** (0.0259)	0.0429** (0.0190)	0.0167 (0.0178)	-0.0938*** (0.0312)	0.0639** (0.0282)
<i>Panel B: Count variable</i>					
Δ Droughts	-0.0269 (0.0170)	0.0148 (0.0136)	-0.000543 (0.00741)	-0.0265** (0.0134)	0.0317*** (0.0103)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.748	0.171	0.236	0.445	0.124
SD Outcome	0.413	0.355	0.396	0.471	0.312
N	1286	1286	1286	1286	1286
adj. R^2	0.590	0.627	0.693	0.661	0.596

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzter (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

I test for the robustness of the results by altering the cutoffs and altering the construction of Δ and including moderate ($-1.5 < \text{SPEI} \leq -1$) or severe ($-2 < \text{SPEI} \leq -1.5$) droughts. The results are qualitatively similar with the estimates smaller in magnitude (Table B39). By relaxing the cutoff for recording a drought, the number of objective drought events increases, and Δ would be smaller by construction, potentially biasing these estimates downwards.

Finally, to further test that results are not driven by an arbitrary measure of objective drought events, I use another dataset that provides a measure of drought

events, the EM-DAT database (EM-DAT, 2022). This dataset contains information on the occurrence and effects of natural disasters (see Section B.6.4). Previous studies have already discussed the limits of EM-DAT as measures of extreme events (Cavallo et al., 2013; Felbermayr and Gröschl, 2014; Noy, 2009). For this reason, results should be interpreted with caution (Table B40).

2.8 Discussion and Conclusion

Scientific estimates have shown that climate change may have severe impacts on agricultural-related activities (IPCC, 2022). Droughts have been described as “one of the world’s most widespread climate disasters affecting agricultural production” (Geng et al., 2016). Farmers’ profits depend on the weather and the decisions they make in response. In particular, their adaptive responses hinge upon their ability to understand and predict the weather conditions they face. Therefore, it is critical to understand farmers’ adaptive behavior and their decision-making processes. The literature has investigated various “adaptation gaps” (Carleton and Hsiang, 2016), for instance, weak incentives to adapt (Annan and Schlenker, 2015), limited access to credit (Burgess et al., 2014), limited information about benefits (Hornbeck, 2012) and access to technologies (Olmstead and Rhode, 2011). Despite recent advancements in the quantification of climate impacts on a series of outcomes accounting for adaptation (e.g., Carleton et al., 2022; Hultgren et al., 2022; Rode et al., 2021), perfect information has so far been assumed, neglecting the role of inaccurate beliefs about climate change and limited rationality (Deryugina and Hsiang, 2017).

In this paper, I develop a theoretical framework allowing for differences between individual climate beliefs and long-run climatic conditions. This framework adapts a behavioral inattention model à la Gabaix (2019) to the context of climate change beliefs and introduces a behavioral friction in a standard farmer profit-maximization problem. The model’s implications show under which circumstances beliefs affect the decision-making process and how they differentially shape farmers’ responsiveness to dryness exposure. I test this model on data on the beliefs of individual farmers and irrigation use combined with a meteorological measure of dryness in Bangladesh.

In a fixed-effect panel analysis, I find, consistent with the conceptual framework, that as long as individual beliefs do not coincide with objective climatic conditions, they heterogeneously drive farmers’ behavioral responses to dryness. In particular, farmers who believe that droughts have increased significantly expand land under irrigation after a period of dryness. The effect is stronger for more severe weather conditions and is heterogeneous across growing seasons, driving decisions only in the monsoon season. In terms of cognitive mechanisms, I document that only self-reported one-year lagged drought events have a strong statistically significant effect on the use of irrigation, highlighting the role of salience, and that recall error can lead to potentially sub-optimal decisions, increasing the share of land left rainfed.

On the contrary, overestimating the frequency of past drought events leads to a behavioral response of increasing irrigated land.

In a counterfactual welfare analysis, I use the baseline estimates to quantify the monetary loss due to inaccurate beliefs. Comparing the predicted use of irrigation as a function of observed beliefs and beliefs based on meteorological records, I find that farmers systematically underuse irrigation compared to the benchmark case if their beliefs were constructed from meteorological records. This result provides evidence of a *belief gap*, that widens for drier climatic conditions. Using estimates of returns to irrigation from the literature, I find that the median monetized loss due to inaccurate beliefs is around \$103 in the monsoon season and \$23 in the winter season, respectively around 26.5% and 4% of the median total seasonal production value. With the estimated changes in climatic conditions, the monetary losses are projected to exacerbate particularly during the monsoon season in light of more erratic and less frequent precipitations.

While the analysis suggests that heterogeneous beliefs differentially shape the responsiveness to dryness conditions, the study has some limitations. First and foremost, in spite of the suite of robustness checks conducted, there remains a possibility that my findings might be spurious. Nevertheless, to the best of my knowledge, this is the first paper that accounts for the incomplete rationality of decision-makers in climate adaptive responses. Second, it is difficult to determine the exact pathway through which these effects work since self-reported measures of drought and beliefs are not measured within each growing season, during which weather conditions in Bangladesh have been shown to differ substantially. Although past work has highlighted the limits of self-reported data in understanding the impacts of extreme events (Guiteras et al., 2015), it is crucial to understand how people's beliefs and exposure to a changing climate characterize differential behavioral responses. The combined use of meteorological records and more precise individual beliefs would help to better understand the mechanisms behind the behavioral responses of rural households and shed light on the cognitive factors at stake. This is a promising avenue for future research.

By addressing questions of beliefs and adaptation strategies, these findings have important implications for the debate on public awareness and adaptation to climate change in developing countries, providing empirical evidence to inform environmental and agricultural policies. The results can help identify the most vulnerable rural households and inform adaptation policies targeting regions with a high degree of exposure to dryness with informational campaigns and providing effective and timely drought communication.

Chapter 3

Drought exposure and accuracy: Motivated reasoning in climate change beliefs

The lack of stringent policies to avert climate change has increased the importance of effective and timely adaptation. Adequate adaptation is particularly important for agricultural communities in developing countries, which may most suffer the consequences of climate change. Evidence is still scarce on how people in the most vulnerable areas form climate change beliefs and whether such beliefs exhibit cognitive biases. Using survey data from rural households in Bangladesh together with a meteorological measure of excess dryness relative to historical averages, I study the effect of long-term average drought exposure and short-term deviations on beliefs about drought frequency and the interpretation of drought events. To explore how individuals interpret past droughts, I use an instrumental variable approach and investigate whether individual beliefs lead to asymmetric distortion of objective information. The results show that individuals recollect and overweight evidence tilted towards their prior beliefs, providing evidence of confirmation bias as a directional motivated reasoning mechanism. The findings highlight the need for models that account for behavioral factors and cognitive biases in the study of climate change beliefs for effective communication and adaptation policies.

Keywords: Beliefs, Climate change, Droughts, Expectation formation, Motivated reasoning

JEL Classification: D10, D80, Q12, Q51, Q54

The material from this chapter was published in the *Environmental and Resource Economics* in May, 2023. The online version can be accessed here: <https://doi.org/10.1007/s10640-023-00779-1>

I am extremely grateful to Katrin Millock for invaluable advice throughout this project. I am thankful to Tamma Carleton for her hospitality and guidance during my stay at UC Santa Barbara. I thank Andrew Clark, Tatyana Deryugina, Fabrice Etilé, Nicolas Jacquemet, Namrata Kala, and an anonymous referee for the FAERE Working Paper Series for their useful comments, as well as seminar participants at the Paris School of Economics. I am also indebted to the Editor and two anonymous referees for their insightful feedback. All remaining errors are mine.

3.1 Introduction

Climate change threatens to alter the frequency, timing, duration, intensity and spatial distribution of extreme weather events, including droughts (IPCC, 2021). Despite broad scientific consensus that human activities are causing climate change (Oreskes, 2004), there is ample disagreement among the general public in the beliefs about climate change and its causes (Lee et al., 2015a). The inertia of policies to avert significant climate change has increased the importance of adaptation. Effective adaptation is particularly important in developing countries and rural areas (Mertz et al., 2009a). The relationship between meteorological conditions and agricultural yields has been extensively empirically documented (Auffhammer and Schlenker, 2014; Carleton and Hsiang, 2016; Hultgren et al., 2022) with implicit models of adaptation that assume agents react to objectively interpreted new information conditional on prior beliefs, fully accounted for by meteorological conditions. Understanding the determinants of beliefs and the existence of cognitive biases among the most vulnerable communities, whose activities heavily rely on natural resources and climate, is of paramount importance since it may have direct implications for adaptive behavioral responses (Zappalà, 2023a).

This paper studies the effect of drought exposure on beliefs about climate change and investigates whether individuals adopt directional motivated reasoning, according to which they tend to overweight evidence that confirms their prior beliefs. I combine a two-wave survey of rural households in Bangladesh with a meteorological measure of dryness at the union-level¹, the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). First, I document how long-term average exposure to dryness and short-term deviations affect individuals' beliefs about drought frequency and their accuracy in interpreting these events. To define accuracy, I compute the deviation between the self-reported number of droughts and meteorological events measured using climatological cut-offs (McKee et al., 1993; Paulo et al., 2012). A positive difference indicates overestimation in the recollection of droughts. Second, I examine the potential cognitive heuristics adopted in the interpretation of droughts. I test whether individuals asymmetrically distort objective information overweighting evidence that confirms their prior beliefs, showing evidence of confirmation bias (Rabin and Schrag, 1999; Kahneman and Tversky, 1982). To identify the causal effect of prior beliefs on how information from drought events is distorted, I adopt an instrumental variable approach using as instrument the twenty-year long-term average exposure to dryness, which exploits quasi-random variation in the SPEI realizations within unions over time. The exogeneity of the instrument relies on the assumption that accounting for time- and individual-specific unobserved heterogeneity, deviations in meteorological conditions

¹Unions are the smallest rural administrative and local government unit in Bangladesh. Administrative units are structured as follows: Division \supset District (*Zila*) \supset Sub-district (*Upazila*) \supset Union. There are 5,158 unions, that have an average size of approximately 10–20 km².

of dryness do not affect the accuracy of recollecting drought events via other channels than beliefs. To assess the validity of this assumption, I perform several checks ruling out other channels such as adaptation, recent deviations in terms of dryness, and information.

The analysis yields two main findings. First, twenty-year long-term average exposure to dryness predicts beliefs of increase in droughts and the interpretation of drought events, whereas short-term deviations in exposure do not matter. Individuals form beliefs based on exposure to their average climatic conditions and beliefs about slow-onset environmental changes are inelastic to short-term deviations. Second, I document that individuals overestimate the number of drought events when they believe that droughts have increased. This result shows that individuals adopt directional motivated reasoning, with the interpretation of droughts biased towards their priors. This finding differs from objective processing of information in a Bayesian setting, where individual prior beliefs do not affect the interpretation of information (Druckman and McGrath, 2019).

The paper makes several contributions to the literature. First, it relates to the branch analysing the determinants of climate change beliefs, widely investigated in developed countries and identified in political orientation, education, and personal experience of weather shocks (e.g., Carlsson et al., 2021; Czarnek et al., 2021; Poortinga et al., 2019; Hoffmann et al., 2022).² A growing attention has been devoted to individuals whose economic livelihood depends on climate, including farmers or fishers. Most evidence is based on US data (Gramig et al., 2013; Rejesus et al., 2013; Arbuckle et al., 2013a,b), whereas it is yet understudied the formation process in developing countries. Understanding climate change awareness in Bangladesh is of paramount importance, where, according to the 2007-2008 Gallup World Poll representative survey, more than 65% of respondents had never heard of climate change, in contrast with the low levels (below 10%) of climate change *skepticism* in high-income countries (Lee et al., 2015a). More than a decade later, in the 2019 Gallup World Risk Poll, more than one-third of the population in Bangladesh was still unable to provide an answer to the potential effects of climate change (Rzepa and Ray, 2020). The paper provides empirical evidence of the determinants of beliefs on the consequences of climate change in a developing country, focusing on slow-onset environmental changes. Importantly, I exploit the unique longitudinal dimension of the survey to account for individual-specific unobserved heterogeneity and study within-individual changes in beliefs.

Second, this paper relates to the strand of literature that investigates cognitive heuristics associated with climate change beliefs, including anchoring, availability, representativeness or motivated reasoning (Joireman et al., 2010; Li et al., 2011;

²A more exhaustive list includes Hansen et al. (2012); Carlton et al. (2016); Howe et al. (2014); McCright et al. (2014); Moore et al. (2019); Weber (2010); Beattie et al. (2019); Konisky et al. (2016); Kaufmann et al. (2017).

Zaval et al., 2014). This paper contributes to this literature testing the confirmation bias hypothesis. Individuals exhibit confirmation bias as a form of directional motivated reasoning if they misread the new evidence as supportive of existing hypotheses, interpreting information and overweighting evidence that confirms their beliefs (Fryer et al., 2019; Agnew et al., 2018b; Faia et al., 2021). Notwithstanding previous theoretical discussions of directional motivated reasoning mechanisms (Druckman and McGrath, 2019) and other cognitive biases (Zhao and Luo, 2021) in climate change beliefs, former empirical studies have focused on other types of cognitive biases, including availability bias (Gallagher, 2014), representativeness and spreading activation (Deryugina, 2013) in the US. The sole exception in rural communities in developing countries finds recency bias among Indian farmers (Kala, 2017).

The literature on motivated reasoning has concluded that prior climate beliefs influence the interpretation of environmental changes (Goebbert et al., 2012; Zanicco et al., 2018). Previous empirical studies testing motivated reasoning neglect potential endogeneity concerns between the interpretation of evidence and beliefs (Howe and Leiserowitz, 2013; Myers et al., 2013; Shao, 2016). I build on studies of motivated reasoning in climate change beliefs (Weber, 1997; Osberghaus and Fugger, 2022; Stahlmann-Brown and Walsh, 2022) to estimate the effect of beliefs on the interpretation of weather events in a developing country. In Bangladesh, where climate change awareness is particularly low (Lee et al., 2015a; Rzepa and Ray, 2020) and drought vulnerability extremely high (Shahid, 2011), examining the drivers of the interpretation of droughts and the presence of cognitive biases is fundamental. This is, to the best of my knowledge, the first study that tests whether individuals display directional motivated reasoning in a developing country, identifying the causal effect of beliefs on how information from weather events is distorted in a quasi-experimental setting.

The remainder of the paper is organized as follows. Section 3.2 describes the data used in the empirical analysis. Section 3.3 defines the conceptual framework for the propositions that I test empirically. Section 3.4 presents the empirical approach. Section 3.5 discusses the results and their robustness. Section 3.6 concludes.

3.2 Data

I combine data from two main sources to measure beliefs and self-reported incidence of drought events at the individual level on the one hand, and meteorological measures of exposure to dryness and occurrence of drought events computed at the union level, on the other.

Beliefs about droughts and self-reported drought events. I measure individual beliefs and self-reported frequency of drought events from the Bangladesh Climate Change Adaptation Survey (BCCAS). The data consist of a two-wave survey

by the International Food Policy Research Institute (2014a), collecting information from 800 agricultural households in 40 randomly selected unions in Bangladesh (Table C1). The first wave was conducted in January 2011 and previously analysed in Delaporte and Maurel (2018). A follow-up wave (International Food Policy Research Institute, 2014b) was conducted in September 2012. More than 97%, i.e., 766 out of 800 households, were reinterviewed in the second wave.³ I construct a binary variable, *Belief of Increase in Droughts*, or simply *Belief*, equal to one if the respondent answers “Longer periods of droughts” to the question “Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed.”

Prior to being asked about their beliefs, individuals are asked a series of questions about their memories of weather events in recent years, as in Weber (1997). I construct the variable *self-reported # droughts* using the question in the first wave “In the last five years, have the household’s properties and productivity been affected by droughts? How many times did it occur?”. The same question in the second wave asks respondents to report the number of droughts since the last interview. This variable is then used to measure the accuracy of recollection of drought events as explained below. Table C2 reports the exact wording and formulation of each question in the two waves.⁴ Although the survey does not provide a formal definition of droughts and does not record differently the intensity of perceived weather events, different interpretation of droughts by different respondents does not pose a challenge to the validity of the empirical analysis that exploits within-individual variation in beliefs over time.⁵

Dryness exposure. To construct a measure of exposure to dryness, I use a climatological measure, the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), which provides information about drought conditions at the global scale, with a 0.5° spatial resolution ($\approx 55\text{km}$ at the Equator) and a monthly time resolution. The SPEI-1 compares the amount of precipitation and potential evapotranspiration to obtain a measure of drought based on water balance accumulated over one month and is constructed using data from the Climatic Research Unit of the University of East Anglia (CRU TS version 4.03). The index is a standardized probability measuring the deviation in dryness relative to the average observed during the available 1901-2018 time period in each grid cell. A value of zero indicates the median amount (half of the historical amounts are below the median, and half are above the median), and the index is negative for dry, and positive for wet conditions. For instance, a value equal to -1 indicates that the difference

³The remaining 34 households could not be interviewed because they migrated (15 households) or were not at home at the time of the survey.

⁴From the BCCAS, I also collect individual and union characteristics from the community questionnaire that I use in subsequent robustness exercises.

⁵The underlying assumption is that individuals do not differentially change their internal definition of droughts between the two survey waves.

between precipitation and potential evapotranspiration is one standard deviation lower than the historical average for a given grid cell.

I build two measures of exposure to dryness at the union level to account for long-term average and short-term deviation (Guiteras et al., 2015; Hsiang and Jina, 2014; Bento et al., 2023).⁶ I construct union-level SPEI monthly realizations as a weighted average of the union surface over each grid cell. Figure C1 displays the relationship between the union boundaries and the SPEI gridded dataset. The long-term exposure is the average of the monthly SPEI across the previous twenty years, indicating whether this period was relatively drier or wetter than the historical average for each union. This measure is constructed as the “objective counterfactual” of the individual beliefs that droughts have increased in the previous twenty years. Beliefs are assumed to be formed from the long-term average exposure in the union of residence.⁷

I construct a short-term deviation measure from the long-term average, as the difference between the average SPEI monthly realizations over the previous five years and the twenty-year long-term average, for the first wave, and the difference between the average SPEI monthly realizations between the two waves and the twenty-year long-term average, for the second wave.⁸

Drought events. To have a measure of individual accuracy of recollection of droughts, I compare the self-reported number with the objectively recorded number of drought events. The climatology literature defines a drought event as the period of consecutive time points in which the SPEI is below certain thresholds (Spinoni et al., 2014). Specifically, there are five classes of droughts: i) non-drought ($\text{SPEI} > -0.5$); ii) mild droughts ($-1 < \text{SPEI} \leq -0.5$); iii) moderate droughts ($-1.5 < \text{SPEI} \leq -1$); iv) severe droughts ($-2 < \text{SPEI} \leq -1.5$); v) extreme droughts ($\text{SPEI} \leq -2$) (Paulo et al., 2012; McKee et al., 1993). Since the SPEI is normally distributed, each of the five classes respectively accounts for about 69.1%, 15%, 9.2%, 4.4% and 2.3% of the set of historical values for each grid cell.

Based on this classification, I compute for each union the number of extreme drought events that have occurred in the five years before the first wave of the survey and between the first and the second wave.⁹ To test the robustness of the results, I employ other cut-offs to define the objective number of droughts, including moderate ($\text{SPEI} \leq -1$) and severe ($\text{SPEI} \leq -1.5$) droughts. Figure C2 shows the

⁶For ease of interpretation of the coefficients in the empirical analysis, these measures are taken in their additive inverse form, meaning that higher values are associated with drier conditions.

⁷Since the survey does not provide information on the place of residence of the respondents over the twenty years before the first wave, I assume they have not moved and have been exposed to the union-average dryness conditions.

⁸This methodology is adopted in order to create a continuous measure of wave-specific variation in exposure to dryness that matches the time period covered by the self-reported number of drought events in the BCCAS.

⁹The choice of the time periods mirrors the time period covered by the survey questions on the number of drought events experienced.

timeline of the survey compared to the construction of the measures of dryness and drought events.

Following this approach, I create a measure of accuracy of recollection of past drought events:

$$\Delta_{it}^{type} = \text{self-reported \# droughts}_{it} - \text{objective \# droughts}_{ut}^{type} \quad (3.1)$$

where Δ_{it}^{type} ($type \in \{\text{moderate}; \text{severe}; \text{extreme}\}$) measures the deviation between the self-reported number of droughts by individual i in survey wave t with the number of droughts recorded using the SPEI in union u over the same time period. These wave-specific measures of interpretation infer whether respondents overestimate or underestimate the number of drought events that they have experienced. For instance, a positive value shows that individuals overestimated the number of drought events. By matching households with objectively recorded drought events at the union level, I measure asymmetric changes in the recollection of drought events for individuals that faced the same course of events and have been exposed to the same set of objective information. I acknowledge that meteorological data are not necessarily the “truth”, but I use them to study a systematic pattern to individual interpretation of drought events as a function of their beliefs.¹⁰

Descriptive statistics. The final sample is composed of 714 individuals. Since the focus is on personal experience, the sample includes only households who have been surveyed in both waves and did not move, and for which the respondent was the same. This setting accounts for individual-level unobserved heterogeneity (including different interpretation of the questions) and allays concerns about the biasedness of the coefficients associated with self-reported subjective measures. Table C3 tests for differences in means for the main variables between the sample of attritors and non-attritors in the first wave and finds no statistically significant differences.

Tables C4 and C5 provide, respectively, summary statistics on self-reported variables and objective measures of drought exposure. On average, half of the sample believes that droughts have increased over the past twenty years. All unions have experienced at least one moderate drought event in both time periods considered in the first and second waves. Although between the two waves only one extreme drought event is recorded in Chaklarhat, in the northwest region of Bangladesh, an

¹⁰Despite the recurrent and devastating nature of droughts, previous studies in Bangladesh have more often focused on floods (Guiteras et al., 2015; Gray and Mueller, 2012; Chen et al., 2017). In spite of data availability on individual beliefs and personal experience of floods in the survey, I focus on droughts since there exist meteorological measures both of exposure to dryness and drought events. Rainfall measures have been shown to be weak proxies for flood exposure, and flood extent is nowadays commonly measured using remote-sensing data from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) (Guiteras et al., 2015; Chen et al., 2017). Nevertheless, differently from drought event recording, to the best of my knowledge, there is no classification for the meteorological number of flood events.

area historically prone to drought events (Alamgir et al., 2015), the share of individuals believing that droughts have increased is 46 percentage points higher in the second wave.

Table C4 shows that respondents on average underestimate the number of droughts when the accuracy measure Δ includes moderate and severe droughts. On the contrary, Δ is on average positive, but close to zero, using only meteorological extreme drought events. Figure C3 displays the frequency distribution of Δ with the three cut-offs for the objective measure. A large share of respondents underestimates droughts with moderate (98.6%) and severe cut-offs (68.6%). There may thus be a systematic upward bias when including these two types of drought events as objective counterfactual of the self-reported number of droughts to construct Δ . This would translate into a downward bias in Δ . Therefore, I construct Δ only including extreme droughts. In this case, most of the respondents (65%) are accurate ($\Delta = 0$) and the distribution is right-skewed with more than 25% of the respondents overestimating. Generally, droughts are shown to have substantial impacts on agriculture when the SPEI is below -1.5, i.e., if the drought is at least severe (Zargar et al., 2011). Hence, extreme drought events may be a valid objective counterfactual for the self-reported droughts, although I test for the robustness of the results including moderate and severe droughts.

3.3 Conceptual Framework

This section describes a conceptual framework, whose objective is two-fold. First, it models the relationship between objective exposure to dryness and self-reported individual beliefs and the way individuals recollect drought events. Second, it sets as a benchmark the Bayesian updating framework in the context of drought events, defining how a Bayesian updater would interpret new information as independent from her prior belief and use both available evidence and prior belief to form a posterior. This is used in comparison to an agent who adopts directional motivated reasoning and interprets evidence as tilted towards her prior beliefs.

3.3.1 Objective Exposure, Beliefs and Accuracy

In the climate impact literature, an outcome of interest y is related to the environmental exposure E , whose functional form f is ex-ante unknown and requires accurate data in order to be unbiased and precisely estimated. The use of accurate data is even more relevant for extreme weather events, where self-reported survey data have been predominantly used in the literature, despite potentially subject to endogeneity concerns (Guiteras et al., 2015). The baseline equation is

$$y = f(E) + \varepsilon \tag{3.2}$$

where y represents the outcome of interest, in this case, the belief of increase in droughts and the interpretation of drought events, and E represents dryness exposure. The use of objectively measured right-hand side variables allays the concern about the presence of correlated measurement error between the explanatory and the outcome variable. Self-reported environmental exposure E would provide little information about the relationship of interest between beliefs and exposure to dryness. For example, poorer households may be more exposed to droughts but less able to assess damages accurately.

Individuals may form their beliefs of increase in droughts using their long-term average exposure to dryness as a reference point to judge deviations from the average. In this case, a household frequently exposed to larger droughts and one not frequently exposed would consider a drought of the same magnitude differently. For this reason, a priori, it is uncertain whether beliefs and the recollection of drought events depend on the average conditions of exposure to dryness, deviations from the average, or both. Low-exposure households may be more likely to change their beliefs if they experience a larger drought, whereas households with a larger long-term average exposure to excess dryness may have a more inelastic reaction to deviations from the mean. The following proposition formulates a first initial prediction about the relationship between drought exposure and beliefs.

Proposition 1: Exposure to excess dryness positively affects the belief of increase in droughts and the recollection of drought events, i.e. $\partial y/\partial E = \partial f(E)/\partial E \geq 0$.

3.3.2 Bayesian Framework

Bayes' rule is commonly used for modeling the belief updating process. In a Bayesian updating framework, new information is embodied into prior beliefs to reach an updated posterior belief. Using the standard law of large numbers, a Bayesian updater who forms beliefs conditional on the full sequence of signals would form with probability equal to one a posterior belief of the correct state of nature.

Consider an agent with a prior belief $\pi(\mu)$, where π denotes the function of belief μ as the probability distribution regarding the true state $\pi(\mu) \sim \mathcal{N}(\widehat{\mu}_0, \widehat{\sigma}_0^2)$, with $\widehat{\mu}_0$, the agent's best guess about the true state of the world, and $\widehat{\sigma}_0^2$, the individual's uncertainty around her guess, where a $\widehat{}$ denotes anything related to perceptions (Druckman and McGrath, 2019). In this study, the individual belief about an increase in droughts in the past twenty years $\pi(\mu)$ includes her estimate of the increase in droughts $\widehat{\mu}_0$ and the confidence in that estimate $\widehat{\sigma}_0^2$.

Bayesian updating occurs when new information, x , is provided to the individual as a draw from the distribution $\mathcal{N}(\mu, \widehat{\sigma}_x^2)$, centered at the true state of the world μ and with variance in the individual perception of the credibility of the new information, $\widehat{\sigma}_x^2$. Agents embody the new information and form an updated posterior

belief, $\pi(\mu|x)$. Here, new information x corresponds to the number of drought events in the union of residence of households.

Druckman and McGrath (2019) discuss the accuracy-driven motivated reasoning in climate change preference formation in the Bayesian framework. Individuals aim at arriving at a correct conclusion, evaluating new information x to maximize the likelihood that the posterior belief is an accurate estimate of the true state of nature. Therefore, the evaluation of x is independent of the individual’s prior belief $\pi(\mu)$. The individual’s prior belief $\pi(\mu)$ does not affect the interpretation of the new information \hat{x} , here the self-reported number of drought events.

Estimating every component of Bayes’ formula and the posterior belief is not feasible in this empirical setting due to the lack of available data. Nevertheless, this theoretical result is used to compare how an accuracy-motivated Bayesian agent would differ from an agent that displays directional motivated reasoning. In the latter case, the individual belief would distort the interpretation of new evidence and bias it towards it.

3.3.3 Directional Motivated Reasoning

In psychology, a “heuristic” is a simplified model for making inferences. Individuals who apply cognitive heuristics may not use all available information or may oversimplify such information when processing it. These cognitive biases are departures from Bayesian updating and some of them have already been documented in the context of climate change belief formation (Gallagher, 2014; Deryugina, 2013; Fryer et al., 2019). Druckman and McGrath (2019) summarize three mechanisms of directional motivated reasoning in climate change preference formation. Under motivated reasoning, the interpretation of personal experience of climatic changes stems from prior beliefs rather than from impartially detecting changes in their local environment (Palm et al., 2017). The first and foremost mechanism is the confirmation bias (Lodge and Taber, 2013).

Individuals subject to confirmation bias are motivated to maintain their prior belief $\pi(\mu)$ after elaborating new information and thus they seek out information that confirms their prior belief. The distribution from which the individual draws the new information x is no longer $\mathcal{N}(\mu, \hat{\sigma}_x^2)$ but $\mathcal{N}(\hat{\mu}_0, \hat{\sigma}_x^2)$, centered at the mean of the individual’s prior beliefs and not at the true state of the world. The individual belief $\pi(\mu)$ thus affects the perceived new information \hat{x} , the self-reported number of drought events.

The interpretation of the information is accurate if $\hat{x} - x = 0$. Using Equation (3.1), individuals are accurate if self-reported and objective number of drought events coincide, i.e. $\Delta = 0$. Following Fryer et al. (2019), the functional form of the confirmation bias and distortion of information relates the interpretation of objective information x compared to the perceived information \hat{x} , as a function of the prior belief μ . Under confirmation bias, the interpretation of information is distorted in

the direction of individual beliefs for a given objective information x . This implication is formulated in the form of the following proposition.

Proposition 2: Individuals display directional motivated reasoning and are subject to confirmation bias if the prior belief μ affects and distorts the interpretation of the information x . Under directional motivated reasoning, the interpretation of drought events measured as the deviation between the self-reported and recorded number of droughts is a function of individual beliefs of increase in droughts μ :

$$\hat{x} - x = \pi(\mu) \tag{3.3}$$

3.4 Empirical Approach

3.4.1 Objective Exposure, Beliefs and Accuracy

I first examine the effect of objective exposure to dryness on the belief of increase in droughts and on how individuals self-report drought events compared to the objectively recorded number. The probability of overestimating the number of droughts is defined as a dummy equal to one if the self-reported number is greater than the number of objectively recorded extreme drought events with the SPEI (i.e., $\Delta > 0$), and zero otherwise. Afterward, I shift the focus to the extent of overestimation, using the Δ measure that takes negative values if individuals underestimate, null if they are accurate and positive if they overestimate the number of drought events.

I employ an OLS regression in a panel setting using individual-specific and year-specific fixed effects. I estimate beliefs of increase in droughts over the previous twenty years and interpretation of droughts as a function of the long-term average exposure, the deviation from long-term average, and their interaction to account for the heterogeneous effect of deviations. This functional form $f(E)$ is adopted since individuals perceive exposure relative to their average environment and use it as a reference point to judge deviations from that average. The full specification is written as:

$$y_{it} = \beta_1 \text{LT Exposure}_{ut} + \beta_2 \text{Deviation}_{ut} + \beta_3 \text{LT Exposure}_{ut} \times \text{Deviation}_{ut} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.4}$$

where y_{it} is the belief of increase in drought or the interpretation of drought events for individual i in survey wave t . The coefficients on all weather variables can be interpreted causally since within-union realizations of weather are plausibly exogenous (Carleton and Hsiang, 2016; Auffhammer and Carleton, 2018). I exploit within-individual variation by accounting for time-invariant individual-specific and year-specific characteristics to identify the effect of drought exposure. Individual-specific fixed effects absorb the effect of all time-invariant factors that differ between

individuals, including unobservable characteristics that could not be accounted for in a cross-sectional empirical design, such as personality traits, gender, location, education level, interpretation of droughts (Hsiang, 2016). Similarly, λ_t controls for unobserved shocks common to all individuals in a given year.

In five cases out of the 40 sampled unions, the 0.5° grid cells of the SPEI data embed more than one union. Standard errors clustered at the union-level would be underestimated. For this reason, I cluster standard errors at the grid cell level to account for correlation and heteroskedasticity across unions, and *a fortiori* individuals, within the same cell.¹¹

3.4.2 Directional Motivated Reasoning

To examine whether individuals exhibit confirmation bias, I formulate a new specification that relates beliefs of increase in droughts to their interpretation. This approach empirically tests Equation (3.3): individuals who display directional motivated reasoning distort the interpretation of new information as a function of their beliefs. Figure C4 provides stylized evidence of this mechanism. The frequency distribution of the measure Δ for individuals holding beliefs that droughts have increased is more left-skewed than for individuals who do not hold such beliefs. The t-test of a difference in means between the two samples is -11.26: Δ has an average of -0.12 among the *non-believers*, and an average of 0.47 among the *believers*, implying a statistical difference between the two samples (p-value < 0.001). This is confirmed by a Kolmogorov-Smirnov test conducted under the null hypothesis of equal distribution of Δ by beliefs, which I fail to accept (p-value < 0.001).

I design an econometric specification that uses as outcome both the probability and the extent to which individuals overestimate. The baseline equation writes

$$\text{Overestimation}_{it} = \gamma \text{Belief}_{it} + \beta \text{Deviation}_{ut} + \alpha_i + \lambda_t + u_{it} \quad (3.5)$$

where Belief_{it} is the binary variable indicating whether individual i in survey wave t believes that droughts have increased over the past twenty years. Deviation_{ut} refers to the short-term deviation in dryness from the LT Exposure and α_i and λ_t are individual and year fixed effects. Standard errors are clustered at the grid cell level.

Even when accounting for the fixed effects, the OLS regression may yield biased estimates of the effect of beliefs on accuracy for several reasons. First, individuals may alter their long-lasting beliefs after receiving new information and therefore beliefs could change as a consequence of the interpretation of drought events. Equation (3.5) may be subject to simultaneity bias and the estimates of the effect of beliefs on the interpretation of drought events would be biased downwards. Second, the

¹¹Union, or grid-cell, fixed effects are superfluous since all individuals in the estimation sample never change place of residence and therefore union-specific unobserved heterogeneity is taken into account by individual-specific fixed effects.

estimate of the coefficient may also be biased because of classical measurement error. This would lead to an attenuation bias and thus $\hat{\gamma}$ would again be biased towards zero. The errors in measurement of the belief may be correlated with the noise u_{it} , which represents other unobservable determinants of outcomes, for example, poorer households might be more exposed to droughts but less able to assess damages accurately. Finally, other omitted time-varying individual-specific characteristics such as risk perceptions may be simultaneously correlated with changes in individuals' beliefs about droughts and in the recollection of drought events.

To address the concerns on endogeneity, I adopt an instrumental variable approach using as an instrument the average long-term exposure to dryness over the previous twenty years. This variable complies with the two restrictions for a valid instrument. The variable is relevant as shown from the estimation of Equation (3.4) (Table 3.1, column 3). A household frequently exposed to large extreme weather events and one not frequently exposed may differently interpret an event of the same magnitude (Guiteras et al., 2015). Average long-term exposure is expected to satisfy the exclusion restriction, by determining individuals' interpretation of past drought events only through their beliefs about these events. The validity of the instrument and the identifying assumption is discussed below. Testing whether the interpretation of new information is tilted towards the beliefs provides evidence of confirmation bias if the estimated coefficient $\hat{\gamma}$ is positive and statistically significant.

Identifying Assumption and Instrument Validity

In an OLS regression, the identification of the effect of beliefs on individuals' interpretation of drought events is threatened by reverse causality, omitted variable bias and classical measurement error. To address these and similar concerns, I adopt an instrumental variable approach and use the twenty-year long-term average exposure to dryness as an instrument for beliefs of increase in droughts. The instrumental variable approach strengthens the causality argument under the exclusion restriction that exposure to dryness does not affect the accuracy of recollecting drought events via other channels besides beliefs.

The variation underlying the instrument, relative changes in long-term exposure to excess dryness, is plausibly as good as random and hence likely exogenous to within-individual variation over time. By retaining only variation in beliefs generated by the quasi-experimental variation in long-term dryness, this approach exploits the rational component of changes in beliefs estimated from variation in dryness exposure. If individuals did not exhibit confirmation bias, using an instrumental variable approach, beliefs should have a null effect on the interpretation of weather events.

There are three major concerns that may violate the exclusion restriction. In what follows, I describe additional tests that assuage concerns on its validity. First, variation in the instrument may have an indirect effect on self-reported evidence

through the omitted variable of subjective well-being and mood (Mellon, 2021). According to the empirical evidence on self-reported life satisfaction (Maddison and Rehdanz, 2011), the estimates of beliefs on recollection of droughts may be downward biased. Droughts have a negative effect on happiness (Sekulova and van den Bergh, 2013; Keshavarz and Karami, 2012) and life satisfaction (Carroll et al., 2009), which could positively affect the overestimation of past weather events (Forgas et al., 2009) and thus threaten the exclusion restriction. Nevertheless, studies using an individual fixed-effect empirical setting (Feddersen et al., 2016) do not detect a relationship between climate and self-reported life satisfaction and find an effect close to zero. These findings allay potential concerns about the validity of the instrument.

Second, objective drought exposure may affect the individual's recollection of past drought events through past adaptation. This concern would arise if past environmental conditions affected past actions, which would in turn impose "historical restraints" on current actions (Lemoine, 2021). Households that adapted due to changes in dryness might experience fewer droughts, and thus underestimate them, than if they had not adapted. For this reason, this potential channel would bias downwards the 2SLS estimates. In order to allay the potential concern about the validity of the instrument, the econometric specification includes a history of transient shocks proxied by the short-term deviation from the long-term exposure to dryness. This should reduce the bias introduced by historical restraints. In Section 3.5, additional robustness checks show that the adaptation channel does not threaten the identification of the effect of beliefs.

Finally, the instrument may be positively correlated with the propensity of individuals to seek weather information and listen to weather forecasts. The literature exploring this channel uses internet search activity data to examine if local short-run weather fluctuations cause people to seek information about climate change, finding that they have an effect on search behavior (Choi et al., 2020), but not always consistent with the projected impacts of climate change (Lang, 2014). The main difference between the previous findings and my design stands in the use of a long-term average in place of short-term fluctuations. The use of long-term exposure to dryness should allay the concern on its potential correlation with seeking information on climate change. Furthermore, if this channel existed, seeking and receiving more weather information would be negatively correlated with the recollection of drought events. A more informed individual would be able to reduce the distance between the self-reported and objective number of droughts. Therefore, this channel would underestimate the effect of beliefs on the overestimation of drought events. The survey does not contain explicit information on the individual use of weather information, however, in Section 3.5, I discuss additional robustness checks that assuage concerns about the validity of the instrument. Table C6 shows the correlations between the instrument and the additional controls included in the robustness exercises. Out of the ten estimates, I find that only one is statistically significant at

the 10% level, which is consistent with sampling variation given the multiple tests carried out, thus strengthening the exogeneity hypothesis of the instrument.

3.5 Results

3.5.1 Objective Exposure, Beliefs and Accuracy

Table 3.1 displays the results for the effect of objective exposure to dryness on beliefs and recollection of drought events. Columns (1) and (2) separately investigate whether short-term deviations and long-term exposure predict self-reported beliefs and the measure of accuracy. Column (3) includes them both, and in column (4) I include their interaction, as in Equation (3.4).

When considering the belief of increase in droughts, both the long-term average exposure (column 1) and the short-term deviation from the reference environment (column 2) have a positive statistically significant effect. The effect of long-term average exposure is more than ten times larger than the effect of short-term deviations. A one standard deviation (SD) increase in long-term exposure is associated with approximately a 1.2 SD increase in the probability of believing that droughts have increased over the previous twenty years ($15.13 \times 0.04 / 0.5$).¹² In contrast, a one SD increase in deviations from the average drought exposure increases the probability of believing in an increase in droughts by around 0.14 SD ($0.729 \times 0.10 / 0.5$). When considering the effect of both LT Exposure and Deviation in column (3) and including their interaction (column 4), only the coefficient associated with long-term exposure is statistically significant.

When regressing the probability of overestimating the number of drought events and the extent of overestimation on the full specification, the effect of short-term deviation and of the interaction term are not statistically different from zero (columns 8 and 12). Long-term exposure continues to have a sizeable positive and statistically significant effect on individuals' overestimation of drought events across all specifications.

The findings suggest that objective exposure matters for climate change belief formation in Bangladesh. Long-term average exposure to dryness predicts beliefs about increases in droughts and overestimation of past droughts, whereas deviations from local average conditions do not matter. On the one hand, these results differ from previous findings that show that, although in a different geographical context, recent, local weather anomalies matter for the formation of climate change beliefs in the United States (Konisky et al., 2016; Kaufmann et al., 2017). On the other hand, these findings add empirical evidence to the result that the experience of a single drought event may not be enough to alter climate change beliefs and what matters is the average dryness condition in the long-term (Carlton et al., 2016). To

¹²Respondents' median age is 45. Baseline results are robust if excluding individuals below 30 years old (around 7% of the sample).

corroborate this hypothesis, I regress beliefs on long-term average exposure and the average number of drought events experienced over the five years before the first wave and between the two waves including different types of droughts (moderate, severe, extreme). Table C7 shows that beliefs are only explained by long-term average exposure.

The results are robust to different estimation methods, using a logit method for the belief of increase in droughts and the probability of overestimating drought events (Table C8) and a Poisson method for the extent of overestimation (Table C9). The results are not specific to the cut-off used to compute the objective number of drought events. I re-estimate Equation (3.4) including moderate and severe drought events (Tables C10 and C11). Long-term exposure to dryness has a positive and statistically significant effect on the extent of overestimating drought events (Column 8). The coefficient is larger in magnitude when including also moderate droughts, smaller when considering severe droughts, but still larger than in the baseline specification in Table 3.1 that only records extreme droughts. An increase in long-term exposure makes the environment more drought-prone, affecting *in primis* the probability of a moderate drought event and thus increasing the probability of overestimating droughts.

Three additional tests check the robustness of the results to other measures of drought exposure. First, results are robust to measuring dryness and meteorological droughts using different time scales of the SPEI. Different time scales define the period considered over which water deficits accumulate. I replicate the baseline results using the SPEI-4, SPEI-6 and SPEI-12 that, respectively, account for water deficits accumulated in the previous four, six and twelve months (Table C12). I also rescale the SPEI monthly realizations relative to each respondent's specific lifetime exposure to dryness conditions. To do so, I compute the individual-specific lifetime mean and standard deviation of dryness conditions using the SPEI and then normalize the SPEI monthly realizations used to construct long-term exposure and short-term deviations. This approach allows for the same SPEI realization in a given union to have different standardized probabilities with respect to each individual's lifetime exposure. Table C13 shows that results for different SPEI time scales are robust, providing suggestive evidence that individuals perceive exposure and form beliefs relative to their average environment based on their lifetime exposure. Figure C5 shows that individuals' beliefs are relatively inelastic to short-term deviations and beliefs depend on the relative long-term average exposure compared to their lifetime experience. Finally, instead of obtaining union-specific values of SPEI based on zonal statistics, I interpolate gridded data based on the inverse squared distance from the union centroids using as distance cut-offs 40, 80 and 120 km. Baseline results hold constructing dryness measures based on this approach (Table C14).

I also restrict the focus to the respondents who (weakly) overestimate the number of past drought events (Table C15). The sample size drops down to around 100

observations when considering those who overestimate severe drought events, therefore while the precision of the estimates deteriorates, the coefficients on deviations are never statistically significant and the coefficients on long-term exposure remain fairly stable across the estimations.

3.5.2 Directional Motivated Reasoning

Next, I shift the focus to the relationship between beliefs and interpretation of drought events. I test the hypothesis that individuals adopt directional motivated reasoning and are subject to confirmation bias. Under this hypothesis, individuals' interpretation of drought events would be biased towards their prior beliefs, such that holding beliefs that droughts have increased has a positive effect on the probability and extent of overestimating the number of droughts.

Since only beliefs of increase in droughts are recorded in the survey, I only focus on the overestimation of the number of past drought events. Further research should explore whether directional motivated reasoning is displayed also by individuals who hold beliefs about a decrease in droughts, leading to a biased underestimation of drought events.

Panel A of Table 3.2 reports the OLS (columns 1 and 2) and 2SLS (columns 3 and 4) estimates of Equation (3.5) using as outcome the indicator that individuals overestimated the number of droughts ($\Delta > 0$) (columns 1 and 3), and the extent to which individuals overestimated droughts (Δ) (columns 2 and 4). Panel B reports the first stage estimates of the instrumental variable approach. The coefficient associated with Belief is positive and strongly statistically significant in both the OLS and 2SLS specifications. Consistent with Proposition 2, the belief of an increase in droughts increases the likelihood of overestimating drought occurrence by about 80 p.p. (column 3). When exploiting the extent of overestimation, beliefs have a positive and statistically significant effect, increasing the overestimation by four (column 4).

The magnitude of the 2SLS coefficient associated with Belief is significantly larger than the OLS estimate both in the probability and extent of overestimation. One potential explanation is that the OLS estimates suffer from reverse causality and attenuation bias due to measurement error.¹³ A second possibility is that the 2SLS estimation identifies a local average treatment effect (LATE) for individuals that were more exposed to variation in excess dryness and thus more likely to update their beliefs about increases in droughts and overestimate their number.

¹³In an OLS setting undermined by reverse causality, the coefficient associated with beliefs would be biased downwards, and under the classical error-in-variables assumption, OLS estimates would suffer from attenuation bias due to measurement error. As shown in Panel B of Table 3.2, long-term average exposure to dryness has a positive, significant effect on belief and the Kleibergen-Paap (K-P) Wald F-statistic for weak identification is 21.736, higher than any critical value reported by Stock and Yogo (2005).

TABLE 3.1: Objective exposure, beliefs and overestimation of drought events

	Belief											
	Belief of Increase in Droughts						Overestimation					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LT Exposure	15.13*** (2.129)		14.60*** (3.132)	15.14*** (3.386)	10.48*** (1.934)		11.64*** (2.871)	12.44*** (3.078)	38.81** (16.96)		59.12*** (16.70)	60.03*** (18.26)
Deviation		0.729*** (0.198)	0.0711 (0.245)	-0.285 (0.748)		0.369* (0.216)	-0.156 (0.255)	-0.683 (0.592)		-0.0576 (1.005)	-2.722*** (0.982)	-3.321 (2.440)
LT Exposure \times Deviation				2.411 (4.024)				3.569 (2.950)				4.058 (14.93)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.281	0.253	0.280	0.279	0.155	0.133	0.155	0.155	0.198	0.128	0.235	0.234

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8) and the measure of overestimation Δ (columns 9-12). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$). Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 3.2: Directional motivated reasoning. OLS and 2SLS estimates.

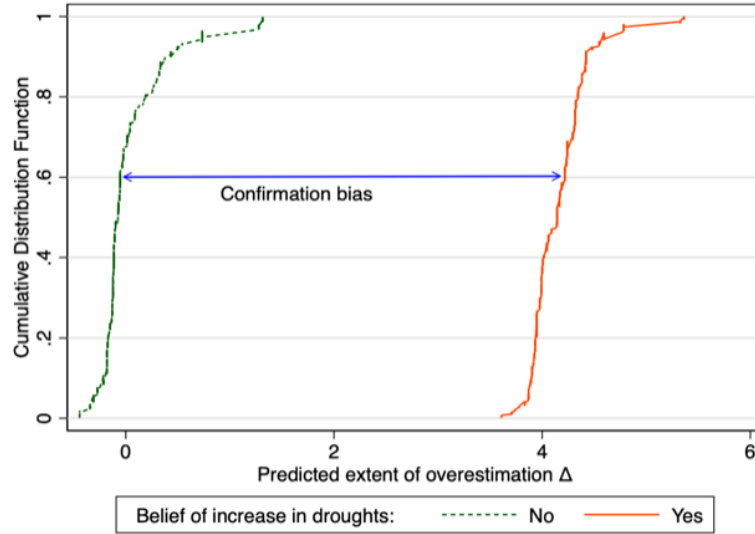
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Panel A:	Probability	Extent	Probability	Extent
Belief	0.166*** (0.0491)	0.368*** (0.115)	0.797*** (0.232)	4.049** (1.541)
Deviation	0.248 (0.211)	-0.326 (0.997)	-0.213 (0.335)	-3.010** (1.421)
F-stat			21.736	21.736
Panel B:	<i>Belief of Increase in Droughts</i>			
LT Exposure			14.60*** (3.135)	14.60*** (3.135)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (3.5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

These results provide suggestive evidence that individuals adopt directional motivated reasoning when interpreting drought events. The information is distorted, and changes in the perception of information for a given objective information set are driven by individual beliefs. Figure 3.1 plots the cumulative distribution functions of the predicted values of the extent of overestimation from Equation (3.5) for the two belief types. The gap between the two distributions shows that individuals with prior beliefs that droughts have increased exhibit confirmation bias and overestimate the number of drought events.

Same number of recorded droughts. Using objectively recorded droughts, all individuals within the same grid cell are exposed to the same set of objective information (the households in the sample do not change place of residence across the two waves). Any variation in the interpretation of droughts stems from asymmetric changes in beliefs. To corroborate this hypothesis, I restrict the sample to the unions that experienced the same objective number of drought events. This setting is similar to an experiment in which all participants are given the same objective evidence (with the clear difference that in this setting the evidence cannot be controlled by the experimenter).

FIGURE 3.1: Differential cumulative distribution functions of predicted overestimation of droughts



Notes: Figure shows the cumulative distribution function (CDF) for the extent of overestimation predicted from Equation (3.5) using a 2SLS approach. The dashed green line shows the CDF for individuals in the estimation sample that did not report that droughts have increased. The solid red line shows the CDF for individuals in the estimation sample with a belief that droughts have increased. The extent of overestimation Δ is computed as explained in Equation (3.1): I use the cut-off for extreme drought events ($\text{SPEI} \leq -2$) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events over the same time period.

Since there is substantial heterogeneity across unions in the number of extreme droughts experienced, this analysis can only be performed for the unions that have not experienced any extreme drought event.¹⁴ With this restriction, all households in the sub-sample did not face any drought in the years before each survey wave, and any residual asymmetric variation in interpretation is explained by changes in individual beliefs (accounting for short-term deviation in excess dryness and individual-specific and year-specific fixed effects). The marginal effect of believing in an increase in drought increases the probability of overestimating droughts by 95 p.p. (Table C16). This result demonstrates that individuals with prior beliefs of increases in droughts, although not recently exposed to extreme droughts, will distort their interpretation and overestimate them.

Measures of drought exposure. I also test for the robustness of the results using different SPEI time scales to construct drought exposure based on different periods over which water deficits accumulate. Table C17 shows similar 2SLS estimates using

¹⁴Since the SPEI values are normally distributed, extreme drought events ($\text{SPEI} \leq -2$) account for about 2.3% of all available historical values. On average, such SPEI values would then be recorded once every 44 months, explaining why no extreme droughts is the only case that brings together several unions.

the SPEI-4, SPEI-6 and SPEI-12. I also normalize the SPEI to individual-specific lifetime exposure to dryness conditions and obtain a robust positive effect of beliefs on the probability and the extent of overestimating droughts across different SPEI temporal scales (Table C18). Finally, the results are robust to the construction of drought exposure based on the interpolation of gridded data weighted by the inverse squared distance from the union centroids using as distance cut-offs 40, 80 and 120 km (Table C19).

Drought cut-offs. The findings are robust to different drought cut-offs to construct Δ (Table C20). The effect of beliefs is larger including moderate droughts (14.03, column 3) and severe droughts (6.92, column 4), compared to the effect on recollection of extreme droughts (4.05, column 4 in Table 3.2). This result suggests that the more ambiguous the signal, the more the evidence is open to interpretation. This situation creates room for the learner to adopt directional motivated reasoning and interpret ambiguous new information as a reinforcement of prior beliefs (Agnew et al., 2018b,a). I also limit the analysis to the sub-sample of individuals who overestimate droughts using the cut-offs of severe and extreme droughts (Table C21). Using extreme drought events, the OLS and 2SLS coefficients are positive, suggesting that individuals distort their interpretation of information due to their beliefs and exhibit directional motivated reasoning.

Historical restraints. As discussed in Section 3.4.2, a potential threat to the validity of the instrument concerns individuals exposed to more harmful conditions of dryness who may be more prone to adapt. Past weather affects past actions (i.e., adaptation), imposing historical restraints on current actions (i.e., interpreting drought events). The inclusion of short-term deviations from long-term average exposure in the baseline specification as a measure of transient shock is a first way to allay the concerns about this potential threat (Lemoine, 2021). Below, I discuss two additional robustness checks to deal with this concern.

Short-term deviations. First, I vary the definition of short-term deviations and include one-year and two-year lagged annual deviation measures from the long-term average exposure to dryness and I also extend the time horizon up to five years. Using a longer history of transient shocks reduces the bias introduced by historical restraints (Lemoine, 2021). The coefficient associated with belief is consistently statistically significant across all specifications and larger in magnitude than in the baseline estimates (Table C22).

Adaptation. Second, I account for different measures at the union-level that proxy for variations in the cost of adaptation (Tables C23 and C24).¹⁵ I include measures of the presence of different types of banks (state-owned Krishi bank, Commercial bank, Grameen bank, or any of the three) that could affect adaptation by relaxing households' financial constraints (columns 1-4). Similarly, I include an indicator of

¹⁵I use the community questionnaire that asks questions regarding each village. Table C2 reports the exact wording and formulation of each question in the two waves.

the presence of agricultural extension or a block officer (column 5), which may alter the weather information set of households. I also account for access to electricity (column 6), which could facilitate the use of electricity-dependent irrigation techniques, and for the presence of a shop for fertilizers or pesticides (column 7), which may influence the input use in agricultural production. The coefficients on beliefs are consistently positive, with no considerable variations in magnitude. When including all controls in column (8), the estimates are larger in magnitude, suggesting that the baseline estimates could be underestimating the effect of beliefs.

Weather information. As explained in Section 3.4.2, the validity of the instrument may be threatened if individuals more exposed to dryness are more likely to seek weather information. This channel would downward bias the effect of beliefs since more informed individuals would be more accurate. Although the survey does not contain detailed information on the propensity of individuals to listen to weather forecasts, I use data on the type of information on agricultural practices that could relate to droughts received from extension agents and whether individuals receive information from other sources besides the extension worker, in particular TV, radio or newspapers.¹⁶ When controlling for these variables, the 2SLS estimates of beliefs are positive, statistically significant and always larger in magnitude than the baseline estimates, suggesting that baseline estimates could be underestimating the true causal effect of beliefs (Table C25).

3.6 Discussion and Conclusion

Despite scientific consensus, beliefs about climate change and its causes vary widely across individuals, and awareness is still very low in the developing world (Lee et al., 2015a). Understanding the determinants of beliefs and any potential biases that individuals may exhibit is essential for the design of more effective policies to help them adapt (Lemos et al., 2019). Particularly so for agricultural communities in developing countries, heavily exposed to the consequences of climate change and whose misinterpretation of weather signals may be considerably harmful. It is critical to understand if individuals misinterpret weather shocks because they lack information or because, instead of striving for accuracy, they pursue directional goals. Individuals may engage in motivated reasoning mechanisms when interpreting weather events and exhibit confirmation bias.

This paper studies the effect of dryness exposure on beliefs of increase in droughts and examines whether individuals adopt directional motivated reasoning in the interpretation of drought events. First, I investigate how long-term average exposure

¹⁶I use the household questionnaire (module M) to construct different versions of a dummy variable of receiving information on soil and water conservation, crop protection, new crop varieties and crop utilization and a binary variable on the sources of information among which TV, radio and newspapers. Table C2 reports the exact wording and formulation of each question in the two waves.

to dryness and short-term deviations affect beliefs and the accuracy of recollecting them, finding that only long-term average conditions matter. This result suggests that beliefs are longstanding, and hence shaped only by long-term conditions rather than short-term deviations and that one single drought event may not be enough to alter climate change beliefs. Second, I document that individuals engage in a form of directional motivated reasoning, adding the first empirical evidence in a developing country. Using an instrumental variable approach to tackle endogeneity concerns, I find that individuals distort the perception of information due to their beliefs. This result, robust to different specifications, provides suggestive evidence that individuals are subject to confirmation bias: they recollect and overweight evidence tilted towards their prior beliefs. From a normative perspective, individuals exhibiting motivated reasoning when it comes to slow-onset environmental changes suggest that policies should target individuals' beliefs to avert ignoring information countering prior beliefs.

Despite recent advancements in accurate estimates of climate impacts accounting for adaptation benefits and costs across sectors (Carleton et al., 2022; Hultgren et al., 2022; Rode et al., 2021; Auffhammer, 2022), the underlying conceptual framework still relies on perfectly informed and rational agents with unbiased beliefs measured by meteorological conditions (Deryugina and Hsiang, 2017). This paper empirically shows for the first time that climate beliefs can exhibit directional motivated reasoning, in support of previous theoretical arguments diverging from Bayesian agents, with asymmetric distortion of objective information as a result of climate beliefs (Druckman and McGrath, 2019). Integrating features of incomplete rationality of decision-makers and individual distortion of weather signals based on prior beliefs can have substantial consequences on climate impact estimates accounting for individual endogenous choices of adaptation.

These findings shed light on a cognitive bias that distorts the mental representation of climate change and may subsequently lead to erroneous interpretation of climate change consequences and prevent or facilitate behavioral responses (Zappalà, 2023a). Drought frequency in Bangladesh is projected to increase in the future, particularly in regions historically considered less prone to droughts (Mohsenipour et al., 2018). Since beliefs are formed on long-run exposure rather than short-term deviations and drive the interpretation of weather events as a result of motivated reasoning, if individuals do not update them, they may not put in place timely adaptation to avert climate damage. Understanding how household beliefs about climate impact and cognitive biases impact adaptive decisions remain interesting questions for future work.

Against this background, it is essential to identify the nature of the bias to propose adequate debiasing tools for effective policies. A solution proposed by Zhao and Luo (2021) involves forward-looking techniques generating arguments for forward-looking options. Accurate information on historical and projected changes in climate

may shape individuals' beliefs on climate change consequences and foster behavioral responses to put in place timely adaptation. Further work should focus on the role of information interventions exogenously varying the information set, and assessing how these affect beliefs and influence cognitive biases.

A limitation of this study opens avenues for future research. The data do not allow to test for the presence of directional motivated reasoning and confirmation bias among those who believe that droughts have decreased over time. Testing whether this prior belief, commonly associated with *climate change deniers'* or climate skeptics' position, leads to biased interpretation of weather events underestimating them, would be of particular interest.

Chapter 4

Climate-induced migration and environmental values

Climate concern as a political priority is crucial for gaining broad public support for climate policies. The drivers of climate attitudes have so far been identified in socio-economic and political factors and direct experience of weather shocks. This paper introduces international migration induced by weather variations as a novel determinant of climate concern. The empirical analysis leverages exogenous variation in weather in non-OECD origin countries to construct a gravity-predicted instrument for asylum demands and study their effect on individual climate concern and voting behavior for Green parties in the European Union between 2000 and 2019. Results show that weather-induced asylum applications heighten concern about climate change as a political priority. Changes in stated preferences, however, do not translate into changes in voting behavior, as there is no effect on Green party votes in the European Parliament elections. These findings are consistent with a drop-out of traditional Green voters, changes in preferences for individuals below the voting age, as well as no changes in the pro-environmental policy manifesto of political parties.

Keywords: Asylum seekers, climate change, climate concern, gravity model, migration, political ideology

JEL Classification: D72, F22, J15, Q54, P16

I am grateful to Katrin Millock for her constant support throughout the development of this paper. I am also thankful to Cevat Aksoy, Cristoph Albert, Toman Barsbai, Tamma Carleton, Andrew Clark, Maria Cotofan, Ruben Durante, Paola Giuliano, Daniel Masterson, Benjamin Michallet, Matto Mildenberger, Giovanni Peri, Hillel Rapoport and Marco Tabellini, as well as participants of the PhD Summer School on Applied Microeconomics by the University of Cyprus, Lancaster University and University of Padova, the 15th RGS Doctoral Conference in Economics, the 2022 RES Symposium of Junior Researchers, the 2nd IZA Workshop on Climate Change and Human Wellbeing, the Paris Migration Economics Seminar, the 15th Carlo Alberto PhD Workshop and the 10th IEB Workshop on Political Economy for helpful comments. All remaining errors are mine.

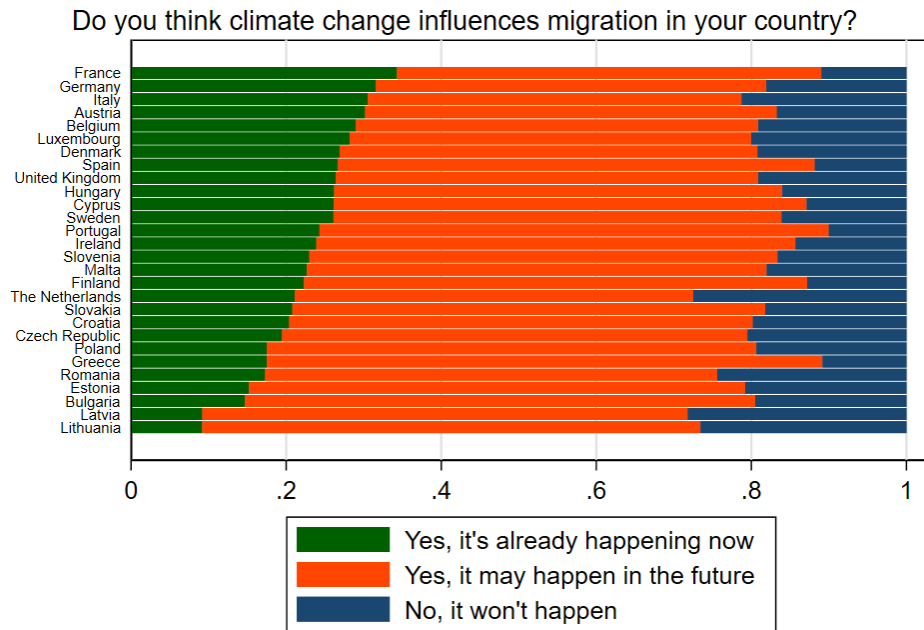
4.1 Introduction

Climate mitigation ambitions are not yet supported by adequate policy measures that are lagging behind. Advancing and implementing green policies requires public climate awareness in the first place. For this reason, the study of the drivers of public concern about climate change as a political priority is of utmost importance in addressing the pressing challenge of climate action. Previous literature has predominantly focused on socio-political determinants (Poortinga et al., 2019) and the direct experience of extreme weather events as the main factors influencing climate concern (Hazlett and Mildenerger, 2020; Hoffmann et al., 2022). Growing global climate awareness is also accompanied by an increasingly accurate understanding of the consequences of climate change, including larger migration flows (Dechezleprêtre et al., 2022). Recent surveys in the European Union suggest respondents see climate change as causing increasing migration inflows in their country (Figure 4.1). Despite growing attention to the effects of economic migration in host countries (Alesina and Tabellini, 2023), the political implications of climate-induced migration remain largely unknown. The indirect exposure to weather anomalies through the rise in migration inflows may reduce the psychological and social distance to such events, fostering greater concern for the underlying cause: climate change.

This paper studies the effect of recent waves of weather-induced asylum seekers in the European Union (EU) on individual climate concern and voting behavior for Green parties from 2000 to 2019. I combine non-OECD outflows of asylum seekers with high-resolution climatological data and several cross-country data sets on individual attitudes, political party agenda, and electoral outcomes. Using data from the Eurobarometer, I analyze the implications of weather-induced asylum demands on individuals' concern about climate change as a political priority. Then, I examine if changes in stated preferences translate into changes in revealed preferences by examining how pro-environment voting behavior is affected by weather-induced asylum applications.

To estimate the causal effect of weather-induced asylum demands, I adopt an instrumental variable approach, constructing a measure of weather-driven asylum seekers from a gravity model leveraging plausibly exogenous variation in weather (Bosetti et al., 2020). I recover an asymmetric U-shaped relationship between temperature and asylum applications and use the estimated semi-elasticities on non-linear functions of temperature and precipitation, holding fixed origin-destination and time-specific characteristics and accounting for multilateral resistance to predict bilateral flows. I then aggregate them to obtain an instrument for actual asylum demands and overcome the potential measurement error in inferring the weather-driven portion of asylum seekers. The time-varying instrument makes it possible to control for unobserved country-, time-, and cohort-specific factors potentially correlated with changes in both asylum demands and climate concern.

FIGURE 4.1: Survey evidence on climate-migration nexus awareness



Source: EIB Climate Survey 2019

Notes: The figure plots the frequency of responses by country to the survey question “Do you think climate change influences migration in your country?” in the European Investment Bank Climate Survey in 2019.

Starting from the survey-level analysis, I find that weather-induced asylum applications increase individual concern about climate change as a political priority. The interaction with asylum seekers considerably varies across birth cohorts and climate change has a differential degree of concern across age categories, as documented by previous surveys (Figure D1, Thompson (2021); Marris (2019)) and recent climate-related school-strikes and demonstrations initiated by younger generations (Bowman, 2020; Kenis, 2021). Exploiting birth-cohort variation in exposure to weather-induced asylum seekers, and accounting for country-specific age trends, I document that individuals who grew up when their country was receiving more asylum applications were, at the time of the survey, more concerned by climate change, finding evidence that environmental values are shaped during the “formative age”, between 16 and 24 years (Krosnick and Alwin, 1989). In my preferred specification, a 50% increase in weather-induced asylum applications (approximately equivalent to the inter-quartile range in the sample) increases an individual’s climate concern by 19% of the sample mean. This is similar to the difference in climate concern between Cyprus and Germany, or that between Hungary and France.

I propose and test for alternative mechanisms behind these results. First, I show that the effect is driven by younger, female individuals who have less trust in national

institutions and more in supra-national ones. Second, I provide descriptive evidence on the relationship between past asylum demands and awareness of the climate-migration nexus in host countries. Third, I rule out the hypothesis that news and media coverage are inflating the effect of weather-induced asylum demands by using data from Google searches. I find no correlation between the predicted measure of weather-induced asylum demands and public attention through online searches and conclude that weather-induced asylum demands are a central driver of climate concern as a political priority and that online searches cannot explain the findings. Last, I test for two alternative underlying psychological mechanisms. On the one hand, asylum demands can reduce the geographical distance of weather anomalies induced by climatic changes and influence climate change perceptions as a global problem; on the other hand, climate-induced migration inflows can be perceived as an additional social cost and a “threat” (Baldwin, 2013) increasing climate concern as a political priority to support further climate action. This empirical finding supports the theoretical result of the role of climate-induced migration in enhancing incentives of host regions to fight climate change documented in Alsina-Pujols (2023). I find that weather-induced asylum applications do not affect any other climate-related attitudes and instead also spur migration concern as a political priority and drive climate concern mostly among right-wing and less-educated individuals, providing suggestive evidence in support of the latter mechanism.

This effect is not translated into changes in revealed preferences as measured by Green party votes in European Parliament elections. At the country level, I document that Green parties in countries more exposed to weather-induced asylum demands between two electoral rounds do not gather larger consensus and if anything, the consensus reduces in response to such flows. I propose several co-existing explanations. First, weather-induced asylum applications do not affect any other party vote shares but decrease electoral turnout, suggesting that the dropout of traditional Green voters of voting polls may partially explain the results. Second, only individuals below the voting age and not yet eligible to vote are more likely to report climate change as an important theme for the electoral campaign for the European Parliament elections, which could explain the gap between stated and revealed preferences at the voting booths. Finally, I examine changes in the supply side of the political process as measured by the pro-environment policy platforms of the parties. Exploiting within-party variation in environmental policy platforms from the Manifesto Project Database, I find no effect of weather-induced asylum applications. This result provides a complementary mechanism for which a lack of supply shifts in the pro-environment policy platform may explain why the rising stated climate concern in response to weather-induced asylum demands did not translate into more pro-environment voting behavior.

This paper contributes to the literature investigating the determinants of climate change perceptions and concern. Various studies focus on the importance of

socio-demographic and economic determinants such as political ideology, education, unemployment, and gender (Carlsson et al., 2021; Hornsey et al., 2016; Czarnek et al., 2021; Duijndam and van Beukering, 2021; Dechezleprêtre et al., 2022), and experience of recent, local and extreme weather events (Konisky et al., 2016; Deryugina, 2013; Hoffmann et al., 2022; Bergquist and Warshaw, 2019). Recent work has also studied the relationship between climate protests and climate concern and pro-environment voting behavior in Germany (Valentim, 2023; Fabel et al., 2022). This paper identifies a new channel for the formation of concerns about climate - weather-induced asylum demands - that reduce the geographical and social distance associated with weather fluctuations induced by changes in climate. Contrary to Deryugina and Shurchkov (2016), which provides experimental evidence that information provision on the scientific consensus on climate change does not impact the belief that policy action is warranted, I document an increase in climate concern as a political priority in response to higher exposure to weather-induced asylum demands.

There is a growing body of work on the relationship between immigration, political attitudes, and voting behavior (Alesina and Tabellini, 2023). Previous research has studied economic immigration and right-wing (anti-immigration) voting in different European countries, such as Austria (Halla et al., 2017; Steinmayr, 2021), Denmark (Harmon, 2018), France (Edo et al., 2019), Germany (Otto and Steinhardt, 2014), Italy (Barone et al., 2016; Campo et al., 2021), Switzerland (Brunner and Kuhn, 2018) and across Europe (Moriconi et al., 2019). Natives' reactions have also been studied through political ideology and preferences for redistribution in Sweden (Dahlberg et al., 2012) and across Europe (Alesina et al., 2021; Moriconi et al., 2022). Recent experimental studies have examined attitudes towards climate migrants in Denmark (Hedegaard, 2022), Germany (Helbling, 2020) and the US (Arias and Blair, 2022), finding a more favorable opinion than for economic migrants, although this paper finds that climate migration spurs greater concern for climate change as a political priority. This paper takes a cross-country perspective to study the political effects of climate-induced migration in an observational setting.

From a methodological standpoint, this paper ties to the literature on the relationship between climate change and international migration. Previous surveys have reviewed this relationship and the underlying mechanisms (Millock, 2015; Hoffmann et al., 2021; Beine and Jeusette, 2021), that has ambiguous findings: positive in certain cases (Cai et al., 2016; Backhaus et al., 2015; Marchiori et al., 2012; Coniglio and Pesce, 2015), null in others (Beine and Parsons, 2015), or conditional on income (Cattaneo and Peri, 2016). Concerning asylum seekers, Missirian and Schlenker (2017b) find that temperature fluctuations affect asylum applications in a non-linear fashion, Abel et al. (2019) document that drought severity and induced armed conflict are important drivers. This paper complements these works by estimating a bilateral gravity model for asylum applications that leverages weather fluctuations

as a push and pull factor and accounts for multilateral resistance to construct a predicted climate-driven measure of asylum demands.

The remainder of this paper is structured as follows. Section 4.2 describes the data. Section 4.3 explains the empirical strategy and the construction of the instrument. Section 4.4 presents the results for the effect of weather-induced asylum demands on individual climate concern. Section 4.5 examines the effect on Green party votes in European Parliament elections and explores alternative mechanisms behind the findings. Section 4.6 concludes.

4.2 Data

I combine data from multiple sources including asylum applications at the country level in the European Union over the period 2000-2019, climatic gridded data, individual attitudes towards climate, Google Trends data on daily searches about migration and climate change, national party political agendas, and the electoral outcomes in the European Parliament elections. This section (with complementary information in the Data Appendix D.2) describes and summarizes the main data sources.

4.2.1 Asylum applications

Bilateral data on asylum applications are sourced from the United Nations High Commissioner for Human Rights. Despite the relatively small size of this facet of migration, around ten percent of the overall migration flows, asylum seekers have already received substantial attention in academia (Hatton, 2020; Missirian and Schlenker, 2017a) and in the policy debate (Byravan and Rajan, 2017; Wennersten and Robbins, 2017).

Around 13,400,000 asylum applications were registered in European Union (EU) countries between 2000 and 2019, of which around 12,950,000 are from non-OECD countries (D2). Following Missirian and Schlenker (2017b), I consider annual asylum applications from each source country outside the OECD to any EU member state. Figure D3 shows the aggregated outflows of asylum applicants from their origin country over the twenty years considered, whereas Figure D4 displays the distribution of the asylum applicants across the EU member countries over the same time period. Additional details on the data can be found in Appendix Section D.2.1.

The motivation behind the use of asylum demands as a measure of human migration induced by climate is two-fold. First, asylum-seeking can be linked to climate-related migration more directly than regular migration which is driven by various other push and pull factors. More importantly, weather-induced conflicts in developing countries spill over to developed countries through asylum applications (Missirian and Schlenker, 2017b) and increases in asylum demands have been associated with climate change through drought increases (Abel et al., 2019) and

conflict (Burke et al., 2015a; Hsiang et al., 2011). Second, whilst refugee flows are also likely to be driven by climate-induced conflict, they are endogenous to a host country’s specific policy in granting refugee status. Moreover, asylum procedures are long and differ across host countries and more than two years can range between application and formal status registration (Campo et al., 2021). Asylum demands are therefore preferred since actual stock and refugee figures can be strongly affected by country-specific political actions. Additional details on the asylum application process can be found in Appendix Section D.2.1.

4.2.2 Weather data

I gather temperature and precipitation data from two sources. The main source is the global reanalysis ERA-5 dataset by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service, 2023), which combines model data with observations from across the world into a globally complete and consistent dataset using information from weather stations, satellites, sondes, and re-analysis. ERA-5 is available on a $0.25^\circ \times 0.25^\circ$ resolution grid ($\approx 28\text{km}$ at the Equator) from 1950 to the present. The original temporal frequency is hourly, but I aggregate it into daily data for the empirical analysis.

To maintain weather variability, I compute nonlinear transformations at the grid cell level before averaging values across space using grid-level weights and accounting for fractional grid cells that partially fall within a country (Hsiang, 2016). Spatial aggregation at the country level is conducted in three ways. First, I simply average all grid cells in a country over the entire year. Second, I use population count in each grid cell as time-invariant weights from the gridded UN-WPP adjusted population count from the Gridded Population of the World (GPW) dataset, v4.11 for the year 2000. Third, since a large share of the population in most origin countries works in agriculture and given that weather is a direct input to the production function of this sector, I construct weather exposure for the maize growing area (Missirian and Schlenker, 2017b), with maize being the staple commodity accounting for the largest share of humans’ caloric intake and grown around the world. I use the gridded data set by Monfreda et al. (2008) to construct the fraction of each climate grid in a country that grows maize (Figure D5 shows the fraction of each grid cell devoted to maize cultivation around the world). I use crop-specific growing season dates from Sacks et al. (2010) to compute the country-specific period of the year in which maize is grown.¹

¹The data set gives the start and end dates of the maize growing season. When I use daily weather data, I construct measures from the median planting date to the median harvest date. When I use monthly weather data, I define the growing season to start on the first of the month of the median planting date and to end on the last of the month of the median harvest date (Missirian and Schlenker, 2017b). If the crop is grown more than once a year, I focus on the first season.

For a sensitivity check, I also use the gridded Climatic Research Unit of the University of East Anglia (CRU) data with a 0.5° spatial resolution ($\approx 55\text{km}$ at the Equator) and a monthly temporal resolution as in Missirian and Schlenker (2017b).

Previous research shows that agricultural productivity is the main pathway linking temperature and migration (Cattaneo and Peri, 2016; Cai et al., 2016; Missirian and Schlenker, 2017b; Bohra-Mishra et al., 2017; Feng et al., 2012; Marchiori et al., 2012; Falco et al., 2019). It could be that higher temperatures have other disruptive effects in countries besides agriculture, e.g. increased conflicts, wars, and effects on health and fertility, which in turn would increase emigration rates. Nevertheless, only certain of these reasons are valid for filing an asylum application (UN, 1951). Although it is beyond the scope of this paper to pin down the exact mechanisms through which weather fluctuations drive outflows in asylum demands, I provide evidence that the agricultural productivity channel through seasonal weather engendering higher “output conflict” (McGuirk and Burke, 2020) can be a valid mechanism for inducing spikes in asylum applications by leading to changes in acceptance rates (see Appendix Section D.4.4).

4.2.3 Individual climate concern

I use the Eurobarometer surveys as the main source for individual stated climate concern across the European Union. The relevant surveys for the scope of the analysis regard those Eurobarometer Standard and Special editions that contain questions on individual perceptions, awareness, and attitudes towards climate change.² Each Eurobarometer survey typically involves 25,000-30,000 respondents from all EU member states. I select two main questions on the individual concern about climate change as a political priority. The two variables, labeled respectively *CC EU Election* and *CC Pol Priority*, measure in a binary fashion whether individuals consider climate change important in the electoral campaign for the European Parliament elections and whether climate change is a priority for European Parliament deliberations. The exact formulation and temporal coverage of the questions used as an outcome, and their summary statistics, are reported in Table D1. Since the interest is in the effect of asylum seeker flows on natives’ awareness of climate change, I restrict the sample to native-born individuals, i.e., born in their current EU country of residence.

4.2.4 Electoral outcomes

I collect data on electoral votes for European Parliament (EP) elections from Schraff et al. (2022). The data cover 28 countries at the NUTS-2 level and contain information for six EP election rounds spanning 25 years from 1994 to 2019. From the

²The surveys also contain information on socio-demographic characteristics of the respondents that are included as controls in the analysis, such as gender, age, education, employment status, and political orientation.

list of parties, I classify parties as Green on the basis of their party family classification in the Manifesto Project electoral program database (Merz et al., 2016) and their membership in the European Green Party, a federation of political parties supporting Green politics across Europe, that forms the G-EFA parliamentary group in the European Parliament. On the basis of this information, I compute the national Green vote share as a fraction of valid votes for Green parties in each country per election round in the four European Parliament elections held after 2000, respectively in 2004, 2009, 2014 and 2019.³

Environmental values in the European political arena date back to the late-20th century, following the rise of environmental awareness and the development of new social movements. In particular, starting in 1984, Green parties agreed on a common platform for the European Parliament elections, and the first Green Members of the European Parliament were elected. They have faced different destinies throughout Europe, accumulating electoral successes mainly in Germany, Belgium, Finland, and France, whereas in other European countries, especially in Central and Eastern Europe, their political relevance is more limited. Since then, Green parties have become a more or less permanent feature on the political scene and they are growing in visibility (Richardson and Rootes, 2006). Despite the variety of electoral mandates, Green parties share the closeness to any environmental, ecological, and climate-related matter, whose salience is here posited to have increased due to the upsurge in weather-induced asylum applications.

I use European Parliament elections since voters are more willing than in national elections to support small parties and properly reveal their electoral preferences (Pearson and Rüdiger, 2020). Being “second-order elections” (Reif and Schmitt, 1980), voters have a lower level of strategies or utilitarian voting and are more likely to “vote with the heart” (Hix and Marsh, 2007). For this reason, vote shares in these elections provide a more accurate snapshot of the revealed preferences of voters (Hoffmann et al., 2022).

4.2.5 Party political agenda

The Manifesto Project Database (MPD) (Merz et al., 2016) contains detailed information on the platforms (i.e., “manifestos”) of political parties in Europe and elsewhere by using a content analysis of their electoral manifestos. Specifically, based on these manifestos, it categorizes 56 different political positions relating to economic, social, foreign policies, and, most importantly, the environment. It also contains vote shares for each party in every legislative election. I retrieve information for 622 European political parties available for elections between 2000 and 2019.

³Two new member states of the European Union, Romania, and Bulgaria, held elections to the European Parliament in 2007 for the Parliament’s mandate 2004-2009, while Croatia entered the European Union on 1 July 2013 and, as a new member state of the European Union, it held European Parliament elections for the first time in 2013, with the elected member serving the remainder of the Parliament’s 2009–2014.

Based on MPD data, I measure preferences on environmentalism as the share of quasi-sentences that positively referred to policies in favour of protecting the environment, fighting climate change and other *green* policies, for instance: general preservation of natural resources, preservation of countryside forests, protection of national parks, animal rights. This topic includes a great variance of policies that have the unified goal of environmental protection. Table D2 reports the number and years of the European Parliament elections for each country and the number of years of national elections covered by the MPD. Table D3 provides additional information on the exact wording of each topic covered in the manifesto used in the analysis.

4.3 Empirical Approach

In this section, I present the baseline empirical approach adopted to estimate the effect of asylum applications on environmental values. In Section 4.3.1, I examine potential changes in individual stated concern about climate using survey data. I investigate this channel by exploiting within-country variation over time and additional mechanisms leveraging within-country between cohort variation in exposure to asylum seeker flows. Section 4.3.2 explains in detail the instrumental variable approach adopted to strengthen the causal identification of the effect driven by the weather-induced portion of asylum demands.

4.3.1 Individual-level analysis

I start by focusing on the demand side of the environmental political process. I use citizens' stated preferences as an initial measure of voters' demand (Calderon et al., 2023). The objective is to estimate the effect of weather-induced asylum demands on citizens' concern about climate change as a political priority in the EU destination countries. By increasing the salience of migration as a consequence of weather fluctuations, higher exposure to weather-induced asylum seekers may foster greater concern about climate change among natives, in turn spurring the demand for climate change policies and attention to the issue. I test this hypothesis with individual-level regressions of the form:

$$Y_i = \beta_1 \log \left(\sum_{\tau=s}^S AsyApp_{d,t-\tau} \right) + X_i' \gamma + Z_{dt}' \delta + \mu_d + \kappa_{t-b} + \zeta_{rt} + \theta_d \times age + \varepsilon_{ibdr} \quad (4.1)$$

where Y_i is a vector of climate-related policy preferences as described in Table D1 of individual i belonging to birth-cohort b in country d in region r in year

of interview t .⁴ The main explanatory variable is $\sum_{\tau=s}^S \text{AsyApp}_{d,t-\tau}$, that is, the sum of all non-OECD asylum applications in country d over various time intervals, to let diffusion mechanisms unfold and to account for the average length of the electoral mandates in the country. The baseline specification accounts for asylum demands over the previous five years; in Appendix D.3.2, I replicate the analysis using other time frames. As the distribution of asylum demands is right-skewed, I always consider logs and estimate relative impacts to allow for concavity in the response and interpret the coefficients as semi-elasticities. I control for a set of individual covariates X'_i , capturing socio-economic characteristics (gender, education, political orientation, and employment status), potentially correlated with climate change preference formation (Nowakowski and Oswald, 2020). Z'_{dt} captures second-order polynomial measures of annual temperature and total precipitation since local weather conditions drive environmental preferences (Hoffmann et al., 2022).

I also include destination country fixed effects (μ_d) to partial out country ideology at birth and anything specific to a certain country of residence that could be unobserved heterogeneity in climate change beliefs (e.g. political, cultural). I add age-specific κ_{t-b} fixed effects to partial out unobserved age-specific determinants of preferences and attitudes (e.g. preferences specific to life-cycle)⁵, and I include region by survey-year fixed effects (ζ_{rt}) that absorb not only time-varying changes in the overall ability of foreigners to migrate and international shocks but also region-specific events in the year of the interview. Finally, I account for interactions of country dummies with linear age trends ($\theta_d \times \text{age}$) to help rule out the possibility that results are driven by country-specific cohort effects. Standard errors are clustered at the country level.

4.3.2 Instrument for asylum applications

In an OLS estimation of Equation (4.1), the coefficient β_1 would produce a measure of the partial correlation between asylum applications and the outcome of interest that may be biased for several reasons. Unobservable characteristics affecting citizens' environmental values (captured in the term ε_{ibdrt}) and correlated with asylum demands would generate such bias. For instance, if asylum seekers are attracted to countries where the attitudes of citizens are more favorable to immigration, and these attitudes are correlated with climate attitudes or voting behavior towards pro-immigration parties, then a spurious correlation could arise. Similarly, social, economic, and demographic changes attracting asylum seekers and changing individual attitudes would also induce bias.

⁴Regions are defined following the UN M49 nomenclature: Eastern Europe (Bulgaria, Hungary, Poland, Romania, Slovakia); Northern Europe (Denmark, Estonia, Finland, Ireland, Latvia, Lithuania, Sweden, United Kingdom); Southern Europe (Croatia, Greece, Italy, Malta, Portugal, Slovenia, Spain); Western Asia (Cyprus); Western Europe (Austria, Belgium, France, Germany, Luxembourg, Netherlands).

⁵I conduct robustness tests including birth year fixed effects instead of age fixed effects since they are not perfectly collinear in a repeated cross-section. This approach does not alter my results.

To address these concerns, in the following section, I explain the construction of an instrument that leverages plausibly exogenous variation in weather in origin countries, measured as a high-order polynomial of temperature and precipitation, accounting for origin-, dyad- and time-specific unobservable characteristics (Bosetti et al., 2020).

Gravity equation and predicting weather-induced flows

I propose an identification strategy exploiting plausibly exogenous variation in weather to construct a predicted measure of asylum seeker flows, using it as an instrumental variable in a 2SLS estimation strategy. I adopt a “gravity” approach that predicts asylum applications based on nonlinear effects of variations in temperature and precipitations in origin countries (Bosetti et al., 2020; Beine et al., 2016).

Gravity models are frequently used in the migration literature to predict the geography-driven portion of migrant flows and estimate the causal impact of migration on receiving countries’ economic performance (Ortega and Peri, 2014; Alesina et al., 2016; Docquier et al., 2016) and probabilities of conflict (Bosetti et al., 2020). I predict bilateral migration using an OLS estimator following Frankel and Romer (1999) for the canonical log-transformation of the gravity equation.⁶ The bilateral gravity equation is written as:

$$\log(AsyApp_{odt}) = f(\mathbf{W}_{ot}; BIL_{od}; \alpha) + \theta_{od} + \mu_{dt} + \chi_{rt} + u_{odt} \quad (4.2)$$

where the dependent variable $\log(AsyApp_{odt})$ is the natural logarithm of the asylum applications from non-OECD origin-country o to EU destination-country d in year t (Missirian and Schlenker, 2017b). To obtain bilateral time-varying variation in weather at the origin, I introduce interaction terms between weather \mathbf{W}_{ot} and bilateral geographic characteristics BIL_{od} . I allow for heterogeneous effects of weather by common border, common official language, common colonial history, and the natural logarithm of bilateral (geodesic) distance between the two capital cities (Cattaneo and Peri, 2016; Beine and Parsons, 2017; Bosetti et al., 2020).

In the baseline specification, I only consider contemporaneous weather and use a fourth-order polynomial of daily average temperatures, summed across the maize growing season, which provides sufficient flexibility to capture important nonlinearities (Carleton et al., 2022). Analogous to temperature, I construct a second-order polynomial of season-total precipitation over the maize growing season. I include

⁶A more common approach in the gravity estimation in trade and migration uses the Poisson Pseudo Maximum Likelihood (PPML) estimator, which reduces concerns of potential inconsistency in the estimation of multiplicative models in log-linearized form, and addresses the issue that OLS estimates may be biased due to many zeros in bilateral flows (Silva and Tenreyro, 2006). I do not adopt this estimation method for two reasons. First, the asylum application data do not contain zeros. Second, most importantly PPML always requires including origin-time fixed effects to control for the resistance term (Beine et al., 2016). By including such dummies, it would not be possible to identify origin-time effects such as the identifying weather variation used in Equation 4.2.

origin-destination fixed effects (θ_{od}) - which absorb the levels of the bilateral geographic characteristics - destination-by-year fixed effects (ψ_{dt}) and region-of-origin-by-year fixed effects (χ_{rt}).⁷ In a set of robustness checks, I explore the sensitivity of the results to alternative definitions of temperature and alternative functional forms, including lower-order polynomials and binned daily average temperatures. Additional robustness checks also include up to four lags of the weather variables to allow for delayed effects. Standard errors are clustered by origin country-year.

One of the major challenges for the estimation of a gravity equation relates to the so-called multilateral resistance term to migration, defined as the confounding influence that the attractiveness of alternative destinations exerts on the bilateral migration rate (Bertoli and Moraga, 2013). Omitting this term can generate biases in the estimation of the coefficients of the determinants of migration, by ignoring the influence of alternative destinations (Beine et al., 2016). This is particularly important since weather fluctuations can be positively correlated between origins and alternative destinations, both over time and space. Therefore, when ignoring this, the origin terms \mathbf{W}_{ot} would pick up both their own effect and the effect of alternative destinations.

Several strategies have been proposed to account for the multilateral resistance term. Bertoli and Moraga (2013); Bertoli et al. (2016) show that under some data-demanding conditions, the resistance term conforms with the common correlated effects (CCE) estimator proposed by Pesaran (2006) and implemented in a climate migration regression in Mullins and Bharadwaj (2021). Against this backdrop, I adopt two different approaches that account for the multilateral resistance term both non-parametrically and parametrically. First, the baseline specification controls for destination-by-year fixed effects (ψ_{dt}) and region-of-origin-by-year fixed effects to capture regional trends (χ_{rt}). Destination-by-year dummies completely account for time-varying multilateral resistances in receiving countries (Feenstra, 2015), the most important aspect in the context of international migration (Beine and Parsons, 2015). Region-of-origin-by-year dummies control for the multilateral resistance to migration that is induced by time-varying heterogeneity in the preference for migration from a specific region of origin while ensuring estimation of origin by time variation. Therefore, the regression only exploits exogenous year-to-year variation in weather in origin countries to predict the flow of asylum seekers and does not rely on baseline difference (e.g., different forms of government might result in a different average number of refugees fleeing a country) to obtain causal estimates of the relationship analyzed.

Second, in Appendix Section D.4.1 I detail the construction of a parametric control of multilateral resistance \mathbf{MR}_{odt} that I include in additional robustness

⁷Following the UN M49 nomenclature, the world is divided into 17 regions: Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Melanesia, Micronesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-Eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, Western Europe.

checks. This measure of multilateral resistance is, for each destination-origin country pair, the average of all the other destinations' weather variables weighted by the marginal propensity to apply for asylum in each destination country, constructed as the ratio of asylum applications over the total asylum applications in the first available year in the sample. These additional regressors account for changes in the attractiveness of alternative destinations weighted by the propensity to migrate to such alternative destinations (Mayda, 2010). Since these proxy variables do not entirely capture the factors affecting changes in attractiveness and cannot be justified theoretically, the inclusion of these parametric controls is to be interpreted only as a robustness test on the stability of the estimates associated with origin weather variation (Head and Mayer, 2014).

The vector of estimated parameters $\hat{\alpha}$'s from Equation (4.2) is used to construct an instrument for the total asylum applications at the destination country-year level. In particular, I define X_{odt} as the matrix of temperature and precipitation variables, including all interactions with bilateral characteristics, the resulting weather-induced asylum seeker inflows predicted for country d in year t is $\widehat{AsyApp}_{dt} = \sum_o \exp(\hat{\alpha}X_{odt})$. To test for the robustness of the results, I construct alternative instruments. In Appendix Section D.4.2, I estimate a regression that does not account for destination-by-year unobservable heterogeneity but includes destination-specific weather as a measure of pull factor. In Appendix Section D.4.3, I estimate host country-specific response functions to weather variations in origin countries, which also accounts in an alternative way for multilateral resistance.

The predictors are based on a fixed-effects gravity regression, however, they do not include the estimated fixed effects (Ortega and Peri, 2014). Hence, the instrument is obtained only from the estimated semi-elasticities to weather fluctuations. This may potentially reduce the predictive power, however, it increases the confidence in isolating the variation in asylum applications solely induced by changes in temperature and precipitation. For this reason, I interpret the finding as the effect of weather-induced asylum applications, as I will refer to them throughout the rest of the paper.⁸

Identifying assumption and instrument validity

The instrument relies on the variation solely induced by deviations in temperature and precipitation in non-OECD origin countries and it is thus free from reverse causality and exogenous to any single EU destination country, and within countries,

⁸Given the constructed nature of the instrumental variable, previous literature adjusts the 2SLS standard errors by applying a correction that takes into consideration information drawn from the first-step gravity equation (Frankel and Romer, 1999; Irwin and Terviö, 2002; Feyrer, 2009, 2019). I do not apply any correction, since the correction is necessary only in the case of a generated regressor, whereas in the case of a generated instrument, the 2SLS standard errors and test statistics are asymptotically valid (Bosetti et al., 2020; Wooldridge, 2010).

to any specific age cohort or national party. The time-varying nature of the instrument allows me to account for destination country-specific factors and shocks common to all destination countries that may be correlated with migration flows and environmental preferences.

A potential violation of the exclusion restriction for the predicted weather-induced asylum seeker flows as a valid instrument could arise if origin-country weather variations were correlated with environmental preferences through channels other than their effect on asylum applications. The key identifying assumption is that only asylum applications are directly affected by the predicted measure of weather-driven asylum applications, conditional on the fixed effects.

A first concern for the credibility of this assumption is that weather anomalies driving asylum demands are spatially correlated. In the individual-level analysis, this concern would arise if, relative to other birth cohorts in the same country, or relative to individuals in the same birth cohorts in other destination countries, cohorts more exposed to asylum applications because of weather fluctuations had also experienced local weather shocks that influenced their preferences. For this reason, all specifications always include both linear and quadratic terms of temperature and precipitation in the destination country. Weather changes are an important factor explaining people's awareness of climate change, although previous studies show that only local weather conditions and direct personal experience of climate-related events matter for individual beliefs about climate change (Bergquist and Warshaw, 2019; Lujala et al., 2015; Lee et al., 2018; Hoffmann et al., 2022; Deryugina, 2013; Hazlett and Mildenberger, 2020; Lee et al., 2015b).

A second concern for the validity of the instrument is that individual climate preferences lie on differential trends as a function of baseline bilateral networks, which may make certain destination countries more likely to change their environmental values due to weather fluctuations in more *salient* origin countries. To allay this concern, I use gradual climatic conditions in the gravity equation and not natural disaster measures such as droughts or floods that may affect the outcome of interest through other channels than the inflows of asylum seekers in the country. The gravity equation also includes time-varying destination-country fixed effects, which absorb the long-run effects of climate on the destination country through colonization history, disease environment, geographical accessibility, as well as the country's institutions.

I also conduct an empirical test by constructing a measure of country-level exposure to temperature and precipitation fluctuations via past migration links. For this, I assume that destination countries that in the past received a higher share of asylum applications from certain origin countries are more likely to receive migrants from these origins when weather fluctuations occur there. I exploit the network channel, according to which migrants tend to choose destinations previously chosen by migrants from their same origin country (Mahajan and Yang, 2020; Card, 2001).

I use the average share of asylum applications from origin country o to destination country d over the average number of asylum applications in destination d in the 2000-2005 baseline period to construct a destination-year level weighted measure of exposure to weather shocks in origin countries via migration links. I then regress the individual-level outcomes on this shift-share measure of exposure to weather fluctuations in origin countries. A statistically significant effect would undermine the validity of the instrumental variable approach by indicating that individuals change their environmental preferences as a function of weather fluctuations in origin countries via the baseline propensity to receive asylum seekers from such countries instead of annual fluctuations in weather-induced migration flows. Figure D10 allays such concern finding a null effect of indirect exposure to weather fluctuations. In additional robustness checks, I also include such measures as a control in the baseline specification (Table D8).

A third concern is posed by weather shocks in origins that could increase higher salience of climate change in media and affect environmental attitudes. To account for this channel, I gather data from Google searches (see Data Appendix Section D.2.3) and use them to test for the correlation between Google searches about climate and migration and the actual asylum demands and include these as additional controls in the baseline estimating equation (see Section 4.4.2 for further details).

A fourth and final concern is that even if one could observe the reason for the asylum application, climate change and weather-related reasons do not apply to the refugee criteria of the 1951 Convention (UN, 1951). People may have a valid claim for refugee status for reasons indirectly affected by climate change (e.g., through disputes, armed conflict, and violence), but would not list climate as a direct cause of asylum application. For this reason, despite being widely used, the term “climate refugee” is not endorsed by institutional bodies, that deem more accurate the use of “persons displaced in the context of disasters and climate change” (UNHCR, 2021). I ascertain that spikes in additional demands induced by weather anomalies are valid for asylum and are thus not due to economic reasons (Missirian and Schlenker, 2017b). I examine the relationship between the number of accepted applications per year and the application anomalies driven by weather fluctuations and find that weather-induced spikes lead to higher acceptance rates, providing suggestive evidence that application anomalies induced by weather fluctuations classify as valid demands for asylum and are thus recognized as refugees by host countries (see Appendix Section D.4.4 for additional details).

Zero stage - Gravity results

Table D4 displays the estimates of the coefficients in the gravity model in Equation (4.2) using the sample of non-OECD countries as the origin and the sample of EU27 + UK as destination countries. I report the estimates using three different

measures of temperature and precipitation: unweighted average annual weather (column 1), weather weighted by maize area during the maize growing season (column 2), weather weighted by the population during the maize growing season (column 3).

To understand the response of international migration to weather variations, I also consider a model without interaction terms with bilateral controls (Tabular results in Table D5). Figure D6 shows a robust asymmetric U-shaped relationship between temperature in the origin and asylum applications, with effects compared to a day at 20°C. The effect is strongly positive and statistically significant only for an additional day hotter than 25°C compared to a 20°C day. Conversely, total precipitation is not an important predictor for migration, consistent with previous findings (Cai et al., 2016). I also include up to three lags of the weather variables to account for delayed increases in asylum demands as a result of past weather fluctuations or forward migration displacement. The contemporaneous effect of temperature persists with the inclusion of up to three lags and asylum demands show a similar response function to past temperature fluctuations (Table D6). Similar estimates are also obtained when including weather conditions in the destination country as a pull factor (Table D7). Appendix Section D.4.1 discusses the results of the specification that controls for the multilateral weather parametrically.

I also explore a non-parametric version of the effect of weather using binned daily average temperatures over the maize growing season. Figures D7 and D8 report the coefficients associated with the 5°C and 3°C bins across the temperature distribution interval. In particular, the positive effect of days with temperatures above 30°C on asylum demands is robust to such alternative specifications. Results are similar when replicating the analysis using monthly averages of temperature and precipitation from CRU weather data (Figure D9).

Figure D11 displays the conditional correlation between the aggregated inflows of asylum seekers in EU destination countries and the predicted weather-induced portion of inflows obtained in the four alternative instruments that, respectively, use origin weather and bilateral characteristics; include the parametric multilateral resistance; include origin and destination weather; obtain destination-specific effects of origin weather.

I visually inspect the variation underlying the instrument by plotting its average annual change in Figure D12. The largest asylum demands induced by weather fluctuations come from Sub-Saharan Africa, the Middle East, and partly Latin America. At the same time, there is substantial variation within the same region, and the instrument predicts lower levels for a number of countries in Central America and South-East Asia. In the presence of heterogeneous treatment effects, the 2SLS estimates identify the impact of asylum demands in destination countries coming from source countries due to exogenous changes in weather, therefore estimating a local average treatment effect (LATE) on the “compliers” (Imbens and Angrist, 1994) in

host countries.

4.4 Individual environmental preferences

4.4.1 Main results

Table 4.1 displays the main results for the effect of weather-induced asylum applications on individual climate concern as a political priority. I report the OLS estimates of Equation (4.1) in columns (1) and (3), and the 2SLS estimates in columns (2) and (4), respectively for the two main survey outcomes.

The OLS estimates reveal a small and, respectively, negative and positive, but never statistically significant correlation between asylum applications and preferences related to climate. Turning to the 2SLS estimates, the Kleibergen-Paap F-stats confirm the validity of the instrument. In contrast with the OLS estimates, the 2SLS coefficients always indicate that weather-induced asylum applications have a strong, positive, and statistically significant effect on individual concern about climate change as a political priority. Country-by-age linear trends absorb country-specific trends in beliefs and rule out the possibility that country-specific cohort effects drive the results.

The magnitude of the 2SLS coefficients for the effects of asylum applications is substantially larger than that of the OLS ones by an order of magnitude. One potential explanation is that OLS estimates suffer from attenuation bias due to measurement error in asylum applications and do not capture the effect of the weather-driven portion of asylum seekers. As speculated above, another possibility is that the estimation strategy identifies a local average treatment effect (LATE) for countries that experienced larger inflows of asylum seekers as a result of weather fluctuations and whose citizens were more likely to update their preferences for climate change. The effect is modest in size but not negligibly small. According to the coefficient reported in columns (2) and (4), doubling the country's weather-induced asylum applications in the five years before the survey increases the probability of reporting climate change as an important theme for the electoral campaigns of the European Parliament elections by 2.3 percentage points (p.p.) and by 4.3 p.p. the probability of reporting climate change as a political priority for the European Parliament deliberations. In the latter case, such a magnitude is similar to the difference between Cyprus's and Germany's country averages. With respect to the mean, that is a 33% increase in the preference for climate as a priority for EP elections and a 41% increase in the preference for climate as a priority over EP deliberations. To put this into context, comparing the effect to the partial correlation of socio-demographic characteristics, the effect of experiencing a doubling in asylum demands over five years on climate as a priority for EP elections is over seven times larger than the effect of being employed and twice the effect of being left-wing leaning.⁹

⁹Table D32 replicates Table 4.1 reporting coefficients on all individual controls.

TABLE 4.1: Weather-induced asylum applications and individuals' environmental values

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)		CC Pol Priority (<i>Mean: .106</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Asylum Applications)	-0.00147 (0.00384)	0.0226** (0.0106)	0.00746 (0.00651)	0.0431** (0.0207)
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		21.566		26.241
<i>N</i>	106614	106614	130068	130068
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-2 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 3-4 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. Columns (2) and (4) report the 2SLS estimates using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, survey year, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Summary of robustness checks. In Appendix D.3.2, I test for the robustness of the findings. First, I account for the average weather conditions in origin countries weighted by the baseline propensity to receive migrants from those countries and find robust and stronger estimates, suggesting that actual migration flows induced by weather fluctuations increase the salience of climate change, inducing updates in individual concern about the issue (Table D8). Second, I replicate the analysis including additional fixed effects (Table D9). Third, I consider alternative gravity-derived instruments including only using origin weather fluctuations, destination-specific effects of temperature in origin countries and constructed using bilateral geographic controls (Table D10). Fourth, I consider alternative time windows over which exposure to asylum applications is defined (Table D11). Fifth, I use alternative regressors considering only the instrumented contemporaneous asylum demands and the measure of weather-induced asylum anomalies constructed in Appendix Section D.4.4 (Table D12). Sixth, results are virtually unchanged when dropping one country at a time from the estimation sample (Figure D19). Seventh, weather-induced asylum applications do not affect concern on any other topic or theme not related to climate, such as terrorism, Euro as a single currency, food safety, or economic growth (Table

D13, see Table D1 for the exact wording). Eighth, results are unchanged and estimates are more precise if I exclude the origin countries with the largest number of asylum seekers (Afghanistan, Iraq, Russian Federation, Serbia, Syria) (Table D14). Ninth, I consider only respondents interviewed before 2015 to exclude the period of the 2015-2016 migration crisis and contemporaneous record-breaking El Niño and find similar results, although with a weaker first stage (Table D15). Finally, I test for the presence of pre-trends, finding no correlation between past climate concern at the country level and leads in actual and predicted asylum demands (Table D16).

4.4.2 Mechanisms

Heterogeneity. The results presented above show that higher exposure to weather-induced asylum applications increases citizens' concern about climate as a political priority. Nevertheless, these effects can be heterogeneous across individual characteristics. To explore this issue, I perform a sub-sample analysis.

First, individuals differentially interact with asylum seekers depending on their age, and preferences are more malleable after exposure to events during certain periods of life (this hypothesis is further explored in Section 4.4.3). Dividing the estimation sample by age terciles, younger individuals are more strongly affected by exposure to higher weather-induced flows. For instance, the effect on the importance of climate for the European Parliament electoral campaigns is not significant for individuals aged above 60 years and is largest in magnitude for individuals between 18 and 40 years old. Similarly, weather-induced asylum applications have a strong positive and statistically significant effect on the probability of reporting climate change as a priority for European Parliament deliberations only for respondents between 18 and 40 years old and between 41 and 59 years old (Table D33). Sub-sample analysis by gender reveals that the effect is substantially driven by females (Table D34).

Finally, political ideologies and preferences may also play a role in determining how individuals form climate preferences as a response to climate-induced migration flows. Since climate concern is surveyed as a political priority at the supra-national political level, the effect of asylum seekers may vary by attitudes toward EU's legitimacy. I test for heterogeneous effects on the subsamples of individuals who trust, respectively, the national government, the national parliament, the European Parliament, and the European Union. Overall, there is suggestive evidence that the effect of weather-induced asylum applications on climate concern is driven by individuals who have less (respectively, more) trust in national (resp. supra-national) institutions (Figure D16).

Channels. In this sub-section, I further explore different channels that may explain the mechanisms at play behind the estimated effect. There are two main puzzles to solve. First, one may wonder about the extent to which asylum demands are informative about shifts in weather distributions in origin countries and how

individuals in destination countries are aware of climate as the driver of refugees seeking asylum in their country - while migrants are unable to state climate change as a reason to apply for asylum. Although descriptively, using a survey conducted in 2019, Figure D17 provides suggestive evidence of a strong positive correlation between the five-year cumulative asylum demands received in a country and the share of respondents that thinks that climate change is already influencing migration in their country (p-value <0.0001). Combined with leveraging only variation in weather conditions in the origin countries to explain changes in asylum demands, this first piece of descriptive evidence strengthens the link between awareness of the climate-migration nexus and the actual flows of migrants in the country.

Second, one may wonder about the reasons behind the changes in individual attitudes toward climate change as a function of weather-induced asylum applications. One major threat to the validity of the instrumental variable approach concerns changes in public attention to the climate-migration nexus. To account for this channel, I use data from Google searches. I leverage these data in two ways. First, I run a horse race between instrumented weather-induced asylum demands and average Google searches for “climate change”, “climate protests”, “migration”, and “refugee” in each country in the baseline specification to ascertain that the instrumental variable approach captures the media channel. The estimates are comparable and slightly larger in magnitude than the baseline estimates in the case of climate change as a political priority (Table D35). Second, I test for correlation between actual and predicted flows and the Google Trends measures. I find a small positive but imprecisely estimated partial correlation between asylum demands and “climate change” searches and a negative correlation with all other searches, significant only in the case of “climate protests” (Table D36). Although I cannot fully rule out that non-migration forces might have independent effects, this analysis provides support for the hypothesis that weather-induced asylum demands are a central driver of climate concern as a political priority and public attention through Google searches cannot explain the findings. To further allay concerns on media coverage mostly explaining the results, I split the sample between EU destination countries above and below the median number of asylum demands received in the time interval and document a positive and significant effect only among countries that receive a larger number of asylum demands, with estimates for countries below the median small and imprecisely estimated (Table D37).

There are two main alternative underlying psychological mechanisms that can explain the effect. On the one hand, weather-induced asylum applications may increase the salience of the drivers of migration flows and reduce the psychological distance to climatic changes (McDonald et al., 2015). Psychological distance refers to the belief that climate change hits geographically distant areas and affects other social groups (Spence et al., 2012). Through this channel, the effect could then be explained by an increase in underlying concern about climate change as a global

problem. On the other hand, individuals in destination countries may see such migration flows as tangible consequences of inaction in climate mitigation efforts and thus update their beliefs about the importance of climate as a political priority in response to increases in asylum demands. In this case, the effect may be explained by changes in attitudes toward migration and by changes in preferences only by specific subsets of the population.

To test for the first hypothesis, I consider two other survey outcomes related to climate change and more specifically to the perception of climate change as a global problem (see Table D1 for the exact wording of the survey questions). Estimating the baseline specification on these survey outcomes, I find a small effect not distinguishable from zero of weather-induced asylum demands, providing suggestive evidence of the absence of such a mechanism (Table D38). I test the second alternative hypothesis in two ways. First, I examine the effect of weather-induced asylum applications on the individual concern about migration as a political priority, in a symmetric manner to the questions asked on climate change (see Table D1 for the exact wording). I find a small and significant effect only on the question of migration as a priority for EP deliberations, suggesting that asylum demands, if anything, also increase the salience of migration (Table D39). Individuals update their concern about climate change as a response to higher costs induced by receiving additional asylum demands, which increase incentives to fight climate change, in line with the hypothesis of climate-induced migration in a “threat” frame (Baldwin, 2013). A final piece of evidence in support of this hypothesis comes in a sub-sample analysis by individual political orientation and education. In contrast with previous findings (Duijndam and van Beukering, 2021; Lee et al., 2015b), the effect is positive and statistically significant for both survey outcomes only among right-wing individuals (Table D40) and individuals without tertiary education (Table D41). Combined with previous heterogeneity findings, these results reveal new dynamics on diverse coalition compositions around climate concern (Bush and Clayton, 2023; Gaikwad et al., 2022).

4.4.3 Exposure during the formative age

Climate change is a particularly important concern for children and young people (Thompson, 2021; Nature, 2021). Recent school strikes and student-led demonstrations illustrate this phenomenon (Ojala, 2012; Bowman, 2020; Kenis, 2021). Building on the heterogeneous effect of weather-induced asylum applications by age documented in the previous section, I further investigate whether the effect is stronger for individuals exposed to such flows during their formative age.

A large strand of the literature in social psychology posits the *impressionable years hypothesis*, according to which core attitudes, beliefs, and values are formed mostly during a period of great mental plasticity in late adolescence and early adulthood, defined as the formative age, between 16 and 24 years of age, and past this

critical age, they change slowly (Krosnick and Alwin, 1989; Cutler, 1974; Sears, 1975; Greenstein, 1965).

This hypothesis has already been tested on early life experiences of economic recessions and preferences for redistribution (Carreri and Teso, 2023), job preferences (Cotofan et al., 2023) and attitudes towards migration (Cotofan et al., 2021), exposure to trade with democracies and attitudes towards democracy (Magistretti and Tabellini, 2023), exposure to disasters and support for environmental public action (Falco and Corbi, 2023), exposure to the 1968 movement and political preferences (Barone et al., 2022) and epidemic exposure and confidence in political institutions (Aksoy et al., 2020).

For individuals belonging to birth cohort b in country d , I define exposure to asylum applications as:

$$exposure_{bd} = \sum_{s=0}^8 (AsyApp)_{d,b+16+s}$$

where $AsyApp$ is country d 's asylum applications received during the impressionable years (from the age of 16 to the age of 24).¹⁰ Figure D14 shows the average exposure to observed and predicted asylum flows by country-cohort during the formative age, while Figure D15 shows the density distribution of asylum seeker flows exposure during the formative age. Such an approach allows me to construct exposure to asylum applications for the entire 2000-2019 period of available data since respondents interviewed in the same year and in the same country can have a different exposure history due to variation in their birth cohort.¹¹ The estimated specification is

$$Y_i = \beta_1 \log(exposure_{bdt}) + X_i' \gamma + Z'_{bdt} \delta + \mu_d + \zeta_{rt} + \kappa_{t-b} + \xi_b + \theta_d \times age + \varepsilon_{ibdt} \quad (4.3)$$

where Y_i is the same vector of outcomes as in Section 4.3.1. The main explanatory variable is $exposure_{bdt}$, in logs to allow for concavity in the response. I also control for a set of individual covariates X_i' , capturing individual socio-economic characteristics (gender, education, political orientation and employment status). Z'_{bdt} accounts for objective local weather conditions (average temperature and precipitation over the period of exposure). I include a wide set of fixed effects (country, region-by-year, age, birth-cohort, country-age linear trends) so that β_1 is estimated from changes across birth cohorts within a country, as compared to changes across the same age groups in other countries, in a given year of interview. Standard errors are clustered at the country level.

¹⁰For the subset of individuals who are too young, I use all available years over the 9-year formative age window.

¹¹Since the data availability for asylum seeker flows in Europe starts from 2000, I limit myself to the birth cohorts whose impressionable years are in the 21st century (i.e., individuals born after 1984 and whose year of age 16 is after 2000).

Results in Table 4.2 show the OLS and 2SLS estimates of Equation (4.3). The 2SLS estimates indicate that being exposed to more weather-induced asylum applications over the impressionable years has a positive and statistically significant effect on the probability of reporting climate change as a priority for the electoral campaign in the European Parliament elections (column 2) and a priority that the European Parliament should deliberate about (column 4).

TABLE 4.2: Formative age exposure to weather-induced asylum seeker flows and environmental values

Dep. variable	CC EU Election (<i>Mean: 0.079</i>)		CC EU Pol Priority (<i>Mean: 0.099</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Exposure ₁₆₋₂₄)	0.00203 (0.00455)	0.0235** (0.00959)	0.0165** (0.00775)	0.0390** (0.0180)
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Birth-cohort FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		26.020		46.347
<i>N</i>	17554	17554	21661	21661
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed and whose formative age (between 16 and 24 years) occurs in the time period in which asylum applications data are available (i.e., after 2000). The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 3, see Table D1 for exact wording and additional details on the construction of the variable). In columns (2) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). Columns (1) and (3) report the OLS estimates using the (log) of the sum of asylum applications in a given country in the time period in which the individual was between 16 and 24 years old (until the year of the interview if younger than 24 years old). Columns (2) and (4) report the 2SLS estimates where the (log) of exposure to asylum applications is instrumented with the symmetric version constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. Individual controls: Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented. Weather Controls: Exposure to average temperature and precipitation over the same time period in which exposure to asylum applications is measured. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

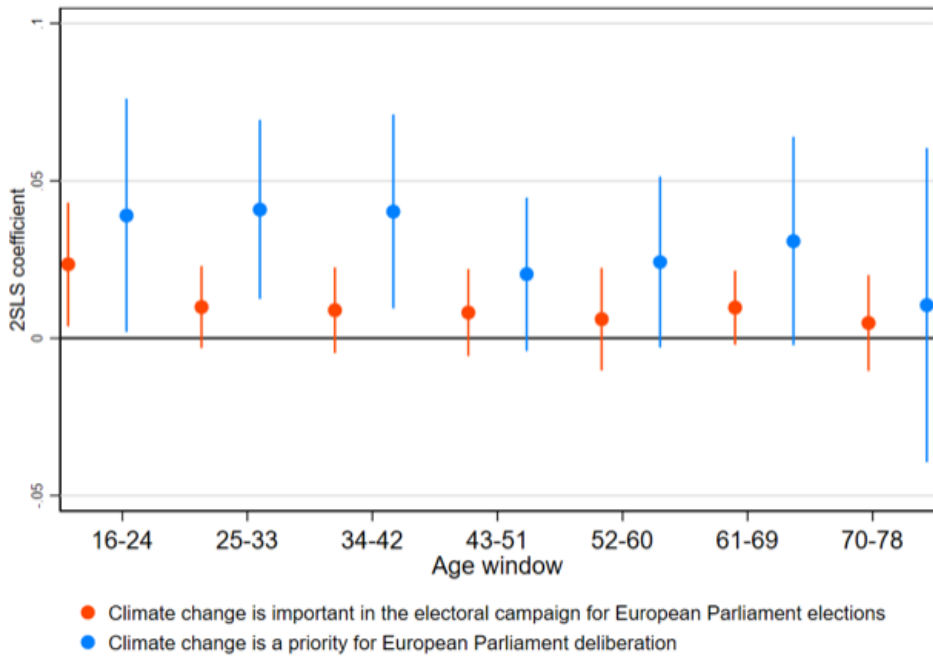
To formalize the intuition that the formation of climate-related political preferences occurs during the formative age, I investigate the effect of weather-induced asylum seekers over different age categories. I decompose the sample of respondents into different age brackets to estimate the heterogeneous age effect.¹² Figure 4.2 presents the 2SLS coefficients associated with exposure in each age window for eight different age categories in which the sample has been split (Tabular results in Table D17). Exposure to weather-induced asylum seeker flows does not appear to be substantially driving climate concern as a political priority in other than the

¹²To define age categories, I first consider the range of the impressionable years assumed before, i.e., from 16 to 24, and then each category is a 9-year age window.

formative age windows, although individuals exposed to higher flows during ages 25-33 and 34-42 are also positively affected only in concern about climate change in EP deliberations.

In terms of magnitude, a 50% increase in exposure during the formative age (approximately equivalent to the interquartile range) increases the probability of reporting climate change as a priority in the electoral campaigns for the European Parliament elections by 15% of the sample mean and of stating climate change as a priority in the political arena by 19% of the sample mean. The latter is similar to the difference between Cyprus and Germany, or that between Hungary and France. Overall, these results seem to provide suggestive evidence that exposure to weather-induced asylum seeker flows during late teenage and early adulthood drives concern about climate change as a political priority debate even later in life. Results are robust to the use of alternative instruments (Table D18) and to alternative definitions of the formative age window (Table D19).

FIGURE 4.2: 2SLS coefficients of weather-induced asylum seeker flows exposure by age window



Notes: The figure plots the 2SLS coefficients estimated regressing the survey response on the total asylum applications experienced during a specific age window of the individual. The point estimates are reported in Table D17. Bins represent the 95% confidence interval.

4.5 From stated to revealed preferences

4.5.1 Green party votes in European Parliament elections

Empirical approach

To what extent do these effects on climate concern translate into political choices? In this section, I move from stated individual climate concern in survey responses to revealed preferences in the form of voting behavior. I focus on Green party votes in European Parliament elections since the use of proportional rules for the allocation of seats in the European Parliament should limit the extent to which voters engage in strategic voting and they should reveal their preferences more than in national elections (Pearson and Rüdig, 2020; Hoffmann et al., 2022). I examine how asylum applications induced by weather variations affect destination country electoral outcomes in the EP elections. I estimate the following specification

$$y_{dt} = \beta_1 \log \left(\sum_{\tau=1}^s \text{AsyApp}_{d,t-\tau} \right) + X'_{dt} \gamma + \alpha_d + \lambda_t + \varepsilon_{dt} \quad (4.4)$$

where y_{dt} is the Green party vote share in European Parliament elections. The main explanatory variable, $\sum_{\tau=1}^s \text{AsyApp}_{d,t-\tau}$, is the sum of all asylum demands in country d during the previous electoral mandate of the European Parliament and it is instrumented with its predicted counterpart that leverages origin weather conditions. The matrix X'_{dt} includes the wide set of country-level covariates. Previous research has shown that Green voters are proportionally younger (Franklin and Rüdig, 1992) and with a higher level of education (Knutsen, 2004). Support for Green parties is also higher among employed people (Knutsen, 2005) and has a strong link with GDP per capita (Pearson and Rüdig, 2020). The equation controls for the population share of 18-23 year-olds, the unemployment rate, the percentage of the population with tertiary education, and the (log) GDP per capita (Moriconi et al., 2019), and electoral turnout to account for the low and declining turnout in European Parliament elections (Van der Eijk and Van Egmond, 2007). I account for second-order polynomials of temperature and precipitation since local weather explains party vote shares (Bassi, 2019; Baccini and Leemann, 2021; Hoffmann et al., 2022), and to allay concerns on the validity of the instrumental variable approach. I also include year- and country-specific fixed effects and regional linear time trends to capture potential unobserved heterogeneity at each of these levels. Standard errors are clustered at the country level.

Main results

Table 4.3 displays the OLS (column 1) and 2SLS estimates (columns 2 to 4) of the effect of asylum demands on Green party vote shares in EP elections. In both cases, the estimates are negative but largely imprecise and not statistically significant at

any conventional level, with the 2SLS estimates quantitatively larger than the OLS ones. Although the sample size is very small ($N=65$), the instrumental variable approach preserves its relevance with the F-stat well above conventional thresholds. To further ascertain the validity of the approach, I check whether the actual or predicted flows of asylum applications induced by weather fluctuations are associated with the Green party vote shares in earlier elections. In both cases, the estimates are very close to zero and imprecisely estimated (Table D20). Overall, the results indicate that Green parties in countries more exposed to weather-induced asylum demands between one electoral round and the following one do not gain in vote share and, instead, their share of votes is lower in response to such flows. Results are robust to the use of alternative instruments (Table D21).

TABLE 4.3: Weather-induced asylum applications and Green party votes in European Parliament elections

Dep. variable	% Green Party in EP elections (<i>Mean: 9.84</i>)			
	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
Log(Asylum Applications)	-0.323 (1.398)	-1.609 (1.711)	-2.392 (1.695)	-4.022 (2.254)
Weather Controls	X	X	X	X
Country Controls	X		X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Regional linear time trends				X
F-Statistic		12.657	23.060	20.882
N	65	65	65	65
Number of countries	20	20	20	20

Notes: The table reports the OLS (columns 1) and 2SLS (columns 2 to 4) coefficients on (log) of total asylum applications in the five years preceding the European Parliament elections. The dependent variable is the share of votes of Green parties in European Parliament elections after 2000 in a EU country. In columns (3) to (6), the (log) of total asylum applications in the five years preceding the elections is instrumented with the gravity-predicted (log) of total asylum applications described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, voter turnout. Weather Controls: Linear and squared average temperature and total precipitation in the country. All columns control for country and year-fixed effects. Column 5 adds region-by-year fixed effects and column 6 accounts for regional linear time trends. F-statistic refers to the Kleibergen-Paap F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Mechanisms

To gain further insight into the findings by which higher exposure to weather-induced asylum applications increases individual climate concern but does not translate into Green party votes in EP elections, I evaluate and test for various possible mechanisms, which are by no means mutually exclusive: anti-immigration party votes, electoral turnout, changes in not-yet-eligible voters' concern and parties' environmental agenda.

Anti-immigration parties. A first potential explanation is that voters do not distinguish between weather-induced asylum seekers and migrants for economic conditions. Electoral preferences may have been shifted towards populist anti-immigrant nationalist parties, as found in national contexts as a result of economic migration, rather than increasing the salience of environmental-related issues. Moreover, Green party votes reflect political support for climate action in a simplified manner and may not capture all relevant aspects of pro-environment voting decisions. Another explanation is that votes may have been directed to other pro-environmental parties than Green parties. Some countries may have more solid Green parties, whereas in other countries longer-term party attachment may prevent climate concern from turning into Green voting. I examine whether any other political groups' electoral outcomes respond to weather-induced asylum demands. The effect is imprecisely estimated for all parties, except for nationalist party votes that are negatively affected by higher exposure to weather-induced asylum demands at the 90% significance level. An opposite positive effect of a similar magnitude, though imprecise, is found in socialist and any other left-wing party votes (Table D22). Overall, the results do not provide evidence in support of this hypothesis.

Turnout dropout. A second hypothesis is that Green party votes decreased as a result of weather-induced asylum applications because traditional voters of the Green parties did not vote in the European Parliament elections. The low participation rate and turnout in the European Parliament elections may explain this finding (Bhatti and Hansen, 2012). To test this mechanism, I check the effect of weather-induced asylum applications on voter turnout in European Parliament elections. The 2SLS estimates of weather-induced asylum applications on electoral turnout are negative and statistically significant (Table D23). Therefore, this mechanism cannot be entirely ruled out, and Green party votes may not have been affected by weather-induced asylum applications, due to an exit, at least partially, of the traditional Green voters from the electoral turnout.

Changes in preferences of young voters. An alternative explanation builds on the heterogeneous effect of exposure to weather-induced asylum application on climate concern by age category. Previous results show that what matters most is exposure during late adolescence and early adulthood. Younger generations are generally more supportive of Green parties (Lichtin et al., 2023). Changes in climate-related preferences in this age category may not be enough to drive overall shifts in voting behavior at the national level. To further investigate this hypothesis, I split the sample of individuals for which the exposure in the formative age can be observed, distinguishing between those below and above the voting age.¹³ Figure D18 shows the results for the two survey outcomes used in Section 4.4 (Tabular

¹³The voting age is a minimum age established by law that a person must attain before they become eligible to vote in a public election. This is set at 18 years for most of the countries in the sample, except for Austria after 2007, Malta after 2018 which set their voting age to 16 years, and Greece after 2017, setting it to 17 years.

results in Table 4.4). Respondents below the voting age are more likely to report climate change as an important theme for the electoral campaign for the European Parliament elections, whereas the effect is not statistically significant for respondents above the voting age. Conversely, exposure has a positive and statistically significant effect on climate change as a priority for European Parliament deliberations only for respondents above the voting age but not for those below. This result may indicate that the increase in concern for climate change and its importance as part of the political agenda in the European Parliament electoral campaigns is driven by individuals not yet eligible to vote and thus explain the gap between states and revealed preferences in voting behavior for Green parties.

TABLE 4.4: Weather-induced asylum applications and environmental values. Heterogeneity by eligibility to vote. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0340** (0.0132)	0.0147 (0.00904)	0.0378 (0.0382)	0.0431** (0.0176)
Voting Age	Below	Above	Below	Above
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	32.155	20.089	48.265	30.174
N	2412	16979	2999	20815

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed and below the age of thirty years old. Odd columns report estimates on the sub-sample of individuals interviewed below the age eligible to vote in national and European elections; even columns report the estimates on the sub-sample of individuals interviewed above the age eligible to vote in the elections. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared average temperature and total precipitation in the country), and country, survey year, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Parties’ environmental agenda. A final mechanism concerns changes on the supply side of the environmental political process defined as the environmental

agenda of political parties (Guiso et al., 2017). For this purpose, I use information on parties' political agenda from the *Manifesto Project Database* (MPD) to measure the degree of environmentalism of each party in national elections and exploit within-party variation in the environmental political agenda across elections (see Appendix Section D.4.6 for additional details). I find that weather-induced asylum applications do not affect the environmental agenda of political parties in national elections across a variety of specifications (Table 4.5). The 2SLS estimates are negative, but small and not statistically significant, while the instrument satisfies the relevance condition.

TABLE 4.5: Weather-induced asylum applications and environmental agenda of parties.

	Party's Environmentalism (Mean=0)			
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
log(Asylum Applications)	-0.0739** (0.0359)	-0.0254 (0.103)	-0.154 (0.112)	-0.158 (0.116)
Weights			Votes	Votes
Votes				Above 5%
Right-left ideological index	X	X	X	X
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Party FE	X	X	X	X
F-Stat		32.570	28.076	27.312
N	641	641	634	469
adj. R^2	0.723	0.082	0.120	0.115

Notes: The analysis is over a sample of parties that are running in multiple elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. The dependent variable is the (normalized) share of quasi-sentences that positively referred to the environment in each party's manifesto in the national elections. Column (1) reports the OLS estimates, and columns (2) to (4) display the 2SLS estimates where (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Columns (3) and (4) weigh each party's observation by the vote gained in the national elections. Column (4) only considers parties that gained at least 5% of the votes. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the baseline specification, each party running in multiple elections has the same weight. Nevertheless, small parties do not have the same influence on the

political system as large parties, and may change their positions more easily. When I weigh each party by the percentage of votes gained in the elections, I find no significant effect. Results are also robust to considering parties that gained at least 5% of votes, to rule out entry/exit or mergers and splits of small parties and potential measurement error in their agendas. Similar results are found using alternative instruments (Table D26), while I find a larger and significant negative effect on party environmentalism when only including larger parties that gained at least 10, 15, or 20% of votes in the elections (Table D27). I also examine the presence of heterogeneous effects by party family masked in the average treatment effect but find small and largely imprecise estimates across the seven party families (Table D28). These findings suggest that weather-induced asylum applications have not shifted parties toward a *greener* environmental agenda and provide one explanation for the rising climate concern in response to climate-induced inflows did not translate into more environmental-related voting behaviors.

Moriconi et al. (2019) show that inflows of less-educated immigrants induce European parties to endorse platforms less favorable to social welfare. To investigate whether asylum demands drive similar mechanisms, I consider alternative dimensions of the manifesto of parties, including attitudes towards refugees, Europe, and multiculturalism (see Table D3 for the exact definition). I find a negligible negative effect that is not statistically significant across all outcomes (Table D29) in response to higher asylum applications.

Environmentalism in national elections. Building on these findings, in the last test, I construct a measure of *environmentalism* at the election-country level obtained as the average percentage of environmentalism in each party's manifesto weighted by its vote share in a given election, and then transform it into a z-score with a mean of zero and a standard deviation of one (Peri et al., 2020). Once again, the 2SLS estimates on weather-induced asylum demands, although positive, are not statistically significant (Table 4.6). Similar null results are obtained when using alternative instruments (Table D24). I also examine if weather-induced asylum demands explain changes in other dimensions of the political agenda of parties but find small and imprecise estimates (Table D25).

4.6 Conclusions

Understanding the drivers of changes in public climate concern and support for Green parties is essential to identify the mechanisms to promote climate action and induce transformations toward a greener more sustainable society. Several studies examine the role of socio-economic determinants (see Drews and van den Bergh (2016) for a review) and direct experience of extreme events (Hazlett and Mildemberger, 2020; Hoffmann et al., 2022). A growing literature has documented the political effects of economic migration in host countries (Alesina and Tabellini,

TABLE 4.6: Weather-induced asylum applications and environmentalism in national elections

Dep. variable	National Elections Environmentalism Index			
	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
Log(Asylum Applications)	-0.0729 (0.107)	0.215 (0.260)	0.232 (0.343)	0.371 (0.501)
Weather Controls	X	X	X	X
Country Controls	X		X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Regional linear time trends				X
F-Statistic		22.366	16.030	13.664
N	119	119	119	119
Number of countries	27	27	27	27

Notes: The table reports the OLS (column 1) and 2SLS (columns 2 to 4) coefficients on (log) of total asylum applications in the years between one national election round and the other. The dependent variable is the normalized index of environmentalism of national elections where the share of quasi-sentences that positively referred to the environment in each party's manifesto is weighted by its vote share in the national elections. In columns 2 to 4, the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old. Weather Controls: Linear and squared average temperature and total precipitation in the country. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2023). Fluctuations in temperature as a result of climatic changes have increased the outflows of asylum seekers from non-OECD countries into the European Union (Missirian and Schlenker, 2017a), possibly altering the individual concern for climate change and leading to eventual changes in electoral voting behavior.

In this paper, I examine the effect of weather-induced asylum applications on citizens' climate concern and pro-environment voting behavior, exploiting exogenous variation in the annual asylum seeker flows generated by weather fluctuations from non-OECD origin countries to the European Union.

I find that exposure to weather-induced asylum applicants increases public climate concern and individuals who grew up when their country received more weather-induced asylum demands are more concerned about climate at the time of the survey, providing support to the formative age hypothesis. The effect of weather-induced asylum applications on climate concern appears to be driven by right-wing voters and to induce joint concern about climate and migration as political priorities rather than increasing public perception of climate change as a world problem. These findings are not mirrored in voting behavior for Green parties in European Parliament elections, which do not respond to larger inflows of weather-induced asylum seekers. Three main co-existing mechanisms behind the results involve a drop out of traditional Green voters of the electoral turnout, a change in public concern mostly

driven by individuals who are not yet eligible to vote, and a lack of change in the pro-environmental policy manifesto of political parties. These findings suggest that a rise in concern for climate-related issues could contribute to achieving a transformation by catalyzing public support for climate action that, however, has not translated yet into concrete policy proposals by parties.

The results suggest several directions for further research. First, the goal of this paper is to provide first evidence and assess the effects of weather-induced asylum application exposure in an international context, aggregating across countries and different types of interactions and time periods (e.g., periods where asylum demands are more or less salient, periods where temperature fluctuations and weather anomalies are more pronounced). However, several aspects of heterogeneity may deserve closer attention, including country-specific case studies both within Europe and in the United States, the world's largest migration destination country. Changes in attitudes and voting behavior may depend on the conditions under which contact occurs and on the characteristics of both immigrants and natives, including the type of climatic push factor, a specific origin place, and other features. Finally, a narrower geographical focus could help analyze in more detail the relationship between actual climate-migration flows and the salience of the phenomenon using its media coverage. Traditional media channels including articles in national newspapers can increase awareness of the issue and its potential impacts, as well as shape perceptions of migrants and the reasons for their migration, which could in turn influence policy.

Bibliography

- Abdullah, H. M. and Rahman, M. M. (2015). Initiating rain water harvest technology for climate change induced drought resilient agriculture: scopes and challenges in Bangladesh. *Journal of Agriculture and Environment for International Development*, 109(2):189–208.
- Abel, G. J., Brottrager, M., Crespo Cuaresma, J., and Muttarak, R. (2019). Climate, conflict and forced migration. *Global Environmental Change*, 54:239–249.
- Acemoglu, D., Akcigit, U., and Kerr, W. (2016a). Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, 30(1):273–335.
- Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016b). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.
- Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.
- Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics*, 65:103207.
- Adhikary, S. K., Das, S., Saha, G., and Chaki, T. (2013). Groundwater drought assessment for Barind irrigation project in Northwestern Bangladesh. In *MOD-SIM2013, 20th International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 2013*, pages 2917–2923. Modelling and Simulation Society of Australia and New Zealand.
- Ado, A. M., Leshan, J., Savadogo, P., Bo, L., and Shah, A. A. (2019). Farmers’ awareness and perception of climate change impacts: Case study of Aguié district in Niger. *Environment, Development and Sustainability*, 21(6):2963–2977.
- Aftab, A., Ahmed, A., and Scarpa, R. (2021). Farm households’ perception of weather change and flood adaptations in northern Pakistan. *Ecological Economics*, 182:106882.
- Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., and Thorp, S. (2018a). First impressions matter: An experimental investigation of online financial advice. *Management Science*, 64(1):288–307.

- Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., and Thorp, S. (2018b). Learning and confirmation bias: Measuring the impact of first impressions and ambiguous signals. *Wharton Pension Research Council Working Paper*, 15.
- Ahmed, A. U. and Sampath, R. K. (1992). Effects of irrigation-induced technological change in Bangladesh rice production. *American Journal of Agricultural Economics*, 74(1):144–157.
- Aksoy, C. G., Eichengreen, B., and Saka, O. (2020). The political scar of epidemics. NBER Working Paper 27401, National Bureau of Economic Research.
- Akyapi, B., Bellon, M., and Massetti, E. (2022). Estimating macro-fiscal effects of climate shocks from billions of geospatial weather observations. *IMF Working Papers*, 2022(156).
- Al Mamun, M. A., Nihad, S. A. I., Sarkar, M. A. R., Aziz, M. A., Qayum, M. A., Ahmed, R., Rahman, N. M. F., Hossain, M. I., and Kabir, M. S. (2021). Growth and trend analysis of area, production and yield of rice: A scenario of rice security in Bangladesh. *PloS one*, 16(12):e0261128.
- Alamgir, M., Shahid, S., Hazarika, M. K., Nashrullah, S., Harun, S. B., and Shamsudin, S. (2015). Analysis of meteorological drought pattern during different climatic and cropping seasons in Bangladesh. *Journal of the American Water Resources Association*, 51(3):794–806.
- Albert, C., Bustos, P., and Ponticelli, J. (2021). The effects of climate change on labor and capital reallocation. NBER Working Papers 28995, National Bureau of Economic Research.
- Alem, Y. and Colmer, J. (2022). Blame it on the rain: Rainfall variability, consumption smoothing, and subjective well-being in rural Ethiopia. *American Journal of Agricultural Economics*, 104(3):905–920.
- Alesina, A., Harnoss, J., and Rapoport, H. (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth*, 21(2):101–138.
- Alesina, A., Murard, E., and Rapoport, H. (2021). Immigration and preferences for redistribution in Europe. *Journal of Economic Geography*, 21(6):925–954.
- Alesina, A. and Tabellini, M. (2023). The Political Effects of Immigration: Culture or Economics? *Journal of Economic Literature*. *Forthcoming*.
- Almer, C., Laurent-Lucchetti, J., and Oechslin, M. (2017). Water scarcity and rioting: Disaggregated evidence from Sub-Saharan Africa. *Journal of Environmental Economics and Management*, 86:193–209.

- Alsina-Pujols, M. (2023). Warming with borders: climate refugees and carbon pricing. *Mimeo*.
- Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1):170–192.
- Angrist, J. D. and Krueger, A. B. (1999). Empirical strategies in labor economics. In *Handbook of Labor Economics*, volume 3. Elsevier.
- Angrist, J. D. and Pischke, J.-S. (2010). The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of Economic Perspectives*, 24(2):3–30.
- Annan, F. and Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review*, 105(5):262–66.
- Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers’ response to extreme heat. *American Economic Journal: Economic Policy*, 13(1):1–35.
- Arbuckle, J. G., Morton, L. W., and Hobbs, J. (2013a). Farmer beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. *Climatic Change*, 118(3):551–563.
- Arbuckle, J. G., Prokopy, L. S., Haigh, T., Hobbs, J., Knoot, T., Knutson, C., Loy, A., Mase, A. S., McGuire, J., Morton, L. W., Tyndall, J., and Widhalm, M. (2013b). Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. *Climatic Change*, 117(4):943–950.
- Arguez, A., Durre, I., Applequist, S., Vose, R. S., Squires, M. F., Yin, X., Heim, R. R., and Owen, T. W. (2012). NOAA’s 1981–2010 US climate normals: an overview. *Bulletin of the American Meteorological Society*, 93(11):1687–1697.
- Arias, S. B. and Blair, C. W. (2022). Changing tides: Public attitudes on climate migration. *The Journal of Politics*, 84(1):560–567.
- Arrow, K. J. and Debreu, G. (1954). Existence of an equilibrium for a competitive economy. *Econometrica: Journal of the Econometric Society*, pages 265–290.
- Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics*, 9(4):254–280.
- Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4):33–52.

- Auffhammer, M. (2022). Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. *Journal of Environmental Economics and Management*, 114:102669.
- Auffhammer, M., Baylis, P., and Hausman, C. H. (2017). Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the united states. *Proceedings of the National Academy of Sciences*, 114(8):1886–1891.
- Auffhammer, M. and Carleton, T. (2018). Regional crop diversity and weather shocks in India. *Asian Development Review*, 35(2):113–130.
- Auffhammer, M., Hsiang, S., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2):181–198.
- Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.
- Baccini, L. and Leemann, L. (2021). Do natural disasters help the environment? How voters respond and what that means. *Political Science Research and Methods*, 9(3):468–484.
- Backhaus, A., Martinez-Zarzoso, I., and Muris, C. (2015). Do climate variations explain bilateral migration? A gravity model analysis. *IZA Journal of Migration*, 4(1):1–15.
- Bakkensen, L. and Barrage, L. (2018). Climate shocks, cyclones, and economic growth: bridging the micro-macro gap. NBER Working Papers 24893, National Bureau of Economic Research.
- Bakkensen, L. A. and Barrage, L. (2022). Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*, 35(8):3666–3709.
- Bakkensen, L. A., Ding, X., and Ma, L. (2019). Flood risk and salience: New evidence from the Sunshine State. *Southern Economic Journal*, 85(4):1132–1158.
- Baldwin, A. (2013). Racialisation and the figure of the climate-change migrant. *Environment and Planning A*, 45(6):1474–1490.
- Bareille, F. and Chakir, R. (2023). The impact of climate change on agriculture: A repeat-ricardian analysis. *Journal of Environmental Economics and Management*, 119:102822.
- Barone, G., de Blasio, G., and Poy, S. (2022). The legacy of 1968 student protests on political preferences. *Economics Letters*, 210:110198.

- Barone, G., D'Ignazio, A., de Blasio, G., and Naticchioni, P. (2016). Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives' voting behavior. *Journal of Public Economics*, 136:1–13.
- Barrage, L. and Nordhaus, W. D. (2023). Policies, projections, and the social cost of carbon: Results from the DICE-2023 Model. NBER Working Papers 31112, National Bureau of Economic Research.
- Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review*, 105(5):247–251.
- Barrot, J.-N. and Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3):1543–1592.
- Bassi, A. (2019). Weather, risk, and voting: An experimental analysis of the effect of weather on vote choice. *Journal of Experimental Political Science*, 6(1):17–32.
- Battiston, G. (2020). Rescue on Stage: Border Enforcement and Public Attention in the Mediterranean Sea. Marco Fanno Working Papers 292, University of Padova.
- Baylis, P. (2020). Temperature and temperament: Evidence from twitter. *Journal of Public Economics*, 184:104161.
- Beattie, G., Han, Y., and La Nauze, A. (2019). Conservation spillovers: The effect of rooftop solar on climate change beliefs. *Environmental and Resource Economics*, 74(3):1425–1451.
- Behringer, W. (2010). *A cultural history of climate*. Polity.
- Beine, M., Bertoli, S., and Fernández-Huertas Moraga, J. (2016). A practitioners' guide to gravity models of international migration. *The World Economy*, 39(4):496–512.
- Beine, M. and Jeusette, L. (2021). A meta-analysis of the literature on climate change and migration. *Journal of Demographic Economics*, 87(3):293–344.
- Beine, M. and Parsons, C. (2015). Climatic Factors as Determinants of International Migration. *The Scandinavian Journal of Economics*, 117(2):723–767.
- Beine, M. and Parsons, C. R. (2017). Climatic Factors as Determinants of International Migration: Redux. *CESifo Economic Studies*, 63(4):386–402.
- Bell, A. R., Bryan, E., Ringler, C., and Ahmed, A. (2015). Rice productivity in Bangladesh: What are the benefits of irrigation? *Land Use Policy*, 48:1–12.

- Bento, A., Miller, N. S., Mookerjee, M., and Severnini, E. R. (2023). A unifying approach to measuring climate change impacts and adaptation. *Journal of Environmental Economics and Management*, 121:102843.
- Bergquist, P. and Warshaw, C. (2019). Does global warming increase public concern about climate change? *The Journal of Politics*, 81(2):686–691.
- Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2):253–272.
- Bertoli, S., Brücker, H., and Moraga, J. F.-H. (2016). The European crisis and migration to Germany. *Regional Science and Urban Economics*, 60:61–72.
- Bertoli, S. and Moraga, J. F.-H. (2013). Multilateral resistance to migration. *Journal of Development Economics*, 102:79–100.
- Bhandari, H. N. (2001). Impact of shallow tubewell irrigation on crop production in the Terai region of Nepal. *Philippine Agricultural Scientist*, 84(1):102–113.
- Bhatti, Y. and Hansen, K. M. (2012). The effect of generation and age on turnout to the European Parliament—How turnout will continue to decline in the future. *Electoral Studies*, 31(2):262–272.
- Blakeslee, D., Fishman, R., and Srinivasan, V. (2020). Way down in the hole: Adaptation to long-term water loss in rural India. *American Economic Review*, 110(1):200–224.
- Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, 101(1):60–75.
- Bohra-Mishra, P., Oppenheimer, M., Cai, R., Feng, S., and Licker, R. (2017). Climate variability and migration in the Philippines. *Population and Environment*, 38:286–308.
- Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies*, 89(1):181–213.
- Bosetti, V., Cattaneo, C., and Peri, G. (2020). Should they stay or should they go? Climate migrants and local conflicts. *Journal of Economic Geography*, page 33.
- Bowman, B. (2020). "They don't quite understand the importance of what we're doing today": The young people's climate strikes as subaltern activism. *Sustainable Earth*, 3(1):1–13.
- Bozzola, M. (2014). Adaptation to climate change: Farmers' risk preferences and the role of irrigation. *Mimeo*.

- Bright, E. and Coleman, P. (2001). Landscan global 2000 [data set]. *Oak Ridge National Laboratory*. <https://doi.org/10.48690/1524196>.
- Brunner, B. and Kuhn, A. (2018). Immigration, cultural distance and natives' attitudes towards immigrants: Evidence from Swiss voting results. *Kyklos*, 71(1):28–58.
- Brüssow, K., Gornott, C., Faße, A., and Grote, U. (2019). The link between smallholders' perception of climatic changes and adaptation in Tanzania. *Climatic Change*, 157(3-4):545–563.
- Bryan, E., Bell, A. R., Ringler, C., and Ahmed, A. U. (2018). Increasing crop production benefits to small producers in Bangladesh. *Asian Journal of Agriculture and Development*, 15(1362-2018-3538):1–21.
- Bun, M. J. and Harrison, T. D. (2019). OLS and IV estimation of regression models including endogenous interaction terms. *Econometric Reviews*, 38(7):814–827.
- Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2014). The unequal effects of weather and climate change: Evidence from mortality in India. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript*.
- Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.
- Burke, M., Hsiang, S., and Miguel, E. (2015a). Climate and conflict. *Annual Review of Economics*, 7:577–617.
- Burke, M., Hsiang, S., and Miguel, E. (2015b). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.
- Burke, M. and Tanutama, V. (2019). Climatic constraints on aggregate economic output. NBER Working Papers 25779, National Bureau of Economic Research.
- Bush, S. S. and Clayton, A. (2023). Facing change: Gender and climate change attitudes worldwide. *American Political Science Review*, 117(2):591–608.
- Byravan, S. and Rajan, S. C. (2017). Taking lessons from refugees in Europe to prepare for climate migrants and exiles. *Environmental Justice*, 10(4):108–111.
- Cachon, G. P., Gallino, S., and Olivares, M. (2012). Severe weather and automobile assembly productivity. *Columbia Business School Research Paper*, (12/37).
- Cai, R., Feng, S., Oppenheimer, M., and Pytlikova, M. (2016). Climate variability and international migration: The importance of the agricultural linkage. *Journal of Environmental Economics and Management*, 79:135–151.

- Calderon, A., Fouka, V., and Tabellini, M. (2023). Racial diversity and racial policy preferences: The great migration and civil rights. *Review of Economic Studies*, 90(1):165–200.
- Camerer, C. F. and Loewenstein, G. (2011). Behavioral Economics: Past, Present, Future. In Camerer, C. F., Loewenstein, G., and Rabin, M., editors, *Advances in Behavioral Economics*, pages 3–52. Princeton University Press.
- Cameron, T. A. (2005). Updating subjective risks in the presence of conflicting information: an application to climate change. *Journal of Risk and Uncertainty*, 30(1):63–97.
- Campenhout, B. V. (2021). The role of information in agricultural technology adoption: Experimental evidence from rice farmers in Uganda. *Economic Development and Cultural Change*, 69(3):1239–1272.
- Campo, F., Giunti, S., and Mendola, M. (2021). The refugee crisis and right-wing populism: Evidence from the Italian dispersal policy. IZA Discussion Paper 14084, IZA.
- Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.
- Carleton, T. (2017). Crop-damaging temperatures increase suicide rates in India. *Proceedings of the National Academy of Sciences*, 114(33):8746–8751.
- Carleton, T. and Hsiang, S. (2016). Social and economic impacts of climate. *Science*, 353(6304).
- Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, 137(4):2037–2105.
- Carlsson, F., Kataria, M., Krupnick, A., Lampi, E., Löfgren, Å., Qin, P., Sterner, T., and Yang, X. (2021). The climate decade: Changing attitudes on three continents. *Journal of Environmental Economics and Management*, 107:102426.
- Carlton, J. S., Mase, A. S., Knutson, C. L., Lemos, M. C., Haigh, T., Todey, D. P., and Prokopy, L. S. (2016). The effects of extreme drought on climate change beliefs, risk perceptions, and adaptation attitudes. *Climatic Change*, 135(2):211–226.
- Carreri, M. and Teso, E. (2023). Economic recessions and congressional preferences for redistribution. *The Review of Economics and Statistics*, 105(3):723–732.

- Carroll, N., Frijters, P., and Shields, M. A. (2009). Quantifying the costs of drought: New evidence from life satisfaction data. *Journal of Population Economics*, 22(2):445–461.
- Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the Great East Japan earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321.
- Carvalho, V. M. and Tahbaz-Salehi, A. (2019). Production networks: A primer. *Annual Review of Economics*, 11:635–663.
- Caselli, F., Koren, M., Lisicky, M., and Tenreyro, S. (2020). Diversification through trade. *The Quarterly Journal of Economics*, 135(1):449–502.
- Casey, G., Fried, S., and Gibson, M. (2021). Understanding climate damages: Consumption versus investment. CESifo Working Paper 9499, CESifo.
- Cattaneo, C. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122:127–146.
- Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.
- Chakravorty, U., Dar, M. H., and Emerick, K. (2023). Inefficient water pricing and incentives for conservation. *American Economic Journal: Applied Economics*, 15(1):319–50.
- Chen, J. J., Mueller, V., Jia, Y., and Tseng, S. K.-H. (2017). Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, 107(5):441–45.
- Chen, S. and Gong, B. (2021). Response and adaptation of agriculture to climate change: Evidence from China. *Journal of Development Economics*, 148:102557.
- Choi, B. C. and Pak, A. W. (2005). A catalog of biases in questionnaires. *Preventing Chronic Disease*, 2(1).
- Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *Review of Financial Studies*, 33(3):1112–1145.
- Chowdhury, N. T. (2013). Marginal product of irrigation expenses in Bangladesh. *Water Resources and Economics*, 4:38–51.
- Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking*, 51(2-3):313–368.

- Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from India. *American Economic Journal: Applied Economics*, 13(4):101–124.
- Coniglio, N. D. and Pesce, G. (2015). Climate variability and international migration: an empirical analysis. *Environment and Development Economics*, 20(4):434–468.
- Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.
- Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.
- Copernicus Climate Change Service, C. D. S. (2023). ERA5 hourly data on single levels from 1940 to present.
- Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.
- Cotofan, M., Cassar, L., Dur, R., and Meier, S. (2023). Macroeconomic conditions when young shape job preferences for life. *The Review of Economics and Statistics*, 105(2):467–473.
- Cotofan, M., Dur, R., and Meier, S. (2021). Does growing up in a recession increase compassion? The case of attitudes towards immigration. Centre for Economic Performance DP 1757, Centre for Economic Performance, LSE.
- Cravino, J. and Levchenko, A. A. (2017). Multinational firms and international business cycle transmission. *The Quarterly Journal of Economics*, 132(2):921–962.
- Cruz, J.-L. and Rossi-Hansberg, E. (2023). The Economic Geography of Global Warming. *The Review of Economic Studies*.
- Cunado, J. and Ferreira, S. (2014). The macroeconomic impacts of natural disasters: The case of floods. *Land Economics*, 90(1):149–168.
- Cutler, N. E. (1974). Aging and generations in politics: The conflict of explanations and inference. *Public Opinion and Political Attitudes*, pages 440–462.
- Czarnek, G., Kossowska, M., and Szwed, P. (2021). Right-wing ideology reduces the effects of education on climate change beliefs in more developed countries. *Nature Climate Change*, 11(1):9–13.
- Dahlberg, M., Edmark, K., and Lundqvist, H. (2012). Ethnic diversity and preferences for redistribution. *Journal of Political Economy*, 120(1):41–76.

- Daily Sun (2021). Govt sets prices to procure Aman paddy, rice. Daily-Sun.com [Online; posted 1-November-2021; Accessed on 18-March-2022].
- Damania, R., Desbureaux, S., and Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102:102335.
- Das, S., Magistretti, G., Pugacheva, E., and Wingender, P. (2022). Sectoral spillovers across space and time. *Journal of Macroeconomics*, 72:103422.
- Debela, N., Mohammed, C., Bridle, K., Corkrey, R., and McNeil, D. (2015). Perception of climate change and its impact by smallholders in pastoral/agropastoral systems of Borana, South Ethiopia. *SpringerPlus*, 4(1):236.
- Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., and Stantcheva, S. (2022). Fighting climate change: International attitudes toward climate policies. NBER Working Paper 30265, National Bureau of Economic Research.
- Delaporte, I. and Maurel, M. (2018). Adaptation to climate change in Bangladesh. *Climate Policy*, 18(1):49–62.
- Delavande, A. (2014). Probabilistic expectations in developing countries. *Annual Review of Economics*, 6(1):1–20.
- Delavande, A., Giné, X., and McKenzie, D. (2011). Measuring subjective expectations in developing countries: A critical review and new evidence. *Journal of Development Economics*, 94(2):151–163.
- Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.
- Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.
- Deressa, T. T., Hassan, R. M., and Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, 149(1):23–31.
- Deryugina, T. (2013). How do people update? The effects of local weather fluctuations on beliefs about global warming. *Climatic Change*, 118(2):397–416.
- Deryugina, T. and Hsiang, S. (2017). The marginal product of climate. NBER Working Paper 24072, National Bureau of Economic Research.

- Deryugina, T. and Shurchkov, O. (2016). The effect of information provision on public consensus about climate change. *PloS one*, 11(4):e0151469.
- Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1):354–385.
- Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4):152–85.
- Deschênes, O. and Meng, K. (2018). Quasi-experimental methods in environmental economics: Opportunities and challenges. In Dasgupta, P., Pattanayak, S. K., and Smith, K., editors, *Handbook of Environmental Economics*, volume 4, pages 285–332. Elsevier.
- Desmet, K. and Rossi-Hansberg, E. (2015). On the spatial economic impact of global warming. *Journal of Urban Economics*, 88:16–37.
- di Giovanni, J. and Levchenko, A. A. (2009). Trade openness and volatility. *The Review of Economics and Statistics*, 91(3):558–585.
- Dietz, S., van der Ploeg, F., Rezai, A., and Venmans, F. (2021). Are economists getting climate dynamics right and does it matter? *Journal of the Association of Environmental and Resource Economists*, 8(5):895–921.
- Dingel, J., Meng, K., and Hsiang, S. (2021). Spatial correlation, trade, and inequality: Evidence from the global climate. NBER Working Papers 25447, National Bureau of Economic Research.
- Docquier, F., Lodigiani, E., Rapoport, H., and Schiff, M. (2016). Emigration and democracy. *Journal of Development Economics*, 120:209–223.
- Doorenbos, J. and Kassam, A. (1979). Yield response to water. *FAO Irrigation and drainage paper*, 33:257.
- Douenne, T. and Fabre, A. (2020). French attitudes on climate change, carbon taxation and other climate policies. *Ecological Economics*, 169:106496.
- Douenne, T. and Fabre, A. (2022). Yellow vests, pessimistic beliefs, and carbon tax aversion. *American Economic Journal: Economic Policy*, 14(1):81–110.
- Drews, S. and van den Bergh, J. C. (2016). What explains public support for climate policies? A review of empirical and experimental studies. *Climate Policy*, 16(7):855–876.

- Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4):549–560.
- Druckman, J. N. and McGrath, M. C. (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change*, 9(2):111–119.
- Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2):601–646.
- Duijndam, S. and van Beukering, P. (2021). Understanding public concern about climate change in Europe, 2008–2017: The influence of economic factors and right-wing populism. *Climate Policy*, 21(3):353–367.
- Eckstein, D., Künzel, V., and Schäfer, L. (2021). *Global Climate Risk Index 2021: Who Suffers Most From Extreme Weather Events? Weather-Related Loss Events in 2019 and 2000-2019*. Germanwatch Nord-Süd Initiative eV.
- Edo, A., Giesing, Y., Öztunc, J., and Poutvaara, P. (2019). Immigration and electoral support for the far-left and the far-right. *European Economic Review*, 115:99–143.
- Elum, Z. A., Modise, D. M., and Marr, A. (2017). Farmer’s perception of climate change and responsive strategies in three selected provinces of South Africa. *Climate Risk Management*, 16:246–257.
- EM-DAT (2022). The Emergency Events Database - Université Catholique de Louvain (UCL) - CRED. CRED, D. Guha-Sapir, Brussels, Belgium.
- Fabel, M., Flückiger, M., Ludwig, M., Rainer, H., Waldinger, M., and Wichert, S. (2022). The power of youth: Did the "Fridays for Future" climate movement trickle-up to influence, voters, politicians, and the media? CESifo Working Paper 9742, CESifo.
- Faia, E., Fuster, A., Pezone, V., and Zafar, B. (2021). Biases in information selection and processing: Survey evidence from the pandemic. NBER Working Paper 28484, National Bureau of Economic Research.
- Falco, C. and Corbi, R. (2023). Natural disasters and preferences for the environment: Evidence from the impressionable years. *Economics Letters*, 222:110946.
- Falco, C., Galeotti, M., and Olper, A. (2019). Climate change and migration: is agriculture the main channel? *Global Environmental Change*, 59:101995.
- Falco, S. D., Adinolfi, F., Bozzola, M., and Capitanio, F. (2014). Crop insurance as a strategy for adapting to climate change. *Journal of Agricultural Economics*, 65(2):485–504.

- Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, 97(1):76–85.
- Fankhauser, S. and Tol, R. S. (2005). On climate change and economic growth. *Resource and Energy Economics*, 27(1):1–17.
- FAO (2014). AQUASTAT Country Profile – Bangladesh. *Food and Agriculture Organization of the United Nations (FAO)*.
- Fasani, F., Frattini, T., and Minale, L. (2021). Lift the ban? Initial employment restrictions and refugee labour market outcomes. *Journal of the European Economic Association*, 19(5):2803–2854.
- Feddersen, J., Metcalfe, R., and Wooden, M. (2016). Subjective wellbeing: why weather matters. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 179(1):203–228.
- Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2):255–298.
- Feenstra, R. C. (2015). *Advanced international trade: Theory and evidence*. Princeton University Press.
- Felbermayr, G. and Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics*, 111:92–106.
- Felbermayr, G., Hiller, S., and Sala, D. (2010). Does immigration boost per capita income? *Economics Letters*, 107(2):177–179.
- Feng, A. and Li, H. (2021). We are all in the same boat: Cross-border spillovers of climate risk through international trade and supply chain. *IMF Working Papers*, 2021(13).
- Feng, S., Oppenheimer, M., and Schlenker, W. (2012). Climate change, crop yields, and internal migration in the United States. NBER Working Paper 17734, National Bureau of Economic Research.
- Fetzer, T. (2020). Can workfare programs moderate conflict? Evidence from India. *Journal of the European Economic Association*, 18(6):3337–3375.
- Feyrer, J. (2009). Distance, trade, and income—the 1967 to 1975 closing of the Suez canal as a natural experiment. NBER Working Paper 15557, National Bureau of Economic Research.
- Feyrer, J. (2019). Trade and income — exploiting time series in geography. *American Economic Journal: Applied Economics*, 11(4):1–35.

- Fishman, R. (2018). Groundwater depletion limits the scope for adaptation to increased rainfall variability in India. *Climatic Change*, 147:195–209.
- Fishman, R., Carrillo, P., and Russ, J. (2019). Long-term impacts of exposure to high temperatures on human capital and economic productivity. *Journal of Environmental Economics and Management*, 93:221–238.
- Foged, M., Hasager, L., and Peri, G. (2022). Comparing the effects of policies for the labor market integration of refugees. NBER Working Paper 30534, National Bureau of Economic Research.
- Forgas, J. P., Goldenberg, L., and Unkelbach, C. (2009). Can bad weather improve your memory? an unobtrusive field study of natural mood effects on real-life memory. *Journal of Experimental Social Psychology*, 45(1):254–257.
- Fosu-Mensah, B. Y., Vlek, P. L., and MacCarthy, D. S. (2012). Farmers’ perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. *Environment, Development and Sustainability*, 14(4):495–505.
- Frankel, J. A. and Romer, D. H. (1999). Does trade cause growth? *American Economic Review*, 89(3):379–399.
- Franklin, M. N. and Rüdiger, W. (1992). The green voter in the 1989 European elections. *Environmental Politics*, 1(4):129–159.
- Freedman, D. A. and Peters, S. C. (1984). Bootstrapping a regression equation: Some empirical results. *Journal of the American Statistical Association*, 79(385):97–106.
- Fryer, R. G., Harms, P., and Jackson, M. O. (2019). Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. *Journal of the European Economic Association*, 17(5):1470–1501.
- Gabaix, X. (2019). Behavioral inattention. In *Handbook of Behavioral Economics: Applications and Foundations 2*, volume 2, pages 261–343. Elsevier.
- GADM (2021). GADM database of Global Administrative Areas, version 3.6.
- Gaikwad, N., Genovese, F., and Tingley, D. (2022). Creating climate coalitions: mass preferences for compensating vulnerability in the world’s two largest democracies. *American Political Science Review*, 116(4):1165–1183.
- Gall, M., Borden, K. A., and Cutter, S. L. (2009). When do losses count? Six fallacies of natural hazards loss data. *Bulletin of the American Meteorological Society*, 90(6):799–810.

- Gallagher, J. (2014). Learning about an infrequent event: evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, pages 206–233.
- Gandhi, S., Kahn, M. E., Kochhar, R., Lall, S., and Tandel, V. (2022). Adapting to flood risk: Evidence from a panel of global cities. NBER Working Papers 30137, National Bureau of Economic Research.
- Gars, J. and Ward, P. S. (2019). Can differences in individual learning explain patterns of technology adoption? Evidence on heterogeneous learning patterns and hybrid rice adoption in Bihar, India. *World Development*, 115:178–189.
- Geng, G., Wu, J., Wang, Q., Lei, T., He, B., Li, X., Mo, X., Luo, H., Zhou, H., and Liu, D. (2016). Agricultural drought hazard analysis during 1980–2008: a global perspective. *International Journal of Climatology*, 36(1):389–399.
- Gentzkow, M. and Shapiro, J. M. (2010). What drives media slant? Evidence from US daily newspapers. *Econometrica*, 78(1):35–71.
- Gibson, M. and Mullins, J. T. (2020). Climate risk and beliefs in New York floodplains. *Journal of the Association of Environmental and Resource Economists*, 7(6):1069–1111.
- Giné, X., Townsend, R., and Vickery, J. (2015). Forecasting when it matters: evidence from semi-arid India. *Manuscript, Federal Reserve Bank of New York*.
- Giroud, X. and Mueller, H. M. (2019). Firms’ internal networks and local economic shocks. *American Economic Review*, 109(10):3617–49.
- Goebbert, K., Jenkins-Smith, H. C., Klockow, K., Nowlin, M. C., and Silva, C. L. (2012). Weather, climate, and worldviews: The sources and consequences of public perceptions of changes in local weather patterns. *Weather, Climate, and Society*, 4(2):132–144.
- Graff Zivin, J., Hsiang, S., and Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105.
- Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.
- Gramig, B. M., Barnard, J. M., and Prokopy, L. S. (2013). Farmer beliefs about climate change and carbon sequestration incentives. *Climate Research*, 56(2):157–167.
- Gray, C. L. and Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences*, 109(16):6000–6005.

- Greenstein, F. I. (1965). *Children and politics*. Yale University Press New Haven.
- Groom, B., Koundouri, P., Nauges, C., and Thomas, A. (2008). The story of the moment: risk averse cypriot farmers respond to drought management. *Applied Economics*, 40(3):315–326.
- Guiso, L., Herrera, H., Morelli, M., and Sonno, T. (2017). Demand and supply of populism. IGIER Working Paper Series 610, IGIER.
- Guiteras, R., Jina, A., and Mobarak, A. M. (2015). Satellites, self-reports, and submersion: exposure to floods in Bangladesh. *American Economic Review*, 105(5):232–36.
- Habiba, U., Shaw, R., and Takeuchi, Y. (2011). Socioeconomic impact of droughts in Bangladesh. In *Droughts in Asian monsoon region*. Emerald Group Publishing Limited.
- Halla, M., Wagner, A. F., and Zweimüller, J. (2017). Immigration and voting for the far right. *Journal of the European Economic Association*, 15(6):1341–1385.
- Hansen, J., Sato, M., and Ruedy, R. (2012). Perception of climate change. *Proceedings of the National Academy of Sciences*, 109(37):E2415–E2423.
- Haque, F. (1975). A comparative analysis of small scale irrigation systems in Bangladesh. *The Bangladesh Development Studies*, 3(1):43–52.
- Harari, M. and La Ferrara, E. (2018). Conflict, climate, and cells: A disaggregated analysis. *Review of Economics and Statistics*, 100(4):594–608.
- Harmon, N. A. (2018). Immigration, ethnic diversity, and political outcomes: Evidence from Denmark. *The Scandinavian Journal of Economics*, 120(4):1043–1074.
- Hatton, T. J. (2020). Asylum migration to the developed world: Persecution, incentives, and policy. *Journal of Economic Perspectives*, 34(1):75–93.
- Hazlett, C. and Mildemberger, M. (2020). Wildfire exposure increases pro-environment voting within democratic but not republican areas. *American Political Science Review*, 114(4):1359–1365.
- Head, K. and Mayer, T. (2014). Gravity equations: Workhorse, toolkit, and cookbook. Chapter 3 in the *Handbook of International Economics Vol. 4*, eds. Gita Gopinath, Elhanan Helpman, and Kenneth S. Rogoff. *Elsevier Ltd., Oxford*, 131:195.
- Hedegaard, T. F. (2022). Attitudes to climate migrants: results from a conjoint survey experiment in Denmark. *Scandinavian Political Studies*, 45(1):25–45.

- Heft-Neal, S., Gould, C. F., Childs, M., Kiang, M. V., Nadeau, K., Duggan, M., Bendavid, E., and Burke, M. (2023). Behavior mediates the health effects of extreme wildfire smoke events. NBER Working Papers 30969, National Bureau of Economic Research.
- Helbling, M. (2020). Attitudes towards climate change migrants. *Climatic Change*, 160(1):89–102.
- Henriet, F., Hallegatte, S., and Tabourier, L. (2012). Firm-network characteristics and economic robustness to natural disasters. *Journal of Economic Dynamics and Control*, 36(1):150–167.
- Henseler, M. and Schumacher, I. (2019). The impact of weather on economic growth and its production factors. *Climatic Change*, 154(3):417–433.
- Heutel, G., Miller, N. H., and Molitor, D. (2021). Adaptation and the mortality effects of temperature across us climate regions. *Review of Economics and Statistics*, 103(4):740–753.
- Hix, S. and Marsh, M. (2007). Punishment or protest? Understanding European Parliament elections. *The Journal of Politics*, 69(2):495–510.
- Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, 7(3):281–312.
- Hoffmann, R., Muttarak, R., Peisker, J., and Stanig, P. (2022). Climate change experiences raise environmental concerns and promote Green voting. *Nature Climate Change*, 12(2):148–155.
- Hoffmann, R., Šedová, B., and Vinke, K. (2021). Improving the evidence base: A methodological review of the quantitative climate migration literature. *Global Environmental Change*, 71:102367.
- Holtermann, L. (2020). Precipitation anomalies, economic production, and the role of “first-nature” and “second-nature” geographies: a disaggregated analysis in high-income countries. *Global Environmental Change*, 65:102167.
- Hornbeck, R. (2012). The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review*, 102(4):1477–1507.
- Hornsey, M. J., Harris, E. A., Bain, P. G., and Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature Climate Change*, 6(6):622–626.
- Hossain, M., Naher, F., and Shahabuddin, Q. (2005). Food security and nutrition in Bangladesh: progress and determinants. *eJADE: electronic Journal of Agricultural and Development Economics*, 2(853-2016-56126):103–132.

- Howe, P. D., Boudet, H., Leiserowitz, A., and Maibach, E. W. (2014). Mapping the shadow of experience of extreme weather events. *Climatic Change*, 127(2):381–389.
- Howe, P. D. and Leiserowitz, A. (2013). Who remembers a hot summer or a cold winter? The asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the US. *Global Environmental Change*, 23(6):1488–1500.
- Hsiang, S. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences*, 107(35):15367–15372.
- Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, 8(1):43–75.
- Hsiang, S. and Jina, A. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. NBER Working Papers 20352, National Bureau of Economic Research.
- Hsiang, S., Meng, K. C., and Cane, M. A. (2011). Civil conflicts are associated with the global climate. *Nature*, 476(7361):438–441.
- Hsiang, S. M. and Burke, M. (2014). Climate, conflict, and social stability: what does the evidence say? *Climatic Change*, 123:39–55.
- Hultgren, A., Carleton, T., Delgado, M., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R. E., Malevich, S. B., et al. (2022). Estimating global impacts to agriculture from climate change accounting for adaptation. *Available at SSRN: <https://ssrn.com/abstract=4222020>*.
- Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1):53–74.
- Imbens, G. W. and Angrist, J. D. (1994). Identification and estimation of local average treatment effects. *Econometrica*, 62(2):467–475.
- IMF (2022). World Economic Outlook - Database WEO Groups and Aggregates Information. *World Economic and Financial Surveys*.
- International Food Policy Research Institute (2014a). Bangladesh Climate Change Adaptation Survey (BCCAS), Round I.
- International Food Policy Research Institute (2014b). Bangladesh Climate Change Adaptation Survey (BCCAS), Round II.

- IPCC (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- IPCC (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Irwin, D. A. and Terviö, M. (2002). Does trade raise income? Evidence from the Twentieth century. *Journal of International Economics*, 58(1):1–18.
- Jacoby, H. G. (2017). "Well-fare" economics of groundwater in South Asia. *The World Bank Research Observer*, 32(1):1–20.
- Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers. *The Economic Journal*, 131(633):392–419.
- Ji, X. and Cobourn, K. M. (2021). Weather fluctuations, expectation formation, and short-run behavioral responses to climate change. *Environmental and Resource Economics*, 78(1):77–119.
- Joireman, J., Truelove, H. B., and Duell, B. (2010). Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology*, 30(4):358–367.
- Jones, M., Kondylis, F., Loeser, J., and Magruder, J. (2022). Factor market failures and the adoption of irrigation in Rwanda. *American Economic Review*, 112(7):2316–52.
- Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.
- Kahn, M. E. (2016). The climate change adaptation literature. *Review of Environmental Economics and Policy*, 10(1).
- Kahn, M. E. (2021). *Adapting to climate change*. Yale University Press.
- Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., and Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, 104:105624.
- Kahneman, D. and Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, 80(4):237.

- Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.
- Kahneman, D. and Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press.
- Kala, N. (2017). Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture. *MIT Center for Energy and Environmental Policy Research Working Paper*, 23.
- Kalkuhl, M. and Wenz, L. (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103:102360.
- Kanemoto, K., Lenzen, M., Geschke, A., and Moran, D. (2011). Building Eora: a global multi-region input output model at high country and sector. In *19th International Input-Output Conference*.
- Kashiwagi, Y., Todo, Y., and Matous, P. (2021). Propagation of economic shocks through global supply chains — Evidence from Hurricane Sandy. *Review of International Economics*, 29(5):1186–1220.
- Kaufmann, R. K., Mann, M. L., Gopal, S., Liederman, J. A., Howe, P. D., Pretis, F., Tang, X., and Gilmore, M. (2017). Spatial heterogeneity of climate change as an experiential basis for skepticism. *Proceedings of the National Academy of Sciences*, 114(1):67–71.
- Kelly, D. L., Kolstad, C. D., and Mitchell, G. T. (2005). Adjustment costs from environmental change. *Journal of Environmental Economics and Management*, 50(3):468–495.
- Kenis, A. (2021). Clashing tactics, clashing generations: The politics of the school strikes for climate in Belgium. *Politics and Governance*, 9(2):135–145.
- Keshavarz, M. and Karami, E. (2012). Drought and happiness in rural Iran. *Journal of Soil Science and Environmental Management*, 3(3):66–76.
- Khanal, U., Wilson, C., Hoang, V.-N., and Lee, B. (2018). Farmers’ adaptation to climate change, its determinants and impacts on rice yield in Nepal. *Ecological Economics*, 144:139–147.
- Knutsen, O. (2004). *Social structure and party choice in western Europe: A comparative longitudinal study*. Springer.
- Knutsen, O. (2005). The impact of sector employment on party choice: A comparative study of eight West European countries. *European Journal of Political Research*, 44(4):593–621.

- Kochhar, R. and Song, R. (2023). Does Market Power in Local Agricultural Markets Hinder Farmer Climate Change Adaptation? *Mimeo*.
- Kocornik-Mina, A., McDermott, T. K., Michaels, G., and Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66.
- Kolstad, C. D. and Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, 14(1).
- Konisky, D. M., Hughes, L., and Kaylor, C. H. (2016). Extreme weather events and climate change concern. *Climatic Change*, 134(4):533–547.
- Kotz, M., Levermann, A., and Wenz, L. (2022). The effect of rainfall changes on economic production. *Nature*, 601(7892):223–227.
- Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., and Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change*, 11(4):319–325.
- Koundouri, P., Nauges, C., and Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics*, 88(3):657–670.
- Krosnick, J. A. and Alwin, D. F. (1989). Aging and susceptibility to attitude change. *Journal of Personality and Social Psychology*, 57(3):416.
- Kruskal, J. B. (1960). Well-quasi-ordering, the tree theorem, and Vazsonyi’s conjecture. *Transactions of the American Mathematical Society*, 95(2):210–225.
- Kunreuther, H. and Slovic, P. (1978). Economics, psychology, and protective behavior. *American Economic Review*, 68(2):64–69.
- Kunze, S. (2021). Unraveling the effects of tropical cyclones on economic sectors worldwide: direct and indirect impacts. *Environmental and Resource Economics*, 78(4):545–569.
- Lang, C. (2014). Do weather fluctuations cause people to seek information about climate change? *Climatic Change*, 125(3):291–303.
- Le Dang, H., Li, E., Nuberg, I., and Bruwer, J. (2014). Understanding farmers’ adaptation intention to climate change: A structural equation modelling study in the Mekong Delta, Vietnam. *Environmental Science & Policy*, 41:11–22.
- Lee, G.-E., Loveridge, S., and Winkler, J. A. (2018). The influence of an extreme warm spell on public support for government involvement in climate change adaptation. *Annals of the American Association of Geographers*, 108(3):718–738.

- Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., and Leiserowitz, A. A. (2015a). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, 5(11):1014–1020.
- Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., and Leiserowitz, A. A. (2015b). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, 5(11):1014–1020.
- Lemoine, D. (2021). Estimating the consequences of climate change from variation in weather. NBER Working Paper 25008, National Bureau of Economic Research.
- Lemos, M. C., Eakin, H., Dilling, L., and Worl, J. (2019). Social sciences, weather, and climate change. *Meteorological Monographs*, 59:26–1.
- Lenzen, M., Kanemoto, K., Moran, D., and Geschke, A. (2012). Mapping the structure of the world economy. *Environmental Science & Technology*, 46(15):8374–8381.
- Leontief, W. (1941). *Structure of American economy, 1919-1929*. Harvard University Press.
- Leontief, W. (1970). Environmental repercussions and the economic structure: an input-output approach. *The Review of Economics and Statistics*, 52(3):262–271.
- Letta, M. and Tol, R. S. (2019). Weather, climate and total factor productivity. *Environmental and Resource Economics*, 73(1):283–305.
- Li, Y., Johnson, E. J., and Zaval, L. (2011). Local warming: Daily temperature change influences belief in global warming. *Psychological Science*, 22(4):454–459.
- Lichtin, F., Van Der Brug, W., and Rekker, R. (2023). Generational replacement and Green party support in Western Europe. *Electoral Studies*, 83:102602.
- Linsenmeier, M. (2021). Seasonal temperature variability and economic cycles. Grantham Research Institute on Climate Change and the Environment Working Paper 374, London School of Economics and Political Science.
- Liu, M., Shamdasani, Y., and Taraz, V. (2023). Climate change and labor reallocation: Evidence from six decades of the indian census. *American Economic Journal: Economic Policy*, 15(2):395–423.
- Loayza, N. V., Olaberria, E., Rigolini, J., and Christiaensen, L. (2012). Natural disasters and growth: Going beyond the averages. *World Development*, 40(7):1317–1336.
- Lodge, M. and Taber, C. S. (2013). *The rationalizing voter*. Cambridge University Press.

- Lucas, R. (1977). Understanding business cycles. *Carnegie–Rochester Conference Series on Public Policy*, 5:7–29.
- Lujala, P., Lein, H., and Rød, J. K. (2015). Climate change, natural hazards, and risk perception: The role of proximity and personal experience. *Local Environment*, 20(4):489–509.
- Maddison, D. and Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics*, 70(12):2437–2445.
- Maertens, A. (2017). Who cares what others think (or do)? Social learning and social pressures in cotton farming in India. *American Journal of Agricultural Economics*, 99(4):988–1007.
- Magistretti, G. and Tabellini, M. (2023). Economic integration and the transmission of democracy. NBER Working Paper 30055, National Bureau of Economic Research.
- Mahajan, P. and Yang, D. (2020). Taken by Storm: Hurricanes, Migrant Networks, and US Immigration. *American Economic Journal: Applied Economics*, 12(2):250–277.
- Mainuddin, M., Alam, M. M., Maniruzzaman, M., Kabir, M. J., Mojid, M. A., Hasan, M. M., Schmidt, E. J., and Islam, M. T. (2021). Yield, profitability, and prospects of irrigated Boro rice cultivation in the North-West region of Bangladesh. *PloS one*, 16(4):e0250897.
- Mainuddin, M., Maniruzzaman, M., Alam, M. M., Mojid, M. A., Schmidt, E. J., Islam, M. T., and Scobie, M. (2020). Water usage and productivity of Boro rice at the field level and their impacts on the sustainable groundwater irrigation in the North-West Bangladesh. *Agricultural Water Management*, 240:106294.
- Majumder, M. K. and Rahman, M. (2011). Impact of introducing low lift pump on improving income of farm households in some areas of Bhola district in Bangladesh. *Journal of the Bangladesh Agricultural University*, 9(2):233–240.
- Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1):373–416.
- Mandal, S. and Singh, R. (2004). Shallow tubewells installation and its impact on farm economy of lower gangetic plain in West Bengal. *Agricultural Economics Research Review*, 17(2):261–272.
- Marchiori, L., Maystadt, J.-F., and Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, 63(3):355–374.

- Marris, E. (2019). Why young climate activists have captured the world's attention. *Nature*, 573(7775):471–473.
- Martey, E. and Kuwornu, J. K. (2021). Perceptions of climate variability and soil fertility management choices among smallholder farmers in Northern Ghana. *Ecological Economics*, 180:106870.
- Marx, S. M., Weber, E. U., Orlove, B. S., Leiserowitz, A., Krantz, D. H., Roncoli, C., and Phillips, J. (2007). Communication and mental processes: Experiential and analytic processing of uncertain climate information. *Global Environmental Change*, 17(1):47–58.
- Masseti, E. and Mendelsohn, R. (2018). Measuring climate adaptation: Methods and evidence. *Review of Environmental Economics and Policy*, 12(2).
- Mayda, A. M. (2010). International migration: A panel data analysis of the determinants of bilateral flows. *Journal of Population Economics*, 23(4):1249–1274.
- McCright, A. M., Dunlap, R. E., and Xiao, C. (2014). The impacts of temperature anomalies and political orientation on perceived winter warming. *Nature Climate Change*, 4(12):1077–1081.
- McDonald, R. I., Chai, H. Y., and Newell, B. R. (2015). Personal experience and the "psychological distance" of climate change: An integrative review. *Journal of Environmental Psychology*, 44:109–118.
- McGuirk, E. and Burke, M. (2020). The economic origins of conflict in Africa. *Journal of Political Economy*, 128(10):3940–3997.
- McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 17, pages 179–183. Boston.
- Mellon, J. (2021). Rain, rain, go away: 176 potential exclusion-restriction violations for studies using weather as an instrumental variable.
- Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *American Economic Review*, 84(4):753–771.
- Mendelsohn, R. O. and Massetti, E. (2017). The use of cross-sectional analysis to measure climate impacts on agriculture: Theory and evidence. *Review of Environmental Economics and Policy*, 11(2):1–20.
- Mérel, P. and Gammans, M. (2021). Climate econometrics: Can the panel approach account for long-run adaptation? *American Journal of Agricultural Economics*, 103(4):1207–1238.

- Mertz, O., Halsnæs, K., Olesen, J. E., and Rasmussen, K. (2009a). Adaptation to climate change in developing countries. *Environmental Management*, 43(5):743–752.
- Mertz, O., Mbow, C., Reenberg, A., and Diouf, A. (2009b). Farmers’ perceptions of climate change and agricultural adaptation strategies in rural Sahel. *Environmental Management*, 43(5):804–816.
- Merz, N., Regel, S., and Lewandowski, J. (2016). The manifesto corpus: A new resource for research on political parties and quantitative text analysis. *Research & Politics*, 3(2).
- Miah, M. G., Abdullah, H. M., and Jeong, C. (2017). Exploring Standardized Precipitation Evapotranspiration Index for drought assessment in Bangladesh. *Environmental Monitoring and Assessment*, 189(11):1–16.
- Michelson, H., Fairbairn, A., Ellison, B., Maertens, A., and Manyong, V. (2021). Misperceived quality: fertilizer in Tanzania. *Journal of Development Economics*, 148:102579.
- Miller, S., Chua, K., Coggins, J., and Mohtadi, H. (2021). Heat waves, climate change, and economic output. *Journal of the European Economic Association*, 19(5):2658–2694.
- Millock, K. (2015). Migration and environment. *Annual Review of Resource Economics*, 7(1):35–60.
- Minor, K., Bjerre-Nielsen, A., Jonasdottir, S. S., Lehmann, S., and Obradovich, N. (2022). Rising temperatures erode human sleep globally. *One Earth*, 5(5):534–549.
- Missirian, A. and Schlenker, W. (2017a). Asylum applications and migration flows. *American Economic Review*, 107(5):436–40.
- Missirian, A. and Schlenker, W. (2017b). Asylum applications respond to temperature fluctuations. *Science*, 358(6370):1610–1614.
- Mohsenipour, M., Shahid, S., Chung, E.-S., and Wang, X.-J. (2018). Changing pattern of droughts during cropping seasons of Bangladesh. *Water Resources Management*, 32(5):1555–1568.
- Mondal, M. S. and Saleh, A. F. M. (2003). Evaluation of some deep and shallow tubewell irrigated schemes in Bangladesh using performance indicators. *Agricultural Water Management*, 58(3):193–207.
- Mondol, M. A. H., Zhu, X., Dunkerley, D., and Henley, B. J. (2021). Observed meteorological drought trends in Bangladesh identified with the Effective Drought Index (EDI). *Agricultural Water Management*, 255:107001.

- Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22(1).
- Moore, F. C. (2017). Learning, adaptation, and weather in a changing climate. *Climate Change Economics*, 8(04):1750010.
- Moore, F. C., Baldos, U., Hertel, T., and Diaz, D. (2017). New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications*, 8(1):1–9.
- Moore, F. C., Obradovich, N., Lehner, F., and Baylis, P. (2019). Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proceedings of the National Academy of Sciences*, 116(11):4905–4910.
- Moriconi, S., Peri, G., and Turati, R. (2019). Immigration and voting for redistribution: Evidence from European elections. *Labour Economics*, 61:101765.
- Moriconi, S., Peri, G., and Turati, R. (2022). Skill of the immigrants and vote of the natives: Immigration and nationalism in European elections 2007–2016. *European Economic Review*, 141:103986.
- Mullins, J. T. and Bharadwaj, P. (2021). Weather, Climate, and Migration in the United States. NBER Working Paper 28614, National Bureau of Economic Research.
- Munro, A. (2020). Using experimental manipulation of questionnaire design and a Kenyan panel to test for the reliability of reported perceptions of climate change and adaptation. *Climatic Change*, 162(3):1081–1105.
- Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., and Leiserowitz, A. A. (2013). The relationship between personal experience and belief in the reality of global warming. *Nature Climate Change*, 3(4):343–347.
- Nath, I. (2020). Climate change, the food problem, and the challenge of adaptation through sectoral reallocation. NBER Working Papers 27297, National Bureau of Economic Research.
- Nath, I., McCusker, K. E., Bolliger, I. W., Carleton, T., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., et al. (2022). The welfare economics of a data-driven social cost of carbon. *AGU Fall Meeting Abstracts*, 2022:GC33A–06.
- Nature (2021). Young people will be key to climate justice at COP26. *Nature*, 598:386.

- Newell, R. G., Prest, B. C., and Sexton, S. E. (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, 108:102445.
- Niles, M. T. and Mueller, N. D. (2016). Farmer perceptions of climate change: Associations with observed temperature and precipitation trends, irrigation, and climate beliefs. *Global Environmental Change*, 39:133–142.
- Nizalova, O. Y. and Murtazashvili, I. (2016). Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5(1):71–77.
- Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science*, 258(5086):1315–1319.
- Nordhaus, W. D. (1993a). Optimal greenhouse-gas reductions and tax policy in the "DICE" model. *American Economic Review*, 83(2):313–317.
- Nordhaus, W. D. (1993b). Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. *Resource and Energy Economics*, 15(1):27–50.
- Nowakowski, A. and Oswald, A. J. (2020). Do Europeans Care about Climate Change? An Illustration of the Importance of Data on Human Feelings. IZA Discussion Paper 13660, IZA.
- Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2):221–231.
- Obradovich, N., Migliorini, R., Mednick, S. C., and Fowler, J. H. (2017). Night-time temperature and human sleep loss in a changing climate. *Science Advances*, 3(5):e1601555.
- Obradovich, N., Migliorini, R., Paulus, M. P., and Rahwan, I. (2018). Empirical evidence of mental health risks posed by climate change. *Proceedings of the National Academy of Sciences*, 115(43):10953–10958.
- Ojala, M. (2012). Hope and climate change: The importance of hope for environmental engagement among young people. *Environmental Education Research*, 18(5):625–642.
- Olmstead, A. L. and Rhode, P. W. (2011). Adapting North American wheat production to climatic challenges, 1839–2009. *Proceedings of the National Academy of Sciences*, 108(2):480–485.
- Oreskes, N. (2004). The scientific consensus on climate change. *Science*, 306(5702):1686–1686.

- Ortega, F. and Peri, G. (2014). Openness and income: The roles of trade and migration. *Journal of International Economics*, 92(2):231–251.
- Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, 11(4):306–312.
- Osberghaus, D. and Fugger, C. (2022). Natural disasters and climate change beliefs: The role of distance and prior beliefs. *Global Environmental Change*, 74:102515.
- Osberghaus, D. and Schenker, O. (2022). International trade and the transmission of temperature shocks. ZEW-Centre for European Economic Research Discussion Paper 22-035, ZEW.
- Ospital, A. (2023). Urban Policy and Spatial Exposure to Environmental Risk. *Mimeo*.
- Otto, A. H. and Steinhardt, M. F. (2014). Immigration and election outcomes — Evidence from city districts in Hamburg. *Regional Science and Urban Economics*, 45:67–79.
- Palm, R., Lewis, G. B., and Feng, B. (2017). What causes people to change their opinion about climate change? *Annals of the American Association of Geographers*, 107(4):883–896.
- Palmer, W. C. (1965). *Meteorological drought*, volume 30. US Department of Commerce, Weather Bureau.
- Pankratz, N. and Schiller, C. (2021). Climate change and adaptation in global supply-chain networks. ECGI Working Paper Series in Finance 775, European Corporate Governance Institute.
- Parvin, L. and Rahman, M. W. (2009). Impact of irrigation on food security in Bangladesh for the past three decades. *Journal of Water Resource and Protection*, 3:216–225.
- Paul, B. and Rashid, H. (2016). *Climatic hazards in coastal Bangladesh: non-structural and structural solutions*. Butterworth-Heinemann.
- Paulo, A., Rosa, R., and Pereira, L. (2012). Climate trends and behaviour of drought indices based on precipitation and evapotranspiration in Portugal. *Natural Hazards and Earth System Sciences*, 12(5):1481–1491.
- Pearson, M. and Rüdiger, W. (2020). The Greens in the 2019 European elections. *Environmental Politics*, 29(2):336–343.
- Peri, G., Rees, D. I., and Smith, B. (2020). Terrorism, Political Opinions, and Election Outcomes: Evidence from Europe. IZA Discussion Paper 13090, IZA.

- Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012.
- Pindyck, R. S. (2013). Climate change policy: what do the models tell us? *Journal of Economic Literature*, 51(3):860–872.
- Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., and Fisher, S. (2019). Climate change perceptions and their individual-level determinants: A cross-European analysis. *Global Environmental Change*, 55:25–35.
- Proctor, J., Rigden, A., Chan, D., and Huybers, P. (2022). Accurate specification of water availability shows its importance for global crop production. *Nature Food*, (3):753–763.
- Rabin, M. and Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, 114(1):37–82.
- Ramankutty, N., Evan, A., Monfreda, C., and Foley, J. A. (2010). Global Agricultural Lands: Croplands, 2000.
- Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management*, 67(3):274–302.
- Reif, K. and Schmitt, H. (1980). Nine second-order national elections - A conceptual framework for the analysis of European Election results. *European Journal of Political Research*, 8(1):3–44.
- Rejesus, R. M., Mutuc-Hensley, M., Mitchell, P. D., Coble, K. H., and Knight, T. O. (2013). US agricultural producer perceptions of climate change. *Journal of Agricultural and Applied Economics*, 45(4):701–718.
- Revesz, R. L., Howard, P. H., Arrow, K., Goulder, L. H., Kopp, R. E., Livermore, M. A., Oppenheimer, M., and Sterner, T. (2014). Global warming: Improve economic models of climate change. *Nature*, 508(7495):173–175.
- Ricart, S., Castelletti, A., and Gandolfi, C. (2022). On farmers’ perceptions of climate change and its nexus with climate data and adaptive capacity. A comprehensive review. *Environmental Research Letters*.
- Richardson, D. and Rootes, C. (2006). *The Green challenge: the development of Green parties in Europe*. Routledge.
- Rode, A., Baker, R. E., Carleton, T., D’Agostino, A., Delgado, M., Foreman, T., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., et al. (2022). Labor disutility in a warmer world: The impact of climate change on the global workforce. Available at SSRN: <http://dx.doi.org/10.2139/ssrn.4221478>.

- Rode, A., Carleton, T., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., Kopp, R. E., McCusker, K. E., et al. (2021). Estimating a social cost of carbon for global energy consumption. *Nature*, 598(7880):308–314.
- Rosenzweig, M. R. and Wolpin, K. I. (1993). Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India. *Journal of Political Economy*, 101(2):223–244.
- Rudik, I., Lyn, G., Tan, W., and Ortiz-Bobea, A. (2022). The economic effects of climate change in dynamic spatial equilibrium. Conference papers 333486, Purdue University, Center for Global Trade Analysis, Global Trade Analysis Project.
- Russ, J. (2020). Water runoff and economic activity: The impact of water supply shocks on growth. *Journal of Environmental Economics and Management*, 101:102322.
- Rzepa, A. and Ray, J. (2020). World risk poll reveals global threat from climate change. News.Gallup.com [Online; posted 6-October-2020; Accessed on 1-March-2023].
- Sacks, W. J., Deryng, D., Foley, J. A., and Ramankutty, N. (2010). Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography*, 19(5):607–620.
- Samuelson, W. and Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, 1(1):7–59.
- Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., and McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US high plains and central valley. *Proceedings of the National Academy of Sciences*, 109(24):9320–9325.
- Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598.
- Schlenker, W. and Taylor, C. A. (2021). Market expectations of a warming climate. *Journal of Financial Economics*, 142(2):627–640.
- Schraff, D., Vergioglou, I., and Demirci, B. B. (2022). EU-NED: The European NUTS-Level Election Dataset.
- Sears, D. (1975). *Political Socialization*. Addison-Wesley.
- Sekhri, S. (2014). Wells, water, and welfare: the impact of access to groundwater on rural poverty and conflict. *American Economic Journal: Applied Economics*, 6(3):76–102.

- Sekulova, F. and van den Bergh, J. C. (2013). Climate change, income and happiness: An empirical study for Barcelona. *Global Environmental Change*, 23(6):1467–1475.
- Severen, C., Costello, C., and Deschenes, O. (2018). A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts? *Journal of Environmental Economics and Management*, 89:235–254.
- Shahid, S. (2011). *Spatial assessment of drought hazard, vulnerability and risk in Bangladesh*, page 215–241. Nova Science Pub Inc.: New York, NY, USA.
- Shahid, S. and Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh. *Natural Hazards*, 46(3):391–413.
- Shahid, S. and Hazarika, M. K. (2010). Groundwater drought in the northwestern districts of Bangladesh. *Water Resources Management*, 24(10):1989–2006.
- Shao, W. (2016). Are actual weather and perceived weather the same? Understanding perceptions of local weather and their effects on risk perceptions of global warming. *Journal of Risk Research*, 19(6):722–742.
- Shrader, J. (2023). Improving climate damage estimates by accounting for adaptation. *Mimeo*.
- Shughrue, C., Werner, B., and Seto, K. C. (2020). Global spread of local cyclone damages through urban trade networks. *Nature Sustainability*, 3(8):606–613.
- Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.
- Silvestri, S., Bryan, E., Ringler, C., Herrero, M., and Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, 12(4):791–802.
- Singh, N. P., Anand, B., and Khan, M. A. (2018). Micro-level perception to climate change and adaptation issues: A prelude to mainstreaming climate adaptation into developmental landscape in India. *Natural Hazards*, 92(3):1287–1304.
- Spence, A., Poortinga, W., and Pidgeon, N. (2012). The psychological distance of climate change. *Risk Analysis: An International Journal*, 32(6):957–972.
- Spinoni, J., Naumann, G., Carrao, H., Barbosa, P., and Vogt, J. (2014). World drought frequency, duration, and severity for 1951–2010. *International Journal of Climatology*, 34(8):2792–2804.
- Stahlmann-Brown, P. and Walsh, P. (2022). Soil moisture and expectations regarding future climate: Evidence from panel data. *Climatic Change*, 171(1):1–20.

- Stantcheva, S. (2022). How to run surveys: A guide to creating your own identifying variation and revealing the invisible. *Annual Review of Economics*, 15.
- Stechemesser, A., Wenz, L., Kotz, M., and Levermann, A. (2021). Strong increase of racist tweets outside of climate comfort zone in Europe. *Environmental Research Letters*, 16(11):114001.
- Steinmayr, A. (2021). Contact versus exposure: Refugee presence and voting for the far right. *Review of Economics and Statistics*, 103(2):310–327.
- Stock, J. H. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, page 80–108. Cambridge University Press.
- Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.
- Tambet, H. and Stopnitzky, Y. (2021). Climate adaptation and conservation agriculture among Peruvian farmers. *American Journal of Agricultural Economics*, 103(3):900–922.
- Taraz, V. (2017). Adaptation to climate change: Historical evidence from the Indian monsoon. *Environment and Development Economics*, 22(5):517–545.
- Taylor, C. (2021). Irrigation and Climate Change: Long-run Adaptation and its Externalities. *Mimeo*.
- Thaler, R. H. (2015). *Misbehaving: The making of behavioral economics*. WW Norton & Company.
- The Business Standard (2022). Food ministry to procure 18 lakh tons of Boro paddy, rice. The Business Standard.com [Online; posted 22-February-2022; Accessed on 18-March-2022].
- Thompson, T. (2021). Young people’s climate anxiety revealed in landmark survey. *Nature*, 597:605.
- Tol, R. S. (2022). A meta-analysis of the total economic impact of climate change. *arXiv preprint arXiv:2207.12199*.
- UN (1951). *Convention Relating to the Status of Refugees, 28 July 1951*. United Nations, Treaty Series, vol. 189, p. 137.
- UNHCR (2021). Climate change and disaster displacement. Accessed on 04.11.2021.
- UNSD (2022). Gross Value Added by Kind of Economic Activity at constant (2015) prices - US dollars. ISIC Revision 3.1.
- Valentim, A. (2023). Repeated exposure and protest outcomes: How Fridays for Future protests influenced voters. *Mimeo*.

- Van der Eijk, C. and Van Egmond, M. (2007). Political effects of low turnout in national and European elections. *Electoral Studies*, 26(3):561–573.
- Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I. (2010). A multi-scalar drought index sensitive to global warming: the Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23(7):1696–1718.
- Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J. J., López-Moreno, J. I., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., and Sanchez-Lorenzo, A. (2012). Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interactions*, 16(10):1–27.
- Vogelsang, T. J. (2012). Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects. *Journal of Econometrics*, 166(2):303–319.
- Waibel, H., Pahlisch, T. H., and Völker, M. (2018). Farmers’ perceptions of and adaptations to climate change in Southeast Asia: the case study from Thailand and Vietnam. In *Climate Smart Agriculture*, pages 137–160. Springer.
- Waldhoff, S., Anthoff, D., Rose, S., and Tol, R. S. (2014). The marginal damage costs of different greenhouse gases: An application of FUND. *Economics*, 8(1):20140031.
- Weber, E. U. (1997). *Perception and expectation of climate change: Precondition for economic and technological adaptation*, page 314–341. San Francisco, CA: Jossey-Bass.
- Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change*, 1(3):332–342.
- Weitzman, M. L. (2010). What is the "damages function" for global warming—and what difference might it make? *Climate Change Economics*, 1(01):57–69.
- Wennersten, J. R. and Robbins, D. (2017). *Rising tides: climate refugees in the twenty-first century*. Indiana University Press.
- Wenz, L. and Levermann, A. (2016). Enhanced economic connectivity to foster heat stress-related losses. *Science Advances*, 2(6).
- Wenz, L., Levermann, A., and Auffhammer, M. (2017). North–south polarization of european electricity consumption under future warming. *Proceedings of the National Academy of Sciences*, 114(38):E7910–E7918.
- Wenz, L. and Willner, S. N. (2022). Climate impacts and global supply chains: an overview. *Handbook on Trade Policy and Climate Change*, pages 290–316.

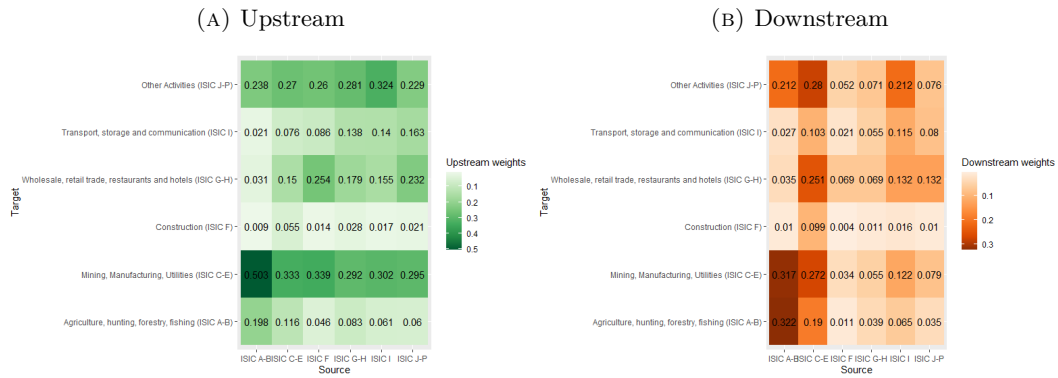
- Winston, J. J., Escamilla, V., Perez-Heydrich, C., Carrel, M., Yunus, M., Streatfield, P. K., and Emch, M. (2013). Protective benefits of deep tube wells against childhood diarrhea in Matlab, Bangladesh. *American Journal of Public Health*, 103(7):1287–1291.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.
- Zahid, A. and Ahmed, S. R. U. (2006). Groundwater resources development in Bangladesh: Contribution to irrigation for food security and constraints to sustainability. *Groundwater Governance in Asia Series*, 1:25–46.
- Zanocco, C., Boudet, H., Nilson, R., Satein, H., Whitley, H., and Flora, J. (2018). Place, proximity, and perceived harm: Extreme weather events and views about climate change. *Climatic Change*, 149(3):349–365.
- Zappalà, G. (2023a). Adapting to climate change accounting for individual beliefs. *Mimeo*.
- Zappalà, G. (2023b). Drought exposure and accuracy: Motivated reasoning in climate change beliefs. *Environmental and Resource Economics*, 85(3):649–672.
- Zargar, A., Sadiq, R., Naser, B., and Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, 19:333–349.
- Zaval, L., Keenan, E. A., Johnson, E. J., and Weber, E. U. (2014). How warm days increase belief in global warming. *Nature Climate Change*, 4(2):143–147.
- Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, 57(298):348–368.
- Zhang, P., Deschênes, O., Meng, K., and Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1–17.
- Zhao, J. and Luo, Y. (2021). A framework to address cognitive biases of climate change. *Neuron*, 109(22):3548–3551.

Appendix A

**Appendix to Chapter 1:
Sectoral impact and
propagation of weather shocks**

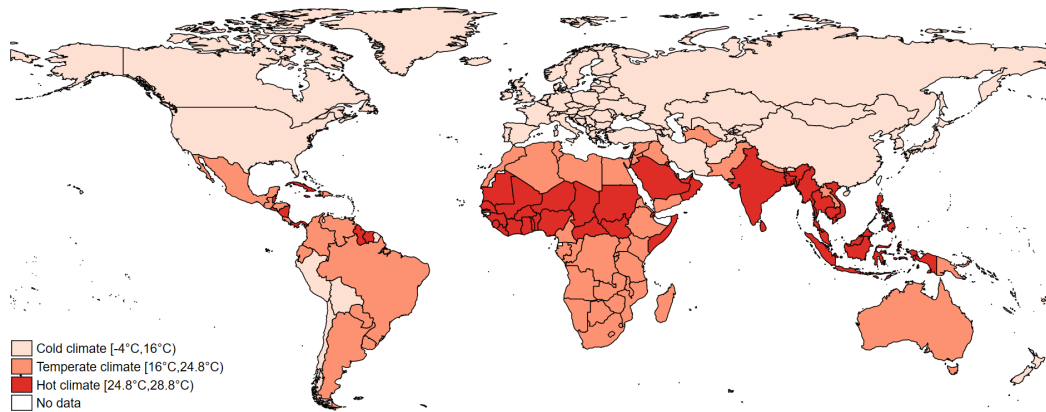
A.1 Additional figures

FIGURE A1: Average upstream and downstream weights across countries



Notes: The figure shows the average upstream and downstream weights across countries by sector. Upstream and downstream weights are constructed from the perspective of Source sectors on the x-axis.

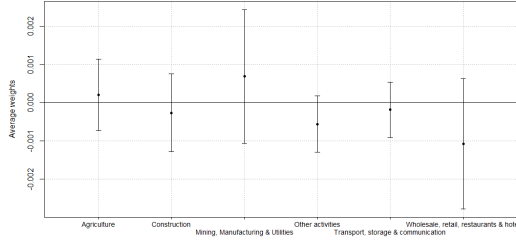
FIGURE A2: Countries in the sample by climatic zone



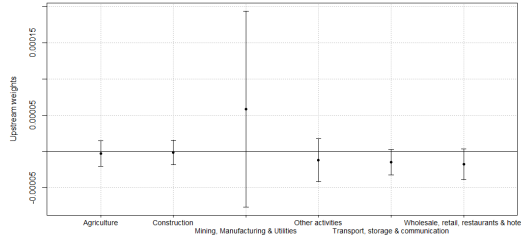
Notes: The map represents the countries in the sample divided by climatic zones, defined as terciles of the average annual temperature from 1970 through 2020. The classification is implemented in order to compute heterogeneous treatment effects as reported in Figure A6.

FIGURE A3: Sectoral interlinkages' response to heat shocks

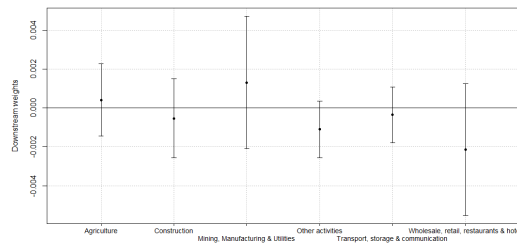
(A) Average weights



(B) Upstream weights

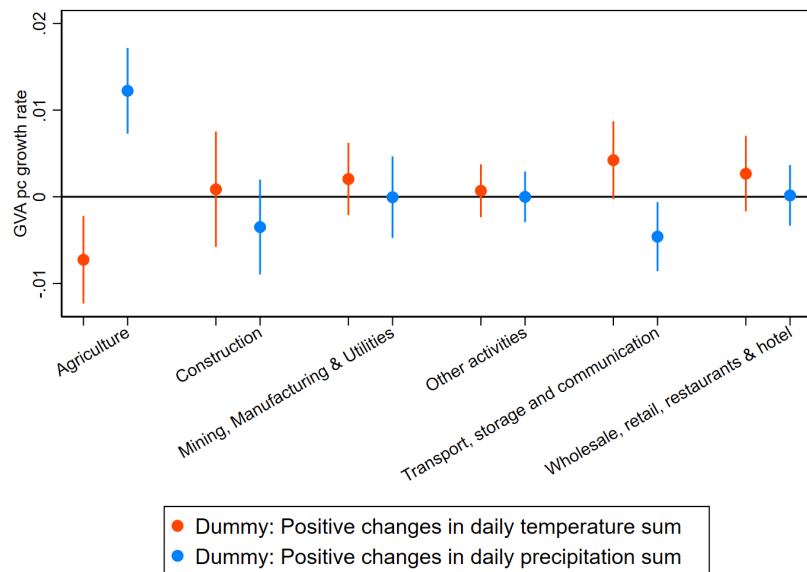


(C) Downstream weights



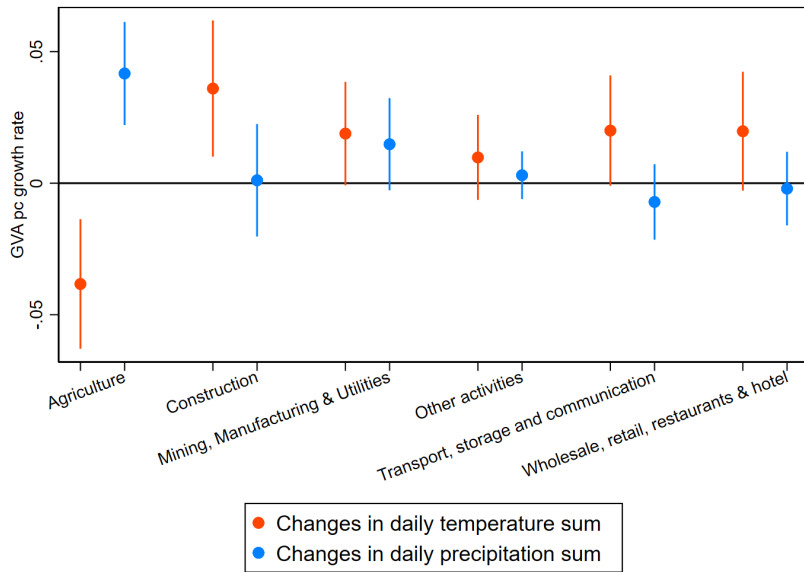
Notes: The figure shows the (standardized) coefficients associated with the response of bilateral sectoral interlinkages to heat shocks (measured as the number of days above the 95th percentile of the temperature distribution) in the period between 1970 and 2019. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and origin-destination bilateral sector, destination sector-country-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A4: Sector-specific impact of positive annual temperature and precipitation changes



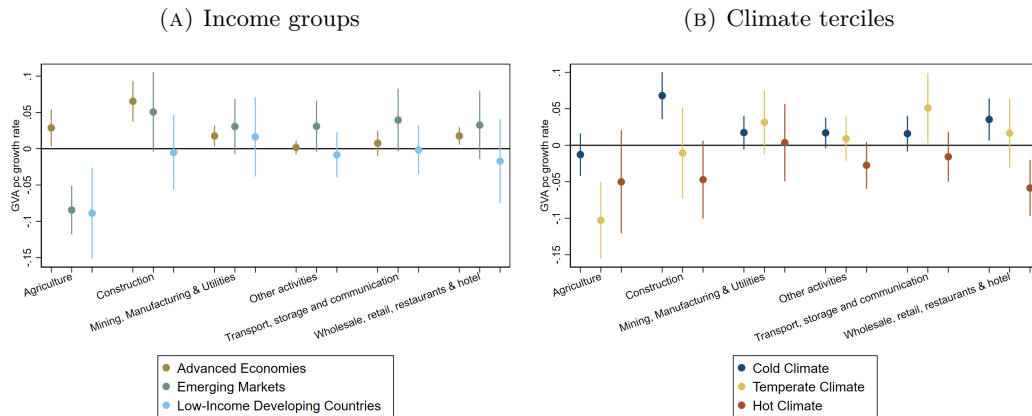
Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to an indicator variable that takes value one if the sum of average daily temperature and precipitation is larger than the previous year's. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

FIGURE A5: Sector-specific impact of annual temperature and precipitation changes



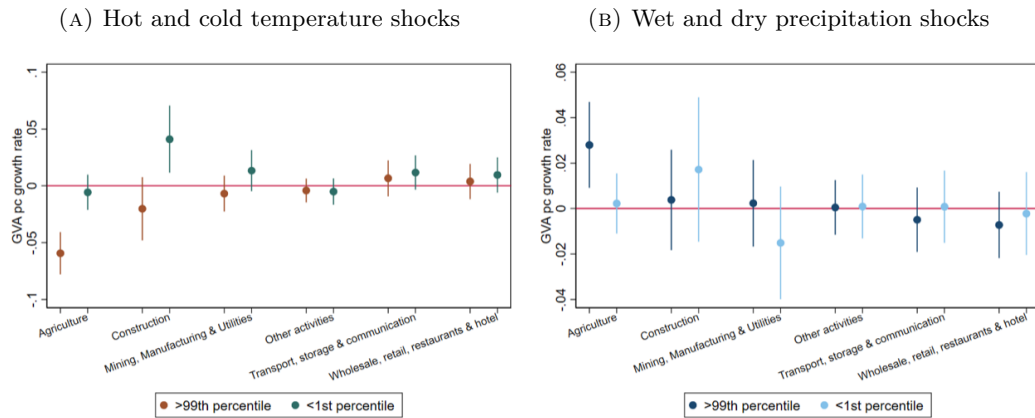
Notes: The figure shows the OLS coefficients associated with the response of sectoral GVA per capita growth rate to changes in the annual sum of average daily temperature. The regression controls for lagged sectoral GVA growth rate, country-sector, sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates. Standard errors are clustered at the country level.

FIGURE A6: Heterogeneity in the GVA response to changes in temperature distribution



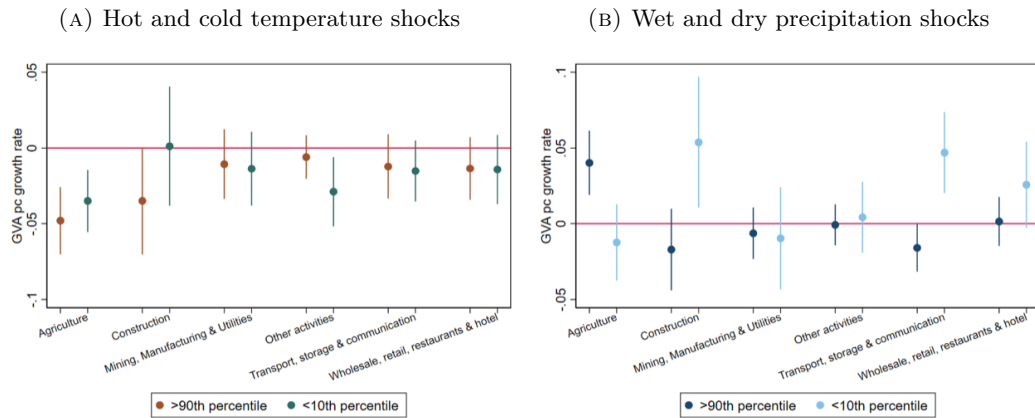
Notes: The figure shows the (standardized) coefficients associated with the response of sectoral GVA per capita growth rate to an increase in the sum of average daily temperature in different sub-samples split by income groups according to the World Economic Outlook (IMF, 2022) and by climate split into terciles using the long-run average temperature. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A7: Abnormal weather realizations using 1st and 99th percentiles



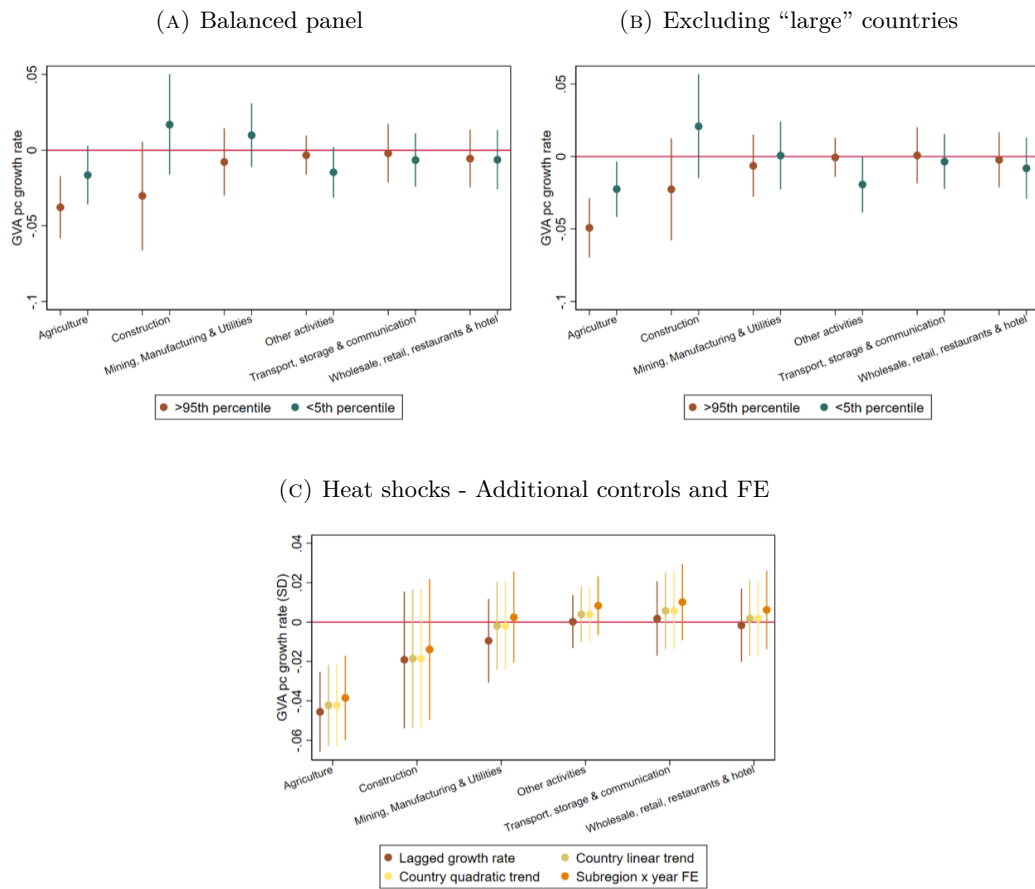
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 99th and below the 1st percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A8: Abnormal weather realizations using 10th and 90th percentiles



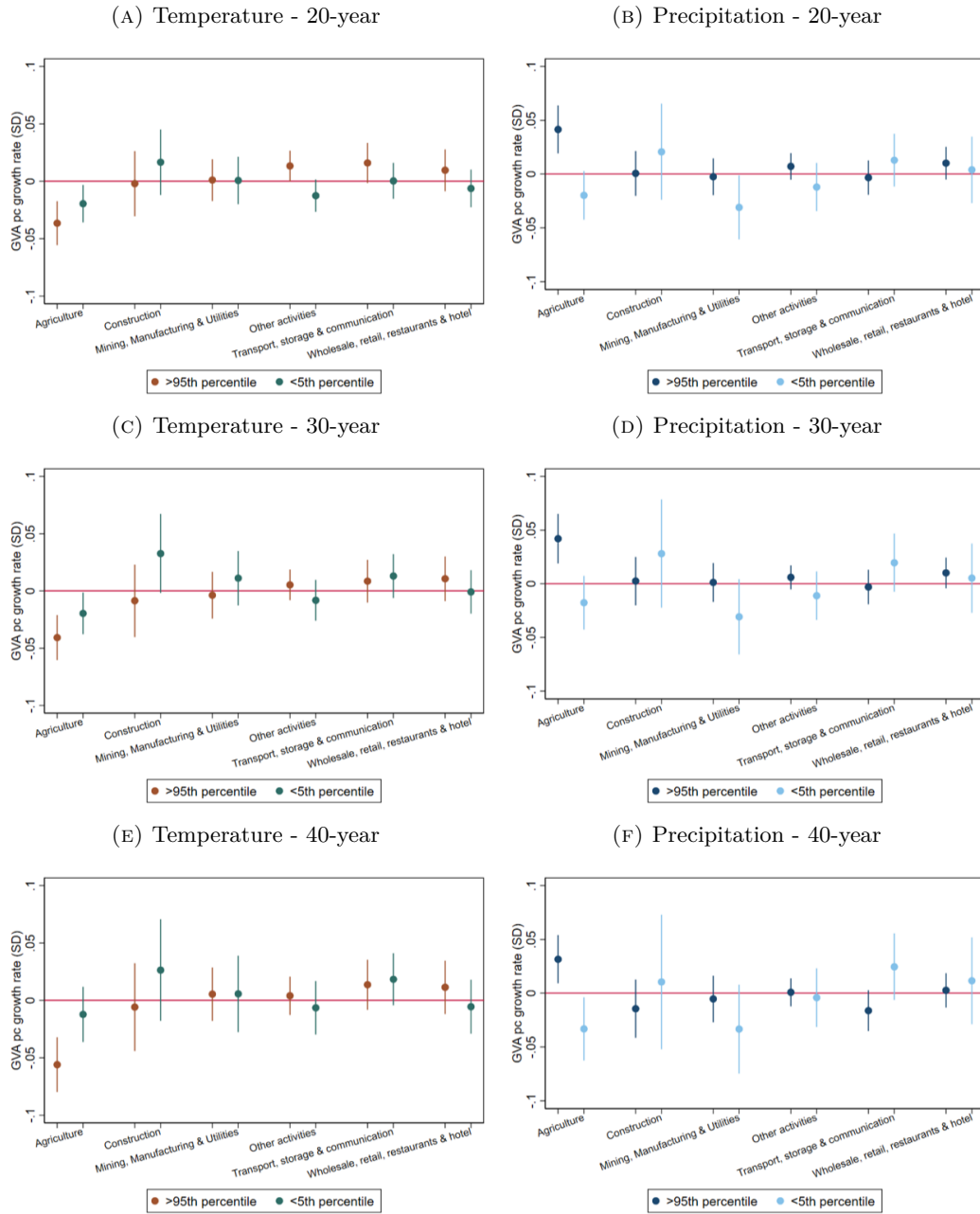
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panel (a)) and in precipitation (Panel (b)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A9: Robustness: Abnormal temperature realizations



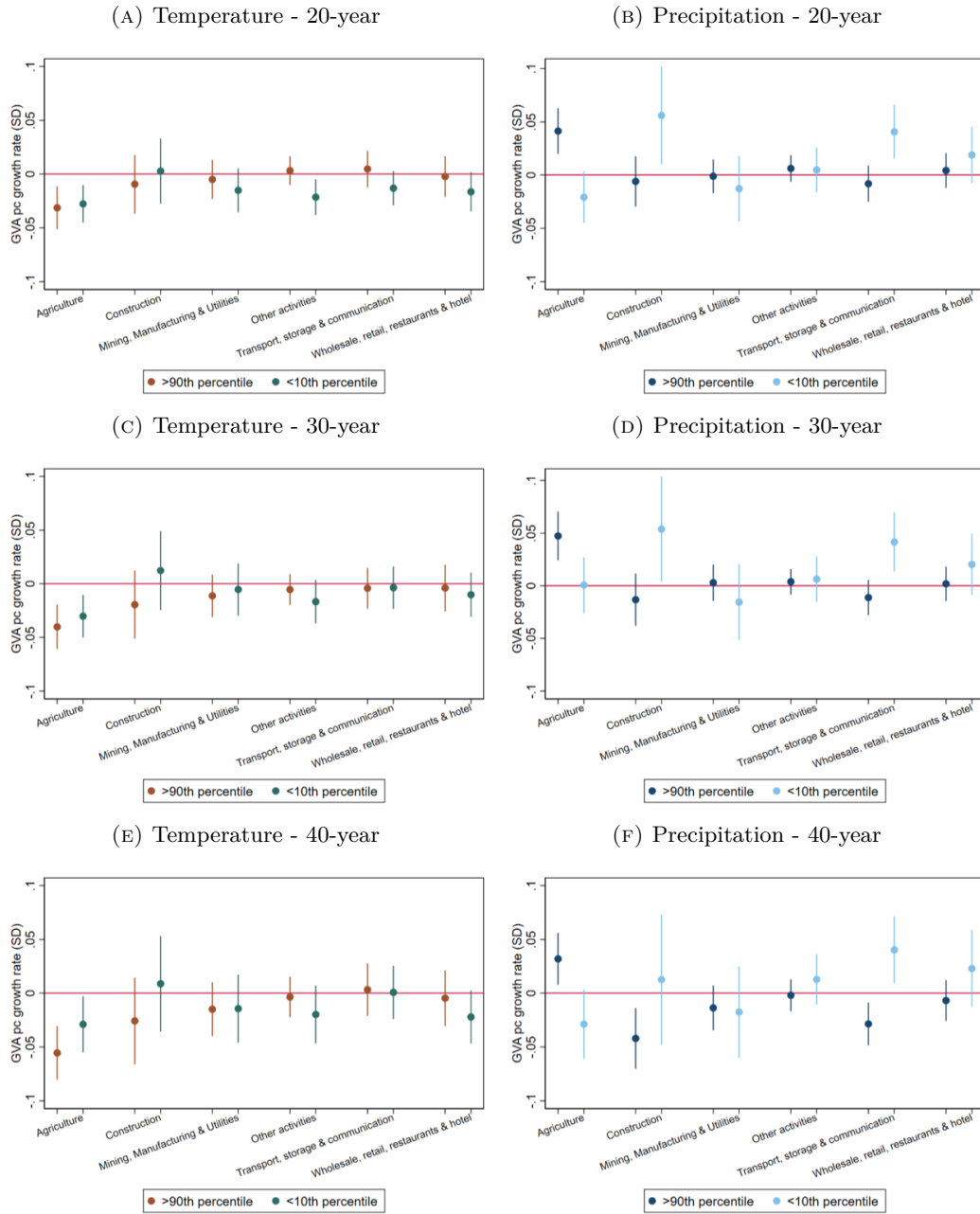
Notes: The figure shows the (standardized) regression estimates for the country-average number of days above the 95th and below the 5th percentile of the daily distribution in temperature using a sector-country balanced panel (Panel (a)), excluding large countries (Brazil, China, India, Russia, US) (Panel (b)), and for days above the 95th percentile including lagged growth rate, country-specific linear and quadratic trends and subregion-by-year fixed effects (Panel (c)). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals around point estimates.

FIGURE A10: Abnormal weather realizations from time-varying climate norms using 5th and 95th percentiles



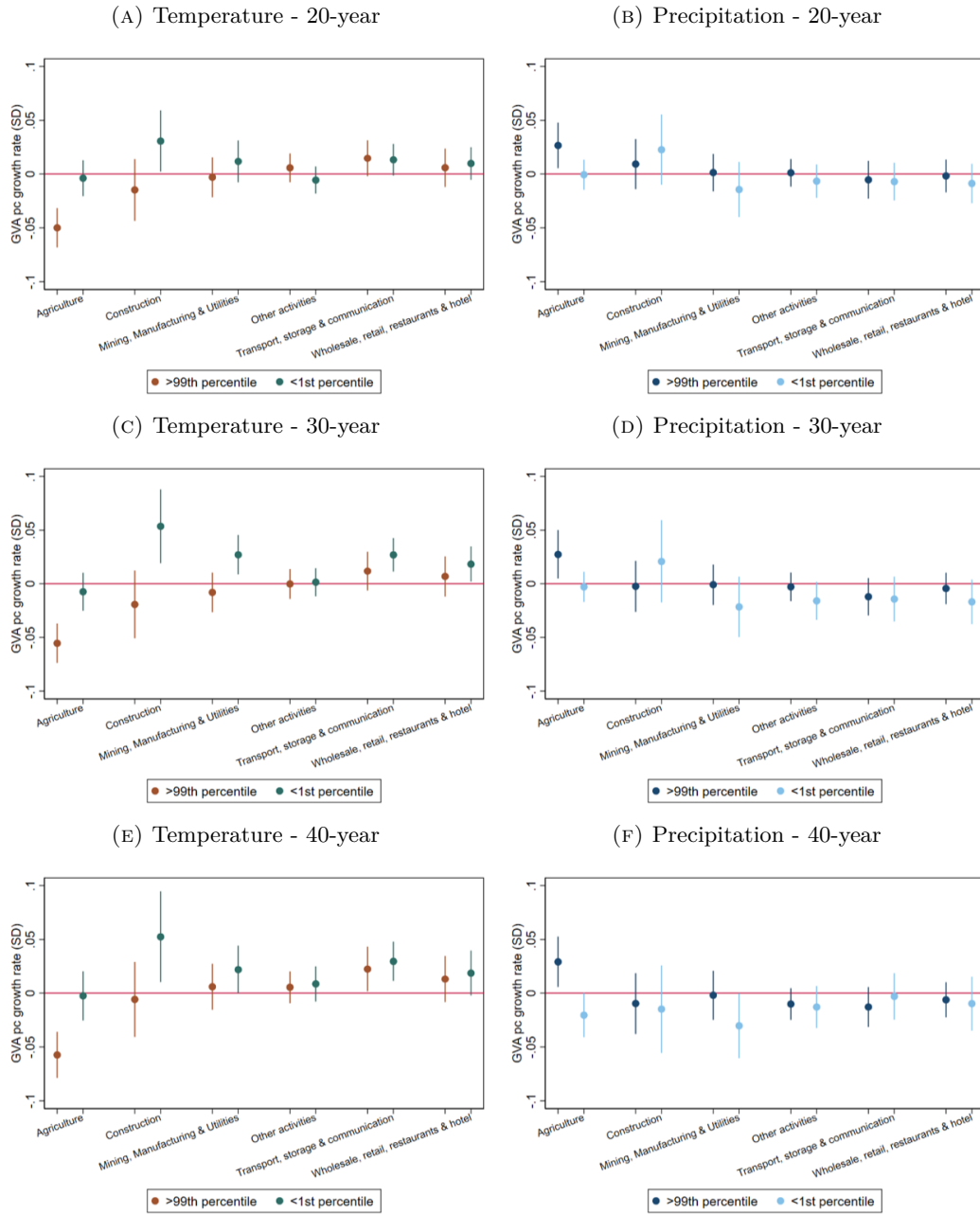
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A11: Abnormal weather realizations from time-varying climate norms using 10th and 90th percentiles



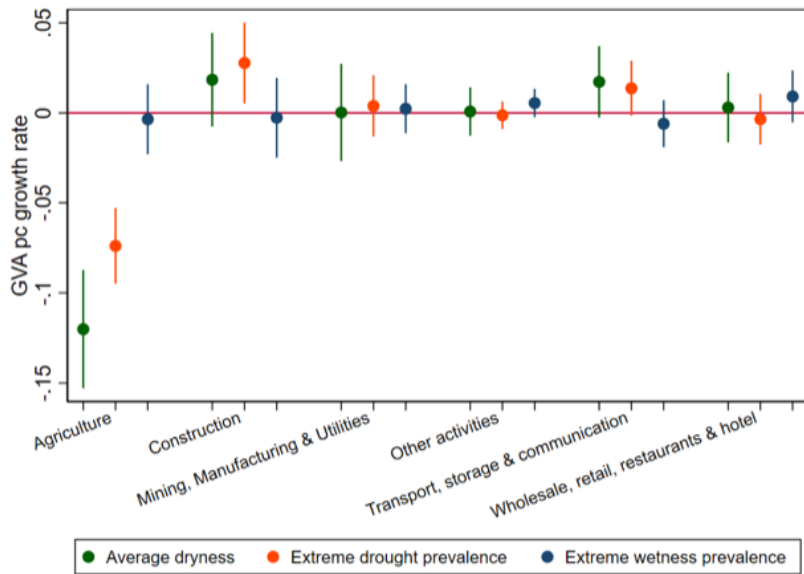
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 90th and below the 10th percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A12: Abnormal weather realizations from time-varying climate norms using 1st and 99th percentiles



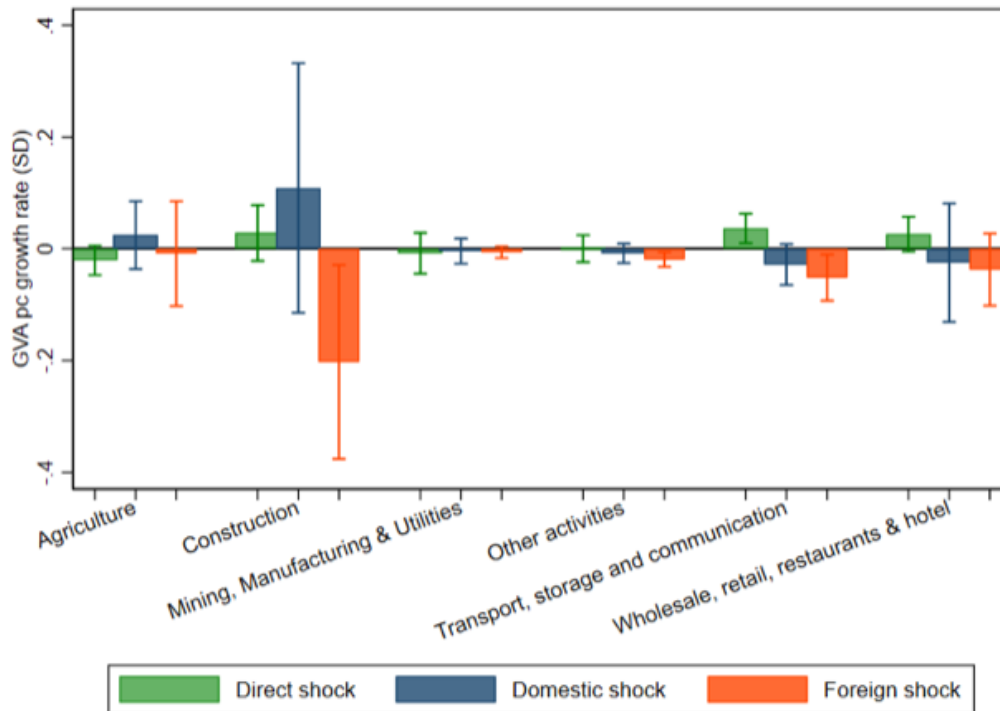
Notes: The figure shows the (standardized) regression coefficients on the number of days above the 99th and below the 1st percentile of the daily distribution in temperature (Panels (a-c-e)) and in precipitation (Panels (b-d-f)) using time-varying distributions (respectively, 20-year, 30-year and 40-year). The estimation sample starts from 1990. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A13: Extreme drought and wetness prevalence and sectoral production



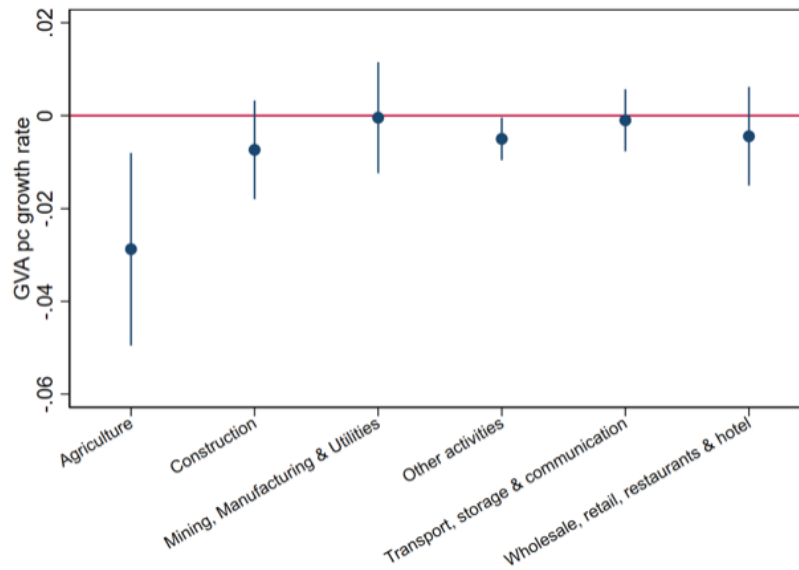
Notes: The figure shows the (standardized) coefficients from a stacked multi-sector regression model where changes in dryness and wetness variables are sector-specific. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A14: Domestic and foreign dry shocks on sectoral production



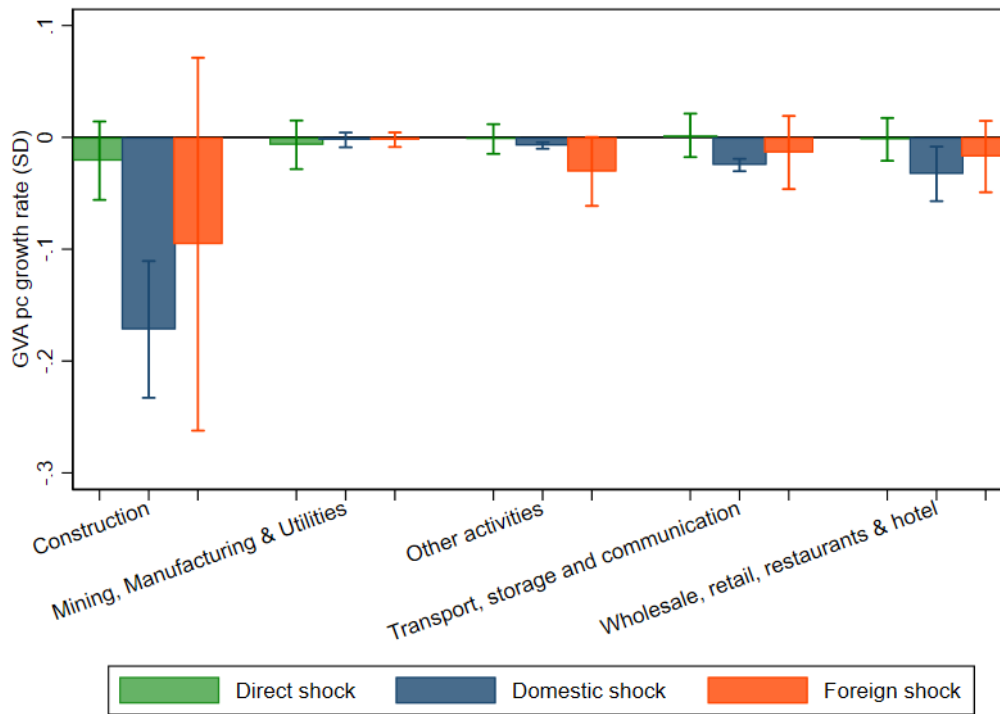
Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days below the 5th percentile of the daily precipitation distribution. Domestic shocks are constructed as the average weather shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th and above the 95th percentile and sector-specific responses to precipitation realizations above the 95th percentile. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A15: Tropical cyclone intensity and sectoral production



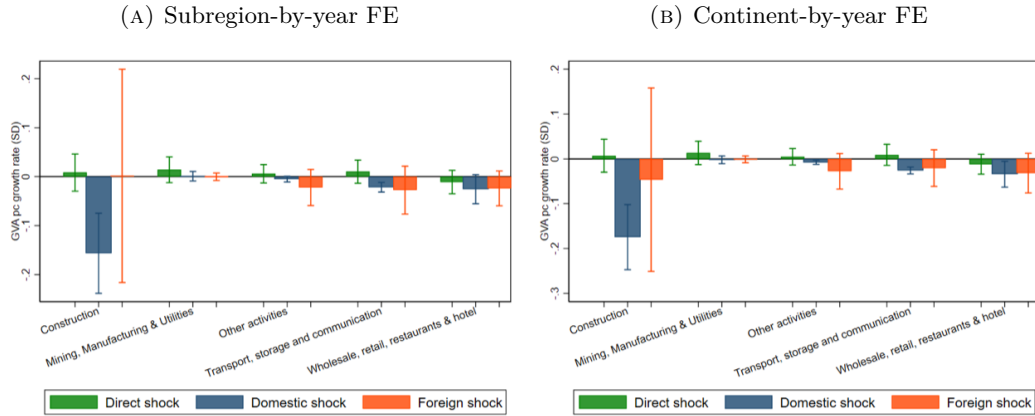
Notes: The figure shows the (standardized) sector-specific coefficients from a stacked multi-sector regression model where the main regressor is measured as first-differenced damage intensity measure of tropical cyclones constructed from wind speed from Kunze (2021). All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and controlling for country-specific linear time trends. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A16: Domestic and foreign agricultural heat shocks on other sectors' production



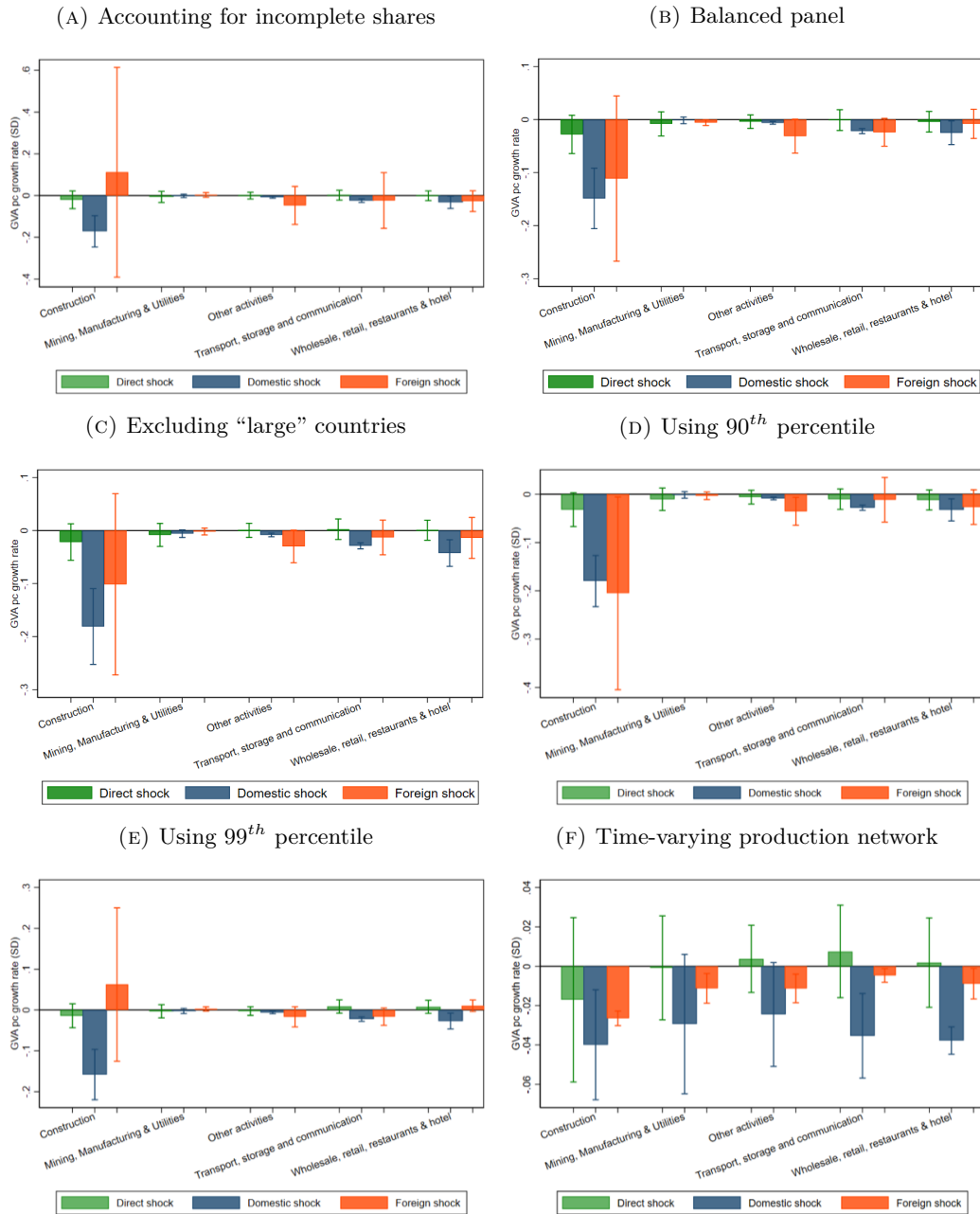
Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic shocks are constructed as the average heat shock in agriculture in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in agriculture in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Bins represent the 95% confidence intervals with standard errors clustered at the country-level.

FIGURE A17: Robustness: Spatial correlation



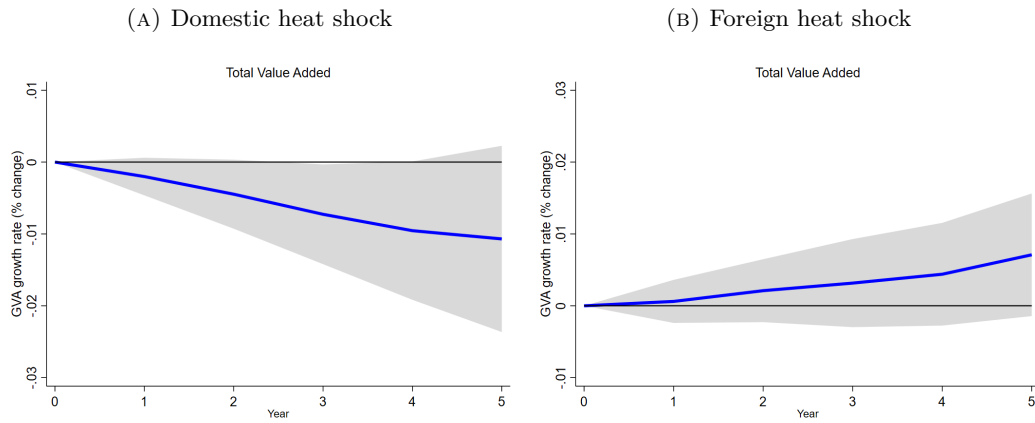
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the average number of days above the 95th percentile of the daily temperature distribution. Domestic shocks are constructed as the average weather shock in agriculture in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in agriculture in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to temperature realizations below the 5th percentile and sector-specific responses to precipitation realizations below the 5th and above the 95th percentile. Panel (a) shows the estimates in a regression that additionally accounts for subregion-by-year fixed effects, Panel (b) shows the estimates in a regression that additionally accounts for continent-by-year fixed effects. Bins represent the 90% confidence intervals around point estimates.

FIGURE A18: Robustness: Domestic and foreign agricultural heat shocks



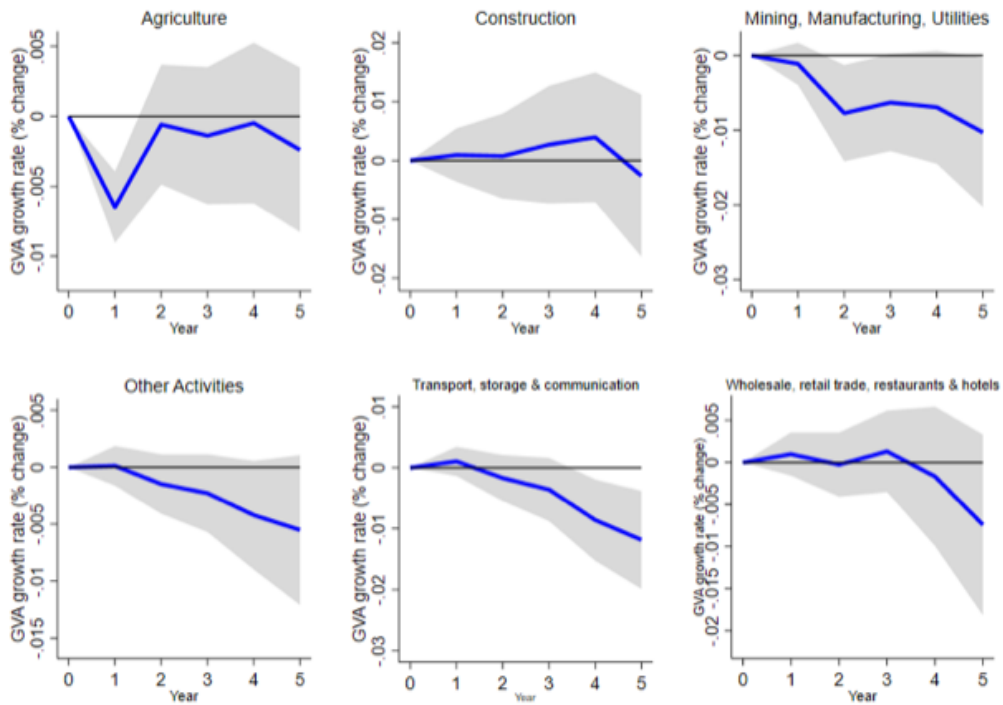
Notes: The figure shows the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign agricultural heat shocks, Panel (a) shows the estimates controlling for sector-year FE interacted with the sum of exposure shares. Panel (b) uses sector-country balanced panel, Panel (c) excludes large countries (Brazil, China, India, Russia, US), Panel (d) and panel (e) respectively used the 90th and the 99th percentile to construct heat shocks. Panel (f) uses a decadal time-varying production network constructed using the average of the first five-year input-output interlinkages for each decade. Bins represent the 90% confidence intervals around point estimates.

FIGURE A19: Local projections of domestic and foreign heat shocks on total value added



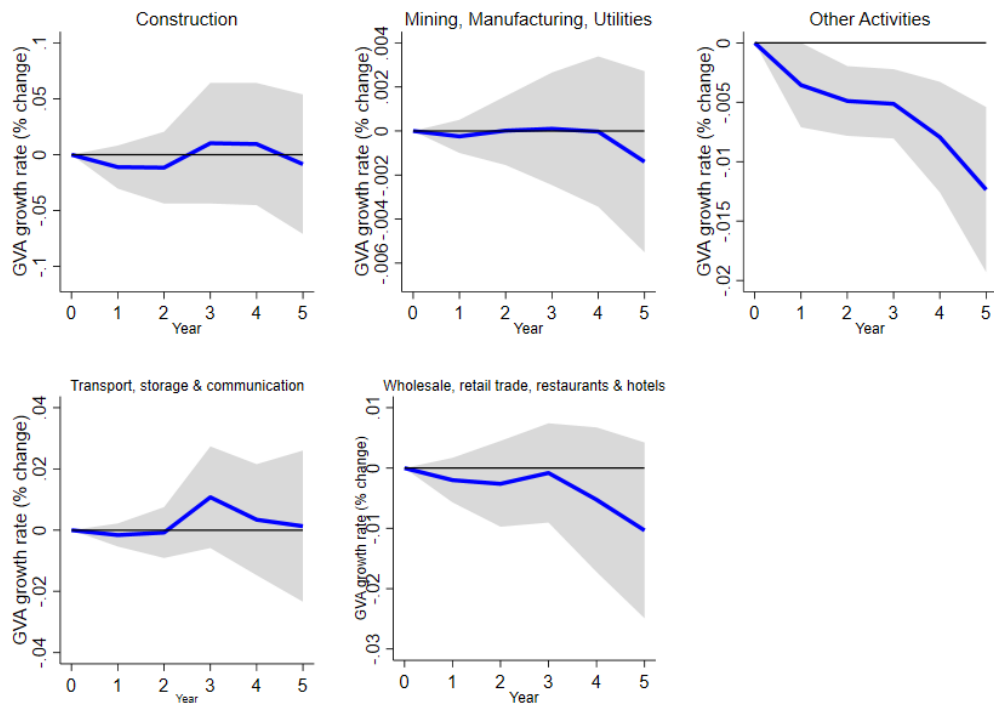
Notes: Panels show the impulse response function of per capita total value added growth rate to a 1 SD increase in heat shocks estimated in a stacked regression model with country and year fixed effects and accounting for abnormally cold temperature shocks (below the 5th percentile) and precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country level. Panel (a) shows the estimates for domestic shocks, and Panel (b) shows the estimates for foreign shocks.

FIGURE A20: Local projections of direct heat shocks on sectoral production



Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to domestic and foreign abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

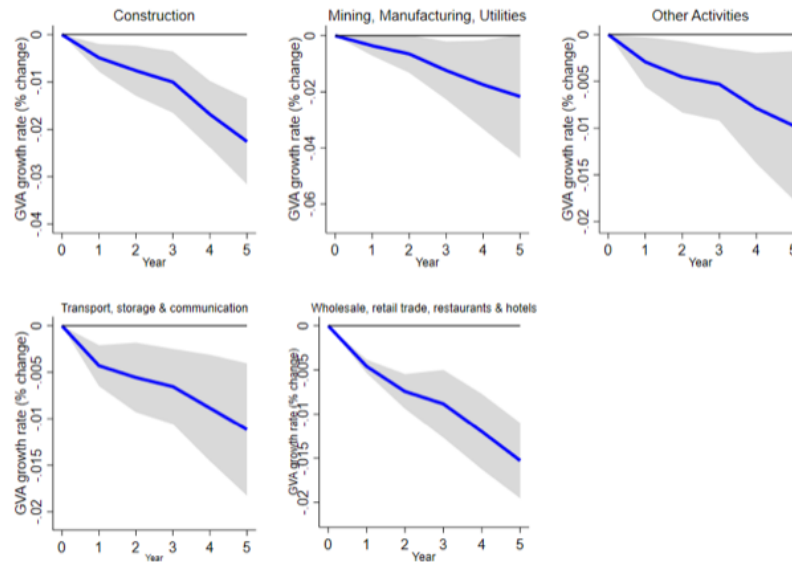
FIGURE A21: Local projections of foreign agricultural heat shocks on sectoral production



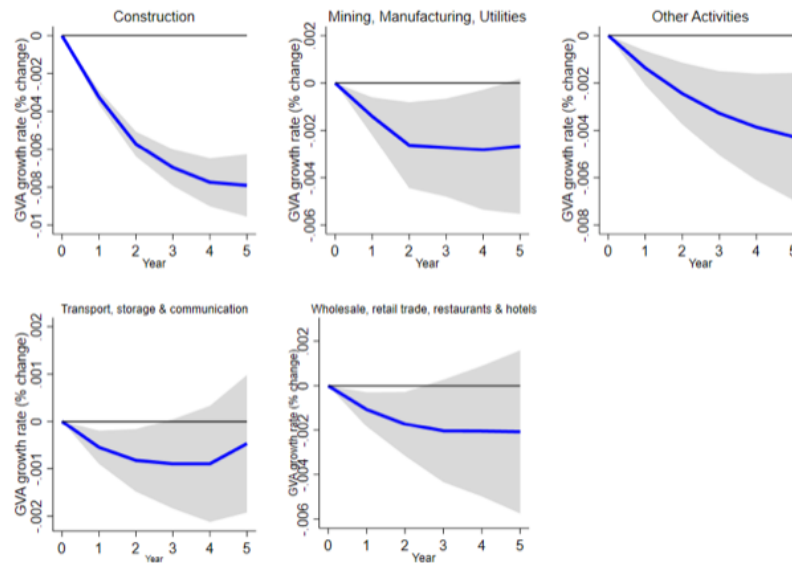
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A22: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Time-varying production networks.

(A) Domestic



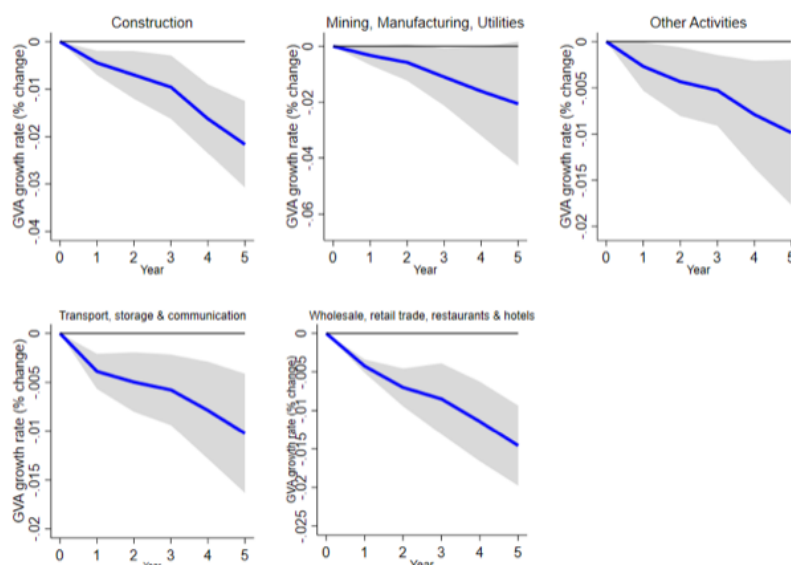
(B) Foreign



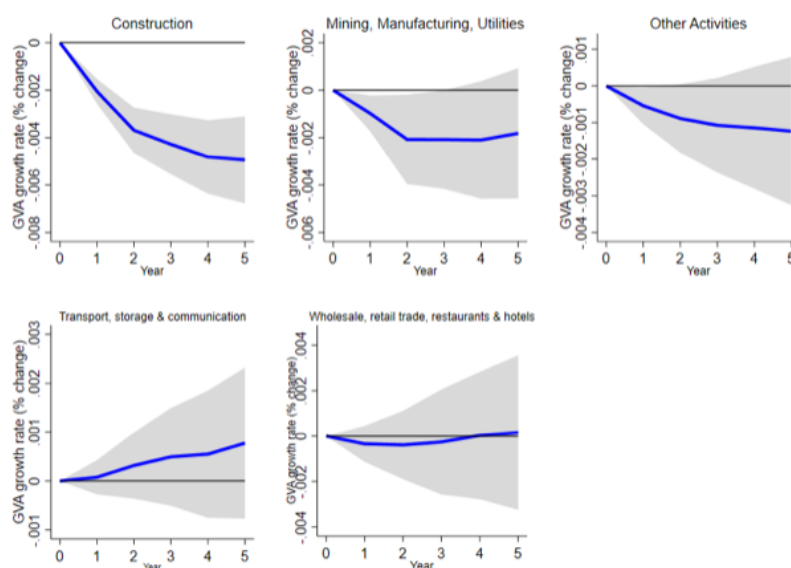
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and region-sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Network shocks are constructed using as weights the first five-year average input-output interlinkages for each decade. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A23: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector-year FE.

(A) Domestic



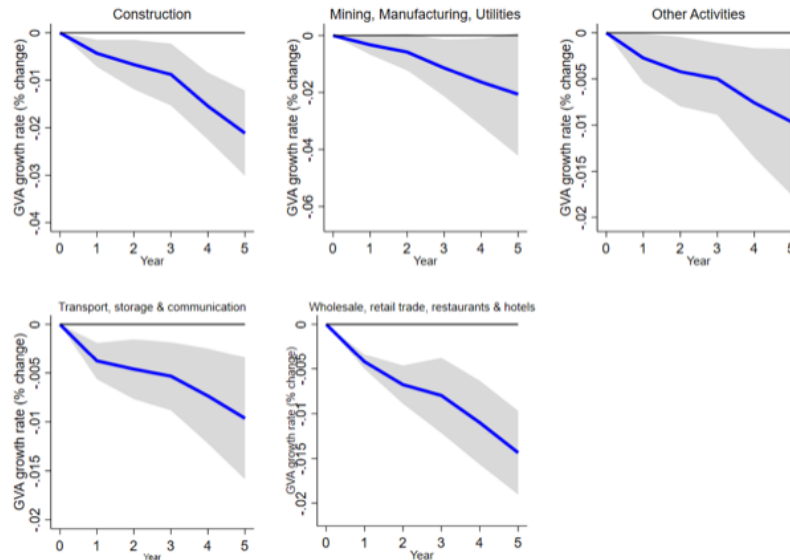
(B) Foreign



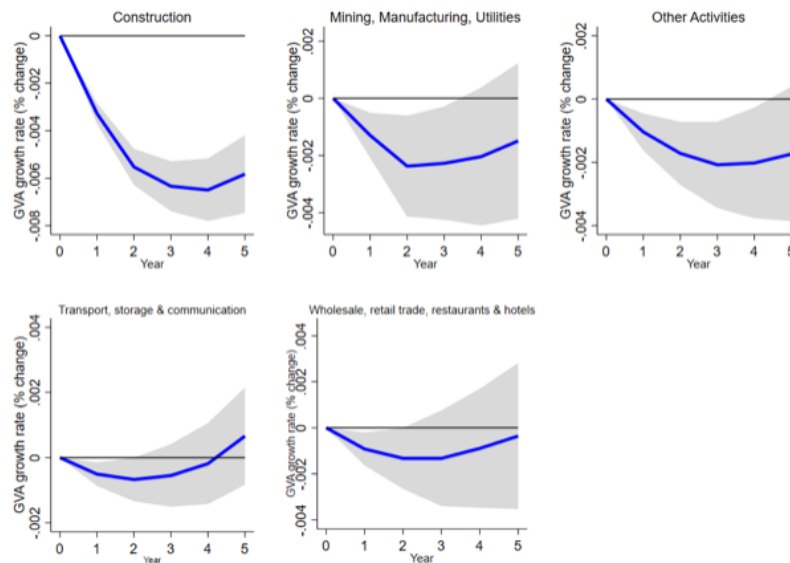
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and continent-sector-year fixed effects and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A24: Local projections of domestic and foreign agricultural heat shocks on sectoral production. Continent-sector linear trends.

(A) Domestic

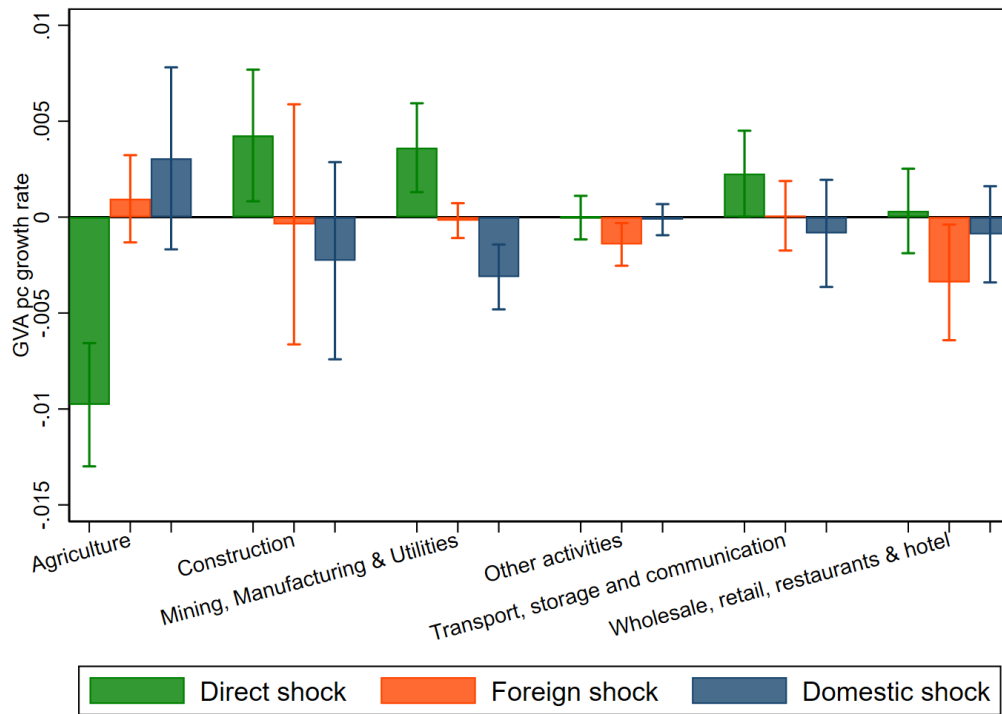


(B) Foreign



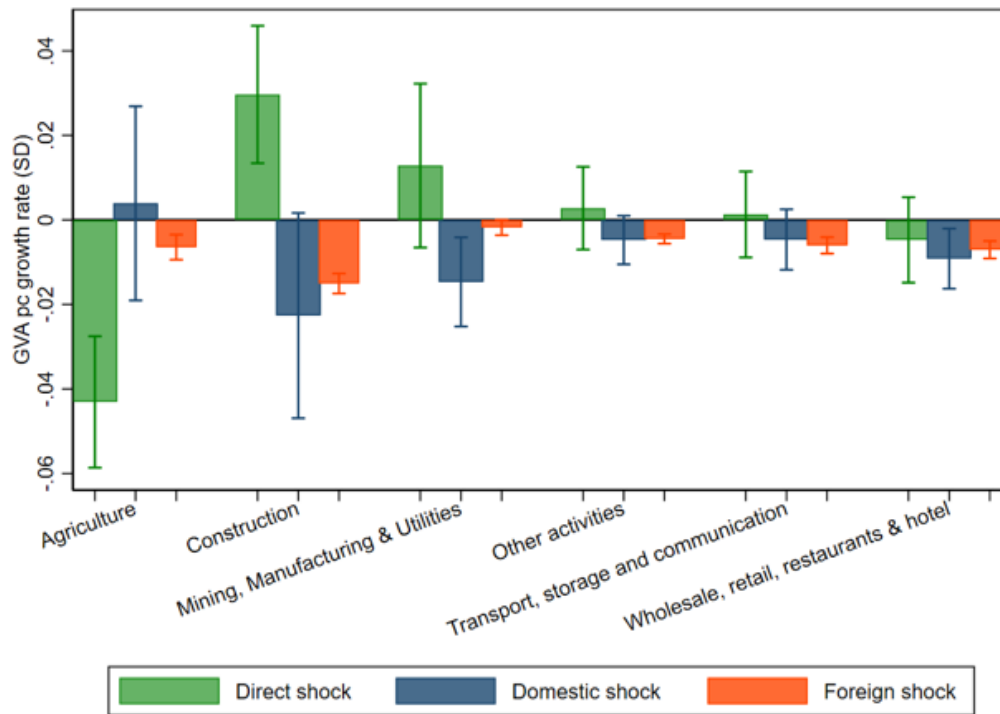
Notes: Panels show the sector-specific impulse response function of sectoral per capita GVA growth rate to a 1 SD increase in the foreign abnormally hot temperature shocks estimated in a stacked regression model fully saturated with country-sector and continent-sector linear annual trends and accounting for sector-specific responses to direct and domestic abnormally hot temperature shocks, to abnormally cold temperature shocks (below the 5th percentile) and to precipitation realizations below the 5th and above the 95th percentile. Horizon 0 is the year of the shock. Shaded areas represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A25: Domestic and foreign drought shocks and sectoral production



Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using changes in extreme drought prevalence. Domestic shocks are constructed as the average shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A26: Domestic and foreign cyclones shocks and sectoral production

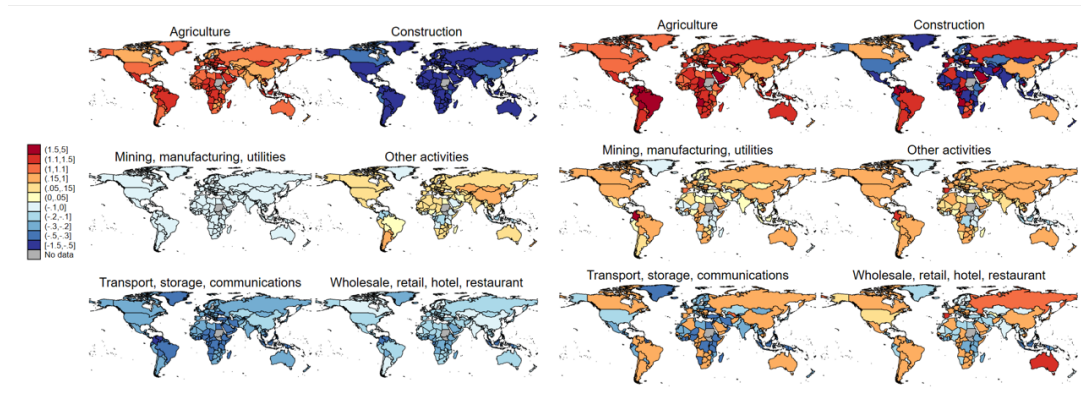


Notes: Bars represent the (standardized) sector-specific coefficients associated with direct shocks and domestic and foreign shocks, using the cubic wind speed measure by Kunze (2021). Domestic shocks are constructed as the average shock in the other sectors in the same country as the sector of interest weighted by the average of upstream and downstream interdependence with each sector. Symmetrically, foreign shocks are constructed as the average weather shock in the other sectors in all the other countries weighted by the average of upstream and downstream interdependence with each sector. All sector-specific coefficients are estimated jointly in a stacked regression model fully saturated with country-sector and sector-year fixed effects. Bins represent the 90% confidence intervals with standard errors clustered at the country-level.

FIGURE A27: Average annual relative sectoral GVA pc losses (%)
due to recent warming

(A) Local sectoral direct shocks

(B) Accounting for indirect shocks



Notes: The figure shows average annual losses (in red) and gains (in blue) in sectoral per capita GVA due to abnormally hot and cold temperature shocks in the 2001-2020 period compared to a counterfactual in which shocks evolved linearly from their 1970-2000 averages. The two panels compare the average annual relative loss (% of per capita GVA) using sector-specific local heat and cold shock estimates (Panel a) and accounting for semi-elasticities to shocks in other partner sectors (Panel b). Averages are obtained from 1000 bootstrap estimations of Equation (1.12), where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. In Panel a), only estimates for Agriculture are statistically significant at 95% level. Table A13 reports the estimated average losses significant at the 95% level for each country-sector when including indirect heat and cold shocks. Summary statistics on direct losses only considering 95% significant estimates: mean is 1.08%, median is 1.09%, IQR is [1.00%, 1.18%]. Summary statistics on losses accounting for indirect shocks only considering 95% significant estimates: mean is 1.29%, median is 1.21%, IQR is [1.04%, 1.44%].

A.2 Additional tables

TABLE A1: Summary statistics on sectoral GVA growth rate

	N	mean	SD	min	max
Log GVA per capita	47,289	6.166	1.789	-2.880	11.534
GVA per capita growth rate	47,289	0.014	0.121	-3.299	2.572
Sector					
Agriculture, hunting, forestry, fishing (ISIC A-B)	7,860	0.002	0.104	-1.691	0.745
Mining, Manufacturing, Utilities (ISIC C-E)	7,900	0.013	0.170	-3.299	2.572
Construction (ISIC F)	7,906	0.010	0.128	-3.169	2.430
Wholesale, retail trade, restaurants and hotels (ISIC G-H)	7,906	0.018	0.087	-1.513	1.261
Transport, storage and communication (ISIC I)	7,857	0.026	0.112	-2.514	2.030
Other Activities (ISIC J-P)	7,860	0.015	0.110	-1.639	1.502
Number of countries	183				
Number of sectors	6				
Number of years per country-sector		44.220	5.235	12	46

TABLE A2: Countries and year-sectors in final sample

Country	Number of years-sectors	Country	Number of years-sectors	Country	Number of years-sectors
Afghanistan	276	French Polynesia	276	Nigeria	276
Albania	276	Gabon	276	North Korea	184
Algeria	276	Gambia	276	North Macedonia	180
Andorra	276	Georgia	180	Norway	276
Angola	276	Germany	276	Oman	276
Antigua and Barbuda	276	Ghana	276	Pakistan	276
Argentina	276	Greece	276	Palestine	180
Armenia	180	Greenland	276	Panama	276
Aruba	276	Grenada	276	Papua New Guinea	276
Australia	276	Guatemala	276	Paraguay	276
Austria	276	Guinea	276	Peru	276
Azerbaijan	180	Guyana	276	Philippines	276
Bahamas	296	Haiti	276	Poland	276
Bahrain	276	Honduras	276	Portugal	276
Bangladesh	276	Hungary	276	Qatar	276
Barbados	276	Iceland	276	Republic of the Congo	276
Belarus	180	India	276	Romania	276
Belgium	276	Indonesia	276	Russia	180
Belize	276	Iran	276	Rwanda	276
Benin	276	Iraq	276	Samoa	276
Bermuda	276	Ireland	276	San Marino	276
Bhutan	276	Israel	276	Saudi Arabia	276
Bolivia	276	Italy	276	Senegal	276
Bosnia and Herzegovina	180	Jamaica	276	Serbia	180
Botswana	276	Japan	276	Seychelles	276
Brazil	276	Jordan	276	Sierra Leone	276
British Virgin Islands	276	Kazakhstan	180	Singapore	276
Brunei	276	Kenya	276	Slovakia	180
Bulgaria	276	Kuwait	276	Slovenia	180
Burkina Faso	276	Kyrgyzstan	180	Somalia	276
Burundi	276	Laos	276	South Africa	276
Cabo Verde	276	Latvia	180	South Korea	276
Cambodia	276	Lebanon	276	South Sudan	72
Cameroon	276	Lesotho	276	Spain	276
Canada	276	Liberia	276	Sri Lanka	276
Cayman Islands	276	Libya	276	Sudan	72
Central African Republic	276	Liechtenstein	276	Suriname	276
Chad	276	Lithuania	180	Swaziland	276
Chile	276	Luxembourg	276	Sweden	276
China	276	Madagascar	276	Switzerland	276
Colombia	276	Malawi	276	Syria	276
Comoros	276	Malaysia	276	São Tomé and Príncipe	276
Costa Rica	276	Maldives	297	Tajikistan	178
Croatia	180	Mali	276	Tanzania	276
Cuba	276	Malta	276	Thailand	276
Cyprus	276	Mauritania	276	Togo	276
Czechia	180	Mauritius	276	Trinidad and Tobago	276
Côte d'Ivoire	276	Moldova	180	Tunisia	276
Democratic Republic of the Congo	276	Monaco	230	Turkey	276
Denmark	276	Mongolia	276	Turkmenistan	180
Djibouti	276	Montenegro	180	Uganda	276
Dominican Republic	276	Morocco	276	Ukraine	180
Ecuador	276	Mozambique	276	United Arab Emirates	276
Egypt	276	Myanmar	276	United Kingdom	276
El Salvador	276	México	276	United States	276
Equatorial Guinea	276	Namibia	276	Uruguay	276
Eritrea	126	Nepal	276	Uzbekistan	180
Estonia	180	Netherlands	276	Vanuatu	276
Ethiopia	180	New Caledonia	276	Venezuela	276
Fiji	276	New Zealand	276	Vietnam	276
Finland	276	Nicaragua	276	Yemen	186
France	276	Niger	276	Zambia	276
				Zimbabwe	276
Total	47,289				

TABLE A3: Mapping between EORA26 sectors and UNSD industries

EORA26 Sector	UNSD industry
Agriculture	Agriculture, hunting, forestry, fishing (ISIC A-B)
Fishing	Agriculture, hunting, forestry, fishing (ISIC A-B)
Mining and Quarrying	Mining, Manufacturing, Utilities (ISIC C-E)
Electricity, Gas and Water	Mining, Manufacturing, Utilities (ISIC C-E)
Food & Beverages	Mining, Manufacturing, Utilities (ISIC C-E)
Textiles and Wearing Apparel	Mining, Manufacturing, Utilities (ISIC C-E)
Wood and Paper	Mining, Manufacturing, Utilities (ISIC C-E)
Petroleum, Chemical and Non-Metallic Mineral Products	Mining, Manufacturing, Utilities (ISIC C-E)
Metal Products	Mining, Manufacturing, Utilities (ISIC C-E)
Electrical and Machinery	Mining, Manufacturing, Utilities (ISIC C-E)
Transport Equipment	Mining, Manufacturing, Utilities (ISIC C-E)
Other Manufacturing	Mining, Manufacturing, Utilities (ISIC C-E)
Recycling	Mining, Manufacturing, Utilities (ISIC C-E)
Construction	Construction (ISIC F)
Maintenance and Repair	Construction (ISIC F)
Wholesale Trade	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Retail Trade	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Hotels and Restaurants	Wholesale, retail trade, restaurants and hotels (ISIC G-H)
Transport	Transport, storage and communication (ISIC I)
Post and Telecommunications	Transport, storage and communication (ISIC I)
Financial Intermediation and Business Activities	Other Activities (ISIC J-P)
Public Administration	Other Activities (ISIC J-P)
Education, Health and Other Services	Other Activities (ISIC J-P)
Private Households	Other Activities (ISIC J-P)
Others	Other Activities (ISIC J-P)
Re-export & Re-import	Other Activities (ISIC J-P)

Notes: Author's classification based on Kunze (2021) and adapted to six UNSD sectors.

TABLE A4: Classification of countries by income group

Group	Countries
Advanced Economies	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Puerto Rico, San Marino, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Emerging Market Economies	Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, The Bahamas, Bahrain, Barbados, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Cabo Verde, Chile, China, Colombia, Costa Rica, Croatia, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Fiji, Gabon, Georgia, Grenada, Guatemala, Guyana, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kuwait, Lebanon, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Montenegro, Morocco, Namibia, Nauru, North Macedonia, Oman, Pakistan, Palau, Panama, Paraguay, Peru, Philippines, Poland, Qatar, Romania, Russia, Samoa, Saudi Arabia, Serbia, Seychelles, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Swaziland, Syria, Thailand, Timor-Leste, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Ukraine, United Arab Emirates, Uruguay, Vanuatu, Venezuela
Low-Income Developing Countries	Afghanistan, Bangladesh, Benin, Bhutan, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of Congo, Côte d'Ivoire, Djibouti, Eritrea, Ethiopia, The Gambia, Guinea, Guinea-Bissau, Haiti, Honduras, Kenya, Kiribati, Kyrgyz Republic, Lao P.D.R., Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Moldova, Mongolia, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, São Tomé and Príncipe, Tajikistan, Tanzania, Togo, Uganda, Uzbekistan, Vietnam, Yemen, Zambia, Zimbabwe

Notes: Author's classification based on IMF World Economic Outlook (IMF, 2022).

TABLE A5: Im-Pesaran-Shin unit-root test for main variables

	Statistic	p-value
GVA growth rate	-6.072	0.000
Abnormally dry precipitation shock (p^1)	-6.782	0.000
Abnormally dry precipitation shock (p^5)	-6.464	0.000
Abnormally dry precipitation shock (p^{10})	-6.456	0.000
Abnormally wet precipitation shock (p^{90})	-6.571	0.000
Abnormally wet precipitation shock (p^{95})	-6.600	0.000
Abnormally wet precipitation shock (p^{99})	-6.832	0.000
Abnormally cold temperature shock (p^1)	-6.541	0.000
Abnormally cold temperature shock (p^5)	-6.134	0.000
Abnormally cold temperature shock (p^{10})	-6.128	0.000
Abnormally hot temperature shock (p^{90})	-6.156	0.000
Abnormally hot temperature shock (p^{95})	-6.258	0.000
Abnormally hot temperature shock (p^{99})	-6.575	0.000

Notes: Null hypothesis of the unit-root test by Im et al. (2003) is that all panels contain unit roots against the alternative hypothesis that some panels are stationary. In performing the test, I do not include lags and remove cross-sectional means and include a time trend in the estimated equation. The test on the growth rate is performed on a balanced sector-country-year panel, whereas the test on weather variables is performed on a balanced country-year panel using population-weighted weather variables.

TABLE A6: Summary statistics on temperature and precipitation variables

	N	mean	SD	min	max
Temperature and precipitation					
Positive difference in daily temperature sum {0;1}	8,572	0.524	0.499	0	1
Positive difference in daily precipitation sum {0;1}	8,572	0.497	0.500	0	1
Changes in daily temperature sum ($\Delta^\circ\text{C}$)	8,572	9.556	197.755	-1594.597	1704.612
Changes in daily precipitation sum (Δ m)	8,572	0.0008	0.010	-0.092	0.095
Temperature above 95 th percentile (days/year)	8,572	18.986	16.5	0	152
Temperature below 5 th percentile (days/year)	8,572	17.870	14.185	0	156
Precipitation above 95 th percentile (days/year)	8,572	18.244	6.613	1	78
Precipitation below 5 th percentile (days/year)	8,572	15.633	10.182	0	86
Temperature above 90 th percentile (days/year)	8,548	37.487	23.610	0	222
Temperature below 10 th percentile (days/year)	8,548	35.907	21.023	0	210
Precipitation above 90 th percentile (days/year)	8,548	36.458	9.907	7	111
Precipitation below 10 th percentile (days/year)	8,548	32.390	16.367	0	114
Temperature above 99 th percentile (days/year)	8,548	3.851	6.145	0	94
Temperature below 1 th percentile (days/year)	8,548	3.563	4.892	0	54
Precipitation above 99 th percentile (days/year)	8,548	3.659	2.539	0	29
Precipitation below 1 th percentile (days/year)	8,548	2.474	3.187	0	32

Notes: Summary statistics are computed using country-year observations. Where Δ is indicated in parentheses, variables are in first-difference, measuring changes in weather conditions from the previous year.

TABLE A7: Annual (binary) changes in temperature and precipitation on sectoral GVA.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
Agriculture, hunting, forestry, fishing	-0.00676** (0.00297)	-0.00726** (0.00305)	-0.00773** (0.00300)
Construction	0.000787 (0.00401)	0.000861 (0.00403)	0.000352 (0.00403)
Mining, Manufacturing, Utilities	0.00229 (0.00251)	0.00205 (0.00253)	0.00162 (0.00256)
Other Activities	0.000665 (0.00183)	0.000697 (0.00184)	0.000157 (0.00183)
Transport, storage and communication	0.00410 (0.00266)	0.00423 (0.00271)	0.00370 (0.00272)
Wholesale, retail trade, restaurants and hotels	0.00284 (0.00260)	0.00266 (0.00264)	0.00220 (0.00266)
Precipitation			
Agriculture, hunting, forestry, fishing	0.0117*** (0.00291)	0.0122*** (0.00299)	0.0117*** (0.00293)
Construction	-0.00378 (0.00337)	-0.00349 (0.00331)	-0.00380 (0.00332)
Mining, Manufacturing, Utilities	-0.000347 (0.00278)	0.000191 (0.00285)	-0.000257 (0.00285)
Other Activities	-0.000128 (0.00171)	-0.00000690 (0.00177)	-0.000466 (0.00175)
Transport, storage and communication	-0.00514** (0.00233)	-0.00460* (0.00240)	-0.00505** (0.00238)
Wholesale, retail trade, restaurants and hotels	-0.000100 (0.00209)	0.000159 (0.00212)	-0.000298 (0.00213)
GVA growth rate _{t-1}		0.0618** (0.0264)	0.0399 (0.0257)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
<i>N</i>	51273	50162	50162
adj. <i>R</i> ²	0.043	0.046	0.060

Notes: The table reports the sector-specific coefficients associated with a binary variable equal to one if the annual temperature (resp. precipitation) is higher than the previous year. Standard errors are clustered at the country level. A graphical representation of the coefficients in column (2) is reported in Figure A4. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A8: Annual changes in temperature and precipitation on sectoral GVA.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature Changes			
Agriculture, hunting, forestry, fishing	-0.0351** (0.0144)	-0.0383** (0.0149)	-0.0379** (0.0149)
Construction	0.0402*** (0.0153)	0.0360** (0.0157)	0.0362** (0.0155)
Mining, Manufacturing, Utilities	0.0220* (0.0112)	0.0189 (0.0119)	0.0193 (0.0118)
Other Activities	0.00974 (0.00950)	0.00980 (0.00978)	0.0101 (0.00973)
Transport, storage and communication	0.0230* (0.0124)	0.0200 (0.0127)	0.0205 (0.0126)
Wholesale, retail trade, restaurants and hotels	0.0217 (0.0135)	0.0197 (0.0137)	0.0201 (0.0137)
Precipitation Changes			
Agriculture, hunting, forestry, fishing	0.0405*** (0.0114)	0.0417*** (0.0119)	0.0409*** (0.0117)
Construction	-0.00187 (0.0129)	0.00110 (0.0129)	0.000722 (0.0129)
Mining, Manufacturing, Utilities	0.0130 (0.0103)	0.0148 (0.0106)	0.0147 (0.0106)
Other Activities	0.00275 (0.00532)	0.00302 (0.00549)	0.00277 (0.00545)
Transport, storage and communication	-0.00857 (0.00821)	-0.00713 (0.00867)	-0.00744 (0.00851)
Wholesale, retail trade, restaurants and hotels	-0.00305 (0.00839)	-0.00207 (0.00846)	-0.00255 (0.00836)
GVA growth rate _{t-1}		0.0616** (0.0264)	0.0400 (0.0257)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
<i>N</i>	50223	49133	49133
adj. <i>R</i> ²	0.044	0.047	0.060

Notes: The table reports the (standardized) sector-specific coefficients associated with changes in annual temperature and precipitation distributions from the previous year's. Standard errors are clustered at the country-level. A graphical representation of the coefficients in column (2) is reported in Figure A5. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A9: Heterogeneous effects of annual changes in temperature and precipitation by income groups.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
<i>Advanced Economies</i>			
Agriculture	0.0272 (0.0176)	0.0287* (0.0153)	0.0284* (0.0151)
Construction	0.0668*** (0.0198)	0.0653*** (0.0170)	0.0651*** (0.0167)
Mining, Manufacturing, Utilities	0.0153** (0.00689)	0.0176** (0.00886)	0.0180** (0.00856)
Other Activities	0.00399 (0.00624)	0.00168 (0.00571)	0.00196 (0.00588)
Transport, storage and communication	0.00634 (0.0104)	0.00756 (0.0106)	0.00818 (0.0108)
Wholesale, retail trade, restaurants and hotels	0.0223*** (0.00844)	0.0176** (0.00720)	0.0177** (0.00716)
<i>Emerging Economies</i>			
Agriculture	-0.0804*** (0.0191)	-0.0844*** (0.0202)	-0.0845*** (0.0202)
Construction	0.0482 (0.0317)	0.0506 (0.0331)	0.0501 (0.0328)
Mining, Manufacturing, Utilities	0.0339 (0.0220)	0.0306 (0.0230)	0.0298 (0.0228)
Other Activities	0.0295 (0.0206)	0.0309 (0.0213)	0.0301 (0.0212)
Transport, storage and communication	0.0440* (0.0254)	0.0395 (0.0261)	0.0389 (0.0260)
Wholesale, retail trade, restaurants and hotels	0.0325 (0.0284)	0.0325 (0.0284)	0.0319 (0.0285)
<i>Low-Income Developing Countries</i>			
Agriculture	-0.0762** (0.0354)	-0.0888** (0.0380)	-0.0852** (0.0384)
Construction	0.0240 (0.0338)	-0.00530 (0.0314)	-0.00178 (0.0315)
Mining, Manufacturing, Utilities	0.0305 (0.0288)	0.0164 (0.0330)	0.0203 (0.0331)
Other Activities	-0.00853 (0.0199)	-0.00845 (0.0188)	-0.00471 (0.0189)
Transport, storage and communication	0.00991 (0.0206)	-0.00175 (0.0204)	0.00231 (0.0200)
Wholesale, retail trade, restaurants and hotels	-0.0119 (0.0331)	-0.0172 (0.0350)	-0.0128 (0.0347)
Precipitation			
<i>Advanced Economies</i>			
Agriculture	0.0650 (0.0446)	0.0608 (0.0450)	0.0605 (0.0442)
Construction	0.0139 (0.0212)	0.00437 (0.0203)	0.00500 (0.0200)
Mining, Manufacturing, Utilities	0.0107 (0.0158)	0.0179 (0.0166)	0.0173 (0.0163)
Other Activities	-0.00760 (0.00644)	-0.0148* (0.00756)	-0.0143* (0.00739)
Transport, storage and communication	-0.0101 (0.0134)	-0.0133 (0.0143)	-0.0130 (0.0137)
Wholesale, retail trade, restaurants and hotels	-0.00675 (0.0133)	-0.0141 (0.0126)	-0.0138 (0.0123)
<i>Emerging Economies</i>			
Agriculture	0.0225* (0.0132)	0.0222* (0.0133)	0.0217 (0.0132)
Construction	-0.0121 (0.0196)	-0.00820 (0.0190)	-0.00856 (0.0188)
Mining, Manufacturing, Utilities	0.00487 (0.00768)	0.00631 (0.00791)	0.00593 (0.00788)
Other Activities	0.0120 (0.00758)	0.0126* (0.00762)	0.0124 (0.00751)
Transport, storage and communication	-0.00251 (0.00680)	-0.00151 (0.00675)	-0.00166 (0.00664)
Wholesale, retail trade, restaurants and hotels	0.00435 (0.00955)	0.00520 (0.00969)	0.00505 (0.00945)
<i>Low-Income Developing Countries</i>			
Agriculture	0.0466** (0.0195)	0.0488** (0.0204)	0.0477** (0.0203)
Construction	0.0233 (0.0293)	0.0234 (0.0301)	0.0236 (0.0301)
Mining, Manufacturing, Utilities	-0.0111 (0.0144)	-0.00924 (0.0151)	-0.00957 (0.0149)
Other Activities	-0.0177 (0.0272)	-0.0153 (0.0273)	-0.0222 (0.0276)
Transport, storage and communication	-0.00977 (0.0241)	-0.00897 (0.0255)	-0.00955 (0.0251)
Wholesale, retail trade, restaurants and hotels	-0.0260 (0.0216)	-0.0237 (0.0216)	-0.0247 (0.0215)
GVA growth rate _{t-1}		0.0566** (0.0280)	0.0344 (0.0272)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
<i>N</i>	46243	45235	45235
adj. <i>R</i> ²	0.047	0.050	0.064

Notes: The table reports the (standardized) income group-sector-specific coefficients associated with changes in annual sum of daily temperature and precipitation. A graphical representation of the coefficients associated with temperature is reported in Figure A6a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A10: Heterogeneous effect of annual changes in temperature and precipitation by climate terciles.

	GVA per capita growth rate		
	(1)	(2)	(3)
Temperature			
<i>Cold Climate</i>			
Agriculture	-0.0105 (0.0173)	-0.0128 (0.0176)	-0.0138 (0.0176)
Construction	0.0769*** (0.0196)	0.0680*** (0.0194)	0.0675*** (0.0193)
Mining, Manufacturing, Utilities	0.0193 (0.0128)	0.0174 (0.0140)	0.0169 (0.0138)
Other Activities	0.0167 (0.0126)	0.0170 (0.0127)	0.0166 (0.0126)
Transport, storage and communication	0.0210 (0.0147)	0.0160 (0.0148)	0.0157 (0.0147)
Wholesale, retail trade, restaurants and hotels	0.0392** (0.0172)	0.0353** (0.0174)	0.0351** (0.0174)
<i>Temperate Climate</i>			
Agriculture	-0.101*** (0.0312)	-0.103*** (0.0319)	-0.0998*** (0.0321)
Construction	-0.0162 (0.0364)	-0.0108 (0.0376)	-0.00972 (0.0371)
Mining, Manufacturing, Utilities	0.0357 (0.0259)	0.0315 (0.0263)	0.0330 (0.0263)
Other Activities	0.00961 (0.0179)	0.00898 (0.0183)	0.00997 (0.0186)
Transport, storage and communication	0.0488* (0.0283)	0.0509* (0.0291)	0.0520* (0.0291)
Wholesale, retail trade, restaurants and hotels	0.0135 (0.0295)	0.0166 (0.0287)	0.0173 (0.0290)
<i>Hot Climate</i>			
Agriculture	-0.0413 (0.0396)	-0.0501 (0.0428)	-0.0470 (0.0425)
Construction	-0.0491 (0.0321)	-0.0471 (0.0323)	-0.0438 (0.0321)
Mining, Manufacturing, Utilities	0.0112 (0.0308)	0.00361 (0.0320)	0.00781 (0.0319)
Other Activities	-0.0260 (0.0184)	-0.0274 (0.0195)	-0.0242 (0.0194)
Transport, storage and communication	-0.0125 (0.0203)	-0.0157 (0.0207)	-0.0118 (0.0203)
Wholesale, retail trade, restaurants and hotels	-0.0555** (0.0235)	-0.0585** (0.0234)	-0.0552** (0.0234)
Precipitation			
<i>Cold Climate</i>			
Agriculture	0.0389* (0.0205)	0.0395* (0.0207)	0.0405** (0.0205)
Construction	-0.00982 (0.0179)	-0.00897 (0.0177)	-0.00710 (0.0176)
Mining, Manufacturing, Utilities	0.0179 (0.0137)	0.0213 (0.0131)	0.0234* (0.0131)
Other Activities	0.00360 (0.00786)	-0.000150 (0.00783)	0.00119 (0.00775)
Transport, storage and communication	-0.00287 (0.0151)	0.000371 (0.0157)	0.00132 (0.0151)
Wholesale, retail trade, restaurants and hotels	-0.0134 (0.0139)	-0.0154 (0.0136)	-0.0146 (0.0134)
<i>Temperate Climate</i>			
Agriculture	0.0417* (0.0216)	0.0428* (0.0224)	0.0411* (0.0222)
Construction	0.00512 (0.0180)	0.00888 (0.0173)	0.00813 (0.0174)
Mining, Manufacturing, Utilities	0.0151 (0.0156)	0.0170 (0.0158)	0.0163 (0.0159)
Other Activities	0.0114 (0.00801)	0.0127 (0.00808)	0.0118 (0.00808)
Transport, storage and communication	0.0113 (0.0104)	0.0131 (0.0108)	0.0122 (0.0108)
Wholesale, retail trade, restaurants and hotels	0.0208* (0.0122)	0.0218* (0.0127)	0.0211* (0.0125)
<i>Hot Climate</i>			
Agriculture	0.0271* (0.0156)	0.0279* (0.0164)	0.0277* (0.0162)
Construction	-0.0193 (0.0248)	-0.0146 (0.0251)	-0.0154 (0.0249)
Mining, Manufacturing, Utilities	0.00861 (0.0209)	0.00897 (0.0218)	0.00857 (0.0218)
Other Activities	-0.00974 (0.0101)	-0.00862 (0.0106)	-0.00881 (0.0105)
Transport, storage and communication	-0.0319** (0.0153)	-0.0314* (0.0163)	-0.0313* (0.0159)
Wholesale, retail trade, restaurants and hotels	-0.0296* (0.0154)	-0.0268* (0.0155)	-0.0274* (0.0154)
GVA growth rate _{t-1}		0.0620** (0.0264)	0.0404 (0.0258)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends			✓
Country quadratic time trends			✓
<i>N</i>	50223	49133	49133
adj. <i>R</i> ²	0.044	0.047	0.060

Notes: The table reports the (standardized) climate tercile-sector-specific coefficients associated with binary variables indicating positive changes in annual sum of daily temperature and precipitation. A graphical representation of the coefficients associated with temperature is reported in Figure A6a. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A11: Dryness and wetness shocks and sectoral GVA.

	Average dryness (1)	Extreme drought prevalence (2)	Extreme wetness prevalence (3)
Agriculture, hunting, forestry, fishing	-0.119*** (0.0197)	-0.0733*** (0.0126)	-0.00346 (0.0116)
Construction	0.0184 (0.0156)	0.0281** (0.0135)	-0.00293 (0.0133)
Mining, Manufacturing, Utilities	0.000256 (0.0162)	0.00354 (0.0102)	0.00218 (0.00818)
Other Activities	0.00204 (0.00813)	-0.000846 (0.00459)	0.00545 (0.00474)
Transport, storage and communication	0.0184 (0.0119)	0.0143 (0.00916)	-0.00588 (0.00785)
Wholesale, retail trade, restaurants and hotels	0.00414 (0.0117)	-0.00304 (0.00846)	0.00900 (0.00869)
GVA growth rate _{t-1}	0.0687** (0.0282)	0.0605** (0.0263)	0.0605** (0.0263)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
<i>N</i>	35911	49578	49578
adj. <i>R</i> ²	0.049	0.047	0.046

Notes: The table reports the (standardized) sector-specific coefficients associated with the three measures in first difference constructed from the SPEI database. A graphical representation of the coefficients is reported in Figure A13. Column (1) uses a measure of average dryness (as the average of monthly negative realizations of SPEI in each country), column (2) uses extreme drought prevalence as the maximum share of grid-months with extreme drought conditions (SPEI<-2); column (3) uses extreme wetness as the maximum share of grid-months with extreme wetness conditions (SPEI>2) in a country in a year. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A12: Tropical cyclones and sectoral GVA.

	GVA per capita growth rate		
	(1)	(2)	(3)
Agriculture, hunting, forestry, fishing	-0.0288** (0.0125)	-0.0297** (0.0126)	-0.0315*** (0.0119)
Construction	-0.00735 (0.00642)	-0.00749 (0.00648)	-0.00717 (0.00651)
Mining, Manufacturing, Utilities	-0.000445 (0.00723)	-0.000488 (0.00737)	0.000405 (0.00767)
Other Activities	-0.00500* (0.00278)	-0.00504* (0.00282)	-0.00603** (0.00289)
Transport, storage and communication	-0.00101 (0.00404)	-0.00107 (0.00410)	-0.000670 (0.00376)
Wholesale, retail trade, restaurants and hotels	-0.00444 (0.00641)	-0.00463 (0.00637)	-0.00412 (0.00657)
GVA growth rate _{t-1}		0.0262 (0.0259)	0.0417 (0.0264)
Country-Sector FE	✓	✓	✓
Sector-Year FE	✓	✓	✓
Country linear time trends		✓	✓
Country quadratic time trends			✓
<i>N</i>	44167	44167	44167
adj. <i>R</i> ²	0.053	0.053	0.053

Notes: The table reports the sector-specific (standardized) coefficients associated with the changes in wind speed as constructed in Kunze (2021). A graphical representation of the coefficients estimated in column (1) is reported in Figure A15. Standard errors are clustered at the country-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Tropical cyclones data are available until 2015.

TABLE A13: Sector-country damages (% loss GVA per capita) significant at 95% level

Country	Sector	Average loss	95% CI	Country	Sector	Average loss	95% CI	Country	Sector	Average loss	95% CI
Afghanistan	Agriculture	1.25	[0.74 ; 1.78]	Japan	Agriculture	0.82	[0.40 ; 1.26]	Ukraine	Agriculture	1.21	[0.58 ; 1.86]
Albania	Agriculture	1.39	[0.81 ; 1.97]	Jordan	Agriculture	1.12	[0.53 ; 1.73]	Uruguay	Agriculture	1.39	[0.77 ; 2.02]
Algeria	Agriculture	1.37	[0.81 ; 1.96]	Kenya	Agriculture	0.99	[0.41 ; 1.58]	Uzbekistan	Agriculture	1.81	[0.71 ; 2.84]
Andorra	Agriculture	1.35	[0.80 ; 1.94]	Kuwait	Agriculture	1.11	[0.53 ; 1.71]	Vannatu	Agriculture	1.35	[0.81 ; 1.93]
Angola	Agriculture	1.74	[0.99 ; 2.50]	Kyrgyzstan	Agriculture	0.91	[0.43 ; 1.41]	Venezuela	Agriculture	1.85	[0.94 ; 2.75]
Antigua	Agriculture	1.62	[0.93 ; 2.32]	Laos	Agriculture	1.12	[0.54 ; 1.72]	Viet Nam	Agriculture	2.03	[0.93 ; 3.12]
Argentina	Agriculture	1.30	[0.76 ; 1.88]	Latvia	Agriculture	1.03	[0.49 ; 1.59]	Yemen	Agriculture	1.53	[0.81 ; 2.24]
Armenia	Agriculture	1.19	[0.67 ; 1.72]	Lebanon	Agriculture	1.13	[0.54 ; 1.73]	Zambia	Agriculture	1.34	[0.79 ; 1.91]
Aruba	Agriculture	1.31	[0.68 ; 1.95]	Lesotho	Agriculture	1.09	[0.52 ; 1.68]	Zimbabwe	Agriculture	1.17	[0.68 ; 1.68]
Australia	Agriculture	1.27	[0.75 ; 1.82]	Liberia	Agriculture	1.03	[0.49 ; 1.59]	Afghanistan	Construction	1.65	[0.26 ; 2.97]
Austria	Agriculture	1.33	[0.79 ; 1.92]	Libya	Agriculture	1.07	[0.51 ; 1.63]	Azerbaijan	Construction	1.59	[0.07 ; 3.04]
Azerbaijan	Agriculture	1.11	[0.61 ; 1.61]	Liechtenstein	Agriculture	1.08	[0.52 ; 1.66]	Angola	Construction	2.30	[0.61 ; 3.77]
Bahamas	Agriculture	1.70	[1.00 ; 2.45]	Lithuania	Agriculture	1.06	[0.50 ; 1.64]	Antigua	Construction	1.49	[0.13 ; 2.74]
Bahrain	Agriculture	1.45	[0.85 ; 2.09]	Luxembourg	Agriculture	1.00	[0.47 ; 1.55]	Armenia	Construction	2.08	[0.53 ; 3.52]
Bangladesh	Agriculture	1.28	[0.74 ; 1.84]	Madagascar	Agriculture	1.26	[0.56 ; 1.94]	Aruba	Construction	3.69	[1.44 ; 5.73]
Barbados	Agriculture	1.71	[0.96 ; 2.46]	Malawi	Agriculture	1.06	[0.52 ; 1.62]	Austria	Construction	1.70	[0.26 ; 3.07]
Belarus	Agriculture	1.20	[0.64 ; 1.78]	Malaysia	Agriculture	1.16	[0.47 ; 1.86]	Bahrain	Construction	1.98	[0.46 ; 3.39]
Belgium	Agriculture	1.20	[0.71 ; 1.71]	Maldives	Agriculture	1.01	[0.43 ; 1.60]	Bangladesh	Construction	1.49	[0.09 ; 2.83]
Belize	Agriculture	1.69	[1.00 ; 2.41]	Mali	Agriculture	1.09	[0.52 ; 1.68]	Barbados	Construction	1.92	[0.38 ; 3.25]
Benin	Agriculture	1.34	[0.78 ; 1.91]	Malta	Agriculture	-0.11	[-0.18 ; -0.04]	Belgium	Construction	1.25	[0.02 ; 2.41]
Bermuda	Agriculture	1.58	[0.91 ; 2.28]	Mauritania	Agriculture	1.03	[0.50 ; 1.58]	Benin	Construction	1.77	[0.43 ; 2.94]
Bhutan	Agriculture	1.63	[0.94 ; 2.34]	Mauritius	Agriculture	0.96	[0.36 ; 1.55]	Bhutan	Construction	2.67	[0.79 ; 4.41]
Bolivia	Agriculture	1.78	[1.01 ; 2.56]	Mexico	Agriculture	1.17	[0.56 ; 1.80]	Bosnia and Herzegovina	Construction	1.38	[0.04 ; 2.67]
Bosnia and Herzegovina	Agriculture	1.43	[0.85 ; 2.05]	Moldova	Agriculture	1.23	[0.59 ; 1.88]	Brazil	Construction	1.39	[0.07 ; 2.63]
Bswana	Agriculture	1.30	[0.77 ; 1.87]	Mongolia	Agriculture	1.21	[0.57 ; 1.86]	Brunei	Construction	2.16	[0.62 ; 3.50]
Brazil	Agriculture	1.66	[0.95 ; 2.39]	Montenegro	Agriculture	1.22	[0.58 ; 1.86]	Bulgaria	Construction	1.43	[0.02 ; 2.77]
British Virgin Islands	Agriculture	1.62	[0.95 ; 2.31]	Morocco	Agriculture	1.01	[0.48 ; 1.55]	Burundi	Construction	1.47	[0.22 ; 2.58]
Brunei	Agriculture	1.57	[0.90 ; 2.26]	Mozambique	Agriculture	1.04	[0.50 ; 1.61]	Cambodia	Construction	1.61	[0.33 ; 2.74]
Bulgaria	Agriculture	1.27	[0.69 ; 1.88]	Myanmar	Agriculture	0.62	[0.29 ; 0.96]	Cambodia	Construction	2.02	[0.51 ; 3.52]
Burkina Faso	Agriculture	1.25	[0.70 ; 1.80]	Namibia	Agriculture	1.16	[0.55 ; 1.79]	Cape Verde	Construction	1.44	[0.07 ; 2.73]
Burundi	Agriculture	1.39	[0.80 ; 2.00]	Nepal	Agriculture	0.98	[0.46 ; 1.52]	Cayman Islands	Construction	1.76	[0.19 ; 3.25]
Cambodia	Agriculture	1.21	[0.71 ; 1.72]	Netherlands	Agriculture	1.00	[0.48 ; 1.53]	Central African Republic	Construction	1.54	[0.24 ; 2.66]
Cameroon	Agriculture	1.39	[0.79 ; 2.00]	New Caledonia	Agriculture	1.03	[0.50 ; 1.58]	Chad	Construction	1.45	[0.03 ; 2.81]
Canada	Agriculture	1.00	[0.58 ; 1.45]	New Zealand	Agriculture	0.89	[0.41 ; 1.38]	Colombia	Construction	1.60	[0.16 ; 2.88]
Cape Verde	Agriculture	1.65	[0.94 ; 2.37]	Nicaragua	Agriculture	0.91	[0.40 ; 1.41]	Congo	Construction	2.14	[0.56 ; 3.52]
Cayman Islands	Agriculture	1.75	[1.01 ; 2.51]	Niger	Agriculture	1.12	[0.54 ; 1.72]	Costa Rica	Construction	1.31	[0.17 ; 2.38]
Central African Republic	Agriculture	1.45	[0.86 ; 2.06]	Nigeria	Agriculture	1.18	[0.56 ; 1.81]	France	Construction	1.28	[0.01 ; 2.50]
Chad	Agriculture	1.52	[0.87 ; 2.20]	North Korea	Agriculture	0.53	[0.19 ; 0.87]	French Polynesia	Construction	1.61	[0.29 ; 2.81]
Chile	Agriculture	1.30	[0.76 ; 1.86]	Norway	Agriculture	0.91	[0.43 ; 1.39]	Gabon	Construction	2.17	[0.64 ; 3.55]
China	Agriculture	0.84	[0.44 ; 1.26]	Oman	Agriculture	1.23	[0.56 ; 1.90]	Gambia	Construction	1.37	[0.10 ; 2.60]
Colombia	Agriculture	1.60	[0.87 ; 2.34]	Pakistan	Agriculture	0.86	[0.40 ; 1.32]	Gambia	Construction	1.40	[0.97 ; 2.67]
Congo	Agriculture	1.50	[0.85 ; 2.17]	Pakistan	Agriculture	1.00	[0.43 ; 1.59]	Rwanda	Construction	2.20	[0.60 ; 3.88]
Costa Rica	Agriculture	0.89	[0.45 ; 1.32]	Papua New Guinea	Agriculture	1.35	[0.57 ; 2.12]	Saudi Arabia	Construction	2.15	[0.44 ; 3.65]
Cote d'Ivoire	Agriculture	1.01	[0.43 ; 1.58]	Paraguay	Agriculture	1.07	[0.50 ; 1.64]	Senegal	Construction	1.17	[0.03 ; 2.27]
Croatia	Agriculture	1.15	[0.55 ; 1.76]	Peru	Agriculture	0.92	[0.39 ; 1.45]	Serbia	Construction	1.42	[0.06 ; 2.72]
Cuba	Agriculture	1.24	[0.60 ; 1.90]	Philippines	Agriculture	1.14	[0.48 ; 1.81]	Slovakia	Construction	1.45	[0.07 ; 2.77]
Cyprus	Agriculture	1.09	[0.52 ; 1.68]	Poland	Agriculture	1.13	[0.54 ; 1.73]	Slovenia	Construction	2.01	[0.43 ; 3.48]
Czech Republic	Agriculture	1.09	[0.52 ; 1.67]	Portugal	Agriculture	1.00	[0.47 ; 1.55]	Somalia	Construction	1.57	[0.17 ; 2.92]
DR Congo	Agriculture	1.18	[0.59 ; 1.88]	Qatar	Agriculture	1.19	[0.56 ; 1.84]	Spain	Construction	2.00	[0.14 ; 3.72]
Denmark	Agriculture	1.01	[0.48 ; 1.54]	Romania	Agriculture	1.44	[0.86 ; 2.07]	Venezuela	Construction	2.02	[0.46 ; 3.37]
Djibouti	Agriculture	1.14	[0.54 ; 1.74]	Russia	Agriculture	1.38	[0.82 ; 1.99]	Aruba	Mining, manufacturing, utilities	1.62	[0.55 ; 3.38]
Dominican Republic	Agriculture	1.22	[0.54 ; 1.88]	Rwanda	Agriculture	1.75	[0.95 ; 2.53]	Colombia	Mining, manufacturing, utilities	2.30	[0.89 ; 4.62]
Ecuador	Agriculture	1.29	[0.56 ; 2.01]	San Marino	Agriculture	1.41	[0.83 ; 2.03]	Spain	Mining, manufacturing, utilities	1.09	[0.09 ; 2.34]
Egypt	Agriculture	1.21	[0.55 ; 1.86]	Sao Tome and Principe	Agriculture	1.10	[0.66 ; 1.58]	Aruba	Other activities	1.32	[0.27 ; 2.48]
El Salvador	Agriculture	1.17	[0.56 ; 1.80]	Saudi Arabia	Agriculture	1.82	[1.04 ; 2.63]	Australia	Other activities	0.57	[0.05 ; 1.07]
Eritrea	Agriculture	1.15	[0.55 ; 1.76]	Senegal	Agriculture	1.16	[0.69 ; 1.67]	Bermuda	Other activities	0.72	[0.10 ; 1.37]
Estonia	Agriculture	0.99	[0.47 ; 1.52]	Serbia	Agriculture	1.25	[0.71 ; 1.80]	Cayman Islands	Other activities	0.73	[0.07 ; 1.42]
Ethiopia	Agriculture	1.09	[0.46 ; 1.72]	Seychelles	Agriculture	1.43	[0.82 ; 2.06]	France	Other activities	0.56	[0.04 ; 1.06]
Fiji	Agriculture	1.16	[0.56 ; 1.78]	Sierra Leone	Agriculture	1.17	[0.69 ; 1.68]	Germany	Other activities	0.57	[0.08 ; 1.14]
Finland	Agriculture	0.94	[0.44 ; 1.45]	Singapore	Agriculture	1.23	[0.55 ; 1.90]	Spain	Other activities	1.48	[0.77 ; 2.65]
France	Agriculture	1.31	[0.77 ; 1.87]	Slovakia	Agriculture	1.33	[0.77 ; 1.89]	Aruba	Transport, storage, communications	2.02	[0.58 ; 3.42]
French Polynesia	Agriculture	1.38	[0.81 ; 1.97]	Slovenia	Agriculture	1.40	[0.83 ; 2.01]	Australia	Transport, storage, communications	0.69	[0.00 ; 1.35]
Gabon	Agriculture	1.28	[0.60 ; 1.95]	Somalia	Agriculture	1.47	[0.82 ; 2.13]	Bolivia	Transport, storage, communications	0.96	[0.03 ; 1.86]
Gambia	Agriculture	1.41	[0.80 ; 2.04]	South Africa	Agriculture	1.39	[0.83 ; 2.00]	Russia	Transport, storage, communications	1.77	[0.01 ; 4.49]
Gaza Strip	Agriculture	1.22	[0.56 ; 1.88]	South Korea	Agriculture	0.80	[0.37 ; 1.24]	Singapore	Transport, storage, communications	1.71	[0.48 ; 2.94]
Georgia	Agriculture	1.14	[0.56 ; 1.74]	Spain	Agriculture	1.21	[0.41 ; 1.94]	Uzbekistan	Transport, storage, communications	1.06	[0.22 ; 1.86]
Germany	Agriculture	1.05	[0.51 ; 1.61]	Sri Lanka	Agriculture	0.90	[0.43 ; 1.38]	Bahamas	Wholesale, retail, hotel, restaurant	1.19	[0.30 ; 2.07]
Ghana	Agriculture	1.05	[0.45 ; 1.65]	Suriname	Agriculture	1.05	[0.44 ; 1.66]	Bahrain	Wholesale, retail, hotel, restaurant	0.79	[0.09 ; 1.47]
Greece	Agriculture	1.22	[0.59 ; 1.87]	Swaziland	Agriculture	0.91	[0.43 ; 1.40]	Belgium	Wholesale, retail, hotel, restaurant	0.83	[0.16 ; 1.49]
Greenland	Agriculture	1.09	[0.47 ; 1.70]	Sweden	Agriculture	0.96	[0.46 ; 1.47]	Bermuda	Wholesale, retail, hotel, restaurant	0.85	[0.10 ; 1.58]
Guatemala	Agriculture	1.19	[0.55 ; 1.83]	Switzerland	Agriculture	1.10	[0.52 ; 1.68]	Brazil	Wholesale, retail, hotel, restaurant	0.81	[0.09 ; 1.51]
Guinea	Agriculture	0.92	[0.43 ; 1.42]	Syria	Agriculture	1.16	[0.55 ; 1.79]	Burkina Faso	Wholesale, retail, hotel, restaurant	1.76	[0.07 ; 4.42]
Guyana	Agriculture	1.10	[0.47 ; 1.75]	TFYR Macedonia	Agriculture	1.15	[0.55 ; 1.76]	Russia	Wholesale, retail, hotel, restaurant	1.08	[0.33 ; 1.84]
Haiti	Agriculture	1.13	[0.51 ; 1.74]	Tajikistan	Agriculture	0.98	[0.47 ; 1.52]	Saudi Arabia	Wholesale, retail, hotel, restaurant	0.84	[0.01 ; 1.61]
Honduras	Agriculture	1.09	[0.52 ; 1.66]	Tanzania	Agriculture	1.29	[0.56 ; 2.01]	Sierra Leone	Wholesale, retail, hotel, restaurant	1.92	[0.93 ; 2.92]
Hungary	Agriculture	1.08	[0.51 ; 1.66]	Thailand	Agriculture	0.90	[0.43 ; 1.38]	Singapore	Wholesale, retail, hotel, restaurant	1.33	[0.51 ; 2.14]
Iceland	Agriculture	1.08	[0.47 ; 1.69]	Togo	Agriculture	0.99	[0.43 ; 1.55]	Spain	Wholesale, retail, hotel, restaurant	1.21	[0.29 ; 2.80]
India	Agriculture	0.93	[0.45 ; 1.42]	Trinidad and Tobago	Agriculture	1.24	[0.50 ; 1.98]	Viet Nam	Wholesale, retail, hotel, restaurant	0.93	[0.17 ; 1.66]
Indonesia	Agriculture	1.22	[0.44 ; 2.00]	Tunisia	Agriculture	1.12	[0.54 ; 1.72]				
Iran	Agriculture	1.01	[0.46 ; 1.55]	Turkey	Agriculture	1.19	[0.57 ; 1.83]				
Iraq	Agriculture	0.91	[0.44 ; 1.40]	Turkmenistan	Agriculture	0.91	[0.43 ; 1.40]				
Ireland	Agriculture	0.87	[0.40 ; 1.34]	UAE	Agriculture	1.24	[0.62 ; 1.88]				
Israel	Agriculture	1.22	[0.56 ; 1.88]	UK	Agriculture	1.01	[0.51 ; 1.52]				
Italy	Agriculture	1.21	[0.58 ; 1.85]	USA	Agriculture	1.04	[0.50 ; 1.58]				
Jamaica	Agriculture	1.23	[0.53 ; 1.94]	Uganda	Agriculture	1.04	[0.44 ; 1.64]				

Notes: The table reports the average loss for each sector as a % loss in GVA per capita relative to the observed production between 2001 and 2020, accounting for own, domestic and foreign heat and cold shocks. 95% confidence intervals are obtained from 1000 estimates from bootstrapping Equation 1.12, where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade.

A.3 Additional weather data

A.3.1 Dryness and wetness

To introduce a measure of dryness and wetness, I use the Standardized Precipitation Evapotranspiration Index (SPEI), a climatological index used by climate scientists to measure dry and wet periods that combines temperature variability, precipitation and potential evapotranspiration to estimate cumulative deviations in soil moisture from normal conditions. This index compares the amount of precipitation in a given area with its evapotranspiration needs, which are a function of temperature. This measure is considered superior to indices that only use information on rainfall to predict droughts caused by climate change.

Vicente-Serrano et al. (2010) show that the effects of increasing temperatures on droughts predicted by global climate models can be clearly seen in the SPEI, whereas indices based only on precipitation data such as the Standardized Precipitation Index (SPI) do not reflect expected changes in drought conditions. The SPEI also outperforms another drought index, the Palmer Drought Severity Index (PDSI) (Palmer, 1965), which lacks the multiscalar character essential for assessing drought in relation to different hydrological systems. By combining the sensitivity of PDSI to changes in evaporation demand, caused by temperature fluctuations and trends, with the multitemporal nature of the SPI, the SPEI is the most accurate climatological measure of dryness and wetness (Vicente-Serrano et al., 2012). To allow for water deficit accumulation over the entire year, I use the SPEI-12, the version of SPEI computed at a 12 months time scale.

The SPEI is constructed using monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia and it is normally distributed within each grid cell with $0.5^\circ \times 0.5^\circ$ resolution (around 56 km at the Equator). Negative values represent conditions drier than the historical average, whereas positive values represent conditions wetter than the historical average. For example, a value of SPEI equal to -1 can be interpreted as the difference between rain and potential evapotranspiration needs being one standard deviation lower than the historical average for a given grid cell.

I construct two types of measures of dryness and wetness. First, I take a weighted average of the negative monthly values in each country and obtain the average annual dryness with respect to historical conditions. Second, to capture extreme conditions during a year I build two variables measuring the share of total grid-months subject to extreme droughts (with SPEI below -2) (Paulo et al., 2012; McKee et al., 1993), and to periods with extreme wetness (with SPEI above 2). For each year, I consider the share of affected grid-cells in the month where the share is at its maximum (Akyapi et al., 2022).

A.3.2 Tropical cyclones

The last type of extreme weather event I consider is tropical cyclones. The measure of tropical cyclones is taken from Kunze (2021), who uses meteorological data on wind speeds to obtain a measure of damage of tropical cyclones as previously introduced in the literature (Hsiang, 2010; Bakkensen and Barrage, 2018; Hsiang and Jina, 2014). The annual measure of tropical cyclones at the country level is a non-linear function of wind speed which includes the cube of wind speed when wind speed is above a 92 km/h threshold, where wind speed is computed accounting for the maximum sustained wind speed, the forward speed, the distance from the storm center and the radius of the maximum wind (see Kunze (2021) for additional methodological details).

A.4 Sectoral interlinkages' response to heat shocks

One of the main assumptions in the theoretical framework in Section 1.2 and the derived empirical approach in Section 1.3.3 is that weather shocks affect economic production via spillovers in a pre-determined exogenous production network that does not adjust in response to weather shocks. This assumption has been shown to hold empirically, reflecting the non-responsiveness of sectoral interlinkages to tropical cyclones exposure mostly due to the stickiness of production processes (Kunze, 2021). I empirically test this assumption by exploiting the time-varying nature of the sectoral interlinkages between 1970 and 2019. I estimate the following specification

$$\text{weight}_{icjkt} = f_i(\mathbf{W}_{ct}) + \alpha_{ic} + \mu_{ij} + \lambda_{jkt} + \varepsilon_{icjkt} \quad (\text{A.1})$$

where the dependent variable $\text{weight}_{icjkt} \in \{\omega; \hat{\omega}; \bar{\omega}\}$, respectively the downstream, upstream and average interlinkage between sector i in country c and sector j in country k in year t . The objective is to exploit inter-annual variation in weather conditions in the origin sector-country ic to test for within bilateral sector ij changes in interlinkages across countries. Given the level of aggregation of the sectors, the major concern on the endogenous adjustment of the production network regards the potential substitution of inputs across trade partners for a given sector. For this reason, the specification accounts for sector-country ic , origin-destination sector ij , and destination sector-country-year jkt fixed effects, where the latter accounts for changes in weather conditions in the destination country. Figure A3 reports the sector-specific coefficients associated with heat shocks on the three measures of sectoral interlinkages, displaying a small and not statistically significant effect across sectors and suggesting that the production network does not endogenously adapt to heat shocks.

A.5 Time-varying production network

Production linkages have intensified over time with more fragmented global supply chains and intensive use of intermediate inputs produced in other domestic and foreign industries. In subsequent robustness checks, I relax the assumption that weather shocks affect economic production via spillovers in a pre-determined exogenous production network. To allow for slow-moving adjustments, I construct decade-specific time-varying production network. I retain the average of the first five-year input-output sectoral interlinkages for each decade τ (e.g., 1970-1974 average for shocks between 1975 and 1984; 1980-1984 average for shocks between 1985 and 1994), such that the downstream weights are constructed as

$$\omega_{i,c,j,k,\tau} = \frac{\overline{input}_{jk\tau \rightarrow ic\tau}}{\sum_{lf \in \Theta_{ic}} \overline{input}_{ic\tau \rightarrow lf\tau}} \quad (\text{A.2})$$

and upstream weights are constructed as

$$\hat{\omega}_{i,c,j,k,\tau} = \frac{\overline{input}_{ic\tau \rightarrow jk\tau}}{\sum_{lf \in \Theta_{ic}} \overline{input}_{ic\tau \rightarrow lf\tau}} \quad (\text{A.3})$$

From this, the construction of network shocks follows as detailed in Section 1.3.3.

A.6 Reduced-form approach to the climate-economy relationship

Kahn et al. (2021) review the three main approaches that study the climate-economy relationship in reduced form in the literature (Dell et al., 2012; Burke et al., 2015b; Kalkuhl and Wenz, 2020), highlighting the restrictive assumptions that each of these models requires to study the effect of temperature on output growth. In this Appendix section, I report an extension of these approaches discussed in Newell et al. (2021) and discuss the assumptions that it relies on. In an attempt to deal with the non-stationarity issue of trended temperatures and allow for the non-linear effect of temperature changes, one could include higher-order polynomials of first-differenced temperature as main regressors (as in Ortiz-Bobea et al. (2021)). Without loss of generality, the estimating equation considering only a second-order polynomial of differenced temperature is written as

$$\Delta y_{it} = \alpha_i + \delta_t + \lambda \Delta T_{it} + \psi \Delta [T_{it}^2] + \varepsilon_{it} \quad (\text{A.4})$$

which uses the growth rate of log-differences of real GDP per capita of country i in year t as the dependent variable, the main regressors are the linear and quadratic differenced temperature, where the latter term is the change in temperature-squared (different from the squared change in temperature), a_i is the country-specific fixed effect and δ_t is the time-specific fixed effect. As in Kahn et al. (2021) and motivated by historical evidence, I assume that

$$T_{it} = a_{T_i} + b_{T_i} t + \nu_{T_{i,t}} \quad (\text{A.5})$$

where, in line with historical evidence, $b_{T_i} > 0$, and $\mathbb{E}(\nu_{T_{i,t}}) = 0$ and $\mathbb{E}(\nu_{T_{i,t}}^2) = \sigma_{T_i}^2$. Substituting Equation (A.5) in Equation (A.4) and taking expectations yields

$$\mathbb{E}(\Delta y_{it}) = \mathbb{E}(\delta_t) + \alpha_i + b_{T_i} [\lambda + 2\psi a_{T_i}] + 2\psi b_{T_i}^2 t \quad (\text{A.6})$$

To ensure that $\mathbb{E}(\Delta y_{it})$ is not trended, there are some restrictions to impose. First, since δ_t is unobserved, one can set $\mathbb{E}(\delta_t) = 0$ (Kahn et al., 2021), and then require that $2\psi b_{T_i}^2 t = 0$ for all i . Therefore, this approach does not resolve the trend problem around the output growth-climate specifications, introducing a trend in the mean output growth, which is not supported empirically. An alternative approach would be to include region-year rt fixed effects in Equation (A.4), such that it becomes

$$\Delta y_{irt} = \alpha_{ir} + \delta_{rt} + \lambda \Delta T_{irt} + \psi \Delta [T_{irt}^2] + \varepsilon_{irt} \quad (\text{A.7})$$

with $T_{irt} = a_{T_{i,r}} + b_{T_{i,r}} t + \nu_{T_{i,r,t}}$, where the shock $\nu_{T_{i,r,t}}$ for country i in region r in year t has zero mean and finite variance. Taking expectations as above, to have

that $\mathbb{E}(\Delta y_{irt})$ is stationary, one would require no trend in temperature $b_{Ti;r} = 0$, or exact cancellation of quadratic trends in temperature at the regional level with the region-year fixed effects, i.e. $\delta_{rt} + \psi \bar{b}_{Tr}^2 t = 0$, for all r , where $\bar{b}_{Tr}^2 = \frac{1}{n} \sum_{i=1}^{n_r} b_{Ti,r}^2$.

A.7 Changes in temperature and precipitation distribution

To provide additional evidence on the heterogeneous sectoral response to weather shocks, I consider first-differenced weather changes. First, I construct a binary measure of annual changes in temperature and precipitation distribution either larger or smaller than the previous year. Then, I consider how much daily temperatures and precipitation are larger/smaller than the previous year. Table A6 shows summary statistics for the measures of temperature and precipitation.

Figure A4 displays the 12 estimated coefficients from the same pooled regression using a binary measure of weather shock indicating whether first-differenced annual changes in daily average temperature and total precipitation are positive or negative. Consistent with prior literature (e.g., Acevedo et al. (2020)), I uncover substantial heterogeneity across sectors in the multicountry sample. The agricultural sector responds the most to both temperature and precipitation fluctuations. In particular, if the daily average temperature is larger than in the previous year, the agricultural GVA growth rate decreases by 0.7 percentage points (point estimates are reported in Table A7), which translates into a 284% decrease with respect to the sample average (0.002). The effect is large but comparable to previous estimates on the effect of heat waves and tropical cyclones on agricultural growth rates (Miller et al., 2021; Kunze, 2021). In contrast, agriculture benefits from more precipitation, as documented in prior literature (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Cunado and Ferreira, 2014). The only other sector that responds elastically to variations in annual temperature and precipitation distribution is transport, storage and communication, which marginally benefits from hotter (15% increase of sample mean) and drier (17% increase of sample mean) conditions that, for instance, facilitate transportation and storage and service communication.

I further investigate the effect of changes in the average daily temperature and precipitation distribution with the variables standardized to facilitate comparison. Figure A5 shows the estimated coefficients (see Table A8 for tabular results). As previously documented, agriculture reacts negatively to hot temperature shocks but benefits from more precipitation. In particular, a 0.01°C daily increase with respect to the previous year's temperature (around 30% of the sample mean) is associated with a decrease in the agricultural per capita growth rate by 3% of the sample mean. Surprisingly, all the other sectors respond positively to increases in the average daily temperatures, although a few sectors' responses are estimated with less precision (other activities; transport, storage and communication; wholesale, retail trade, restaurants and hotels). In contrast, production in other sectors does not respond to changes in precipitation, except for the transportation sector which benefits from drier conditions.

Heterogeneity across adaptation potential. Until now, results referred to the average treatment effect for each sector across countries. One may however expect the marginal effect of changes in the temperature distribution to differ as a result of factors that influence the adaptation potential of countries, namely climate and income. First, a hotter climate may differentially incentivize governments and individuals to invest in adaptive behavior as returns to adaptation would be relatively higher for more frequent temperature changes. Second, richer countries have less binding budget constraints and wider adaptation capacity to cope with weather fluctuations. Omitting income and climate differences while allowing for heterogeneous marginal effects of temperature can lead to biased estimates by attributing part of the response to income or climate effects.

To model heterogeneity in the temperature-production relationship accounting for adaptation, I consider income groups as defined by the World Economic Outlook (IMF, 2022) and average temperature over fifty years (i.e., long-run climate). These two factors account for differential adaptation potential (Kahn et al., 2021; Acevedo et al., 2020; Carleton et al., 2022). First, I augment the baseline specification with an interaction term distinguishing between advanced economies, emerging market economies, and low-income developing countries. Second, I include an interaction term that splits the sample of countries in terciles depending on the average long-run temperature in the fifty years for countries with cold, temperate and hot climate (Figure A2 shows the sample composition). I obtain sector-specific response functions that are also income group- and climate-specific allowing for these adaptation margins to influence the shape of the output-temperature relationship. Since neither climate terciles nor income groups have quasi-experimental variation as opposed to weather, the heterogeneous results are interpreted as associational (Carleton et al., 2022).

Figure A6 graphically presents the results for the coefficient associated with annual changes in the average daily temperature distribution interacted with income groups (Panel a) and with climate terciles (Panel b). Tabular results are reported in Table A9 and A10. As conjectured, results are consistent with the hypothesis that income is protective (Figure A6a). Advanced economies are not harmed by increases in the temperature distribution. Importantly, agriculture production is sheltered in advanced economies to the extent that the coefficient is positive and statistically significant. Some other sectors (construction; mining, manufacturing, utilities; transport, storage and communication; wholesale, retail trade, restaurants and hotels) also benefit from temperature increases among the richest countries. Nevertheless, the effect of temperature increases on agriculture remains strongly negative for emerging market economies and low-income developing countries. Moreover, these two income groups do not appear to benefit from increases in temperatures in other sectors, with low-income developing countries' estimates that are always smaller in magnitude than for emerging market economies.

Very similar estimates are obtained exploring the climate adaptive margin. Figure A6b shows a persistent and negative effect of increases in temperature on agricultural production across different climates (smaller in magnitude in absolute value in the cold climate countries and imprecisely estimated in the hot climate countries). Increases in temperature harm other sectors in hot climate countries (construction; other activities; wholesale, retail trade, restaurants and hotels), whereas they benefit production in both the industrial and services sectors (construction; mining, manufacturing, utilities; other activities; wholesale, retail trade, restaurants and hotels) in cold climate countries.

A.8 Sectoral impact of extreme weather events

The set of results in Section 1.5 has shown that consistent with prior literature, agriculture is the most directly harmed sector by temperature and, to a lesser extent, precipitation fluctuations and anomalies. In this section, I investigate whether similar results hold when using measures of extreme weather events for droughts and cyclones.

A.8.1 Dryness and wetness

First, I study the effect of changes in average dryness conditions as the first-differenced average of monthly negative values of the SPEI in a country in a year. Next, I focus on the changes in the prevalence of extreme dryness and wetness conditions, using the annual maximum share of grid-months with extreme drought ($\text{SPEI} < -2$) and extreme wetness ($\text{SPEI} > 2$) conditions in a country. Figure A13 shows the (standardized) sector-specific coefficients obtained from a multi-country, sector-specific response function for the three different measures of dryness and wetness. Tabular results are reported in Table A11. As previously documented, I find a strong negative effect of dry conditions on agriculture. In particular, a 1 SD increase in changes in average dryness conditions is associated with a 75% decrease in the agricultural growth rate with respect to its sample mean. All other sectors are not significantly affected.

Moving to measures of extreme drought and wetness prevalence, the results are consistent with previous findings. Agriculture's growth rate is largely negatively affected by changes in extreme drought prevalence. In other sectors, where precipitation can negatively affect the productivity of workers and the operation of machinery and infrastructure, the effect varies. The construction sector's growth rate benefits from positive changes in droughts, and so does the transport, storage and communication sector, although imprecisely estimated, whereas all the other sectors are not affected. These findings confirm that sectors that rely on roads, building construction and storage infrastructure may benefit from relatively drier conditions than historical averages with no excessive water surplus. The negative, although imprecisely estimated, coefficient associated with extreme wetness prevalence on production in the transport sector corroborates this hypothesis. These sectors are characterized by "interface" areas, such as loading and unloading areas (Cachon et al., 2012), which are more subject to weather variations and difficult to be protected with shelters (Colacito et al., 2019). In all the other sectors, extreme wetness conditions do not have any statistically significant effect, as previously documented using wet precipitation shocks.

A.8.2 Tropical cyclones

Tropical cyclones are the only extreme weather event on which there is previous evidence of their impact on sectoral growth worldwide (Kunze, 2021). I replicate and extend Kunze (2021)'s analysis estimating a pooled stacked multi-sector regression with jointly estimated sector-specific coefficients instead of separate regressions, which allows me to directly compare the coefficients estimated in the same model and identify the effect of tropical cyclones.¹ As in previous estimations, I do not allow for a relationship between the GVA sector and the level of intensity in tropical cyclones as measured by wind speed, and instead, consider changes.

Figure A15 presents the sector-specific (standardized) coefficients associated with changes in tropical cyclone intensity. Tabular results are displayed in Table A12. Tropical cyclones have the largest negative effect on agriculture. A 1 SD increase in changes in tropical cyclone intensity is associated with a drop by 2.8 percentage points in the annual growth rate of agriculture (comparable to a 2.62 decrease documented in Kunze (2021)). Results differ, however, for the other sectors. Most importantly, I document that changes in wind speed have a strong negative effect on other activities, suggesting that this sector contracts production in response to positive changes in cyclone intensity. I also do not recover a significant negative effect on the wholesale, retail trade, restaurants and hotel sector but I find a small effect indistinguishable from zero. Although similar results are found in the analysis of the effect of tropical cyclones in the agricultural sector (Hsiang, 2010; Loayza et al., 2012), the contraction in economic production in the other activities sector, which includes the financial and government sectors, is a new result, suggesting a negative effect on the economy overall in the short-run.

¹My analysis also differs in the definition of the sectors since I do not account for the manufacturing sector separately as explained in Section 1.3.1.

A.9 Propagation of extreme weather events

A.9.1 Droughts

I consider changes in drought shocks hitting trade partners domestically and abroad. Dryness conditions have been shown to directly harm agriculture and marginally benefit sectors that would be less productive under wetter conditions than the historical average, such as transportation and construction. The structure of Figure A25 is identical to that of examining abnormal temperature shocks. The results are also similar. For example, agriculture is the only sector that is directly harmed by drought shocks, with a sizeable negative effect of 0.09 p.p. (sample mean is 0.002) associated with a 1 SD increase in the dryness conditions in the country. Conversely, own drought shocks strongly benefit economic production in other sectors (construction; mining, manufacturing and utilities; and transport, storage and communication sectors) improving the precision of the positive estimates obtained when omitting network shocks. Industries in the tertiary sector at later stages of the value chain, such as wholesale, retail trade, restaurants and hotel, and other activities, are virtually not impacted at all by their own drought shocks, with a coefficient very close to zero.

Focusing on network shocks, domestic shocks have a strong negative effect only on economic production in mining, manufacturing and utilities, whereas their negative effect on construction; transport, storage and communication; and wholesale, retail trade, restaurants and hotels are imprecisely estimated. Conversely, foreign shocks have a sizable negative effect on other activities and wholesale, retail trade, restaurants and hotels suggesting strong propagation of drought shocks through the economy and across countries in later stages of the supply chain. Peculiar and outstanding is the case of the mining, manufacturing and utilities sector which is strongly harmed by domestic drought shocks, with a magnitude comparable to the coefficient associated with direct shocks, suggesting that the net effect of drought shocks in a country on this sector is not as positive as own shocks alone indicated. Accounting for both domestic and foreign network shocks sheds light on the true overall sectoral damage due to drought shocks accounting for shocks hitting other partner sectors.

A.9.2 Tropical cyclones

I consider the propagation of tropical cyclones' intensity as measured by wind speed. This shock has been shown in Section A.8.2 to have the widest impact across sectors, damaging agriculture and other activities. Since cyclones are extreme weather events that may also have a direct impact on capital stock destruction, trade linkages may either amplify or mitigate the aggregate damage suffered by sectors.

Figure A26 decomposes the network shocks by geographic location into foreign and domestic, besides including the sector-specific direct shock. Agriculture remains

the only sector directly harmed by tropical cyclones. Both domestic and foreign shocks have strong negative effects on construction; mining, manufacturing and utilities; transport, storage and communication; other activities; wholesale, retail trade, restaurants and hotels sectors.

A.10 Computing the economic cost of the propagation of recent warming

To understand the differential cost of propagation of recent warming, I use the estimates of the effect of own, domestic, and foreign heat and cold shocks to simulate how much slower or faster each sector would have grown annually over the 2001-2020 period, compared to a scenario under which daily temperature evolves linearly based on its historical trend of 1970-2000. To do so, I estimate country-specific regressions of the type $T_{dmct} = \alpha_c + \lambda_{dm} + \beta_{ct} + \varepsilon_{dmct}$ on the 1970-2000 sample, where T_{dmct} is the average temperature in day d in month m in year t in country c . I obtain country-specific historical trends in daily temperature exploiting within day-month variation between 1970 and 2000 and use $\hat{\beta}_c$ to construct a counterfactual daily temperature \tilde{T}_{dmct} between 2001 and 2020 that is then used to compute the counterfactual number of *cold* and *hot* days. I assume that the trend is linear and that such a trend does not affect the volatility of temperature shocks, which most likely results in an underestimation of the adverse effects of abnormal temperatures.

I then average these effects over the 2001-2020 period to obtain a sector-specific relative measure of estimated losses in value added. I finally compare the estimated losses in value added omitting and accounting for the transmission of shocks across countries through trade interlinkages. This computation does not necessarily represent the differential impact of recent anthropogenic warming accounting for network shocks and is instead agnostic to the cause of recent warming (Burke and Tanutama, 2019).

First, I compute the annual cost/benefit of annual warming in 2001-2020 compared to a counterfactual temperature which evolves linearly from the estimated trend over the period 1970-2000, and distinguish between omitting and accounting for weather shocks in trade partners:

$$\begin{aligned}
 g_{ict}^{direct} &= \widehat{\gamma}_i^{95}(T_{ict}^{95} - \tilde{T}_{ict}^{95}) + \widehat{\gamma}_i^5(T_{ict}^5 - \tilde{T}_{ict}^5) & (A.8) \\
 g_{ict}^{spillover} &= (\widehat{\gamma}_i^{95}T_{ict}^{95} + \widehat{\gamma}_i^{D,95}T_{ict}^{95,D} + \widehat{\gamma}_i^{F,95}T_{ict}^{95,F} + \widehat{\gamma}_i^5T_{ict}^5 + \widehat{\gamma}_i^{D,5}T_{ict}^{5,D} + \widehat{\gamma}_i^{F,5}T_{ict}^{5,F}) \\
 &\quad - (\widehat{\gamma}_i^{95}\tilde{T}_{ict}^{95} + \widehat{\gamma}_i^{D,95}\tilde{T}_{ict}^{95,D} + \widehat{\gamma}_i^{F,95}\tilde{T}_{ict}^{95,F} + \widehat{\gamma}_i^5\tilde{T}_{ict}^5 + \widehat{\gamma}_i^{D,5}\tilde{T}_{ict}^{5,D} + \widehat{\gamma}_i^{F,5}\tilde{T}_{ict}^{5,F}) & (A.9)
 \end{aligned}$$

where T_{ict}^{95} is the observed number of days above 95th percentile in sector i in country c in year t , \tilde{T}_{ict}^{95} is the counterfactual predicted number had the 1970-2000 average evolved linearly, $T_{ict}^{95,J}$ is the weighted average number of days above 95th percentile in trade partners J (where $J \in \{\text{Foreign, Domestic}\}$) from the perspective of sector i in country c in year t . $\widehat{\gamma}_i^{95}$'s are the sector-specific estimates for the effect of own, domestic and foreign heat shocks on the sectoral growth rate (symmetrically for $\widehat{\gamma}_i^5$) obtained from bootstrapping 1000 times the underlying panel estimates from

Equation (1.12) where indirect shocks are constructed with a time-varying production network that uses the first five-year average input-output interlinkages for each decade. I compute sector i 's counterfactual value added levels in year t omitting and accounting for indirect shocks

$$\hat{Y}_{ict}^p = Y_{ict-1} + y_{ict} + g_{ict}^p \quad (\text{A.10})$$

where hatted term indicates a counterfactual, Y is the (log) GVA per capita, y is the observed growth rate and $p \in \{\text{direct, spillover}\}$. I can then compute the average relative loss in GVA for sector i in country c over the 2001-2020 period as

$$\% \overline{\text{LOSS}}_{ic}^p = \frac{1}{T} \sum_{t=2001}^{2020} \frac{e^{\hat{Y}_{ict}^p} - e^{Y_{ict}}}{e^{Y_{ict}}} \quad (\text{A.11})$$

to obtain a measure of the average cost of recent warming at the sector level omitting and accounting for the propagation of heat shocks (reported in Figure A27).

The aggregated average loss in GVA across sectors for country c is

$$\% \overline{\text{LOSS}}_c^p = \sum_s \% \lambda_{ic} \overline{\text{LOSS}}_{ic}^p \quad (\text{A.12})$$

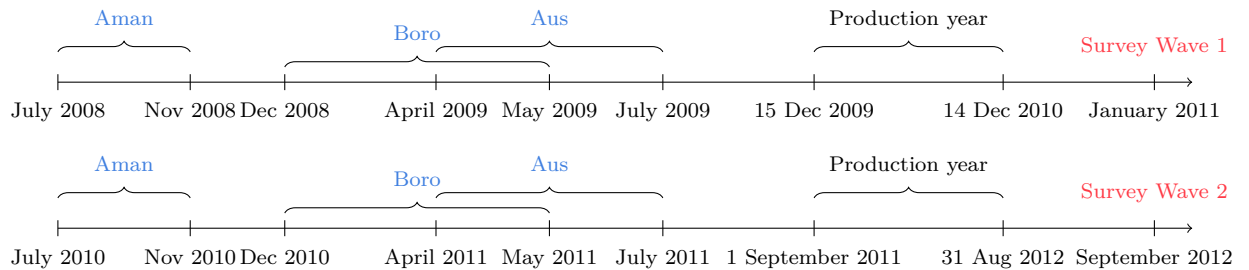
where λ_{ic} is the baseline five-year average share of total GVA of sector i in country c between 1996 and 2000. The country-level losses omitting and accounting for indirect heat shocks are reported in Figure 1.6.

Appendix B

Appendix to Chapter 2: Adapting to climate change accounting for individual beliefs

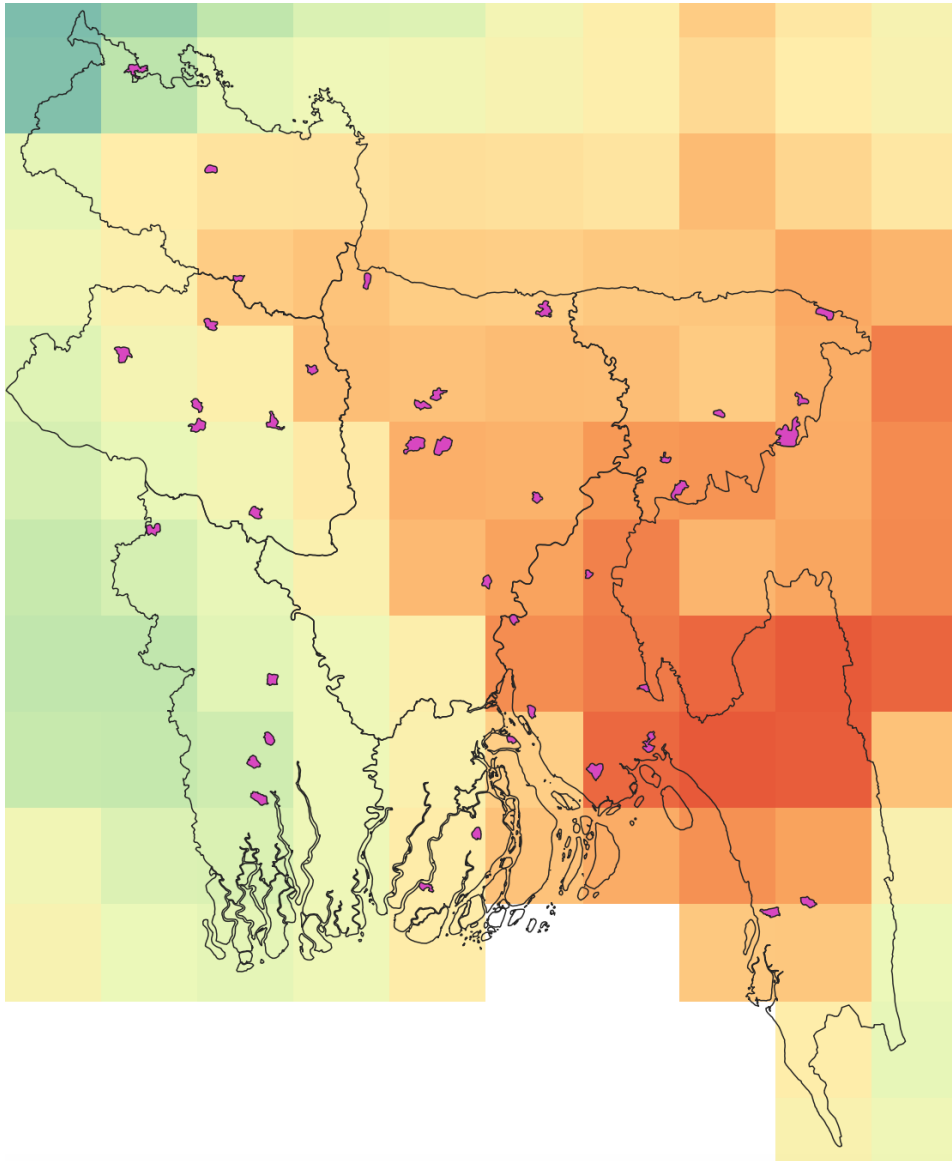
B.1 Additional figures

FIGURE B1: Timeline of BCCAS survey waves and growing seasons in Bangladesh



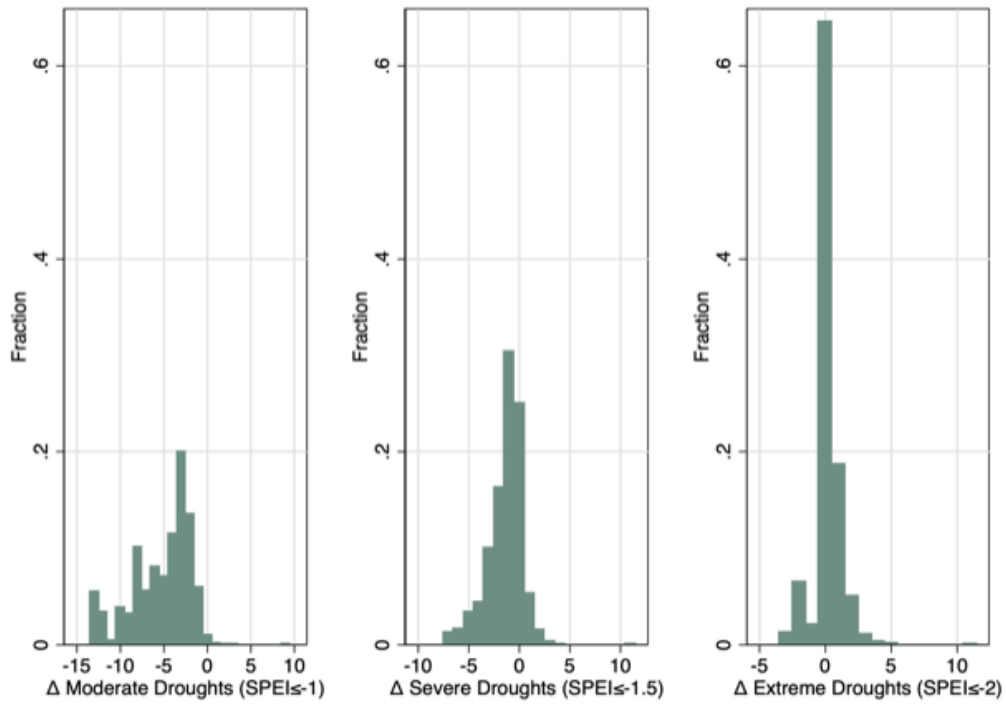
Notes: Each timeline shows the relative time interval of the growing seasons for each survey wave based on Sacks et al. (2010) and the period to which the information on irrigation decisions refer in the BCCAS (International Food Policy Research Institute, 2014a,b). Since the SPEI data has a monthly time resolution, I define each growing season to start on the first of the month of the average planting date and to end on the last of the month of the average harvest date as in Missirian and Schlenker (2017a). The exact dates of each growing season in Sacks et al. (2010) are: *Aus*: 14th April - 25th July, *Aman*: 5th July - 28th November, *Boro*: 19th December - 8th May.

FIGURE B2: Map of Bangladesh with surveyed unions and SPEI gridded data



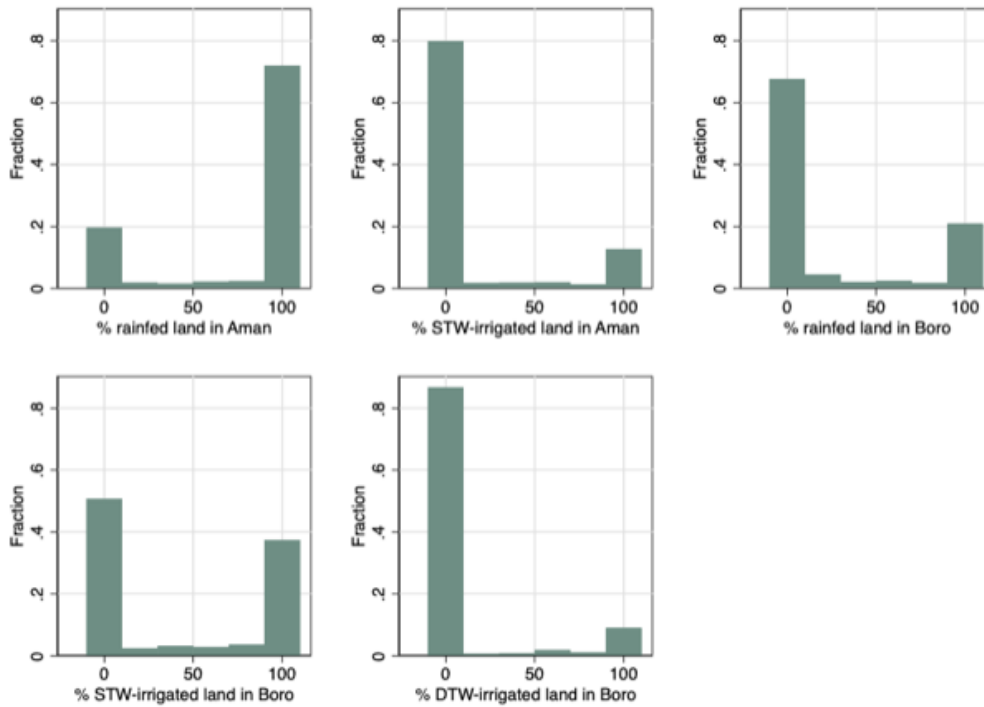
Notes: Map of Bangladesh with regional boundaries. The map plots the administrative boundaries of the 40 surveyed unions in purple. The administrative layer (from GADM (2021)) is overlaid to the raster SPEI gridded data from Vicente-Serrano et al. (2010) with 0.5 degree resolution (≈ 55 km at the Equator) with September 2012 values, where colors range from red to green, with red being negative values and blue being positive, respectively from a drier to a wetter environment. In five cases, there are two unions within the same grid cell, thus sharing the same SPEI values. The five cases are Adabaria and Arpangashia; Char Darbesh and Char Jabbar; Dakatia and Kakrajan; Kushmail and Naogaon. In one case, there are three unions within the same grid cell: Kalilnagar, Laskar and Rudaghara. The remaining 28 unions are uniquely matched with SPEI grid cell values.

FIGURE B3: Frequency distribution of Δ using moderate, severe and extreme drought cut-offs



Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-offs for moderate (SPEI ≤ -1), severe (SPEI ≤ -1.5) and extreme drought events (SPEI ≤ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period as in Equation (3.1) in the main text. When using moderate or severe drought events as 'objective counterfactual' of the self-reported number of droughts, there is systematic underestimation of the frequency of droughts among individuals.

FIGURE B4: Frequency distribution of the share of cultivated land rainfed and irrigated in *Aman* and *Boro* seasons



Notes: The sample includes the 1428 observations across the two waves for the 714 individuals interviewed. Each graph plots the binned frequency distribution (using 5 bins) of the share of cultivated land that is left rainfed, irrigated with STW and with DTW in *Aman* and *Boro* growing seasons.

B.2 Data Appendix

TABLE B1: Number of unions and households drawn by agroecological zone covered in the survey

Agroecological zone	Unions	Households
Barind Tract	4	80
Beel and Haor Basin	5	100
Floodplain	10	200
Himalayan Piedmont Plain	5	100
Modhupur Tract	4	80
Northern and Eastern Hills	5	100
Tidal Floodplain	7	140
Total	40	800

TABLE B2: Number of unions and households per AEZ covered in the estimation sample

Agroecological zone	Union	Households
Barind Tract	4	71
Beel and Haor Basin	5	89
Floodplain	10	181
Himalayan Piedmont Plain	5	89
Modhupur Tract	4	75
Northern and Eastern Hills	5	92
Tidal Floodplain	7	117
Total	40	714

TABLE B3: Unions and number of households in the BCCAS sample

Number of households				Number of households			
Division	District	Upazila	Union	Division	District	Upazila	Union
Barisal	Barguna	Amtali	Arpangashia	Khulna	Jessore	Bagher Para	Jamdia
Barisal	Barisal	Mehendiganj	Gobindapur	Khulna	Meherpur	Gangni	Kazipur
Barisal	Patuakhali	Bauphal	Adabaria	Khulna	Khulna	Paikgachha	Laskar
Chittagong	Chandpur	Matlab Uttar	Sadullapur	Khulna	Satkhira	Tala	Khalimnagar
Chittagong	Chittagong	Banshkhali	Chambal	Rajshahi	Bogra	Sariakandi	Kamalpur
Chittagong	Chittagong	Lohagara	Charamba	Rajshahi	Joypurhat	Khetlal	Mamudpur
Chittagong	Comilla	Chauddagram	Jagannath Dighi	Rajshahi	Naogaon	Atrai	Panchupur
Chittagong	Comilla	Muradnagar	Purba Purbachhair	Rajshahi	Naogaon	Niamatpur	Bhabicha
Chittagong	Feni	Sonagazi	Char Darbesh	Rajshahi	Natore	Natore Sadar	Piprul
Chittagong	Lakshmipur	Roypur	Char Mohana	Rajshahi	Pabna	Pabna Sadar	Gayeshpur
Chittagong	Noakhali	Subarnachar	Char Jabbar	Rajshahi	Sirajganj	Tarash	Deshigram
Dhaka	Jamalpur	Bakshiganj	Battajore	Rangpur	Dinajpur	Ghoraghat	Ghoraghat
Dhaka	Mymensingh	Bhaluka	Dakatia	Rangpur	Panchagarh	Panchagarh Sadar	Chaklarhat
Dhaka	Mymensingh	Fulbaria	Kushmail	Rangpur	Rangpur	Taraganj	Ekarchali
Dhaka	Mymensingh	Fulbaria	Naogaon	Sylhet	Habiganj	Chumarughat	Deorgachh
Dhaka	Narayanganj	Narayanganj Sadar	Siddhiganj Paurashava	Sylhet	Habiganj	Habiganj Sadar	Nizampur
Dhaka	Narsingdi	Manohardi	Gotashia	Sylhet	Maulvibazar	Juri	Paschim Juri
Dhaka	Netrakona	Kalmakanda	Nazirpur	Sylhet	Maulvibazar	Kulaura	Karmadha
Dhaka	Tangail	Sakhipur	Kakrajan	Sylhet	Maulvibazar	Maulvi Bazar Sadar	Kamalpur
Khulna	Khulna	Dumuria	Rudaghara	Sylhet	Sylhet	Kanaighat	Paschim Lakshmip Rasad

TABLE B4: BCCAS main variables' definition and construction

VARIABLE	SURVEY QUES- TION CODE	WAVE	SURVEY QUESTION
Belief increase in drought (0/1)	L.11	1	Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)
Belief increase in drought (0/1)	Q.04-Q.07	2	Have you noticed any long term changes in rainfall variability over the last 20 years? If yes, what changes have you noticed? (1 if "Longer periods of droughts" and 0 otherwise) Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)
Drought _{t-1} (0/1)	L.02	1	In the last five years, have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2009", 0 otherwise)
Drought _{t-1} (0/1)	L.02	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2011", 0 otherwise)
Drought _{t-2} (0/1)	L.02	1	In the last five years, have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2008", 0 otherwise)
Drought _{t-2} (0/1)	L.02	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? In which years most badly affected? (1 if "2010", 0 otherwise)
self-reported droughts	# L.03	1	In the last five years, have the HH's properties and productivity been affected by droughts? How many times did it occur in these two years?
self-reported droughts	# L.03	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? How many times did it occur in these two years?

Notes: The variable self-reported # droughts is used to compute the variable Δ , subtracting the objective # droughts, being the recorded number of (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period as the survey question, as explained in the main text in Equation (3.1).

TABLE B5: Summary statistics of BCCAS estimation sample by survey wave

	Mean		SD	
	2011	2012	2011	2012
<i>A. Respondent characteristics</i>				
Age	46	47.9	13.5	13.5
Male	0.945	0.945	0.227	0.227
Completed years of education by head of household	3.49	3.49	4.19	4.21
Farmer	0.718	0.644	0.45	0.479
<i>B. Household characteristics</i>				
Household size	5.05	5.46	2.21	2.46
Number of agricultural workers in household	0.113	0.105	0.396	0.384
At least 1 HH member is self-employed in HH farming activities	0.745	0.71	0.436	0.454
Receives information from extension agents	0.176	0.359	0.381	0.48
Household with electricity	0.47	0.56	0.50	0.49
<i>C. Agricultural characteristics</i>				
Total land holdings (in hectares)	0.68	0.793	1.3	1.3
Total cultivated land (in hectares)	0.56	0.69	1.2	1.27
Share of clay cultivated land	0.039	0.0293	0.183	0.158
Share of loam cultivated land	0.252	0.171	0.422	0.358
Share of sandy cultivated land	0.0283	0.0219	0.15	0.131
Share of clay-loam cultivated land	0.468	0.505	0.486	0.481
Share of sandy-loam cultivated land	0.213	0.272	0.395	0.425
Ownership of Shallow Tube Wells (STWs)	0.102	0.103	0.303	0.305
Ownership of Deep Tube Wells (DTWs)	0.013	0.014	0.112	0.112
Observations	714	714		

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. Shares of soil type are weighted by the total size of the cultivated plots as reported by the household.

TABLE B6: T-tests for differences in means for attritors versus non-attritors

	Non Attritors (N=714)		Attritors (N=86)		Difference	
	Mean	SD	Mean	SD	Mean	<i>p</i> -value
Head of household is a farmer	0.718	0.016	0.617	0.052	0.102	(0.0491)
Household with electricity	0.469	0.018	0.406	0.053	0.062	(0.275)
Receives information from extension agents	0.176	0.014	0.139	0.0375	0.037	(0.392)
Belief increase in drought	0.252	0.016	0.290	0.049	-0.038	(0.439)
Δ Droughts	0.102	0.047	0.314	0.143	-0.211	(0.144)
Drought _{<i>t</i>-1}	0.038	0.007	0.034	0.019	0.002	(0.228)
Drought _{<i>t</i>-2}	0.014	0.004	0	0	0.014	(0.424)
Total area land holdings in hectares	0.680	0.048	0.505	0.045	0.175	(0.216)
Share of clay cultivated land	0.038	0.006	0.024	0.014	0.014	(0.479)
Share of loam cultivated land	0.248	0.015	0.187	0.041	0.241	(0.201)
Share of sandy cultivated land	0.027	0.005	0.054	0.023	-0.026	(0.142)
Share of clay-loam cultivated land	0.462	0.018	0.526	0.053	-0.064	(0.247)
Share of sandy-loam cultivated land	0.210	0.014	0.183	0.041	0.026	(0.557)
Ownership of Shallow Tube Wells (STWs)	0.154	0.013	0.117	0.035	0.037	(0.819)
Ownership of Deep Tube Wells (DTWs)	0.052	0.008	0.035	0.020	0.017	(0.124)
Share of irrigated cultivated land	0.511	0.012	0.501	0.039	0.010	(0.536)
Share of STW irrigated land	0.317	0.013	0.288	0.038	0.029	(0.464)
Share of DTW irrigated land	0.056	0.006	0.058	0.019	-0.002	(0.641)
Share of rainfed cultivated land in Aman	0.741	0.015	0.706	0.048	0.034	(0.956)
Share of STW irrigated land in Aman	0.178	0.013	0.162	0.037	0.016	(0.802)
Share of rainfed cultivated land in Boro	0.281	0.015	0.295	0.048	-0.013	(0.306)
Share of STW irrigated land in Boro	0.457	0.017	0.413	0.051	0.043	(0.319)
Share of DTW irrigated land in Boro	0.089	0.009	0.082	0.028	0.006	(0.505)

Notes: The table compares the differences in means between the final estimation sample of non-attritors (N=714) and the sample of attritors that have not been interviewed in the second wave because they migrated, they were not at home at the time of the survey or the respondent changed from the first wave. Shares of soil type and irrigated land are weighted by the total size of the cultivated land as reported by the household.

TABLE B7: Summary statistics of area-weighted agricultural plot utilization

	N	Mean	SD	Min	Max
Aus	714	0.09	0.17	0.00	0.86
Aman	714	0.37	0.27	0.00	1.00
Boro	714	0.34	0.32	0.00	1.00
Potato	714	0.01	0.05	0.00	0.58
Wheat	714	0.01	0.05	0.00	0.58
Jute	714	0.02	0.08	0.00	0.77
Chili	714	0.01	0.05	0.00	0.50
Eggplant	714	0.01	0.07	0.00	1.00
Other	714	0.14	0.15	0.00	1.00
Observations	714				

Notes: Proportion of cultivated crop over total agricultural plot utilization weighted by planted area. Data refer only to survey wave 1, since the module is absent in survey wave 2.

TABLE B8: Summary statistics of production-weighted rice types

	N	Mean	SD	Min	Max
Aus	714	0.07	0.14	0.00	1.00
Aman	714	0.31	0.27	0.00	1.00
Boro	714	0.35	0.33	0.00	1.00
Local Aus	714	0.01	0.07	0.00	0.86
Local Improved Variety (LIV) Aus	714	0.01	0.05	0.00	0.50
High Yield Variety (HYV) Aus	714	0.05	0.12	0.00	1.00
HYV Transplanted Aus	714	0.01	0.07	0.00	1.00
Local Aman	714	0.05	0.15	0.00	1.00
LIV Transplanted Aman	714	0.01	0.09	0.00	1.00
HYV Transplanted Aman	714	0.24	0.26	0.00	1.00
Hybrid Aman	714	0.01	0.08	0.00	1.00
HYV Boro	714	0.27	0.32	0.00	1.00
Hybrid Boro	714	0.06	0.20	0.00	1.00
Observations	714				

Notes: Share of rice production weighted by the total agricultural production of the household. Three different types of rice depending on the growing season: aus, aman and boro. Data refer only to survey wave 1, since the module is absent in survey wave 2.

TABLE B9: Summary statistics on shares of cultivated land by irrigation status

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Share of irrigated cultivated land	714	0.49	0.34	0.00	1.00
Share of STW irrigated cultivated land	714	0.32	0.36	0.00	1.00
Share of DTW irrigated cultivated land	714	0.06	0.17	0.00	1.00
Panel B. Survey Wave 2 (2012)					
Share of irrigated cultivated land	714	0.49	0.31	0.00	1.00
Share of STW irrigated cultivated land	714	0.28	0.37	0.00	1.00
Share of DTW irrigated cultivated land	714	0.08	0.21	0.00	1.00
Panel C. Changes					
Share of irrigated cultivated land	714	-0.01	0.26	-1.00	1.00
Share of STW irrigated cultivated land	714	-0.04	0.29	-1.00	1.00
Share of DTW irrigated cultivated land	714	0.02	0.17	-1.00	1.00
Panel D. Total					
Share of irrigated cultivated land	1428	0.49	0.33	0.00	1.00
Share of STW irrigated cultivated land	1428	0.30	0.35	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.07	0.19	0.00	1.00
Observations	1428				

Notes: Share of cultivated land under each irrigation status across *Aman* and *Boro*, weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C “Roster of land and water bodies owned or under operation” and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. STW: Shallow Tube Well; DTW: Deep Tube Well. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

TABLE B10: Summary statistics on shares of cultivated land by irrigation status by growing season

	N	Mean	SD	Min	Max
Aus					
Share of rainfed cultivated land	1428	0.79	0.39	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.01	0.00	0.35
Share of LLP irrigated cultivated land	1428	0.02	0.14	0.00	1.00
Share of STW irrigated cultivated land	1428	0.13	0.32	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.01	0.10	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.03	0.15	0.00	1.00
Aman					
Share of rainfed cultivated land	1428	0.76	0.40	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.04	0.00	1.00
Share of treadle pump irrigated cultivated land	1428	0.01	0.01	0.00	0.46
Share of LLP irrigated cultivated land	1428	0.02	0.12	0.00	1.00
Share of STW irrigated cultivated land	1428	0.16	0.35	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.02	0.14	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.01	0.10	0.00	1.00
Boro					
Share of rainfed cultivated land	1428	0.26	0.41	0.00	1.00
Share of traditional method irrigated cultivated land	1428	0.01	0.08	0.00	1.00
Share of rower pump irrigated cultivated land	1428	0.01	0.03	0.00	1.00
Share of LLP irrigated cultivated land	1428	0.10	0.28	0.00	1.00
Share of STW irrigated cultivated land	1428	0.43	0.47	0.00	1.00
Share of DTW irrigated cultivated land	1428	0.11	0.30	0.00	1.00
Share of irrigated cultivated land using other methods	1428	0.07	0.24	0.00	1.00
Observations	1428				

Notes: Share of cultivated land under each irrigation status during each growing season weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C “Roster of land and water bodies owned or under operation” and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. LLP: Low Lift Pump; STW: Shallow Tube Well; DTW: Deep Tube Well. *Aus* refers to the pre-monsoon growing season, *Aman* refers to the monsoon growing season, *Boro* refers to the winter growing season.

TABLE B11: Summary statistics on share of cultivated land under main irrigation statuses by growing season

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
<i>Aman</i>					
Share of rainfed cultivated land	714	0.74	0.42	0	1
Share of STW irrigated cultivated land	714	0.18	0.36	0	1
<i>Boro</i>					
Share of rainfed cultivated land	714	0.28	0.42	0	1
Share of STW irrigated cultivated land	714	0.46	0.47	0	1
Share of DTW irrigated cultivated land	714	0.09	0.27	0	1
Panel B. Survey Wave 2 (2012)					
<i>Aman</i>					
Share of rainfed cultivated land	714	0.78	0.39	0	1
Share of STW irrigated cultivated land	714	0.15	0.33	0	1
<i>Boro</i>					
Share of rainfed cultivated land	714	0.24	0.40	0	1
Share of STW irrigated cultivated land	714	0.41	0.47	0	1
Share of DTW irrigated cultivated land	714	0.13	0.33	0	1
Panel C. Changes					
<i>Aman</i>					
Share of rainfed cultivated land	714	0.04	0.39	-1	1
Share of STW irrigated cultivated land	714	-0.03	0.33	-1	1
<i>Boro</i>					
Share of rainfed cultivated land	714	-0.04	0.29	-1	1
Share of STW irrigated cultivated land	714	-0.04	0.39	-1	1
Share of DTW irrigated cultivated land	714	0.04	0.27	-1	1
Panel D. Total					
<i>Aman</i>					
Share of rainfed cultivated land	1428	0.78	0.39	0	1
Share of STW irrigated cultivated land	1428	0.15	0.33	0	1
<i>Boro</i>					
Share of rainfed cultivated land	1428	0.24	0.40	0	1
Share of STW irrigated cultivated land	1428	0.41	0.47	0	1
Share of DTW irrigated cultivated land	1428	0.13	0.33	0	1

Notes: Share of cultivated land under each irrigation status during each growing season weighted by the size of the cultivated land reported by the households in the survey. The percentage is constructed by using Module C “Roster of land and water bodies owned or under operation” and considering only the plots of cultivated / arable land type and own operated. The module asks to report the irrigation status of each plot for each growing season. LLP: Low Lift Pump; STW: Shallow Tube Well; DTW: Deep Tube Well. *Aus* refers to the pre-monsoon growing season, *Aman* refers to the monsoon growing season, *Boro* refers to the winter growing season. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

TABLE B12: Summary statistics on individual beliefs of climate change

	N	Mean	SD
Panel A. Survey Wave 1 (2011)			
Belief increase in drought	714	0.25	0.43
Belief increase in erratic rainfall	714	0.27	0.44
Belief decrease in precipitations	714	0.22	0.41
Panel B. Survey Wave 2 (2012)			
Belief increase in drought	714	0.71	0.45
Belief increase in erratic rainfall	714	0.86	0.34
Belief decrease in precipitations	714	0.88	0.32
Panel C. Changes			
Belief increase in drought	714	0.46	0.62
Belief increase in erratic rainfall	714	0.59	0.59
Belief decrease in precipitations	714	0.66	0.53
Panel D. Total			
Belief increase in drought	1428	0.48	0.49
Belief increase in erratic rainfall	1428	0.57	0.50
Belief decrease in precipitations	1428	0.55	0.50
Observations	1428		

Notes: Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

TABLE B13: Balance test. Farmer characteristics by beliefs of increase in drought.

	Perception increase in drought		<i>p</i> -value
	No	Yes	
<i>Panel A: Farmer characteristics</i>			
Farmer	0.703	0.657	0.061
Receives information from extension agents	0.206	0.334	<0.001
Household with electricity	0.497	0.537	0.127
Ownership of Shallow Tube Wells (STWs)	0.100	0.106	0.718
Ownership of Deep Tube Wells (DTWs)	0.009	0.017	0.191
Perception increase in erratic rainfall	0.391	0.762	<0.001
Perception decrease in precipitations	0.352	0.767	<0.001
Land holdings (in hectares)	0.688	0.789	0.144
Share of clay cultivated land	0.034	0.033	0.884
Share of loam cultivated land	0.197	0.220	0.261
Share of sandy cultivated land	0.029	0.020	0.196
Share of clay-loam cultivated land	0.476	0.482	0.800
Share of sandy-loam cultivated land	0.252	0.224	0.190
Number of individuals	739	689	
<i>Panel B: Wave 1 - Wave 2 changes in farmer characteristics</i>			
Farmer	-0.058	-0.080	0.566
Receives information from extension agents	0.180	0.183	0.960
Household with electricity	0.131	0.078	0.0875
Ownership of Shallow Tube Wells (STWs)	-0.01	0.006	0.221
Ownership of Deep Tube Wells (DTWs)	-0.005	0.004	0.344
Perception increase in erratic rainfall	0.458	0.644	<0.001
Perception decrease in precipitations	0.507	0.717	<0.001
Land holdings (in hectares)	0.136	0.103	0.278
Share of clay cultivated land	-0.003	-0.012	0.525
Share of loam cultivated land	-0.120	-0.064	0.033
Share of sandy cultivated land	-0.007	-0.006	0.926
Share of clay-loam cultivated land	0.038	0.032	0.869
Share of sandy-loam cultivated land	0.098	0.040	0.048
Number of individuals	205	509	

Notes: The table compares the differences in means between the group of respondents who did and did not perceive an increase in droughts, across the two waves in Panel A, and in the second wave in Panel B comparing changes in farmer characteristics between the two waves. *p*-value column shows the *p*-values of the hypotheses that the mean outcomes of the groups by beliefs of increase in droughts are equal.

TABLE B14: Two-way frequency table observed and accurate beliefs

Belief increase drought	Accurate beliefs		Accurate beliefs in Aman		Accurate beliefs in Boro	
	No (0)	Yes (1)	No (0)	Yes (1)	No (0)	Yes (1)
No (0)	194 13.59%	545 38.17%	74 5.18%	665 46.57%	459 32.14%	280 19.61%
Yes (1)	117 8.19%	572 40.06%	136 9.52%	553 38.73%	179 12.54%	510 35.71%

Notes: The table shows the two-way frequency and relative percentages for Belief increase drought (b) in rows and Accurate beliefs (b^*) over the year, in Aman and in Boro, in columns. Accurate belief (b^*) is equal to one if (seasonal) long-run exposure is strictly above zero (i.e., environment relatively drier than historical averages), and zero otherwise.

TABLE B15: Summary statistics of SPEI meteorological measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
<i>A. Exposure Measures</i>					
Long-run dryness	34	0.07	0.04	-0.01	0.15
Deviation	34	0.04	0.04	-0.03	0.15
Aman Long-run dryness	34	0.09	0.06	-0.05	0.20
Boro Long-run dryness	34	-0.01	0.04	-0.08	0.10
Aman Deviation	34	0.27	0.14	-0.10	0.48
Boro Deviation	34	0.42	0.11	0.23	0.68
<i>B. Number of Drought Events</i>					
# Moderate Droughts	34	8.20	3.02	3	13
# Severe Droughts	34	2.44	2.01	0	7
# Extreme Droughts	34	0.47	0.89	0	3
Panel B. Survey Wave 2 (2012)					
<i>A. Exposure Measures</i>					
Long-run dryness	34	0.11	0.04	0.03	0.16
Deviation	34	-0.06	0.10	-0.38	0.05
Aman Long-run dryness	34	0.09	0.07	-0.04	0.22
Boro Long-run dryness	34	0.04	0.05	-0.02	0.18
Aman Deviation	34	0.22	0.21	-0.61	0.51
Boro Deviation	34	-0.09	0.14	-0.41	0.24
<i>B. Number of Drought Events</i>					
# Moderate Droughts	34	3.18	1.09	1	6
# Severe Droughts	34	1.09	0.71	0	3
# Extreme Droughts	34	0.03	0.17	0	1
Panel C. Changes					
<i>A. Exposure Measures</i>					
Long-run dryness	34	0.03	0.01	0.01	0.05
Deviation	34	-0.10	0.12	-0.52	0.03
Aman Long-run dryness	34	0.01	0.02	-0.05	0.04
Boro Long-run dryness	34	0.05	0.01	0.02	0.08
Aman Deviation	34	-0.05	0.28	-1.09	0.32
Boro Deviation	34	-0.51	0.21	-0.99	-0.20
<i>B. Number of Drought Events</i>					
# Moderate Droughts	34	-5.03	2.78	-10	0
# Severe Droughts	34	-1.35	1.72	-5	2
# Extreme Droughts	34	-0.44	0.82	-2	0
Panel D. Total					
<i>A. Exposure Measures</i>					
Long-run dryness	68	0.09	0.04	-0.01	0.16
Deviation	68	-0.01	0.09	-0.38	0.15
Aman Long-run dryness	68	0.09	0.06	-0.05	0.22
Boro Long-run dryness	68	0.01	0.05	-0.08	0.18
Aman Deviation	68	0.25	0.18	-0.61	0.50
Boro Deviation	68	0.16	0.29	-0.41	0.68
<i>B. Number of Drought Events</i>					
# Moderate Droughts	68	5.69	3.39	1	13
# Severe Droughts	68	1.76	1.65	0	7
# Extreme Droughts	68	0.25	0.68	0	3

Notes: The sample includes the 34 grid cells that uniquely match the 40 sampled unions as explained in Figure B2.

TABLE B16: Summary statistics of main regressors using SPEI and BCCAS

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Drought _{t-1}	714	0.04	0.19	0	1
Drought _{t-2}	714	0.01	0.12	0	1
Inaccuracy	714	0.98	0.14	0	1
Overestimation (Moderate)	714	0.00	0.00	0	0
Overestimation (Severe)	714	0.03	0.18	0	1
Overestimation (Extreme)	714	0.15	0.35	0	1
Δ Droughts (Moderate)	714	-7.83	2.92	-13	0
Δ Droughts (Severe)	714	-2.13	1.94	-7	3
Δ Droughts (Extreme)	714	-0.12	1.11	-3	4
Panel B. Survey Wave 2 (2012)					
Drought _{t-1}	714	0.24	0.42	0	1
Drought _{t-2}	714	0.01	0.05	0	1
Inaccuracy	714	0.80	0.40	0	1
Overestimation (Moderate)	714	0.01	0.09	0	1
Overestimation (Severe)	714	0.11	0.32	0	1
Overestimation (Extreme)	714	0.36	0.48	0	1
Δ Droughts (Moderate)	714	-2.74	1.35	-6	9
Δ Droughts (Severe)	714	-0.59	1.08	-3	11
Δ Droughts (Extreme)	714	0.45	0.84	-1	11
Panel C. Total					
Drought _{t-1}	1428	0.14	0.34	0	1
Drought _{t-2}	1428	0.01	0.09	0	1
Inaccuracy	1428	0.89	0.31	0	1
Overestimation (Moderate)	1428	0.00	0.06	0	1
Overestimation (Severe)	1428	0.07	0.26	0	1
Overestimation (Extreme)	1428	0.25	0.44	0	1
Δ Droughts (Moderate)	1428	-5.29	3.41	-13	9
Δ Droughts (Severe)	1428	-1.36	1.75	-7	11
Δ Droughts (Extreme)	1428	0.16	1.03	-3	11

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. Inaccuracy is a dummy variable that takes value one if individuals do not report to have been hit by the most harmful drought the year preceding the survey ($Drought_{t-1} = 0$) and the minimum SPEI monthly realization was recorded in the same year. The variable Δ is constructed as explained in Equation (3.1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. Overestimation is a dummy variable that takes value one if Δ is strictly positive. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C displays the values across the two waves.

TABLE B17: Balance in covariates. Long-run dryness on farmer's characteristics.

Covariate	Long-run dryness	
	Estimate	Standard errors
Farmer	0.621	(2.094)
Receives information from extension agents	-0.729	(1.699)
Household size	-2.519	(2.953)
Household with electricity	-0.731	(1.481)
Ownership of Shallow Tube Wells (STWs)	0.195	(0.564)
Ownership of Deep Tube Wells (DTWs)	-0.906	(0.579)
Perception increase in erratic rainfall	11.18	(3.393)
Perception decrease in precipitations	5.392	(2.631)
Land holdings (in hectares)	-0.660	(1.305)
Share of clay cultivated land	-1.001	(0.706)
Share of loam cultivated land	1.014	(1.531)
Share of sandy cultivated land	-0.408	(0.444)
Share of clay-loam cultivated land	-1.137	(1.742)
Share of sandy-loam cultivated land	2.474	(1.542)

Notes: The panel presents point estimates and standard errors for 14 regressions of a covariate (listed at the left) on long-run dryness. I use a time-varying measure of long-run dryness to account for changes between the two waves. All estimates are based on OLS regressions with individual and year fixed effects. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation.

B.3 Why do people change their beliefs?

Table B12 shows substantial heterogeneity across waves in the self-reported beliefs of changes in climatic conditions. Most notably, around 52% of the respondents did not report a perceived increase in droughts in the first wave and reported it in the second wave, while only around 7% had an opposite reporting pattern. This is even more relevant since only one union in the sample (Chaklarhat) recorded an extreme drought event between the two waves, in which 30% of the respondents changes beliefs and reported a perceived increase in droughts and 60% did not change their beliefs across the two waves. A potential explanation of this result is that individuals have their own definition of droughts. This would not pose a problem to the analysis so long as this is time-invariant, which is plausible given the temporal proximity of the two waves.

I examine whether belief updates come from informational or social channels. First, I compare the variance in beliefs across unions between the two waves to investigate a potential local convergence or divergence phenomenon of beliefs update. The average variance is 0.178 in the first wave and 0.171 in the second wave, providing evidence that there is slight convergence in beliefs within each union, although the difference is not statistically significant at any conventional level. Another possibility is that beliefs can be influenced by the land management strategies designed to adapt to unfavorable conditions (Niles and Mueller, 2016), up to the point that reverse causality may undermine this study. This possibility is explored and ruled out in Section 2.5.2.

Another potential channel of belief update is the role of social learning (Conley and Udry, 2010). Farmers compare neighbors' productivity to theirs and update their beliefs to align with the input adjustments of those who were successful in the previous period. I test this hypothesis by regressing the differences between the deviations from the union's averages in beliefs over the two waves on the differences between the deviations from the union's averages in the share of irrigated land. Under the assumption that irrigation has positive returns on productivity (Bell et al., 2015), a negative and statistical significant coefficient on the double difference (over time and from union's average) of use of irrigation would provide evidence of the social learning channel for beliefs update. Table B18 displays the coefficients on the double difference of use of irrigation that are never statistically different from zero, ruling out the social learning channel.

B.4 Additional Tables

TABLE B18: Social learning channel of belief update

<i>Dependent variable:</i>	$\Delta\Delta$ Belief increase drought					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\Delta$ Irrigation	0.138 (0.110)	-0.0326 (0.0591)	-0.0576 (0.0707)			
Δ_{t-1} Irrigation				0.00295 (0.136)	-0.163 (0.0996)	-0.130 (0.0965)
Season	Annual	<i>Aman</i>	<i>Boro</i>	Annual	<i>Aman</i>	<i>Boro</i>
<i>N</i>	714	714	714	714	714	714

Notes: Each column refers to an OLS specification where the sample is a cross-section of 714 rural households' respondents. The outcome variable is the difference between the deviation from the union's average in beliefs of increases in drought over the two survey waves (formally, $\text{perception}_{it} - \overline{\text{perception}}_{ut} - (\text{perception}_{it-1} - \overline{\text{perception}}_{ut-1})$). The main regressors of interest are the differences in deviations from the union's average in the share of irrigated cultivated land. All regressions control for main occupation of the respondent is farmer, the household receives extension advice, access to electricity, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; union fixed effects. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B19: Individual beliefs and long-run exposure to dryness

<i>Dependent variable:</i>	Belief increase drought		
	(1)	(2)	(3)
Long-run dryness	16.23*** (2.475)	6.383*** (0.914)	-1.691 (2.740)
Deviation	-0.431* (0.222)	-0.0193 (0.0761)	0.192 (0.163)
Season	Annual	<i>Aman</i>	<i>Boro</i>
Fixed Effects	X	X	X
<i>N</i>	1428	1428	1428

Notes: Each column refers to an OLS specification where the outcome variable is the binary variable on beliefs of increases in droughts. The main regressors of interest are the annual or seasonal (*Aman* in col.2 and *Boro* in col.3) twenty-year average dryness and short-run deviations from the year prior to the production year. All regressions control for individual and year fixed effects. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B20: Ex-ante input decision. Contemporaneous weather realizations and irrigation decisions.

	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Deviation _t	0.0867 (0.0734)	-0.0691 (0.0703)	0.00204 (0.0480)	-0.0180 (0.0390)	0.0157 (0.0237)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
<i>N</i>	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.560	0.573	0.749	0.665	0.588

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. The specification controls for beliefs of increases in droughts, the interaction term with long-run dryness and the set of controls as in baseline specification (2.10): seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B21: Sub-sample analysis.

	<i>Dependent variable: Share of irrigated cultivated land</i>				
	(1)	(2)	(3)	(4)	(5)
Belief increase drought	-0.0759*** (0.0210)	-0.101*** (0.0245)	-0.0746*** (0.0243)	-0.0875*** (0.0235)	-0.0785*** (0.0218)
Belief increase in drought \times Long-run dryness	0.835*** (0.243)	0.872*** (0.305)	0.543* (0.288)	0.757** (0.295)	0.722** (0.292)
Sub-sample	Irrigated land \neq 0 in wave 1	Irrigated land \neq 0	Aman & Boro producers	No STW/DTW owners	At least one extreme drought
Mean Outcome	0.548	0.576	0.488	0.474	0.474
SD Outcome	0.296	0.276	0.323	0.332	0.334
N	1278	1212	1330	1270	1390
adj. R^2	0.563	0.502	0.695	0.716	0.700

Notes: The outcome variable is the average share of cultivated land in *Aman* or *Boro* growing seasons. Column (1) estimates the regression excluding farmers with share of irrigated land equal to zero in the first wave. Column (2) excludes farmers that never irrigate. Column (3) includes only farmers self-reporting the quantity of *Aman* and *Boro* rice produced in the first wave. Column (4) excludes farmers owning STWs or DTWs. Column (5) excludes unions where no drought occurred over the twenty years. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. All specifications include individual and year fixed effects, and the same controls as in the baseline regression in Table 2.1. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B22: Individual beliefs and irrigation use accounting for water balance variability.

<i>Dependent variable:</i> Share of cultivated land	Irrigated	STW	Irrigated	STW
	(1)	(2)	(3)	(4)
Belief increase in drought	-0.172 (0.149)	-0.465** (0.184)	-0.139 (0.400)	-0.440 (0.530)
Belief increase in drought \times Long-run dryness	0.724*** (0.262)	0.982** (0.445)	0.599* (0.360)	0.507** (0.217)
Belief increase in drought \times Seasonal variability	0.222 (0.229)	0.763** (0.314)		
Belief increase in drought \times Interannual variability			0.102 (0.450)	0.449 (0.589)
Controls	X	X	X	X
Fixed Effects	X	X	X	X
Mean Outcome	0.489	0.299	0.489	0.299
SD Outcome	0.327	0.354	0.327	0.354
<i>N</i>	1428	1428	1428	1428

Notes: Table reports the OLS estimates of a regression where the outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (columns 1-3), irrigated with STW (columns 2-4). Seasonal variability is computed using the average intra-annual standard deviation in monthly water balance in *Aman* and *Boro* over the twenty years prior to the first wave of the survey. Interannual variability is computed as the between-year standard deviation of the seasonal average monthly water balance over the twenty years prior to the first wave of the survey. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, seasonal year-to-year variability in excess dryness relative to seasonal twenty-year long-run variability in dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, the share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B23: Other adaptation responses to beliefs and dryness

<i>Dependent variable</i>	Livestock buffer			Off-farm work	Domestic labor in HH		
	Value Livestock Sold (1)	Sold livestock (2)	Consumed livestock (3)	Has off-farm job (4)	# agricultural workers (5)	# crop farmers (6)	# self-employed in agricultural activities (7)
Belief increase drought	13644.1 (9901.2)	-0.00841 (0.0577)	0.0933 (0.0699)	-0.0277 (0.0249)	0.0350 (0.0295)	0.0101 (0.0456)	-0.00217 (0.0498)
Belief increase in drought \times Long-run dryness	-210060.1 (159026.5)	-0.215 (0.700)	-0.996 (0.800)	0.589 (0.385)	-0.780 (0.571)	-0.442 (0.515)	-0.00172 (0.612)
Mean Outcome	9418.782	0.500	0.627	0.141	0.109	0.835	0.939
<i>N</i>	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.086	0.176	0.139	0.681	0.487	0.737	0.705

Notes: Each column refers to an OLS specification on the sample of 714 individuals. All specifications include individual and year fixed effects, and the same controls as in the baseline regression in Table 2.1. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The outcome in column 1 is measured in Taka. Regressions in columns 2, 3, and 4 have a binary outcome variable.

TABLE B24: Monetized loss of inaccurate beliefs. Estimates using returns to irrigation from the literature.

Reference	Geographical Context	Crop Production	Irrigation technology	$\Delta yield / \Delta irrigation$	Median value loss \$ [IQR]
Haque (1975)	Bangladesh	<i>Aman</i> rice	STW	2490kg ha ⁻¹	\$102.80 [\$95.63, \$115.98]
		<i>Boro</i> rice	STW	3504.74kg ha ⁻¹	\$23.55 [\$12.11, \$42.06]
Parvin and Rahman (2009)	Bangladesh	<i>Boro</i> rice	-	3220 kg ha ⁻¹	\$21.64 [\$10.82, \$38.64]
Bhandari (2001)	Nepal	Rice	STW	850kg ha ⁻¹	<i>Aman</i> : \$35 [\$32.64, \$39.57] <i>Boro</i> : \$5.7 [\$2.86, \$10.2]
		<i>Kharif</i> rice	STW	500kg ha ⁻¹	<i>Aman</i> : \$20.64 [\$19.2, \$23.28]
Mandal and Singh (2004)	West Bengal (India)	<i>Rabi</i> rice	STW	1100kg ha ⁻¹	<i>Boro</i> : \$7.40 [\$3.7, \$13.2]
Sekhri (2014)	rural India	mixed	access to groundwater	1235.53 rupees ha ⁻¹ *	<i>Aman</i> : \$2.04 [\$1.90, \$2.31] <i>Boro</i> : \$.33 [\$.16, \$.59]
Jones et al. (2022)	Rwanda	dry season crops	hillside irrigation schemes	375-562.5 USD ha ⁻¹ †	<i>Boro</i> : \$5.25-7.88 [\$2.63-3-94, \$9.38-14.06]

* The effect is computed at the district level exploiting variation in the technology required to access groundwater at a depth of eight meters. Agricultural yields are originally reported in rupees per acre and converted to USD using the exchange rate in the study period: 1 USD = 62 rupees.

† Dry season goes from June to August, when in Bangladesh is the monsoon season. I use the exchange rate in the study period reported in Jones et al. (2022): 800 Rwf = 1 USD. The effect is mostly driven by changes in agricultural production, shifting from staples (primarily maize and beans) to horticulture.

B.5 Heterogeneity by socio-demographic characteristics

TABLE B25: Baseline estimates. Heterogeneity by age.

	Irrigated			STW			DTW		
	18-44 (1)	45+ (2)	18-44 (3)	45+ (4)	18-44 (5)	45+ (6)			
Belief increase in drought (β_1)	-0.0689** (0.0303)	-0.128*** (0.0298)	-0.0484 (0.0350)	-0.121*** (0.0359)	0.00485 (0.0194)	0.0408 (0.0256)			
Belief increase in drought \times Long-run dryness (β_2)	0.576 (0.431)	1.265*** (0.356)	0.769* (0.445)	1.105*** (0.419)	-0.357 (0.246)	-0.463 (0.299)			
Controls	X	X	X	X	X	X			
Fixed Effects	X	X	X	X	X	X			
Mean Outcome	0.495	0.482	0.316	0.284	0.066	0.070			
SD Outcome	0.331	0.324	0.365	0.344	0.184	0.198			
N	675	753	675	753	675	753			
adj. R^2	0.695	0.695	0.681	0.679	0.548	0.631			

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Controls: Annual deviation in excess dryness relative to twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. Fixed Effects: Individual, Year.

TABLE B26: Baseline estimates. Heterogeneity by education.

	Irrigated		STW		DTW	
	No education (1)	≥ one year (2)	No education (3)	≥ one year (4)	No education (5)	≥ one year (6)
Belief increase in drought (β_1)	-0.0515** (0.0257)	-0.111*** (0.0271)	-0.0481 (0.0513)	-0.0961*** (0.0290)	0.0247 (0.0217)	0.0182 (0.0231)
Belief increase in drought \times Long-run dryness (β_2)	0.299 (0.285)	1.163*** (0.379)	0.332 (0.517)	1.185*** (0.371)	-0.310 (0.252)	-0.414 (0.258)
Controls	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X
Mean Outcome	0.489	0.488	0.304	0.295	0.066	0.070
SD Outcome	0.335	0.321	0.360	0.349	0.190	0.192
N	666	762	666	762	666	762
adj. R^2	0.762	0.649	0.701	0.668	0.656	0.548

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Controls: Annual deviation in excess dryness relative to twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. Fixed Effects: Individual, Year.

TABLE B27: Heterogeneity by age and education in Aman

	Age						Education		
	Rainfed		STW		Rainfed		STW		
	18-44 (1)	45+ (2)	18-44 (3)	45+ (4)	No education (5)	≥ one year (6)	No education (7)	≥ one year (8)	
Belief increase in drought (β_1)	0.0804*** (0.0303)	0.118*** (0.0455)	-0.0542* (0.0296)	-0.0679** (0.0299)	0.0744** (0.0340)	0.102*** (0.0382)	-0.0461 (0.0345)	-0.0496** (0.0247)	
Belief increase in drought \times Long-run dryness (β_2)	-0.614** (0.263)	-0.890** (0.412)	0.666** (0.286)	0.601** (0.279)	-0.401 (0.255)	-0.951*** (0.348)	0.407* (0.237)	0.683** (0.268)	
Controls	X	X	X	X	X	X	X	X	
Fixed Effects	X	X	X	X	X	X	X	X	
Mean Outcome	0.751	0.773	0.183	0.145	0.759	0.766	0.169	0.158	
SD Outcome	0.411	0.399	0.366	0.331	0.410	0.400	0.354	0.344	
N	675	753	675	753	666	762	666	762	
adj. R^2	0.550	0.567	0.502	0.634	0.598	0.524	0.545	0.589	

Notes: Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiaung (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Controls: Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. Fixed Effects: Individual, Year.

B.6 Robustness Checks

B.6.1 Individual beliefs and adaptive decisions

TABLE B28: Individual beliefs and irrigation use. OLS estimates with inverse probability weights for attrition.

<i>Dependent variable:</i> Share of cultivated land	Irrigated (1)	STW (2)	DTW (3)
Belief increase in drought (β_1)	-0.0370*** (0.0120)	-0.0303** (0.0146)	0.00971 (0.0109)
Belief increase in drought \times Long-run dryness (β_2)	0.739** (0.308)	0.813* (0.436)	-0.487* (0.282)
Controls	X	X	X
Fixed Effects	X	X	X
Mean Outcome	0.489	0.299	0.068
SD Outcome	0.327	0.354	0.191
N	1428	1428	1428

Notes: Table reports the OLS estimates of a regression where the outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (columns 1), irrigated with STW (column 3) and with DTW (column 4). Observations are weighted by the inverse probability weight for attrition, obtained from the estimation of a logit regression to obtain the probability of attrition based on all the covariates in the regression. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, the share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B29: Baseline results. Spatial and temporal cutoffs for standard errors adjustment.

<i>Dependent variable: Share of cultivated land</i>	Irrigated (1)	STW (2)	DTW (3)
<i>Panel A: 100 km and 2-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0278)	-0.0626** (0.0285)	0.0190 (0.0221)
Belief increase in drought \times Long-run dryness (β_2)	0.600** (0.267)	0.543** (0.261)	-0.260 (0.195)
<i>Panel B: 200 km and 5-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0258)	-0.0626** (0.0305)	0.0190 (0.0187)
Belief increase in drought \times Long-run dryness (β_2)	0.600** (0.271)	0.543* (0.286)	-0.260 (0.189)
<i>Panel C: 400 km and 2-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0200)	-0.0626** (0.0264)	0.0190 (0.0149)
Belief increase in drought \times Long-run dryness (β_2)	0.600*** (0.220)	0.543** (0.271)	-0.260 (0.183)
<i>Panel D: 400 km and 5-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0217)	-0.0626** (0.0279)	0.0190 (0.0160)
Belief increase in drought \times Long-run dryness (β_2)	0.600** (0.237)	0.543* (0.284)	-0.260 (0.167)
<i>Panel E: 800 km and 5-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0205)	-0.0626** (0.0243)	0.0190 (0.0144)
Belief increase in drought \times Long-run dryness (β_2)	0.600*** (0.221)	0.543** (0.243)	-0.260 (0.161)
<i>Panel F: 800 km and 999-year cutoffs</i>			
Belief increase in drought (β_1)	-0.0821*** (0.0222)	-0.0626** (0.0259)	0.0190 (0.0155)
Belief increase in drought \times Long-run dryness (β_2)	0.600** (0.237)	0.543** (0.257)	-0.260 (0.159)
<i>N</i>	1428	1428	1428

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Spatial and temporal cutoffs are varying and reported in the heading of each panel. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions control for 20-year long-run average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; individual and year fixed effects.

TABLE B30: Baseline results by growing season. Spatial and temporal cutoffs for standard errors adjustment.

<i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
<i>Panel A: 100 km and 2-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0296)	-0.0498** (0.0203)	0.0229 (0.0201)	-0.0234 (0.0232)	0.0188 (0.0214)
Belief increase in drought \times Long-run dryness (β_2)	-0.545** (0.276)	0.437** (0.219)	0.275 (0.306)	0.0254 (0.333)	-0.296 (0.220)
<i>Panel B: 200 km and 5-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0280)	-0.0498** (0.0202)	0.0229 (0.0176)	-0.0234 (0.0237)	0.0188 (0.0194)
Belief increase in drought \times Long-run dryness (β_2)	-0.545* (0.285)	0.437* (0.243)	0.275 (0.285)	0.0254 (0.318)	-0.296 (0.215)
<i>Panel C: 400 km and 2-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0225)	-0.0498*** (0.0168)	0.0229 (0.0142)	-0.0234 (0.0177)	0.0188 (0.0158)
Belief increase in drought \times Long-run dryness (β_2)	-0.545** (0.234)	0.437** (0.203)	0.275 (0.229)	0.0254 (0.269)	-0.296 (0.189)
<i>Panel D: 400 km and 5-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0243)	-0.0498*** (0.0184)	0.0229 (0.0152)	-0.0234 (0.0190)	0.0188 (0.0168)
Belief increase in drought \times Long-run dryness (β_2)	-0.545** (0.245)	0.437** (0.212)	0.275 (0.250)	0.0254 (0.286)	-0.296 (0.204)
<i>Panel E: 800 km and 5-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0224)	-0.0498*** (0.0176)	0.0229 (0.0139)	-0.0234 (0.0172)	0.0188 (0.0150)
Belief increase in drought \times Long-run dryness (β_2)	-0.545*** (0.208)	0.437** (0.176)	0.275 (0.236)	0.0254 (0.247)	-0.296 (0.191)
<i>Panel F: 800 km and 999-year cutoffs</i>					
Belief increase in drought (β_1)	0.0871*** (0.0241)	-0.0498*** (0.0191)	0.0229 (0.0150)	-0.0234 (0.0185)	0.0188 (0.0161)
Belief increase in drought \times Long-run dryness (β_2)	-0.545** (0.220)	0.437** (0.185)	0.275 (0.256)	0.0254 (0.265)	-0.296 (0.206)
<i>N</i>	1428	1428	1428	1428	1428

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). Spatial and temporal cutoffs are varying and reported in the heading of each panel. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions control for 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, weighted share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam by hectares; individual and year fixed effects.

TABLE B31: Baseline results. Clustered standard errors at the grid cell-level.

<i>Dependent variable:</i> Share of cultivated land	Irrigated (1)	STW (2)	DTW (3)
Belief increase in drought (β_1)	-0.0470*** (0.0140)	-0.0340* (0.0175)	0.00386 (0.0113)
Belief increase in drought \times Long-run dryness (β_2)	0.649** (0.288)	0.725** (0.352)	-0.377 (0.228)
Controls	X	X	X
Fixed Effects	X	X	X
Mean Outcome	0.489	0.299	0.068
SD Outcome	0.327	0.354	0.191
N	1428	1428	1428
adj. R^2	0.699	0.689	0.601

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Standard errors are clustered at the grid cell-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* year-to-year deviation in excess dryness relative to twenty-year long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B32: Baseline results by growing season. Clustered standard errors at the grid cell-level.

<i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Belief increase in drought (β_1)	0.0871** (0.0359)	-0.0498* (0.0243)	0.0229 (0.0231)	-0.0234 (0.0296)	0.0188 (0.0266)
Belief increase in drought \times Long-run dryness (β_2)	-0.545* (0.272)	0.437* (0.228)	0.275 (0.329)	0.0254 (0.384)	-0.296 (0.287)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are clustered at the grid cell-level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B33: Individual beliefs and irrigation status. Time-varying long-run dryness.

<i>Dependent variable:</i> Share of cultivated land	Irrigated (1)	STW (2)	DTW (3)
Belief increase in drought (β_1)	-0.0821*** (0.0244)	-0.0626** (0.0292)	0.0190 (0.0178)
Long-run dryness (β_2)	-1.971* (1.038)	-1.018 (1.458)	-0.406 (0.905)
Belief increase in drought \times Long-run dryness (β_3)	0.600** (0.257)	0.543** (0.273)	-0.260 (0.183)
Controls	X	X	X
Fixed Effects	X	X	X
Mean Outcome	0.489	0.299	0.068
SD Outcome	0.327	0.354	0.191
N	1428	1428	1428
adj. R^2	0.698	0.682	0.593

Notes: The outcome variable is the average share of cultivated land across the two main growing seasons under any irrigation status (column 1), irrigated with STW (column 2) and with DTW (column 3). Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* year-to-year deviation in excess dryness relative to twenty-year long-run average, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B34: Individual beliefs and irrigation status by growing season. Time-varying long-run dryness.

<i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Belief increase in drought (β_1)	0.0871*** (0.0265)	-0.0498*** (0.0188)	0.0229 (0.0167)	-0.0234 (0.0227)	0.0188 (0.0185)
Long-run dryness (β_2)	-0.634 (0.823)	0.539 (0.732)	0.551 (1.977)	2.761** (1.216)	-0.561 (0.834)
Belief increase in drought \times Long-run dryness (β_3)	-0.545** (0.276)	0.437* (0.236)	0.275 (0.267)	0.0254 (0.303)	-0.296 (0.200)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.763	0.163	0.260	0.435	0.112
SD Outcome	0.405	0.348	0.411	0.470	0.300
N	1428	1428	1428	1428	1428
adj. R^2	0.560	0.572	0.750	0.669	0.583

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B35: Baseline results by growing season. Hectares of cultivated land as the outcome variable.

<i>Dependent variable:</i> Hectares of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Belief increase in drought (β_1)	0.0908** (0.0374)	-0.0340** (0.0142)	0.0131 (0.0191)	-0.0105 (0.0143)	0.0260*** (0.00973)
Belief increase in drought \times Long-run dryness (β_2)	-0.785** (0.394)	0.227* (0.138)	-0.300 (0.268)	0.271 (0.220)	-0.242 (0.167)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.502	0.080	0.185	0.257	0.050
SD Outcome	1.230	0.227	0.479	1.122	0.184
N	1428	1428	1428	1428	1428
adj. R^2	0.968	0.652	0.812	0.973	0.498

Notes: The outcome variable is the total hectares of cultivated land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B36: Baseline results by growing season. Extensive margin of irrigation status as outcome.

	Aman		Boro		
	(1) Rainfed	(2) STW	(3) Rainfed	(4) STW	(5) DTW
Belief increase in drought (β_1)	0.0885*** (0.0314)	-0.0694*** (0.0221)	-0.00844 (0.0222)	-0.0166 (0.0254)	0.00666 (0.0181)
Belief increase in drought \times Long-run dryness (β_2)	-0.877** (0.353)	0.610*** (0.228)	-0.863 (0.571)	0.259 (0.443)	-0.591 (0.476)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
Mean Outcome	0.819	0.204	0.363	0.496	0.135
SD Outcome	0.385	0.403	0.481	0.500	0.342
N	1428	1428	1428	1428	1428
adj. R^2	0.456	0.582	0.621	0.641	0.618

Notes: The outcome variable is a dummy variable that takes value one if the share of cultivated land under each irrigation status or rainfed is strictly positive and zero otherwise. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

TABLE B37: Reverse Causality: Irrigation status and individual beliefs

	Belief increase in drought in wave 2			Δ Belief increase in drought		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg share of irrigated land in wave 1	0.0283 (0.0973)			-0.00667 (0.137)		
Avg share of irrigated land in Aman in wave 1		0.00228 (0.0452)			-0.0518 (0.0760)	
Avg share of irrigated land in Boro in wave 1			0.0399 (0.111)			0.0806 (0.143)
N	714	714	714	714	714	714
adj. R^2	0.152	0.152	0.153	0.112	0.113	0.113

Notes: The table estimates the potential reverse causality of past adaptation decisions on future beliefs. Each column refers to an OLS specification where the sample is a cross-section of 714 rural households' respondents. The dependent variable is the dichotomous variable on the perceived increase in drought measured in the second wave of the survey in columns 1-3 and the difference between perceived increase in drought in wave 2 and wave 1 in columns 4-6. The main regressors of interest are the share of irrigated cultivated land in the first wave. All regressions control for: main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings, age, gender and years of education of the respondent, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam, weighted by hectares. All regressions also control for union fixed effects. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.6.2 Saliency

TABLE B38: Saliency of objective drought events and irrigation status in *Boro*

<i>Dependent variable: Share of cultivated land</i>	Objective Drought			Most Harmful Objective Drought		
	Rainfed (1)	STW (2)	DTW (3)	Rainfed (4)	STW (5)	DTW (6)
Obj Drought _{t-1}	-0.0942** (0.0436)	-0.0550* (0.0335)	0.0614** (0.0278)	0.00724 (0.0205)	-0.134*** (0.0313)	0.122*** (0.0266)
Belief increase in drought	0.0192 (0.0172)	-0.0256 (0.0227)	0.0212 (0.0183)	0.0221 (0.0160)	-0.00916 (0.0221)	0.00583 (0.0180)
Belief increase in drought × Long-run dryness	0.311 (0.258)	0.0465 (0.310)	-0.320 (0.199)	0.266 (0.266)	0.203 (0.263)	-0.457* (0.235)
Controls	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X
<i>N</i>	1428	1428	1428	1428	1428	1428
adj. <i>R</i> ²	0.751	0.669	0.584	0.750	0.679	0.604

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in the *Boro* growing season. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* 20-year long-run seasonal average exposure to dryness, Seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

B.6.3 Overestimation

TABLE B39: Extent of overestimation of drought frequency using other objective drought cutoffs.

Dependent variable: Share of cultivated land	Moderate Droughts					Severe Droughts				
	Aman		Boro		DTW (5)	Aman		Boro		DTW (10)
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)		Rainfed (6)	STW (7)	Rainfed (8)	STW (9)	
Δ Drought	-0.0169*** (0.00629)	0.0111* (0.00592)	0.00489 (0.00493)	-0.00286 (0.00517)	0.00213 (0.00474)	-0.00595 (0.00970)	0.000368 (0.00870)	-0.00123 (0.00709)	-0.00866 (0.00732)	0.00794* (0.00479)
Controls	X	X	X	X	X	X	X	X	X	X
Fixed Effects	X	X	X	X	X	X	X	X	X	X
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.563	0.574	0.750	0.669	0.583	0.559	0.572	0.750	0.669	0.584

Notes: The outcome variable is the share of land under each irrigation status or left rainfed in Aman or Boro growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Comley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

B.6.4 Alternative data source for drought events

In Section 2.7.3, I examine the role of overestimating drought events in the irrigation decisions of farmers. To test for the robustness of the results, I also use another source of objective drought events to compute the objective counterfactual of the number of droughts that occurred. I use the EM-DAT (2022) database collected by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain. The EM-DAT database has worldwide coverage and contains data on the occurrence and effects of natural disasters from 1900 to the present. A disaster is defined by the CRED as a natural event that overwhelms local capacity, necessitating a request for external assistance. The database includes information on the locations within the country that have been hit by natural disasters. In order to be recorded in the EM-DAT database, a disaster needs to satisfy at least one of the following criteria: i) 10 or more people are reported to have been killed; ii) 100 people have been reported affected; iii) a state of emergency is declared; iv) international assistance is called for.

The use of this source for objective records of extreme events might be problematic due to the potential threshold and accounting biases in loss information that the database could suffer from (Gall et al., 2009). Nevertheless, the use of loss information is out of the scope of this research, which is limited to analyzing the number of drought events recorded. Limits in the use of EM-DAT records as objective measures have been discussed in the literature (Noy, 2009; Felbermayr and Gröschl, 2014; Cavallo et al., 2013). Given the threshold conditions that the disaster needs to satisfy to be recorded, potential measurement error in the data would bias downward the information from the database.

I adopt the same methodology used in Section 2.3.2 to compute the objectively recorded number of drought events that have occurred in the five years before the first wave of the survey (between 2006 and 2010) and between the first and the second wave (2011 and 2012). Following this approach, round-specific measures of accuracy are created by comparing the number of self-reported drought events by the household and the recorded number of drought events as reported by EM-DAT:

$$\Delta \text{Drought}_{it} = \text{self-reported } \#_{it} - \text{objective } \# \text{ droughts}_{ut} \quad (\text{B1})$$

These round-specific measures of accuracy infer whether respondents overestimate or underestimate the number of drought events that they have experienced.

TABLE B40: Extent of overestimation of drought frequency using EM-DAT objective drought records.

<i>Dependent variable:</i> Share of cultivated land	Aman		Boro		
	Rainfed (1)	STW (2)	Rainfed (3)	STW (4)	DTW (5)
Δ Drought	-0.00435 (0.0156)	0.00211 (0.0149)	0.00943 (0.00838)	-0.0155 (0.00943)	0.0155** (0.00730)
Belief increase in drought	0.0885*** (0.0289)	-0.0505** (0.0209)	0.0202 (0.0178)	-0.0191 (0.0235)	0.0144 (0.0183)
Belief increase in drought \times Long-run dryness	-0.550** (0.277)	0.440* (0.238)	0.296 (0.269)	-0.00877 (0.308)	-0.262 (0.199)
Controls	X	X	X	X	X
Fixed Effects	X	X	X	X	X
N	1428	1428	1428	1428	1428
adj. R^2	0.559	0.572	0.397	0.750	0.669

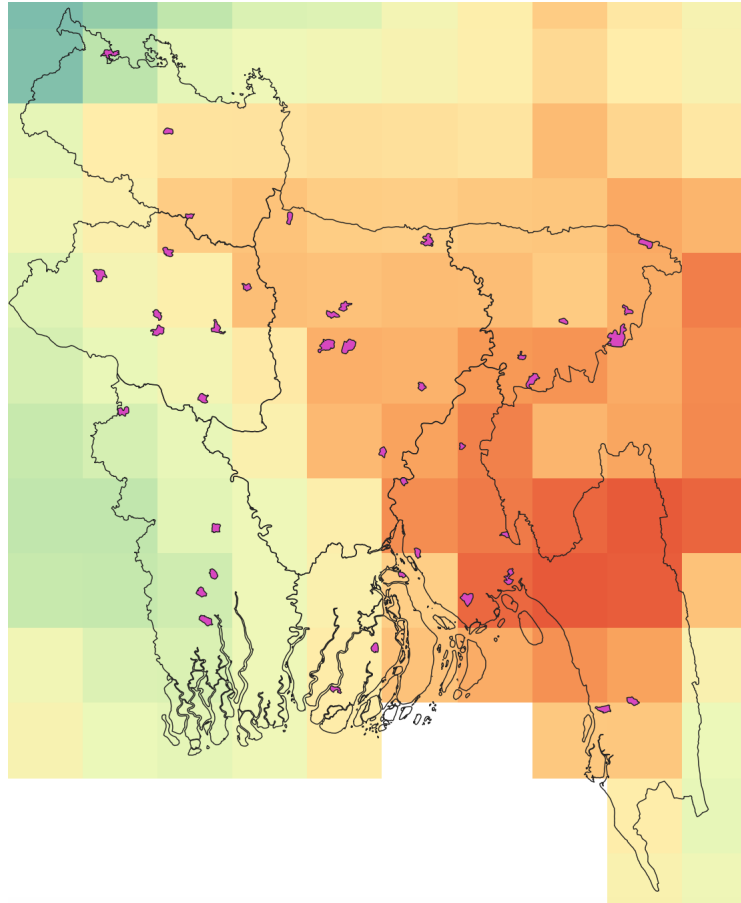
Notes: The outcome variable is the share of land under each irrigation status or left rainfed in *Aman* or *Boro* growing seasons. Standard errors are computed adjusting for temporal and spatial correlation using the methods developed by Fetzer (2020) and based on Hsiang (2010) and Conley (1999). I use a 2-year time lag and a distance cutoff of 200 kilometers for spatial correlation. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Controls:* 20-year long-run seasonal average exposure to dryness, seasonal year-to-year deviation in excess dryness relative to seasonal twenty-year long-run dryness, main occupation of the respondent is farmer, the household receives extension advice, access to electricity, perception of decrease in precipitation, perception of more erratic rainfall, hectares of total land holdings; ownership status of STW and DTW, share of cultivated land of i) clay; ii) loam; iii) sandy; iv) clay-loam; v) sandy-loam. *Fixed Effects:* Individual, Year.

Appendix C

Appendix to Chapter 3: Drought exposure and accuracy: Motivated reasoning in climate change beliefs

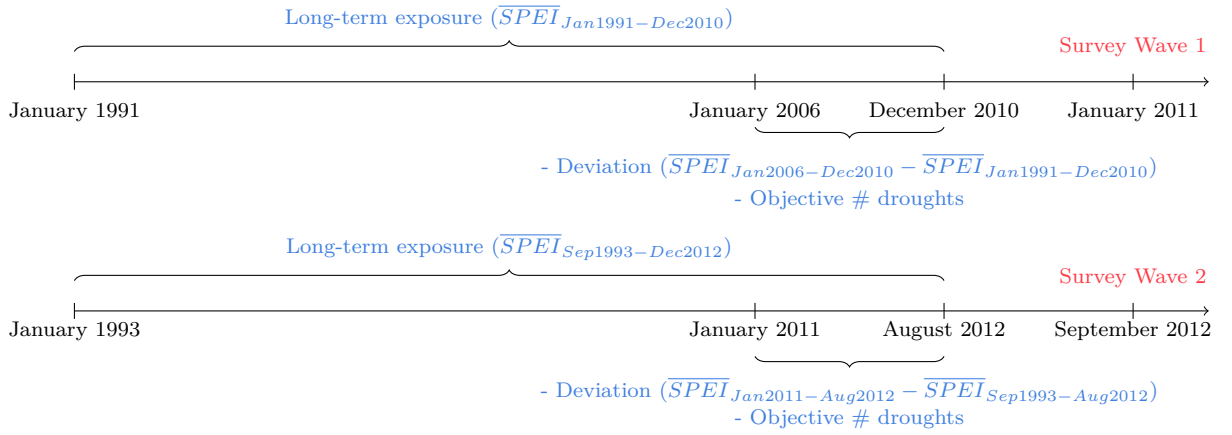
C.1 Additional figures

FIGURE C1: Bangladesh map with surveyed unions and SPEI grid cell data



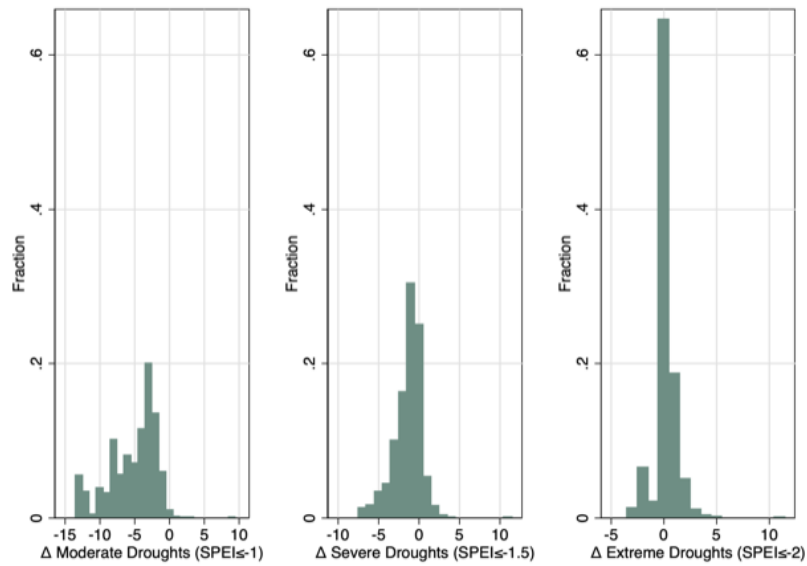
Notes: The map plots the administrative boundaries of the 40 surveyed unions in purple and the regional boundaries of Bangladesh. The administrative layer (from GADM (2021)) is overlaid to the raster SPEI gridded data from Vicente-Serrano et al. (2010) with 0.5 degree resolution (≈ 55 km at the Equator) with September 2012 values, where colors range from red to blue, respectively from a drier to a wetter environment. In five cases, there are two unions within the same grid cell, thus sharing the same SPEI values. The five cases are Adabaria and Arpangashia; Char Darbesh and Char Jabbar; Dakatia and Kakrajan; Kushmail and Naogaon. In one case, there are three unions within the same grid cell: Kalilnagar, Laskar and Rudaghara. The remaining 28 unions are uniquely matched with SPEI grid cells.

FIGURE C2: Timeline of BCCAS survey waves and dryness and drought events variables



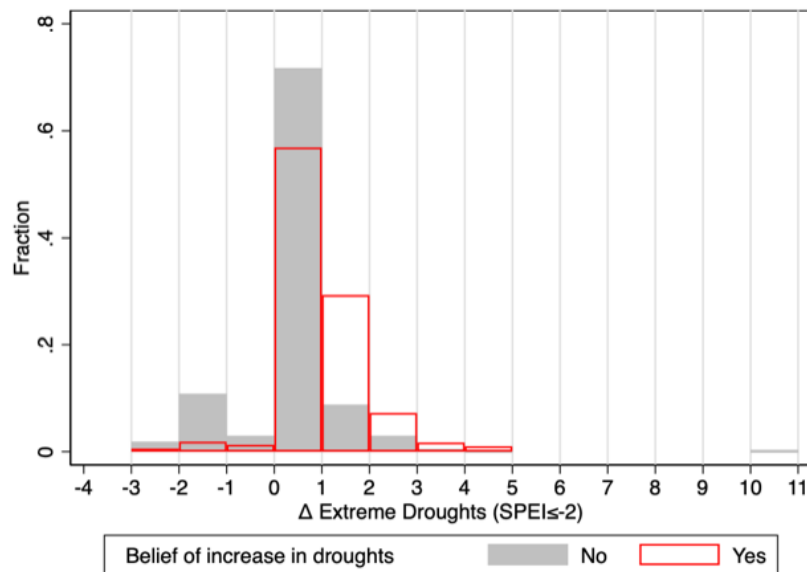
Notes: The timelines display the time horizon of the variables of exposure to dryness for each survey wave, respectively conducted in January 2011 and September 2012. Long-term exposure is the average monthly SPEI ($\times(-1)$) over the twenty years preceding each survey wave. Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and long-term exposure ($\times(-1)$). The number of objective droughts (Objective # droughts) is computed over the same time horizon covered by *self-reported # droughts* in each survey wave, and it records the number of (non-consecutive) SPEI monthly realizations below a certain cut-off (-1 for moderate, -1.5 for severe, -2 for extreme).

FIGURE C3: Frequency distribution of Δ for moderate, severe and extreme droughts



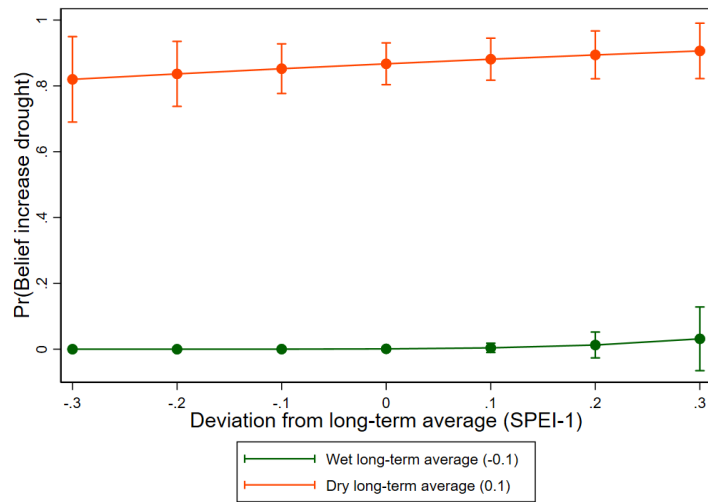
Notes: Author's computation using SPEI, BCCAS and cut-offs from Mc-Kee et al. (1993) and Paulo et al. (2012). I use the cut-offs for moderate (SPEI ≤ -1), severe (SPEI ≤ -1.5) and extreme drought events (SPEI ≤ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period as in Equation (3.1). When using moderate or severe drought events as 'objective counterfactual' of the self-reported number of droughts, there is systematic underestimation of the frequency of droughts among individuals.

FIGURE C4: Frequency distribution of overestimation for extreme droughts by belief of increase in droughts



Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-off for extreme drought events ($SPEI \leq -2$) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period, as explained in Equation (3.1). The grey bars show the frequency distribution of the measure Δ for individuals who did not hold a belief that droughts have increased over the past twenty years, the red-border bars display the frequency distribution of the measure Δ for individuals who reported that droughts have increased over the past twenty years.

FIGURE C5: Interaction between long-term drought exposure and deviations relative to lifetime



Notes: The figure shows the predicted marginal effects of deviations from long-term average exposure at different values of long-term average exposure, respectively -0.1 (in green) and 0.1 (in red). Positive values indicate drier conditions than the individuals' lifetime exposure and negative values wetter conditions. The estimates are obtained from a logit regression that determines the probability of reporting a belief of increase in droughts as a function of long-term average exposure, the short-term deviation from the average and their interaction using the SPEI-1 rescaled to each individual's specific lifetime exposure and year- and individual-specific fixed effects.

C.1.1 Data

TABLE C2: Survey variables' definition and construction

VARIABLE	SURVEY QUESTION CODE	WAVE	SURVEY QUESTION	SOURCE
Belief of increase in droughts (0/1)	L.11	1	Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
Belief of increase in droughts (0/1)	Q.04-Q.07	2	Have you noticed any long term changes in rainfall variability over the last 20 years? If yes, what changes have you noticed? (1 if "Longer periods of droughts" and 0 otherwise) Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
self-reported # droughts	L.03	1	In the last five years, have the HH's properties and productivity been affected by droughts? How many times did it occur in last 5 years?	BCCAS Household Questionnaire
self-reported # droughts	L.03	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? How many times did it occur in these two years?	BCCAS Household Questionnaire
Information on soil and water conservation and crop protection	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection", 0 otherwise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection and new crop varieties	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties", 0 otherwise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection, new crop varieties and crop utilization	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties" or "Information on crop utilization", 0 otherwise)	BCCAS Household Questionnaire
Information from TV/Radio/Newsletter	M.08	1 & 2	"Do you receive information from sources besides the extension worker? If yes, what are those sources?" (1 if "Radio", "Television" or "Newsletter", and 0 otherwise)	BCCAS Household Questionnaire
Krishi Bank	C.01 (Question ID 11)	1 & 2	"Do you have a Bangladesh Krishi Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Commercial Bank	C.01 (Question ID 12)	1 & 2	"Do you have a Commercial bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Grameen Bank	C.01 (Question ID 13)	1 & 2	"Do you have a Grameen Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Agriculture extension officer	C.01 (Question ID 20)	1 & 2	"Do you have an agriculture extension officer/Block supervisor in this village?" (Yes/No)	BCCAS Community Questionnaire
Access to electricity	C.01 (Question ID 21)	1 & 2	"Do you have access to electricity in this village?" (Yes/No)	BCCAS Community Questionnaire
Shop for pesticides and/or fertilizer	C.01 (Question ID 19)	1 & 2	"Do you have a Shop for pesticides and/or fertilizer in this village?" (Yes/No)	BCCAS Community Questionnaire

Notes: The variable self-reported # droughts is used to compute the variable Δ , subtracting the objective # droughts, being the recorded number of (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period as the survey question, as explained in Equation (3.1).

C.2 Tables

C.2.1 Descriptive Statistics

TABLE C3: T-tests for differences in means for attritors versus non-attritors

	Non Attritors (N=714)		Attritors (N=96)		Difference	
	Mean	SD	Mean	SD	Mean	t-test
<i>Panel A. Subjective measures</i>						
Belief of increase in droughts	0.252	0.016	0.290	0.049	-0.038	(-0.77)
Δ Drought (Moderate)	-7.834	0.109	-7.360	0.338	-0.474	(-1.41)
Δ Drought (Severe)	-2.127	0.072	-1.953	0.200	-0.174	(-0.79)
Δ Drought (Extreme)	-0.125	0.041	0.023	0.140	-0.148	(-1.14)
<i>Panel B. Objective exposure measures</i>						
LT Exposure	0.070	0.001	0.061	0.004	0.009	(2.08)
Deviation	0.041	0.001	0.040	0.003	0.001	(0.26)
<i>Panel C. Objective number of droughts</i>						
# Moderate Droughts (SPEI ≤ -1)	8.110	0.106	7.779	0.321	0.331	(1.01)
# Severe Droughts (SPEI ≤ -1.5)	2.403	0.071	2.372	0.190	0.031	(0.14)
# Extreme Droughts (SPEI ≤ -2)	0.400	0.031	0.395	0.086	0.005	(0.05)

Notes: The sample compares the means in the estimation sample of the 714 individuals interviewed in both survey waves in January 2011 and September 2012 and the 96 individuals who have not been reinterviewed in the second wave (because they migrated, they were not at home in the moment of the survey or the respondent changed from wave 1). The variable Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. LT Exposure is the average SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Panel A shows the summary statistics for subjective variables that use information from the BCCAS. Panel B and C report values computed using the SPEI. The values in Panels B and C differ from those in Panel A in Table C5 since they are computed at the individual level and not at the grid cell level. The average LT Exposure is the only variable statistically different at the 5% level in the estimation sample of non-attritors from the sample of attritors. However, this result should not raise concern on the validity of the findings since the difference is negligible, less than one percent of SD, and the sample of non attritors has an average LT Exposure higher than the one of the sample of attritors.

TABLE C4: Summary statistics of subjective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Belief of increase in droughts	714	0.25	0.43	0	1
Δ Drought (Moderate)	714	-7.83	2.92	-13	0
Δ Drought (Severe)	714	-2.13	1.94	-7	3
Δ Drought (Extreme)	714	-0.12	1.11	-3	4
Panel B. Survey Wave 2 (2012)					
Belief of increase in droughts	714	0.71	0.45	0	1
Δ Drought (Moderate)	714	-2.74	1.35	-6	9
Δ Drought (Severe)	714	-0.59	1.08	-3	11
Δ Drought (Extreme)	714	0.45	0.84	-1	11
Panel C. Changes					
Belief of increase in droughts	714	0.46	0.62	-1	1
Δ Drought (Moderate)	714	5.09	2.95	-3	14
Δ Drought (Severe)	714	1.53	2.02	-4	12
Δ Drought (Extreme)	714	0.57	1.35	-4	11
Panel D. Total					
Belief of increase in droughts	1428	0.48	0.50	0	1
Δ Drought (Moderate)	1428	-5.29	3.41	-13	9
Δ Drought (Severe)	1428	-1.36	1.75	-7	11
Δ Drought (Extreme)	1428	0.16	1.03	-3	11

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. The variable Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

TABLE C5: Summary statistics of objective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
<i>A. Exposure measures</i>					
LT Exposure	34	0.07	0.04	-0.01	0.15
Deviation	34	0.04	0.03	-0.03	0.15
LT Exposure x Deviation	34	0.01	0.01	-0.01	0.02
<i>B. Objective number of droughts</i>					
# Moderate Droughts (SPEI \leq -1)	34	8.20	3.02	3	13
# Severe Droughts (SPEI \leq -1.5)	34	2.44	2.02	0	7
# Extreme Droughts (SPEI \leq -2)	34	0.47	0.89	0	3
Panel B. Survey Wave 2 (2012)					
<i>A. Exposure measures</i>					
LT Exposure	34	0.10	0.04	0.03	0.15
Deviation	34	-0.09	0.11	-0.44	0.06
LT Exposure x Deviation	34	0.01	0.01	-0.07	0.01
<i>B. Objective number of droughts</i>					
# Moderate Droughts (SPEI \leq -1)	34	3.23	1.10	1	6
# Severe Droughts (SPEI \leq -1.5)	34	1.15	0.74	0	3
# Extreme Droughts (SPEI \leq -2)	34	0.03	0.17	0	1
Panel C. Changes					
<i>A. Exposure measures</i>					
LT Exposure	34	0.03	0.01	-0.01	0.05
Deviation	34	-0.13	0.12	-0.57	0.04
LT Exposure x Deviation	34	-0.01	0.02	-0.09	0.01
<i>B. Objective number of droughts</i>					
# Moderate Droughts (SPEI \leq -1)	34	-4.97	2.68	-10	0
# Severe Droughts (SPEI \leq -1.5)	34	-1.29	1.64	-5	2
# Extreme Droughts (SPEI \leq -2)	34	-0.44	0.82	-2	0
Panel D. Total					
<i>A. Exposure measures</i>					
LT Exposure	68	0.09	0.04	-0.01	0.16
Deviation	68	-0.02	0.10	-0.43	0.15
LT Exposure x Deviation	68	0.01	0.01	-0.07	0.02
<i>B. Objective number of droughts</i>					
# Moderate Droughts (SPEI \leq -1)	68	5.72	3.37	1	13
# Severe Droughts (SPEI \leq -1.5)	68	1.79	1.64	0	7
# Extreme Droughts (SPEI \leq -2)	68	0.25	0.67	0	3

Notes: Statistics computed at the grid-cell level. LT Exposure is the average SPEI over the previous twenty years (\times (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure (\times (-1)). The number of drought events is computed using the classification of drought events in the literature (Paulo et al., 2012; McKee et al., 1993): moderate/severe/extreme droughts include all (non-consecutive) monthly realizations in the previous five years for survey wave 1 and between January 2011 and September 2012 for survey wave 2 in which the SPEI \leq -1/-1.5/2. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

C.2.2 Robustness Checks

TABLE C6: Drought exposure effect on information seeking variables and union-level adaptive margins

	Information on soil and water conservation					Presence of a bank				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LT Exposure	-2.893 (2.436)	-1.701 (2.123)	-0.246 (2.156)	3.075 (2.304)	-1.602 (3.735)	-2.456 (2.542)	-1.441 (2.711)	8.489 (10.85)	8.120 (5.847)	16.27 ^{**} (8.092)
Deviation	0.0719 (0.258)	0.131 (0.211)	0.0159 (0.216)	-0.120 (0.175)	0.215 (0.364)	0.292 (0.292)	0.302 (0.307)	0.381 (1.015)	-0.391 (0.608)	-0.490 (0.705)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the OLS estimates of a regression of adaptive margins and variables on information seeking behavior by individuals on the long-run exposure to drought and short-term deviations. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$). Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). All regressions control for individual and year fixed effects. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C7: Objective exposure, beliefs and average number of droughts.

	Belief of Increase in Droughts					
	(1)	(2)	(3)	(4)	(5)	(6)
LT Exposure	13.13*** (1.855)	14.52*** (3.101)	11.74*** (1.955)	11.11*** (2.300)	13.85*** (2.140)	13.86*** (2.262)
# Drought Events	-0.0306 (0.0356)	0.0159 (0.114)	-0.205*** (0.0583)	-0.253* (0.144)	0.0704 (0.186)	0.0564 (0.866)
LT Exposure \times # Drought Events		-0.465 (0.958)		0.516 (1.285)		0.153 (8.969)
Drought type	Moderate		Severe		Extreme	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428
adj. R^2	0.278	0.277	0.286	0.285	0.277	0.276

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years. All regressions control for individual and year fixed effects. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), # Drought Events is the average number of drought events recorded in the five years before the first wave and between the two survey wave. Columns 1-2 include at least moderate droughts (SPEI<-1), columns 3-4 include at least severe droughts (SPEI<-1.5) and columns 5-6 include only extreme droughts (SPEI<-2). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C8: Objective exposure, beliefs and probability of overestimation. Logit estimates.

	Belief of Increase in Droughts				Probability of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	84.79*** (6.736)		84.54*** (7.640)	82.14*** (8.581)	50.10*** (5.724)		49.40*** (7.480)	48.30*** (7.910)
Deviation		-9.277*** (2.101)	-0.0596 (0.781)	-2.111 (3.321)		-7.322*** (2.121)	-0.212 (1.458)	-1.784 (4.112)
LT Exposure \times Deviation				14.91 (23.31)				12.62 (29.87)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	846	846	846	846	540	540	540	540

Notes: The table displays the coefficients obtained by the estimation of Equation (3.4) using Logit. The sample includes in columns (1)-(4) (resp., columns 5-8) the 423 individuals (resp., 270) for which there is variation in the outcome once conditioning on individual and year fixed effects. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C9: Objective exposure and extent of overestimation. Poisson estimates.

	Extent of Overestimation			
	(1)	(2)	(3)	(4)
LT Exposure	16.16*** (3.442)		14.88*** (5.002)	13.62*** (4.999)
Deviation		-2.458** (1.197)	-0.512 (1.212)	-3.083 (3.804)
LT Exposure \times Deviation				22.41 (29.38)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	534	534	534	534

Notes: The table displays the coefficients obtained by the estimation of Equation (3.4) using Poisson estimation method, where the dependent variable is the variable Δ excluding the 142 individuals with negative values (i.e., who underestimated the number of droughts). The sample also excludes 752 observations because of only one observation over time and because of no variation in the outcome once conditioning on individual and year fixed effects. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C10: Objective exposure and overestimation of drought events using moderate objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	0.467*		0.539	0.610	131.9**		204.9***	181.7***
	(0.273)		(0.440)	(0.472)	(49.82)		(43.05)	(43.30)
Deviation		0.0147	-0.00960	-0.0564		-0.554	-9.789***	5.435
		(0.0218)	(0.0336)	(0.0736)		(2.770)	(1.920)	(6.161)
LT Exposure \times Deviation				0.317				-103.2**
				(0.331)				(40.64)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.003	0.001	0.002	0.001	0.716	0.642	0.760	0.777

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of moderate drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1 for moderate events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C11: Objective exposure and overestimation of drought events using severe objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	6.510*** (1.947)		4.302 (2.721)	3.673 (2.812)	87.93** (32.83)		101.0*** (33.46)	92.47** (35.31)
Deviation		0.490*** (0.162)	0.296 (0.223)	0.709* (0.416)		2.798 (1.988)	-1.756 (1.558)	3.865 (4.519)
LT Exposure \times Deviation				-2.797 (2.070)				-38.10 (30.81)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.015	0.013	0.021	0.021	0.491	0.387	0.496	0.504

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of severe drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1.5 for severe events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C12: Objective exposure, beliefs and overestimation of drought events using other SPEI time scales

	Overestimation			Overestimation			Overestimation		
	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LT Exposure	9.661*** (1.907)	8.793*** (2.781)	37.65* (20.17)	6.168*** (1.196)	5.781*** (1.526)	15.98** (7.062)	3.078*** (0.602)	3.302*** (0.607)	6.173*** (2.210)
Deviation	-0.119 (0.257)	-0.458 (0.309)	-1.665 (2.046)	0.00369 (0.146)	-0.652** (0.259)	-2.427* (1.268)	-0.109 (0.0926)	-0.333*** (0.0950)	-1.012* (0.500)
LT Exposure \times Deviation	0.109 (0.682)	1.244 (1.057)	5.315 (8.317)	0.00950 (0.359)	1.260* (0.631)	4.073 (3.364)	0.108 (0.325)	0.337 (0.251)	-0.979 (1.839)
SPEI Temporal Scale	4 months			6 months			12 months		
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.290	0.185	0.492	0.287	0.184	0.337	0.274	0.194	0.221

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 4 months (columns 1 to 3), 6 months (columns 4 to 6) and 12 months (columns 7 to 9). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C13: Lifetime exposure, beliefs and overestimation of drought events using different SPEI time scales

	Overestimation			Overestimation			Overestimation			Overestimation		
	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LT Exposure	8.384** (3.091)	9.538*** (1.952)	33.98** (14.18)	6.041*** (1.712)	6.897*** (1.709)	28.53** (11.93)	5.047*** (1.139)	6.419*** (1.245)	19.84*** (5.408)	3.145*** (0.625)	3.825*** (0.595)	7.217*** (2.399)
Deviation	1.151*** (0.234)	0.561** (0.222)	1.459* (0.846)	0.682*** (0.133)	0.371** (0.153)	2.727*** (0.836)	0.489*** (0.102)	-0.0875 (0.149)	-0.538 (0.744)	0.0853 (0.0607)	-0.133* (0.0712)	-1.045*** (0.352)
LT Exposure \times Deviation	-10.73*** (2.743)	-6.587** (2.840)	-47.34** (18.82)	-3.732*** (0.886)	-2.018* (1.028)	-16.75** (7.033)	-2.246*** (0.527)	-0.509 (0.556)	-3.971 (3.254)	-0.555** (0.254)	-0.181 (0.259)	-1.460 (1.495)
SPEI Temporal Scale		1 month			4 months			6 months				12 months
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.274	0.157	0.249	0.281	0.178	0.491	0.282	0.182	0.347	0.273	0.197	0.242

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 1 month (columns 1 to 3), 4 months (columns 4 to 6), 6 months (columns 7 to 9) and 12 months (columns 10 to 12). The monthly realizations of SPEI have been rescaled to the lifetime exposure for each individual. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C14: Objective exposure, beliefs and overestimation of drought events using SPEI interpolated values

	Overestimation			Overestimation			Overestimation		
	Belief	Probability	Extent	Belief	Probability	Extent	Belief	Probability	Extent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LT Exposure	16.93*** (3.943)	12.49*** (3.775)	61.98*** (21.02)	16.49*** (4.049)	13.97*** (4.164)	62.95** (24.83)	17.18*** (4.331)	13.87*** (4.617)	73.97*** (21.75)
Deviation	-0.505 (0.765)	-0.828 (0.702)	-3.361 (2.458)	-0.295 (0.875)	-1.184 (0.838)	-4.857* (2.721)	-0.314 (0.951)	-1.215 (0.935)	-5.948** (2.543)
LT Exposure \times Deviation	3.319 (4.062)	4.608 (3.511)	2.919 (15.72)	2.230 (4.930)	6.748 (4.626)	12.60 (17.43)	2.509 (5.497)	7.296 (5.222)	19.55 (15.65)
Distance cut-off	40 km			80 km			120 km		
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.279	0.146	0.257	0.278	0.149	0.224	0.277	0.146	0.229

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4-7), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 2-5-8) and the measure of overestimation Δ (columns 3-6-9). All regressions control for individual and year fixed effects. The measures of dryness and drought events are constructed by interpolating the gridded SPEI values using the inverse squared distance between each grid and the union centroids, considering all data points within the radius of 40 km (columns 1 to 3), 80 km (columns 4 to 6) and 120 km (columns 7 to 9). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C15: Objective exposure, beliefs and overestimation. Subsample of individuals with $\Delta \geq 0$

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought (1)	Extreme Drought (2)	Severe Drought (3)	Extreme Drought (4)
LT Exposure	6.393 (17.46)	14.73*** (4.536)	14.20 (30.50)	14.02 (9.089)
Deviation	-1.731 (1.656)	-0.856 (0.531)	-1.514 (2.756)	-0.919 (1.332)
LT Exposure \times Deviation	9.119 (7.517)	4.355* (2.480)	6.907 (11.97)	4.964 (6.725)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	102	1166	102	1166
adj. R^2	0.057	0.143	0.032	0.067

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure C3), this can only be done when constructing the measure Δ with the objective number of severe ($\text{SPEI} \leq -1.5$) or extreme ($\text{SPEI} \leq -2$) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). All regressions control for individual and year fixed effects. LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times (-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C16: Directional motivated reasoning. Subsample with same number of recorded droughts.

	OLS		2SLS	
	(1) Probability	(2) Extent	(3) Probability	(4) Extent
Belief	0.190*** (0.0528)	0.270** (0.101)	0.950** (0.359)	1.029 (0.610)
Deviation	0.232 (0.198)	0.163 (0.376)	-0.295 (0.377)	-0.364 (0.633)
F-stat			13.986	13.986
<i>FIRST STAGE: Belief of Increase in Droughts</i>				
LT Exposure			18.40*** (4.92)	18.40*** (4.92)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	1142	1142	1142	1142

Notes: The sample includes the 571 individuals surveyed in both survey waves in unions where no extreme drought event ($SPEI \leq -2$) was recorded both in the five years before the first wave and between the two waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period (in this case always equal to zero by construction). The table reports the OLS estimates of Equation (3.5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C17: Directional motivated reasoning. 2SLS Results using SPEI-4, SPEI-6 and SPEI-12.

	Overestimation					
	(1) Probability	(2) Extent	(3) Probability	(4) Extent	(5) Probability	(6) Extent
Belief	0.904*** (0.318)	3.872* (2.174)	1.005*** (0.343)	2.811*** (1.022)	1.100*** (0.347)	1.860** (0.705)
Deviation	-0.0609 (0.173)	0.0320 (1.010)	-0.338** (0.149)	-1.406** (0.585)	-0.157** (0.0676)	-1.112*** (0.249)
F-stat	26.156	26.156	27.928	27.928	27.216	27.216
SPEI Temporal Scale	4 months		6 months		12 months	
FIRST STAGE: <i>Belief of Increase in Droughts</i>						
LT Exposure	9.655*** (1.888)	9.655*** (1.888)	6.171*** (1.168)	6.171*** (1.168)	3.119*** (0.598)	3.119*** (0.598)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5) and the measure of overestimation Δ (columns 2-4-6). The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 4 months (columns 1-2), 6 months (columns 3-4) and 12 months (columns 5-6). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (3.5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C18: Directional motivated reasoning. 2SLS estimates using relative life exposure with SPEI-1, SPEI-4, SPEI-6 and SPEI-12.

	Overestimation							
	(1) Probability	(2) Extent	(3) Probability	(4) Extent	(5) Probability	(6) Extent	(7) Probability	(8) Extent
Belief	0.966*** (0.347)	4.082** (1.655)	1.289** (0.501)	4.354*** (1.387)	1.529*** (0.472)	4.596*** (1.443)	1.199*** (0.362)	2.037*** (0.594)
Deviation	-0.430 (0.405)	-3.182* (1.589)	-0.282 (0.325)	0.139 (0.845)	-0.544** (0.230)	-1.823** (0.745)	-0.141* (0.0781)	-0.622*** (0.176)
F-stat	9.447	9.447	11.358	11.358	18.278	18.278	27.150	27.150
SPEI Temporal Scale	1 month		4 months		6 months		12 months	
FIRST STAGE: <i>Belief of Increase in Droughts</i>								
LT Exposure	9.908*** (3.224)	9.908*** (3.224)	6.012*** (1.784)	6.012*** (1.784)	5.043*** (1.180)	5.043*** (1.180)	3.183*** (0.611)	3.183*** (0.611)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5-7) and the measure of overestimation Δ (columns 2-4-6-8). The measures of dryness and drought events are constructed using different time scales over which water deficits accumulate, respectively 1 month (columns 1-2), 4 months (columns 3-4), 6 months (columns 5-6) and 12 months (columns 7-8). The monthly realizations of SPEI have been rescaled to the lifetime exposure for each individual. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (3.5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C19: Directional motivated reasoning. 2SLS Results using SPEI interpolated values

	Overestimation					
	(1) Probability	(2) Extent	(3) Probability	(4) Extent	(5) Probability	(6) Extent
Belief	0.700*** (0.223)	3.824** (1.509)	0.761*** (0.237)	3.745** (1.679)	0.710*** (0.230)	4.145** (1.583)
Deviation	-0.134 (0.334)	-2.887** (1.367)	-0.205 (0.345)	-3.119** (1.453)	-0.170 (0.350)	-3.281** (1.531)
F-stat	20.538	20.538	18.482	18.482	17.403	17.403
Distance cut-off	40 km		80 km		120 km	
FIRST STAGE: <i>Belief of Increase in Droughts</i>						
LT Exposure	15.99*** (3.529)	15.99*** (3.529)	15.86*** (3.690)	15.86*** (3.690)	16.42*** (3.935)	16.42*** (3.935)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3-5) and the measure of overestimation Δ (columns 2-4-6). The measures of dryness and drought events are constructed by interpolating the gridded SPEI values using the inverse squared distance between each grid and the union centroids, considering all data points within the radius of 40 km (columns 1-2), 80 km (columns 3-4) and 120 km (columns 5-6). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (3.5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C20: Directional motivated reasoning using different cut-offs of objective drought events

	Probability of Overestimation		Extent of Overestimation	
	Moderate Drought (1)	Severe Drought (2)	Moderate Drought (3)	Severe Drought (4)
<i>Panel A: OLS</i>				
Belief	-0.00538 (0.00321)	0.0491* (0.0287)	0.818*** (0.264)	0.602*** (0.173)
Deviation	0.0186 (0.0224)	0.454*** (0.165)	-1.150 (2.703)	2.359 (1.954)
<i>Panel B: 2SLS</i>				
Belief	0.0369 (0.0335)	0.295 (0.179)	14.03*** (3.727)	6.919*** (2.408)
Deviation	-0.0122 (0.0380)	0.275 (0.237)	-10.79*** (3.783)	-2.248 (2.065)
F-stat	21.736	21.736	21.736	21.736
<i>Panel C: First Stage. Dependent Variable is Belief of Increase in Droughts</i>				
LT Exposure	14.60*** (3.131)	14.60*** (3.131)	14.60*** (3.131)	14.60*** (3.131)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of droughts recorded using the (non-consecutive) monthly realizations of the SPEI below -1 (resp., -1.5) for moderate (resp., severe) drought events over the same time period. The table reports the OLS estimates of Equation (3.5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C21: Directional motivated reasoning. Subsample of individuals with $\Delta \geq 0$.

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought (1)	Extreme Drought (2)	Severe Drought (3)	Extreme Drought (4)
<i>Panel A: OLS</i>				
Belief	-0.00898 (0.115)	0.179*** (0.0527)	0.0784 (0.136)	0.258** (0.0996)
Deviation	-0.00702 (0.212)	0.236 (0.195)	0.110 (0.357)	0.172 (0.371)
<i>Panel B: 2SLS</i>				
Belief	0.105 (1.571)	0.845** (0.377)	0.979 (2.310)	0.788 (0.627)
Deviation	-0.0984 (1.203)	-0.225 (0.385)	-0.614 (1.740)	-0.195 (0.652)
F-stat	0.539	11.536	0.539	11.536
<i>Panel C: First Stage. Dependent Variable is Belief of Increase in Droughts</i>				
LT Exposure	10.40 (14.17)	15.83*** (4.662)	10.40 (14.17)	15.83*** (4.662)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	102	1166	102	1166

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure C3), this can only be done when constructing the measure Δ with the objective number of severe ($\text{SPEI} \leq -1.5$) or extreme ($\text{SPEI} \leq -2$) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The table reports the OLS estimates of Equation (3.5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C22: Directional motivated reasoning. History of transient shocks

	OLS				2SLS			
	Probability		Extent		Probability		Extent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.160*** (0.0496)	0.165*** (0.0510)	0.298*** (0.104)	0.302*** (0.103)	0.775*** (0.253)	1.418** (0.530)	2.764** (1.295)	4.253** (1.668)
Deviation _{t-1}	0.309*** (0.0918)	0.486* (0.255)	2.072*** (0.373)	1.895** (0.827)	0.0561 (0.140)	0.473 (0.296)	1.057* (0.611)	1.853* (0.981)
Deviation _{t-2}	-0.264 (0.276)	-0.105 (0.330)	-3.365*** (0.644)	-2.961*** (0.626)	-0.449* (0.244)	-0.540 (0.380)	-4.108*** (0.982)	-4.332*** (1.207)
Deviation _{t-3}		-0.0216 (0.506)		-0.383 (2.467)		1.343 (0.992)		3.916 (3.336)
Deviation _{t-4}		-0.573 (0.380)		-1.931** (0.773)		-1.081* (0.606)		-3.531** (1.511)
Deviation _{t-5}		1.258* (0.743)		0.855 (2.062)		1.116 (1.184)		0.407 (3.660)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat					14.832	10.307	14.832	10.307
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2 and 5-6) and the measure of overestimation Δ (columns 3-4 and 7-8). The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (3.5) in columns (1)-(4) and the 2SLS estimates in columns (5)-(8). LT Exposure is the average monthly SPEI over the previous twenty years ($\times (-1)$). Deviation_{t- τ} is the difference between the average monthly SPEI in $t - \tau$ years before each survey wave and LT Exposure ($\times (-1)$). The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (5)-(8). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C23: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Probability of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.778*** (0.234)	0.776*** (0.232)	0.746*** (0.228)	0.750*** (0.238)	0.840*** (0.250)	0.756*** (0.231)	0.833*** (0.252)	0.842*** (0.269)
Deviation	-0.190 (0.342)	-0.185 (0.342)	-0.124 (0.334)	-0.142 (0.347)	-0.189 (0.349)	-0.182 (0.327)	-0.227 (0.340)	-0.136 (0.357)
Krishi Bank	-0.104 (0.149)							-0.00869 (0.169)
Commercial Bank		-0.0949* (0.0515)						0.548*** (0.169)
Grameen Bank			-0.323** (0.149)					-0.600*** (0.102)
Any Bank				-0.212 (0.126)				
Agriculture extension officer					-0.0640 (0.0562)			-0.107* (0.0628)
Access to electricity						0.0788 (0.0994)		0.0597 (0.0963)
Shop for pesticides and/or fertilizer							-0.0309 (0.0948)	0.0209 (0.118)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (3.5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$. The sample includes the 714 individuals surveyed in both survey waves. The measure Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table C2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C24: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Extent of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	3.947** (1.503)	3.927** (1.504)	3.918** (1.474)	3.907** (1.473)	4.076** (1.545)	4.013** (1.594)	4.381*** (1.582)	4.271** (1.590)
Deviation	-2.891** (1.410)	-2.853* (1.406)	-2.785* (1.373)	-2.797* (1.392)	-2.995** (1.447)	-2.984* (1.476)	-3.140** (1.464)	-3.010* (1.525)
Krishi Bank	-0.548 (0.534)							-0.498 (0.640)
Commercial Bank		-0.537*** (0.192)						1.041* (0.578)
Grameen Bank			-0.824*** (0.209)					-1.106*** (0.249)
Any Bank				-0.642** (0.271)				
Agriculture extension officer					-0.0398 (0.257)			0.0473 (0.264)
Access to electricity						0.0679 (0.487)		0.132 (0.495)
Shop for pesticides and/or fertilizer							-0.288 (0.410)	-0.308 (0.494)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (3.5) using as dependent variable the measure Δ . The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table C2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C25: Directional motivated reasoning. Information channel. 2SLS Estimates.

	Probability				Extent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.816*** (0.236)	0.810*** (0.236)	0.798*** (0.232)	0.809*** (0.240)	4.062** (1.535)	4.064** (1.546)	4.050** (1.543)	4.110** (1.604)
Deviation	-0.221 (0.339)	-0.227 (0.337)	-0.216 (0.333)	-0.218 (0.337)	-3.016*** (1.420)	-3.027*** (1.425)	-3.013** (1.420)	-3.036** (1.440)
Information on soil and water conservation and crop protection	0.102* (0.0528)				0.0702 (0.201)			
crop protection and new crop varieties		0.108* (0.0549)				0.123 (0.188)		
crop protection, new crop varieties and crop utilization			0.118** (0.0567)				0.0996 (0.201)	
Information from TV/Radio/Newsletter				-0.0456 (0.0704)				-0.246 (0.303)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	21.864	21.785	21.908	21.501	21.864	21.785	21.908	21.501
N	1428	1428	1428	1428	1428	1428	1428	1428

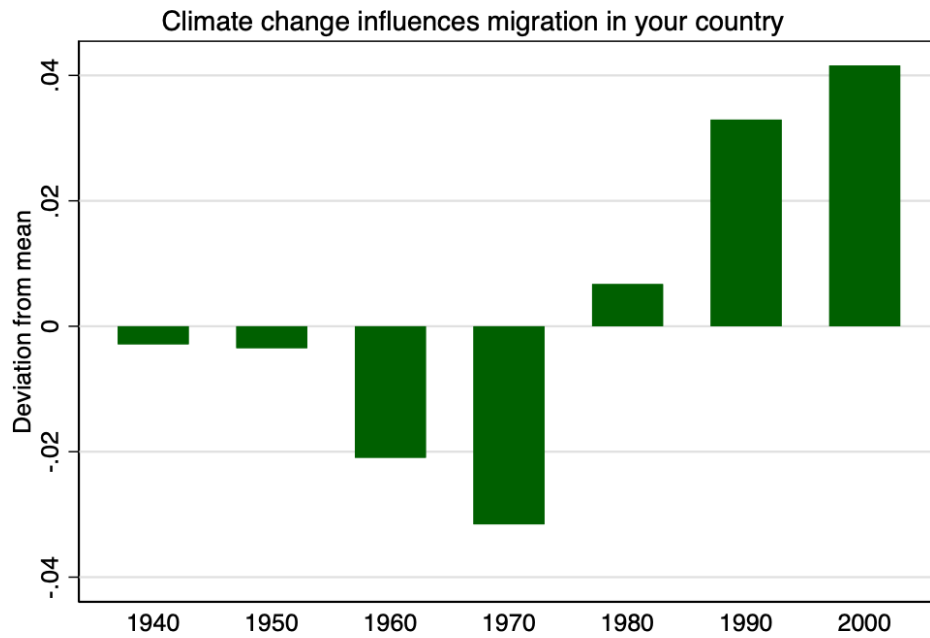
Notes: The table reports the 2SLS estimates of Equation (3.5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure Δ (columns 5-9). The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (3.1), by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a proxy of information (see Table C2 for the definition of each variable). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instruments. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D

Appendix to Chapter 4: Climate-induced migration and environmental values

D.1 Additional Figures

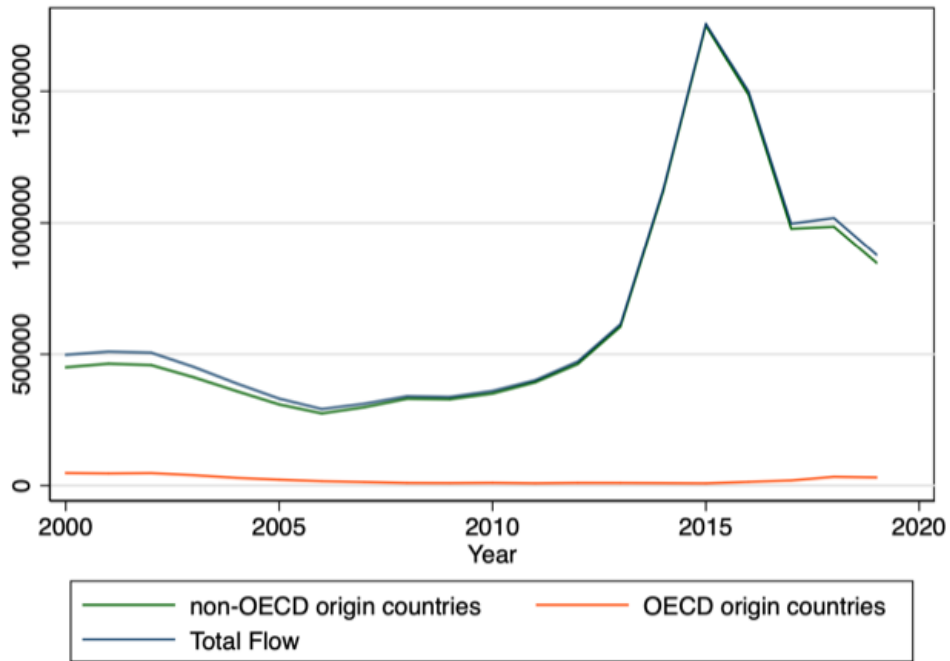
FIGURE D1: Climate-migration nexus awareness by birth-decade



Source: EIB Climate Survey 2019

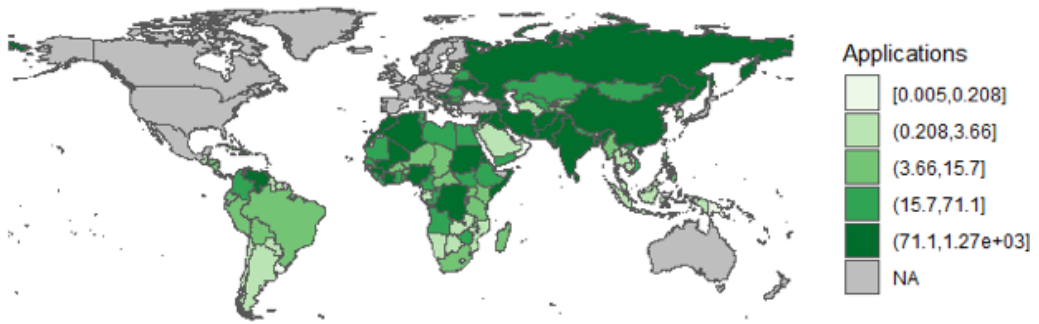
Notes: The graph shows average deviations from overall country means among respondents who belong to 10-year cohorts born in the 1940s and onwards using a binary version of the question “Do you think climate change influences migration in your country?” in the European Investment Bank Climate Survey in 2019, coded as value 1 if individuals answers “Yes, it’s already happening now” to the survey question in the European Investment Bank Climate Survey in 2019.

FIGURE D2: Asylum Applications in EU between 2000 and 2019



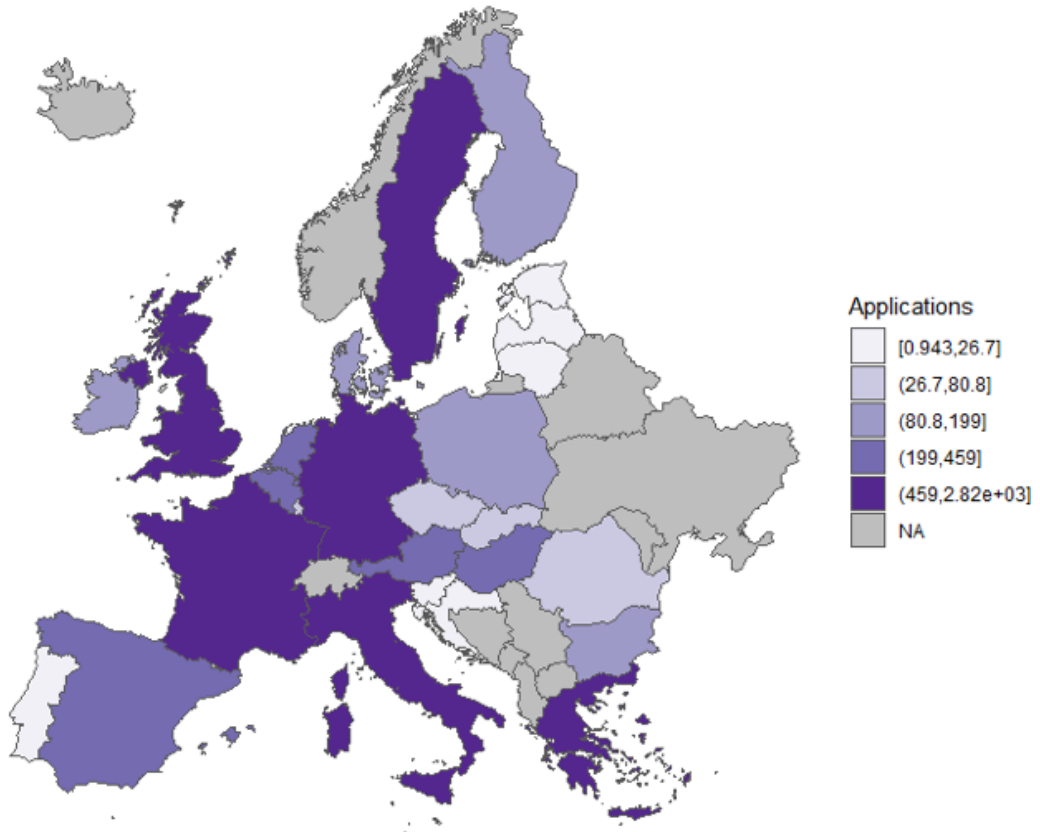
Notes: UNHCR (2020). Author's computation. Cumulative annual asylum demands in EU27+UK countries from 2000 to 2019.

FIGURE D3: Asylum applications (in 1000s) from non-OECD countries between 2000 and 2019



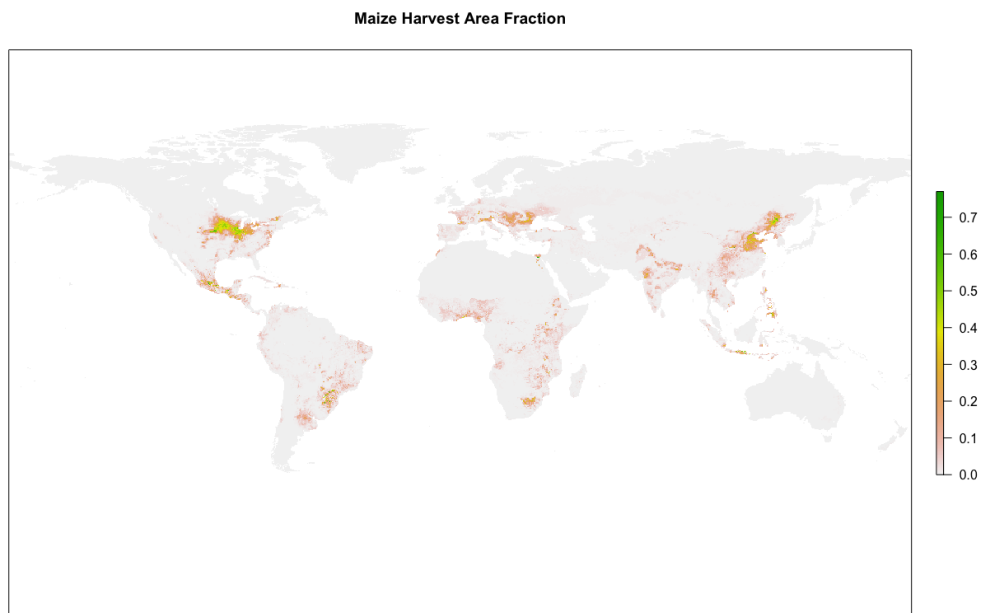
Notes: The map shows total asylum applications (in thousands) from non-OECD countries between 2000 and 2019.

FIGURE D4: Asylum applications (in 1000s) in EU27 + UK between 2000 and 2019



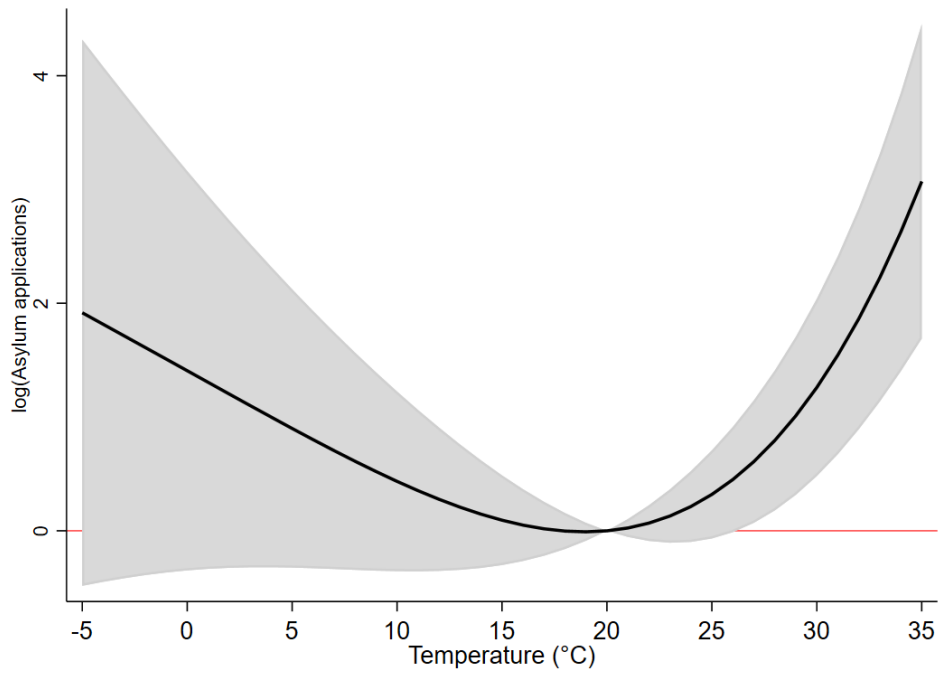
Notes: The map shows total asylum applications (in thousands) in EU27+UK countries between 2000 and 2019.

FIGURE D5: Maize Harvest Area Fraction



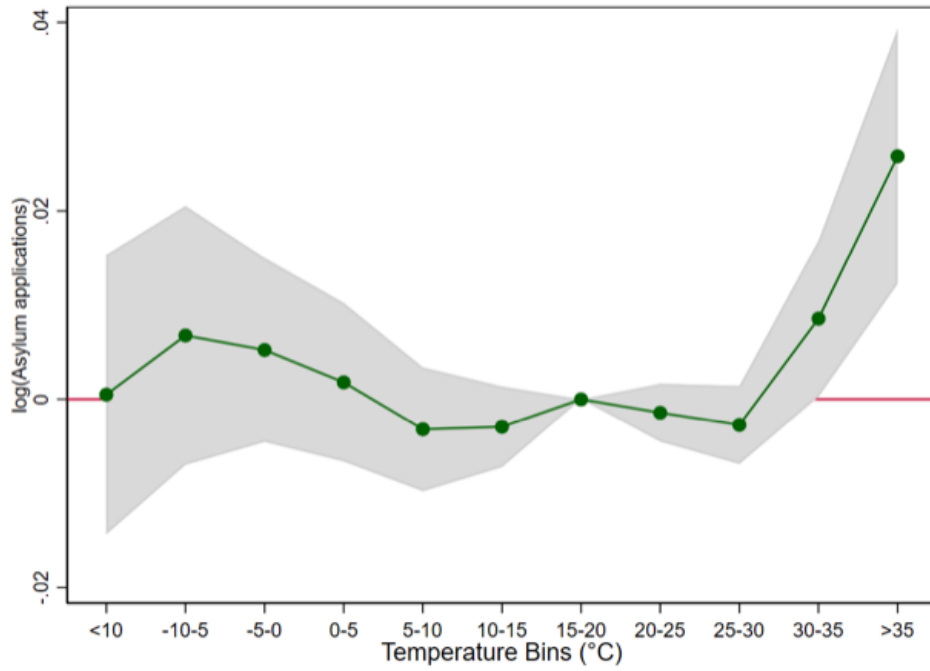
Notes: The figure displays the fraction of each grid cell in Monfreda et al. (2008) used to harvest maize and used as a weighting scheme to construct season-specific measures of climate variables giving relatively more importance to cells where maize is grown.

FIGURE D6: Response of asylum applications to the EU with respect to the temperature over the maize growing season



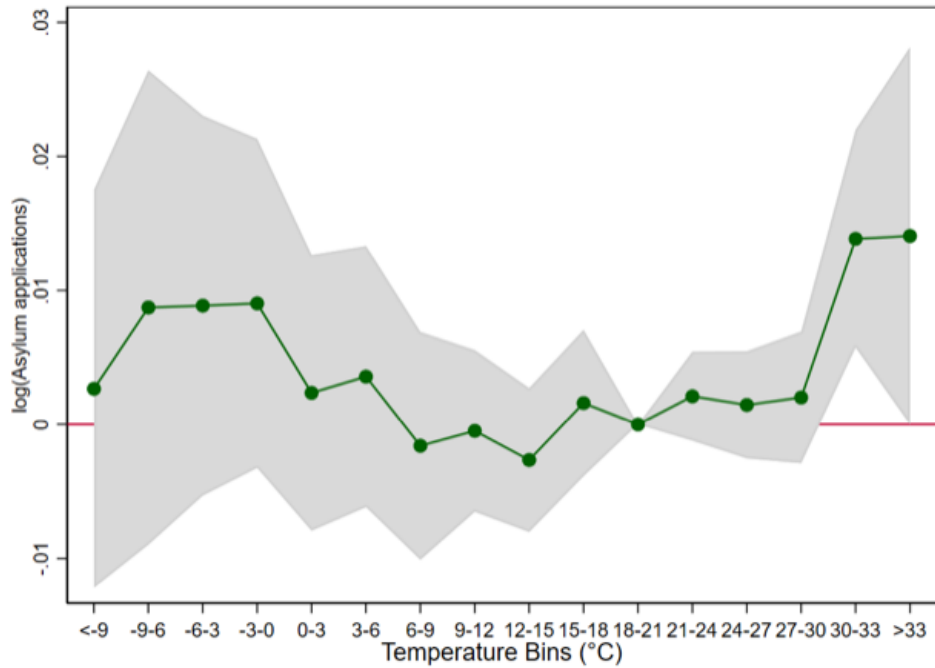
Notes: The figure represents a predicted asylum applications-temperature response function for the applications coming from non-OECD countries in the EU. Regression estimates are from a fourth-order polynomial in daily average temperature over the maize growing season weighted by maize area in each grid cell. The response function is estimated in a regression model that controls for a quadratic function in season-total precipitation, multilateral weather, as well as destination-by-year, region-of-origin-by-year, and dyad-specific fixed effects. See Table D5 (column 2) for point estimates. Shaded areas are the associated 95% confidence interval using clustered standard errors at the origin country-year level.

FIGURE D7: Response of asylum applications to 5°C binned daily temperature over the maize growing season



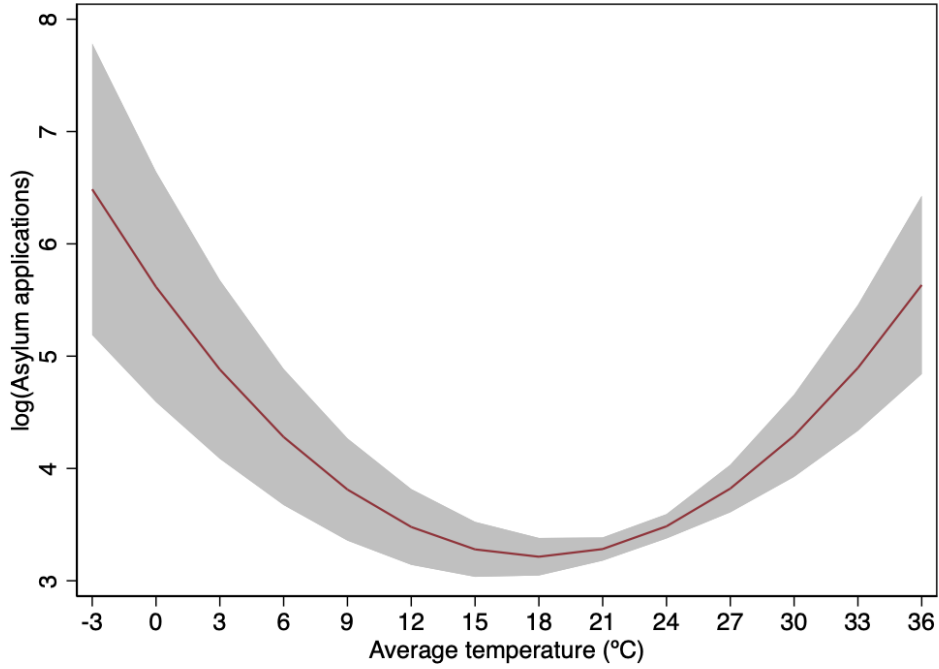
Notes: The figure represents a predicted asylum applications-temperature response function for the applications coming from non-OECD countries in the EU. Regression estimates are from binned daily average temperature over the maize growing season with bins 5°C wide weighted by maize area in each grid cell. The response function is estimated in a regression model that controls for a quadratic function in season-total precipitation, as well as destination-by-year, region-of-origin-by-year, and dyad-specific fixed effects. Shaded areas are the associated 95% confidence interval using clustered standard errors at the origin country-year level.

FIGURE D8: Response of asylum applications to the 3°C binned daily temperature over the maize growing season



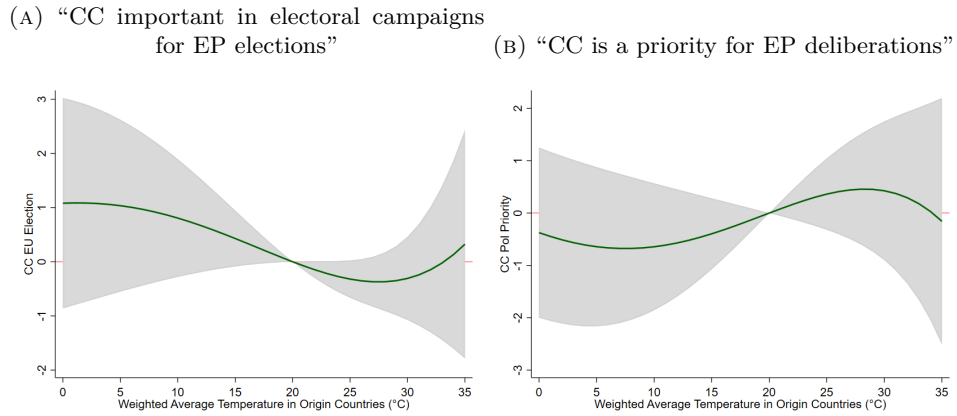
Notes: The figure represents a predicted asylum applications-temperature response function for the applications coming from non-OECD countries in the EU. Regression estimates are from binned daily average temperature over the maize growing season with bins 3°C wide weighted by maize area in each grid cell. The response function is estimated in a regression model that controls for a quadratic function in season-total precipitation, as well as origin-, destination-by-year, region-of-origin-by-year, and dyad-specific fixed effects.

FIGURE D9: Response of asylum applications to the EU with respect to the annual average temperature over the maize growing season using CRU data



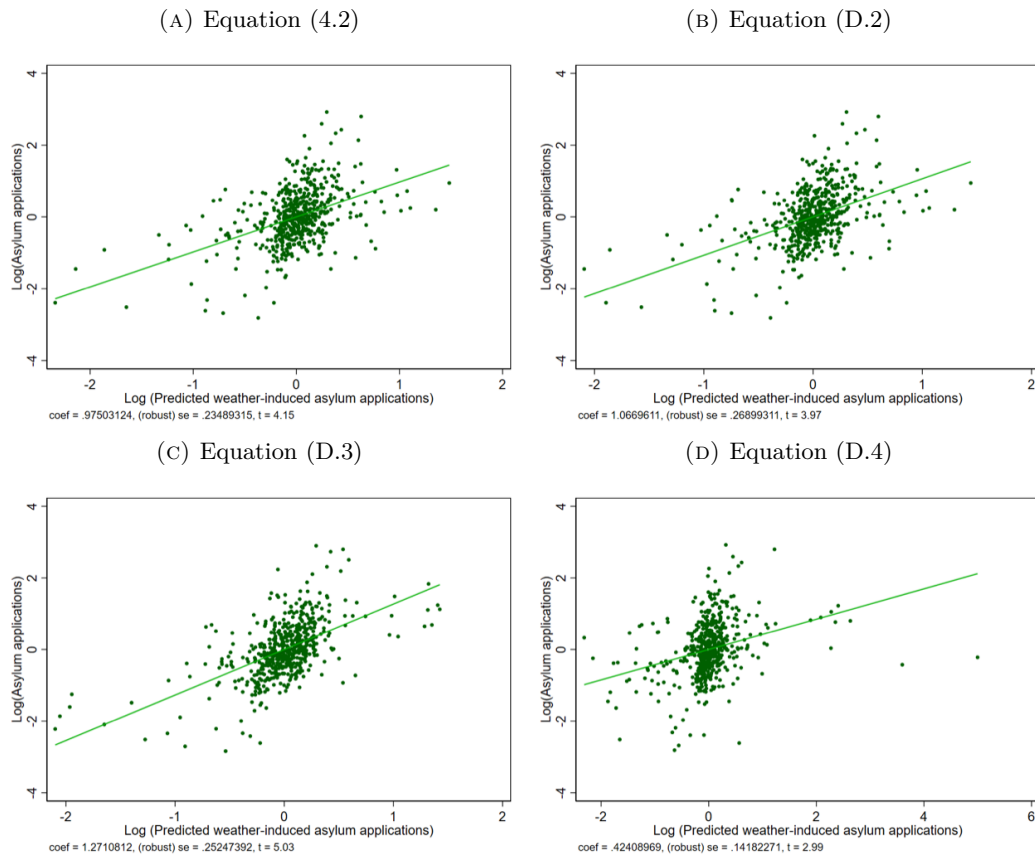
Notes: The quadratic response function is shown as a solid brown line. The y-axis indicates the relative impact of changing temperatures on asylum applications. The model controls for a quadratic function in season-total precipitation using CRU data as in Missirian and Schlenker (2017b), as well as origin-, -by-year, dyad-specific fixed effects.

FIGURE D10: Effect of migration-weighted exposure to weather shocks in origin countries on Climate Change (CC) concern



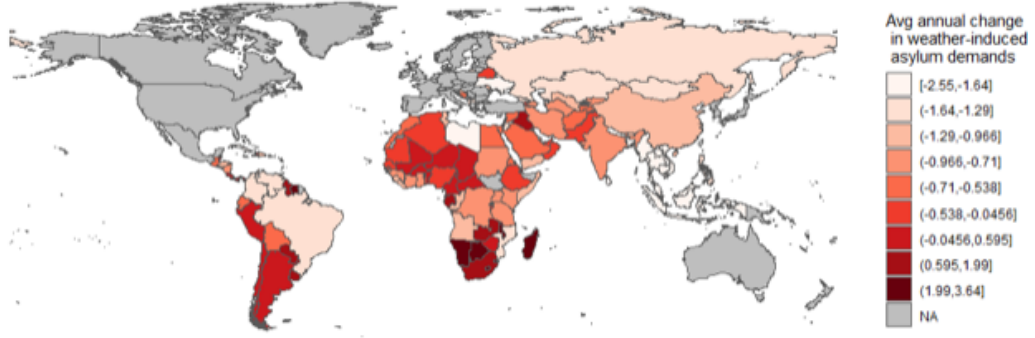
Notes: The figure shows the predicted individual preference-temperature response function (normalized at 20° C) using a baseline migration-weighted exposure measure of weather fluctuations in asylum application origin countries. Each origin country’s weather realizations is weighted by the average number of asylum applications from the origin country to the destination country over the total average number of asylum applications of the destination country in the baseline 2000-2005 period. Regressions estimates are from a fourth-order polynomial in season average temperature and total precipitation fully saturated with country-, year-, age-, region-by-year and country-by-age linear trends. Shaded areas are the associated 95% confidence interval.

FIGURE D11: Observed and predicted log weather-induced asylum applications. Predicted measure constructed by estimating the Equation in the label.



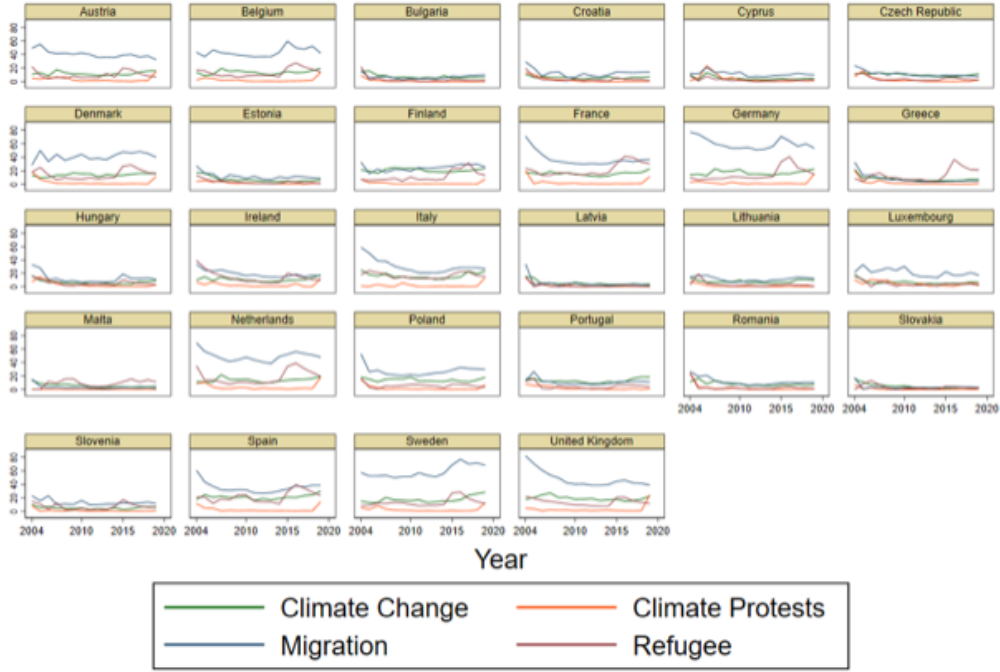
Notes: The vertical axis shows the observed logarithm of flows of asylum applications. The horizontal axis shows the logarithm of predicted weather-induced flows of asylum applications in EU obtained by estimating different gravity equations as reported in the title. Each point in the scatterplot represents the residuals of the two variables for each country-year observation, after filtering out country and year fixed effects. Standard errors are clustered at the country level. The green line refers to the slope of the regression of the actual (log) of asylum applications on the predicted weather-driven counterpart.

FIGURE D12: Average Change in Predicted Weather-Induced Asylum Applications



Notes: The figure plots the deciles of the average annual change in the log of predicted weather-induced asylum demands in EU member countries for the non-OECD countries from the estimation of Equation (4.2).

FIGURE D13: Annual average attention (measured with Google Trends) for climate change, climate protests, migration and refugee by country



Notes: The figure plots the average annual searches for “climate change”, “climate protests”, “migration”, “refugee” from Google Trends. Additional details on the construction of the four indices can be found in Appendix Section D.2.3.

FIGURE D14: Country-cohort exposure to observed and predicted flows during formative age

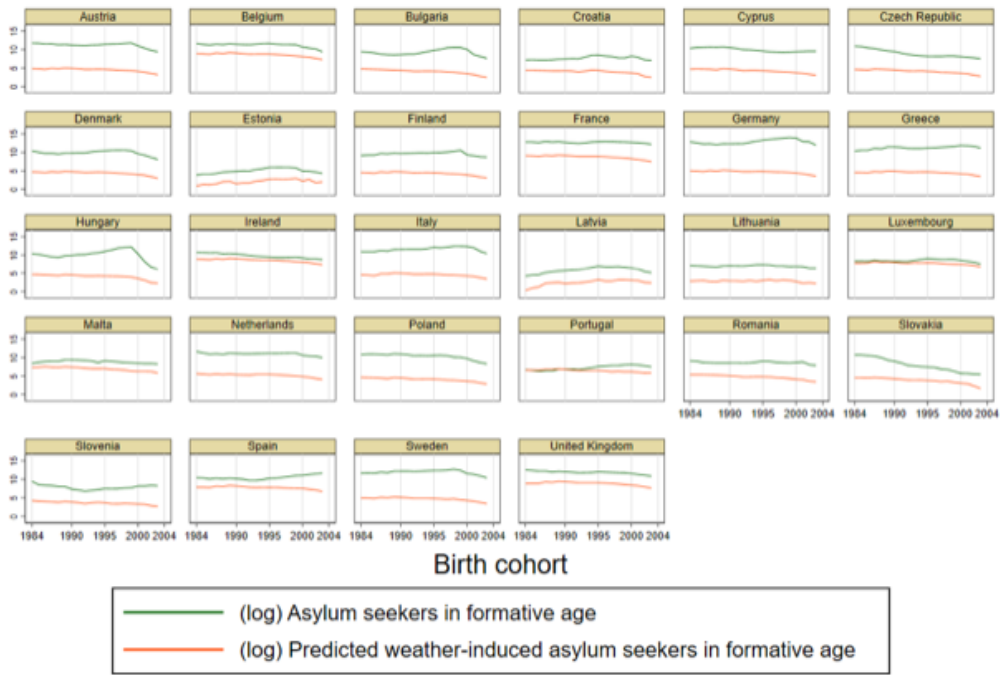


FIGURE D15: Density distribution of observed asylum flows during formative age in the estimation sample

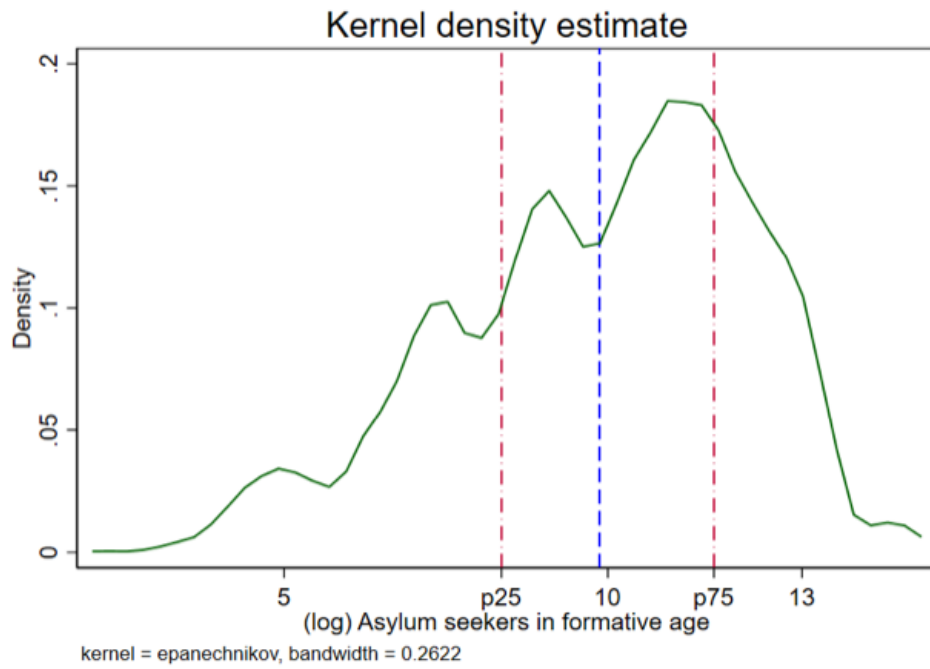
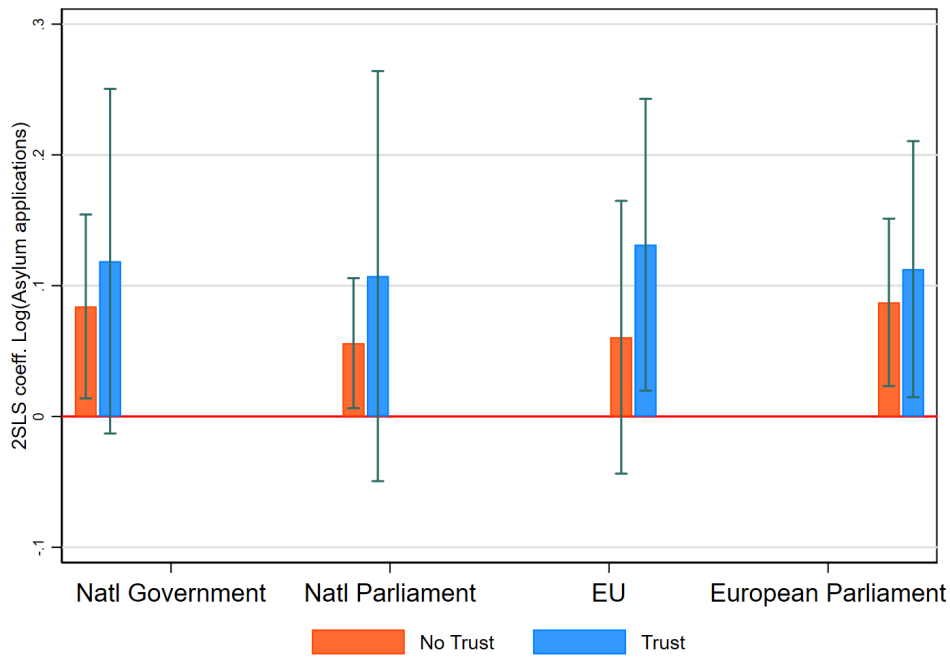
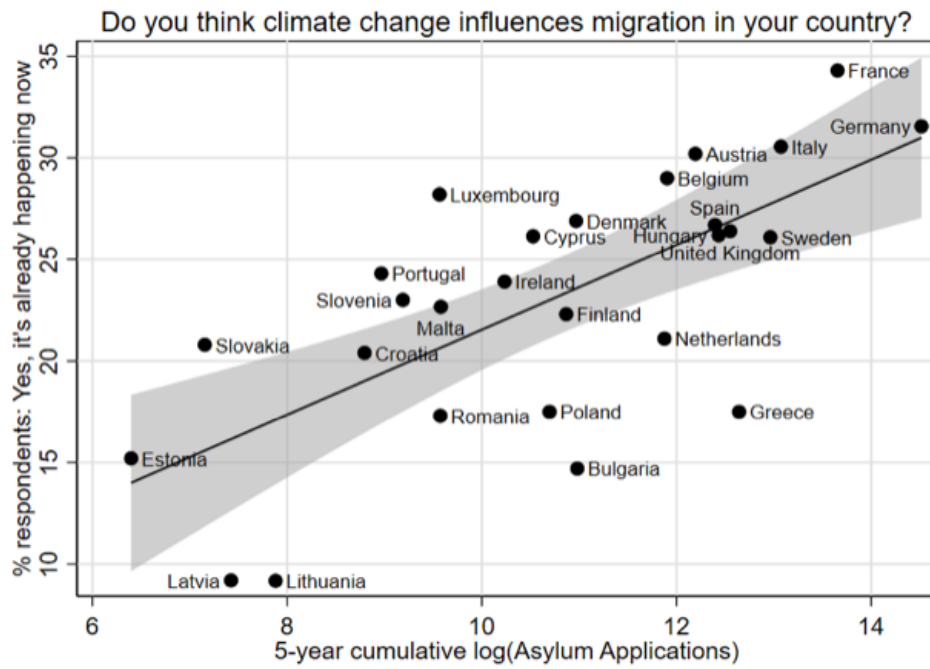


FIGURE D16: Heterogeneous effect of asylum applications on climate concern for EU Elections by trust in institutions



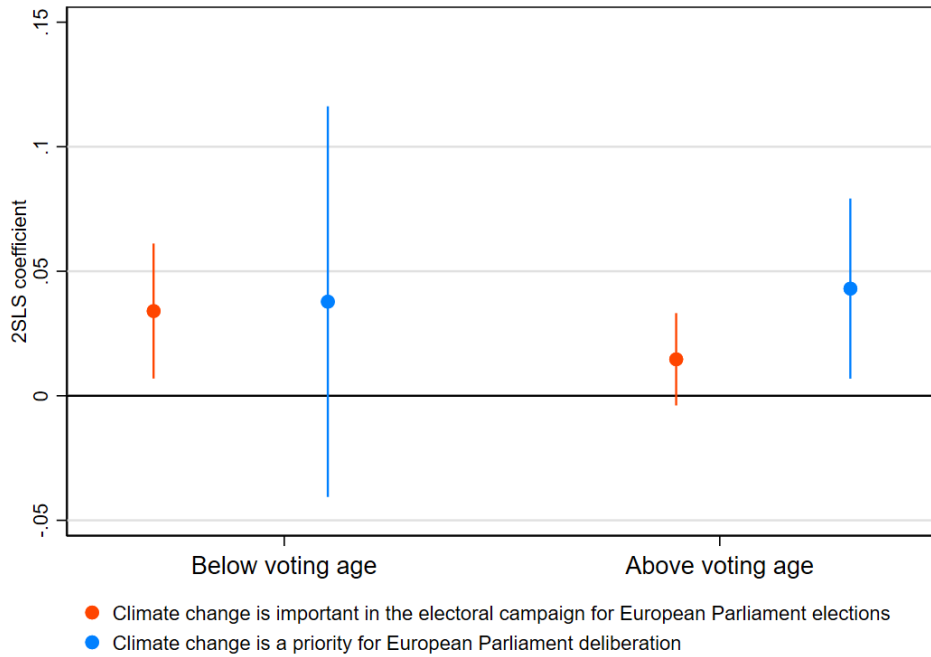
Notes: The figure plots the 2SLS coefficients (with corresponding 95% confidence intervals) for the effects of the log of five-year asylum applications on the survey response to the question “Climate change is important in the electoral campaign for European Parliament elections”, after controlling for individual covariates (gender; education level; unemployment status; left-wing orientation) and country-level covariates (linear and squared average temperature and precipitation) and country-, age-, region-by-year fixed effects and country-age linear trends. Orange (resp., blue) bars refer to individuals who reported no trust (resp. trust) in the institution reported on the x-axis. Standard errors are clustered at the country level. Since the question is not asked across all survey waves, I cannot control for this variable in the baseline specification and only test this for the outcome variable CC EU Election.

FIGURE D17: Asylum demands and climate-migration nexus awareness



Notes: The figure plots the share of respondents that answered “Yes, it’s already happening now” to the statement “Do you think climate change influences migration in your country?” in the European Investment Bank Climate Survey in 2019 against the cumulative asylum applications received in the country over the period five years (in logs).

FIGURE D18: 2SLS coefficients of weather-induced asylum seeker flows exposure by eligibility to vote



Notes: The figure plots the 2SLS coefficients estimated regressing the survey response on the total asylum applications experienced during the formative age period in the sample of individuals interviewed above or below the voting age threshold in the country. The point estimates are reported in Table 4.4. Bins represent the 95% confidence interval.

D.2 Data Appendix

D.2.1 Asylum applications data

The applications generally refer to the number of applicants or persons, rather than the number of applications or families. Only those persons who have officially filed a formal request for asylum are included. Other refugees who, for whatever reason, are either unwilling or unable to file an asylum request, and illegal immigrants are not included. The UNHCR data lists the year an application was filed, which allows for a clear temporal link on the intention to migrate, even if asylum is granted with a delay. The UNHCR also provides, at the same spatial and temporal resolution, the number of decisions. A decision corresponds to the closure of an application because the refugee status has been either granted (“recognized”), denied (“rejected”), denied but the applicant is given a complementary form of protection (“other decision”), or not determined before the application got closed for administrative reasons (“otherwise closed”) (Missirian and Schlenker, 2017a).

Asylum application process

The asylum application process can substantially differ across European countries, however, there are certain common characteristics that they share which are described in what follows. Individuals fleeing their country have the right to ask for protection in a European country they have entered if they are afraid to return to the country of their current residence because their life or that of their family members is in danger. To register the request for asylum, individuals usually contact the national Police upon their arrival and, if needed, can ask to be hosted in a reception center, and have the right to be welcomed in a special center, have a temporary residence permit, and remain on the national territory waiting for their application to be examined. As long as their status as asylum seekers last, individuals cannot leave the national territory. Labor market integration of refugees differs across countries with lasting negative consequences of delayed entry into the destination country labor market due to employment restrictions while waiting for asylum (Fasani et al., 2021). In Denmark since 2013, refugees can work before asylum adjudication (Foged et al., 2022); in Italy, two months after the compilation of the application form at the Immigration Office of the Police, asylum seekers have the right to work regularly (Campo et al., 2021). Other countries, such as Germany in 2017, grant asylum seekers access to training and employment program during the pre-asylum phase (Fasani et al., 2021).

D.2.2 Additional covariates

I retrieve variables on geographic time-invariant bilateral characteristics that are included in the estimation of the gravity equation. The geographic controls come from the BACI dataset and provided by CEPII (Head and Mayer, 2014). In particular, I include variables on whether countries have a common border, a common official language, a common colonial history and a variable measuring the natural logarithm of bilateral (geodesic) distance between capitals (Abel et al., 2019; Beine and Parsons, 2015; Bosetti et al., 2020). The use of these time-invariant dyad-specific covariates provides an alternative specification to the gravity equation with bilateral fixed effects.

In the country-level specification, I include time-varying country-level covariates to account for potential confounders of the determinants of voting behavior that are also correlated with changes in asylum seeker inflows. Immigration may be driving per capita income levels in the destination country (Felbermayr et al., 2010), which has also been found to be associated with higher support for Green parties (Pearson and Rüdiger, 2020). For this reason, I retrieve GDP and population data from the Penn World Table, version 10.0. In particular, I use Output-side real GDP at chained PPPs (in millions 2017 US\$) and population in the country in millions. I also obtain yearly unemployment rate data from the World Bank indicator on total unemployment (as a percentage of total labor force

based on International Labor Organization estimates), tertiary-level educational attainment (in the percentage of the total population) from Eurostat and the percentage of population between 18 and 23 years old from the United Nations Department of Economics and Social Affairs¹ as proxies of institutional determinants of migrants' decision of destination countries and as explanatory factors of the support for Green parties.

D.2.3 Google Trends Data

Google Trends data consist of the volume of daily searches by word, or list of words, in a given country, over time in all languages. I leverage these data to measure public attention to migration, refugees, and climate change. I collect the volume of searches for several keywords to construct a measure of relative attention to the following topics (keywords in parentheses) “climate change” (climate change, drought*, flood*, heat wave*, global warming, storm*), “climate protests” (climate protest*, climate strike*, Fridays for future), “migration” (migration, migrants) and “refugee” (refugee*, asylum seeker*). Search trends are computed based on a random sample of the total searches on Google, and this might produce measurement error issues. To diminish such worries, I draw the time series three times and take an average. I then construct the four indices as an unweighted average of the searches of each keyword. Figure D13 plots the evolution of Google searches about the four indices by destination country. Each line represents the annual average of Google searches over time. Before averaging, the value is normalized, assigning 100 to the weekly maximum. Google searches strongly correlate with news articles (Battiston, 2020). Ideally, one would gather data from news articles to compare the two and include them in the estimating equation. This channel would be particularly relevant since newspapers' language and sentiment largely respond to readers' demands (Gentzkow and Shapiro, 2010). Given the wide cross-national scope of this analysis, it is difficult and beyond the aim of this paper to construct a comprehensive dataset of EU member states' newspaper coverage of climate and migration issues. This is left as a promising avenue for future research.

¹Source: <https://population.un.org/wpp/Download/Standard/Interpolated/>

D.2.4 Additional tables

TABLE D1: *Eurobarometer* Outcome Variables Definition

VARIABLE	DESCRIPTION	MEAN (SD)	SURVEY WAVES [Sample Size]	SOURCE
CC EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections? (Combating climate change and protecting the environment)	0.06 (0.24)	2008; 2009; 2018 [106,614]	Eurobarometer
CC EU Pol Priority (0-1)	The EP makes decisions on European legislation which directly impacts every citizen's life. In your opinion which of the following should be given priority by the European Parliament? (Combating climate change and protecting the environment)	0.107 (0.31)	2008; 2009; 2012; 2013; 2014; 2018 [130,068]	Eurobarometer
CC World Problem (0-1)	In your opinion, which of the following do you consider to be the most serious problem currently facing the world as a whole? (Global Warming / Climate Change)	0.37 (0.48)	2008; 2009; 2011; 2013; 2015; 2017; 2019 [116,879]	Eurobarometer
CC Seriousness (1-10)	How serious a problem do you think climate change is at this moment? Please use a scale from 1 to 10, '1' would mean that it is "not at all a serious problem" and '10' would mean that "it is a problem extremely serious".	7.57 (2.14)	2008; 2009; 2011; 2013; 2015; 2017; 2019 [164,779]	Eurobarometer
Migration EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections? (Migration)	0.08 (0.27)	2008; 2009; 2018 [106,613]	Eurobarometer
Migration EU Pol Priority (0-1)	The EP makes decisions on European legislation which directly impacts every citizen's life. In your opinion which of the following should be given priority by the European Parliament? (Migration)	0.08 (0.28)	2008; 2009; 2012; 2013; 2014; 2018 [130,067]	Eurobarometer
Economic growth EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next EP elections? (Economy and growth)	0.16 (0.37)	2008; 2009; 2018 [106,614]	Eurobarometer
Euro single currency EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next EP elections? (Euro as single currency)	0.03 (0.16)	2008; 2009; 2018 [53,799]	Eurobarometer
Terrorism EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next EP elections? (Fight against terrorism)	0.06 (0.23)	2008; 2009; 2018 [106,614]	Eurobarometer
Food safety EU Election (0-1)	Which of the following themes should be discussed as a matter of priority during the electoral campaign for the next EP elections? (Consumer protection and food safety)	0.05 (0.21)	2008; 2009; 2018 [106,614]	Eurobarometer
Terrorism EU Pol Priority (0-1)	The EP makes decisions on European legislation which directly impacts every citizen's life. In your opinion which of the following should be given priority by the EP? (Fight against terrorism)	0.11 (0.31)	2008; 2009; 2012; 2013; 2014; 2018 [130,068]	Eurobarometer

Notes: The survey waves used include Eurobarometer 69.2 (2008), 71.1 (2009), 78.2 (2012), 79.5 (2013), 82.5 (2014), 83.4 (2015), 87.1 (2017), 90.1 (2018).

TABLE D2: European Parliament elections and National elections
by country and year in the estimation sample

COUNTRY	# European Parliament Elections	Years with Green party votes	# National Elections	Years
Austria	4	2004; 2009; 2014; 2019	4	2006; 2013; 2017; 2019
Belgium	4	2004; 2009; 2014; 2019	4	2003; 2007; 2010; 2019
Bulgaria	0		5	2001; 2005; 2013; 2014; 2017
Croatia	0		4	2007; 2011; 2015; 2016
Cyprus	0		0	
Czech Republic	3	2004; 2009; 2014	5	2002; 2006; 2010; 2013 ; 2017
Denmark	3	2009; 2014; 2019	6	2001; 2005; 2007; 2011; 2015; 2019
Estonia	2	2009; 2019	4	2003; 2007; 2011; 2015
Finland	4	2004; 2009; 2014; 2019	5	2003; 2007; 2011; 2015; 2019
France	4	2004; 2009; 2014; 2019	4	2002; 2007; 2012; 2017
Germany	4	2004; 2009; 2014; 2019	4	2002; 2009; 2013; 2017
Greece	3	2004; 2009; 2019	4	2004; 2009; 2012; 2015
Hungary	2	2014; 2019	4	2002; 2006; 2010; 2014
Ireland	4	2004; 2009; 2014; 2019	3	2002; 2007; 2011
Italy	0		2	2008; 2018
Latvia	0		6	2002; 2006; 2010; 2011; 2014; 2018
Lithuania	2	2014; 2019	0	
Luxembourg	4	2004; 2009; 2014; 2019	2	2009; 2013
Malta	4	2004; 2009; 2014	0	
Netherlands	4	2004; 2009; 2014; 2019	6	2002; 2003; 2006; 2010; 2012; 2017
Poland	0		2	2001; 2005
Portugal	2	2014; 2019	4	2009; 2011; 2015; 2019
Romania	0		2	2012; 2016
Slovakia	0		5	2002; 2006; 2010; 2012; 2016
Slovenia	2	2004; 2019	4	2004; 2008; 2011; 2018
Spain	3	2009; 2014; 2019	6	2004; 2008; 2011; 2015; 2016; 2019
Sweden	4	2004; 2009; 2014; 2019	5	2002; 2006; 2010; 2014; 2018
United Kingdom	4	2004; 2009; 2014; 2019	5	2001; 2005; 2010; 2015; 2019

TABLE D3: *Manifesto* Outcome Variables Definition

VARIABLE	DESCRIPTION	MANIFESTO SOURCE VARIABLE	
Environmentalism	Environmental Protection. General policies in favour of protecting the environment, fighting climate change, and other “green” policies. For instance: General preservation of natural resources; Preservation of countryside, forests, etc.; Protection of national parks; Animal rights. May include a great variance of policies that have the unified goal of environmental protection.	per501	Manifesto Project Dataset
Europe +	Favourable mentions of European Community/Union in general. May include the: - Desirability of the manifesto country joining (or remaining a member);- Desirability of expanding the European Community/Union; - Desirability of increasing the ECs/EUs competences; - Desirability of expanding the competences of the European Parliament.	per108	Manifesto Project Dataset
Europe -	European Community/Union: Negative. Negative references to the European Community/Union. May include: Opposition to specific European policies which are preferred by European authorities; Opposition to the net-contribution of the manifesto country to the EU budget.	per110	Manifesto Project Dataset
Multiculturalism +	Multiculturalism: Positive. Favourable mentions of cultural diversity and cultural plurality within domestic societies. May include the preservation of autonomy of religious, linguistic heritages within the country including special educational provisions	per607	Manifesto Project Dataset
Multiculturalism -	Multiculturalism: Negative. The enforcement or encouragement of cultural integration. Appeals for cultural homogeneity in society	per608	Manifesto Project Dataset
Refugees +	Favourable mentions of, or need for, assistance to people who left their homes because of the war (for instance, on the territory of ex-Yugoslavia) or were forcibly displaced.	per706_2	Manifesto Project Dataset
Cultural Autonomy +	Cultural Autonomy: Positive. Favourable mentions of cultural autonomy	per607_1	Manifesto Project Dataset

D.3 Robustness Checks

D.3.1 Robustness Checks for Gravity Equation

TABLE D4: Gravity model for asylum applications in non-OECD origin countries & EU destination countries with dyadic controls

	(1)	(2)	(3)
	Log Asylum Applications	Log Asylum Applications	Log Asylum Applications
Temperature	-1.436* (0.759)	-1.782** (0.885)	-1.803* (0.912)
Temperature ²	0.0824** (0.0414)	0.0411 (0.0321)	0.0440 (0.0312)
Temperature ³	0.000838 (0.00133)	0.00167 (0.00191)	0.00189 (0.00217)
Temperature ⁴	-0.0000331 (0.0000381)	-0.0000313 (0.0000424)	-0.0000432 (0.0000421)
Temperature * Contiguity	0.803*** (0.220)	0.438 (0.283)	0.407 (0.302)
Temperature * Common Language	-0.0391 (0.245)	0.188 (0.366)	0.403 (0.356)
Temperature * Common Colonial History	0.690*** (0.232)	0.427** (0.202)	0.398* (0.214)
Temperature* Log(distance)	0.192** (0.0927)	0.212* (0.108)	0.217* (0.110)
Temperature ² * Contiguity	0.0135 (0.0101)	0.0222* (0.0127)	0.0161 (0.0116)
Temperature ² * Common Language	-0.0148 (0.0198)	-0.00947 (0.0435)	-0.0386 (0.0400)
Temperature ² * Common Colonial History	-0.0129 (0.00950)	-0.00911 (0.00954)	-0.00710 (0.00962)
Temperature ² * Log(distance)	-0.0107** (0.00499)	-0.00532 (0.00391)	-0.00568 (0.00377)
Temperature ³ * Contiguity	0.0000449 (0.000237)	-0.0000907 (0.000813)	-0.000164 (0.000845)
Temperature ³ * Common Language	0.00109 (0.00143)	0.000372 (0.00193)	0.00165 (0.00179)
Temperature ³ * Common Colonial History	-0.00105* (0.000573)	-0.000375 (0.000474)	-0.000279 (0.000563)
Temperature ³ * Log(distance)	-0.000131 (0.000155)	-0.000205 (0.000221)	-0.000236 (0.000250)
Temperature ⁴ * Contiguity	-0.0000167 (0.0000113)	-0.0000253 (0.0000216)	-0.0000149 (0.0000214)
Temperature ⁴ * Common Language	-0.0000160 (0.0000260)	-0.00000441 (0.0000276)	-0.0000220 (0.0000261)
Temperature ⁴ * Common Colonial History	0.0000290* (0.0000160)	0.0000122 (0.00000875)	0.00000904 (0.0000119)
Temperature ⁴ * Log(distance)	0.00000527 (0.00000469)	0.00000436 (0.00000507)	0.00000582 (0.00000498)
Precipitation	13.96 (61.82)	57.91 (58.40)	28.07 (53.17)
Precipitation ²	1322.5 (42959.9)	-31071.0 (55904.3)	-13403.8 (46178.8)
Precipitation * Contiguity	19.86 (23.97)	11.38 (50.60)	7.539 (49.79)
Precipitation * Common Language	2.262 (5.220)	8.100 (6.195)	9.380 (5.725)
Precipitation * Common Colonial History	10.02 (15.02)	2.529 (21.68)	-4.058 (19.06)
Precipitation* Log(distance)	-1.665 (6.900)	-6.851 (6.530)	-3.423 (6.008)
Precipitation ² * Contiguity	30550.1 (20185.6)	15682.9 (46456.1)	24834.9 (47742.0)
Precipitation ² * Common Language	-984.3 (2459.8)	-2068.1 (3198.1)	-3416.1 (2768.5)
Precipitation ² * Common Colonial History	490.4 (5056.8)	1716.9 (7668.4)	3725.7 (6566.9)
Precipitation ² * Log(distance)	-233.0 (4802.8)	3414.2 (6220.4)	1481.8 (5181.1)
Weather	Annual	Maize GS over maize area	Maize GS over pop density
Country-pair FE	X	X	X
Destination-year FE	X	X	X
Region of origin-by-year FE	X	X	X
Number of country pairs	2084	2084	2084
Number of origin countries	141	141	141
Destination Sample	EU27 + UK	EU27 + UK	EU27 + UK
Mean Outcome	3.733	3.733	3.733
Dep Var SD	1.858	1.858	1.858
N	25951	25951	25951
adj. R ²	0.796	0.796	0.796

Notes: Standard errors are clustered by origin country-year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (1) uses annual weather, column (2) uses weather weighted by maize area over maize-growing season, column (3) uses weather weighted by population over maize-growing season.

TABLE D5: Gravity model for asylum applications without bilateral controls interactions.

	(Log) Asylum Applications		
	(1)	(2)	(3)
Temperature origin	0.121 (0.0988)	-0.0905 (0.0747)	-0.0806 (0.0771)
Temperature origin ²	-0.00453 (0.00316)	-0.000517 (0.00219)	-0.000177 (0.00220)
Temperature origin ³	-0.000194** (0.0000856)	0.0000301 (0.0000766)	0.00000463 (0.0000851)
Temperature origin ⁴	0.00000852*** (0.00000293)	0.00000287 (0.00000212)	0.00000281 (0.00000221)
Precipitation origin	0.581 (3.515)	3.096 (4.675)	1.875 (4.491)
Precipitation origin ²	-820.6 (1452.4)	-2278.6 (1853.8)	-1302.9 (1690.7)
Weather	Annual	Maize GS over maize area	Maize GS over pop density
Country-pair FE	X	X	X
Destination-by-year FE	X	X	X
Region of origin-by-year FE	X	X	X
Number of country pairs	2138	2138	2138
Number of origin countries	145	145	145
Destination Sample	EU27 + UK	EU27 + UK	EU27 + UK
Mean Outcome	3.751	3.751	3.751
SD Outcome	1.873	1.873	1.873
<i>N</i>	26533	26533	26533
adj. <i>R</i> ²	0.798	0.799	0.799

Notes: The table reports the coefficients associated with the weather variables in origin country in Equation (4.2) in the text. The sample is restricted to non-OECD 145 origin countries and to EU27 member countries + UK as destinations. Standard errors are clustered by origin country-year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (1) uses annual weather, column (2) uses weather weighted by maize area over maize growing season, column (3) uses weather weighted by population over maize growing season. The estimated fixed effects are not used in building the predictors for asylum applications. All regressions control for country-pair, destination-by-year, and region-of-origin-by-year fixed effects.

TABLE D6: Gravity model for asylum applications with lags of weather

	(Log) Asylum Applications			
	(1)	(2)	(3)	(4)
Temperature origin	-0.0905 (0.0747)	-0.0745 (0.0739)	-0.118 (0.0747)	-0.136* (0.0739)
Temperature origin ²	-0.000517 (0.00219)	-0.000805 (0.00218)	0.000291 (0.00221)	0.000464 (0.00221)
Temperature origin ³	0.0000301 (0.0000766)	0.0000431 (0.0000777)	0.000118 (0.0000886)	0.000158* (0.0000908)
Temperature origin ⁴	0.00000287 (0.00000212)	0.00000269 (0.00000207)	0.000000433 (0.00000223)	-0.000000152 (0.00000228)
Precipitation origin	3.096 (4.675)	7.652 (5.198)	6.963 (5.393)	4.693 (5.505)
Precipitation origin ²	-2278.6 (1853.8)	-3691.6* (2056.9)	-2861.5 (2013.5)	-2162.3 (2023.6)
L1.Temperature origin		-0.0879 (0.0806)	-0.0901 (0.0777)	-0.121 (0.0774)
L1.Temperature origin ²		0.000103 (0.00231)	0.000468 (0.00230)	0.00248 (0.00230)
L1.Temperature origin ³		0.0000770 (0.0000795)	0.0000886 (0.0000813)	0.000136 (0.0000937)
L1.Temperature origin ⁴		0.00000113 (0.00000213)	0.000000591 (0.00000214)	-0.00000161 (0.00000224)
L1.Precipitation origin		8.156 (5.079)	10.55* (5.418)	9.637* (5.559)
L1.Precipitation origin ²		-3606.5* (1972.5)	-4332.6** (2056.5)	-3174.5 (2094.9)
L2.Temperature origin			-0.126 (0.0890)	-0.125 (0.0882)
L2.Temperature origin ²			0.00446* (0.00252)	0.00574** (0.00247)
L2.Temperature origin ³			0.000164* (0.0000985)	0.000166* (0.0000994)
L2.Temperature origin ⁴			-0.00000413 (0.00000260)	-0.00000511** (0.00000254)
L2.Precipitation origin			7.458 (5.287)	8.168 (5.654)
L2.Precipitation origin ²			-3135.3 (2063.5)	-2986.7 (2165.7)
L3.Temperature origin				-0.249*** (0.0961)
L3.Temperature origin ²				0.00612** (0.00258)
L3.Temperature origin ³				0.000308*** (0.000100)
L3.Temperature origin ⁴				-0.00000725*** (0.00000261)
L3.Precipitation origin				7.050 (5.717)
L3.Precipitation origin ²				-2574.3 (2190.6)
Country-pair FE	X	X	X	X
Destination-by-year FE	X	X	X	X
Region of origin-by-year FE	X	X	X	X
Mean Outcome	3.751	4.029	4.175	4.276
SD Outcome	1.873	1.844	1.828	1.820
N	26533	21890	19109	16942
adj. R ²	0.799	0.799	0.805	0.811

Notes: The table reports the coefficients associated with the weather variables in origin country in Equation (4.2) in the text. The sample is restricted to non-OECD 145 origin countries and to EU27 member countries + UK as destinations. Standard errors are clustered by origin country-year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions use weather weighted by maize area over maize growing season with different lags of weather. All regressions control for country-pair, -by-year, and region-of-origin-by-year fixed effects.

TABLE D7: Gravity model for asylum applications with destination weather

	(Log) Asylum Applications		
	(1)	(2)	(3)
Temperature origin	-1.650** (0.657)	-2.036*** (0.603)	-2.102*** (0.615)
Temperature origin ²	0.0793** (0.0316)	0.0448 (0.0289)	0.0470 (0.0293)
Temperature origin ³	0.000990 (0.00119)	0.00206 (0.00183)	0.00237 (0.00188)
Temperature origin ⁴	-0.0000350 (0.0000328)	-0.0000445 (0.0000366)	-0.0000578 (0.0000352)
Precipitation origin	-16.45 (55.75)	18.63 (66.72)	-9.071 (63.21)
Precipitation origin ²	28112.6 (36210.8)	4645.8 (48527.1)	22074.1 (41935.2)
Temperature destination	-0.0564** (0.0231)	-0.0467** (0.0229)	-0.0472** (0.0228)
Temperature destination ²	0.00391*** (0.000889)	0.00395*** (0.000879)	0.00395*** (0.000880)
Precipitation destination	6.303* (3.814)	6.304* (3.803)	6.292* (3.804)
Precipitation destination ²	1034.1 (4398.2)	1160.2 (4393.4)	1241.9 (4396.6)
Weather	Annual	Maize GS over maize area	Maize GS over pop density
Country-pair FE	X	X	X
Region of origin-by-year FE	X	X	X
Mean Outcome	3.748	3.748	3.748
SD Outcome	1.873	1.873	1.873
<i>N</i>	25957	25957	25957
adj. <i>R</i> ²	0.749	0.749	0.749

Notes: The table reports the coefficients associated with the weather variables in the origin country in Equation (4.2) in the text. The sample is restricted to non-OECD 141 origin countries and to EU27 member countries + UK as destinations. Standard errors are clustered by origin country-year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3.2 Robustness Checks for Individual Level Analysis

TABLE D8: Weather-induced asylum applications and individuals' environmental values. Accounting for shift-share weather in origin countries.

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)		CC Pol Priority (<i>Mean: .106</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Asylum Applications)	0.00209 (0.00463)	0.0313** (0.0138)	0.0147* (0.00825)	0.0532** (0.0214)
Weighted weather in origin	X	X	X	X
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		16.931		39.206
<i>N</i>	106614	106614	130068	130068
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-2 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 3-4 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications are the cumulative asylum applications in a country in the five years preceding the survey year, as defined in Equation 4.1. Columns (2) and (4) report the 2SLS estimates using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation). All columns control for a fourth-order polynomial of seasonal temperature and a second-order polynomial of total precipitation in all origin countries of asylum demands weighted by baseline propensity to migrate to that host country. All columns include country, age, region-by-survey-year fixed effects, and country-by-age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D9: Weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative Specifications.

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)			CC Pol Priority (<i>Mean: 0.106</i>)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Asylum Applications)	0.0217** (0.0102)	0.0222** (0.0104)	0.0232** (0.0108)	0.0427** (0.0202)	0.0432** (0.0208)	0.0476** (0.0218)
Weather Controls	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X
Country-by-age FE	X			X		
Birth cohort FE	X			X		
Country-by-birth cohort FE		X	X		X	X
Country-age linear trends	X	X		X	X	
F-Statistic	21.341	21.367	21.427	27.410	27.317	27.438
<i>N</i>	106547	106613	106542	130010	130067	130004
Number of countries	28	28	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-3 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 4-6 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. All columns report the 2SLS estimates using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation). Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D10: Weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative Instruments.

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)			CC Pol Priority (<i>Mean: 0.106</i>)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Asylum Applications)	0.0205** (0.00972)	0.0134* (0.00788)	0.0181* (0.00893)	0.0417* (0.0203)	0.0458** (0.0197)	0.0495** (0.0200)
Weather Controls	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Age FE	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X
Country-age linear trends	X	X	X	X	X	X
Instrument	w/ MR	Destination-weather	Destination-specific	w/ MR	Destination-weather	Destination-specific
F-Statistic	22.384	20.107	19.944	27.810	26.549	28.592
N	106614	106614	106614	130068	130068	130068
Number of countries	28	28	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-3 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 4-6 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. Each column uses a different instrument for predicted weather-induced asylum applications, constructed from the predicted values in the estimation of Equation (D.2), (D.3) and (D.4). All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D11: Weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative time windows.

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)				CC Pol Priority (<i>Mean: 0.106</i>)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Asylum Applications)	0.0226** (0.0106)	0.0209** (0.00993)	0.0154* (0.00798)	0.0174** (0.00807)	0.0431** (0.0207)	0.0383* (0.0212)	0.0369* (0.0196)	0.0359* (0.0188)
Weather Controls	X	X	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X	X	X
Country FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Age FE	X	X	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X	X	X
Country-age linear trends	X	X	X	X	X	X	X	X
Window exposure	5 years	4 years	4 years (excl. contemp.)	5 years (excl. contemp.)	5 years	4 years	4 years (excl. contemp.)	5 years (excl. contemp.)
F-Statistic	22.106	17.934	20.835	26.397	27.252	28.695	31.225	31.223
N	106614	106614	106614	106614	130068	130068	130068	130068
Number of countries	28	28	28	28	28	28	28	28

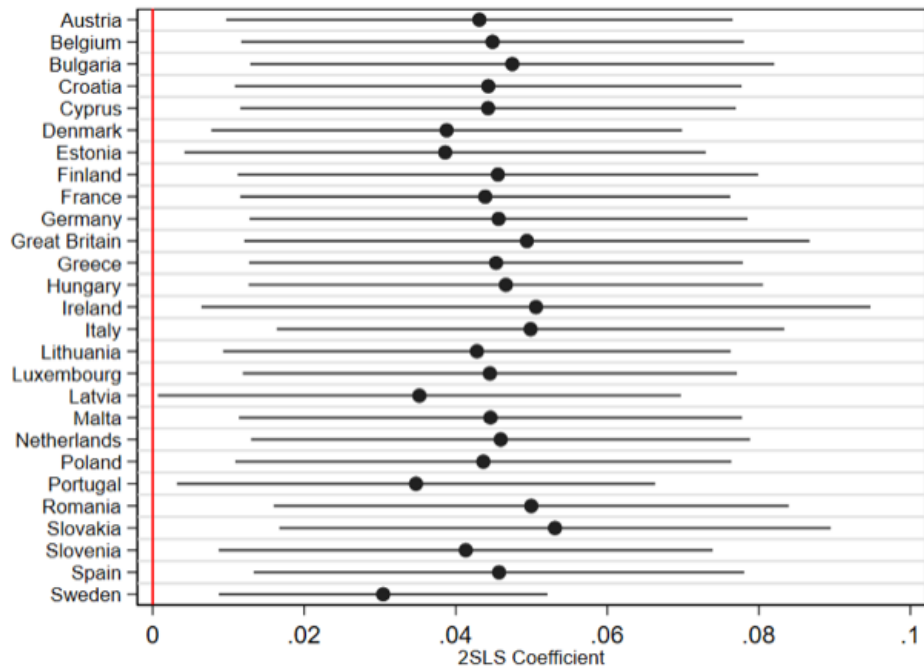
Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-3 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 4-6 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. The 2SLS estimates are obtained using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D12: Weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative treatments.

Dep. variable	CC EU Election (1)	CC Pol Priority (2)	CC EU Election (3)	CC Pol Priority (4)
Asylum Applications	0.0151* (0.00776)	0.0213* (0.0120)	0.0244*** (0.00629)	0.0204** (0.00927)
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
Regressor	log annual flow		weather-induced asylum anomaly	
F-Statistic	29.737	11.569		
N	106614	130068	106614	130068
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-2 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 3-4 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). The first two columns report the 2SLS estimates where Asylum Applications is the log of asylum applications in a given country in the survey year and is instrumented using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. Columns 3-4 report the OLS estimates where Asylum Applications is the measure of weather-induced asylum application spikes n_{dt} constructed in Appendix Section D.4.4. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE D19: 2SLS estimate of weather-induced asylum applications on climate concern as a political priority leaving out one country



Notes: This figure reports the 2SLS coefficient estimates of the effect of weather-induced asylum applications on CC EU Pol Priority when each country in the y-axis is excluded once at a time from the estimation sample. The whiskers indicate the 90% standard error confidence intervals.

TABLE D13: Weather-induced asylum applications and individual concern on other topics. 2SLS estimates.

Dep. variable	Economic growth EU Election (1)	Euro EU Election (2)	Terrorism EU Election (3)	Food safety EU Election (4)	Terrorism Pol Priority (5)
log(Asylum Applications)	-0.00226 (0.0165)	-0.0458 (0.0814)	-0.00383 (0.00804)	-0.0193 (0.0130)	0.0126 (0.0153)
Weather Controls	X	X	X	X	X
Individual Controls	X	X	X	X	X
Country FE	X	X	X	X	X
Year FE	X	X	X	X	X
Age FE	X	X	X	X	X
Region-by-year FE	X	X	X	X	X
Country-age linear trends	X	X	X	X	X
F-Statistic	14.434	9.437	14.434	14.434	21.434
N	106614	53799	106614	106614	130068
Number of countries	28	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports economic growth (in col. 1), euro single currency (col. 2), terrorism (col. 3) and food safety (col. 4) as a theme that the European Parliament should give priority to when deliberating. The dependent variable in column 5 is a dummy equal to 1 if the respondent reports terrorism as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording). The estimates refer to the 2SLS coefficients obtained using the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D14: Weather-induced asylum applications and environmental values. No top-5 countries of origin for asylum seekers. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	-0.000120 (0.00437)	0.0160* (0.00854)	0.0145* (0.00760)	0.0507*** (0.0178)
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat		23.737		22.552
N	106614	106614	130068	130068

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). Asylum demands do not account for the top-5 countries of origin for asylum seekers in the sample (Afghanistan, Iraq, Russian Federation, Serbia, Syria). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D15: Weather-induced asylum applications and environmental values. Before 2015. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0715** (0.0305)	0.459* (0.272)	0.0143 (0.00847)	0.0551* (0.0323)
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat		11.711		10.114
<i>N</i>	53799	53799	103700	103700

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed before 2015. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D16: Country average climate concern and leads of actual and predicted asylum demands.

Dep. variable	Asy Applications		5-year Asy Applications		Predicted Asy Applications	
	(1)	(2)	(3)	(4)	(5)	(6)
CC EU Election	-2.045 (3.103)		0.132 (4.075)		-2.498 (2.382)	
CC EU Pol Priority		1.483 (1.282)		1.659 (1.224)		1.005 (0.674)
Weather Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
N	83	164	83	164	83	164
adj. R^2	0.883	0.872	0.903	0.930	0.962	0.973

Notes: All estimates are obtained from country-level regressions. The main regressors are country-average responses for CC EU Election and CC EU Pol Priority. The first two columns use one-year ahead asylum applications, columns 3 and 4 use five-year ahead cumulative asylum applications, and columns 5 and 6 use the one-year ahead predicted weather-induced asylum applications. The predicted measure of weather-induced asylum applications is constructed from the estimation of Equation (D.4). All columns control for linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation, and country, and survey year fixed effects. Robust standard errors, clustered at the country level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D17: 2SLS Estimates: Exposure to weather-induced asylum demands by age range.

	(1)	(2)
	CC EU Election (<i>Mean: 0.079</i>)	CC EU Pol Priority (<i>Mean: 0.099</i>)
Log(Exposure _{16–24})	0.0235** (0.00959)	0.0390** (0.0180)
F-statistic	48.091	54.376
<i>N</i>	17554	21661
Log(Exposure _{25–33})	0.00990 (0.00635)	0.0409*** (0.0139)
F-statistic	41.019	37.483
<i>N</i>	21324	26359
Log(Exposure _{34–42})	0.00889 (0.00661)	0.0403** (0.0150)
F-statistic	41.939	40.211
<i>N</i>	24389	30320
Log(Exposure _{43–51})	0.00815 (0.00673)	0.0209 (0.0135)
F-statistic	38.166	36.681
<i>N</i>	25698	31544
Log(Exposure _{52–60})	0.00605 (0.00792)	0.0167 (0.0145)
F-statistic	40.667	37.419
<i>N</i>	27558	33144
Log(Exposure _{61–69})	0.00971 (0.00573)	0.0286** (0.0131)
F-statistic	34.782	35.594
<i>N</i>	24344	29936
Log(Exposure _{70–78})	0.00484 (0.00740)	0.00553 (0.0255)
F-statistic	28.925	22.865
<i>N</i>	15234	18158
Log(Exposure ₇₉₊)	0.0120 (0.0376)	0.0304 (0.0352)
F-statistic	21.008	22.046
<i>N</i>	5269	6315
Weather Controls	X	X
Individual Controls	X	X
Country FE	X	X
Year FE	X	X
Age FE	X	X
Birth-cohort FE	X	X
Region-by-year FE	X	X
Country-age linear trends	X	X

Notes: Each cell reports the 2SLS estimate of the coefficient associated with the (log) exposure to asylum applications as the (log) of the cumulative asylum applications in the country in a given age range of an individual. The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed and whose exposure period occurs in the time period in which asylum application data are available (i.e., after 2000). The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 3, see Table D1 for exact wording and additional details on the construction of the variable). In columns (2) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). The 2SLS estimates use the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. Individual controls: Gender, Education (Up to 15 years; 16–19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented. Weather Controls: Exposure to average temperature and precipitation over the same time period in which exposure to asylum applications is measured and contemporaneous linear and quadratic terms of temperature and precipitation. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D18: Formative age exposure to weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative Instruments.

Dep. variable	CC EU Election (<i>Mean: 0.079</i>)			CC Pol Priority (<i>Mean: 0.099</i>)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Asylum Applications)	0.0213** (0.00905)	0.0222*** (0.00799)	0.0260** (0.0104)	0.0379** (0.0177)	0.0386** (0.0153)	0.0497*** (0.0177)
Weather Controls	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Age FE	X	X	X	X	X	X
Birth-cohort FE	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X
Country-age linear trends	X	X	X	X	X	X
Instrument	w/ MR	Destination-weather	Destination-specific	w/ MR	Destination-weather	Destination-specific
F-Statistic	47.711	3.310	53.500	51.456	2.848	42.149
N	17554	17554	17554	21661	21661	21661
Number of countries	28	28	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-3 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 4-6 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. Each column uses a different instrument for predicted weather-induced asylum applications, constructed from the predicted values in the estimation of Equation (D.2), (D.3) and (D.4). All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, survey year, age, birth-year, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D19: Exposure to weather-induced asylum applications and individuals' environmental values. 2SLS estimates. Alternative definitions for formative age.

Dep. variable	CC EU Election						CC Pol Priority					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(Asylum Applications)	0.0235** (0.00959)	0.0379** (0.0160)	0.0130* (0.00721)	0.0123* (0.00750)	0.01097 (0.00772)	0.01196* (0.00716)	0.0383** (0.0153)	0.0461* (0.0261)	0.0282* (0.0147)	0.0286* (0.0148)	0.0307** (0.0138)	0.0303** (0.0129)
Weather Controls	X	X	X	X	X	X	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X	X	X	X	X	X	X
Country FE	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Age FE	X	X	X	X	X	X	X	X	X	X	X	X
Birth-cohort FE	X	X	X	X	X	X	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X	X	X	X	X	X	X
Country-age linear trends	X	X	X	X	X	X	X	X	X	X	X	X
Formative age	16-24	16-25	17-24	17-25	18-24	18-25	16-24	16-25	17-24	17-25	18-24	18-25
F-Statistic	26.020	20.808	27.368	27.073	29.487	29.414	46.347	33.767	45.758	44.988	43.767	44.128
N	17554	9542	18230	18230	18704	18704	21661	11915	22384	22384	22956	22956
Number of countries	28	28	28	28	28	28	28	28	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-6 is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 7-12 is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. The 2SLS estimates use the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, survey year, age, birth-year, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3.3 Robustness Checks for Country Level Analysis

TABLE D20: Green party votes and leads of actual and predicted asylum demands

Dep. variable	Actual asylum demands (1)	Predicted asylum demands (2)
% EP Green Party votes	0.0454 (0.0300)	-0.00227 (0.00860)
Country Controls	X	X
Weather Controls	X	X
Country FE	X	X
Year FE	X	X
N	42	42
adj. R^2	0.957	0.999

Notes: The table reports the OLS estimates associated with the % of Green party votes in EP elections on the leads of actual and predicted weather-induced asylum demands in logarithm as constructed in Equation (D.3). Robust standard errors, clustered at the country level, in parentheses. Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old. Weather Controls: Linear and squared average temperature and total precipitation in the country. All columns account for country- and year-specific fixed effects. F-statistic refers to the Kleibergen-Paap F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D21: Weather-induced asylum applications and Green party votes in European Parliament elections. 2SLS estimates. Alternative instruments.

Dep. variable	% Green Party votes in EP elections (<i>Mean: 9.84</i>)			
	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
Log(Asylum Applications)	-2.952 (1.745)	-2.733 (1.751)	-3.255 (2.083)	-3.670 (2.371)
Instrument	w/out MR	w/ MR	Destination-weather	Destination-specific
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
F-Statistic	18.779	16.925	14.819	16.805
<i>N</i>	65	65	65	65
Number of countries	20	20	20	20

Notes: The table reports the 2SLS coefficients on (log) of total asylum applications in the five years preceding the European Parliament elections. The dependent variable is the share of votes of Green parties in European Parliament elections after 2000 in an EU country. Respectively, in each column, asylum demands are instrumented with its predicted counterpart as described in Equations (4.2), (D.2), (D.3) and (D.4). Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old between the two election rounds and in the year of the elections, voter turnout. Weather Controls: Linear and squared average temperature and total precipitation in the country between the two election rounds and in the year of the elections. All columns control for country- and year-specific fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the Kleibergen-Paap F-statistic for weak instrument. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D22: Weather-induced asylum applications and other parties' votes in EP elections. 2SLS estimates. Other parties.

Dep. variable: % votes	Socialist/Left	Social democrats	Liberal	Christian democrats	Conservative	Nationalist
	(1)	(2)	(3)	(4)	(5)	(6)
log(Asylum Applications)	4.399 (2.840)	-1.287 (1.617)	-0.884 (3.839)	-0.447 (2.807)	2.434 (2.376)	-4.895** (2.059)
Country Controls	X	X	X	X	X	X
Weather Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
<i>N</i>	67	99	83	65	73	84
F-stat	15.273	16.410	25.556	10.922	13.949	22.641
Number of countries	20	27	24	18	20	25

Notes: The table reports the 2SLS coefficients on (log) of total asylum applications in the five years preceding the European Parliament elections. The dependent variable is the share of votes of other parties by party family as classified in the Manifesto database in European Parliament elections after 2000 in an EU country. The (log) of total asylum applications in the five years preceding the elections is instrumented with the gravity-predicted (log) of total asylum applications described in Equation (4.2) in the text. Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old between the two election rounds and in the year of the elections, voter turnout. Weather Controls: Linear and squared average temperature and total precipitation in the country between the two election rounds and in the year of the elections. All countries control for country-specific, year-specific fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the Kleibergen-Paap F-statistic for weak instrument. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D23: Weather-induced asylum applications and electoral turnout in EP elections

Dep. variable	% Voter Turnout (<i>Mean: 46.134</i>)			
	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
Log(Asylum Applications)	1.097 (1.617)	-3.785 (3.061)	-2.428* (1.360)	-3.256* (1.912)
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X		X	X
Year FE	X	X	X	X
Regional linear time trends				X
F-Statistic		9.468	15.536	11.083
<i>N</i>	65	65	65	65
Number of countries	28	28	28	28

Notes: The table reports the OLS (column 1) and 2SLS (columns 2 to 4) coefficients on (log) of total asylum applications in the five years preceding the European Parliament elections. The dependent variable is the share of electoral turnout in European Parliament elections after 2000 in an EU country. The (log) of total asylum applications in the five years preceding the elections is instrumented with the gravity-predicted (log) of total asylum applications described in Equation (4.2) in the text. The sample is the same as in baseline results using Green party votes. Country Controls: (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old between the two election rounds and in the year of the elections, voter turnout. Weather Controls: Linear and squared average temperature and total precipitation in the country between the two election rounds and in the year of the elections. All countries control for country-specific, year-specific fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the Kleibergen-Paap F-statistic for weak instrument. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D24: Weather-induced asylum applications and environmentalism in national elections. 2SLS Estimates. Alternative instruments.

Dep. variable	National Elections Environmentalism Index			
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.232 (0.343)	0.193 (0.252)	0.602 (0.806)	0.300 (0.381)
Instrument	w/out MR	w/ MR	Destination-weather	Destination-specific
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
<i>N</i>	119	119	119	119
F-Stat	16.030	24.236	12.467	13.813

Notes: The dependent variable is the normalized index of environmentalism of national elections where the share of quasi-sentences that positively referred to the environment in each party's manifesto is weighted by its vote share in the national elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. Respectively, in each column, asylum demands are instrumented with its predicted counterpart as described in Equations (4.2), (D.2), (D.3) and (D.4). All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D25: Weather-induced asylum applications and other dimensions of national elections. 2SLS Estimates.

	Europe + (1)	Europe - (2)	Multiculturalism + (3)	Multiculturalism - (4)	Refugees + (5)	Cultural Autonomy + (6)
log(Asylum Applications)	0.226 (0.182)	0.0865 (0.174)	-0.232 (0.160)	0.156 (0.343)	-0.186 (0.150)	0.287 (0.353)
Country Controls	X	X	X	X	X	X
Weather Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
F-Stat	16.030	16.030	16.030	16.030	16.030	16.030
N	119	119	119	119	119	119

Notes: The dependent variable is the normalized index of each topic of national elections where the share of quasi-sentences that referred to each topic as described in Table D3 in each party's manifesto is weighted by its vote share in the national elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other, obtained using an instrumental variable approach, where the instrument is constructed using the predicted values in Equations (D.3). Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3.4 Robustness Checks for Party Level Analysis

TABLE D26: Weather-induced asylum applications and environmental agenda of parties. 2SLS estimates. Alternative instruments.

	Party's Standardized Environmentalism			
	(1)	(2)	(3)	(4)
<i>Panel A: Unweighted</i>				
log(Asylum Applications)	-0.119 (0.107)	-0.123 (0.105)	-0.103 (0.0842)	0.523 (0.975)
F-Stat	51.412	61.676	57.782	10.524
<i>Panel B: Weighted by votes</i>				
log(Asylum Applications)	-0.194* (0.111)	-0.194* (0.103)	-0.0989 (0.0738)	-0.404 (0.876)
F-Stat	40.407	48.326	58.945	0.362
Instrument	w/out MR	w/ MR	Destination-weather	Destination-specific
Right-left ideological index	X	X	X	X
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Party FE	X	X	X	X
<i>N</i>	520	520	520	520

Notes: The analysis is over a sample of parties that are running in multiple elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. The dependent variable is the (normalized) share of quasi-sentences that positively referred to the environment in each party's manifesto in the national elections. All columns report the 2SLS estimates where (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications respectively described in Equations (4.2), (D.2), (D.3) and (D.4). All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Panel B weighs each party's observation by the vote gained in the national elections. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D27: Weather-induced asylum applications and environmental agenda of parties. 2SLS estimates. Alternative vote cutoffs.

	Party's Standardized Environmentalism			
	(1)	(2)	(3)	(4)
<i>Panel A: Unweighted</i>				
log(Asylum Applications)	-0.0583 (0.108)	-0.334** (0.145)	-0.365** (0.165)	-0.347** (0.153)
F-Stat	32.421	25.869	20.066	15.168
<i>Panel B: Weighted by party votes</i>				
log(Asylum Applications)	-0.158 (0.116)	-0.274* (0.147)	-0.314* (0.160)	-0.297* (0.148)
F-Stat	27.312	23.909	19.597	14.649
Votes above	5%	10%	15%	20%
Right-left ideological index	X	X	X	X
Country Controls	X	X	X	X
Weather Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Party FE	X	X	X	X
<i>N</i>	469	293	210	170

Notes: The analysis is over a sample of parties that are running in multiple elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. The dependent variable is the (normalized) share of quasi-sentences that positively referred to the environment in each party's manifesto in the national elections. All columns report the 2SLS estimates where (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications respectively described in Equations (D.3). Panel B weighs each party's observation by the vote gained in the national elections. Column (1) only considers parties that gained at least 5% of the votes, column (2) only considers parties that gained at least 10% of the votes, column (3) only considers parties that gained at least 15% of the votes, column (4) only considers parties that gained at least 20% of the votes. All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D28: Weather-induced asylum applications and environmental agenda by party family. 2SLS Estimates.

	Green/Ecologist	Socialist/Left	Social democrats	Liberal	Christian democrats	Conservative	Nationalist
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Panel A: Unweighted</i>							
log(Asylum Applications)	-3.200	-0.542	-0.274	-0.0154	0.872	0.353	-0.0183
	(2.885)	(2.005)	(0.171)	(0.149)	(1.104)	(0.206)	(0.0777)
F-Stat	1.289	2.491	25.802	47.751	2.713	10.025	46.526
<i>Panel B: Weighted by party votes</i>							
log(Asylum Applications)	-3.498	4.474	-0.355**	0.0478	-5.050	0.440	-0.0829
	(3.845)	(14.88)	(0.155)	(0.156)	(24.31)	(0.293)	(0.0916)
F-Stat	1.605	2.080	34.013	64.349	2.060	5.542	50.383
Right-left ideological index	X	X	X	X	X	X	X
Country Controls	X	X	X	X	X	X	X
Weather Controls	X	X	X	X	X	X	X
Country FE	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Party FE	X	X	X	X	X	X	X
N	52	73	105	84	72	66	68

Notes: The analysis is over a sample of parties that are running in multiple elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. The dependent variable is the (normalized) share of quasi-sentences that positively referred to the environment in each party's manifesto in the national elections. Each column only considers the parties belonging to a specific party family as defined by the Manifesto database. The coefficients reported are the 2SLS estimates where (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Panel B weighs each party's observation by the vote gained in the national elections. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D29: Weather-induced asylum applications and other dimensions of parties' manifestos. 2SLS Estimates.

	Europe + (1)	Europe - (2)	Multiculturalism + (3)	Multiculturalism - (4)	Refugees + (5)	Cultural Autonomy + (6)
<i>Panel A: Unweighted</i>						
log(Asylum Applications)	-0.269 (0.314)	0.0538 (0.103)	0.0161 (0.172)	-0.0953 (0.0791)	-0.0899 (0.0886)	-0.164 (0.159)
F-Stat	51.412	51.412	51.412	51.412	51.412	51.412
<i>Panel B: Weighted by party votes</i>						
log(Asylum Applications)	-0.0494 (0.181)	0.0756 (0.0803)	-0.0217 (0.0829)	-0.135 (0.0894)	0.000911 (0.000963)	-0.000171 (0.00318)
F-Stat	40.407	40.407	40.407	40.407	40.407	40.407
Right-left ideological index	X	X	X	X	X	X
Country Controls	X	X	X	X	X	X
Weather Controls	X	X	X	X	X	X
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Party FE	X	X	X	X	X	X
<i>N</i>	520	520	520	520	520	520

Notes: The analysis is over a sample of parties that are running in multiple elections. The table reports the coefficients associated with (log) of the sum of asylum applications in the period between one election year and the other. The dependent variable is the (normalized) share of quasi-sentences that refers to each dimension as described in Table D3 in each party's manifesto in the national elections. The coefficients reported are the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. All columns control for the normalized right-left ideological index provided in the MPD. Country controls: averages between two elections of (log) GDP per capita, % tertiary education, unemployment rate, population rate between 18 and 23 years old, and in the year of the elections. Weather controls: averages between two elections of linear and squared temperature and precipitation and in the year of the elections. All columns control for country, year, and party fixed effects. Panel B weighs each party's observation by the vote gained in the national elections. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.4 Additional Results

D.4.1 Parametric multilateral resistance term

The confounding influence that the attractiveness of alternative destinations exerts on the bilateral migration rate, known as the multilateral resistance term, can generate biases in the estimation of the push and pull factors of migration in a gravity equation. In an alternative specification of the baseline estimating gravity equation (Equation (4.2)), I account for multilateral resistance in two ways. Since the equation is estimated using OLS and not PPML, the use of fixed effects is not enough to account for outward and inward multilateral resistance indexes (Fally, 2015). For this reason, I also account for “inward” multilateral resistance term to migration (Anderson and Van Wincoop, 2003) parametrically.² The parametric version of the multilateral resistance term is constructed for each of the six weather vectors W (fourth-order polynomial of temperature and second-order polynomial of precipitation) as follows:

$$MR_{odt} = \sum_{k \neq d} \omega_{ok} W_{kt} \quad (\text{D.1})$$

where ω_{ok} is the ratio of asylum applications from origin country o to destination country k over the total asylum applications received by country k in the first available year. This weighting scheme accounts for the relative propensity to apply for asylum in each country k among the EU27+UK set of destination countries. The weighted average of weather conditions across the k destination countries except for d accounts for changes in the attractiveness of alternative destinations that would otherwise be inflated in W_{ot} . The six dyad-specific time-varying regressors are included in the estimating equation in the multilateral resistance term MR_{odt} . This approach also allows me to account for costs of migration common to all asylum seekers within a particular bilateral link comprising both a time-invariant component, captured by the fixed effects, and a time-varying component as a function of networks and weather conditions in other destinations. The resulting estimating equation is written as

$$\log(AsyApp_{odt}) = f(W_{ot}; BIL_{od}; \alpha) + g(MR_{odt}; \beta) + \theta_{od} + \mu_{dt} + \chi_{rt} + u_{odt} \quad (\text{D.2})$$

Table D30 displays the coefficients associated with the uninteracted origin temperature and precipitation from Equation (4.2) respectively omitting and accounting for the multilateral resistance term both non-parametrically, with the additional suite of fixed effects, and parametrically, with the MR_{odt} matrix. Both temperature and precipitation estimates substantially vary across the four specifications, suggesting that accounting also parametrically for multilateral resistance changes the semi-elasticity of migration to origin weather.

D.4.2 Gravity equation accounting for weather in host countries

To introduce an additional bilateral source of variation in the predicted values of asylum demands, I include as regressors a measure of pull factors, measured as linear and squared terms of temperature and precipitation in the destination country. The econometric specification is written as

$$\log(AsyApp_{odt}) = f(W_{ot}, BIL_{od}, \alpha) + g(W_{dt}, \beta) + \theta_{od} + \chi_{rt} + u_{odt} \quad (\text{D.3})$$

²Since the objective of the gravity equation is to estimate the impact of weather fluctuations on asylum seeker outflows, the “outward” multilateral resistance term that captures alternative source countries’ conditions is not necessary for this context.

TABLE D30: Gravity model for asylum applications accounting for multilateral resistance

	(Log) Asylum Applications			
	(1)	(2)	(3)	(4)
Temperature origin	-2.055** (0.601)	-1.782** (0.634)	-2.133** (0.602)	-1.925** (0.634)
Temperature origin ²	0.0456 (0.0289)	0.0411 (0.0293)	0.0478 (0.0290)	0.0434 (0.0294)
Temperature origin ³	0.00208 (0.00184)	0.00167 (0.00190)	0.00214 (0.00184)	0.00181 (0.00191)
Temperature origin ⁴	-0.0000445 (0.0000366)	-0.0000313 (0.0000392)	-0.0000471 (0.0000366)	-0.0000355 (0.0000393)
Precipitation origin	20.07 (66.69)	57.91 (69.39)	26.15 (67.09)	63.51 (69.81)
Precipitation origin ²	5016.9 (48460.4)	-31071.0 (51003.8)	4780.5 (48429.6)	-32224.7 (50950.6)
Multilateral weather p-value (Multilateral weather = 0)			X 0.000	X 0.000
Country-pair FE	X	X	X	X
Origin FE	X	X	X	X
Year FE	X		X	
Destination FE	X		X	
Destination-by-year FE		X		X
Region of origin-by-year FE		X		X
Number of country pairs	2084	2084	2084	2084
Number of origin countries	141	141	141	141
Destination Sample	EU27 + UK	EU27 + UK	EU27 + UK	EU27 + UK
Mean Outcome	3.733	3.733	3.733	3.733
SD Outcome	1.858	1.858	1.858	1.858
<i>N</i>	25951	25951	25951	25951
adj. <i>R</i> ²	0.747	0.796	0.748	0.796

Notes: The estimated equation always uses origin-specific seasonal temperature and precipitation. Robust standard errors, clustered at the origin-year level, in parentheses. Interaction terms between all weather variables and bilateral controls are included in the regression but not displayed. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

where I account for a second-order polynomial of daily average temperatures and daily precipitation in the destination country. This alternative specification does not account for destination-by-year fixed effects, collinear with the pull factors. Predicted values of asylum demands are then constructed as $\widehat{AsyApp}_{dt} = \sum_{o \neq d} \exp(\widehat{\alpha}_M X_{odt} + \widehat{\beta}_M W_{dt})$. Table D7 displays the results for the three different alternative measures of temperature and precipitation.

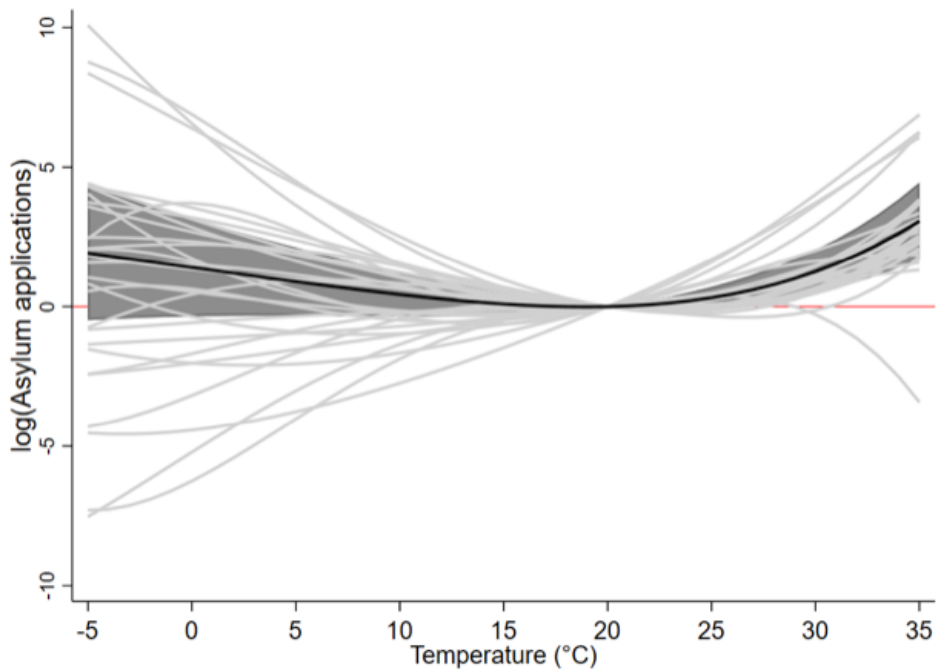
D.4.3 Destination-specific response function to weather fluctuations

To account for the fact that weather deviations in the origin country have differential effects for each destination country, I estimate destination-specific response functions. I estimate the following equation in a pooled sample of origin-specific asylum demands to the EU27 + UK destination countries.

$$\log(AsyApp_{odt}) = f(\mathbf{W}_{ot}, \alpha_d) + \theta_{od} + \psi_{dt} + \chi_{rt} + u_{odt} \quad (\text{D.4})$$

where I use the same vector of origin weather W_{ot} including a fourth-order polynomial of daily average temperatures, summed across the maize growing season and a second-order polynomial of daily precipitation across the growing season and estimate destination-specific functions of this vector. This alternative specification serves two purposes. First, by estimating destination-specific responses to weather fluctuations in origin countries, the predicted values obtained leveraging only weather variation are time-varying and pair-specific. Second, the equation now accounts for multi-lateral resistance in an alternative manner by allowing the effect of push factors to be different across destinations while controlling for time-varying destination-specific effects. Figure D20 displays the destination-specific response functions to season-total temperature in origin countries.

FIGURE D20: Destination-specific response functions to temperature in origin countries over maize growing season



Notes: The figure plots the predicted asylum applications-temperature response function for each destination country for the applications coming from non-OECD countries in the EU27+UK. Regression estimates are from a fourth-order polynomial in daily average temperature over the maize growing season weighted by maize area in each grid cell. The response function is estimated in a regression model that controls for a quadratic function in season-total precipitation, as well as destination-by-year, region-of-origin-by-year, dyad-specific fixed effects. The solid black line reports the pooled average response function as displayed in Figure D6 and its associated 95% confidence interval using country-year clustered standard errors.

D.4.4 Weather-induced anomalies in asylum applications lead to higher acceptance rate

Weather anomalies and climate change are not valid criteria for asylum applications (UN, 1951). There are two main channels through which weather fluctuations can increase asylum demands.

On the one hand, asylum applications can increase due to economic reasons, on the other one, they can increase due to conflict or persecution, for instance, as a result of crop failures or tightening of natural resource constraints. Only in the latter case, asylum applications could be deemed valid by the host countries. I test whether application decisions respond positively to weather-induced asylum demands, providing an indirect test of the validity of weather-induced asylum applications as in Missirian and Schlenker (2017b).

I compute anomalies in weather-induced asylum demands as the predicted change in the number of applications from an origin country to a destination country as explained by deviations in the weather variables from their respective sample averages. The weather-induced application anomaly from origin o to destination d in year t is

$$n_{odt} = e^{\widehat{W_{ot}}\widehat{\alpha} + \widehat{\theta}_{od} + \widehat{\pi}_t + \widehat{\lambda}_o + \widehat{\mu}_d + \widehat{\psi}_{dt} + \widehat{\chi}_{rt} + \frac{\widehat{\sigma}_u^2}{2}} - e^{\overline{\widehat{W_{ot}}\widehat{\alpha} + \widehat{\theta}_{od} + \widehat{\pi}_t + \widehat{\lambda}_o + \widehat{\mu}_d + \widehat{\psi}_{dt} + \widehat{\chi}_{rt} + \frac{\widehat{\sigma}_u^2}{2}}} \quad (\text{D.5})$$

where the parameters are the coefficients from the baseline gravity in Equation (4.2) of log asylum applications on weather, and $\widehat{\sigma}_u^2$ is the predicted variance of the error term from the same regression. Then, I examine asylum decisions (acceptances) d_{odt} in the following two years.

$$d_{odt} = \sum_{\tau=0}^2 \gamma n_{od(t-\tau)} + \theta_{od} + \pi_t + \lambda_o + \mu_d + \psi_{dt} + \chi_{rt} + \nu_{odt} \quad (\text{D.6})$$

Table D31 displays the coefficients on how weather-induced asylum anomalies translate into additional acceptances accounting for up to two-year lagged application anomalies. Accounting for both recognized refugee status and complementary protections granted (column 2), contemporaneous and one-year lagged anomalies are positive and statistically significant and the sum of the three coefficients is 45.23 (p-value: 0.001) for the baseline fourth-order polynomial model in temperature. These findings suggest that weather-induced shocks to applications are deemed valid by host countries at a much higher rate. Similar to findings in Missirian and Schlenker (2017b) in a unilaterally-specified equation estimated on a sample until 2014, I find that weather shocks induce people to flee and be recognized as needing international protection through refugee status.

TABLE D31: Weather-induced asylum application anomalies and acceptance

	(1)	(2)
n_{odt}	31.80* (18.59)	36.25** (17.73)
n_{odt-1}	12.22*** (3.148)	18.90*** (3.742)
n_{odt-2}	1.207 (5.624)	7.947 (6.327)
Outcome	Recognized decisions	Recognized decisions & Complementary Protection
p-value ($\gamma_1 + \gamma_2 + \gamma_3 = 0$)	0.024	0.001
F-Stat ($\gamma_1 + \gamma_2 + \gamma_3 = 0$)	5.076	10.822
Mean Outcome	150.547	513.577
Average acceptance rate	0.061	0.326
N	19125	19125
adj. R^2	0.362	0.442

Notes: The estimated equation includes origin-, destination-, origin-destination, year-, region-of-origin-by-year, destination-by-year fixed effects. Robust standard errors, clustered at the origin-destination pair level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.4.5 Additional individual level results

TABLE D32: Weather-induced asylum applications and environmental values. All controls.

Dep. variable	CC EU Election (<i>Mean: 0.068</i>)		CC Pol Priority (<i>Mean: 0.106</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Asylum Applications)	-0.00147 (0.00384)	0.0226** (0.0106)	0.00746 (0.00651)	0.0431** (0.0207)
Male	-0.0119*** (0.00395)	-0.0118*** (0.00395)	-0.00795** (0.00367)	-0.00777** (0.00363)
<i>Education categories</i> (baseline: Up to 15 years)				
Between 16 and 19 years	0.0126*** (0.00225)	0.0124*** (0.00221)	0.00752** (0.00274)	0.00717** (0.00278)
20 years or older	0.0377*** (0.00451)	0.0378*** (0.00451)	0.0193*** (0.00404)	0.0193*** (0.00403)
Still studying	0.0483*** (0.00693)	0.0478*** (0.00691)	0.0299*** (0.00757)	0.0293*** (0.00770)
No education	-0.0159 (0.00978)	-0.0160 (0.00994)	-0.0323*** (0.0110)	-0.0309*** (0.0106)
Unemployed	-0.00673* (0.00331)	-0.00592* (0.00314)	-0.00812** (0.00346)	-0.00735** (0.00352)
Left Political Orientation	0.0343*** (0.00943)	0.0342*** (0.00943)	0.0234*** (0.00770)	0.0232*** (0.00768)
Weather controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		21.566		26.241
N	106614	106614	130068	130068
Number of countries	28	28	28	28

Notes: The table replicates Table 4.1 reporting all individual controls included in the regressions. The 2SLS estimates use the predicted asylum applications constructed from the gravity-predicted asylum application flows as described in Equation (4.2) in the text. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D33: Weather-induced asylum applications and environmental values. Heterogeneity by age. 2SLS estimates.

Dep. variable	CC EU Election			CC Pol Priority		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Asylum Applications)	0.0264** (0.0108)	0.0233* (0.0118)	0.0181 (0.0124)	0.0514** (0.0209)	0.0374** (0.0169)	0.0386 (0.0264)
Sample	14-40	41-59	60+	14-40	41-59	60+
Country FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Age FE	X	X	X	X	X	X
Region-by-year FE	X	X	X	X	X	X
Country-age linear trends	X	X	X	X	X	X
F-Stat	15.657	13.808	13.840	24.611	20.910	19.226
<i>N</i>	35938	36455	34221	44395	44428	41245

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D34: Weather-induced asylum applications and environmental values. Heterogeneity by gender. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0160*	0.0137	0.0454**	0.0400
	(0.00916)	(0.00819)	(0.0183)	(0.0241)
Sample	Female	Male	Female	Male
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	20.414	21.154	27.587	21.963
N	58446	48168	70963	59103

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D35: Weather-induced asylum applications, environmental values, and Google Trends. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0181* (0.00934)	0.0162* (0.00890)	0.0454** (0.0191)	0.0417*** (0.0142)
Google Trends “Climate change”	0.00209* (0.00102)	0.00282** (0.00125)	-0.00243 (0.00266)	0.000430 (0.00227)
Google Trends “Climate protests”	-0.000550 (0.00441)	0.000628 (0.00488)	0.0243** (0.00943)	0.0185** (0.00835)
Google Trends “Migration”		0.00187 (0.00137)		-0.00345* (0.00202)
Google Trends “Refugee”		-0.00198 (0.00278)		-0.00118 (0.00310)
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	23.481	26.961	29.272	43.920
<i>N</i>	106614	106614	130068	130068

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D36: Asylum applications and Google Trends. OLS and 2SLS estimates.

Google Trends for	Climate change		Climate protests		Migration		Refugee	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Predicted Asylum Applications)	0.333 (0.381)		-0.705** (0.308)		-1.037 (0.690)		-0.624 (0.738)	
log(Asylum Applications)		0.372 (0.415)		-0.786* (0.433)		-1.157 (0.826)		-0.696 (0.966)
Country FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Outcome Mean		11.15		2.38		23.92		9.36
Outcome SD		5.96		3.82		18.32		9.36
F-Stat		17.318		17.318		17.318		
N	444	444	444	444	444	444	444	444

Notes: Country-level estimates regressing annual average Google Searches for “Climate change” (columns 1-2), “Climate protests” (columns 3-4), “Migration” (columns 5-6), “Refugee” (columns 7-8) on the instrument (odd columns) and the actual flows instrumented with the instrument (even columns). The gravity-predicted (log) of asylum applications is obtained from the predicted values from Equation (D.3) in the text. All columns control for country and survey year fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D37: Weather-induced asylum applications and environmental values. Heterogeneity by destination country. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.00807 (0.00585)	0.0193* (0.0115)	0.0213 (0.0167)	0.0515* (0.0301)
Destination country sub-sample	Below median	Above median	Below median	Above median
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	13.865	11.286	14.272	12.929
N	49384	57228	59095	70972

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). Odd columns report the estimates in the sub-sample of countries below the median number of asylum demands received, even columns report the estimates in the sub-sample of countries above the median number of asylum demands received (Austria, Belgium, Denmark, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Spain, Sweden, United Kingdom). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D38: Weather-induced asylum applications and perception of climate change as a global problem

Dep. variable	CC World Problem (<i>Mean: 0.37</i>)		CC Seriousness(1-10) (<i>Mean: 7.57</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Asylum Applications)	0.00646 (0.00666)	0.00108 (0.0113)	0.0239 (0.0451)	-0.129 (0.110)
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		20.995		21.172
<i>N</i>	116879	116879	116110	116110
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-2 is a dummy equal to 1 if the respondent reports climate change or global warming as the most serious problem the world is currently facing as a whole. The dependent variable in columns 3-4 is a categorical variable ranging from 1 to 10 that indicates the level of seriousness of climate change as a world problem perceived by the respondent (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. Columns (2) and (4) report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D39: Weather-induced asylum applications and migration as political priority

Dep. variable	Migration EU Election (<i>Mean: 0.078</i>)		Migration Pol Priority (<i>Mean: .085</i>)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
log(Asylum Applications)	0.0135 (0.00999)	0.00585 (0.0163)	0.0126 (0.00853)	0.0383** (0.0162)
Weather Controls	X	X	X	X
Individual Controls	X	X	X	X
Country FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Statistic		14.434		21.434
<i>N</i>	106613	106614	130067	130068
Number of countries	28	28	28	28

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable in columns 1-2 is a dummy equal to 1 if the respondent reports migration as a theme that the European Parliament should give priority to when deliberating. The dependent variable in columns 3-4 is a dummy equal to 1 if the respondent reports migration as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (see Table D1 for exact wording and additional details on the construction of the variable). Asylum Applications is the sum of the asylum applications in a given country in the five years preceding the survey year, as defined in Equation 4.1. Columns (2) and (4) report the 2SLS estimates using the predicted asylum applications from the gravity equation with bilateral fixed effects using destination-specific coefficients of weather fluctuations in origin countries. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D40: Weather-induced asylum applications and environmental values. Heterogeneity by political orientation. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0250** (0.0100)	0.0191 (0.0174)	0.0444** (0.0187)	0.0326 (0.0327)
Sample	Right-wing	Left-wing	Right-wing	Left-wing
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	24.332	16.237	25.334	11.061
<i>N</i>	79947	26666	97464	32604

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared annual average temperature and total precipitation in the country; Population), and country, survey year, birth-year and country by year of birth fixed effects. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D41: Weather-induced asylum applications and environmental values. Heterogeneity by education. 2SLS estimates.

Dep. variable	CC EU Election		CC Pol Priority	
	(1)	(2)	(3)	(4)
log(Asylum Applications)	0.0174* (0.00901)	0.0103 (0.0107)	0.0334** (0.0142)	0.0633 (0.0386)
Sample	Non Tertiary	Tertiary	Non Tertiary	Tertiary
Country FE	X	X	X	X
Year FE	X	X	X	X
Age FE	X	X	X	X
Region-by-year FE	X	X	X	X
Country-age linear trends	X	X	X	X
F-Stat	14.028	16.635	22.434	23.388
<i>N</i>	73229	33382	89513	40555

Notes: The sample is restricted to survey respondents that have the same nationality as the country in which they are interviewed. The dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that should be discussed as a matter of priority during the electoral campaign for the next European Parliament elections (columns 1 and 2, see Table D1 for exact wording and additional details on the construction of the variable). In columns (3) and (4) the dependent variable is a dummy equal to 1 if the respondent reports climate change as a theme that the European Parliament should give priority to when deliberating (see Table D1 for exact wording and additional details on the construction of the variable). All columns report the 2SLS estimates where the (log) of asylum applications is instrumented with the gravity-predicted (log) of asylum applications described in Equation (4.2) in the text. All columns control for individual characteristics (Gender, Education (Up to 15 years; 16-19 years; 20 years or older; still studying; no education), Unemployed, Left-wing oriented) and country-level covariates (Linear and squared five-year average temperature and total precipitation, linear and squared annual temperature and total precipitation), and country, age, region-by-survey-year fixed effects and country by age linear trends. Robust standard errors, clustered at the country level, in parentheses. F-statistic refers to the K-P F-statistic for weak instruments. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.4.6 Party-level empirical approach

In Section 4.5.1, I explore the aspects of the supply side and the political dynamics of the party system, by investigating whether changes in asylum applications have determined a shift in the supply side of the climate-related political process. I use the information on parties' political agenda related to the environment from the *Manifesto Project Database* (MPD) to measure the degree of environmentalism of each party in national elections. Using a similar approach to Moriconi et al. (2019), I exploit within-party variation in the environmental political agenda across elections. The econometric specification writes as follows:

$$environmentalism_{pdt} = \beta_1 \log \left(\sum_{\tau=1}^s AsyApp_{d,t-\tau} \right) + X'_{dt} \gamma + Z'_{pt} \delta + \alpha_p + \mu_d + \lambda_t + \varepsilon_{pdt} \quad (D.7)$$

where $environmentalism_{pdt}$ is the normalized share with mean equal to 0 and standard deviation equal to 1 of quasi-sentences that positively referred to policies in favor of protecting the environment and fighting climate change in the political manifesto of party p in country d in election year t . The main variable of interest is $\sum_{\tau=1}^s AsyApp_{d,t-\tau}$, which is the cumulative number of asylum applications between one election and the other. In X'_{dt} , I include country-level socio-economic and environmental characteristics averaged over the period between two consecutive elections in a country that may confound the effect of migration flows on electoral outcomes. The use of party-specific fixed effects α_p and country-specific fixed effects μ_d identifies the effect of asylum applications on the political agendas only through changes within parties over time. Any time-invariant feature of countries and parties will not affect identification, since it will be filtered out by these fixed effects. Election-year fixed effects (λ_t) capture common trends over time. Standard errors are clustered at the country level. The inclusion of party- and country-fixed effects guarantees the identification of the effect of weather-induced asylum seeker flows on parties' environmental preferences only through changes in agendas for parties that were present in at least two elections. This approach captures changes in the agendas of existing parties in response to changes in weather-induced flows, rather than the entry or exit of new parties.