



HAL
open science

Three essays in sustainable finance

Quentin Moreau

► **To cite this version:**

Quentin Moreau. Three essays in sustainable finance. Business administration. Université Paris sciences et lettres, 2022. English. NNT : 2022UPSLD012 . tel-03828549

HAL Id: tel-03828549

<https://theses.hal.science/tel-03828549>

Submitted on 25 Oct 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



THÈSE DE DOCTORAT

DE L'UNIVERSITÉ PSL

Préparée à l'Université Paris-Dauphine

Trois essais en finance durable

Soutenue par

Quentin MOREAU

Le 06 septembre 2022

Ecole doctorale n° ED 543

Ecole doctorale SDOSE

Spécialité

Gestion

Composition du jury :

François, BELOT
Professeur
CY Cergy Paris Université
Examineur, Président du jury

Patricia, CRIFO
Professeur
Ecole Polytechnique
Rapporteur

Edith, GINGLINGER
Professeur
Université Paris-Dauphine
Directeur de thèse

Yannick, LE PEN
Maître de conférences
Université Paris-Dauphine
Examineur

Luc, PAUGAM
Associate professor
HEC Paris
Rapporteur

Remerciements

Ce travail a été facilité grâce à l'aide et aux conseils de nombreuses personnes.

Je tiens en premier lieu à remercier vivement Edith Ginglinger pour avoir accepté d'encadrer cette thèse doctorale. J'ai sincèrement apprécié la qualité de ses conseils, sa rigueur et sa disponibilité.

Je remercie ensuite chaleureusement François Belot, Patricia Crifo, Yannick Le Pen et Luc Paugam pour avoir accepté de faire partie du jury de cette thèse. J'ai essayé de fournir dans cette thèse des travaux de la meilleure qualité possible. Cependant, à n'en pas douter, les remarques des membres du jury me permettront d'améliorer significativement mes travaux.

Je souhaite maintenant exprimer ma reconnaissance vis-à-vis de Tristan Jourde, qui m'a fait le plaisir d'être mon co-auteur pour l'un des chapitres de ce travail doctoral.

Je tiens également à remercier l'équipe de DRM Finance pour son aide tout au long de mon doctorat. Je salue notamment le travail de Françoise Carbon et Carole Gresse. Sans leur appui administratif et financier, cette thèse n'aurait pas pu être menée à bien. Mes remerciements vont aussi à Hubert de La Bruslerie et Marie-Aude Laguna, membres de mon comité de suivi de thèse, pour leurs conseils. Je souhaite de plus exprimer une gratitude particulière à l'égard de Tamara Nefedova, Evgenia Passari et Ryan Williams. Leur soutien m'a été crucial dans l'obtention d'un premier poste de maître de conférences.

Je suis en outre reconnaissant vis-à-vis de Laura Starks, qui a eu la gentillesse de m'accueillir à l'université du Texas à Austin au début de l'année 2020.

J'adresse tous mes remerciements à l'Institut Louis Bachelier et à l'Association Française des Investisseurs Institutionnels pour leur soutien financier.

Je rends de plus hommage à tous les doctorants, de DRM Finance ou d'ailleurs, avec qui j'ai eu la chance d'échanger tout au long de ce travail de thèse ; ainsi qu'à tous ceux ayant pris le temps de commenter mes travaux et que j'aurais omis de citer ici.

Je remercie enfin, bien sûr, tous mes proches pour leur soutien durant mes années doctorales.

L'Université Paris-Dauphine n'entend donner aucune approbation, ni improbation aux opinions émises dans cette thèse ; elles doivent être considérées comme propres à leur auteur.

Table des matières

Introduction.....	9
Définitions et mesures	12
Les pratiques responsables	16
Les pratiques responsables des entreprises	16
Les pratiques responsables des investisseurs	17
Les pratiques responsables en France	18
Conséquences sur les entreprises	19
Les conséquences des pratiques responsables sur les entreprises	19
Les conséquences du risque climatique sur les entreprises	20
Structuration de cette thèse doctorale.....	22
Premier chapitre : Risque climatique systémique.....	22
Deuxième chapitre : Les effets informationnels des initiatives de soutenabilité	23
Troisième chapitre : Risque climatique et structure du capital	25
Bibliographie	26
1. Systemic Climate Risk.....	31
1.1. Introduction.....	32
1.2. Data and methodology.....	38
1.2.1. Systemic risk measure	38
1.2.2. VaR estimation	40
1.2.3. Factor construction	43
1.2.4. Data sources	44
1.2.5. Descriptive statistics.....	47
1.3. Empirical results	48
1.3.1. Measure of systemic risk.....	48
1.3.2. Individual exposures of financial institutions to tail climate risks	48
1.3.3. The effect of tail climate risks on systemic risk.....	50
1.3.4. Individual characteristics of financial institutions and tail climate risks.....	51
1.3.5. Tail climate risks and environmental disclosure policies	52
1.4. Conclusion	53
1.5. References.....	55
1.6. Figures and tables.....	60
2. The informational effects of corporate sustainability initiatives	78
2.1. Introduction.....	79
2.2. Hypothesis development	85
2.3. Data	89

2.4.	Empirical results	92
2.4.1.	Visible sustainability initiatives and general public attention.....	92
2.4.2.	The effect of visible ESG initiatives on investors' and customers' attention to environmental considerations	94
2.4.3.	Visible sustainability initiatives and environmental ratings.....	97
2.4.4.	Do firms become more transparent after undertaking visible sustainability initiatives? 102	
2.4.5.	Robustness tests.....	104
2.5.	Conclusion	105
2.6.	References.....	107
2.7.	Figures and tables.....	111
3.	Climate Risk and Capital Structure	130
3.1.	Introduction.....	131
3.2.	Hypothesis development: the effect of physical climate risk on leverage	140
3.2.1.	Climate risks and operating costs.....	141
3.2.2.	Climate risks and bankruptcy costs	142
3.2.3.	Climate risk and leverage: is there a supply effect?.....	143
3.3.	Data	144
3.3.1.	Physical climate risk measures	144
3.3.2.	Credit ratings	148
3.3.3.	Financial and accounting data.....	149
3.3.4.	Bank loan and bond issuance data	150
3.4.	Empirical results	151
3.4.1.	Leverage and climate risk.....	151
3.4.2.	Difference-in-differences in leverage and climate risk: the Paris Agreement	155
3.4.3.	Climate risk and firm characteristics around the 2015 Paris Agreement	156
3.4.4.	Credit ratings and climate risk.....	157
3.4.5.	Climate risk and leverage: demand or supply effect?.....	159
3.4.5.1.	Climate risk and leverage: the demand effect	159
3.4.5.2.	Climate risk and leverage: the supply effect	160
3.4.6.	Robustness checks.....	162
3.5.	Conclusion	165
3.6.	References.....	168
3.7.	Main tables.....	172
3.8.	Internet Appendix	186
	Conclusion	203

Introduction

En accroissant globalement les ressources à disposition de l'Homme, le processus de croissance économique vise à desserrer la contrainte qui limite l'accomplissement des buts humains. Toutefois, le rapport du club de Rome (Meadows et al. 1972) soulignait, il y a 50 ans, un paradoxe : la poursuite de la croissance économique peut éroder certaines ressources, notamment via l'épuisement des ressources non-renouvelables et la détérioration de l'environnement, voire plus généralement remettre en cause la capacité à accroître le stock global de richesses sur le long terme. C'est dans ce contexte qu'émerge la notion de développement durable, visant à trouver un équilibre intergénérationnel permettant de « satisfaire les besoins des générations présentes, sans compromettre la capacité des générations futures à satisfaire leurs propres besoins » (Brundtland 1987).

Le développement durable vise à la préservation de ressources communes. A ce titre, la promotion du développement durable s'effectue notamment via la coopération internationale, par le biais de l'Organisation des Nations Unies (ONU). Cette coopération internationale vise en particulier à limiter l'impact de l'activité humaine sur le changement climatique. La convention-cadre des Nations unies sur les changements climatiques, établie au sommet de la Terre de Rio de Janeiro en 1992, a permis de rassembler 197 pays signataires autour de l'objectif de réduction des émissions de gaz à effet de serre. Cinq ans plus tard, le Protocole de Kyoto a précisé les ambitions chiffrées de réduction d'émission de gaz à effet de serre pour la période 2008-2012, puis a été étendu jusqu'à 2020. L'Accord de Paris sur le climat a ensuite succédé au Protocole de Kyoto, en mettant davantage l'accent sur des cibles de réduction d'émissions déterminées volontairement et au niveau national. Cet Accord de Paris cherche à garantir un réchauffement planétaire nettement inférieur à 2 degrés Celsius (comparativement à l'ère préindustrielle) et si possible limité à 1,5 degré.

Toutefois, malgré ces efforts en matière de coopération internationale, le Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC) souligne dans un rapport publié en 2022 que l'augmentation des températures sera probablement supérieure à 1,5 degré d'ici 2040, même en cas de très fortes réductions d'émissions de gaz à effet de serre, ce qui engendrerait une hausse des risques climatiques et menacerait les écosystèmes.¹

Dans ce contexte, le sondage « Les Français et l'économie », commandé en 2021 par la Banque de France, indique que 62% des Français considèrent que « le concept de croissance du PIB est dépassé ou doit être réorienté vers des objectifs sociaux, de bien-être et d'environnement. »² Ces préoccupations, couplées aux limites de la coopération internationale dans la lutte contre le changement climatique, amènent les agents économiques en capacité de financement à repenser leurs décisions d'épargne. Ceci favorise l'émergence de la finance durable, définie par la Banque de France comme « l'ensemble des pratiques financières visant à favoriser l'intérêt de la collectivité sur le long terme »³. En particulier, les ménages cherchent à obtenir une rentabilité financière satisfaisante tout en se souciant de la performance extra-financière générée par leurs placements.⁴

Pour défendre leurs préférences, les investisseurs peuvent tenter d'influencer la gestion de l'entreprise ou, si cette solution s'avère infructueuse, vendre les titres de la firme concernée (McCahery et al. 2016). Dans une vision qualifiée d'actionnariale, la seule responsabilité de l'entreprise serait à l'égard de ses actionnaires et correspondrait à la maximisation des profits (Friedman, 1970). Toutefois, une position promouvant la richesse créée pour l'ensemble des parties prenantes est opposée à cette vision actionnariale (Freeman, 2010). Selon cette position

¹ Voir [ici](#).

² Voir [ici](#).

³ Voir [ici](#).

⁴ A titre d'illustration, une étude d'opinion menée en 2021 pour l'Autorité des Marchés Financiers a révélé que 76% des Français considèrent que l'impact des placements financiers sur l'environnement est un sujet « important ». Voir [ici](#).

« parties prenantes », les entreprises devraient internaliser les externalités que leurs activités génèrent et rendre des comptes à la société (Liang et Renneboog, 2020). C'est ce que l'on nomme Responsabilité Sociale d'Entreprise (RSE). Sous la pression d'investisseurs attachant une importance à la responsabilité sociale, mais aussi de mouvements anti-mondialisations, d'organisations non-gouvernementales ou de consommateurs, les entreprises prennent ainsi en compte les enjeux extra-financiers (Déjean et Gond 2004).

Face à ces changements des attentes des investisseurs, ou du moins des attentes d'un nombre significatif certains d'entre eux, les marchés de capitaux évoluent eux aussi. De nouveaux placements financiers et de nouvelles modalités de financement des entreprises émergent. La montée en puissance des fonds d'investissement socialement responsables en est l'un des faits marquants dans les pays occidentaux. Par exemple, selon le Forum américain de l'investissement soutenable et responsable, un tiers des actifs sous gestion professionnelle aux Etats-Unis sont investis selon des principes d'ISR.⁵ L'apparition des prêts durables en est une autre manifestation notable. Les obligations vertes, des titres de dette ayant vocation à financer des projets bénéfiques à l'environnement, représentent plus de la moitié de ces prêts durables.⁶ Toutefois, ces initiatives sont suspectes d'écoblanchiment. Ces suspicions sont confirmées par certains travaux de recherche académique. Dans le cas des fonds d'investissement responsable, Raghunandan et Rajgopal (2021a) documentent des décalages entre l'intention de gestion de ces fonds et leurs pratiques : comparativement aux autres fonds d'investissement commercialisés par le même gestionnaire d'actifs, les fonds d'investissement socialement factureraient des frais de gestion plus élevés et présenteraient une plus faible performance financière, sans pour autant atteindre de meilleurs fondamentaux environnementaux ou sociaux.

⁵ Voir [ici](#).

⁶ Voir [cet article](#) de Bloomberg.

Selon la Banque de France⁷, la finance durable, parfois aussi appelée finance soutenable, recouvre trois concepts : finance responsable, finance verte et finance solidaire. La finance responsable correspond à la prise en compte de critères environnementaux, sociaux ou de gouvernance dans les pratiques des entreprises et des investisseurs. La finance verte recouvre les initiatives financières recherchant un impact positif sur l'environnement « en favorisant la transition énergétique et la lutte contre le réchauffement climatique ». Enfin, la finance solidaire vise « au financement de projets destinés à lutter contre l'exclusion et à améliorer la cohésion sociale ». Ce travail doctoral analysera soit les aspects environnementaux, sociaux et de gouvernance pris dans leur ensemble, soit spécifiquement certaines questions environnementales et climatiques. Cette thèse relève donc avant tout de la finance responsable et de la finance verte.

Cette introduction permettra d'offrir un panorama du développement de la finance durable en section 1 et de présenter brièvement en section 2 les trois articles de recherche contenus dans cette thèse doctorale.

Définitions et mesures

En 2015, l'Organisation des Nations Unies a défini 17 objectifs de développement durable, retranscrits ci-après. Ces objectifs peuvent servir de cadre aux différents acteurs de la finance durable.

⁷ Voir [ici](#).



Source : <https://onu.delegfrance.org/>

La performance RSE, évaluée au regard de la contribution de l'entreprise à la réalisation d'objectifs de développement durable tels que ceux définis par l'ONU, est généralement décomposée selon trois dimensions : Environnementale, Sociale, et Gouvernance (ESG). Bien que la lutte contre le changement climatique soit l'un des objectifs généralement admis comme relevant du pilier environnemental de la performance RSE, la RSE ou sa composante environnementale sont à dissocier de la notion du risque climatique. La RSE se concentre sur les externalités positives ou négatives créées par l'entreprise dans le cadre son activité, alors que le risque climatique regroupe les menaces découlant d'événements liés au climat et à son évolution.

L'impact du risque climatique est une thématique largement étudiée en économie (Dell et al. 2014). En revanche, la recherche académique en finance a, jusqu'à récemment, accordé peu d'importance aux risques climatiques (Diaz-Rainey et al. 2017). Les risques climatiques sont généralement décomposés en deux catégories. La première catégorie est celle des risques physiques, résultant des changements du climat. Ces risques se matérialisent par l'augmentation de la probabilité ou de la sévérité d'événements chroniques (tels que la hausse des températures

moyennes ou la montée des eaux) ou extrêmes (tels que les vagues de chaleur ou les ouragans). La seconde catégorie correspond aux risques de transition, résultant de changements de réglementation pouvant affecter négativement certaines entreprises, ou d'innovations technologiques apparaissant comme réponses à l'évolution du climat (Krueger et al. 2020).

En raison de la montée en puissance des considérations extra-financières de nombreuses parties prenantes, les années récentes ont vu le développement d'indicateurs de performance RSE, évaluant les entreprises selon les trois dimensions Environnementale, Sociale et de Gouvernance. D'après CFA Institute (2017), une majorité des analystes financiers et des gestionnaires d'actifs intègrent des critères de performance extra-financière dans leur pratique professionnelle, les scores ESG étant l'une de leurs principales sources d'information. En conséquence, les entreprises ayant les meilleures notations ESG tendent à attirer les flux d'investissement (Amel-Zadeh et al. 2021), cette pression à l'achat pouvant être à l'origine de survalorisations boursières ou contribuer à résorber la sous-valorisation (Bofinger et al. 2022).

Toutefois, les indicateurs mesurant la performance ESG et le risque climatique présentent des limites méthodologiques. Contrairement aux notations de crédit, pour lesquelles les divergences entre les agences de notation s'avèrent minimales, les notations extra-financières sont peu corrélées entre elles. Dans le cas des notations ESG, cette faible corrélation s'expliquerait par des différences de mesure, de périmètre et de pondération (Berg et al. 2020). De plus, l'écart entre les notations attribuées par différentes agences tend à s'accroître lorsque les entreprises divulguent davantage d'informations (Christensen et al. 2022). Ces notations s'avèrent en effet très complexes. Par exemple, MSCI ESG, l'une des agences de référence, évalue chaque entreprise de son périmètre sur 35 dimensions différentes, puis agrège ces notations pour déterminer les scores de performance environnementale, sociale, et de

gouvernance.⁸ De la même façon, Hain et al. (2022) documentent une assez faible corrélation entre différents scores d'exposition au risque physique. Ces divergences proviennent de l'utilisation de sources différentes, de l'hétérogénéité des méthodes d'agrégation des sources, de la diversité des horizons temporels et des scénarios climatiques utilisés pour mesurer le risque, ou encore de la définition en termes absolus ou au contraire relatifs du risque (mesure-t-on le niveau du risque ou le compare-t-on à une référence historique ou aux autres risques existant dans l'économie ?). Deux grands types de méthode se distinguent pour mesurer le risque climatique. La première repose sur l'utilisation de modèles de projection des périls climatiques, ces projections étant croisées avec des données relatives aux implantations géographiques et sectorielles des entreprises afin de définir à un score de risque climatique par entreprise. C'est l'approche retenue par plusieurs bases de données commerciales telles que Carbone 4, Four Twenty Seven, ou Trucost. La seconde se fonde sur les communications de l'entreprise. Cette approche est utilisée notamment par Sautner et al. (2020) et Li et al. (2020). Ces deux articles mènent une analyse textuelle des conférences téléphoniques sur les résultats, afin d'évaluer la fréquence des mots relatifs au climat. Cette fréquence est ensuite utilisée pour déterminer le score de risque climatique de chaque entreprise étudiée. Ce second type de méthode repose sur le postulat que les participants aux conférences téléphoniques sur les résultats (représentants de l'entreprise et analystes financiers) aborderont différents sujets en proportion de leur importance respective pour l'entreprise. Ces indicateurs présentent également l'inconvénient de ne faire référence à aucun scénario climatique ni à aucun horizon temporel précis. Cependant, ce type d'approche présente au moins deux avantages. Premièrement, la démarche autorise la définition de scores par couple entreprise-année, alors que les bases de données commerciales fournissent un score statique par entreprise. Deuxièmement, les chercheurs construisant leur propre méthode de mesure de risque climatique

⁸ Voir [ici](#).

peuvent, sans restriction, identifier les caractéristiques causant ou du moins étant corrélées avec le risque climatique, alors que cette démarche d'ingénierie inverse pourra être proscrite contractuellement avec certaines bases de données commerciales.

Les pratiques responsables

Les pratiques responsables des entreprises

Gillan et al. (2021) fournissent une revue de littérature synthétisant les caractéristiques que différents travaux de recherche ont établi comme étant significativement associées au degré de responsabilité sociale des entreprises. La responsabilité sociale des entreprises s'avère corrélée avec différents attributs liés à la structure de l'actionnariat, la composition des conseils d'administration ou des comités exécutifs et l'affiliation géographique ou sectorielle de l'entreprise. Notamment, l'orientation à long terme des actionnaires, conseils d'administration et des hauts dirigeants pousse les entreprises à accroître leur niveau de responsabilité sociale. Cette orientation à long terme est généralement mesurée à travers la présence d'investisseurs institutionnels, familiaux ou étatiques pour ce qui concerne les actionnaires ; via l'âge, la structure de compensation financière ou la durée du mandat dans les cas des administrateurs et des hauts dirigeants. Plusieurs caractéristiques, telles que les préférences prévalentes dans la zone d'implantation de l'entreprise ou dans son secteur d'activité, influencent aussi les pratiques de responsabilité sociale d'entreprise et rendent essentielle la prise en compte de l'affiliation géographique et sectorielle. La responsabilité sociale dépend enfin notablement des ressources dont l'entreprise dispose : la profitabilité est positivement associée à la responsabilité sociale, alors que les contraintes financières tendent à amoindrir la responsabilité sociale.

Les pratiques responsables des investisseurs

Du point de vue des investisseurs, différentes stratégies sont envisageables afin d'intégrer les préférences responsables. La première stratégie est l'exclusion, visant à ne pas investir dans certains secteurs controversés tels que l'armement, les jeux d'argent ou les énergies polluantes. La deuxième stratégie est l'intégration, visant à surpondérer en portefeuille les entreprises considérées comme vertueuses du fait de leur secteur d'activité ou de leurs notations extra-financières. Toutefois, ces stratégies sont coûteuses car, en contraignant l'univers d'investissement, elles amènent à diminuer le ratio rentabilité-risque (Pástor et al. 2021). La troisième et dernière stratégie est l'activisme, visant à pousser les dirigeants d'entreprise à intégrer les enjeux de responsabilité sociale. Là encore, cette stratégie peut être coûteuse, mais Bauer et al. (2021) montrent que certains investisseurs individuels sont en effet prêts à sacrifier une partie des rentabilités si cela permet d'obtenir de meilleurs résultats sur des objectifs de développement durable, en cohérence avec la vision de la philanthropie déléguée développée par Bénabou et Tirole (2010).

L'investissement socialement responsable peut être réalisé par tout type d'investisseur, de façon directe ou par l'intermédiaire de fonds d'investissement spécialisés. Toutefois, les investisseurs institutionnels et les investisseurs individuels semblent se distinguer dans ce type d'investissements. En effet, Dyck et al. (2019) notent que les investisseurs institutionnels, en raison de leur orientation à long terme, sont particulièrement présents sur ce type d'investissement. Riedl et Smeets (2017) montrent quant à eux que les investisseurs individuels réalisent des investissements socialement responsables en raison de leurs convictions bien plus qu'en fonction du gain financier espéré, et que l'orientation à long terme est là aussi un déterminant important de ce choix d'investissement.

Les pratiques responsables en France

Les dirigeants d'entreprise français s'avèrent particulièrement réceptifs à l'idée que les entreprises auraient une responsabilité à l'égard de la société dans son ensemble (Brounen et al. 2004). Cette perception semble se matérialiser par une meilleure performance extra-financière constatée plus globalement pour les entreprises issues de pays de droit civil (Liang and Renneboog 2017). En outre, la France est aussi caractérisée par une présence actionnariale de l'Etat plus forte que la plupart des autres pays développés. L'étude de Hsu et al. (2021) montre que les entreprises détenues majoritairement par l'Etat tendent à avoir une meilleure performance extra-financière.

Dans le cas français, la Responsabilité Sociale d'Entreprise (RSE) a fait l'objet de nombreuses réglementations, visant prioritairement à une meilleure transparence des entreprises. La loi relative aux nouvelles réglementations économiques (NRE) a, dès 2001, conduit à la prise en compte des aspects extra-financiers dans les rapports annuels des entreprises cotées en bourse. Les lois Grenelle 1 et 2, respectivement en 2009 et 2010, ont ensuite étendu ces exigences aux entreprises non cotées. Plus récemment, l'article 173 de la loi sur la transition énergétique du 17 août 2015, l'article 29 de la loi énergie-climat du 8 novembre 2019, ainsi que la directive européenne *Sustainable Finance Disclosure Regulation* (SFDR) ont accru les exigences de transparence sur les aspects extra-financiers pour les entreprises financières et les investisseurs institutionnels. En outre, la loi PACTE du 22 mai 2019 affirme que l'entreprise « *est gérée dans son intérêt social, en prenant en considération les enjeux sociaux et environnementaux de son activité.* »

Conséquences sur les entreprises

Les conséquences des pratiques responsables sur les entreprises

L'impact des pratiques de RSE sur la valeur de l'entreprise est une question débattue empiriquement. Krüger (2015) ou Masulis et Reza (2015) trouvent que les cours boursiers réagissent négativement lorsque les entreprises annoncent des initiatives RSE. Cette réaction négative traduirait des coûts d'agence : les dirigeants d'entreprise investiraient dans la RSE bien que cela soit contraire aux intérêts des actionnaires. D'autres résultats, par exemple Flammer (2015), indiquent une réaction boursière positive à l'annonce d'actions favorisant la RSE. Différents canaux sont avancés pour expliquer le lien positif entre RSE et valeur de l'entreprise. La RSE peut être un élément de motivation des employés (Flammer et Luo 2017), favoriser la confiance des différentes parties prenantes (Lins et al. 2017), fidéliser les clients ou améliorer la position concurrentielle de l'entreprise grâce à une meilleure différenciation des produits (Albuquerque et al. 2019).

Une autre question, différente mais néanmoins conceptuellement assez proche, consiste à analyser l'effet de la responsabilité sociale sur les coûts de financement des entreprises. Notamment, El Ghouli et al. (2011) et Chava (2014) montrent que les entreprises responsables tendent à bénéficier de coûts plus faibles de financement. Toutefois, Breuer et al. (2018) nuancent ce résultat, en précisant que cette relation est vérifiée seulement pour les pays où la protection juridique des actionnaires est élevée. Au contraire, les coûts de financement tendent à augmenter avec l'engagement RSE dans les pays n'accordant qu'une faible protection aux actionnaires. Cette dichotomie s'explique ainsi : l'existence d'une forte protection des actionnaires assure que l'engagement RSE est créateur de valeur, son absence favorise les coûts d'agence liés à l'engagement inefficace dans la RSE.

Il est intéressant de noter que la responsabilité sociale d'entreprise est une notion parfois distinguée de l'irresponsabilité sociale d'entreprise (voir par exemple Krüger 2015),

généralement afin de souligner les conséquences asymétriques pouvant exister entre surperformance et sous-performance sociale d'entreprise, par exemple dans le cas du risque de faillite (Kölbel et al. 2017) ou la réussite d'opérations de fusions-acquisitions (Hawn 2021).

Les conséquences du risque climatique sur les entreprises

Face à l'émergence des risques climatiques, deux stratégies sont généralement mises en avant. La première stratégie est celle de l'atténuation, visant à contenir le changement climatique et ainsi à limiter les risques en découlant. Concernant l'atténuation, la littérature académique en finance s'est largement concentrée sur l'impact de l'atténuation ou de l'absence d'atténuation sur les prix des actifs (Giglio et al. 2020). Bolton et Kacperczyk (2021) et Hsu et al. (2022) trouvent que les entreprises les plus polluantes ont des rentabilités boursières plus élevées. En effet, ces entreprises présentent un risque de transition car les stratégies d'atténuation du changement climatique définies politiquement pourraient les pénaliser dans le futur (amendes, limitation ou interdiction de certaines activités, etc.). Toutefois, ce résultat est contesté par Gørgen et al. (2020), dont l'analyse conclut à l'absence de prime de risque carbone. Ilhan et al. (2021). Les limites des stratégies d'atténuation rendent crédibles l'augmentation de l'intensité et de la fréquence des périls climatiques. Bernstein et al. (2019), Hong et al. (2019), Baldauf et al. (2020) ou encore Huynh et Xia (2021) font état d'un impact négatif des catastrophes climatiques passées ou projetées sur les prix boursiers et immobiliers. En outre, Choi et al. (2020) révèlent que des températures anormalement élevées conduisent les investisseurs individuels à réviser leurs croyances vis-à-vis du changement climatique, ce qui les pousse ensuite à désinvestir des entreprises polluantes et in fine engendre une sous-performance boursière des entreprises polluantes.

La seconde stratégie face aux risques climatiques correspond à l'adaptation. Pankratz et Schiller (2021) montrent que les clients sont davantage enclins à changer de fournisseurs lorsque ces derniers sont touchés par des chocs climatiques, alors que Li et al. (2020) trouvent que le risque climatique augmente l'investissement. Outre l'impact sur les opérations, les choix de gestion financière sont également affectés. En particulier, Huang et al. (2018) documentent que l'exposition au risque climatique est de nature à augmenter le niveau de trésorerie des entreprises, ainsi qu'à faire diminuer le montant des dividendes en numéraire versés aux actionnaires. Pérez-González et Yun (2013) indiquent quant à eux que certaines entreprises mettent en place des stratégies de couverture contre le risque climatique et que celles-ci ont des valorisations plus élevées. Les stratégies de couverture sont aussi envisageables du point de vue des investisseurs. Andersson et al. (2016) dans le cas du risque de transition, et Engle et al. (2020), prenant en compte le risque de transition et le risque climatique, proposent tous deux une approche de couverture dynamique du risque climatique à partir de l'actualité climatique.

La prise en compte des enjeux climatiques pourrait s'avérer cruciale pour la préservation de la stabilité financière (Carney 2015). A ce titre, les banques centrales et autorités de supervision financières tendent maintenant à intégrer les enjeux climatiques dans leur mandat, dans une démarche à la fois d'atténuation et d'adaptation. Le développement du Réseau des banques centrales et des superviseurs pour le verdissement du système financier (NGFS) en est l'une des matérialisations les plus notables. Composé de 8 membres à sa création en décembre 2017, le NGFS rassemble, en avril 2022, 114 banques centrales et superviseurs.⁹ Ce réseau vise à partager les bonnes pratiques et à contribuer au développement de la gestion des risques climatiques dans le secteur financier. Cet élargissement du rôle des banques centrales et régulateurs est toutefois contesté. D'un point de vue normatif, Hansen (2022) considère que les questions climatiques devraient avant tout être traitées par la politique budgétaire, sous peine

⁹ Voir [ici](#).

de menacer la crédibilité des institutions monétaires et leur indépendance vis-à-vis du pouvoir politique. Une littérature académique se développe sur la thématique du lien entre risque climatique et stabilité financière. Notamment, Dietz et al. (2016) et Roncoroni et al. (2021) proposent des estimations de la vulnérabilité future des entreprises financières ou des marchés financiers dans leur ensemble. Jung et al. (2021) choisissent une option différente et estiment la vulnérabilité d'institutions financières aux risques climatiques sur une période récente, arguant que cette approche historique pourra permettre de mieux appréhender les risques futurs. Ce champ de recherche pourra venir nourrir la réflexion des banques centrales et superviseurs, si la tendance à l'intégration des questions climatiques dans leur mandat se poursuit.

Structuration de cette thèse doctorale

Cette thèse de doctorat est composée de trois chapitres, chacun de ces chapitres correspondant à un article de recherche analysant une problématique de finance durable. Le premier chapitre examine l'impact du risque climatique sur le risque systémique au sein du secteur financier. Le deuxième chapitre analyse les conséquences, en matière d'attention des participants de marché et de transparence des entreprises, générés par les initiatives de développement durable. Le troisième chapitre évalue l'impact du risque climatique physique sur la structure de financement des entreprises.

Premier chapitre : Risque climatique systémique

Le premier chapitre, co-écrit avec Tristan Jourde, propose une nouvelle méthode de mesure du risque climatique et l'applique aux institutions financières européennes sur la période 2005-2022. Cet indicateur original permet d'identifier les institutions les plus exposées

aux risques physiques et de transition et de déterminer les caractéristiques individuelles corrélées avec une plus grande exposition climatique.

Nos résultats indiquent que, contrairement au risque physique, le risque de transition est porteur de contagion systémique. Ce résultat fait écho à certaines études récentes (Krueger et al. 2020, Stroebel et Wurgler 2021) montrant que, comparativement au risque physique, le risque de transition inquiète davantage les chercheurs et praticiens de la finance pour le futur proche. En analysant les caractéristiques corrélées avec nos indicateurs, nous trouvons que les institutions financières exposées au risque de transition diffèrent des institutions exposées aux risques physiques. Toutes choses égales par ailleurs, les institutions ayant une plus grande (faible) capitalisation, un plus grand (faible) bêta des capitaux propres, et de moindres (plus importantes) réserves de trésorerie s'avèrent plus exposées au risque de transition (physique). Toutefois, dans le cas du risque de transition comme dans celui du risque physique, les institutions financières tendent à être moins risquées climatiquement lorsqu'elles s'engagent à gérer leurs risques environnementaux, ainsi que lorsqu'elles fournissent à leurs dirigeants et administrateurs des incitations à la prise en considération du long terme. En outre, le risque de transition influence les politiques de divulgation extra-financières. Les institutions les plus exposées au risque de transition ont une plus forte propension à divulguer leurs émissions de gaz à effet de serre.

Deuxième chapitre : Les effets informationnels des initiatives de soutenabilité

Le deuxième chapitre analyse les effets informationnels engendrés par les initiatives de soutenabilité les plus visibles. En effet, les entreprises s'engagent de plus en plus fréquemment dans des opérations publiques et fortement visibles de responsabilité sociale (Hawn et Ioannou 2016). Rationnellement, les entreprises adoptant ce type d'initiatives devraient y trouver un

intérêt. D'un point de vue financier, la création de valeur pour les actionnaires est probablement le premier effet que l'on pourrait suspecter l'entreprise de rechercher à travers ces initiatives RSE. Toutefois, l'étude académique du lien entre engagement RSE et valeur de l'entreprise a donné des résultats contrastés (voir par exemple Flammer 2015 et Krüger 2015). Cet article se concentre ainsi sur les gains pouvant exister en matière de diffusion de l'information. Pour mener cette étude, j'utilise deux cas d'initiatives très visibles de soutenabilité, ayant l'avantage d'avoir des dates d'annonce clairement identifiables : les émissions d'obligations vertes et la signature de la déclaration de la Business Roundtable (par laquelle les entreprises signataires affirment leur engagement dans la responsabilité sociale). Flammer (2015) montre qu'en moyenne les obligations vertes ont un impact environnemental tangible, alors que Raghunandan et Rajgopal (2021b) que la déclaration de la Business Roundtable n'a eu aucun effet tangible. En comparant ces deux initiatives, je peux ainsi évaluer le degré de similarité entre les gains obtenus par les entreprises à la suite de simples déclarations d'intentions RSE et les gains obtenus par les entreprises ayant des initiatives RSE plus tangibles.

En ayant recours à des données mondiales d'utilisation du moteur de recherche Google, je suis l'évolution hebdomadaire de l'intérêt porté par le grand public pour les entreprises s'engageant dans des initiatives de soutenabilité. Je montre que ces entreprises arrivent à attirer l'attention des investisseurs individuels. En utilisant ensuite des données annuelles provenant de l'organisation non-gouvernementale CDP, je montre que les participants de marché professionnels ne réagissent pas aux initiatives purement déclaratives. En outre, les agences de notation environnementale tendent à réagir aux initiatives de soutenabilité très visibles, à travers des effets de transparence et d'attention. Les entreprises peuvent ainsi améliorer certains de leurs scores environnementaux via de simples déclarations d'intention ne s'ensuivant pas de résultats tangibles, probablement en raison de la difficulté d'interprétation d'informations molles et des ressources limitées dont disposent les agences de notation extra-financières.

Troisième chapitre : Risque climatique et structure du capital

Le premier chapitre, co-écrit avec Edith Ginglinger, part du constat également établi par Engle et al. (2020) : la rareté des données mesurant l'exposition des entreprises au risque climatique est un frein au développement de la recherche en finance climatique. Face à ce problème, nous mettons à profit trois bases de données devenues récemment disponibles. Ceci nous permet de mesurer l'exposition aux risques climatiques physiques futurs des plus grandes entreprises du monde.

En utilisant un échantillon international de très grandes entreprises non-financières sur la période 2010-2019, nous appliquons ces données de mesure au cas de la structure financière des entreprises. Nous montrons que le risque climatique physique est devenu un déterminant important de la structure financière des firmes sur les années récentes. Nos résultats indiquent que les entreprises les plus exposées tendent à se financer plus par capitaux propres et moins par dette après 2015. Ceci provient à la fois d'un effet de demande, via lequel les entreprises les plus exposées choisissent de réduire leur part de dette, et d'un effet d'augmentation des taux d'intérêt. En décomposant par type de péril climatique physique, nous montrons que l'effet du risque physique sur la structure de financement des entreprises est principalement dû aux périls extrêmes. En outre, nous constatons que les notations de crédit ne reflètent pas l'exposition au risque climatique physique, du moins sur l'échantillon étudié, ce qui confirme l'intérêt d'utiliser des données spécialisées dans la mesure de l'exposition au risque climatique physique. Enfin, nos résultats révèlent que les entreprises démontrant les meilleures facultés d'anticipation, tel que mesuré par différents scores de performance environnementale, n'ajustent pas leur structure de capital face au risque climatique physique. Ceci témoigne d'une substitution entre les stratégies d'adaptation visant à réduire l'impact du risque climatique sur le risque opérationnel et la baisse du risque financier via un ajustement à la baisse du niveau d'endettement.

Bibliographie

- Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10), 4451-4469.
- Amel-Zadeh, A., Lustermsans, R., & Pieterse-Bloem, M. (2021). Sustainability and private wealth investment flows. Available at SSRN 3576687.
- Andersson, M., Bolton, P., & Samama, F. (2016). Hedging climate risk. *Financial Analysts Journal*, 72(3), 13-32.
- Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3), 1256-1295.
- Bauer, R., Ruof, T., & Smeets, P. (2021). Get real! Individuals prefer more sustainable investments. *The Review of Financial Studies*, 34(8), 3976-4043.
- Bénabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica*, 77(305), 1-19.
- Berg, F., Kölbel, J. F., & Rigobon, R. Aggregate Confusion: The Divergence of ESG Rating. *Review of Finance*.
- Bernstein, A., Gustafson, M. T., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics*, 134(2), 253-272.
- Bofinger, Y., Heyden, K. J., & Rock, B. (2022). Corporate social responsibility and market efficiency: Evidence from ESG and misvaluation measures. *Journal of Banking & Finance*, 134, 106322.
- Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk?. *Journal of financial economics*, 142(2), 517-549.
- Breuer, W., Müller, T., Rosenbach, D., & Salzmann, A. (2018). Corporate social responsibility, investor protection, and cost of equity: A cross-country comparison. *Journal of Banking & Finance*, 96, 34-55.
- Brounen, D., De Jong, A., & Koedijk, K. (2004). Corporate finance in Europe: Confronting theory with practice. *Financial management*, 71-101.
- Brundtland, G. H. (1987). Our common future—Call for action. *Environmental Conservation*, 14(4), 291-294.
- Carney, M. (2015). Breaking the tragedy of the horizon—climate change and financial stability. *Speech given at Lloyd's of London*, 29, 220-230.
- CFA Institute. (2017). Environmental, social and governance (ESG) survey.
- Chang, Y., He, W., & Mi, L. (2021). Climate Risk and Corporate Payout Policies around the World. Available at SSRN 3950421.
- Chava, S. (2014). Environmental externalities and cost of capital. *Management science*, 60(9), 2223-2247.
- Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3), 1112-1145.

- Christensen, D. M., Serafeim, G., & Sikochi, A. (2022). Why is corporate virtue in the eye of the beholder? The case of ESG ratings. *The Accounting Review*, 97(1), 147-175.
- Déjean, F., & Gond, J. P. (2004). La responsabilité sociétale des entreprises: enjeux stratégiques et méthodologies de recherche. *Finance Contrôle Stratégie*, 7(1), 5-31.
- Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3), 740-98.
- Diaz-Rainey, I., Robertson, B., Wilson, C., 2017. Stranded research? Leading finance journals are silent on climate change. *Climatic Change* 143, 243–260.
- Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). ‘Climate value at risk’ of global financial assets. *Nature Climate Change*, 6(7), 676-679.
- Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of financial economics*, 131(3), 693-714.
- El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital?. *Journal of banking & finance*, 35(9), 2388-2406.
- Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.
- Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science*, 61(11), 2549-2568.
- Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499-516.
- Flammer, C., & Luo, J. (2017). Corporate social responsibility as an employee governance tool: Evidence from a quasi-experiment. *Strategic Management Journal*, 38(2), 163-183.
- Freeman, R. E. (2010). *Strategic management: A stakeholder approach*. Cambridge university press.
- Friedman, M. (1970). A Friedman doctrine: The social responsibility of business is to increase its profits. *The New York Times Magazine*, 13(1970), 32-33.
- Giglio, S., Kelly, B. T., & Stroebel, J. (2020). *Climate finance* (No. w28226). National Bureau of Economic Research.
- Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of ESG and CSR research in corporate finance. *Journal of Corporate Finance*, 66, 101889.
- Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020). Carbon risk. *Available at SSRN 2930897*.
- Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let’s get physical: Comparing metrics of physical climate risk. *Finance Research Letters*, 46, 102406.
- Hansen, L. P. (2022). Central banking challenges posed by uncertain climate change and natural disasters. *Journal of Monetary Economics*, 125, 1-15.
- Hawn, O. (2021). How media coverage of corporate social responsibility and irresponsibility influences cross-border acquisitions. *Strategic Management Journal*, 42(1), 58-83.

- Hawn, O., & Ioannou, I. (2016). Mind the gap: The interplay between external and internal actions in the case of corporate social responsibility. *Strategic Management Journal*, 37(13), 2569-2588.
- Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, 208(1), 265-281.
- Hsu, P. H., Li, K., & Tsou, C. Y. (2022). The pollution premium. *Journal of Finance*, Forthcoming.
- Hsu, P. H., Liang, H., & Matos, P. (2021). Leviathan Inc. and corporate environmental engagement. *Management Science*.
- Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5), 633-656.
- Huynh, T. D., & Xia, Y. (2021). Panic selling when disaster strikes: Evidence in the bond and stock markets. *Management Science*.
- Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3), 1540-1571.
- Jung, H., Engle, R. F., & Berner, R. (2021). Climate stress testing. *FRB of New York Staff Report*, (977).
- Kölbel, J. F., Busch, T., & Jancso, L. M. (2017). How media coverage of corporate social irresponsibility increases financial risk. *Strategic Management Journal*, 38(11), 2266-2284.
- Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067-1111.
- Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of financial economics*, 115(2), 304-329.
- Li, Q., H. Shan, Y. Tang, and V. Yao (2020). Corporate climate risk: Measurements and responses. Working Paper. Available at SSRN: <https://ssrn.com/abstract=3508497>.
- Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, 72(2), 853-910.
- Liang, H., & Renneboog, L. (2020). Corporate social responsibility and sustainable finance: A review of the literature. *European Corporate Governance Institute–Finance Working Paper*, (701).
- Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *the Journal of Finance*, 72(4), 1785-1824.
- Masulis, R. W., & Reza, S. W. (2015). Agency problems of corporate philanthropy. *The Review of Financial Studies*, 28(2), 592-636.
- McCahery, J. A., Sautner, Z., & Starks, L. T. (2016). Behind the scenes: The corporate governance preferences of institutional investors. *The Journal of Finance*, 71(6), 2905-2932.
- Meadows, D. H., Meadows, D. H., Randers, J., & Behrens III, W. W. (1972). The limits to growth: a report to the club of Rome (1972). *Google Scholar*, 91.

- Pankratz, N., & Schiller, C. (2021, June). Climate change and adaptation in global supply-chain networks. In *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC, European Corporate Governance Institute–Finance Working Paper* (No. 775).
- Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2), 550-571.
- Pérez-González, F., & Yun, H. (2013). Risk management and firm value: Evidence from weather derivatives. *The Journal of Finance*, 68(5), 2143-2176.
- Raghunandan, A., & Rajgopal, S. (2021a). Do ESG Funds Make Stakeholder-Friendly Investments?. Available at SSRN 3826357.
- Raghunandan, A., & Rajgopal, S. (2021b). Do socially responsible firms walk the talk?. Available at SSRN 3609056.
- Riedl, A., & Smeets, P. (2017). Why do investors hold socially responsible mutual funds?. *The Journal of Finance*, 72(6), 2505-2550.
- Roncoroni, A., Battiston, S., Escobar-Farfán, L. O., & Martínez-Jaramillo, S. (2021). Climate risk and financial stability in the network of banks and investment funds. *Journal of Financial Stability*, 54, 100870.
- Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2020). Firm-level climate change exposure. *European Corporate Governance Institute–Finance Working Paper*, (686).
- Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance?. *Journal of Financial Economics*, 142(2), 487-498.

1. Systemic Climate Risk

Joint work with Tristan Jourde

Abstract

This paper proposes a new framework to study systemic climate risks in the financial sector. Using market-based measures of physical and transition climate risks, we identify which European financial institutions are the most vulnerable to climate risks and test whether climate risks can generate tail dependence among financial institutions. We show that, unlike physical risk, transition risk significantly impacts systemic risk. The exposure to transition risks appears lower for institutions with cleaner investment and lending portfolios. Besides, the financial institutions most exposed to transition risk tend to engage more in carbon disclosure.

1.1. Introduction

In 2015, the governor of the Bank of England stated that climate change can profoundly affect asset prices and financial stability (Carney, 2015). Since then, the potential systemic impact of climate risks has become a central concern in the financial community (Stroebel and Wurgler, 2021). Climate risks are generally decomposed into physical risks, stemming from the effects of climate change and climate-related hazards (e.g., heat waves, extreme precipitation, wildfires, etc.), and transition risks, arising from changes in regulation and climate-related technological disruption (Krueger et al., 2020). Physical and transition risks can adversely affect financial institutions through, for example, losses in the value of financial portfolios, increases in claims paid by insurers, or decreases in the creditworthiness of borrowers. These shocks can pose a threat to financial stability if they occur simultaneously or if an extreme individual shock is transmitted to other institutions through a strong network of financial interconnections. We refer to these threats to the financial system emanating from climate risks as “systemic climate risk.”

This article proposes a new framework based on environmental and stock market data to empirically assess whether climate risks affect systemic risk within the financial sector. From a theoretical perspective, the economic rationale for using a market-based approach to assess the effect of climate risks on systemic risk is that climate risks should lead to a repricing of securities held by financial institutions. Our framework provides a tool to identify *which* financial institutions are the most vulnerable to climate risks and explore *how* financial institutions and policymakers might undertake actions to reduce systemic climate risk. While existing papers focus on individual vulnerabilities (e.g., Alessi et al., 2021; Huang et al., 2022; Jung et al., 2021; Ojea-Ferreiro et al., 2022), our framework also test whether climate risks can exacerbate tail dependence among financial institutions, which is a key element to assess the level of systemic risk in the financial sector (e.g., Billio et al., 2012). Therefore, our approach

has the advantage of taking into account potential second-round effects of climate risks within the financial sector, these effects being generally overlooked but representing an important source of systemic climate risk (Duarte and Eisenbach, 2021).¹⁰ Indeed, common holdings of different market participants, direct interdependencies among financial institutions, and potential fire-sale dynamics could amplify the impact of climate risks on financial stability.

We proceed in several steps. *First*, for the purpose of our study, we design a new systemic risk measure, related to the methods suggested by Adams et al. (2014), Adrian and Brunnermeier (2016), and Kelly and Jiang (2014). Specifically, using a GARCH model, we estimate time-varying Value-at-Risk (VaR) measures from the stock returns of financial institutions. Equity returns are intended to be informative about the risks of financial institutions and may reflect information more quickly than accounting variables. The use of tail risk measures meets our objective of analyzing whether climate risks threaten financial stability. Then, based on a principal component analysis, we extract the first principal component from the correlation matrix among the time variations in individual VaR measures. The first principal component provides a dynamic indicator of systemic risk that captures common dynamics in financial institution tails, i.e., tail risk dependence within the financial sector. The loadings of each institution on the first principal component represent their respective contribution to global downside risk.

Second, we construct climate risk factors. Using a large sample of dead and alive stocks (excluding financial sector companies), we build two long-short factor mimicking portfolios, respectively based on carbon emission intensity and physical risk scores (see Section 2). Since we are interested in extreme climate risks and for consistency with the first step, we estimate

¹⁰ See also [here](#).

the VaR of each climate risk factor based on the aforementioned approach. To the best of our knowledge, this article is the first to focus on extreme climate risks in this context.

Third, we propose a two-pass procedure to assess whether climate risks can exacerbate tail risk dependence among financial institutions. We build on the protocol suggested by Pukthuangthong et al. (2019) to evaluate whether factors are related to stock return comovements and extend their approach to tail risks. In addition, we propose a robustness test that exploits cross-sectional information on individual climate risk exposures and individual loadings on systemic risk. More precisely, we start by running a time-series regression of the variations in systemic risk on climate risk factors and a list of control variables representing other potential determinants of systemic risk. This step allows us to verify whether a rise in climate risks is associated with an overall increase in downside risk within the financial sector. We then perform a cross-sectional regression of financial institutions' contributions to systemic risk on financial institutions' exposures to climate risks. We control for other risk exposures and include fixed effects for financial industries. This step examines whether the institutions most exposed to climate risks contribute more to global downside risk. Financial institutions' exposures to climate risks are derived from the sensitivity of the time variations in the VaR of each financial institution to climate risk factors. This individual measure is an extension of Adrian and Brunnermeier's (2016) work, akin to a "Climate" Exposure CoVaR measure, that incorporates extreme climate risks as potential stress factors for financial institutions.

Fourth, we investigate the characteristics of the financial institutions that are correlated with individual climate risk exposures. Understanding these characteristics is essential for regulators and financial practitioners to undertake actions to mitigate systemic climate risks. Specifically, we examine the effect of various financial characteristics, as well as environmental and governance characteristics, on the level of climate risk exposure. We then analyze how financial institutions adapt to these climate risks, with a focus on carbon disclosure policies.

Overall, our framework provides a tool to evaluate the current level of vulnerability of financial institutions to climate risks and dynamically monitor whether the effect of climate risks on financial stability is becoming a growing threat for investors. Our approach can also help financial institutions and supervisors identify levers to mitigate systemic climate risks. Our findings can also be exploited as a starting point in stress-testing exercises (e.g., Dietz et al., 2016; Battiston et al., 2017; Roncoroni et al., 2021) and should be considered complementary to research on the development of climate scenarios and assumptions about the future impact of climate risks on asset prices, which is subject to considerable uncertainty (Barnett et al., 2020).

Our empirical analysis is based on a sample of European stocks, spanning from 2005 to 2022 and extracted from Refinitiv Datastream. For financial institutions, we focus on a sample of 332 stocks with a market capitalization above €100 million in 2022. Our results indicate that transition risks significantly affect the VaR of financial institutions and, more importantly, can exacerbate tail dependence within the financial sector. By contrast, we do not find evidence of such an effect in the case of physical climate risks. This result is in line with recent surveys (Krueger et al., 2020; Stroebel and Wurgler, 2021) indicating that financial researchers and practitioners consider that the materialization of regulatory risk is more immediate than that of physical risks.

Looking at the characteristics of institutions correlated with climate risks, we find that climate risk exposure is lower for financial institutions that engage in environmentally responsible initiatives and incentivize board members to consider the longer term. Using Scope 3 carbon data emissions from Carbone4, we also show that institutions with cleaner investment and lending portfolios are less exposed to transition risks. Lastly, our analysis indicates that transition risk exposure is a significant determinant of carbon disclosure decisions among financial institutions.

Our study is linked to the literature on how climate risks impact financial markets. Many papers find premiums associated to climate risks in equity markets (e.g., Ardia et al., 2020; Bolton and Kacperczyk, 2021; Choi et al., 2020; Görden et al., 2020), real estates (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020) or bond markets (e.g., Flammer, 2021; Zerbib, 2019). Despite these premiums, other papers point out that climate risks remain underestimated by market participants (e.g., Hong et al., 2019; Alok et al., 2020; Krutli et al., 2020).¹¹ Andersson et al. (2016) and Engle et al. (2020) suggest approaches to dynamically hedge climate risks using climate news. Besides, several papers examine how financial institutions adjust their operations as a consequence of climate events (e.g., Manconi et al., 2016; Schüwer et al., 2019; Ge and Weisbach, 2021; Massa and Zhang, 2021). We contribute to this literature by exploring whether climate risks can impact the tail risk of financial institutions, highlighting how financial institutions adapt to these risks, and identifying the levers financial institutions might have to reduce their exposure to climate risks.

Another strand of literature focuses on the effect of various Environmental, Social, and Governance (ESG) and climatic dimensions on extreme returns. Lins et al. (2017) show that firms with good ESG scores are less exposed to extreme risks, while Ilhan et al. (2021b) find that brown stocks are more exposed to downside tail risks. Several articles examine how certain individual ESG characteristics may help reduce systemic risk measures, such as $\Delta CoVaR$ and *SRISK* (Anginer et al., 2018; Scholtens and van't Klooster, 2019; Cerqueti et al., 2021; Kleymenova and Tuna, 2021; Aevoae et al., 2022). Jung et al. (2021) develop a climate systematic risk measure (*CRISK*), derived from the *SRISK* indicator (Brownlees and Engle, 2017), which focuses on banks' exposure to fossil fuels. Related methodologies to assess

¹¹ All these articles should be conceptually distinguished from studies assessing how considerations on Corporate Social Responsibility (CSR) affect asset returns, for example Lins et al. (2017), Pástor et al. (2021), and Pedersen et al. (2021). CSR is defined by Liang and Renneboog (2020) as the internalization by firms of the externalities they create.

individual climate risk exposures have also been proposed by Alessi et al. (2021) and Ojea-Ferreiro et al. (2022). Our contributions to this literature are threefold. First, our study includes all types of financial institutions and focuses on both transition and physical extreme climate risks. Second, we propose a novel individual climate risk measure for financial institutions derived from Adrian and Brunnermeier's (2016) work. Third, our framework places a central focus on tail dependence among financial institutions, a key aspect of systemic risk, allowing us to capture the potential second-round effects of climate risks. Overall, compared to previous studies, we provide a more comprehensive study on the quantification and financial stability implications of climate risks for financial institutions.

We also contribute to the literature on the determinants and consequences of nonfinancial reporting. On the one hand, many papers have investigated the determinants of voluntary nonfinancial disclosure. Firm size, regulations regarding disclosure, profitability, leverage, and industry affiliation are significant predictors of the choice of disclosing nonfinancial information (e.g., Cormier and Magnan, 1999; Brammer and Pavelin, 2006; Dhaliwal et al., 2011). Ilhan et al. (2021a) further show that institutional ownership increases the likelihood of voluntarily disclosing non-financial information, while Cormier and Magnan (1999) find that concentrated ownership decreases it. The characteristics of CEOs, shareholder resolutions, and the threat of new regulations also influence non-financial disclosure (e.g., Haniffa and Cooke, 2005; Reid and Toffel, 2009; Lewis et al., 2014). On the other hand, several papers have studied the impact of voluntary or mandatory non-financial disclosure on various outcomes such as firm value (e.g., Matsumura et al., 2014; Plumlee et al., 2015; Griffin et al., 2017; Grewal et al. 2019), cost of equity (e.g., Dhaliwal et al., 2011), analyst forecast accuracy (e.g., Dhaliwal et al., 2012), or subsequent non-financial performance (e.g., Christensen et al., 2017; Kim et al., 2022). We contribute to this literature by showing that exposure to climate transition risks significantly increases the propensity of financial institutions to disclose their carbon emissions.

The rest of the paper is as follows. We present the data and methodology in Section 2, the empirical results in Section 3, and we conclude in Section 4.

1.2. Data and methodology

1.2.1. Systemic risk measure

We define a new measure of systemic risk among financial institutions based on common variations in the VaR of financial institutions. It relates to Adrian et al. (2016) CoVaR measure insofar as it examines how one institution's tail risk evolves conditional on the others. Our setup also shares similarities with Adams et al. (2014), as we first estimate the VaR (see Section 2.2) of each financial institution and then investigate their comovements. We extract common variations in VaR based on a principal component analysis. We argue that this approach is better suited to relatively large samples than the vector autoregressive models proposed by Adams et al. (2014). Cooley and Thibaud (2019) also suggest an approach to extract principal components from a tail dependence matrix based on multivariate extreme value analysis. We believe that one advantage of working with time-varying VaR is that the estimation of tail dependence can be performed on the entire sample instead of a small number of extreme observations. Finally, our method is linked to that of Kelly and Jiang (2014) who directly estimate common dynamics in the tail risk of firms using the cross-section of returns. However, unlike their approach, we can use our setup to derive time-varying individual measures of tail risk.

The principal component analysis is based on a singular value decomposition of the matrix:

$$\Xi = [diag(\Sigma)]^{-1/2} \Sigma [diag(\Sigma)]^{-1/2} \quad (1)$$

with $\Sigma = N^{-1}T^{-1}\overline{\Delta VaR' \Delta VaR}$, N being the number of financial institutions, T the length of the period, and $\overline{\Delta VaR}$ a matrix of de-measured VaR measures, in first difference to ensure

stationarity. We can define the estimator of systemic risk and its loadings from Equations (2) and (3):

$$\widehat{\Omega} = T^{1/2} \xi' \quad (2)$$

$$\widehat{X} = T^{-1} \overline{\Delta VaR} \widehat{\Omega}' \quad (3)$$

where $\xi: [\xi_1, \dots, \xi_j]$ are the normalized eigenvectors corresponding to the largest eigenvalues of Ξ . Our time series estimator of systemic risk is given by $\widehat{\Omega}_1$, the first principal component extracted from Ξ . The loadings of each financial institution to $\widehat{\Omega}_1$ are given by \widehat{X}_1 , a $N \times 1$ vector extracted from the \widehat{X} matrix.

Our two-pass regression procedure to test whether climate risks can generate tail dependence among financial institutions consists of the following steps. We start by running a time-series OLS regression of $\widehat{\Omega}_1$ onto a set of climate risk factors, BMG and VMS , and control risk factors f :

$$\widehat{\Omega}_{1,t} = \alpha + \beta_{BMG} BMG_t + \beta_{VMS} VMS_t + \sum_{i=3}^I \beta_{f_i} f_{i,t} + \varepsilon_t, \quad i, i, d. \quad \varepsilon \sim \mathcal{N}(0,1) \quad (4)$$

where BMG_t and VMS_t are the transition and physical climate risk factors, described in Section 2.3, and f is a $T \times (I-3)$ matrix containing a list of control variables. We use a modified version of Fama and French (2015) factors and other variables capturing the degree of risk aversion, interbank market liquidity, default premium, and the state of the economic activity. This regression estimates the effect of an increase in climate risks on simultaneous changes in the downside risk of financial institutions.

By successively replacing $\widehat{\Omega}_1$ in Equation (4) by $\widehat{\Delta VaR}_j$, the VaR of each financial institution j , where $j \in [1: N]$, we obtain $\widehat{\beta}$, a $N \times I$ matrix of the sensitivity of the VaR of each financial institution to our climate extreme risk factors as well as other control variables mentioned

above. This measure is akin to a “Climate” Exposure CoVaR indicator, as it analyzes how climate risks contribute to each financial institution’s stress.

We then perform a cross-sectional OLS regression of \hat{X}_1 , the loadings of each financial institutions j to $\hat{\Omega}_1$, onto $\hat{\beta}$:

$$\hat{X}_{1,j} = \alpha + \gamma_{BMG}\hat{\beta}_{BMG,j} + \gamma_{VMS}\hat{\beta}_{VMS,j} + \sum_{i=3}^I \gamma_{f_i}\hat{\beta}_{f_i,j} + \varepsilon_j, \quad i, j, d. \quad \varepsilon \sim \mathcal{N}(0,1) \quad (5)$$

This second regression tests whether the financial institutions most exposed to climate risks have stronger tail dependence with the rest of the financial sector.

We consider that climate risks exacerbate tail dependence among financial institutions if the respective coefficients $\hat{\beta}_{BMG,j}$, $\hat{\beta}_{VMS,j}$, $\hat{\gamma}_{BMG}$, $\hat{\gamma}_{VMS}$ are both positive and significant. We estimate standard errors based on Newey and West (1987) for time-series regressions and White (1980) for cross-sectional regressions.

1.2.2. VaR estimation

Our approach requires estimating the VaR of financial institutions, which in turn are used as inputs in a correlation matrix to assess tail risk dependences. Existing articles estimate asset comovements based on returns, volatility, and VaR (e.g, Diebold and Yilmaz, 2009; Adams et al., 2014). We argue that measuring comovements among tail risk indicators is better suited to capture systemic risk than relying on return comovements. Besides, Table 1 shows that the largest interconnections between financial institutions are different whether we use the comovements among returns or VaR to identify them.

The VaR is the estimated loss of a financial institution that, within a given period, will not be exceeded with a certain probability θ . Thus, if θ is equal to 95%, the 1-month θ -VaR shows the negative return that will not be exceeded within this month with a 95% probability:

$$\text{prob}[return_t < -VaR_t | \Omega_t] = \theta \quad (6)$$

VaR can be estimated dynamically based on Equation (7):

$$\overline{VaR}_{i,t} = \hat{\mu}_{i,t} + \hat{\sigma}_{i,t|t-1} F(1 - \theta)^{-1} \quad (7)$$

where $\hat{\sigma}_{i,t|t-1}$ is the conditional standard deviation given the information at $t - 1$, F^{-1} is the inverse probability density function of a skewed normal distribution and $\hat{\mu}_{i,t}$ is the mean returns of institution i at time t . For simplicity, $\hat{\mu}_{i,t}$ is estimated using the overall sample mean instead of a rolling window, as its effect on the overall variation in VaR is very limited. Following Kuester, Mittnik, and Paoletta (2006), we model $\hat{\sigma}_{i,t}$ by extracting the conditional standard deviation from a GARCH model. This procedure captures the time-varying volatility of returns and significantly improves the responsiveness of VaR to shifts in the return process. For most of our return series, we empirically observe that negative returns at time $t - 1$ impact the variance at time t more strongly than positive returns (leverage effect). To reflect this effect, we apply the threshold GARCH model of Glosten et al. (1993) presented in Equation (8). This is the simplest asymmetric GARCH specification, which seems appropriate given our relatively small sample. We confirm that the parameter γ in Equation (8) is positive for 257 financial institutions and positive and significant at the 10% level for 111 series out of 332.

$$\hat{\sigma}_{i,t}^2 = \omega + (\alpha + \gamma \mathbb{I}_{t-1}) \varepsilon_{t-1}^2 + \beta \hat{\sigma}_{i,t-1}^2 \quad (8)$$

$$\mathbb{I}_{t-1} = \begin{cases} 0, & r_{t-1} < \mu \\ 1, & r_{t-1} \geq \mu \end{cases}$$

All the parameters (μ , ω , α , γ , and β) are estimated simultaneously, by maximizing the log-likelihood.

Table 2 tests the ability of our model to fit the data and capture tail risk. In Panel A, we present the Akaike, Bayes, Shibata, and Hannan Quinn information criteria for different model specification and error distribution assumptions. We show that the GJR-GARCH model of Glosten et al. (1993) fits the data best compared to alternatives. This finding is consistent with the work of Brownlees et al. (2011), which shows that the GJR-GARCH model works best to forecast stock volatility. Since we are primarily interested in tail risk measurement, we now turn our attention to the result of the VaR exceedance tests presented in Panel B. The unconditional coverage test of Kupiec (1995) assesses whether the observed frequency of VaR exceedances is consistent with expected exceedances. The conditional coverage test of Christoffersen et al. (2001) complements the previous test by considering the potential dependence between the occurrences of exceedances. Finally, the test of Christoffersen and Pelletier (2004) focuses on the duration between VaR exceedances. We show that the GJR-GARCH model seems appropriate to reflect the level of tail risk of financial institutions. Potential alternatives would be the exponential GARCH model of Nelson (1991) or the component GARCH of Engle and Lee (1999). Interestingly, although the skew-normal distribution is not the best fit for the distribution of the data as a whole (panel A), it is more effective than most other distributions in fitting tail behavior (Panel B). In particular, the skew-normal distribution is associated with the lowest standard deviation around the expected number of exceedances for our sample of return series. It also leads to the lowest number of rejections in the Christoffersen et al. (2001) test. Our result is in line with Brownlees et al. (2011) who mention that despite the prevalence of fat-tailed financial returns, they find no advantage in using heavier-tailed error distribution. Overall, our results are robust to other GARCH specifications and assumptions on the error distribution.

1.2.3. Factor construction

The climate finance literature has suggested several approaches to building climate risk indicators. Ardia et al. (2021) and Engle et al. (2020) apply natural language processing to assess the degree of media attention to climate change from newspapers. Choi et al. (2020) rely on Google trends. Brière and Ramelli (2021) construct a climate stress indicator using investor flows toward sustainable ETFs. Finally, some articles explore investors' attention to climate risks by building long-short portfolios based on market and environmental variables (e.g., Gørgen et al., 2020; Hsu, et al., 2022). We follow this last approach and construct two climate risk factors using a large sample of dead and alive European stocks (excluding financial sector companies). The factors are based on long-short mimicking portfolios following the standard approach in the asset pricing literature (e.g., Fama and French, 1992, 2015). Since we are interested in extreme climate risks and for consistency with the first step, we estimate the VaR of each climate risk factor based on a GARCH model, as described in Section 2.1.

In the case of transition risks, the long and short positions are determined by their carbon emission intensity. We use both reported and estimated emissions, Scopes 1 & 2, divided by net sales, from Refinitiv Datastream. To mitigate correlation with existing factors (see Table 3), the transition risk factor is constructed using six value-weighted portfolios formed on market capitalization (B for “Big”, S for “Small”, see Equation 9), book-to-market (H for “High”, L for “Low”), and the two lowest and highest deciles of carbon emissions (G for “Green”, B for “Brown”). We disentangle “Big” and “Small” firms, as well as “High” and “Low” firms based on the median value of the market capitalization and the book-to-market in our sample.

$$BMG_t = \frac{LB_t + HB_t + SB_t + BB_t}{4} - \frac{LG_t + HG_t + SG_t + BG_t}{4} \quad (9)$$

where BMG , which stands for “Brown-minus-Green”, represents the returns of the transition risk factor, LB , HB , SB , BB are the returns of the brown portfolios, LG , HG , SG , and BG are

the returns of the green portfolios, and t represents monthly observations. Even if carbon emission data are updated at a yearly frequency, the portfolios are rebalanced monthly according to the previous month's value of the respective characteristics. We only include in the portfolios the stocks for which all data are available. In 2005, data were available for about 400 European non-financial stocks, compared to 2,070 in 2022. Our study starts in 2005 because there is not enough data available on CO2 emissions before this date.

In the case of physical risks, the long and short positions are defined based on the physical scores provided by Trucost. In contrast with *BMG*, the correlation between the physical climate factor and the “value” factor (*HML*) is naturally low (see Table 3), so we only filter portfolios based on market capitalization. Therefore, the physical climate factor is built using four value-weighted portfolios formed on size (B for “Big”, S for “Small”) and the two lowest and highest deciles of Trucost physical scores (V for “Vulnerable”, S for “Safe”):

$$VMS_t = \frac{SV_t + BV_t}{2} - \frac{SS_t + BS_t}{2} \quad (10)$$

where *VMS* stands for “Vulnerable-minus-Safe”, the returns of the physical risk factor, *SV* and *BV* are the returns of the vulnerable portfolios, *SS* and *BS* are the returns of the safe portfolios, and t represents monthly observations. As for *BMG*, the allocation of *VMS* is rebalanced on a monthly basis, but the physical scores are fixed over time. As a result, all portfolios are constructed from a sample of 2,237 European non-financial stocks.

1.2.4. Data sources

From Refinitiv Datastream, we obtain an initial list of over 21,805 active and dead European stocks (including members of the European Union, Norway, Switzerland, and the United Kingdom) for which we download a large set of financial variables in euros, such as prices

(including dividends), market capitalizations, book values of equity, cash holdings, total assets, incomes, net sales, and fixed assets.¹² We compute log returns from the available price series (17,454) and apply several filters recommended by Landis and Skouras (2021) to deal with implausible returns, illiquidity, and unusually high or low volatility. First, we eliminate from our sample the series for which more than 95% of the returns have the same sign (positive or negative). Second, we discard the series for which more than 25% of the returns are equal to zero, as this is a sign of illiquidity. Finally, we eliminate stocks for which the monthly standard deviation of returns is greater than 40% or less than 0.01%.

Based on this dataset, we select financial institutions according to the Refinitiv Datastream sector denomination (Banks, Life Insurance, Nonlife Insurance, Financial Services, Real Estate Investment and Services, and Real Estate Investment Trusts). Similar to other articles (see e.g., Acharya et al., 2017; Engle et al., 2015), we focus on large financial institutions, as these institutions are the primary sources of systemic risk. More precisely, we include all financial institutions in Europe with a market capitalization greater than 100 million euros in April 2022. Our final sample consists of 332 financial institutions, including 119 banks, 10 life insurance companies, 29 non-life insurance companies, 86 financial services companies, 65 real estate investment and services firms (REIS), and 23 real estate investment trusts (REITs).

We download several financial and environmental variables for this sample of financial institutions (see the list and definitions in Appendix A). Financial variables, as well as Scope 1 & 2 carbon emissions and variables on environmentally responsible initiatives and board member incentives, are from Refinitiv Datastream. Physical risk scores are downloaded from Trucost. Finally, we use Scope 3 carbon emissions from Carbone4, which estimate indirect

¹² For prices, we use the following function on Datastream (“DPL#(X(RI)~E,9)”), which allows us to obtain enough decimal digits to avoid confusing small returns with illiquidity.

emissions of financial institutions that primarily come from their investments and loans portfolio.¹³

To construct climate risk factors, we only keep the stocks for which information on climate risks (Carbon emissions or physical scores), as well as other relevant financial information (market capitalization, book-to-market, and net sales) are available. We also download Fama and French (2015) and Carhart (1997) factors from Kenneth French website. The European Fama and French (2015) factors comprise the market factor (*MKT*, returns of the European market portfolio minus the risk-free rate), the Small-minus-Big factor (*SMB*) based on market capitalization, the High-minus-Low factor (*HML*) based on the book-to-market, the Robust-minus-Weak factor (*RMW*) based on profitability, the Conservative-minus-Aggressive factor (*CMA*) based on investment profile. Carhart (1997) also proposes the Winner-minus-Loser factor (*WML*), which captures a momentum effect. For consistency with the transformation applied for climate risk factors and financial institutions' stock returns, we focus on the tail risk of each of these factors.

Besides, we construct several market stress factors. We download the risk reversal on the USD/EUR options from Bloomberg (*RR*), for which a negative value implies that expectations are skewed towards depreciation of the euro. Then, we construct a series of fixed income spreads. The 3-month Euribor rate against the OIS represents interbank market liquidity (*IM*). The 10-year against the 2-year euro area interest rates captures the slope of the yield curve (*YC*). The 10-year German sovereign bond rate against an average of Greece, Ireland Italy, Spain, and Portugal's 10-year rates reflects the divergence in rates between countries of the North and the South of the Euro Area (*NS*). The high yield euro corporate rates against the 3-month

¹³ For example, for the banks, Scope 3 emissions mainly correspond to emissions linked to corporate financing, property investments, and credits made to clients. For real estate activities, Scope 3 emissions are estimated from the energy consumed in the operation of buildings owned or managed by the company.

Euribor rate represents the default premium (*DP*). Lastly, we use an economic sentiment (*ES*) indicator based on surveys from Eurostat. In the regressions, a positive coefficient associated with one of these variables indicates that a deterioration in the indicator leads to an increase in systemic risk. Additional information on data sources is available in Appendix A.

1.2.5. Descriptive statistics

Table 3 reports the correlation matrix between our tail climate risk measures, *BMG* (transition risk factor) and *VMS* (physical risk factor), the five factors of Fama and French (2015), the momentum factor of Carhart (1997), and several market stress factors. Overall, the correlation of climate risk factors with existing factors is low. *BMG* is slightly correlated with *WML* (Momentum factor), *CMA* (Conservative minus Aggressive factor), and *HML* (High minus Low factor), at 23%, 21%, and -20%, respectively. *VMS* is moderately correlated with *ES* (Economic sentiment factor) and *MKT* (Market factor), at 24% and 21%, respectively. The highest correlations among risk factors are between *ES* and *HML*, *ES* and *MKT*, and *RMW* (Robust minus Weak) and *HML*, at 63%, 48%, and 47%, respectively. The correlation between *BMG* and *VMS* amounts to 8%.

In Table 4, Panels A and B report the characteristics of the factor constituents. As of 2022, the transition risk factor comprises 414 low transition risk firms and 414 high transition risk firms. We observe a high sector concentration in both the long and short portfolio allocations. For example, the personal goods industry, a low-carbon sector, is most represented in the low-risk group, while the oil and gas production industry, a very carbon-intensive sector, is most often found in the high-risk group. The weighted average market capitalization amounts to €19,115 million (€10,703 million) for low (high) transition risk factor constituents, while the weighted average carbon intensity is 0.28% (618%). Whereas the divergence in size is relatively

small compared to the difference in carbon intensity, we still control for the size effect in the construction of the transition risk factor (see Equation 9).

Table 5 presents the descriptive statistics of the 332 European financial institutions included in our sample. The average (median) market capitalization of our institutions is €914 million (€816 million), with an average net income to total assets ratio of 0.025 (median = 0.010), an average market-to-book of 1.291 (median = 1.004), and an average beta of 0.831 (median = 0.780).

1.3. Empirical results

1.3.1. Measure of systemic risk

Figure 1 represents our time-varying systemic risk indicator ($\widehat{\Omega}_1$) from February 2005 to April 2022. $\widehat{\Omega}_1$ captures common variations in financial institutions' tail risk. Large increases in systemic risk occurred after the bankruptcy of Lehman Brothers in September 2008, during the July-August 2011 eurozone stock market crash, after the Brexit referendum in June 2016, and the European Covid-19 outbreak in March 2020. Compared to the financial crisis, the Covid-19 shock led to a more sudden increase in market volatility, which explains that the extremum is reached during the Covid-19 outbreak.

1.3.2. Individual exposures of financial institutions to tail climate risks

Figure 2 plots the distribution of transition and physical risk exposures of financial institutions. We observe that the distribution of transition risk exposures is skewed to the right, indicating that there is a larger proportion of financial institutions with high transition risk exposures. The same is true for physical risk exposures but to a lesser extent.

Table 6 presents the 30 largest individual exposures to tail transition risk. Among the 30 financial institutions, 13 are from the United Kingdom. The largest exposure is the Bank of Ireland with a coefficient of 3.36: if transition risk worsens by one percentage point, the VaR at the 95% level of the Bank of Ireland will worsen by 3.36 percentage points. For these largest transition risk exposures, the mean exposure corresponds to a 1.51 percentage point increase in the VaR of the financial institution for a one percentage point increase in the VaR of the transition risk factor. This group comprises 8 financial institutions with a market capitalization above €10 billion, of which 3 life insurers (Aviva, Legal and General, Prudential), 3 non-life insurers (AXA, Sampo, Swiss Re), and 2 banks (Barclays and Lloyds Banking Group).

Table 7 reports the 30 largest exposures to tail physical risk. Among these 30 largest exposures, 8 are Norwegian institutions. The Norwegian financial services provider Aker has the largest exposure to physical risk, with an individual VaR worsening by 2.69 percentage points when physical risk worsens by one point. For these largest exposures to physical risk, the mean exposure corresponds to a 0.86 percentage point increase in the VaR of the financial institution for a one percentage point increase in the VaR of the physical risk factor. This group only comprises 1 financial institution with a market capitalization above €10 billion (Swedbank). We also remark a relative overrepresentation of REITs in the largest exposures to tail physical risk, with 4 out of the 23 REITs of our sample being among the 30 largest exposures to tail physical risk. The mean exposure of these 4 REITs corresponds to a 1.15 percentage point increase in the VaR when the VaR of the physical risk factor increases by one point.¹⁴

¹⁴ One possible explanation is that REITs tend to have more tangible assets compared to other financial institutions, and are therefore more vulnerable to asset destructions stemming from extreme climate events.

1.3.3. The effect of tail climate risks on systemic risk

In Table 8, we examine whether tail climate risks significantly contribute to tail dependence among financial institutions, after taking into account several factors known to be predictors of systemic risk. We start by running time-series regressions of $\hat{\Omega}_1$, our indicator of systemic risk capturing common time variations in the VaR of financial institutions, on our climate risk factors (*BMG* for transition risk and *VMS* for physical risk) while controlling for various other potential determinants of systemic risk (Panel A). In column (1), we observe a positive and significant impact of transition risks on systemic risk, after controlling for the *MKT*, *SMB*, and *HML* factors, while physical risk has no significant impact. We confirm these results when we add controls for (i) *RMB*, *CMA*, and *WML* (column 2), (ii) various market stress indicators (*RR*, *ML*, *DP*, *YC*, *NS*, *ES* in column 3), and all control variables together (column 4). For ease of interpretation, we change the sign of some variables so that a positive coefficient always indicates that a rise in market risk or a degradation in the economic situation is associated with an increase in systemic risk. We note that most of the market stress indicators are positively associated with systemic risk.

Next, we carry out a cross-sectional analysis (Panel B) to check whether the financial institutions most exposed to climate risks ($\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$) contribute more to the tail dependence in the financial sector (\hat{X}_1), after controlling for the exposures to other risk factors. Again, we observe a positive and significant coefficient associated with the exposure to transition risks, while the exposure to physical risk does not seem to affect the contribution to global risk. The results are robust to the inclusion of fixed effects for the type of financial industry. Interestingly, the coefficients of the time series and cross-sectional regressions are not always in line, as illustrated by the effect of *ML*, the interbank market liquidity, only appears significant in the cross-sectional regressions. This discrepancy indicates that the two-pass regression procedure is useful to ensure that the results are robust.

Overall, our findings indicate that transition risk is a significant contributor to systemic risk, both in the time series and the cross section. On the contrary, physical risk does not appear to impact systemic risk.

1.3.4. Individual characteristics of financial institutions and tail climate risks

In this section, we investigate which institution-level characteristics are associated with tail climate risks. To the best of our knowledge, only Li et al. (2020) and Sautner et al. (2020) investigate which firm-level characteristics correlated with firm-level climate risk.

We report our results in Table 9 in the case of tail transition risks. We start by regressing our measure of tail transition risks on the natural logarithm of market capitalization, net income, market-to-book, cash, equity beta, as well as country and industry fixed effects. Our results, reported in column (1), indicate that market capitalization and equity beta are positively associated with individual tail transition risk, while transition risk exposure is negatively correlated with cash levels. We then augment our regressions with various additional characteristics. We first investigate the impact of Scope 3 CO₂ emissions (CO₂ emissions indirectly emitted by the financial institutions, primarily through their investment and loan portfolios). We find that higher Scope 3 emissions intensity is positively associated with transition risk exposures (column 2). We then assess the association between committing to managing environmental issues in project financing, as proxied by being an Equator Principles signatory, and transition risks. Our results indicate that financial institutions managing environmental issues in project financing tend to have lower transition risk exposures (column 3). In column (4), we investigate the relationship between the long-term incentives given to board members and transition risks. We find that exposures to transition risks are significantly lower when board members have long-term incentives.

In Table 10, we examine which institution-level characteristics correlate with higher exposure to physical risks. Financial institutions with higher exposures to physical risks have a lower market capitalization, higher cash holdings, and lower equity beta (column 1). As with transition risks, physical risks tend to be lower for institutions committing to managing environmental issues in project financing (column 2) and giving long-term incentives to board members and executives (column 3).

These findings suggest that the characteristics of financial institutions exposed to tail transition risks are different from those of institutions exposed to physical risks. However, financial institutions tend to have lower exposure to both transition and physical risks when they commit to taking environmental considerations, or more broadly long-term considerations, into account.

1.3.5. Tail climate risks and environmental disclosure policies

We have seen in previous sections that tail transition risks contribute to systemic risk within the financial sector. In this section, we investigate whether financial institutions take action to adapt to tail climate risks. More specifically, we assess the impact, if any, of tail climate risks on carbon disclosure policies. Our results are reported in Table 11. In column (1), we start by regressing *CO2 disclosure*, a dummy variable equal to one if the financial institution reports its Scope 1 and/or Scope 2 emissions, on our measure of transition risk, after controlling for the natural logarithm of the market capitalization, net income, market-to-book, cash, beta, as well as year fixed effects. All our control variables are lagged by one year to mitigate potential endogeneity issues. Then, in columns (2) and (3), we add country and industry fixed effects to control for year effects as well as time-invariant industry and country characteristics. Across our specifications, our findings indicate a positive and significant effect of tail transition risks

on the disclosure of CO₂ emissions, after controlling for various determinants of CO₂ emissions disclosure. A one standard deviation increase in tail transition risks is associated with a 2.6 to 3.2 percentage point increase in the probably to disclose CO₂ emissions, corresponding to a 10 to 11% increase from the mean. However, our findings could be biased by endogeneity. Omitted time-invariant institution characteristics might bias our results. In column (4), we thus redefine our transition risk measure on 3-year intervals. Having multiple transition risk scores per financial institution allows us to confirm the positive impact of transition risk after the inclusion of financial institution fixed effects. Another endogeneity concern is reverse causality. To mitigate this concern, we implement an instrumental variable approach, in which we instrument our 3-year transition score by the average 3-year transition score within the same sector-year group, the underlying assumption being that peer institutions' transition risk does not influence the carbon disclosure decisions of the focal firm. Our results are reported in columns (5) and (6) and indicate that a one standard deviation increase in transition risk increases by 6.4 percentage points the probability to disclose carbon emissions.

Overall, our results indicate that tail transition risks positively impact the propensity of financial institutions to engage in carbon disclosure.

1.4. Conclusion

In this paper, we develop a new framework for analyzing systemic climate risks based on environmental and stock market data. This framework aims to identify the institutions that are the most vulnerable to climate risks and assess whether climate risks can exacerbate tail dependence within the financial sector. We apply our approach to a sample of Europe's largest financial institutions. We present a list of financial institutions that appear most exposed to transition and physical climate risks. We then show that transition climate risks can exacerbate

tail dependence among financial institutions, which is a key aspect of systemic risk. By contrast, we do not find evidence of such spillovers in the case of physical climate risks.

Studying the institution-level characteristics associated with climate risks, we find that climate risk exposure is lower for financial institutions committed to environmental risk management and for those providing long-term incentives to board members. Our findings also highlight that financial institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. Finally, our results reveal that financial institutions are more prone to disclosing carbon emissions when they are more exposed to transition risks.

For the managers of financial institutions, central bankers, and financial supervisors, our results suggest that there are levers that might help to reduce systemic climate risks. However, our analysis is silent on the tradeoff that might exist between these reductions in risk and the potential costs of implementing these actions. Furthermore, the framework we propose could be used to assess other emerging threats to financial stability, such as cybersecurity risk.

1.5. References

- Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, 30(1), 2-47.
- Adams, Z., Füss, R., & Gropp, R. (2014). Spillover effects among financial institutions: A state-dependent sensitivity value-at-risk approach. *Journal of Financial and Quantitative Analysis*, 49(3), 575-598.
- Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7), 1705-1741.
- Aevoae, G. M., Andries, A. M., Ongena, S., & Sprincean, N. (2022). ESG and Systemic Risk. *Swiss Finance Institute Research Paper*, (22-25).
- Alessi, L., Ossola, E., & Panzica, R. (2021). What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures. *Journal of Financial Stability*, 54, 100869.
- Alogoskoufis, S., Dunz, N., Emambakhsh, T., Hennig, T., Kaijser, M., Kouratzoglou, C., ... & Salleo, C. (2021). *ECB economy-wide climate stress test: Methodology and results* (No. 281). ECB Occasional Paper.
- Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3), 1146-1183.
- Andersson, M., Bolton, P., & Samama, F. (2016). Hedging climate risk. *Financial Analysts Journal*, 72(3), 13-32.
- Anginer, D., Demirguc-Kunt, A., Huizinga, H., & Ma, K. (2018). Corporate governance of banks and financial stability. *Journal of Financial Economics*, 130(2), 327-346.
- Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2020). Climate change concerns and the performance of green versus brown stocks. *National Bank of Belgium, Working Paper Research*, (395).
- Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3), 1256-1295.
- Barnett, M., Brock, W., & Hansen, L. P. (2020). Pricing uncertainty induced by climate change. *The Review of Financial Studies*, 33(3), 1024-1066.
- Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability.
- Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4), 283-288.
- Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. *Review of Finance*, 21(1), 109-152.
- Bernstein, A., Gustafson, M. T., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics*, 134(2), 253-272.
- Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3), 535-559.

- Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk?. *Journal of Financial Economics*, 142(2), 517-549.
- Brammer, S., & Pavelin, S. (2006). Voluntary environmental disclosures by large UK companies. *Journal of Business Finance & Accounting*, 33(7-8), 1168-1188.
- Briere, M., & Ramelli, S. (2021). Green sentiment, stock returns, and corporate behavior. Available at SSRN 3850923.
- Brownlees, C., & Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1), 48-79.
- Brownlees, C. T., Engle, R. F., & Kelly, B. T. (2011). A practical guide to volatility forecasting through calm and storm. Available at SSRN 1502915.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1), 57-82.
- Carney, M. (2015). Breaking the tragedy of the horizon—climate change and financial stability. *Speech given at Lloyd's of London*, 29, 220-230.
- Cerqueti, R., Ciciretti, R., Dalò, A., & Nicolosi, M. (2021). ESG investing: A chance to reduce systemic risk. *Journal of Financial Stability*, 54, 100887.
- Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3), 1112-1145.
- Christensen, H. B., Floyd, E., Liu, L. Y., & Maffett, M. (2017). The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records. *Journal of Accounting and Economics*, 64(2-3), 284-304.
- Christoffersen, P., Hahn, J., & Inoue, A. (2001). Testing and comparing value-at-risk measures. *Journal of empirical finance*, 8(3), 325-342.
- Christoffersen, P., & Pelletier, D. (2004). Backtesting value-at-risk: A duration-based approach. *Journal of Financial Econometrics*, 2(1), 84-108.
- Cooley, D., & Thibaud, E. (2019). Decompositions of dependence for high-dimensional extremes. *Biometrika*, 106(3), 587-604.
- Cormier, D., & Magnan, M. (1999). Corporate environmental disclosure strategies: determinants, costs and benefits. *Journal of Accounting, Auditing & Finance*, 14(4), 429-451.
- Council, F. S. O. (2021). Report on Climate-Related Financial Risk 2021. *Financial Stability Oversight Council*. <https://home.treasury.gov/system/files/261/FSOC-Climate-Report.pdf>.
- Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The accounting review*, 86(1), 59-100.
- Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The accounting review*, 87(3), 723-759.

- Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158-171.
- Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). 'Climate value at risk' of global financial assets. *Nature Climate Change*, 6(7), 676-679.
- Duarte, F., & Eisenbach, T. M. (2021). Fire-sale spillovers and systemic risk. *The Journal of Finance*, 76(3), 1251-1294.
- Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The journal of finance*, 48(5), 1749-1778.
- Engle, R. F., & White, H. (1999). *Cointegration, causality, and forecasting: a Festschrift in Honour of Clive WJ Granger*. Oxford University Press on Demand.
- Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.
- Engle, R., Jondeau, E., & Rockinger, M. (2015). Systemic risk in Europe. *Review of Finance*, 19(1), 145-190.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2), 427-465.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1), 1-22.
- Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499-516.
- Ge, S., & Weisbach, M. S. (2021). The role of financial conditions in portfolio choices: The case of insurers. *Journal of Financial Economics*, 142(2), 803-830.
- Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, 13, 15-36.
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5), 1779-1801.
- Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020). Carbon risk. *Available at SSRN 2930897*.
- Grewal, J., Riedl, E. J., & Serafeim, G. (2019). Market reaction to mandatory nonfinancial disclosure. *Management Science*, 65(7), 3061-3084.
- Griffin, P. A., Lont, D. H., & Sun, E. Y. (2017). The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research*, 34(2), 1265-1297.
- Haniffa, R. M., & Cooke, T. E. (2005). The impact of culture and governance on corporate social reporting. *Journal of accounting and public policy*, 24(5), 391-430.
- Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies*, 33(3), 1011-1023.
- Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, 208(1), 265-281.

- Hsu, P. H., Li, K., & Tsou, C. Y. (2022). The pollution premium. *Journal of Finance*, *Forthcoming*.
- Huang, B., Punzi, M. T., & Wu, Y. (2022). Environmental regulation and financial stability: Evidence from Chinese manufacturing firms. *Journal of Banking & Finance*, *136*, 106396.
- Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2021a). Climate risk disclosure and institutional investors. *Swiss Finance Institute Research Paper*, (19-66).
- Ilhan, E., Sautner, Z., & Vilkov, G. (2021b). Carbon tail risk. *The Review of Financial Studies*, *34*(3), 1540-1571.
- Jung, H., Engle, R. F., & Berner, R. (2021). Climate stress testing. *FRB of New York Staff Report*, (977).
- Kelly, B., & Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, *27*(10), 2841-2871.
- Kim, J. B., Wang, C., & Wu, F. (2022). The real effects of risk disclosures: evidence from climate change reporting in 10-Ks. *Review of Accounting Studies*, 1-48.
- Kleymenova, A., & Tuna, İ. (2021). Regulation of compensation and systemic risk: Evidence from the UK. *Journal of Accounting Research*, *59*(3), 1123-1175.
- Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067-1111.
- Kruttli, M. S., Roth Tran, B., & Watugala, S. W. (2021). Pricing Poseidon: Extreme weather uncertainty and firm return dynamics.
- Kuester, K., Mittnik, S., & Paoletta, M. S. (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics*, *4*(1), 53-89.
- Kupiec, P. H. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, *3*(2), 73-84.
- Landis, C., & Skouras, S. (2021). Guidelines for asset pricing research using international equity data from Thomson Reuters Datastream. *Journal of Banking & Finance*, *130*, 106-128.
- Li, Q., Shan, H., Tang, Y., & Yao, V. (2020). Corporate climate risk: Measurements and responses. *Available at SSRN 3508497*.
- Liang, H., & Renneboog, L. (2020). Corporate social responsibility and sustainable finance: a review of the literature. *European Corporate Governance Institute–Finance Working Paper*, (701).
- Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *the Journal of Finance*, *72*(4), 1785-1824.
- Manconi, A., Massa, M., & Zhang, L. (2016). Bondholder concentration and credit risk: Evidence from a natural experiment. *Review of Finance*, *20*(1), 127-159.
- Massa, M., & Zhang, L. (2021). The spillover effects of Hurricane Katrina on corporate bonds and the choice between bank and bond financing. *Journal of Financial and Quantitative Analysis*, *56*(3), 885-913.

- Matsumura, E. M., Prakash, R., & Vera-Munoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review*, 89(2), 695-724.
- Murfin, J., & Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate?. *The Review of Financial Studies*, 33(3), 1217-1255.
- Nanda, V., Wu, W., & Zhou, X. A. (2019). Investment commonality across insurance companies: Fire sale risk and corporate yield spreads. *Journal of Financial and Quantitative Analysis*, 54(6), 2543-2574.
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, 347-370.
- Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3), 703-708.
- Ojea-Ferreiro, J., Reboredo, J. C., & Ugolini, A. (2022). *The impact of climate transition risks on financial stability. A systemic risk approach* (No. 2022-01).
- Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2), 550-571.
- Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2), 572-597.
- Plumlee, M., Brown, D., Hayes, R. M., & Marshall, R. S. (2015). Voluntary environmental disclosure quality and firm value: Further evidence. *Journal of accounting and public policy*, 34(4), 336-361.
- Pukthuanthong, K., Roll, R., & Subrahmanyam, A. (2019). A protocol for factor identification. *The Review of Financial Studies*, 32(4), 1573-1607.
- Reid, E. M., & Toffel, M. W. (2009). Responding to public and private politics: Corporate disclosure of climate change strategies. *Strategic management journal*, 30(11), 1157-1178.
- Roncoroni, A., Battiston, S., Escobar-Farfán, L. O., & Martinez-Jaramillo, S. (2021). Climate risk and financial stability in the network of banks and investment funds. *Journal of Financial Stability*, 54, 100870.
- Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2020). Firm-level climate change exposure. *European Corporate Governance Institute–Finance Working Paper*, (686).
- Scholtens, B., & van't Klooster, S. (2019). Sustainability and bank risk. *Palgrave Communications*, 5(1), 1-8.
- Schüwer, U., Lambert, C., & Noth, F. (2019). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *Review of Finance*, 23(1), 75-116.
- Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance?. *Journal of Financial Economics*, 142(2), 487-498.
- White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*, 817-838.
- Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98, 39-60.

1.6. Figures and tables

Figure 1

Time variations in systemic risk from February 2005 to April 2022.

The indicator represents the first principal component $\hat{\Omega}_1$, extracted from Equations (2) and (3), and accounts for the common variations in the VaR of financial institutions.

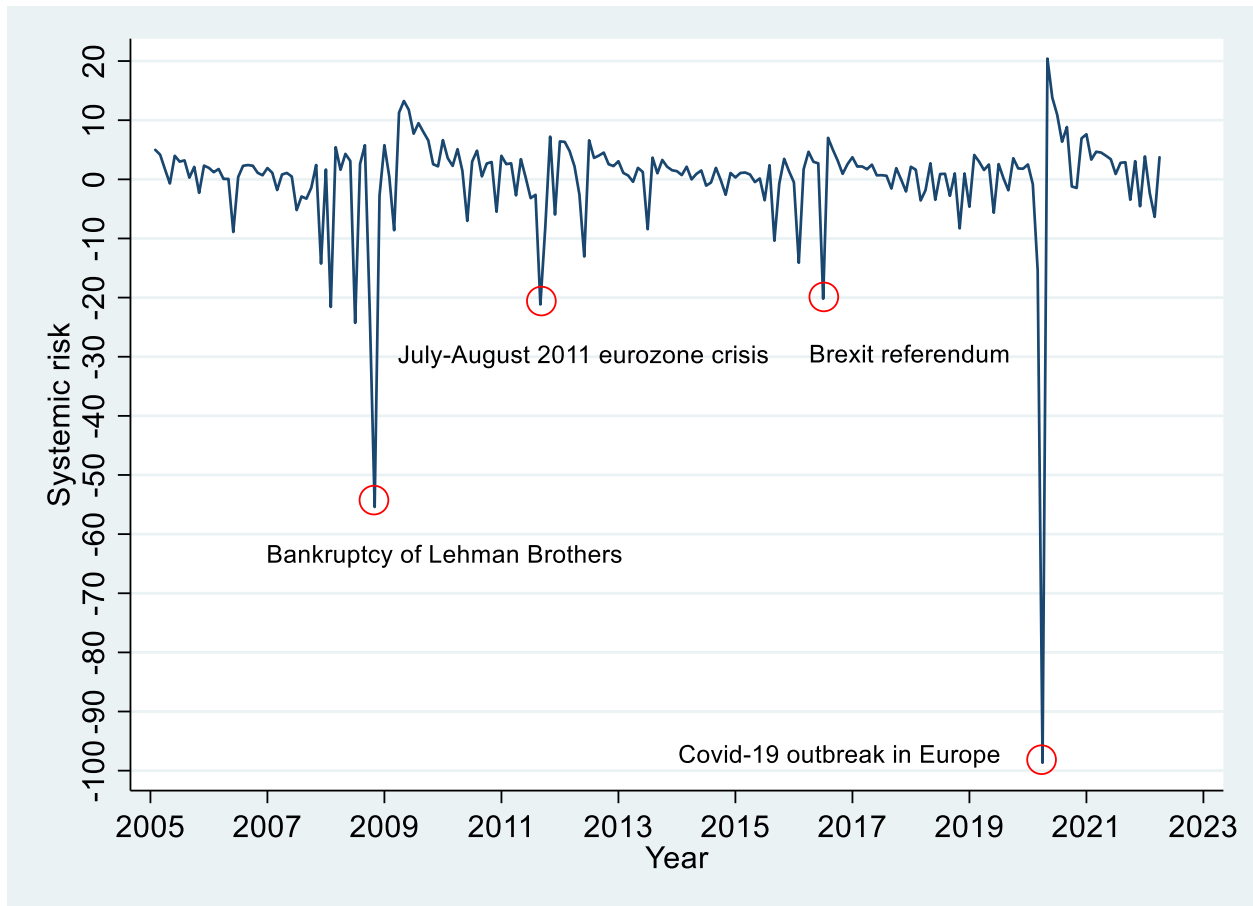


Figure 2

Distribution of climate risk exposures for financial institutions.

The figure represents the distribution of the vectors of financial institutions' exposures to climate risks $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$ estimated in Equation (4) by replacing $\hat{\Omega}_1$ by the time variations in the VaR of financial institutions.

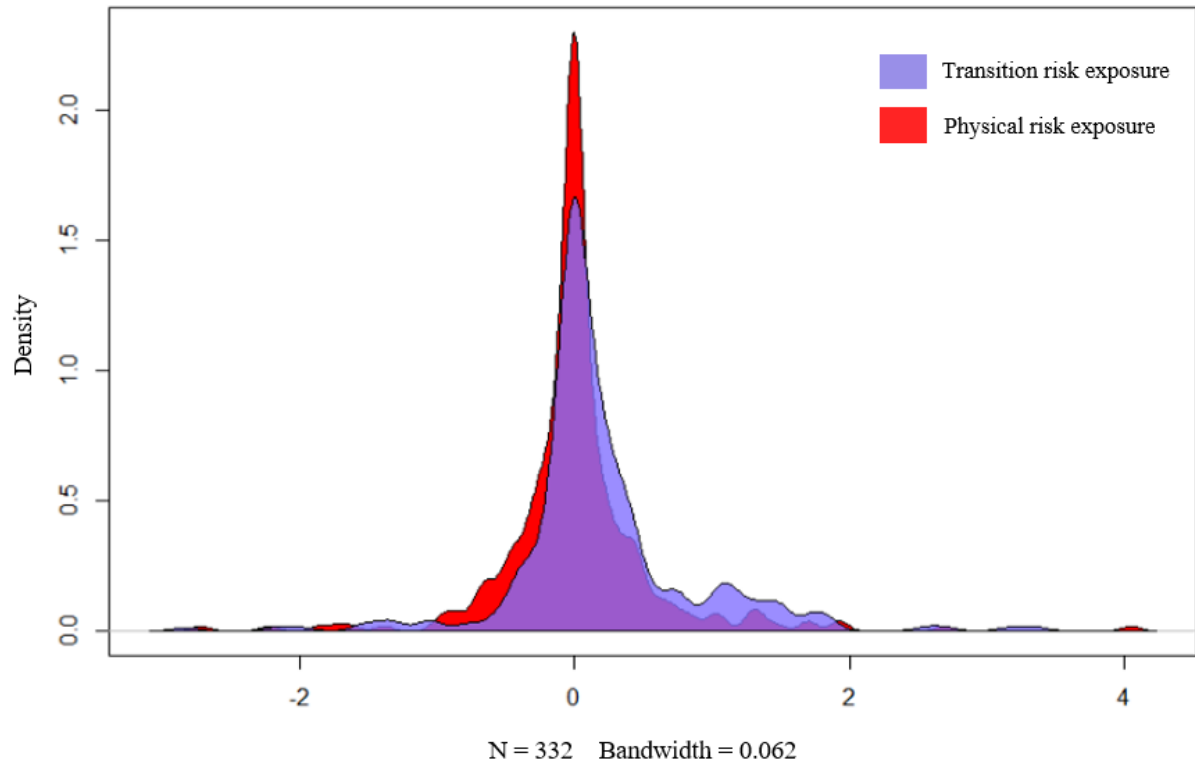


Table 1

Most interconnected institutions based on VaR and returns.

This table reports a list of the most interconnected institutions based on VaR and returns using the loading of each financial institution \hat{X}_1 on the first principal component $\hat{\Omega}_1$. The acronyms REITs and REIS stand for “Real Estate Investment Trusts” and “Real Estate Investment Services”, respectively.

Top 30 contributors to Systemic Risk based on VaR measures			Top 30 contributors to Systemic Risk based on stock returns		
Financial institutions	Sector	\hat{X}_1	Financial institutions	Sector	\hat{X}_1
Banco Santander	Banks	8,3%	Banco Santander	Banks	7,8%
Bank Polska Kasa Opieki	Banks	8,4%	Barclays	Banks	7,6%
Barclays	Banks	8,3%	BBVA	Banks	7,6%
BBVA	Banks	8,1%	BNP	Banks	7,8%
BNP	Banks	7,9%	Credit Agricole	Banks	8,0%
CRCAM de Normandie	Banks	8,7%	DNB Bank	Banks	7,8%
Credit Agricole	Banks	8,2%	Erste Group Bank	Banks	8,1%
Erste Group Bank	Banks	9,2%	KBC Ancora	Banks	7,7%
Intesa Sanpaolo	Banks	8,3%	KBC Group	Banks	7,5%
Investec	Banks	8,4%	Lloyds Banking Group	Banks	7,5%
Jyske Bank	Banks	7,9%	Nordea Bank	Banks	7,9%
Komerčni Banka	Banks	8,0%	OTP Bank	Banks	7,5%
Nordea Bank	Banks	8,8%	Societe Generale	Banks	8,3%
PKO Bank	Banks	8,1%	Unicredit	Banks	7,7%
Societe Generale	Banks	8,8%	Eurazeo	Financial Services	8,2%
Sparebank 1 Helgeland	Banks	8,2%	GBL New	Financial Services	8,1%
Sparebank 1 SMN Ords	Banks	8,7%	Industrivarden A	Financial Services	7,7%
Unicredit	Banks	8,0%	Intermediate Capital Group	Financial Services	7,7%
Vontobel Holding	Banks	8,2%	Peugeot Invest	Financial Services	7,8%
Eurazeo	Financial Services	8,5%	Wendel	Financial Services	8,3%
Intermediate Capital Group	Financial Services	8,2%	Aviva	Life Insurance	7,6%
Peugeot Invest	Financial Services	8,7%	Legal and General	Life Insurance	8,1%
Wendel	Financial Services	8,4%	Prudential	Life Insurance	7,6%
CNP Assurances	Life Insurance	8,7%	Swiss Life Holding	Life Insurance	7,5%
Storebrand	Life Insurance	7,9%	Allianz	Nonlife Insurance	7,8%
Nexity	REIS	7,9%	AXA	Nonlife Insurance	8,0%
Olav Thon Eiendomsselskap	REIS	8,0%	Helvetia Holding N	Nonlife Insurance	7,7%
Hammerson	REITS	8,1%	Mapfre	Nonlife Insurance	7,4%
Land Securities Group	REITS	8,2%	Sampo 'A'	Nonlife Insurance	8,0%
Unibail Rodamco	REITS	7,9%	Vienna Insurance Group A	Nonlife Insurance	7,7%

Table 2

Model selection.

This table performs diagnostic tests for model selection and error distribution assumptions (see Equation 8). Panel A reports the information criteria of Akaike, Bayes, Shibata, and Hannan Quinn. Panel B runs the VaR exceedance tests: the UC test of Kupiec (1995), the CC test of Christoffersen et al. (2001), and the Duration test of Christoffersen and Pelletier (2004). GJR-GARCH, E-GARCH, NA-GARCH, and C-GARCH respectively stand for the model of Glosten et al. (1993), the Exponential GARCH model of Nelson (1991), the Nonlinear Asymmetric GARCH model of Engle and Ng (1993), and the component GARCH of Engle and Lee (1999).

Panel A: Information criteria

Model	Error distribution	Akaike	Bayes	Shibata	Hannan Quinn
	Normal	6,925	7,006	6,924	6,958
	Skew-normal	6,909	7,005	6,908	6,948
	Student	6,820	6,917	6,819	6,859
	Skew-student	6,816	6,929	6,814	6,862
GJR-GARCH	Generalized error	6,814	6,910	6,812	6,852
	Skew-generalized error	6,818	6,931	6,816	6,864
	Normal inverse gaussian	6,823	6,935	6,820	6,868
	Generalized Hyperbolic	6,827	6,955	6,824	6,878
	Johnson's SU	6,818	6,931	6,816	6,864
GARCH		6,943	7,023	6,942	6,976
GJR-GARCH		6,909	7,005	6,908	6,948
E-GARCH	Skew-normal	6,923	7,019	6,921	6,961
NA-GARCH		7,216	7,312	7,214	7,255
CS-GARCH		6,956	7,068	6,954	7,001

Panel B: VaR exceedance tests

Model	Error distribution	Expected VaR 5% exceed	Realized VaR 5% exceed	Standard deviation around 10	Number of rejections		
					VaR UC test	VaR CC test	VaR Duration test
GJR-GARCH	Normal	10	10,33	2,67	3	7	9
	Skew-normal	10	9,72	2,31	6	4	12
	Student	10	11,34	3,59	8	11	11
	Skew-student	10	10,77	2,83	2	5	6
	Generalized error	10	10,67	5,88	14	14	13
	Skew-generalized error	10	9,64	2,71	5	9	9
	Normal inverse Gaussian	10	10,03	2,41	2	5	9
	Generalized Hyperbolic	10	12,44	8,01	25	25	17
	Johnson's SU	10	10,40	2,90	2	5	9
GARCH		10	9,90	2,40	5	16	8
GJR-GARCH		10	9,72	2,31	6	4	12
E-GARCH	Skew-normal	10	9,48	2,25	2	6	8
NA-GARCH		10	10,14	9,97	6	13	9
CS-GARCH		10	10,08	2,38	1	6	11

Table 3

Correlation matrix for risk factors.

This table presents the correlation matrix among risk factors. Appendix A presents variable definitions.

	BMG	VMS	MKT	SMB	HML	RMW	CMA	WML	RR	ML	DP	YC	NS
VMS	8%												
MKT	2%	21%											
SMB	7%	6%	12%										
HML	-20%	10%	38%	10%									
RMW	1%	-5%	32%	6%	47%								
CMA	21%	17%	32%	11%	-1%	15%							
WML	23%	15%	27%	12%	21%	23%	16%						
RR	-4%	-13%	3%	2%	14%	11%	-11%	11%					
ML	-5%	-6%	30%	15%	10%	31%	13%	11%	12%				
DP	-1%	12%	41%	4%	5%	16%	30%	1%	-31%	15%			
YC	-2%	10%	1%	0%	2%	1%	0%	0%	-2%	13%	4%		
NS	-4%	16%	16%	-4%	17%	-4%	1%	8%	-6%	3%	-1%	19%	
ES	-6%	24%	48%	19%	63%	11%	12%	19%	-4%	6%	21%	0%	17%

Table 4

Descriptive statistics of climate risk factor constituents.

This table reports the summary statistics of the climate risk factor constituents. **Panel A** presents the descriptive statistics for observations used in the transition risk factor. The transition risk factor is constructed as a long-short portfolio based on estimated carbon emission data (scopes 1 & 2) for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies) between 2005 and 2022. The portfolio is long on the high climate risk firms (>80th percentile) and short on the low climate risk firms (<20th percentile).

Panel A: Transition risk factor

Sectors	Number of firms		% in portfolio		Average market capitalization (in million euros)		Average CO2 emissions (scopes 1 & 2), in tons		Average carbon intensity (Ratio of scope 1 & 2 emissions to sales)	
	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Def.	1	1	0.0%	0.2%	222	4,708	700	164,478	0.42%	655%
Alternative Energy	5	6	0.6%	0.1%	3,035	327	10,856	389,836	0.27%	1105%
Automobiles		3	0.0%	0.2%		1,626		446,032		22%
Beverages	1	1	0.1%	0.0%	2,471	593	88	70,292	0.02%	15%
Chemicals		27	0.0%	7.8%		7,750		3,932,167		62%
Construction and Mat.	7	15	0.1%	2.2%	491	4,000	4,038	2,556,202	0.34%	144%
Electricity	4	35	0.5%	15.3%	2,817	11,679	1,207	10,411,782	0.12%	141%
Electronic Equipment	7	1	0.2%	0.1%	654	1,935	1,881	485,900	0.39%	41%
Fixed Line Telecom.	7	7	1.7%	0.7%	5,683	2,492	10,713	353,920	0.30%	45%
Food and Drug Retail	7		1.3%	0.0%	4,286		14,334		0.27%	
Food Producers	1	17	0.1%	1.0%	2,615	1,611	1,970	7,547,522	0.28%	680%
Forestry and Paper	1	14	0.0%	1.8%	181	3,460	0	1,237,697	0.00%	59%
Gas, Water	1	12	0.0%	7.8%	740	17,428	1,842	24,236,625	0.51%	118%
General Industrials	2	18	0.3%	2.0%	3,294	2,927	7,725	2,668,725	0.49%	52%
General Retailers	37	2	5.3%	0.0%	3,382	575	10,926	174,412	0.27%	21%
Health Care	13	5	2.0%	0.6%	3,719	3,465	3,517	183,066	0.28%	38%
Household Goods	9	2	0.8%	0.1%	2,034	710	5,293	174,499	0.31%	27%
Industrial Engineering	3	1	0.6%	0.0%	4,957	156	26,792	26,760	0.35%	20%
Metals and Mining		17	0.0%	1.7%		2,711		5,989,661		13872%
Industrial Transport.	7	30	1.5%	4.0%	5,204	3,550	31,017	2,431,281	0.32%	169%
Leisure Goods	4		0.2%	0.0%	1,211		819		0.24%	
Media	32	1	5.3%	1.3%	3,916	35,388	6,940	114,084	0.29%	37%
Mining		36	0.0%	11.2%		8,295		3,162,160		2369%
Oil and Gas Prod.		41	0.0%	26.3%		17,112		7,072,139		121%
Oil Equipment	2	17	0.2%	1.9%	2,639	2,955	290	938,869	0.10%	113%
Personal Goods	13	3	28.0%	0.1%	50,977	554	44,366	963,673	0.29%	29%
Pharmaceuticals	12	9	10.2%	2.0%	20,230	5,827	8,767	100,642	0.22%	62%
Software	108	4	12.7%	0.2%	2,777	1,020	3,091	1,241,990	0.32%	1138%
Support Services	21	6	1.7%	0.4%	1,902	1,793	6,334	574,565	0.23%	53%
Technology Hardware	14	3	2.4%	0.1%	4,061	1,328	11,540	217,997	0.27%	34%
Travel and Leisure	15	31	2.1%	3.6%	3,240	3,111	7,804	2,634,532	0.25%	105%
Unclassified	80	49	22.1%	7.4%	6,550	4,032	6,718	8,025,306	0.27%	209%
Total	414	414	100%	100%	19,115	10,703	17,895	7,136,674	0.28%	618%

Panel B presents the descriptive statistics for observations used in the physical risk factor. The physical risk factor is constructed as a long-short portfolio based on Trucost physical climate risk scores for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies) between 2005 and 2022. The portfolio is long on the high climate risk firms (>80th percentile) and short on the low climate risk firms (<20th percentile).

Panel B: Physical risk factor

Sector	Number of stocks		% of portfolio		Average market capitalization (in million euros)		Average physical score (moderate 2050)	
	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Defense	2	7	0,8%	1,9%	2 319	5 305	31	62
Alternative Energy	4	6	0,6%	0,0%	785	138	35	67
Automobiles and Parts	6	1	1,1%	0,0%	995	1	33	73
Beverages	8	4	2,3%	0,1%	1 606	742	33	65
Chemicals	7	10	0,6%	5,1%	458	10 147	33	62
Construction and Materials	19	18	2,2%	1,3%	635	1 460	33	62
Electricity	8	2	0,7%	0,8%	467	7 948	32	62
Electronic and Electrical Equipment	5	3	0,9%	0,0%	1 022	320	31	68
Fixed Line Telecommunications	6	4	2,2%	0,7%	2 004	3 715	27	60
Food and Drug Retailers	4	2	1,6%	0,1%	2 161	552	33	65
Food Producers	20	16	6,3%	0,7%	1 731	880	31	64
Forestry and Paper	5	3	2,2%	0,2%	2 455	1 404	32	61
Gas, Water and Multiutilities		3	0,0%	0,5%		3 544		63
General Industrials	13	11	1,1%	1,2%	473	2 193	32	63
General Retailers	25	8	5,4%	0,1%	1 176	207	33	62
Health Care Equipment and Services	20	11	5,6%	3,1%	1 522	5 527	33	61
Household Goods and Home Construction	16	7	3,3%	0,2%	1 126	504	33	62
Industrial Engineering	14	7	4,0%	0,8%	1 560	2 209	34	63
Industrial Metals and Mining	7	6	0,8%	0,1%	598	490	30	63
Industrial Transportation	18	15	15,6%	4,7%	4 759	6 238	33	64
Leisure Goods	6	4	0,2%	0,3%	202	1 406	32	62
Media	5	25	0,1%	5,0%	110	3 996	30	62
Mining	19	22	0,4%	0,1%	118	104	32	63
Oil and Gas Producers	12	9	2,7%	13,0%	1 232	28 821	32	64
Oil Equipment and Services	7	6	0,4%	0,2%	292	568	30	65
Personal Goods	3	8	0,9%	0,7%	1 691	1 644	35	64
Pharmaceuticals and Biotechnology	42	24	6,8%	14,8%	892	12 245	31	62
Software and Computer Services	39	37	6,0%	9,1%	836	4 888	31	61
Support Services	11	14	1,6%	4,3%	772	6 042	34	61
Technology Hardware and Equipment	25	16	1,9%	4,7%	427	5 875	32	62
Travel and Leisure	15	21	5,6%	2,8%	2 056	2 606	32	61
Unclassified	99	91	16,1%	23,3%	888	5 095	31	62
Total	490	421	100%	100%	1 786	9 293	32	62

Table 5

Descriptive statistics of financial institutions.

This table reports the summary statistics of the financial institutions in our sample. Appendix A presents variable definitions. The sample comprises all European financial institutions from 2005 to 2022, with a market capitalization above €100 million as of June 2022.

	N	Mean	SD	Median	P25	P75
$\hat{\beta}_{VMS}$	5,757	0.017	0.500	-0.004	-0.166	0.142
$\hat{\beta}_{BMG}$	5,757	0.177	0.572	0.051	-0.039	0.341
LogMarketValue	5,757	6.818	1.860	6.705	5.451	8.012
LogAssets	5,757	15.527	2.459	15.345	13.697	17.083
NetIncome	5,757	0.025	0.058	0.010	0.004	0.041
MtoB	5,757	1.291	1.095	1.004	0.668	1.526
Cash	5,757	0.088	0.134	0.035	0.011	0.107
Beta	5,757	0.831	0.558	0.780	0.392	1.180
EarningsVol	5,757	0.032	0.036	0.018	0.003	0.051
Scope3 Emissions	1,959	6.907	8.062	3.512	0.853	11.327
Equator Principles Signatory	2,637	0.100	0.301	0.000	0.000	0.000
Board LT incentives	5,624	0.033	0.179	0.000	0.000	0.000
CO2 Disclosure	5,757	0.267	0.442	0.000	0.000	1.000

Table 6

Transition risk exposures.

This table presents the Top 30 institutions with large and significant exposures to BMG_t , our transition risk factor. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. The acronyms REITs and REIS stand for “Real Estate Investment Trusts” and “Real Estate Investment Services”, respectively. The Code corresponds to the Datastream symbol.

Financial institutions	Code	Sector	Country	$\hat{\beta}_{BMG}$	
Banca Carige	I:CRG	Banks	Italy	1.80*	(0.92)
Bank of Ireland Group	IE:BIRG	Banks	Ireland	3.36***	(1.15)
Barclays	BARC	Banks	United Kingdom	1.05***	(0.37)
Lloyds Banking Group	LLOY	Banks	United Kingdom	1.49**	(0.68)
Permanent TSB Group Holdings	IE:IL0A	Banks	Ireland	1.81*	(0.97)
Sparebanken Vest	N:SVEG	Banks	Norway	1.10*	(0.64)
Brewin Dolphin	BRW	Financial Services	United Kingdom	1.13*	(0.58)
Hellenic Exchanges Holdings	G:HEL	Financial Services	Greece	1.32*	(0.72)
Intermediate Capital Group	ICP	Financial Services	United Kingdom	1.67***	(0.63)
Lebon	F:LBON	Financial Services	France	1.18**	(0.52)
Saint James's Place	STJ	Financial Services	United Kingdom	1.03**	(0.42)
Aviva	AV.	Life Insurance	United Kingdom	1.15**	(0.52)
Legal and General	LGEN	Life Insurance	United Kingdom	1.50***	(0.53)
Prudential	PRU	Life Insurance	United Kingdom	1.01*	(0.56)
AXA	F:MIDI	Nonlife Insurance	France	1.51**	(0.65)
FBD Holdings	IE:EG7	Nonlife Insurance	Ireland	1.34*	(0.77)
Sampo 'A'	M:SAMA	Nonlife Insurance	Finland	0.92**	(0.39)
Swiss Re	S:SREN	Nonlife Insurance	Switzerland	1.51*	(0.79)
Boot (Henry)	BOOT	REIS	United Kingdom	2.70***	(0.89)
Echo Investment	PO:ECH	REIS	Poland	1.15*	(0.69)
Grainger	GRI	REIS	United Kingdom	1.29**	(0.64)
JM	W:JMBF	REIS	Sweden	1.80**	(0.80)
Nexity	F:NXI	REIS	France	1.38**	(0.65)
Risanamento	I:RN	REIS	Italy	1.73*	(0.93)
British Land	BLND	REITs	United Kingdom	1.01***	(0.38)
Carmila	F:CARM	REITs	France	3.17*	(1.88)
Land Securities Group	LAND	REITs	United Kingdom	0.93**	(0.37)
Unibail Rodamco	H:UBL	REITs	France	1.24***	(0.41)
Unite Group	UTG	REITs	United Kingdom	1.45**	(0.69)

Table 7

Physical risk exposures.

This table presents the Top 30 institutions with large and significant exposures to VMS_t , our physical risk factor. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. The Code corresponds to the Datastream symbol.

Financial institutions	Code	Sector	Country	$\hat{\beta}_{VMS}$
Aareal Bank	D:ARL	Banks	Germany	1.01** (0.44)
Investec	INVP	Banks	United Kingdom	0.66*** (0.13)
Sandnes Sparebank	N:SADG	Banks	Norway	1.32*** (0.49)
Sparebank 1 Helgeland	N:HELG	Banks	Norway	0.19*** (0.06)
Sparebank 1 Nord-Norge	N:NONG	Banks	Norway	0.33** (0.13)
Sparebank 1 SMN Ords	N:MING	Banks	Norway	0.44*** (0.17)
Sparebanken More	N:MORG	Banks	Norway	0.24* (0.09)
Sparebanken Vest	N:SVEG	Banks	Norway	1.38** (0.58)
Swedbank A	W:SWED	Banks	Sweden	0.44*** (0.17)
Vseobec Uver Bank	SK:VUB	Banks	Slovakia	0.47** (0.23)
Aker	N:AKER	Financial Services	Norway	2.69*** (0.89)
Gimv	B:GIM	Financial Services	Belgium	0.16* (0.09)
Impax Asset Management Group	IPX	Financial Services	United Kingdom	0.36** (0.16)
Oresund Investment	W:ORF	Financial Services	Sweden	0.56** (0.25)
Ratos B	W:RTBF	Financial Services	Sweden	0.18* (0.09)
Saint James's Place	STJ	Financial Services	United Kingdom	0.64* (0.33)
Personal Group Holdings	PGH	Nonlife Insurance	United Kingdom	0.27** (0.13)
Castellum	W:CAST	REIS	Sweden	0.30*** (0.10)
Deutsche Euroshop	D:DEQ	REIS	Germany	1.91*** (0.54)
Fastighets Balder B	W:BALB	REIS	Sweden	0.16** (0.07)
JM	W:JMBF	REIS	Sweden	1.05*** (0.34)
Nexity	F:NXI	REIS	France	0.58** (0.28)
Olav Thon Eiendomsselskap	N:OLT	REIS	Norway	0.45*** (0.13)
Risanamento	I:RN	REIS	Italy	1.29** (0.58)
Retail Estates	B:RET	REITs	Belgium	1.48* (0.77)
Unibail Rodamco	H:UBL	REITs	France	1.32*** (0.42)
Warehouses de Pauw	B:WDP	REITs	Belgium	0.13* (0.07)
Wereldhave Belgium	B:WEHB	REITs	Belgium	1.68* (0.88)

Table 8

Determinants of systemic risk.

This table presents the determinants of systemic risk. Panel A presents the time-series analysis, as described in Equation (4). We use $\widehat{\Omega}_1$, the systemic risk measures derived from the first principal component defined in Equation (2), as the dependent variable. Newey-West standard errors are reported in parentheses. Panel B presents the cross-sectional analysis, as described in Equation (5). The dependent variable \widehat{X}_1 represents the loadings of each financial institution on $\widehat{\Omega}_1$. The explicative variables are the coefficients $\widehat{\beta}$ extracted from Equation (4) when we replace $\widehat{\Omega}_1$ by the VaR of each financial institution. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. In the regressions, a positive coefficient associated with one of the explicative variables indicates that a deterioration in the indicator leads to an increase in systemic risk.

Panel A: Time-series analysis

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	2.333*** (0.692)	1.878*** (0.634)	2.181* (1.173)	1.442*** (0.518)
VMS	1.070 (1.022)	0.831 (0.860)	1.146 (0.779)	0.288 (0.424)
MKT	3.296*** (0.369)	3.213*** (0.440)		2.667*** (0.443)
SMB	5.675*** (1.724)	5.363*** (1.633)		3.091** (1.400)
HML	6.736*** (2.736)	6.810*** (2.275)		2.373* (1.325)
RMW		-1.851 (3.955)		3.644 (2.617)
CMA		0.394 (0.666)		0.288 (0.418)
WML		0.542** (0.249)		0.493*** (0.174)
RR			2.088*** (0.585)	-0.128 (0.416)
ML			32.297 (20.273)	6.035 (5.411)
DP			0.943** (0.477)	-0.827** (0.340)
YC			-0.289 (1.331)	0.541 (0.844)
NS			3.155** (1.503)	0.428 (1.147)
ES			2.229*** (0.206)	1.295*** (0.199)
Constant	-0.060 (0.289)	-0.066 (0.274)	-0.063 (0.316)	-0.055 (0.238)
Observations	207	207	207	207
R-squared	0.805	0.812	0.684	0.893
Adj R-squared	0.800	0.804	0.671	0.885

Panel B: Cross-sectional analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)
	\hat{X}_1	\hat{X}_1	\hat{X}_1	\hat{X}_1	\hat{X}_1
$\hat{\beta}_{BMG}$	0.007** (0.003)	0.005** (0.003)	0.005** (0.002)	0.005** (0.003)	0.005** (0.003)
$\hat{\beta}_{VMS}$	-0.001 (0.003)	0.003 (0.003)	0.001 (0.003)	-0.004 (0.003)	-0.002 (0.003)
$\hat{\beta}_{MKT}$	0.029*** (0.004)	0.024*** (0.005)		0.032*** (0.004)	0.029*** (0.004)
$\hat{\beta}_{SMB}$	0.003** (0.001)	0.002* (0.001)		-0.001 (0.001)	0.0002 (0.001)
$\hat{\beta}_{HML}$	0.009*** (0.002)	0.012*** (0.002)		0.007*** (0.003)	0.006** (0.003)
$\hat{\beta}_{RMW}$		0.001 (0.001)		0.001 (0.001)	0.001 (0.001)
$\hat{\beta}_{CMA}$		0.001 (0.003)		0.009*** (0.002)	0.009*** (0.002)
$\hat{\beta}_{WML}$		0.027*** (0.007)		0.003 (0.006)	0.003 (0.006)
$\hat{\beta}_{RR}$			-0.002 (0.002)	-0.008*** (0.003)	-0.008*** (0.003)
$\hat{\beta}_{ML}$			0.0005*** (0.0002)	0.0004** (0.0002)	0.0004** (0.0002)
$\hat{\beta}_{DP}$			0.005* (0.003)	-0.014*** (0.003)	-0.012*** (0.004)
$\hat{\beta}_{YC}$			0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)
$\hat{\beta}_{NS}$			0.001 (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
$\hat{\beta}_{ES}$			0.078*** (0.009)	0.042*** (0.009)	0.045*** (0.010)
Constant	0.019*** (0.003)	0.018*** (0.003)	0.021*** (0.003)	0.012*** (0.003)	0.018*** (0.004)
Observations	332	332	332	332	332
R-squared	0.262	0.285	0.254	0.389	0.425
Adjusted R-squared	0.250	0.268	0.236	0.362	0.390
Industry fixed effects	No	No	No	No	Yes

Table 9

Tail transition risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' exposures to climate transition risk, $\hat{\beta}_{BMG}$, estimated from Equation (4) by replacing $\hat{\Omega}_1$ by the VaR of each financial institution. Appendix A presents variable definitions. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
	$\hat{\beta}_{BMG}$	$\hat{\beta}_{BMG}$	$\hat{\beta}_{BMG}$	$\hat{\beta}_{BMG}$
Log Market Value	0.0207*** (0.00495)	0.0324*** (0.0115)	0.0430*** (0.00998)	0.0218*** (0.00510)
NetIncome	-0.268 (0.174)	-0.276 (0.502)	0.0953 (0.230)	-0.250 (0.177)
MtoB	0.00527 (0.00795)	-0.0210 (0.0162)	0.0255** (0.0121)	0.00668 (0.00803)
Cash	-0.127* (0.0658)	-0.492** (0.197)	0.233* (0.120)	-0.119* (0.0674)
Beta	0.0702*** (0.0180)	0.0870*** (0.0285)	0.0786*** (0.0268)	0.0801*** (0.0184)
Scope3 Emissions		0.00514** (0.00203)		
Equator Principles Signatory			-0.0828** (0.0326)	
Board LT incentives				-0.122*** (0.0396)
Constant	-0.207*** (0.0774)	-0.494*** (0.0991)	-0.775*** (0.115)	-0.239*** (0.0792)
Observations	5,757	1,959	2,637	5,624
R-squared	0.172	0.301	0.275	0.175
Adjusted R-squared	0.167	0.292	0.266	0.170
Country Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

Table 10

Tail physical risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' exposures to physical climate risk, $\hat{\beta}_{VMS}$, estimated from Equation (4) by replacing $\hat{\Omega}_1$ by the VaR of each financial institution. Appendix A presents variable definitions. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS}$	(2) $\hat{\beta}_{VMS}$	(3) $\hat{\beta}_{VMS}$
Log Market Value	-0.0111*** (0.00430)	-0.0372*** (0.00776)	-0.0103** (0.00451)
NetIncome	-0.0440 (0.130)	0.191 (0.199)	-0.0626 (0.133)
MtoB	-0.00181 (0.00662)	0.0180* (0.00991)	0.000390 (0.00668)
Cash	0.255*** (0.0620)	-0.00129 (0.0718)	0.235*** (0.0623)
Beta	-0.0747*** (0.0160)	-0.0984*** (0.0213)	-0.0692*** (0.0161)
Equator Principles Signatory		-0.112*** (0.0338)	
Board LT incentives			-0.129*** (0.0389)
Constant	0.299*** (0.0504)	0.689*** (0.0749)	0.289*** (0.0519)
Observations	5,757	2,637	5,624
R-squared	0.171	0.247	0.173
Adjusted R-squared	0.166	0.238	0.168
Country Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Table 11

Tail climate transition risk and carbon disclosure.

This table presents estimates of the effect of tail climate transition risk on carbon disclosure. In columns (1) to (3), $\hat{\beta}_{BMG}$ is a static institution-level measure of tail transition risk. In columns (4) to (6), $\hat{\beta}_{BMG}$ is an institution-level measure of tail transition risk defined on three-year windows. Regressions (1) to (4) use a linear probability model. Regressions (5) and (6) use 2SLS regressions, where the average value of $\hat{\beta}_{BMG}$ at the sector-year level is used as an instrument for $\hat{\beta}_{BMG}$ in the first stage. Appendix A presents variable definitions. Standard errors are clustered by financial institution and reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	CO2 Disclosure	CO2 Disclosure	CO2 Disclosure	CO2 Disclosure	CO2 Disclosure	CO2 Disclosure
	(t)	(t)	(t)	(t)	(t)	(t)
$\hat{\beta}_{BMG}$	0.0553** (0.0227)	0.0485*** (0.0187)	0.0453** (0.0188)	0.00838* (0.00429)	0.113** (0.0446)	0.112** (0.0444)
LogMarketValue (t-1)	0.120*** (0.00563)	0.121*** (0.00552)	0.117*** (0.00571)	0.0286** (0.0117)	0.0379*** (0.0132)	0.0251* (0.0149)
NetIncome (t-1)	-0.00697 (0.131)	-0.120 (0.117)	-0.0394 (0.113)	0.0746 (0.0975)	-0.0556 (0.147)	-0.0328 (0.147)
MtoB (t-1)	-0.00175 (0.0121)	-0.0195** (0.00971)	-0.0163* (0.00875)	-0.0185* (0.0102)	-0.0350*** (0.0132)	-0.0304** (0.0140)
Cash (t-1)	0.0177 (0.0811)	-0.0274 (0.0722)	0.141* (0.0722)	0.0230 (0.0679)	0.0285 (0.0682)	0.0222 (0.0682)
Beta (t-1)	0.114*** (0.0212)	0.0958*** (0.0199)	0.108*** (0.0196)	0.0271 (0.0200)	0.0244 (0.0233)	0.0171 (0.0236)
Constant	-0.710*** (0.0455)	-0.810*** (0.0508)	-0.778*** (0.0634)	0.0505 (0.0830)	-0.0875 (0.123)	0.0992 (0.105)
Observations	5,454	5,454	5,454	5,454	5,454	5,454
R-squared	0.417	0.481	0.496	0.653		
Adjusted R-squared	0.414	0.476	0.491	0.629		
Country Fixed Effects	No	Yes	Yes		Yes	
Financial Institution Fixed Effects	No	No	No	Yes	No	Yes
Industry Fixed Effects	No	No	Yes		Yes	
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A. Variable definitions

Variable	Description
Beta	Equity beta (897E in Datastream).
BMG	Transition risk factor, constructed as a long-short portfolio based on estimated carbon emission data (scopes 1 & 2) for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies).
Board LT incentives	Dummy variable equal to one if board members have long-term compensation incentives (from CGCPDP052 in Refinitiv ESG).
Cash	Ratio of cash (item WC02005 in Worldscope Datastream) to total assets (item WC02999 in Worldscope Datastream).
CMA	Difference between the returns on portfolios of low and high investment stocks (Conservative-Minus-Aggressive factor) from Kenneth French website library.
DP	Default premium computed as the spread between the ICE high yield euro corporate rates against the 3-month Euribor rate (Fred database)
Equator Principles	Dummy variable equal to one if the financial institution has signed (from ENPIDP036 in Refinitiv ESG).
ES	Economic Sentiment indicator (Eurostat).
HML	Difference between the returns on portfolios of high and low book-to-market stocks (High-Minus-Low factor) from Kenneth French website library.
LogMarketValue	Natural logarithm of market capitalization (item MV in Datastream, expressed in million euros).
MKT	Difference between the returns on the market portfolio and the risk-free rate (Market factor) from Kenneth French website library.
ML	Interbank Market Liquidity indicator, calculated as the spread between the 3-month Euribor rate against the equivalent Overnight Indexed Swap rate.
MtoB	Ratio of market value of equity (item MV in Datastream, expressed in million euros) to book value of equity (item WC03501 in Worldscope Datastream, expressed in thousand euros, multiplied by 1,000).
NetIncome	Ratio of net income (item WC01751 in Worldscope Datastream) to total assets (item WC02999).
NS	North-South spread, computed as the difference between the 10-year German sovereign bond rate against an average of Greece, Ireland Italy, Spain, and Portugal 10-year rates (European Central Bank)
RMW	Difference between the returns of robust and weak stocks (Robust-Minus-Weak factor) from Kenneth French website library.
RR	Risk Reversal on the USD/EUR options from Bloomberg.
Scope3 Emissions	Ratio of Scope3 emissions in tonnes (from Carbone 4) to sales (WC01001 in Worldscope Datastream, expressed in euros).
SMB	Difference between the returns on portfolios of small and large stocks (Small-Minus-Big factor) from Kenneth French website library.
VMS	Physical risk factor, constructed as a long-short portfolio based on Trucost physical climate risk scores for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies).
WML	Difference between the returns on portfolios of the past winner and past loser stocks (Momentum factor) from Kenneth French website library.
YC	Yield Curve indicator, computed as the spread between 10-year and 2-year Euro Area composite rates (European Central Bank).

2. The informational effects of corporate sustainability initiatives

Abstract:

This study examines the informational effects of highly visible sustainability initiatives. I show that highly visible initiatives, such as issuing green bonds or signing the Business Roundtable (BRT) Statement on the Purpose of a Corporation, have a significant impact on firms' information environments. Using Google search volume data, I show that the attention of the general public increases after such initiatives. Additionally, investors and customers become more likely to request information on environmental considerations after green bond issuances but not after firms' signature of the BRT Statement, which suggests that investors and customers do not react to purely declarative initiatives. Moreover, using two different environmental data providers, I find that visible sustainability initiatives can either positively or negatively affect environmental ratings through attention and transparency effects. My findings contribute to the current understanding of why firms engage in highly visible sustainability actions despite their potential costs.

2.1. Introduction

According to Friedman (1970), the sole responsibility of a company is profit. However, on August 19, 2019, the Business Roundtable (BRT), an association of chief executive officers (CEOs) from the United States' largest companies, modified its definition of the purpose of a corporation. This new definition “*moves away from shareholder primacy*” and “*includes a commitment to all stakeholders*”.¹⁵ Therefore, companies, or at least some of them, seem to integrate corporate social responsibility (CSR) into their objective functions. This echoes a growing demand from investors: since 1995, sustainable and responsible investment (SRI) has grown at an annual rate of 13.6% in the United States. SRI now represents 26% of the assets under management in the United States.¹⁶

Companies are implementing various initiatives to address investor and societal expectations on CSR. In addition to the BRT Statement, green bonds represent one the most remarkable manifestations of this growing integration of CSR by companies. Green bonds account for 3.5% of total global bond issuance (Ehlers, Mojon, and Packer, 2020) and more than half of the entire sustainable debt market.¹⁷ However, these initiatives can be costly. First, following socially responsible objectives might be detrimental to firm value.¹⁸ Second, undertaking sustainability initiatives potentially exposes firms to subsequent legal and reputational costs if they do not “walk the talk”, that is, if the substance of their sustainability initiatives falls short of their claims.¹⁹

¹⁵ The complete Statement is available [here](#).

¹⁶ For details, see [this report](#) from the Forum for Sustainable and Responsible Investment.

¹⁷ See this [article](#) from Bloomberg.

¹⁸ Several papers, for instance, McWilliams and Siegel (2000) and Flammer (2015), have found mixed evidence regarding the conflict that might exist between CSR and shareholder value maximization. Krüger (2015) interprets negative stock market reactions to positive CSR news as evidence that implementing CSR policies is costly and the expected benefits from implementing these policies fall short of the costs.

¹⁹ For instance, in the United Kingdom, beginning in 2022, the Competition and Markets Authority will review the environmental claims made by companies and take legal actions against misleading green claims. See this

In this paper, I investigate some of the nonfinancial benefits companies derive from their sustainability initiatives. These benefits may explain why some companies undertake CSR actions despite their expected costs. More precisely, I study the impact of highly visible sustainability initiatives, i.e., salient CSR initiatives, on the transmission of environmental, social and corporate governance (ESG) information to market participants (a firm's ESG information environment). I use two types of initiatives, namely, green bond issuances and the signing of the BRT Statement on August 19, 2019, to study how companies might attract the attention of the general public, environmental raters, customers, and investors through their implementation of highly visible CSR initiatives. My choice of these two initiatives is motivated by several factors. First, green bond issuances and the BRT Statement are arguably two of the most visible firm-level sustainability initiatives. Second, they present the advantage of having clear announcement dates. Third, the BRT Statement is a nonbinding statement, while green bonds are used to finance identifiable sustainability projects. This allows me to assess whether companies that make purely declarative statements of intent and firms that actually invest in identifiable sustainability projects derive similar benefits.

I begin my empirical analysis by estimating the relationship between visible sustainability initiatives and general public attention. Specifically, I regress global firm-week Google search volume on dummy variables capturing visible CSR initiatives. I find that global firm-week search volume increases after these initiatives after controlling for fixed effects at various levels. Then, I examine the impact of visible sustainability initiatives on the attention of investors and customers. To that end, I rely on questionnaires sent to firms by the Carbon Disclosure Project (CDP), a not-for-profit organization, on behalf of a network of large

[article](#) from Bloomberg. Moreover, this [article](#) from Forbes argues that greenwashing negatively affects employee motivation and retention.

investors and customers.²⁰ I use the sending of a questionnaire to a given firm as a proxy for the attention investors and customers pay to that firm. I find that companies are more likely to receive attention from investors and customers after the issuance of green bonds, whereas signing the BRT Statement does not yield a similar increase in attention. These findings suggest that the attention of customers and investors increases in reaction to visible sustainability initiatives but only when these initiatives are not purely declarative. I then analyze the effect of visible sustainability initiatives on the attention of environmental raters. Using two different environmental rating providers (MSCI and CDP), I show that green bond issuances increase environmental performance scores. However, across my specifications, green bond size (relative to firm size) generally has no significant impact on environmental ratings, which suggests that environmental raters primarily react to a firm's status as a green bond issuer rather than the portion of assets it allocates to green projects. I also find that the effect of issuing green bonds on environmental ratings decreases after 2016, i.e., when green bonds became more widely used. Regarding the effect of signing the BRT Statement on environmental ratings, I find a positive effect of this action on CDP ratings but a negative effect on MSCI scores. In summary, my results on environmental ratings are consistent with the views that visible sustainability initiatives impact the attention of environmental raters, that such initiatives have weaker effects when they become less differentiating, and that purely declarative initiatives can positively or negatively affect environmental ratings, as they increase raters' margins for interpretation. However, another factor that could explain my results on environmental ratings is transparency: visible sustainability initiatives could influence the amount of environmental information disclosed by firms, thus affecting the information collected by raters. I measure transparency based on firms' answers to the CDP questionnaires. I find that issuing green bonds tends to positively affect transparency, while signing the BRT Statement has a negative impact

²⁰ See [this page](#) on the website of the CDP for more information.

on transparency. This implies that a decrease in information asymmetry is, at least for some environmental raters, not a necessary condition for a positive reaction of environmental ratings to visible sustainability initiatives. Overall, my results suggest that firms obtain informational benefits by undertaking highly visible sustainability actions. However, these benefits are more nuanced in the case of purely declarative initiatives due to both a lack of concrete commitments to achieve sustainable goals and a lack of transparency.

Endogeneity might stem from several sources. Indeed, in addition to ESG considerations, other observed and unobserved factors could drive the decision to undertake sustainability actions. I use several strategies to mitigate these concerns. To account for observable differences, I conduct my analysis on a matched sample. Specifically, for each firm that implements visible sustainability initiatives, I identify the five nearest neighbors within the same year and industry. I also include several control variables and fixed effects in my regressions. In addition to observable factors, several unobservables could be at play. Notably, environmental performance scores and sustainable actions could be codetermined. Moreover, firms' willingness to increase their environmental performance is unobservable and could affect both their environmental scores and their decisions to issue green bonds or sign the Business Roundtable Statement, thereby creating an omitted variable problem. Finally, firms might self-select into the green bond issuer (Business Roundtable signatory) group due to the expected benefits of issuing (signing). To account for endogeneity due to unobservable factors, I suggest a two-stage approach to account for the nonrandomness of issuing and signing decisions (selection into treatment). My results are robust to these approaches. Furthermore, using data from MSCI IVA and the CDP, I can assess whether my results on environmental ratings are specific to a data provider. This is crucial, as several articles have highlighted a lack of methodological agreement between ESG rating providers; see, for instance, Berg, Koelbel, and Rigobon (2020) or Chatterji et al. (2016).

My paper contributes to several lines of research. First, my paper contributes to the literature on visibility and information production. Several articles have addressed the determinants of the information production decisions of third parties, such as those related to the coverage initiation of financial analysts (Ertimur, Muslu, and Zhang, 2011), analyst coverage interruption (Mola, Rau, and Khorana, 2013), or credit rating coverage (Faulkender and Petersen, 2006). In the context of CSR, Durand, Paugam, and Stolowy (2019) show that CSR visibility can increase financial analyst coverage. In a univariate setting, Lys, Naughton, and Wang (2015) remark that, in their early years, ESG ratings tended to cover larger firms. Several articles have also analyzed the firm-level determinants of ESG and climate risk disclosure, for instance, initiations of voluntary nonfinancial disclosure (see, for instance, Dhaliwal et al., 2011) or carbon disclosure (Ilhan, Sautner, and Vilkov, 2021, Matsumura, Prakash, and Vera-Munoz, 2014).²¹ These articles consistently show that firm size, measuring firms' general visibility, positively predicts the information production of third parties and firms. However, to the best of my knowledge, my article is the first to analyze how firms can strategically use sustainability initiatives as a tool to attract the attention of the general public, customers, investors, and environmental raters.

Second, my paper is related to the literature questioning the validity of commonly used proxies for CSR.²² Studying the adoption of the United Nations Principles for Responsible Investment (UNPRI), Gibson et al. (2020) highlight that US-based signatories that partially implement ESG strategies invest in companies with lower ESG scores than those invested in by US-based nonsignatories. In a similar spirit, Kim and Yoon (2020) prove that many active mutual funds use their UNPRI status to attract capital but do not improve their fund-level ESG

²¹ Christensen, Hail, and Leuz (2019) provide an extensive literature review on the determinants of CSR reporting. Specifically, see Table A1 for firm-level determinants of CSR reporting.

²² This literature should be distinguished from papers assessing the ability of ESG ratings to create value for shareholders (see, for example, Daines, Gow, and Larcker, 2010, Guest and Nerino, 2020, Lehman, 2019).

scores afterward. Several papers go further and cast doubt on the ability of ESG ratings to accurately reflect corporate social performance. Using a regulation passed in the US to limit greenwashing, Yang (2019) shows that the MSCI environmental ratings of affected firms diminished by 0.4 to 0.5 points after the regulation (representing a 9% decrease). Raghunandan and Rajgopal (2020) find that ESG ratings are negatively affected by negative environmental or social news coverage but unaffected by violations of environmental or social laws. Moreover, Yang (2019) shows that good environmental ratings positively predict future negative CSR-related news, future lawsuits, and future regulatory penalties. In addition, ESG raters might exhibit biases that penalize some industries. Cohen, Gurun, and Nguyen (2020) find that energy producers have ESG scores that are consistently lower than those of other firms and are less rewarded for their green innovation efforts despite producing more green innovation both qualitatively and quantitatively. Furthermore, higher levels of CSR disclosure lead to greater disagreement across rating agencies because subjective information disclosure expands opportunities for interpretation (Christensen, Serafeim, and Sikochi, 2021), larger companies tend to have better ESG scores because they have more resources to disclose sustainability-related information (Drempetic, Klein, and Zwergel, 2020), and ESG scores tend to be inflated when rated firms share institutional investors with their rating agencies (Tang, Yan, and Yao, 2021). My paper contributes to this stream of literature by showing that firms can influence their environmental ratings by undertaking visible sustainability initiatives and that some environmental raters might incentivize firms to undertake sustainability actions with only minimal substance.

Third, this research is related to the literature on green bonds. Baker et al. (2018) and Zerbib (2019) show that, due to the pro-environmental preferences of (some) investors, green bonds are issued at lower yields than equivalent conventional bonds. However, Larcker and Watts (2020) argue that such a green premium does not exist and that the difference stems from

methodological design misspecifications. Tang and Zhang (2020) find positive cumulative abnormal returns around green bond issuance announcements. Thus, certain preliminary pieces of evidence indicate that green bond issuances are associated with financial benefits for corporations. Less research has been done on the relationship between green bonds and nonfinancial performance. Using CO₂ emissions data and environmental ratings from ASSET4, Flammer (2021) finds that green bond issuances act as a transparency device reducing information asymmetries, and that they are therefore associated with increases in environmental ratings in subsequent years. However, Ehlers, Mojon, and Packer (2020) find no evidence that green bond issuances are associated with any reduction in carbon intensities over time at the firm level. According to these authors, the driving force of this null result is that issuing green bonds does not preclude firms from engaging in carbon-intense activities in other areas. My paper expands this literature by showing that companies can derive nonfinancial benefits by undertaking visible sustainability initiatives such as green bond issuances mainly through increased attention from the general public, customers, investors, and environmental raters.

The rest of this paper is structured as follows. In section 2, I present my hypotheses. In section 3, I present my dataset. I analyze my empirical results in section 4, and section 5 concludes.

2.2. Hypothesis development

My goal is to identify the reactions of the general public, customers, investors, and environmental raters to visible sustainability initiatives. This reaction is measured at the firm-week level with global weekly Google search volume over a one-year window around visible sustainability initiatives. As argued by Da, Engelberg, and Gao (2011), Google search volumes likely capture the attention of retail investors. Barber and Odean (2008) find that the behavior

of retail investors is influenced by attention-grabbing events whether such events pertain to small or large firms. On the one hand, recent papers show that public attention is sensitive to sustainability-related events (Choi, Gao, and Jiang, 2020, Ilhan, Sautner, and Vilkov, 2021). On the other hand, several articles show that firms can impact attention, for instance, through advertising (Grullon, Kanatas, and Weston, 2004, Lou, 2014), international cross-listing (Baker, Nofsinger, and Weaver, 2002), modifying their names (Green and Jame, 2013), or changing their disclosure language (Boulland, Degeorge, and Ginglinger, 2017). According to Hawn and Ioannou (2016), in the context of CSR, firms use *“public and highly visible initiatives and patterns of communication that involve the undertaking of ceremonies to gain legitimacy, primarily through the seeking of public endorsement of the organization and its practices by outside audiences.”* Therefore, undertaking visible sustainability initiatives could foster public awareness. This leads me to the following hypothesis:

Hypothesis 1: Visible sustainability initiatives attract general public attention.

My measure of investor and customer attention is based on questionnaires sent by the CDP on behalf of its network of large institutional investors and major purchasers. Recent evidence has shown that institutional investors and customers pay attention to firm sustainability practices (Ilhan et al., 2020, Schiller, 2018). Notably, green bond announcements are associated with subsequent increases in institutional ownership, positive market reactions and improved liquidity (Flammer, 2021, Tang and Zhang, 2020). However, Raghunandan and Rajgopal (2020) show that the release of the BRT Statement did not cause any significant stock market reaction. A key distinction might explain this discrepancy: green bonds are associated with identifiable projects, whereas signing the BRT Statement is a purely declarative initiative. Consistent with this perspective, Flammer (2021) finds that the average green bond issuer

diminishes its CO₂ emissions post-issuance, while Raghunandan and Rajgopal (2020) document that BRT Statement signatories have higher polluting emissions after signing than matched control firms. Hence, the attention of investors and customers to environmental considerations should be positively affected by only visible sustainability initiatives that have the potential to impose real effects:

Hypothesis 2: Visible sustainability initiatives attract the attention of investors and customers if and only if they are not purely declarative.

Most papers implicitly assume that ESG ratings capture the “true” environmental and social performance of firms or at least represent a viable proxy (Raghunandan and Rajgopal, 2020). I do not make such an assumption. I posit that ESG ratings are important *per se*, as a significant number of market participants rely on this source of information. Indeed, CFA Institute (2017) finds that 73% of portfolio managers and research analysts take ESG factors into consideration. Among them, 66% rely on third-party research. Using the introduction of the Morningstar sustainability ratings in 2016 as a natural experiment, Hartzmark and Sussman (2019) show that mutual funds categorized as highly sustainable experienced net inflows of more than \$24 billion during the study period, while low-sustainability funds faced net outflows of more than \$12 billion. Furthermore, Amel-Zadeh, Lusterms, and Pieterse-Bloem (2021) document an analogous result using firm-level sustainability ratings. Moreover, several articles, including Chava (2014) and El Ghouli et al. (2011), find that having good ESG scores decreases firms’ cost of capital, while Albuquerque, Koskinen, and Zhang (2019) provide evidence that ESG scores positively affect firm valuations. Lins, Servaes, and Tamayo (2017) show that firms with high ESG scores are more able to resist crisis periods, and Huynh and Xia (2020) show that investors are willing to pay a premium for bonds issued by firms with better environmental

performance scores when climate change concerns are high. As a result, regardless of their potential limitations, ESG ratings are outcomes of interest, particularly for firms (Chatterji and Toffel, 2010).

The need for visible CSR actions stems from the inability of market participants to fully identify and reward substantive CSR actions (Hawn and Ioannou, 2016). Focusing on the content of ESG ratings, Delmas, Etzion, and Nairn-Birch (2013) find that the environmental processes implemented by firms account for 46% to 53% of the variance in environmental performance scores, and environmental outcomes only account for 33% to 41% of this variance. Thus, information dissemination plays a critical role in shaping sustainability scores. Visible sustainability initiatives can impact these scores through two informational channels, which can coexist. The first channel is transparency: visible sustainability initiatives are a means by which firms can clarify their sustainability approaches, for instance, through the disclosure of new reports related to their initiatives. According to this view, visible sustainability initiatives curb adverse information asymmetries. The second channel is attention.²³ PwC (2020) states that *“by leaving a communication gap for third parties to fill, corporates are losing control over their ESG story”*; hence, firms need to *“shape the narrative around their brand and practices.”* According to this view, visible initiatives could help create a positive CSR narrative and attract the attention of ESG raters.²⁴ This attention effect could specifically stem from the resource constraints of ESG raters.²⁵

²³ Both the transparency and attention channels should be distinguished from greenwashing (undertaking symbolic projects with no real environmental or social benefits). The question of potential greenwashing relates to the content of sustainability initiatives, while the transparency and attention channels pertain to the mechanisms through which ESG raters react to these initiatives.

²⁴ Consistent with the coexistence of the transparency and attention channels, the Climate Bonds Initiative, a nonprofit organization promoting green bonds, argues in [Explaining green bonds](#) that issuing green bonds allows companies to *“highlight their green assets”* and generate a *“positive marketing story”*.

²⁵ For instance, MSCI ESG acknowledges that its approximately 250 analysts cover more than 8,700 companies on 35 key issues, and each key issue is subdivided into an exposure score and a management score. Each score is updated at least annually based on company disclosures, media sources, and specialized datasets. This means that the average analyst defines at least $8,700 \times 35 \times 2 / 250 = 2,436$ scores per year. See this [brochure](#) and the [MSCI ESG ratings methodology](#).

In my setting, I use two types of sustainability initiatives. The first one, green bond issuances, is accompanied by documents justifying the use of the bond proceeds and explaining how these funds will help attain sustainability goals. We can reasonably expect that this information is then made available to environmental raters at a relatively low cost. The second type of initiative, signing the BRT Statement, is purely declarative and does not detail concrete approaches to sustainability performance improvement. Christensen, Serafeim, and Sikochi (2021) argue that disagreements between ESG raters tend to decrease when more objective information is available but increase with the availability of subjective information, as the latter leaves opportunities for different interpretations. Thus, issuing green bonds should give raters less margin for interpretation, thereby eliciting homogeneous reactions from them, while signing the BRT Statement should give raters an increased margin for interpretation and therefore provoke heterogeneous reactions. This leads me to the following hypothesis:

Hypothesis 3: Visible sustainability initiatives affect both firms' transparency and the attention of environmental raters. The effect of visible sustainability initiatives on environmental ratings depends on the relative importance of each channel.

2.3. Data

First, I identify all the corporate green bond issuances reported by Bloomberg between 2013 and 2020. This corresponds to 3,292 operations conducted by 856 different firms. I retrieve complete firm-year information (the book value of assets, market value of assets, profitability, Tobin's Q, R&D expenses, tangible assets, debt ratio, Standard Industrial Classification (SIC) code, and country of company headquarters of each firm) from Compustat for the 329 issuing companies included. Then, I repeat this procedure for the 181 firms that signed the Business

Roundtable Statement on August 19, 2019, retrieving complete firm-year information from Compustat for the 149 signatory companies in the sample. All the Compustat variables are winsorized at the 1st and 99th percentiles.

For the tests shown in Table 1, I obtain internet search activity from Google Trends. I download the global weekly search volume of each company in my sample corresponding to a one-year window around the relevant event date (for green bond issuers, the announcement date of their first green issuance; August 19, 2019 for the BRT Statement signatories).²⁶ Next, I drop any firms with low search volumes (where at least 10% of the firm-week observations are equal to zero with search volumes ranging from 0 to 100). I also drop firms that issued their first green bonds after July 2020, as I do not have complete postevent windows for such firms. This leaves 231 firms that issued green bonds and 149 firms that signed the BRT Statement.

For the tests shown in the other tables, I match my Compustat data with environmental performance scores from two different data providers, namely, MSCI IVA and the CDP. Among the 329 firms that issued green bonds, 187 (167) firms received MSCI IVA (CDP) ratings in the year preceding their issuance. I find the five nearest neighbors of each of these firms within the same year and industry.²⁷ My matching variables are the following: environmental score (in the year before the firms' green bond issuance), profitability, R&D expenses, Tobin's Q, the tangibility of assets, the leverage ratio, the natural logarithm of the book value of assets, and the natural logarithm of the market value of assets.²⁸ This procedure, which I conduct using Mahalanobis matching with replacement and with adjustment for biases

²⁶ I rely on topics rather than search terms, as the former takes into account misspellings and adapts to different languages. See [here](#) for an explanation of the differences between topics and search terms.

²⁷ More precisely, I follow the SIC Manual division of SIC codes into 10 different industries. Kahle and Walkling (1996) warn us that this classification is an accurate breakdown of economic activities while using one-digit SIC codes is incorrect.

²⁸ I include both the natural logarithm of the book value of assets and the natural logarithm of the market value of assets of each firm to improve the covariate balance on firm size between the treated firms and controls. However, as these two variables are strongly correlated (94%), I only include the natural logarithm of the book value of assets in my regressions.

generated by matching on multiple continuous variables (see Abadie and Imbens, 2006, and Abadie and Imbens, 2011), allows me to match 129 (120) green bond issuers with MSCI ratings (with CDP ratings) to 484 (499) counterfactual firms that did not issue green bonds.²⁹ I proceed similarly for the BRT Statement signatories. Among my 149 signatories, 90 (83) have MSCI (CDP) ratings for the year preceding the signature. My matching procedure allows me to match 75 (71) treated firms with 346 (224) control firms.

I then repeat the matching for tests on transparency. The treated group is identical to that described in the case of CDP ratings. The only difference is that instead of matching on the ex ante value of *CDP leadership level* (the environmental score), I match on the ex ante level of *Transparency*. This enables me to identify 485 (214) counterfactual firms for my 120 (71) green bond issuers (BRT Statement signatories).

Finally, I turn to firms that did not receive a CDP rating during the preceding year. The CDP rates firms only based on the demand of investors and customers.³⁰ Therefore, I use the receipt of a CDP questionnaire by firms that did not receive such a questionnaire during the preceding year as a proxy for investor and customer attention. I repeat my matching procedure using the same seven observable financial characteristics. This procedure allows me to identify 122 (26) firms that issued green bonds (signed the BRT Statement) and did not receive attention from investors and customers during the preceding year. There are 568 and 100 counterfactual firms, respectively.

The descriptive statistics related to Google Trends are shown in Table 1 (Panel A). The other descriptive statistics are reported in Table 2. For the sake of brevity, only the descriptive statistics pertaining to the green bond issuers and their matched control firms are reported in

²⁹ Matching with replacement implies that the same control firm can be the nearest neighbor of multiple treated firms, and this explains why the size of my control group is less than five times that of my treatment group.

³⁰ CDP questionnaires are sent at the request of large investors and customers; see [here](#) for details.

Table 2. These descriptive statistics indicate that my matching procedure successfully removes most of the differences in observable characteristics. All the variables are defined in Appendix 1.

2.4. Empirical results

2.4.1. Visible sustainability initiatives and general public attention

The descriptive statistics of this study's variables are reported in Table 1 (Panel A). The average Google search volume is 55.31 (58.38) for the green bond issuers (BRT Statement signatories); on average, the firms' global weekly search volume represents 55.31% (58.38%) of the two-year maximum.

I start my analysis by plotting the evolution of the firms' Google search volume around their initial green bond issuance announcements (Figure 1). In contrast to the BRT Statement signing date, the announcement date of a green bond issuance is firm-specific; therefore, this figure is arguably less confounded by time trends. Figure 1 suggests that Google search volumes are higher before an issuance than afterward.

I then conduct a multivariate analysis using the following model:

$$Google\ Trends_{i,t} = \alpha + \beta_1 Visible\ ESG\ initiative_{i,t} + \beta_2 Z_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $Google\ Trends_{i,t}$ is the global weekly search volume of firm i in week t ; $Visible\ ESG\ initiative_{i,t}$ refers to *Green bond (3 months)*, *BRT Statement (3 months)*, *After green bond*, or *After BRT Statement*, depending on the specification; and $Z_{i,t}$ is a vector of fixed effects. Clustering effects could bias the statistical significance of the results due to cross-sectional dependence. Thus, when estimating my regressions, I apply the

procedures described by Petersen (2009) related to adjusting standard errors when clustering by firm.

When year fixed effects are controlled, issuing green bonds generates an increase in Google search volume of 0.95 (column 1, Panel B) during the 3 months following the announcement date and an increase of 2.56 (column 2, Panel B) during the year following the announcement date. Signing the BRT Statement yields an effect of +1.88 (column 1, Panel C) during the 3 months following August 19, 2019; however, this effect is nonsignificant during the year following the announcement date. However, year fixed effects might be insufficient to control for temporal effects. When both year and month effects are controlled, issuing green bonds generates an increase in Google search volume of 1.09 (column 3, Panel B) in the 3 months following the announcement date and an increase of 2.81 (column 4, Panel B) in the year following the announcement date. Signing the BRT Statement yields an effect of +2.52 (column 3, Panel C) in the 3 months following August 19, 2019 and an effect of +1.47 (column 4, Panel C) in the year following the BRT Statement.

Alternatively, I apply a firm-month-year fixed effects regression to control for any invariant characteristics within a firm-month-year. My previous results are confirmed: issuing green bonds generates an increase in Google search volume of 1.41 (column 5, Panel B) during the 3 months following the announcement date and an increase of 1.47 (column 6, Panel B) during the year following the announcement date, while signing the BRT Statement yields an effect of +2.76 (column 5, Panel C) during the 3 months following August 19, 2019 and an effect of +1.96 (column 6, Panel C) during the year following the BRT Statement. The results of these conservative specifications indicate that issuing green bonds generates an increase in Google search volume amounting to between 2.54% and 2.65% of the mean search volume and that an increase ranging from 3.36% to 4.98% of the mean search volume occurs after signing the BRT Statement.

Overall, my results indicate that undertaking highly visible sustainability initiatives generates public attention as proxied by Google search volume. These findings are in line with my first hypothesis.

2.4.2. The effect of visible ESG initiatives on investors' and customers' attention to environmental considerations

Thus far, my analysis has shown that visible sustainability initiatives influence general public attention. I now examine whether visible sustainability initiatives affect the attention of investors and customers (stakeholders). My regression model is as follows:

$$\text{Stakeholder attention}_{i,t} = \alpha + \beta_1 \text{Visible ESG initiative}_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{i,t} + \varepsilon_{i,t} \quad (2)$$

where *Stakeholder attention*_{*i,t*} is a dummy variable equal to one if company *i* received a questionnaire from the CDP for the first time during year *t*. *Visible ESG initiative*_{*i,t*} refers to my measure of visible sustainability initiatives, which is either *Green bond issued*_{*i,t*}, a dummy variable equal to one if firm *i* issued green bonds during year *t*, or *BRT Statement*_{*i,t*}, a dummy variable equal to one if firm *i* signed the BRT Statement on August 19, 2021. *X*_{*i,t*} is a vector of controls, and *Z*_{*i,t*} is a vector of fixed effects. This regression includes only firms that did not receive attention from investors and customers during the preceding year.

To the best of my knowledge, my article is, with Ilhan et al. (2020), one of the first to analyze the determinants of the attention given by customers and investors to environmental considerations. However, several articles have addressed various related questions pertaining to the determinants of the information production of third parties, such as the determinants of financial analysts' coverage initiation (Ertimur, Muslu, and Zhang, 2011), the loss of analyst coverage (Mola, Rau, and Khorana, 2013), and credit rating coverage (Faulkender and Petersen, 2006). I build on these related papers in choosing my set of control variables. I control for the

size (natural logarithm of the book value of assets), profitability, Tobin's Q, R&D expenses, tangible assets, and debt ratio of each firm. Furthermore, I include country fixed effects, 2-digit SIC code industry fixed effects, and year fixed effects to control for any determinant of the attention given by investors and customers to environmental considerations that is constant within a country, industry, or year.

My results are reported in Table 3. Controlling for these firm financial characteristics, as well as country, industry, and year fixed effects, I find that size is consistently associated with higher levels of attention given by customers and investors to environmental considerations. Turning to my two variables capturing visible sustainability initiatives, I find that issuing green bonds increases the probability of receiving an information request on environmental issues from customers and investors. Issuing green bonds is associated with a 7.24 percentage point increase in the probability of receiving an information request during the year of issuance (column 1).

However, a natural concern is endogeneity. Notably, simultaneity issues might affect the results reported in column 1. Therefore, in column 2, I use *stakeholder attention* as measured during the year following each firm's issuance. Due to the novelty of green bonds, this approach comes at the cost of discarding a substantial part of my observations: as my data cover a period ending in 2020, I study green bonds issued up to 2019. My findings indicate a 15.2 percentage point increase in the probability of receiving an information request from investors and customers during the year after a firm's issuance. I also follow a two-stage approach to account for the nonrandomness of issuing decisions that uses a treatment effect model (see, for instance, Acharya and Zu (2017) for a description of this method).³¹ Indeed, the benefits of issuing green bonds might differ across firms and thereby affect the probability of issuing green bonds. In

³¹ As explained in Lennox, Francis, and Wang (2012), this method should be distinguished from sample selection, i.e., cases where regressions are estimated on a subsample of observations.

other words, there might be selection into the treatment group. To correct for this potential selection, I run, in the first stage of my treatment effect model, a probit regression in which the probability of issuing green bonds is regressed on profitability, R&D expenses, tangible assets, Tobin's Q, the leverage ratio, the log-value of total assets, and the average value of *Green bond issued* of country-industry-year peer firms. The results of the first step indicate that a 1% increase in the propensity of country-industry-year peers to issue green bonds is associated with a 0.08% increase in the probability of issuing green bonds (Appendix 2, Panel A, column 1). In the second step, I add the inverse Mills ratio obtained during the first step to the regression reported in Table 3, column 1. My results, which are reported in Appendix 2 (Panel B, column 1), indicate that issuing green bonds increases the probability of attracting the attention of investors and customers by 7.45 percentage points during the year of issuance.

Regarding BRT Statement signatories, my regressions indicate a nonsignificant negative effect of signing the BRT Statement on the attention given by investors and customers to environmental issues (Table 3, columns 3 and 4). The results regarding my treatment effect highlight that firms become 0.07% more likely to sign the BRT Statement when the propensity of their country-industry-year peers to sign it increases by 1% (Appendix 2, Panel A, column 2). After adjusting for selection, I find that being a BRT Statement signatory significantly decreases a firm's probability of attracting investors' and customers' attention by 15.4 percentage points (Appendix 2, Panel B, column 2). One caveat of this test is that most BRT Statement signatories were already included in the scope of the CDP before signing the Statement; therefore, my findings rely on a relatively small number of signatories (26 firms).

Overall, my results suggest that investors and customers give more attention to the environmental profiles of companies that undertake visible sustainability initiatives, but only when these initiatives are not purely declarative. These results are consistent with my second hypothesis.

2.4.3. Visible sustainability initiatives and environmental ratings

We have seen in previous tests that visible sustainability initiatives are associated with increased general public attention and, in the case of green bonds, increased attention from investors and customers. I now investigate whether environmental ratings are impacted by visible sustainability initiatives.

In my multivariate analysis, I regress the examined environmental ratings on my two dummy variables that are proxies for visible sustainability initiatives after controlling for traditional determinants of CSR performance, namely, Tobin's Q, profitability, firm size, R&D expenses, the leverage ratio, the tangibility of assets, and country, industry, and year fixed effects; see, for instance, Cronqvist and Yu (2017), Dyck et al. (2019) and Liang and Renneboog (2017) for comparable specifications. My baseline regression is as follows:

$$\text{Environmental Score}_{i,t} = \alpha + \beta_1 \text{Visible ESG initiative}_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{i,t} + \varepsilon_{i,t} \quad (3)$$

where *Environmental Score*_{*i,t*} refers to my measures of environmental performance scores, either *MSCI environmental score (t)* or *CDP leadership level (t)*; *Visible ESG initiative*_{*i,t*} refers to either *Green bond issued*_{*i,t*} or *BRT Statement*_{*i,t*}; *X*_{*i,t*} is a vector of controls that have been shown to affect a firm's level of ESG performance; and *Z*_{*i,t*} is a vector of fixed effects.

As the results in Table 4 indicate, a larger size is associated with a higher environmental performance score. This result remains similar when MSCI IVA scores (columns 1 and 2) or CDP scores (columns 3 and 4) are used. Furthermore, by including country fixed effects, 2-digit SIC code industry fixed effects, and year fixed effects, I control for any determinant of environmental performance that is constant within a country, industry, or year.

Controlling for several financial characteristics of firms, as well as country, industry, and year fixed effects, I find that issuing green bonds increases a firm's environmental performance score: a firm's issuance is associated, in the year of issuance, with a 0.66 increase in its MSCI environmental score (Panel A, column 1) and a 9.33 percentage point increase in the probability of the firm being identified by the CDP as a leading company in terms of environmental performance (Panel A, column 3). These effects correspond to increases of 11% and 33%, respectively. My treatment effect model indicates slightly higher but nonsignificant effects in Appendix 3: a green issuance is associated with a 0.82 increase in a firm's MSCI score (Panel B, column 1) and a 9.65 percentage point increase in the firm's probability of being identified by the CDP as an environmental leader (Panel B, column 2); these are increases of 14% and 34%, respectively. The results of the first stage underline that the probability of issuing green bonds increases by 0.06 to 0.07% when the propensity of peer firms to issue such securities increases by 1% (Panel A, columns 1 and 2). Issuing green bonds also positively impacts environmental scores in the subsequent year, with a 0.58 increase in the MSCI environmental score (Panel A, column 3) and a 15.8 percentage point increase in the probability of being identified by CDP as among the best performers (Panel A, column 4). These variations correspond to increases of 10% and 56%, respectively.

My findings regarding the effect of signing the BRT Statement on environmental ratings are more nuanced. Using MSCI environmental scores, I find that signing the BRT Statement is associated with a 0.43 decrease in a firm's environmental score during the year of signature (Panel B, column 1) and a nonsignificant decrease of 0.25 during the following year (Panel B, column 2). On the other hand, using data from the CDP, I find that signing the BRT Statement improves a firm's chances of being identified as an environmental leader by 11.1 to 12.2 percentage points (Panel B, columns 3 and 4). These results are confirmed by my treatment effect model (Appendix 3). In columns 3 and 4 of Panel A, my first-stage findings underline

that a company becomes 0.07 to 0.09% more likely to sign the BRT Statement when the percentage of its peer firms that are signatories increases by 1%. Columns 3 and 4 of Panel B corroborate that signing the BRT Statement negatively impacts a firm's MSCI environmental score (-0.76) but positively affects its probability of being identified by the CDP as a top environmental performer (+15.2 percentage points). In summary, the effect of signing the BRT Statement on firms' MSCI scores is negative and ranges from -4% to -13%, while the impact of this action on the probability of a firm being identified by the CDP as a sustainability leader is positive, ranging from 39% to 54%.

Next, I evaluate the economic channels that drive these results. In Table 5, I exploit variations in the size of green bond issuances to investigate whether the size of a green bond issuance (in terms of the percentage of a firm's balance sheet) has additional explanatory power regarding the level of environmental ratings beyond the corresponding firm's binary status as a green bond issuer or nonissuer. To address this question, I introduce two variables. The first variable, *Large green bond*, is a dummy variable equal to one if the focal company has issued green bonds and the proceeds to total assets ratio is greater than the median among firms that have issued green bonds. The second, *Green bond size*, represents the proceeds to total assets ratio. If environmental ratings primarily react to the substance of CSR actions, companies that issue larger green bonds (in terms of the percentage of their balance sheets) should experience larger increases in their environmental ratings, as they are dedicating a larger share of their resources toward green projects. When both firms' green bond issuer status and their green bond size are included as explanatory variables, both variables should be significantly associated with higher environmental scores if these scores reflect both the substance of visible CSR actions and the informational effects that these actions entail. In contrast, a firm's green bond issuer status (green bond size) should be the only significant variable if environmental ratings reflect only the informational effects (substance) of these actions.

Panel A reports the results regarding MSCI environmental scores. In columns (1) to (4), I find that the size of green bond issuances has a positive but generally nonsignificant effect. Columns (1) and (2) indicate that, compared to firms that issue small green bonds (with proceeds to total assets ratios less than the median among green bond issuers), firms that issue green bonds larger than the median experience an nonsignificant 0.05 to 0.18 additional increase in their environmental ratings. These effects represent 0.9% to 3.1% of the mean environmental rating. Columns (3) and (4) further report that increasing the proceeds to total assets ratio by one percentage point only yields a 0.06- (nonsignificant) to 0.09-point increase in the firms' MSCI environmental scores, which corresponds to an increase of between 1% and 1.6% of the mean rating. Panel B shows that CDP ratings react positively but nonsignificantly to a firm's status as a large issuer (columns 1 and 2). Panel B reports the results regarding CDP environmental scores. Across my specifications, the results reported in columns (1) and (4) indicate that firms issuing larger green bonds (with respect to the size of their balance sheet) experience a nonsignificant additional increase in their probability of being identified as a sustainability leader.

The mainly fixed benefits of green bond issuances highlighted in Table 5 suggest a predominance of informational channels (transparency and attention) in the relationship between visible sustainability initiatives and environmental ratings. Indeed, undertaking visible sustainability initiatives could induce firms to become more transparent in terms of their approaches to sustainability issues, thereby facilitating environmental raters' information collection and ability to assess environmental performance. In addition to transparency, attention effects could be at play, notably because of the resource-constrained nature of raters. To further analyze the channels underlying the positive reaction of environmental ratings to visible sustainability initiatives, in Table 6, I investigate the impact of green bonds on environmental ratings around the year 2016. If the attention channel predominates, the effect

of green bonds on environmental ratings should be lower after 2016, i.e., during the second half of my sample period, when green bonds became more widely used. If the transparency channel prevails, the difference in transparency between the green bond issuers and counterfactual firms should become smaller after the publication of the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD) and the implementation of the Non-Financial Reporting Directive (NFRD) in the European Union, as both the TCFD and NFRD fostered increased environmental disclosure. In either case (the predominance of attention effects or transparency effects), the relationship between green bond issuances and environmental ratings should be positive but weaker after 2016. My results are consistent with this conjecture regarding informational channels. The examined green bonds issued after 2016 exhibit an impact on MSCI environmental scores that is 0.44 to 0.89 (columns 1 and 2) lower than that of green bonds issued before 2016 and an impact on the probability of being classified by the CDP as a leading company in terms of environmental performance that is 35 to 48 percentage points (columns 3 and 4) lower than that of such firms.

Thus, across my specifications, I find that green bond issuances improve firms' environmental performance scores at the end of the year of issuance and during the subsequent year. This result holds across two different CSR data providers and after the use of several different strategies to mitigate endogeneity concerns. These findings, obtained on a matched sample, cannot be explained by ex ante differences in environmental ratings, as the pre-event differences between the environmental scores of the treated and control firms are nonsignificant. However, there is no clear evidence of a positive association between the size of green bond issuances and the reaction of environmental performance scores. In addition, the relationship between green bond issuances and environmental scores decreased in magnitude after 2016, when green bonds became more commonly used and environmental disclosures became more widespread. The results regarding BRT Statement signatories are more mixed, as

the relationship between signing the BRT Statement and MSCI environmental scores is negative, while this relationship is positive when CDP environmental scores are used. These findings suggest that informational channels, namely, attention and transparency, are the main driving forces of the relationship between visible sustainability initiatives and environmental ratings, and these informational effects can either positively or negatively impact environmental ratings. These results are consistent with my third hypothesis.

2.4.4. Do firms become more transparent after undertaking visible sustainability initiatives?

The results in the previous section indicate that environmental ratings react to visible sustainability initiatives primarily through informational channels. To further understand the source of this reaction, I exploit a special feature of CDP data. Indeed, the CDP sends questionnaires to companies and, based on the companies' answers, gives them environmental scores ranging between A and D-. Companies that are “*requested to disclose their data and fail to do so, or fail to provide sufficient information to CDP to be evaluated will receive an F. An F does not indicate a failure in environmental stewardship.*”³² Econometrically, this means that I can observe these companies' transparency. My regression is as follows:

$$Transparency_{i,t} = \alpha + \beta_1 Visible\ ESG\ initiative_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{i,t} + \varepsilon_{i,t} \quad (4)$$

$Transparency_{i,t}$ is a dummy variable equal to one if the focal company received a score between A and D- and zero if it received an F; $Visible\ ESG\ initiative_{i,t}$ refers to either $Green\ bond\ issued_{i,t}$ or $BRT\ Statement_{i,t}$; $X_{i,t}$ is a vector of controls; and $Z_{i,t}$ is a vector of fixed effects.

³² See the [website](#) of the CDP.

Both the attention channel perspective and the transparency channel perspective predict that visible sustainability initiatives affect environmental scores. However, the first perspective posits that these changes stem from the creation of a CSR narrative to which environmental raters react, while the second channel argues that these effects are caused by variations in the level of information asymmetries. Consequently, the transparency channel should be validated (invalidated) if firms increase (do not increase) their transparency after undertaking visible sustainability initiatives.

First, I focus on the effect of green bond issuances on environmental transparency. Columns (1) and (2) in Table 7 report the results. After controlling for profitability, R&D expenses, the tangibility of assets, Tobin's Q, the leverage ratio, size, and country, industry, and year fixed effects, my results indicate that companies are 10.0 to 13.7 percentage points more likely to be environmentally transparent following green bond issuances. When using a treatment effect model, the effect, reported in column (1) of Panel B in Appendix 4, increases by 20.4 percentage points. Then, I analyze the effect of signing the BRT Statement on environmental transparency in columns (3) and (4) in Table 7. The results reveal a negative but nonsignificant impact of signing the BRT Statement on the environmental transparency of signatories. After I adjust for selection into treatment, the effect of signing the BRT Statement on environmental transparency becomes significantly negative. BRT Statement signatories are 41.3 percentage points less likely to be transparent on their environmental information; see column (2) of Panel B in Appendix 4.

Overall, my results indicate that undertaking visible CSR initiatives has a positive impact on environmental transparency only when these initiatives are not purely declarative. Indeed, green bond issuances positively influence transparency, while signing the BRT Statement has a negative effect that is statistically significant after adjusting for selection into treatment. Taken together with the results in the previous section, my findings highlight that a decrease in

information asymmetry is, at least for some environmental raters, not a necessary condition for a positive reaction of environmental ratings to visible sustainability initiatives and that the increased attention caused by visible CSR initiatives can be sufficient to positively impact environmental ratings. Nonetheless, purely declarative initiatives have mixed impacts on environmental ratings, consistent with the idea that such actions create informational noise and thereby give an increased margin for interpretation to environmental raters. These findings, obtained on a matched sample, cannot be explained by ex ante differences in transparency, as the pre-event differences in transparency levels between the treated and control firms are nonsignificant.

2.4.5. Robustness tests

In unreported tests, I verify that my results remain qualitatively similar when I use other matching procedures, for instance, when peer firms are not identified within the same industry-year but within the same year, when I do not use a matching procedure, and when financial firms are excluded. I also verify that my results hold when standard errors are clustered at alternative levels, namely, the industry, country, year, country-industry, country-year, and industry-year levels. My results also remain similar when using fixed effects at the country-industry, country-year, or industry-year levels. This alleviates the concern that the effects attributed to my visible sustainability initiative variables could in fact capture more general industry-year or country-year trends, such as the development of sustainable practices in certain industries or the evolution of countries' institutional characteristics over time. I also rerun the tests reported in Table 4 using environmental scores from ASSET4. Using these ASSET4 scores, I find that visible sustainability initiatives have a positive impact on environmental scores, both in the case of green bond issuances and in that of the signature of the BRT

Statement. One important caveat of this test, however, is that historical ASSET4 scores tend to be rewritten on an ongoing basis (Berg, Fabisik, and Sautner, 2021).

2.5. Conclusion

In this article, I assess whether companies derive informational benefits from undertaking highly visible sustainability initiatives. In conducting my analysis, I rely on two types of initiatives, namely, the issuance of green bonds and the decision to sign the Statement released by the Business Roundtable on August 19, 2019. I choose these two types of initiatives due to several of their appealing features: they allow for a firm-level rather than a fund-level analysis, they are arguably among the most visible sustainability initiatives, and they have clearly identifiable announcement dates. I find that the attention of the general public, as proxied by Google search volumes, increases after firms undertake such actions. Moreover, I show that issuing green bonds increases the probability that investors and customers request information on environmental considerations, whereas signing the Business Roundtable Statement has a negative impact that becomes significant after adjusting for selection bias. This implies that sustainability initiatives positively affect the attention of investors and customers only when they are associated with identifiable sustainability projects and that purely declarative initiatives can have negative consequences in terms of attention. Furthermore, using several environmental data providers, I also find that sustainability initiatives consistently increase environmental ratings in the case of issuing green bonds but have a more nuanced effect in the case of signing the Business Roundtable Statement. Using the examined firms' issuance dates and the sizes of their green bond issuances, I find that increases in environmental ratings are unrelated to the size of issuances (in terms of the percentage of a firm's balance sheet). I also show that this increase became less important after 2016, i.e., when counterfactual companies

became more transparent in terms of their environmental reporting due to both the publication of the TCFD recommendations and the implementation of the NFRD in the European Union and when green bonds became more common. This result suggests that environmental ratings primarily react to such initiatives through informational channels, namely, transparency and attention. Companies increase their transparency after issuing green bonds, whereas signing the Business Roundtable Statement has a negative impact on transparency. This implies that, at least for some environmental raters, the attention effect is sufficient to generate a positive impact on environmental ratings. All these findings are robust to various strategies used to address endogeneity concerns.

The findings suggest that companies derive informational benefits by undertaking highly visible sustainability initiatives. They imply that firms can successfully influence the perceptions of the general public and (some of) their environmental ratings through highly visible sustainability initiatives, even purely declarative initiatives. These results contribute to our understanding of why companies engage in such activities despite their costs. My findings have important implications, as previous research has shown that the attention of the general public, investor and customer attention, and ESG ratings impact investment flows, costs of financing, and firm valuations.

2.6. References

- Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1), 235-267.
- Abadie, A., & Imbens, G. W. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics*, 29(1), 1-11.
- Acharya, V., & Xu, Z. (2017). Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, 124(2), 223-243.
- Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10), 4451-4469.
- Amel-Zadeh, A., Lustermsans, R., & Pieterse-Bloem, M. (2021). Sustainability and Private Wealth Investment Flows. Available at SSRN 3576687.
- Baker, H. K., Nofsinger, J. R., & Weaver, D. G. (2002). International cross-listing and visibility. *Journal of Financial and Quantitative Analysis*, 37(3), 495-521.
- Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2018). *Financing the response to climate change: The pricing and ownership of US green bonds* (No. w25194). National Bureau of Economic Research.
- Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, 21(2), 785-818.
- Berg, F., Fabisik, K., & Sautner, Z. (2021). Is History Repeating Itself? The (Un)Predictable Past of ESG Ratings. *European Corporate Governance Institute–Finance Working Paper*, 708. Available at SSRN 3722087.
- Berg, F., Koelbel, J. F., & Rigobon, R. (2020). Aggregate confusion: the divergence of ESG ratings. Available at SSRN 3438533.
- Boulland, R., Degeorge, F., & Ginglinger, E. (2017). News dissemination and investor attention. *Review of Finance*, 21(2), 761-791.
- CFA Institute. (2017). Environmental, social and governance (ESG) survey.
- Chatterji, A. K., Durand, R., Levine, D. I., & Touboul, S. (2016). Do ratings of firms converge? Implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37(8), 1597-1614.
- Chatterji, A. K., & Toffel, M. W. (2010). How firms respond to being rated. *Strategic Management Journal*, 31(9), 917-945.
- Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, 60(9), 2223-2247.
- Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3), 1112-1145.
- Christensen, D. M., Serafeim, G., & Sikochi, S. (2021). Why is corporate virtue in the eye of the beholder? The case of ESG ratings. *The Accounting Review*, <https://doi.org/10.2308/TAR-2019-0506>.

Christensen, H. B., Hail, L., & Leuz, C. (2019). Adoption of CSR and sustainability reporting standards: Economic analysis and review (No. w26169). *National Bureau of Economic Research*.

Cohen, L., Gurun, U. G., & Nguyen, Q. H. (2020). *The ESG-innovation disconnect: Evidence from green patenting* (No. w27990). National Bureau of Economic Research.

Cronqvist, H., & Yu, F. (2017). Shaped by their daughters: Executives, female socialization, and corporate social responsibility. *Journal of Financial Economics*, 126(3), 543-562.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The journal of finance*, 66(5), 1461-1499.

Daines, R. M., Gow, I. D., & Larcker, D. F. (2010). Rating the ratings: How good are commercial governance ratings?. *Journal of Financial Economics*, 98(3), 439-461.

Delmas, M. A., Etzion, D., & Nairn-Birch, N. (2013). Triangulating environmental performance: What do corporate social responsibility ratings really capture?. *Academy of Management Perspectives*, 27(3), 255-267.

Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review*, 86(1), 59-100.

Drempetic, S., Klein, C., & Zwergel, B. (2020). The Influence of Firm Size on the ESG Score: Corporate Sustainability Ratings Under Review. *Journal of Business Ethics*, 167(2), 333-360.

Durand, R., Paugam, L., & Stolowy, H. (2019). Do investors actually value sustainability indices? Replication, development, and new evidence on CSR visibility. *Strategic Management Journal*, 40(9), 1471-1490.

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics*, 131(3), 693-714.

Ehlers, T., Mojon, B., & Packer, F. (2020). Green bonds and carbon emissions: exploring the case for a rating system at the firm level. *BIS Quarterly Review*, September 2020.

El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, 35(9), 2388-2406.

Ertimur, Y., Muslu, V., & Zhang, F. (2011). Why are recommendations optimistic? Evidence from analysts' coverage initiations. *Review of Accounting Studies*, 16(4), 679-718.

Faulkender, M., & Petersen, M. A. (2006). Does the source of capital affect capital structure? *The Review of Financial Studies*, 19(1), 45-79.

Fernandes, N., & Ferreira, M. A. (2008). Does international cross-listing improve the information environment. *Journal of Financial Economics*, 88(2), 216-244.

Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science*, 61(11), 2549-2568.

Flammer, C. (2021). Corporate Green Bonds. *Journal of Financial Economics*, Forthcoming.

Friedman, M. (1970). A Friedman doctrine: the social responsibility of business is to increase its profits. *The New York Times Magazine*, 13(1970), 32-33.

- Gibson, R., Glossner, S., Krueger, P., Matos, P., & Steffen, T. (2020). Responsible institutional investing around the world. *Swiss Finance Institute Research Paper*, (20-13).
- Green, T. C., & Jame, R. (2013). Company name fluency, investor recognition, and firm value. *Journal of Financial Economics*, 109(3), 813-834.
- Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *The Review of Financial Studies*, 17(2), 439-461.
- Guest, P. M., & Nerino, M. (2020). Do corporate governance ratings change investor expectations? Evidence from announcements by Institutional Shareholder Services. *Review of Finance*, 24(4), 891-928.
- Hartzmark, S. M., & Sussman, A. B. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance*, 74(6), 2789-2837.
- Hawn, O., & Ioannou, I. (2016). Mind the gap: The interplay between external and internal actions in the case of corporate social responsibility. *Strategic Management Journal*, 37(13), 2569-2588.
- Huynh, T., & Xia, Y. (2020). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, 1-25.
- Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2020). Climate risk disclosure and institutional investors. *Swiss Finance Institute Research Paper*, (19-66).
- Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3), 1540-1571.
- Kahle, K. M., & Walkling, R. A. (1996). The impact of industry classifications on financial research. *Journal of financial and quantitative analysis*, 31(3), 309-335.
- Kim, S., & Yoon, A. (2020). Analyzing Active Managers' Commitment to ESG: Evidence from United Nations Principles for Responsible Investment. Available at SSRN 3555984.
- Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of financial economics*, 115(2), 304-329.
- Larcker, D. F., & Watts, E. M. (2020). Where's the greenium? *Journal of Accounting and Economics*, 101312.
- Lehmann, N. (2019). Do corporate governance analysts matter? Evidence from the expansion of governance analyst coverage. *Journal of Accounting Research*, 57(3), 721-761.
- Lennox, C. S., Francis, J. R., & Wang, Z. (2012). Selection models in accounting research. *The Accounting Review*, 87(2), 589-616.
- Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, 72(2), 853-910.
- Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *the Journal of Finance*, 72(4), 1785-1824.
- Lou, D. (2014). Attracting investor attention through advertising. *The Review of Financial Studies*, 27(6), 1797-1829.

- Lys, T., Naughton, J. P., & Wang, C. (2015). Signaling through corporate accountability reporting. *Journal of Accounting and Economics*, 60(1), 56-72.
- Matsumura, E. M., Prakash, R., & Vera-Munoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review*, 89(2), 695-724.
- Mola, S., Rau, P. R., & Khorana, A. (2013). Is there life after the complete loss of analyst coverage?. *The Accounting Review*, 88(2), 667-705.
- McWilliams, A., & Siegel, D. (2000). Corporate social responsibility and financial performance: correlation or misspecification?. *Strategic management journal*, 21(5), 603-609.
- Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: comparing approaches. *The Review of Financial Studies*, 22(1), 435-480.
- PwC (2020). Mind the gap: the continued divide between investors and corporates on ESG. <https://www.pwc.com/us/en/services/assets/pwc-esg-divide-investors-corporates.pdf>
- Raghunandan, A., & Rajgopal, S. (2020). Do the socially responsible walk the talk?. *Available at SSRN 3609056*.
- Schiller, C. (2018). Global supply-chain networks and corporate social responsibility. *Available at SSRN 3089311*.
- Tang, D. Y., Yan, J., & Yao, C. Y. (2021). The determinants of ESG ratings: Rater ownership matters. *Available at SSRN 3889395*.
- Tang, D. Y., & Zhang, Y. (2020). Do shareholders benefit from green bonds?. *Journal of Corporate Finance*, 61, 101427.
- Yang, R. (2019). What Do We Learn From Ratings About Corporate Social Responsibility (CSR)?. *Available at SSRN 3165783*.
- Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: evidence from green bonds. *Journal of Banking & Finance*, 98, 39-60.

2.7. Figures and tables

Figure 1

Google search volume around the examined firms' initial green bond issuance announcements.

This figure represents the median Google search volume around the firms' initial green bond issuance. Google search volume is measured as a four-week moving average of global weekly search volume.

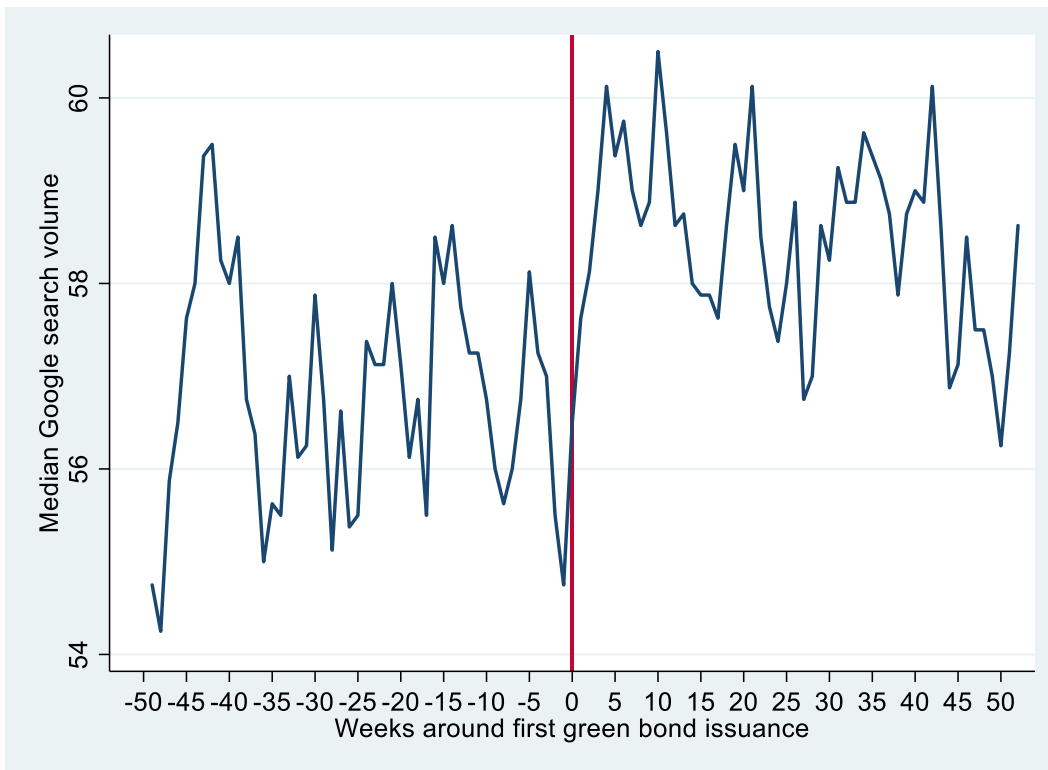


Table 1

Google search volume.

This table presents estimates of the effect of green bond issuances and the BRT Statement on global weekly Google search volume. The global weekly Google search volume of each firm is measured over a one-year window around the event date (announcement date for green bonds; August 19, 2019 for BRT Statement signatories). Panel A reports the descriptive statistics. Panel B reports estimates for the green bond issuers. Panel C reports estimates for the BRT Statement signatories. The regressions reported in columns (1) and (2) include year fixed effects. The regressions reported in columns (3) and (4) include year and month fixed effects. The regressions reported in columns (5) and (6) include firm-month-year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. Descriptive statistics

		N	Mean	SD	Median	P25	P75
<i>Green bond issuers</i>	GoogleTrend (-1Y,+1Y)	24,200	55.306	23.788	58.000	37.000	75.000
	Green bond (3 months)	24,200	0.124	0.329	0.000	0.000	0.000
	After green bond	24,200	0.496	0.500	0.000	0.000	1.000
<i>BRT Statement signatories</i>	GoogleTrend (-1Y,+1Y)	15,750	58.384	21.668	61.000	43.000	75.000
	BRT Statement (3 months)	15,750	0.124	0.329	0.000	0.000	0.000
	After BRT Statement	15,750	0.505	0.500	1.000	0.000	1.000

Panel B. Green bond issuers

VARIABLES	(1) GoogleTrend (-1Y,+1Y)	(2) GoogleTrend (-1Y,+1Y)	(3) GoogleTrend (-1Y,+1Y)	(4) GoogleTrend (-1Y,+1Y)	(5) GoogleTrend (-1Y,+1Y)	(6) GoogleTrend (-1Y,+1Y)
Green bond (3 months)	0.946* (1.770)		1.087** (2.043)		1.406* (1.756)	
After green bond		2.562** (2.242)		2.806** (2.365)		1.468 (1.133)
Observations	24,200	24,200	24,200	24,200	24,200	24,200
R-squared	0.016	0.018	0.020	0.022	0.810	0.810
Year fixed effects	Yes	Yes	Yes	Yes		
Month fixed effects			Yes	Yes		
Firm-month-year fixed effects					Yes	Yes

Panel C. BRT Statement signatories

VARIABLES	(1) GoogleTrend (-1Y,+1Y)	(2) GoogleTrend (-1Y,+1Y)	(3) GoogleTrend (-1Y,+1Y)	(4) GoogleTrend (-1Y,+1Y)	(5) GoogleTrend (-1Y,+1Y)	(6) GoogleTrend (-1Y,+1Y)
BRT Statement (3 months)	1.882*** (3.608)		2.520*** (5.655)		2.757*** (4.606)	
After BRT Statement		-0.783 (-1.443)		1.474** (2.198)		1.960** (2.521)
Observations	15,750	15,750	15,750	15,750	15,750	15,750
R-squared	0.002	0.001	0.008	0.008	0.880	0.879
Year fixed effects	Yes	Yes	Yes	Yes		
Month fixed effects			Yes	Yes		
Firm-month-year fixed effects					Yes	Yes

Table 2

Descriptive statistics.

This table reports the summary statistics of this study. Panel A presents the descriptive statistics of the firm-year observations involving the issuance of green bonds (only those that did not receive the attention of investors and customers during the year preceding the issuance) and their five nearest neighbors within the same industry and year (control firms). Panel B shows the descriptive statistics of the firm-year observations involving the issuance of green bonds that have MSCI environmental scores for the preceding year and their five nearest neighbors within the same industry and year (control firms). Panels C and D show the descriptive statistics of the firm-year observations involving the issuance of green bonds that have CDP ratings for the preceding year and their five nearest neighbors within the same industry and year (control firms). The matching procedures use the variables detailed in each panel. All the Compustat variables are winsorized at the 1st and 99th percentiles. See Appendix 1 for variable definitions.

Panel A. Stakeholder attention (green bond issuers)

	<i>Green bond issuers</i>				<i>Control firms</i>				Diff	T-stat
	N	Mean	SD	Median	N	Mean	SD	Median		
EBIT (t)	122	0.039	0.037	0.038	568	0.040	0.036	0.036	-0.003	0.382
R&D expenses (t)	122	0.003	0.009	0.000	568	0.002	0.008	0.000	0.000	0.469
Tangible assets (t)	122	0.291	0.306	0.179	568	0.297	0.302	0.219	-0.006	-0.196
TobinQ (t)	122	1.275	0.680	1.024	568	1.218	0.478	1.043	0.057	0.885
Leverage ratio (t)	122	0.374	0.201	0.349	568	0.369	0.192	0.364	0.006	0.299
Log total assets (t)	122	8.971	2.005	9.254	568	8.751	1.966	8.849	0.220	1.105

Panel B. MSCI environmental scores (green bond issuers)

	<i>Green bond issuers</i>				<i>Control firms</i>				Diff	T-stat
	N	Mean	SD	Median	N	Mean	SD	Median		
MSCI environmental score (t-1)	129	5.977	2.002	6.200	484	5.718	2.030	5.900	0.259	1.303
EBIT (t)	129	0.040	0.031	0.039	484	0.044	0.030	0.043	-0.004	-1.408
R&D expenses (t)	129	0.003	0.010	0.000	484	0.004	0.010	0.000	-0.001	-0.823
Tangible assets (t)	129	0.265	0.281	0.212	484	0.294	0.278	0.234	-0.029	-1.035
TobinQ (t)	129	1.205	0.035	1.062	484	1.308	0.418	1.179	-0.103	-2.601
Leverage ratio (t)	129	0.331	0.169	0.337	484	0.335	0.163	0.342	-0.003	-0.199
Log total assets (t)	129	9.990	1.273	10.363	484	9.780	1.282	9.969	0.211	1.667

Panel C. CDP Scores (green bond issuers)

	<i>Green bond issuers</i>				<i>Control firms</i>				Diff	T-stat
	N	Mean	SD	Median	N	Mean	SD	Median		
CDP leadership level (t-1)	120	0.283	0.453	0.000	499	0.240	0.428	0.000	0.043	0.941
EBIT (t)	120	0.039	0.029	0.030	499	0.041	0.032	0.036	-0.003	-0.835
R&D expenses (t)	120	0.003	0.010	0.000	499	0.003	0.010	0.000	-0.000	-0.250
Tangible assets (t)	120	0.218	0.267	0.024	499	0.223	0.273	0.035	-0.005	-0.183
TobinQ (t)	120	1.214	0.611	1.023	499	1.248	0.607	1.034	-0.034	-0.555
Leverage ratio (t)	120	0.316	0.179	0.317	499	0.312	0.179	0.310	0.004	0.208
Log total assets (t)	120	10.143	1.108	10.644	499	9.972	1.160	10.305	0.171	1.505

Panel D. Transparency (green bond issuers)

	<i>Green bond issuers</i>				<i>Control firms</i>				T-stat	
	N	Mean	SD	Median	N	Mean	SD	Median		Diff
Transparency (t-1)	120	0.750	0.435	1.000	485	0.699	0.459	1.000	0.051	1.138
EBIT (t)	120	0.039	0.029	0.030	485	0.043	0.031	0.040	-0.005	-1.571
R&D expenses (t)	120	0.003	0.010	0.000	485	0.003	0.010	0.000	-0.000	-0.465
Tangible assets (t)	120	0.218	0.267	0.024	485	0.234	0.271	0.083	-0.015	-0.563
TobinQ (t)	120	1.214	0.611	1.023	485	1.261	0.587	1.054	-0.047	-0.762
Leverage ratio (t)	120	0.316	0.179	0.317	485	0.316	0.179	0.325	0.000	0.001
Log total assets (t)	120	10.143	1.108	10.644	485	9.884	1.123	10.027	0.259	2.282

Table 3

The effect of visible sustainability initiatives on investors' and customers' attention toward environmental considerations.

This table presents OLS estimates of the effects of visible sustainability initiatives on investors' and customers' attention toward environmental considerations. Columns (1) and (2) use *Green bond issued* as the independent variable. Columns (3) and (4) use *BRT Statement signatory* as the independent variable. The estimations reported in columns (1) and (3) are conducted with firm-year observations from between 2013 and 2020. The estimations reported in columns (2) and (4) are conducted with firm-year observations from between 2013 and 2019. All the regressions include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) Stakeholder attention (t)	(2) Stakeholder attention (t+1)	(3) Stakeholder attention (t)	(4) Stakeholder attention (t+1)
Green bond issued (t)	0.0724** (2.303)	0.152*** (3.299)		
BRT Statement signatory (t)			-0.0929 (-1.199)	-0.134 (-1.563)
EBIT (t)	0.0242 (0.548)	-0.00126 (-0.0162)	-0.0102 (-0.0655)	0.0746 (0.239)
R&D expenses (t)	-0.317 (-0.752)	0.181 (0.278)	0.344 (0.771)	-0.177 (-0.302)
Tangible assets (t)	0.0114 (0.582)	0.0828** (2.098)	-0.123 (-1.084)	-0.176 (-0.852)
TobinQ (t)	0.00205* (1.814)	0.00909 (1.261)	0.00605 (1.453)	0.0103 (1.471)
Leverage ratio (t)	-0.0260 (-1.400)	-0.0479 (-1.156)	-0.00967 (-0.165)	-0.0413 (-0.363)
Log total assets (t)	0.0175*** (6.887)	0.0340*** (7.287)	0.0129 (1.439)	0.0261* (1.761)
Constant	-0.0430 (-1.052)	-0.406*** (-6.036)	0.109 (1.370)	-0.660*** (-4.884)
Observations	3,727	2,677	866	607
R-squared	0.095	0.170	0.227	0.288
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Table 4

Visible sustainability initiatives and environmental ratings.

This table presents OLS estimates of the effects of green bond issuances on environmental ratings. Panel A reports estimates for the green bond issuers. Panel B reports estimates for the BRT Statement signatories. The estimations reported in columns (1) and (3) are conducted with firm-year observations from between 2013 and 2020. The estimations reported in columns (2) and (4) are conducted with firm-year observations from between 2013 and 2019. Columns (1) and (2) use *MSCI environmental score* as the dependent variable. Columns (3) and (4) use *CDP leadership level* as the dependent variable. All the regressions include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. Green bond issuers

VARIABLES	(1) MSCI environmental score (t)	(2) MSCI environmental score (t+1)	(3) CDP leadership level (t)	(4) CDP leadership level (t+1)
Green bond issued (t)	0.664*** (4.380)	0.580*** (3.410)	0.0933*** (2.592)	0.158*** (3.520)
EBIT (t)	2.993 (1.333)	4.955 (1.528)	0.764** (2.089)	1.305*** (2.614)
R&D expenses (t)	26.81*** (2.974)	31.83** (2.088)	-3.357* (-1.671)	6.993** (2.145)
Tangible assets (t)	0.147 (0.266)	0.319 (0.520)	-0.0773 (-0.942)	-0.0604 (-0.585)
TobinQ (t)	0.0251 (0.675)	0.0694*** (2.774)	-0.0142 (-1.040)	0.0105 (1.621)
Leverage ratio (t)	-0.386 (-0.706)	-0.797 (-1.118)	-0.00511 (-0.0599)	-0.166* (-1.662)
Log total assets (t)	0.436*** (5.648)	0.413*** (4.322)	0.0882*** (5.999)	0.0770*** (4.701)
Constant	-2.197** (-2.583)	-2.042** (-2.083)	-0.791*** (-4.173)	-0.238 (-1.220)
Observations	2,574	1,739	2,368	1,800
R-squared	0.409	0.470	0.219	0.307
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Panel B. BRT Statement signatories

VARIABLES	(1) MSCI environmental score (t)	(2) MSCI environmental score (t+1)	(3) CDP leadership level (t)	(4) CDP leadership level (t+1)
BRT Statement signatory (t)	-0.428** (-1.983)	-0.249 (-1.165)	0.111* (1.895)	0.122** (2.064)
EBIT (t)	-1.228 (-0.775)	-1.261 (-0.688)	0.743** (2.141)	0.753* (1.904)
R&D expenses (t)	-4.099 (-1.561)	-5.265* (-1.738)	1.129 (1.394)	0.466 (0.537)
Tangible assets (t)	-1.628 (-1.630)	-1.501 (-1.500)	-0.302** (-2.045)	-0.146 (-0.860)
TobinQ (t)	0.0809** (2.131)	0.0252 (0.972)	-0.00950* (-1.879)	-0.0170*** (-2.899)
Leverage ratio (t)	-0.0297 (-0.0477)	-0.389 (-0.537)	-0.280* (-1.836)	-0.293* (-1.872)
Log total assets (t)	0.549*** (5.050)	0.503*** (4.360)	0.0680*** (2.742)	0.0971*** (3.646)
Constant	-1.295 (-0.699)	1.869* (1.701)	0.153 (0.426)	-0.794*** (-3.023)
Observations	2,012	1,696	1,766	1,507
R-squared	0.442	0.458	0.238	0.295
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Table 5

Size of green bond issuances and environmental ratings.

This table presents OLS estimates of the effects of the size of green bond issuances on environmental ratings. Panel A reports estimates using *MSCI environmental score* as the dependent variable. Panel B reports estimates using *CDP leadership level* as the dependent variable. The estimations reported in columns (1) and (3) are conducted with firm-year observations from between 2013 and 2020. The estimations reported in columns (2) and (4) are conducted with firm-year observations from between 2013 and 2019. All the regressions include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. MSCI environmental scores

VARIABLES	(1) MSCI environmental score (t)	(2) MSCI environmental score (t+1)	(3) MSCI environmental score (t)	(4) MSCI environmental score (t+1)
Green bond issued (t)	0.579** (2.533)	0.559** (2.480)	0.547*** (2.982)	0.429** (2.225)
Large green bond (t)	0.184 (0.616)	0.0520 (0.171)		
Green bond size (t)			5.716 (1.544)	9.297** (2.192)
EBIT (t)	2.997 (1.336)	4.958 (1.529)	3.005 (1.341)	5.004 (1.546)
R&D expenses (t)	26.77*** (2.969)	31.81** (2.086)	26.75*** (2.973)	31.48** (2.067)
Tangible assets (t)	0.145 (0.263)	0.319 (0.519)	0.139 (0.251)	0.308 (0.502)
TobinQ (t)	0.0252 (0.680)	0.0696*** (2.805)	0.0252 (0.694)	0.0742*** (3.438)
Leverage ratio (t)	-0.387 (-0.708)	-0.799 (-1.119)	-0.389 (-0.711)	-0.806 (-1.129)
Log total assets (t)	0.436*** (5.651)	0.412*** (4.317)	0.439*** (5.675)	0.415*** (4.347)
Constant	-2.192** (-2.577)	-2.038** (-2.076)	-2.206*** (-2.602)	-2.039** (-2.090)
Observations	2,574	1,739	2,574	1,739
R-squared	0.409	0.470	0.409	0.470
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Panel B. CDP scores

VARIABLES	(1) CDP leadership level (t)	(2) CDP leadership level (t+1)	(3) CDP leadership level (t)	(4) CDP leadership level (t+1)
Green bond issued (t)	0.0559 (1.255)	0.130** (2.407)	0.0875** (2.370)	0.155*** (3.376)
Large green bond (t)	0.0977 (1.348)	0.0961 (1.054)		
Green bond size (t)			0.297 (1.071)	0.137 (0.466)
EBIT (t)	0.766** (2.092)	1.308*** (2.617)	0.763** (2.085)	1.305*** (2.611)
R&D expenses (t)	-3.383* (-1.686)	6.955** (2.130)	-3.362* (-1.675)	6.987** (2.142)
Tangible assets (t)	-0.0789 (-0.962)	-0.0607 (-0.587)	-0.0778 (-0.948)	-0.0610 (-0.590)
TobinQ (t)	-0.0140 (-1.010)	0.0120* (1.821)	-0.0142 (-1.029)	0.0107* (1.663)
Leverage ratio (t)	-0.00604 (-0.0709)	-0.168* (-1.684)	-0.00728 (-0.0852)	-0.167* (-1.671)
Log total assets (t)	0.0883*** (6.017)	0.0765*** (4.678)	0.0885*** (5.998)	0.0771*** (4.699)
Constant	-0.807*** (-4.231)	-0.933*** (-4.401)	-0.798*** (-4.186)	-0.240 (-1.228)
Observations	2,368	1,800	2,368	1,800
R-squared	0.220	0.307	0.219	0.307
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Table 6

The effect of green bond issuances on environmental ratings around the year 2016.

This table presents OLS estimates of the effects of the size of green bond issuances on environmental ratings around the year 2016. Columns (1) and (2) report estimates using *MSCI environmental score* as the dependent variable. Columns (3) and (4) report estimates using *CDP leadership level* as the dependent variable. The estimations reported in columns (1) and (3) are conducted with firm-year observations from between 2013 and 2020. The estimations reported in columns (2) and (4) are conducted with firm-year observations from between 2013 and 2019. All the regressions include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) MSCI environmental score (t)	(2) MSCI environmental score (t+1)	(3) CDP leadership level (t)	(4) CDP leadership level (t+1)
Green bond issued (t)	1.436*** (3.425)	0.942** (2.330)	0.418** (2.517)	0.600*** (4.259)
Green bond issued (t)*after 2016	-0.889** (-2.076)	-0.439 (-1.007)	-0.345** (-2.028)	-0.481*** (-3.224)
EBIT (t)	2.961 (1.317)	4.907 (1.513)	0.752** (2.056)	1.276** (2.567)
R&D expenses (t)	26.96*** (2.989)	31.91** (2.095)	-3.327* (-1.656)	7.013** (2.154)
Tangible assets (t)	0.148 (0.267)	0.316 (0.514)	-0.0739 (-0.901)	-0.0548 (-0.532)
TobinQ (t)	0.0253 (0.676)	0.0691*** (2.722)	-0.0142 (-1.052)	0.00981 (1.479)
Leverage ratio (t)	-0.374 (-0.684)	-0.784 (-1.097)	-0.00722 (-0.0849)	-0.173* (-1.736)
Log total assets (t)	0.437*** (5.650)	0.413*** (4.324)	0.0880*** (5.988)	0.0763*** (4.685)
Constant	-2.220*** (-2.602)	-2.068** (-2.099)	-0.787*** (-4.160)	-0.228 (-1.171)
Observations	2,574	1,739	2,368	1,800
R-squared	0.410	0.470	0.221	0.311
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Table 7

Visible sustainability initiatives and the reporting behavior of companies.

This table presents OLS estimates of the effects of visible sustainability initiatives on the reporting behavior of companies that have received CDP questionnaires. Columns (1) and (2) use *Green bond issued* as the independent variable. Columns (3) and (4) use *BRT Statement signatory* as the independent variable. The estimations reported in columns (1) and (3) are conducted with firm-year observations from between 2013 and 2020. The estimations reported in columns (2) and (4) are conducted with firm-year observations from between 2013 and 2019. All the regressions include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) Transparency (t)	(2) Transparency (t+1)	(3) Transparency (t)	(4) Transparency (t+1)
Green bond issued (t)	0.100*** (3.221)	0.137*** (3.641)		
BRT Statement signatory (t)			-0.0357 (-0.879)	-0.0633 (-1.488)
EBIT (t)	0.329 (0.802)	-0.295 (-0.474)	0.610*** (2.882)	0.683*** (2.638)
R&D expenses (t)	2.090* (1.826)	3.199 (1.228)	0.121 (0.218)	-0.336 (-0.557)
Tangible assets (t)	0.109 (0.788)	0.186 (1.096)	-0.385** (-2.152)	-0.334* (-1.745)
TobinQ (t)	-0.00441 (-0.601)	-0.00277 (-0.365)	-0.00756* (-1.919)	-0.00897*** (-4.079)
Leverage ratio (t)	0.203 (1.416)	0.346** (2.249)	0.106 (1.160)	-0.0892 (-0.812)
Log total assets (t)	0.0798*** (4.951)	0.123*** (5.454)	-0.00437 (-0.302)	-0.00405 (-0.248)
Constant	-0.0342 (-0.155)	-1.750*** (-4.945)	0.287** (2.212)	0.206 (1.208)
Observations	2,399	1,736	1,742	1,443
R-squared	0.375	0.386	0.355	0.403
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Appendix 1. Variable Definitions

Observation frequency	Variable	Description
Firm-week (tests on Google search volumes)	After BRT Statement	Equals one after the company has signed the Business Roundtable Statement.
	After green bond	Equals one after the company has issued green bonds.
	BRT Statement (3 months)	Equals one if the company signed the Business Roundtable Statement less than 3 months ago.
	GoogleTrend (-1Y,+1Y)	Global weekly search volume from Google Trends.
	Green bond (3 months)	Equals one if the company issued green bonds for the first time less than 3 months ago.
Firm-year (other tests)	After 2016	Equals one for observations after 2016 and zero otherwise.
	BRT Statement signatory	Equals one if the company has signed the BRT Statement.
	BRT Statement signature by peers (t)	Equal to the average value of BRT Statement signatory for peer firms (firms in the same country, industry, and year).
	CDP leadership level	Equals one if the company is rated A or A- by CDP for the climate change score. Set to missing if the company did not receive a CDP questionnaire.
	EBIT	Ratio of EBIT to book assets. EBIT/AT in Compustat.
	Green bond issuances by peers	Equal to the average value of Green bond issued for peer firms (firms in the same country, industry, and year).
	Green bond issued	Equals one if the company has issued green bonds. Set to missing for years after the firm's initial issuance.
	Green bond size	Ratio of the amount of green bonds issued to book assets. Set to zero if the company did not issue green bonds during the focal year. Set to missing for years after the firm's initial issuance.
	Large green bond	Equals one if the firm's green bond is larger than the median among the green bond issuers and zero otherwise. Set to missing for years after the firm's initial issuance.
	Leverage ratio	Ratio of long-term debt to book assets. DLTT/AT in Compustat.
	Log total assets	Natural logarithm of book assets (AT in Compustat). Book asset values are converted to US dollars using year-end exchange rates from the US Department of the Treasury. ³³
	MSCI environmental score	Environmental pillar score given alongside MSCI ESG ratings.
	R&D expenses	Ratio of R&D expenses to book assets. XRD/AT in Compustat.
	Stakeholder attention	Equals one if the company has received a CDP questionnaire. Set to missing if the company received a questionnaire during the preceding year.
	Tangible assets	Ratio of net tangible assets to book assets. PPENT/AT in Compustat.
	TobinQ	Ratio of the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity to book asset value. $(AT-CEQ+PRCC_F*CSHO)/AT$ in Compustat North America and $(AT-CEQ+PRCCD*CSHOC)/AT$ in Compustat Global.
Transparency	Equals one if the company has sufficiently answered the CDP questionnaire such that the CDP is able to give it a rating (between A and D-). Set to missing if the company was not questioned by CDP.	

³³ Data available [here](#).

Appendix 2. The effect of visible sustainability initiatives on investors' and customers' attention toward environmental considerations: Treatment effect model.

This table presents estimates of the effects of visible sustainability initiatives on customers' and investors' attention to environmental considerations using a treatment effect model. The estimations are conducted with firm-year observations from between 2013 and 2020. Panel A reports the results of the first step of the treatment effect model. In column (1), the probability of issuing green bonds is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *Green bond issued* of its peer firms. In column (2), the probability of signing the BRT Statement is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *BRT Statement signatory* of its peer firms. A company's peer firms are defined as companies operating in the same country-industry-year group. Panel B reports the second-stage results. All the regressions in Panel B include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. First-stage results

VARIABLES	(1) Green bond issued (t)	(2) BRT Statement (t)
Green bond issuances by peers (t)	5.567*** (5.355)	
BRT Statement signature by peers (t)		15.07*** (2.919)
EBIT (t)	-0.537 (-1.021)	7.047** (2.472)
R&D expenses (t)	4.823 (1.452)	6.603* (1.890)
Tangible assets (t)	0.0895 (0.584)	0.112 (0.251)
TobinQ (t)	-0.0354 (-0.640)	-0.384** (-2.131)
Leverage ratio (t)	0.368* (1.889)	-0.812 (-1.138)
Log total assets (t)	0.0761*** (2.983)	0.237** (2.218)
Constant	-2.680*** (-9.469)	-3.894*** (-3.311)
Observations	3,658	896

Panel B. Second-stage results

VARIABLES	(1) Stakeholder attention (t)	(2) Stakeholder attention (t)
Green bond issued (t)	0.0745** (2.311)	
BRT Statement signatory (t)		-0.154* (-1.709)
EBIT (t)	0.0210 (0.463)	-0.425 (-1.602)
R&D expenses (t)	-0.321 (-0.771)	1.826 (1.539)
Tangible assets (t)	0.0116 (0.578)	-0.0674 (-0.381)
TobinQ (t)	0.00212* (1.880)	0.0116* (1.756)
Leverage ratio (t)	-0.0299 (-1.593)	-0.0634 (-0.679)
Log total assets (t)	0.0178*** (7.028)	0.0248* (1.864)
Inverse Mills ratio	-0.00462 (-0.268)	0.103 (1.483)
Constant	-0.130*** (-4.289)	0.0150 (0.109)
Observations	3,658	896
Country fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Appendix 3. Visible sustainability initiatives and environmental ratings: Treatment effect model.

This table presents estimates of the effects of visible sustainability initiatives on environmental ratings using a treatment effect model. The estimations are conducted with firm-year observations from between 2013 and 2020. Panel A reports the first step of the treatment effect model. In columns (1) and (2), the probability of issuing green bonds is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *Green bond issued* of its peer firms. In columns (3) and (4), the probability of signing the BRT Statement is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *BRT Statement signatory* of its peer firms. A company's peer firms are defined as companies operating in the same country-industry-year group. Panel B reports the second stage results. Columns (1) and (3) report estimates using the MSCI environmental score as the dependent variable. Columns (2) and (4) report estimates using CDP leadership level as the dependent variable. All the regressions in Panel B include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. First-stage results

VARIABLES	(1) Green bond issued (t)	(2) Green bond issued (t)	(3) BRT Statement (t)	(4) BRT Statement (t)
Green bond issuances by peers (t)	5.628*** (3.943)	4.722*** (4.103)		
BRT Statement signature by peers (t)			22.91*** (5.108)	13.20*** (4.450)
EBIT (t)	-1.138 (-0.904)	-1.074 (-0.837)	3.511*** (2.822)	4.132*** (2.973)
R&D expenses (t)	1.335 (0.332)	-0.193 (-0.0464)	0.963 (0.512)	0.748 (0.305)
Tangible assets (t)	-0.0791 (-0.539)	-0.0940 (-0.575)	-0.646** (-2.137)	-0.553* (-1.860)
TobinQ (t)	-0.608*** (-4.741)	-0.124 (-0.853)	-0.115 (-1.549)	-0.133 (-1.581)
Leverage ratio (t)	0.0815 (0.356)	0.333 (1.410)	0.822** (2.046)	0.841** (1.965)
Log total assets (t)	0.0976*** (3.072)	0.119*** (3.046)	0.292*** (4.599)	0.344*** (4.812)
Constant	-1.641*** (-4.084)	-2.681*** (-5.889)	-5.132*** (-7.509)	-5.581*** (-7.347)
Observations	2,220	2,246	2,007	1,754

Panel B. Second-stage results

VARIABLES	(1) MSCI environmental score (t)	(2) CDP leadership level (t)	(3) MSCI environmental score (t)	(4) CDP leadership level (t)
Green bond issued (t)	0.823 (1.424)	0.0965 (1.216)		
BRT Statement signatory (t)			-0.758** (-2.167)	0.152* (1.830)
EBIT (t)	2.362 (1.050)	0.744** (1.960)	-1.186 (-0.765)	0.739** (2.167)
R&D expenses (t)	25.60*** (2.667)	-3.269 (-1.621)	-3.986 (-1.557)	1.099 (1.381)
Tangible assets (t)	-0.0530 (-0.0907)	-0.0599 (-0.760)	-1.630* (-1.668)	-0.297** (-2.051)
TobinQ (t)	0.0233 (0.643)	-0.0151 (-1.073)	0.0775** (2.167)	-0.00962* (-1.937)
Leverage ratio (t)	0.266 (0.471)	0.00818 (0.0960)	0.00167 (0.00273)	-0.281* (-1.892)
Log total assets (t)	0.400*** (5.370)	0.0877*** (5.883)	0.554*** (5.216)	0.0687*** (2.839)
Inverse Mills ratio	-0.0902 (-0.598)	0.00694 (0.0673)	0.107 (1.151)	-0.0480 (-0.561)
Constant	3.117*** (3.552)	-0.448*** (-2.868)	-0.441 (-0.406)	-0.0705 (-0.236)
Observations	2,220	2,246	2,007	1,754
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Appendix 4. Visible sustainability initiatives and reporting behavior of companies: Treatment effect model.

This table presents estimates of the effects of visible sustainability initiatives on the reporting behavior of companies using a treatment effect model. The estimations are conducted with firm-year observations from between 2013 and 2020. Panel A reports the results of the first step of the treatment effect model. In column (1), the probability of issuing green bonds is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *Green bond issued* of its peer firms. In column (2), the probability of signing the BRT Statement is estimated with a probit model based on each firm's EBIT, R&D expenses, tangible assets, Tobin's Q, leverage ratio, and total assets in logarithmic form as well as the average value of *BRT Statement signatory* of its peer firms. A company's peer firms are defined as companies operating in the same country-industry-year group. Panel B reports the second-stage results. All the regressions in Panel B include country, industry, and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. First-stage results

VARIABLES	(1) Green bond issued (t)	(2) BRT Statement (t)
Green bond issuances by peers (t)	4.034*** (4.346)	
BRT Statement signature by peers (t)		10.18*** (3.967)
EBIT (t)	-1.696 (-1.392)	3.395** (2.149)
R&D expenses (t)	0.146 (0.0334)	0.787 (0.389)
Tangible assets (t)	-0.163 (-0.988)	-0.796*** (-2.890)
TobinQ (t)	-0.0667 (-0.541)	-0.0629 (-0.744)
Leverage ratio (t)	0.547** (2.192)	0.469 (1.292)
Log total assets (t)	0.121*** (2.792)	0.336*** (5.230)
Constant	-2.867*** (-5.728)	-5.212*** (-7.732)
Observations	2,385	1,737

Panel B. Second-stage results

VARIABLES	(1) Transparency (t)	(2) Transparency (t)
Green bond issued (t)	0.204*** (3.188)	
BRT Statement signatory (t)		-0.413*** (-9.117)
EBIT (t)	0.294 (0.732)	0.707*** (3.373)
R&D expenses (t)	2.148* (1.918)	0.186 (0.357)
Tangible assets (t)	0.110 (0.812)	-0.421** (-2.488)
TobinQ (t)	-0.00430 (-0.597)	-0.00847** (-2.038)
Leverage ratio (t)	0.180 (1.279)	0.122 (1.339)
Log total assets (t)	0.0777*** (4.940)	0.00535 (0.373)
Inverse Mills ratio	-0.140** (-2.349)	0.697*** (9.820)
Constant	0.127 (0.789)	0.868*** (5.375)
Observations	2,385	1,737
Country fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

3. Climate Risk and Capital Structure

Joint work with Edith Ginglinger

Abstract:

We use firm-level data that measure forward-looking physical climate risk to examine the impact of climate risk on capital structure. We find that greater physical climate risk leads to lower leverage in the post-2015 period, i.e., after the Paris Agreement and the first step of standardization of disclosure of climate risk information. Our results hold after controlling for firm characteristics known to determine leverage, including credit ratings. Our evidence shows that the reduction in leverage related to climate risk is shared between a demand effect (the firm's optimal leverage decreases) and a supply effect (bankers and bondholders increase the spreads when lending to firms with the greatest risk). Our results are consistent with the hypothesis that physical climate risk affects leverage via larger expected distress costs and higher operating costs.

3.1. Introduction

As the Intergovernmental Panel on Climate Change (IPCC) assessment reports highlight, climate change is accelerating, with a documented increase in average temperature³⁴ and dramatic effects of sea-level rise and weather-related natural catastrophes, such as droughts, storms, heatwaves, floods, and wildfires. Several recent papers emphasize that climate risk affects the pricing of stocks, bonds, and real estate (Bernstein et al. 2019, Painter 2020, and Seltzer et al. 2020), and a majority of institutional investors believe that climate risk is an important concern (Krueger et al. 2020). Investors face potential losses from climate change consequences in terms of physical and transition risks. Physical climate risks may lead to a reassessment of the value of a large range of firms' assets (plants, property, and equipment) and to increased operating costs, such as relocation costs and insurance costs, resulting in lower profits and reduced repayment capacity. The transition risks stem from the necessary change of companies' business models to produce fewer carbon emissions. Our analysis focuses on physical risks. Several articles have analyzed the impact of past major climate events on companies' value and financial decisions.³⁵ However, quantifying the future physical risks that will threaten the company requires relying on scientists' projections and assessment of the company's exposure to these risks.

In this paper, we use forward-looking firm-level measures to examine whether the physical climate risks faced by a firm have an impact on its capital structure. Under a Modigliani and Miller (1958) framework, climate risk should play no role. However, in the presence of market frictions, climate risk is likely to alter the tradeoff between the benefits and costs of debt. We hypothesize that physical climate risk may affect financial leverage via two possible

³⁴ The [IPCC Assessment Report 6, Working Group 1 report](#) (2021) points out that global surface temperature was 1.09°C higher in 2011–2020 than 1850–1900. The estimated increase in temperature since the previous report in 2013 is principally due to further warming since 2003–2012.

³⁵ See for example Hong et al. (2019), Bansal et al. (2016), Brown et al. (2021).

channels: larger expected distress costs and higher operating costs.³⁶ We find strong support for the conclusion that greater climate risk leads to lower leverage in the post-2015 period, i.e., after the Paris Agreement (COP21), a historic global climate deal to limit warming to 2°C by 2100 (and preferably 1.5°C), which was signed by 195 countries in December 2015 and supported by a high degree of commitment from large firms, institutional investors and central banks.³⁷ The Paris Agreement raised awareness of the extent of climate risks among all stakeholders, leading to a consensus on the need to measure and disclose the long-term risks associated with climate change borne by companies, financial institutions and insurers.³⁸ In 2015, the Financial Stability Board (FSB) established the Task Force on Climate-related Financial Disclosures (TCFD), a major step on this path. Regarding physical climate risks, the Task Force recommends that organizations describe the potential financial impacts of, in particular, damage to assets, supply chain interruptions and increased insurance premiums. The TCFD framework has since become a global standard for climate risk disclosure.³⁹

Measuring firm-level exposure to future physical climate risk is challenging. In this paper, we use different metrics of physical climate risk at the firm level. We first rely on the “Climate Risk Impact Screening” (CRIS) methodology developed by a French firm, Carbone 4, with support from several institutional investors and public agencies, including the French Development Agency (AFD) and Caisse des Dépôts et Consignations (CDC). The CRIS risk rating is a forward-looking measure that captures the increase in intensity or frequency of

³⁶ Although some firms will benefit from increased climate risk, for example, those specialized in providing services for adjusting to this risk, most will see negative effects on their earnings. In a study of the effects of climate change and weather effects on earnings for the firms in the S&P500 index, more than 90% of the mentions were negative ([S&P Global \(2018\)](#)).

³⁷ Before 2015 and the Paris Agreement, despite trying for decades, the world failed to reach a global agreement on climate change due to coordination and free-riding problems (see Andersson et al. 2016). Section A in the internet Appendix discusses why the Paris Agreement can be considered as a breakthrough step in the consideration of climate risk.

³⁸ In their systematic international evidence from survey and portfolio holdings data on the preferences of institutional investors, Ilhan et al. (2019) find that investors have a strong demand for climate risk disclosure, whether regulatory, physical or other climate risks.

³⁹ In 2022, most international standard setters and regulators promote disclosure requirements based on the TCFD framework (for example IFRS, European Commission, Central Bank of Brazil). The March 2022 SEC proposal to mandate climate-risk disclosures by US public companies also refers to TCFD guidelines.

climate-related hazards due to climate change at two time horizons, 2050 and 2100. For each firm in the MSCI World Index, climate risk grades are quantified based on climate projections from IPCC models, the geographical division of activities, country-specific vulnerabilities and industry-specific vulnerabilities.

As a second measure of climate risk, we use alternative data provided by Four Twenty Seven, a provider of data related to physical climate and environmental risks that has been part of Moody's ESG solutions since July 2019.⁴⁰ Four Twenty Seven's models assess projected exposure to climate hazards at the facility level aggregated at the firm level. They also assess a firm's dependence on natural resources threatened by climate change. Four Twenty Seven provides a composite climate risk score for each firm.

The methods used by these two data providers to quantify physical climate risk are model-based and rely on different scientific databases, granularities, scenarios, and weightings, although their projections are consistent with each other (see details in Section 3 and Appendix B). Climate data providers are subject to various criticisms concerning their lack of transparent scientific validation and proprietary, black-box technology (Keenan, 2019). We have had access to detailed methodological guides describing the scientific choices and the procedures used to construct the indicators and in-depth discussions with members of the teams, including climate scientists. We are thus confident in the reliability of the providers' approach, even if we recognize the complexity of raw climate data and their processing.⁴¹

To complement these data, we also use as a robustness test an alternative measure relying on a language-based methodology, the Sautner et al. (2020) physical climate risk metric that builds on transcripts of earnings conference calls to capture firms' exposure to climate risk.

⁴⁰ Moody's ESG Solutions, a unit of Moody's Corporation, operates independently of Moody's Investors Service, the credit rating agency.

⁴¹ Fiedler et al. (2021) underline that the relatively immaturity of the financial sector in understanding what climate data can provide may lead to a false sense of security. Their critics do not only target climate data providers. They also stress that there is little evidence of climate science involvement in the development of TCFD recommendations.

In contrast to our main metrics, which measure the fundamental exposure to future physical climate risks, the Sautner et al. (2020) metric captures the attention of analysts and other market participants to climate risks by estimating the share of the conversation in a transcript devoted to that topic. The authors argue that earnings calls are largely forward-looking compared to metrics relying on firms' annual reports.⁴²

We begin our empirical analysis by estimating the relationship between a firm's leverage ratio and our measures of climate risk. Specifically, we regress the observed debt ratios of the firms that belong to the MSCI World Index over the period 2010-2019 on climate risk measures for each firm in addition to several fixed effects and other control variables. We find that an increased physical climate risk reduces firms' leverage in the post-2015 period, i.e., after the Paris Agreement and the increased climate risk disclosure requirements. Our results are both statistically and economically significant. The patterns that we observe in our baseline tests remain after various robustness checks that involve changes in empirical specifications, variable construction methods and sampling restrictions. Furthermore, by using the 2015 Paris Agreement as a shock to the awareness of firms, bankers and investors of climate risks, we also conduct a difference-in-differences approach to compare the leverage of high climate risk firms versus low climate risk firms before and after the Paris Agreement. Our findings remain unchanged.

Climate risk could also be a component of the overall corporate credit risk; therefore, credit rating agencies (CRAs) should include it in their risk assessment, with credit ratings also reflecting climate risk. Rating agencies are increasingly aware of the need to incorporate the

⁴² Several papers focus on firms' disclosure to measure firms' exposure to climate risks. Berkman et al. (2021) use a firm-specific climate risk measure based on textual analysis and find that firm value is negatively related to climate risk. Gostlow (2020) argues that a measure built on textual information found in Form 8-K for firms regulated in the US can detect physical risks that are missed in other research using textual analysis. Bingler et al (2022) stress the potential for greenwashing of firms' disclosure and point to the need for an external assessment of climate risks. Despite the limits of voluntary disclosure, the implementation of reporting standards has contributed to increase awareness of climate risk among stakeholders. In addition, companies that identify their climate risks will make financial decisions that take them into account, even if they may be tempted to practice greenwashing for their stakeholders by publishing only part of their identified risks.

risks and opportunities associated with environmental and climate (E&C) factors into their corporate credit ratings.⁴³ However, our results suggest that credit ratings do not reflect all the information related to physical climate risk, confirming that CRAs are conservative in adjusting their ratings (Altman and Rijken 2004).⁴⁴ In all our tests, we control for credit ratings and find that the physical climate risk grades provide additional information that is not already embedded in credit ratings. We also find that our measures of climate risk do not impact credit ratings when controlling for the usual determinants of credit ratings. Recently, major CRAs have acquired extrafinancial rating agencies, which leads to the reinforcement of their expertise in climate risk rating and could result in better recognition of climate risk in the future.⁴⁵

Our tests include several variables to control for other characteristics (size, tangible assets, profitability) that might affect leverage. However, if firms have a discontinuity in characteristics around the 2015 Paris Agreement, these characteristics may be driving our results that leverage decreases for high climate risk firms after 2015. For example, oil prices fell by more than 50% between 2014 and 2016. The strong decrease in oil prices may reduce the debt capacity of firms highly exposed to variations in oil prices.⁴⁶ If climate risk is also high for these firms, oil prices could be an alternative explanation for our results. To account for firms' differentiated exposure to oil price changes, we include oil betas, calculated similarly to Ilhan et al. (2021), in all our regressions. We also include an interaction term oil beta * post-2015 to account for the specific oil price pattern around the 2015 Paris Agreement, without

⁴³ For example, Standard and Poor's (S&P) examined 9,000 updates between July 2015 and August 2017 to gauge how these factors have featured in S&P Global Ratings' corporate credit analysis. E&C factors were an important consideration in the analysis of 717 cases and a driver for rating changes in 106 cases. Interestingly, of the examples that have an environmental or climate factor that was key to a rating change in the S&P analysis, most are linked to physical climate risks. [See this report from S&P Global Ratings.](#)

⁴⁴ Some anecdotal evidence point in this direction: [this article by Fitch](#); [this article by a former Moody's senior vice president](#). See also [this article](#) on municipal bonds.

⁴⁵ For example, S&P acquired Trucost, a provider of carbon and environmental data and risk analysis (2016), and Robecom SAM (2019), a European ESG rating agencies, and besides Four Twenty Seven, Moody's acquired Vigeo-Eiris, a global leader in ESG data (2019).

⁴⁶ For an analysis of the 2014-2016 oil price collapse, see Stocker et al. (2018), Baumeister and Kilian (2016) and Lehn and Zhu (2016).

altering our findings, which also remain similar when we exclude oil and gas industries. Furthermore, we conduct sensitivity tests for other firms' characteristics, all of which support our conclusions that physical climate risk is driving our results.

Although Bolton and Kacperczyk (2021) underline that transition risk does not appear to be significantly related to different exposures to physical risk, one might be concerned that there is a link between physical risk and transition risk and that our results partly reflect the effect of transition risk. We find that our results remain similar when controlling for transition risk, measured by Sautner et al. (2020) regulatory risk exposure, and its interaction with the dummy post-2015, which confirms that physical risk has an effect on leverage, independent of transition risk.

In the traditional empirical capital structure literature, debt supply frictions are not observed, and the firms' characteristics are the main determinants of leverage. In this framework, the observed reduction in leverage would result entirely from firms becoming aware of their climate risks and lowering their leverage. To adjust their leverage, in addition to lowering their demand for debt, high climate risk firms can increase shareholders' equity. We find that, after 2015, high climate risk firms increase their net equity offerings, suggesting that at least a fraction of the reduction in leverage results from a demand effect. Another way to examine the demand side is to review firms' CSR performance. As Engle et al. (2020) underline, CSR expenses may act as a hedge against physical and regulatory risks. Our results related to the impact of climate risk on leverage remain unchanged after considering CSR scores, which suggests that physical climate risk is an additional risk besides the environmental issues that nonfinancial rating agencies usually rate. Furthermore, we find that the reduction in leverage is mainly observed for firms with low CSR performance, suggesting that high CSR firms are likely to take proactive actions, for example, implementing appropriate risk management tools, to handle their climate risk rather than decrease their leverage.

On the supply side, bondholders and bankers may be willing to reduce their exposure to climate risks by limiting the amount of debt that they lend to high climate risk firms or by increasing the cost of debt for these firms. To test whether a supply effect occurs, we use loan-level data to examine interest rates charged on bank loans and bonds issues. We find that greater climate risk implies higher spreads on both bank loans and bond issues in the post-2015 period.

Overall, our findings suggest that the reduction in leverage related to climate risk is shared between a demand effect, whereby firms lower their demand for debt or issue more equity, and a supply effect, whereby bankers and bondholders increase the interest rate that they charge to high climate risk firms.

Our paper contributes to several lines of research. First, this research is related to the literature on physical climate risk and its impacts on firms and investors. The macroeconomic literature provides a great deal of evidence of global warming and extreme natural events that affect agricultural output, industrial output, energy demand, labor productivity, health, conflict, political stability and economic growth.⁴⁷ Evidence on a microeconomic level gives rise to a recently growing body of literature. For example, Barrot and Sauvagnat (2016) examine the impact of natural disasters on sales growth and find that disasters negatively affect both the sales growth of directly exposed firms and their largest customers. Pankratz and Schiller (2021) find that firms adapt their supply chain networks when weather shocks at the locations of their suppliers become more frequent, which can impose a substantial cost on their suppliers. Bansal et al. (2016), Addoum et al. (2019), Hugon and Law (2019), and Pankratz et al. (2019) observe that abnormal temperature negatively impacts firms' earnings and equity valuations, and Brown et al. (2021) examine the effects of climatic events on firms' drawing of bank credit lines. Kruttli et al. (2019) find that the uncertainty surrounding natural disasters is priced in option and stock prices. Bernstein et al. (2019) find that coastal properties exposed to projected sea-

⁴⁷ See Dell et al. (2014) and Jones and Olken (2010).

level rise (SLR) sell at an approximately 7% discount relative to otherwise similar properties. This SLR exposure discount is primarily driven by properties unlikely to be inundated for over half a century, which suggests that this discount is due to investors pricing long-horizon SLR costs.⁴⁸ This result emphasizes how climate risk discounts asset values and potentially reduces their pledgeability, which, in turn, may be part of the explanation of the leverage reduction that we document in our study.

Second, our research also contributes to the literature on the impact of climate risk on credit risks. Painter (2020) examines municipal bonds and finds that counties more likely to be affected by sea level rise pay more in underwriting fees and initial yields. Correa et al. (2021) estimate reactions in loan spreads for at-risk corporate borrowers who are not directly affected by natural disasters. Banks charge approximately 8 basis points higher rates for these indirectly affected borrowers.⁴⁹ Furthermore, Faiella and Natoli, 2019 find that flood risks decrease the amount of loans granted to corporations. Our results not only confirm these supply-side effects for physical climate risks but also underline that they occur mainly after 2015. Several other articles also find post-2015 effects for transition risks. For example, Zerbib (2019) finds negative yield premiums for green bonds after May 2016, and Seltzer et al. (2020) provide evidence of a causal relation between climate regulatory risks and bond yield spreads after the 2015 Paris Agreement. Bolton and Kacperczyk (2021) find a significant increase in the carbon premium after the Paris Agreement, especially for firms belonging to G20 countries. Our paper underlines that the Paris Agreement has also been important in reshaping companies' and investors' beliefs about physical climate risk. Overall, there is currently a strong set of results

⁴⁸ On the impact of SLR on real estate, other results are less clear. For example, Baldauf et al. (2020) find that houses projected to be underwater in “believer” neighborhoods tend to sell at a discount compared to houses in “denier” neighborhoods. Murfin and Spiegel’s (2020) results suggest limited price effects.

⁴⁹ Several papers find that transition climate risks also increase bond spreads (Seltzer et al. 2020, Huynh and Xia 2021) as well as bank spreads (Delis et al. 2019, Anginer et al. 2020).

that emphasize the tangible effects of the rising awareness of bankers and institutional investors regarding climate risks, whether transition risks or physical risks, in the post-2015 period.

Third, our paper is also related to the literature that examines the impact of operating costs on firms' financial leverage. Physical climate risks may increase operating costs (climate resilience expenses, costs related to operational disruptions, supply chain changes, insurance premiums), which could lead to a substitution effect between operating and financial leverage. Several authors examine various types of operating costs and risks and find a negative relationship between operating leverage and financial leverage. Petersen (1994) examines the firm's pension choice, Reinartz and Schmid (2016) consider production flexibility, Chen et al. (2019) use selling, general and administrative expenses to proxy for operating leverage, and Kahl et al. (2019) develop a measure of operating leverage by estimating the sensitivity of operating costs to changes in sales. Chen et al. (2011) argue that the presence of labor unions reduces operating flexibility and underline that "the concept of operating leverage in its nature is forward-looking". In our paper, we rely on forward-looking climate risk measures to proxy for increased operating costs and find that after 2015, the risk related to climate change, even if not yet materialized, leads to a reduction in the leverage of the world's largest firms. Our results also highlight that more CSR-oriented firms are better able to manage their operational risk and offset the negative impact of physical climate risks on their capital structure. These findings are in line with Sharfman and Fernando (2008), who find that improved environmental risk management allows for more leverage. They are also consistent with Lins et al. (2017), who find that during the 2008-2009 financial crisis, high CSR firms were able to raise more debt, and Amiraslani et al. (2019), who show that these firms benefited from lower spreads, better credit ratings, and longer maturities. Finally, our results also echo Huynh and Xia's (2022) findings that firms with strong environmental profiles experience lower selling pressure when exposed to natural disasters. These firms benefit from investing in corporate environmental

policies, which pay off when physical climate change risk is materialized. The rest of the paper is structured as follows. In section 2, we present our hypotheses. In section 3, we present our climate risk measures and our dataset. We analyze our empirical results in section 4, and section 5 concludes.

3.2. Hypothesis development: the effect of physical climate risk on leverage

Static tradeoff theory, pecking order, and market timing are the three preeminent theories of capital structure. Static tradeoff theory suggests that firms choose their capital structure to balance the benefits (corporate tax savings) and the costs (bankruptcy costs, agency costs) of debt financing and manage their leverage toward a target (see, for example, Bradley et al. 1984, Fischer et al. 1989, Leland 1994, Flannery and Rangan 2006). Pecking order theory predicts a financing hierarchy in which firms use internal funds first, then debt, and issue equity only as a last resort due to adverse selection costs of issuing equity (Myers and Majluf 1984). Finally, the market timing hypothesis posits that firms issue equity when they perceive the relative cost of equity is low and issue debt otherwise (Baker and Wurgler 2002). All these models involve tradeoffs between costs and benefits but differ in their assessment of which market frictions are the most relevant. There are a large number of empirical studies, often aimed at providing support for one of these theories. Overall, although the results vary over time and depend on the type of sample selected and the methodology that is used, the evidence suggests that firms borrow more when they are subject to lower debt issuance costs, higher corporate taxes, lower bankruptcy costs, a higher liquidation value of assets and lower operating costs and earnings volatility.⁵⁰ To assess the impact of climate risk on corporate leverage, we focus on two variables: operating costs and bankruptcy costs.

⁵⁰ For a review of empirical capital structure research, see Parsons and Titman (2008), Frank and Goyal (2009), and Graham and Leary (2011).

3.2.1. Climate risks and operating costs

Firms exposed to physical climate risks will incur climate resilience expenses due to two major factors: first, costs related to operational disruptions, production adjustments, and supply chain changes, and second, increased insurance premiums. Manufacturing operations are increasingly global, complex, and geographically concentrated. For example, 92% of the world's most advanced semiconductor manufacturing capacity is currently located in Taiwan⁵¹, which is at risk from various natural disasters, such as floods and typhoons. Thailand floods in 2011 caused a 37% (55%) loss of operating profit for Toyota (Honda) due to the lack of parts from suppliers whose plants were flooded, Thailand being one of the production hubs for Japanese automakers (Haraguchi and Lall, 2015). In 2017, Hurricane Maria made landfall on Puerto Rico, where 10% of US pharmaceutical product manufacturing is based and led to critical shortages throughout the US.⁵² In a survey on supply chain resilience⁵³, respondents cite adverse weather as one of the top three causes of supply chain disruptions. In addition, anecdotal evidence shows that some companies prefer to take the risk of increasing operating costs rather than relocating their production facilities.⁵⁴

The increase in insurance premiums is another major factor in the rise in operating costs. Two key variables affect the insurability of climate risk events. First, natural disasters are hardly diversifiable, as they simultaneously hit thousands of insurance policies for property, cars, and business interruptions. This systematic nature of climate risks will require additional capital and safety margins in premium calculations (Kunreuther and Michel-Kerjan, 2007, and Charpentier, 2008). Second, it is becoming less and less relevant to rely only on past events to

⁵¹ Source: [Insurability in the face of climate risk](#), Institute for sustainability leadership, University of Cambridge (2014), and [BCG report \(2021\)](#).

⁵² See [DHS report \(2018\)](#).

⁵³ BCI, [Supply chain resilience report \(2019\)](#).

⁵⁴ See US department of commerce report (2022) "[Assessment of the critical supply chains supporting the US ICT industry](#)", p74-75. Before 2011, Thailand produced approximately 45% of the world's hard disk drive (HDD) components. After the 2011 floods, while experts called for increased geographic diversity, HDD production further consolidated in Thailand, increasing the potential impact of future natural disasters.

estimate future climate risk. However, if insurers update their models and add a large margin to the premium to allow for uncertainty, the likelihood of an agreement between insurers and policyholders on the perception of risk, and thus on the premiums to be paid, decreases. As a result, a significant number of insurers exit this market (Born and Viscusi 2006). In addition, as a growing number of insurers are considering not renewing insurance contracts for clients or sectors most at risk, increased uncertainty and reduced competition will inevitably lead to higher insurance premiums in the future.⁵⁵

The existence since 2015, thanks to the TCFD, of standards for the disclosure of the companies' climate risks could have made it possible for companies and insurers to more easily converge in their assessments of the actual increasing risk and facilitate the insurability of risks at a higher premium. Similarly, disclosure requirements have probably also led companies to an increased awareness of the risks of their entire supply chain and a more accurate assessment of the consequences of these risks. Following the prior literature (Reinartz and Schmid 2016, Chen et al. 2019), we hypothesize a substitution effect between operating and financial leverage.

3.2.2. Climate risks and bankruptcy costs

Second, climate risk can impact the costs associated with a possible failure. The value of a firm's assets may be reduced if they are located in areas subject to significant climatic risks. The impairment may be related to direct asset destruction by an extreme climatic event or to a

⁵⁵ In 2020, the French Prudential Control and Supervision Authority subjected French insurance companies to a climate stress test. Even though France is relatively spared in the IPCC scenarios, in property damage, the results show an evolution in claims with a multiplier factor to two to five for all physical climate risk combined (floods, drought, marine flooding, cyclonic storms), leading to an expected rise of insurance premiums from 130 to 200% over thirty years (see [ACPR, 2021](#)). Examples of current increased insurance premiums: TWIA, the insurer of last resort for wind and hail in counties along the Texas coast, more than doubled insurance premiums since 2000 and states its commercial rates are still inadequate by 50 percent. See [here](#). In the ten Californian counties with highest fire risk exposure, nonrenewed homeowners insurance policies increased by 203% from 2018 to 2019. See [here](#), p.7 and [here](#). For further analysis of wildfires insurance, see Hazra and Gallagher (2022). For a study of the consequences of droughts on the insurance coverage for commercial enterprises, see Kornfeld (2019).

reduction of asset value due to their exposure to future climate risks (for example, seashore property exposed to a sea-level rise). In addition, a loss in the assets' market value may also result from the inability to sell these assets to an acquirer due to increased climate risks.⁵⁶ Insurance companies can partly mitigate the first type of cost (asset destruction by extreme events) but do not cover the second type. In a way, the increased awareness of climate risk leads to a re-evaluation of the firm's operating environment and its risk of bankruptcy, a situation similar to the periods of regulation/deregulation in specific industries. For example, Ovtchinnikov (2010) finds a decline in leverage of firms in sectors affected by the waves of deregulation from the 1970s to the 1990s, due in particular to increased bankruptcy risk.

The traditional hypothesis in the empirical capital structure literature is that the observed level of debt equals the firm's demand level, which means that there is no supply friction. Firm characteristics are then the main determinants of leverage. Therefore, our first hypothesis is that firms with greater climate risk exposure will reassess their operating costs and distress costs, which should lead them to reduce their leverage compared to firms with low exposure to climate risk. To adjust their leverage, high climate risk firms may decrease their demand for debt or issue new shares.

3.2.3. Climate risk and leverage: is there a supply effect?

Supply-side factors are likely to be important in explaining capital structure (Faulkender and Petersen 2006). There may be climate effects related to the debt supply if bankers and bondholders become increasingly aware of climate risk and subject firms to more stringent regulations and disclosure requirements. The climate risk effects can occur directly through a

⁵⁶ There are also several papers on stranded assets, i.e., assets at risk of becoming obsolete, especially in the oil and electricity industries (see for example Atanasova and Schwartz 2020 and Hickey et al. 2021). However, these impairments are mainly the results of regulatory risks (for example regulations on the reduction of carbon emissions) rather than physical climate risks.

quantity channel if lenders are willing to lend less to firms exposed to higher climate risk or indirectly through a price channel if lenders are increasing the cost of debt for high climate risk firms. To verify this last effect, we conduct empirical tests by using loan-level data, specifically bank loans on the one hand and bond issues on the other hand. Therefore, our second hypothesis is that climate risk should increase the cost of debt.

To the extent that the many recent climate change initiatives and disclosure requirements have increased the attention of firms, investors, and central banks to climate risk, we assume that the effects of climate risks on capital structure will mainly materialize in the period after 2015.

3.3. Data

3.3.1. Physical climate risk measures

The assessment of climate risk at the firm level depends on both geographical factors and vulnerability factors specific to the firm's activity. In this paper, we use two climate risk measures, described in detail in Appendix B. The first is the CRIS methodology, which was developed by the French firm Carbone 4 in cooperation with several financial institutions.⁵⁷ Their approach is based on models and data from the Coupled Model Intercomparison Project (CMIP).⁵⁸ The CRIS measures aim at assessing the climate-related physical risks that face firms and their business units in the future by breaking down the firm's activity into geographical and industrial segments and by assessing the future climate risk for each country-industry pair. Each climate risk rating is a function of location-specific climate hazards and sector-specific vulnerabilities. Industry information comes from the GICS, ICB, and NAICS codes. The geographical division of activities is based on sales, tangible assets, or a combination of both, depending on the low, high or medium capital intensity of the sector to which the firm belongs.

⁵⁷ More information is available [here](#).

⁵⁸ See for example Taylor et al. (2012)

Geographical information depends on the granularity of the information disclosed by the firms. Six of the seven largest countries (Brazil, Canada, China, India, Russia, and the US) are further divided into 4 subcountries. At its broadest level, climate risk is measured through an index that aggregates 7 hazards: 4 of these hazards are acute (extreme) hazards, i.e., heatwaves, rainfall extremes, drought, and storms, and 3 are chronic hazards, i.e., increases in average temperature, changes in rainfall patterns and sea-level rise. The aggregated risk rating is based on the weighted geometric mean of all the risk ratings calculated for each of the seven hazards.

The CRIS measures are split into two time horizons (2050 and 2100) and three intensity cases (low, medium, high), which reflect the Intergovernmental Panel on Climate Change (IPCC) scenarios in Assessment Report 5 (AR5) and are formally named Representative Concentration Pathways (RCPs).⁵⁹ The CRIS risk rating does not capture the absolute risk from future climate or weather but does capture the increased risk due to the increase in the intensity or frequency of the climate-related hazards in the future due to global warming compared to historical reference average hazards. Final ratings are attributed on a scale of 0 to 99, and when the rating is higher, the risk is greater. As the rating scale is relative, a low rating does not necessarily imply low risk in absolute terms but rather means that the risk is in the lower part of the gradient in relative terms. For a firm with multiple business segments (various sectors in various countries), for each hazard, the risk rating is based on the weighted arithmetic mean of all the risk ratings calculated for each of the firm's business segments for this same hazard. The weighting is proportional to the breakdown of the firm's revenue or fixed assets (if capital intensive) in its various segments. For each hazard, the risk rating of a specific sector in a specific country is a combination of the hazard rating of the country and the vulnerability rating

⁵⁹ The RCPs include a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0) and one scenario with very high GHG emissions (RCP8.5). Scenarios without additional efforts to constrain emissions ("baseline scenarios") lead to pathways that range between RCP6.0 and RCP8.5. Currently, the RCP2.6 scenario feasibility is seriously in question. Therefore, the CRIS measures rely on the RCP4.5 (low), RCP6.0 (medium) and RCP8.5 (high) scenarios. See [IPCC AR5](#).

of the sector. The country rating is built upon the aggregation of various underlying indicators covering the three main components of vulnerability (exposure, sensitivity, and adaptive capacity). The sector rating is based on the aggregation of the vulnerability of 13 financial items covering assets, expenses, and sales.

In this paper, for the sake of clarity, we use a unique CRIS rating that corresponds to the 2050 horizon and medium intensity risk. This horizon seems distant, as the majority of bond issues have a maturity of less than 30 years, but the reader should keep in mind that climate risk will gradually materialize over the coming years. As Krueger et al. (2020) show in their survey on climate risk, most institutional investors believe that climate risks will materialize within the next few years. The CRIS ratings cover the sphere of the MSCI World Index for 2016.

The second measure of climate risk that we use is provided by Four Twenty Seven.⁶⁰ Each firm is scored on three components of physical climate risk: operations risk (70%), supply chain risk (15%), and market risk (15%), with a time horizon of 2030 to 2040. A firm's operations risk is based on its facility-level exposure to hurricanes and typhoons, sea-level rise, floods, extreme heat, and water stress. The spatial scale depends on the subrisk considered (90 m x 90 m for sea-level rise and flood frequency and severity, 25 km x 25 km for heat stress, wildfires, and hurricanes and typhoons). The Four Twenty Seven measures are therefore more granular than the CRIS measures.⁶¹ 15% of the Four Twenty Seven score relies on supply chain risk, which is evaluated with two indicators, the country of origin indicator (a measure of climate risk in countries that export commodities that a company depends on for the production and delivery of products and services) and the resource demand indicator (a measure of the industry-level dependence on climate-sensitive resources such as water, land, and energy across the supply chain). Market risk is based on countries of sales and weather sensitivity for market risk.

⁶⁰ See [here](#) for more information.

⁶¹ Fiedler et al. (2021) suggest that due to nonlinearities in the climate system, downscaling is unlikely to provide more reliable data for decision-making.

Four Twenty Seven scores consider projected climate impacts in the 2030-2040 time period under a single RCP scenario, RCP 8.5 (the worst scenario). The IPCC report underlines that the likelihood of individual scenarios is not part of the assessment. There is considerable uncertainty about the probability of each of the scenarios. For some authors, the RCP8.5 scenario is extreme and highly unlikely (van Vuuren, 2011). On the other hand, Christensen et al. (2018) suggest a greater than 35% probability that emissions concentrations will exceed those assumed in RCP 8.5 due to higher uncertainty in per-capita GDP growth rates than in commonly used forecasts. However, as [IPCC working group 1 assessment report 6](#) indicates, for a time horizon up to 2040, the best estimate of the average temperature increase is +1.5°C for all scenarios, except for a slight difference for the worst one (+1.6°C). Thus, the fact that the providers of our two climate risk metrics use different scenarios for a similar horizon should have a limited impact on our results. It is only for more distant horizons that larger discrepancies appear (1.4°C for the most favorable scenario, 4.4°C for the worst scenario, on a horizon of 2081-2100). However, it is unlikely that companies, bankers, and investors will consider such a long time horizon when making decisions about corporate debt. For example, in our sample of bond issues, only 1% of offerings have a maturity of over 40 years.

To summarize, CRIS proposes the analysis of three scenarios and two horizons, while Four Twenty Seven has only one. The Four Twenty Seven score is based partly on an assessment of historical climate risk. It uses more detailed facility location data than CRIS, which relies solely on data disclosed by the companies. Four Twenty Seven offers a finer granularity, while CRIS examines risks at the country level (possibly broken down into zones for the largest ones). Four Twenty Seven explicitly analyzes supply chains, but part of the information is at the industry level, whereas CRIS conducts an in-depth analysis of the industry-specific vulnerabilities.

As climate risk scores are determined based on a 2050 horizon (CRIS) or 2030-2040 (Four Twenty Seven), we assume that this risk remains stable over the period studied (2010-2019)

and that the firm's activities and locations do not undergo major changes over the period, which is the hypothesis adopted by the two rating companies.⁶²

After excluding financial firms and observations with missing data (see below), we are left with 1,212 firms. In Table 1, Panel A presents the descriptive statistics for our climate risk ratings. The average overall CRIS rating is 35.161 (median = 36.994, standard deviation 10.833). The number of observations available for the Four Twenty Seven scores is slightly smaller than that for the CRIS scores, as all MSCI firms are not yet graded. The average overall Four Twenty Seven rating is 42.828 (median = 43.510, standard deviation 13.225).

3.3.2. Credit ratings

Credit ratings at the issuer level are obtained from Thomson Reuters. This variable is based on the S&P Long-term Issuer Rating when available. If this rating is not available, we rely on Moody's Long-term Issuer Rating, and we rely on Fitch's Long-term Issuer Default Rating if both previous measures are missing. Similar to Baghai et al. (2014), we linearize these ratings from 1 to 20. Investment-grade ratings are coded between 11 and 20, whereas high-yield ratings are coded between 1 and 10. Missing ratings are coded 0.

Of our firm-year observations, 67% are rated and therefore have potential access to public debt markets, which reflects the fact that the sample comprises the world's largest listed firms that belong to the MSCI World Index. The average credit rating is 12.28 (median 12), which corresponds to an S&P grade of BBB.

⁶² One question that may arise is how these measures of future climate risk relate to historical climate risk. The Four Twenty Seven score explicitly considers historical risk in assessing future operational risk. The CRIS score assesses the increase in risk over the time horizon under consideration relative to historical risk. Although both measures contain more information than a purely historical measure, we acknowledge that they are not unrelated to the historical risk.

3.3.3. Financial and accounting data

The financial and accounting data are from Compustat North America and Compustat Global. We first matched the firms covered by the CRIS grades with the data available in Compustat for fiscal years 2010 to 2017, which yields 11,836 firm-year observations. By relying on 2-digit SIC codes, we excluded SIC codes 60 to 69, as financial firms are subject to special regulations concerning their capital structure. Missing values for long-term debt, EBIT, R&D expenses and issuer ratings were set to zero. This assumption is noncritical, as only 71 observations have missing values of long-term debt. Missing ages were set to 1 to use the natural logarithm. We have three additional observations with missing EBIT. We excluded the observations with missing values of operating expenses and the observations for which we were unable to compute Tobin's Q. Therefore, we were left with 9,138 firm-year observations that cover 1,212 firms. These figures are sound, as, on the one hand, 1,604 firms are covered by CRIS, and on the other hand, the MSCI World Index covers approximately 1,600 firms, with 16.33% of them belonging to the financial sector.⁶³ We extended our database to 2019, when the data became available. In total, our database covers 11,367 firm-year observations for 1,212 firms.

Our main measure of leverage for firm i in year t is a book leverage variable defined as follows:

$$BookLev_{it} = \frac{DLTT_{it}}{AT_{it}};$$

where $DLTT_{it}$ is the amount of long-term debt that exceeds a maturity of one year, and AT_{it} is the book value of total assets. We exclude the debt in current liabilities because of the long-term nature of climate risks.

Similarly, we define the market leverage for firm i in year t as follows:

⁶³ See [here](#) for more details.

$$MarketLev_{it} = \frac{DLTT_{it}}{AT_{it} - CEQ_{it} + PRCC_F * CSHO}$$

if the firm is covered by Compustat North America; and

$$MarketLev_{it} = \frac{DLTT_{it}}{AT_{it} - CEQ_{it} + PRCCD * CSHOC}$$

if the firm is covered by Compustat Global.

All the variables computed from Compustat are winsorized at the 1% level to prevent the effect of potential outliers. Country fixed effects are based on headquarters locations, and industry fixed effects are based on the two-digit SIC codes.

In Table 1, Panel B, the means (medians) of various firm characteristics are reported for the full sample and are then disaggregated between low climate risk (below the 40th percentile) and high climate risk (above the 60th percentile) firms. The average long-term book leverage is 21.8%. High climate risk firms (with an average CRIS rating of 43.5) are less leveraged (18.3%) than low climate risk firms (with an average CRIS rating of 23.5) (24.2%). Market leverage is also significantly lower for high versus low climate risk firms, even if the difference is smaller (13.4% versus 15.5%). High climate risk firms are larger and have more tangible assets, more R&D expenses, and a lower Tobin's Q than low climate risk firms. The results are similar when considering the Four Twenty Seven scores to disaggregate the sample between high climate risk (average Four Twenty Seven rating of 55.6) and low climate risk (average Four Twenty Seven rating of 29.8).

3.3.4. Bank loan and bond issuance data

We obtain bank loan data by using Dealscan and focus on loans with maturities greater than three years and amounts greater than \$100 million. We use the item Margin(Bps) as our measure of the cost of the loan. Therefore, we exclude the observations for which this item is unavailable. We also exclude the observations for which at least one of the independent variables used in

our regressions is unavailable. This bank-loan level dataset is then matched with the data described in the previous sections. The correspondence between Dealscan and Compustat data is achieved with the linking database developed by Chava and Roberts (2008). Our total number of bank loan observations is 3,388. The descriptive statistics are detailed in internet Appendix, Table IA1.

Furthermore, we extract bond issuance data from Thomson-Reuters by focusing on vanilla, fixed-coupon bonds with an amount issued of at least \$100 million. Bessembinder et al. (2018) define small corporate bonds as those with an issue size under \$500 million. Helwege and Wang (2019) find that only 30% of bond issuances are under \$292 million in 2002 dollars. For these reasons, and as our dataset covers the world's largest firms, our \$100 million cutoff seems to be appropriate to gauge whether the decrease in leverage could come from a supply effect. In Dealscan, interest rates charged on bank loans are expressed in terms of basis points added to a reference rate (spreads). To draw a parallel between bank loans and bond issuances, we match our bond data from Thomson Reuters with the benchmark spread at issue reported in Bloomberg. To the best of our knowledge, this variable is the closest equivalent to Dealscan's spread. Our total number of bond issue observations is 5,105. The descriptive statistics are detailed in internet Appendix, Table IA1.

The characteristics of firms in the samples of bank borrowers and bond issuers are similar overall, even if bond issuers are larger and older than bank borrowers. The climate risk is larger for bond issuers. The average maturity is larger for bond issues (9.85 years) than for bank loans (4.85 years).

3.4. Empirical results

3.4.1. Leverage and climate risk

The descriptive statistics show that firms with high climate risk are less highly leveraged. It may be that firms with high climate risk are also the firms that find debt less

valuable. However, as these firms are larger and have more tangible assets, the theory predicts that they should demand more debt, which suggests that they are not in a situation in which they would attach less value to debt. Based on the literature on capital structure determinants, we regress the firm's leverage on a set of firm characteristics, including credit ratings and climate risk measures. Clustering effects could bias the statistical significance of the results because of firm leverage persistence over time. Thus, in estimating our regressions, we apply the procedures described in Petersen (2009) to adjust the standard errors for clustering by firm. Our baseline regression is as follows:

$$LTDebt_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 X_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (1)$$

$LTDebt_{it}$ refers to our measure of long-term debt, either $BookLev_{it}$ or $MarketLev_{it}$. $Climate_i$ represents the value of the overall climate change risk exposure of a firm, X_{it} is a vector of controls that have been shown to affect the level of debt holdings and Z_{it} is a vector of fixed effects. $Climate\ risk$ is also interacted with $Post2015$, a dummy equal to one after 2015, to take into account the Paris Agreement effect. For these regressions, the equation is as follows:

$$LTDebt_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 Climate\ risk_i * Post2015 + \beta_3 X_{it} + \beta_4 Z_{it} + \varepsilon_{it} \quad (2)$$

Our results are presented in Table 2 for book leverage and in Table 3 for market leverage. In Tables 2 and 3, CRIS data are used to measure climate risk in columns 1 to 5, whereas regressions in columns 6 to 10 use Four Twenty Seven data. Our findings confirm the previous work on capital structure. Firms with more tangible assets, as measured by a firm's property, plant, and equipment to total asset ratio, have a higher debt ratio. In contrast, intangible assets, as measured as research and development expenses scaled by total assets,

reduce a firm's leverage. More profitable firms (EBIT/total assets) and firms with a higher proportion of operating expenses are less leveraged. Furthermore, by including country-industry fixed effects and year fixed effects (Table 2, columns 1,2,6 and 7), we can completely control for any determinant of leverage that is constant within a year or a pair industry-country. Thus, we control for any specific industry structure or regulation in a country. Alternatively, we apply a firm fixed effect regression to control for all time-invariant firm characteristics (Table 2, columns 3 and 8).

Controlling for these fundamental differences between firms, we find that increased physical climate risk reduces leverage for the whole period when using CRIS climate scores (Table 2, column 1). This result is not confirmed when using Four Twenty Seven data to measure climate risk (Table 2, column 6). The year 2015 was a pivotal year for considering climate risk that resulted from the Paris Agreement (COP21) and the implementation of the TCFD. Therefore, we examine whether the impact of climate risk on leverage changed after 2015 by interacting our climate risk measure with a dummy variable equal to one for the post-2015 period. We find that the climate risk effect on leverage materializes mainly after 2015: a one standard deviation increase in climate risk reduces debt by 1.53% (-0.00139×10.833) with the CRIS score (column 3) or 1.38% (-0.00104×13.225) with the Four Twenty Seven score (column 7). This effect is economically significant, as it represents 6.91% of the leverage (CRIS scores) and 6.31% of the leverage (Four Twenty Seven scores).

Climate risk could also be a component of the overall corporate credit risk. Graham and Harvey (2001) find that for CFOs, credit ratings are their second-highest concern when determining their capital structure. If credit ratings already reflect climate risk, adding climate risk variables would not provide any additional information to the determinants of leverage. To verify that our climate risks measures are not mere proxies for credit risk, we add in all our regressions a variable that linearizes the credit ratings from 1 (D) to 20 (AAA) for firms that

benefit from a rating and is zero otherwise. We find that firms with more favorable ratings have more long-term debt than firms that are poorly rated.⁶⁴

Our findings may result from a reverse causality between the credit rating and leverage. To address this potential problem, we use an instrumental variables approach. In the first stage, we estimate the endogenous variable (CreditRating) as a function of the exogenous variable in the second stage plus an additional instrument. Our credit rating variable instrument is based on its means for groups by year/sector/country. This instrument is correlated with our credit rating variable, although it is unlikely that the debt level of a given firm will depend on the average rating of the sector for a given year and country once fixed effects are considered. Our results are confirmed, and the magnitude of the coefficients of the climate risk measure remains similar for book leverage (Table 2, columns 4 and 5 for CRIS, and columns 9 and 10 for Four Twenty Seven scores).

When market values are considered (Table 3), leverage increases with size and tangible assets and decreases with profitability, Tobin's Q, and the proportion of operational expenses, confirming the prior literature. Our main results remain similar, even if their amplitude is attenuated: a one standard deviation increase in climate risk decreases market leverage after 2015 by 0.59% to 0.65% (CRIS scores) or by 0.61% to 0.65% (Four Twenty Seven scores).

These findings suggest that our climate risk measures provide an additional risk factor that has an impact on leverage after 2015 and that is not already included in the credit risk ratings. After the strong signals sent to all participants in the financial system in 2015 regarding the necessity to develop climate-related disclosures and better understand their exposure to climate-related risks, both managers and investors became more aware of climate risks, which, in turn, can explain the reduction in leverage that we observe.

⁶⁴ In unreported tests, we also introduce a dummy variable that is equal to 1 if the firm is not rated by any of the three major rating agencies of Standard and Poor's, Moody's and Fitch. Confirming previous results (Faulkender and Petersen, 2006), we find that firms without a credit rating are significantly less leveraged. Our main results remain similar.

3.4.2. Difference-in-differences in leverage and climate risk: the Paris Agreement

Our analysis has thus far used continuous variables (CRIS or Four Twenty Seven scores) to explain firms' leverage. Our results identify a negative effect of physical climate risk on leverage concentrated in the post-2015 period, i.e., after the Paris Agreement. A first question arises about the possibility of our climate risk measure being endogenous. Our climate risk measures are both forward-looking measures that reflect the probability of future climate events that are highly exogenous. However, we acknowledge that this risk measure depends on the location of the firm's activities and the choice of business segments that are more or less vulnerable to climate risk, which are factors that may also impact the firm's leverage. To mitigate these potential endogeneity problems, we conduct additional tests in a difference-in-differences setting by using the 2015 Paris Agreement as a shock to firms, banks, and investors' awareness of physical climate risks. We define treatment variables based on our two climate risk scores. For each score, a firm is considered to belong to the treated group if the risk indicator has a value above the 60th percentile. Firms below the 40th percentile fall into the control group. For a clearer distinction between the treatment and control groups, we exclude firms between the 40th and 60th percentiles. The results are reported in Table 4. Column 1 reports a treatment effect of -2.22% on book leverage when defining the treatment with respect to the CRIS score. This result is qualitatively similar to the result in Table 2, column 3, which indicates a marginal effect of -2.82% ($-0.134\% \times 21.05$, the difference in the overall climate risk indicator between firms below the 40th percentile and firms above the 60th percentile being 21.05 points). Column 2 reports a treatment effect of 2.58% on book leverage when using the Four Twenty Seven score to define the treated and control groups. When considering market leverage (Columns 3 and 4), the effect is -1.34% for the Four Twenty Seven scores and insignificantly negative for the CRIS scores. Overall, our results in a difference-in-differences setting are

consistent with the findings highlighted in Tables 2 and 3. Internet Appendix Figure 1 shows the leverage dynamics in the years around the Paris Agreement for High and Low Climate Risk firms, confirming that 2015 is pivotal in the consideration of climate risk. Low climate risk firms were able to increase their leverage over time, whereas high climate risk firms were not able to do so. It can be noted that throughout 2014, in preparation for COP21, there were many private initiatives around climate risks (see internet Appendix, Section A), which may explain the shift in leverage appearing as early as 2014.

3.4.3. Climate risk and firm characteristics around the 2015 Paris Agreement

As descriptive statistics in Table 1, panel B, show, high climate risk firms are larger, less profitable, and have a smaller Tobin's Q. If these characteristics vary around the 2015 Paris Agreement, they may be driving our results that leverage decreases for high climate risk firms after 2015. In particular, one item of focus is the oil price, which fell by more than 50% between 2014 and 2016. The strong decrease in oil prices may reduce the debt capacity of firms highly exposed to variations in oil prices, for example, oil firms. Our tests would be contaminated if these firms were also exposed to high physical climate risk. Therefore, we include oil betas in all our regressions to account for firms' differentiated exposure to oil price changes. We also include an interaction term oil beta * post-2015 to account for the specific oil price pattern around the 2015 Paris Agreement. Our results in Table 5, columns 1 and 2 support our initial conclusion that climate risk, and not oil price, is the driving factor behind the reduction in leverage for high climate risk firms after 2015. Our results also remain similar when we exclude oil and gas industries (Table 5, columns 3 and 4) and when we split our sample into two subsamples depending on whether the oil beta is positive or negative (Table 5, columns 5 to 8).

We further investigate whether other variations in firm characteristics around the 2015 Paris Agreement may affect our results. We add to our regressions an interaction term between

profitability, Tobin's Q, operational expenses, size, tangible assets, and the dummy variable post-2015. Internet Appendix, Table IA2, Panels A and B, present the results that further support our conclusions that physical climate risks drive the negative impact on leverage after 2015.

3.4.4. Credit ratings and climate risk

We have seen in previous tests that the climate risk rating provides additional information compared to the credit rating to explain a firm's leverage after 2015. In this paragraph, we intend to explore the relationship between credit risk and climate risk in more detail. Credit ratings are fundamentally forward-looking; they are beliefs about the downside risks that surround promised future outcomes and the probability of financial distress. CRAs thus evaluate the fundamental drivers of creditworthiness over the long term. Climate change may affect creditworthiness through potential economic impact, physical damage to assets, and indirect impacts from supply chain disruption. Credit ratings should at least partially reflect climate risks, even if they do not consider them in their entirety. Rating agencies are multiplying the announcements related to environmental and climate risk factors, with a primary focus on sovereign and municipal bonds. For example, Moody's has changed its sovereign bond methodology to capture the effects of physical climate change in a broad set of rating factors that influence a sovereign's ability and willingness to repay its debt (Moody's, 2016). Over recent years, rating agencies have reinforced their expertise in climate risk rating by acquiring agencies specializing in corporate environmental performance ratings.

We acknowledge that credit ratings are not perfectly correlated with publicly observable and quantifiable information about firms' characteristics and that they bring a holistic creditworthiness assessment beyond financial and accounting ratios. Nevertheless, variables such as interest coverage, profitability, size, and risk measures are well-known determinants of

rating levels and their corresponding expected default losses (see, for example, Standard and Poor's, 2013). To check whether credit ratings reflect climate risk, we estimate the following equation:

$$CreditRating_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 X_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (3)$$

$CreditRating_{it}$ refers to our linearized credit rating variable, $Climate\ risk_i$ represents the overall risk exposure of a firm, X_{it} is a vector of controls that have been shown to affect the level of credit ratings, and Z_{it} is a vector of fixed effects. $Climate\ risk$ is also interacted with the dummy $Post2015$. Table 6 presents our findings. We regress the credit rating variable on the following explanatory variables: profitability, interest coverage, size, age, Tobin's Q, working capital divided by total assets, operating expenses divided by total assets, R&D expenses divided by total assets, oil beta, and the fraction of tangible assets. We control for year fixed effects to consider that rating standards have tightened over time (see Jorion et al. 2009, Baghai et al. 2014), for country-industry fixed effects (as business risk varies across sectors and the sovereign rating represents in almost all cases a ceiling for the private sector) and firm fixed effects to control for time-invariant firm characteristics. As the results in Table 6 indicate, the coefficient of our climate risk variable is not significantly different from zero, either before or after 2015, whether using CRIS scores or Four Twenty Seven scores, which suggests that credit ratings do not reflect physical climate risk specific to the firm beyond the headquarters country climate risk that is captured by the country-industry dummies.

Accordingly, physical climate risk as measured by the CRIS or Four Twenty Seven ratings does not seem to be reflected in the credit ratings issued by the rating agencies, at least over the period that we examine.

3.4.5. Climate risk and leverage: demand or supply effect?

The observed level of debt is a function of a firm's demand for debt: the empirical capital structure literature traditionally assumes that in the absence of frictions, firms can borrow up to their optimum leverage, which depends on their characteristics. However, the reduction in leverage that we observe in the post-2015 period may also be the result of supply factors.

3.4.5.1. Climate risk and leverage: the demand effect

To adjust their leverage to climate risk, firms can reduce their demand for debt in line with the variation of their characteristics or issue new equity. We first examine whether firms subject to higher climate risk increase their net equity issuance (equity offerings minus repurchases). Table 7 presents our results. In columns (1) and (2), we use the CRIS climate risk score, and in columns (3) and (4), we use the Four Twenty Seven score. The results in columns (1) to (3) show a significantly positive coefficient associated with our variable climate risk*post-2015, suggesting that after 2015, net equity issuance increases with climate risk. The marginal effect of a one standard deviation increase in the climate risk after 2015 is between +0.19% and +0.25%.

An alternative way to examine the demand side is to focus on CSR performance. We first check whether our measure of climate risk is not a mere proxy for a more general CSR assessment. In Table 8, Panel A, we verify that our results remain unaffected after controlling for various CSR indicators. The regressions in columns (1) and (3) use the general CSR score given by the MSCI IVA ratings. The regressions in columns (2) and (4) use a dummy variable based on CDP data (carbon disclosure) that equals 1 if the firm is rated A (best grade) by CDP. Whatever the measure for CSR performance, our results on the impact of climate risk on leverage are qualitatively unchanged, which suggests that our climate risk measure is not a mere proxy for CSR performance.

On the other hand, CSR expenses may allow firms to adapt their activities to climate risk and decrease operational risk. A reduction in operating leverage may be an alternative to a reduction in leverage. In Table 8, Panel B, we construct subsamples based on the values of the CSR variables. Columns 1 and 2 report the regressions conducted on firms with an above-median overall CSR score and firms with below or equal to the median overall CSR score, respectively. Only low CSR firms significantly reduce their leverage after 2015. In regressions (3) and (4), we split our sample between firms included and firms not included on CDP's A list. Firms on the A list have had a smaller decrease in their leverage ratio post-2015 compared to firms not on the A list. In columns (5) to (8), regressions are presented using the Four Twenty Seven score, and the results are similar. All differences between high CSR and low CSR firms are significant at the 1% level (except between columns (3) and (4), significant at the 10% level). Taken together, these results are consistent with the view that firms with better CSR scores are more likely to take proactive actions, for example, implementing appropriate risk management tools, to hedge their climate risk, thereby reducing the need for a decrease in their debt ratio.

3.4.5.2. Climate risk and leverage: the supply effect

To test whether supply factors are involved, we examine loan-level data that cover bond issues on the one hand and bank loans on the other hand. If a supply effect exists, the reluctance to finance high climate risk firms should materialize as higher spreads.

Climate risk and public debt markets

We first focus on the impact of physical climate risks on the cost of bonds. With the benchmark spread at issue as our measure of the cost of borrowing, we find a post-2015 rise in interest rates in bond markets. Columns (1) to (6) in Table 9 report the results. The effect is

concentrated in high-risk firms. We find that post-2015, a one standard deviation increase in climate risk generates a 6.02 basis point increase ($1.094 \times 5.505 = 6.02$, with 5.505 being the standard deviation of the CRIS indicator within the high-risk group) in the spread at issue in the high-risk group when using CRIS scores (column 2) and a 9.82 basis point increase when using Four Twenty Seven scores (column 5). In both cases, we do not find any significant effect within the low-risk group, and the difference in the coefficients is significant between the two risk subgroups when using CRIS scores. In addition to firm fixed effects and year fixed effects, we include fixed effects to account for the number of loans to the firm on the same date, loan purpose and secured/unsecured status. Our findings indicate a significant impact of physical climate risks on public debt cost in the post-2015 period.

Climate risk and bank loans

Table 10 reports the results for bank loans. Similar to bonds, the effect of climate risk in the post-2015 period is concentrated in high-risk firms. For these firms, the effect of a one standard deviation increase in climate risk, as measured by CRIS scores, is 23.37 basis points (Table 10, column 2). We do not find any significant effect within the low-risk group (column 3), and the difference in the coefficients between the two risk subgroups is significant. When using the Four Twenty Seven scores, the coefficient of our climate risk measure for high-risk firms is positive but insignificant. The Dealscan data are heavily biased toward the US (see Florou and Kosi, 2015). When we match our climate risk data with the Dealscan data, US firms represent 73% of bank loans, compared to 39% in our main sample. In addition, the data matching process leads to the disappearance of a significant fraction of non-US high-risk firms for the Four Twenty Seven sample, especially after 2015. Therefore, we rerun our regressions for the US high-risk firm subsample (Table 10, columns 7 and 8). Our effect using the Four Twenty Seven score is significant at the 10% level.

Overall, our findings suggest that physical climate risks affect debt supply by increasing the cost of debt for high climate risk firms.

3.4.6. Robustness checks

We conduct several robustness checks using an alternative measure of physical climate risks, considering other fixed effects, the decomposition of climate risk in subrisks, and different horizons and scenarios. We also propose several tests to verify that our results reflect only physical climate risk, not transition risk.

Alternative measure of physical climate risk

Sautner et al. (2020) propose a method that identifies firm-level climate change exposure to climate change. They use transcripts of earnings conference calls by listed firms to build firm-year climate change measures. Their metrics include an overall exposure measure and topic-based measures, including a physical climate risk exposure measure, that we use in our tests. We re-estimate our basic regressions (equation 2). Table 11 reports our results that confirm previous findings with the CRIS and Four Twenty Seven climate risk measures.

Other fixed effects and controls

Our results are qualitatively unchanged when using country, industry, and year fixed effects (internet Appendix, Table IA3, columns 1 and 6). As an alternative to year fixed effects, we also add country-year fixed effects to control for variables that vary at the country-year level and could affect leverage, such as corporate taxes and the institutional characteristics of countries (Table IA3, columns 2 and 7). Including country-year and firm fixed effects also lead to similar results (columns 3 and 8). To consider the possibility of time effects that are specific to certain industries, we re-estimate our basic regressions, including industry-year fixed effects

(columns 4 and 9) or industry-year and firm fixed effects (columns 5 and 10), and the results remain unchanged. We also rerun our regressions, including several dummy variables for each level of credit rating rather than our linearized variable, and our results remain.

Acute risks and chronic risks

CRIS climate risk ratings combine information on the following seven direct climate hazards: three chronic hazards (increases in average temperature, changes in rainfall patterns, and sea level rise) and four acute hazards (heat waves, droughts, rainfall extremes, and storms). For each hazard, the rating is based on the analysis of information on the magnitude, duration, and frequency of the hazard (particularly relevant for acute hazards). To build a rating of 0 to 99 for each climate variable and each country, the relative changes are first extracted in the future time horizons compared to the historical reference period and then normalized across all scenarios and time horizons. These direct hazards are associated with information on the risk-aggravating context to capture indirect hazards. For example, the impact of heavy rainfall is larger when the proportion of high slopes in the area is high because of increased landslide risks, and extreme droughts lead not only to water scarcity but also to wildfires.

We examine the impact of each of these 7 climate subrisks on the leverage of firms. In equations (1) and (2), the overall climate risk variable is replaced by subrisk measures. Since the risk variables by category are normalized, their values are of the same magnitude as the overall rating. Therefore, the regression coefficients reflect the relative impact of the risk variables on debt but not the weight of each risk in the total risk to explain the climate impact on debt. The results in internet Appendix, Table IA4, Panel A, indicate that the four acute risks have a significant negative impact on leverage after 2015. After 2015, a one standard deviation increase in the subrisk rating is associated with a 1.53% decrease in the long-term book debt ratio for heavy rain risks, 1.41% for drought risks, 0.91% for heat wave risks and 1.38% for

storms. Among chronic risks, sea level rise has an impact that is comparable to acute risks (1.17%), whereas temperature rise in itself has no impact on leverage. When the Four Twenty Seven scores are considered, the impact of subrisks is significant after 2015, with a magnitude of 1.22% for operating risks, 1.58% for floods, 0.96% for hurricanes and typhoons, and 1.27% for sea level rise (Table IA4, Panel B).

These results emphasize that the impact of aggregate climate risk on leverage is primarily because of the potential increase in the risks of extreme events on the 2030-2050 horizon.

Horizons and scenarios

One might be concerned that the two climate risk rating agencies use different scenarios to assess corporate risk. We verify that our results remain similar for alternative scenarios and horizons. We use low (RCP4.5) and high-intensity (RCP8.5) risks and consider the 2100 horizon rating as an alternative to our 2050 horizon and medium intensity (RCP6.0) CRIS climate risk rating. The results, reported in internet Appendix Table IA5, are qualitatively unchanged, although the coefficients of the variables change slightly depending on the chosen combination. Internet Appendix Table IA6 reports similar results for CRIS subrisks and alternative risk intensity and horizon.

Our tests show that CRAs do not appear to consider credit risk over the period studied. However, the rating agencies could be using other, more moderate scenarios than those considered in our study, which could explain our results. We replicate our regressions using the CRIS climate risk measure for the RCP4.5 scenario, and the results remain similar: we are unable to detect any effect of climate risk on credit ratings (internet Appendix, Table IA7).

Physical risk versus transition risks

We also verify that the results are robust to the exclusion of firms threatened by transition risks by running additional regressions excluding the 5 and 10 largest carbon-emitting industries identified in Ilhan et al. (2021). Our results that physical climate risk reduces leverage after 2015 remain similar (internet Appendix, Table IA8). We thus rule out the possibility that our findings account for transition risks rather than physical risks. Moreover, we verify that these results are not driven by some particular industries, as they remain qualitatively unchanged after the exclusion of the 5 or 10 most represented in-sample industries or after the elimination of the 5 most represented industries in each of the 2 risk-level groups. Our results are also similar when we rerun our tests for each industry group, constructed as in Kahle and Walking (1996), that has at least 1000 firm-year observations in our sample (internet Appendix, Table IA9).

Finally, to ensure that physical climate risk represents an additional effect when considered in addition to the transition risk, we also verify that our results remain similar when we add Sautner et al. (2020) regulatory risk measure to the regressions, as well as its interaction with the dummy post-2015 (internet Appendix, Table IA10). These findings confirm that after 2015, leverage also decreases with the transition risk, but the effect of the physical climate risk remains unchanged.

3.5. Conclusion

In this paper, we analyze the impact of the climate risk rating on firms' leverage. We use forward-looking measures for physical climate risk at the firm level. Our work builds on the capital structure and climate risk literature. We find that firms exposed to greater climate risk are less leveraged in the post-2015 period, i.e., after the Paris Agreement (COP21) and the call from the Financial Stability Board for standard measures and disclosures of climate risks.

We also show that the reduction in debt related to climate risk is shared between a demand effect and a supply effect. On the one hand, we find that, after 2015, increased climate risk lowers financial leverage and increases net equity issuance. The reduction in leverage is mainly observed for firms with low CSR performance, suggesting that high CSR firms are likely to take proactive actions to handle their climate risk rather than decrease their leverage. On the other hand, we find that the reduction in debt related to climate risk is at least partly due to a supply effect, as bondholders and bankers charge higher interest rates to high climate risk firms. Overall, our results suggest that over the recent period, climate risk has become an important factor in understanding the capital structure of firms.

Our findings offer several managerial implications. Despite the growing importance of climate change risks, accurate information about companies' exposure to climate change risks is still scarce. Our research emphasizes the importance of disclosing information about how physical climate risk affects corporate activity and what strategic actions firms take to manage and mitigate climate risks. The company must be able to think about the short-term and long-term consequences of climate change. For example, maintaining production lines in countries with high climate risk may be a short-term solution to minimize operating costs, but it may also have immediate and future consequences on the cost or access to financing. Similarly, the company may prefer to pay higher insurance premiums to address its climate risk but may also anticipate that this risk may no longer be insurable in the long term and choose to opt for other locations or strategies. The 2015 Paris Agreement was a warning signal to companies about the potential consequences of their exposure to climate risk on the value of their assets and their operating costs but also on their access to financing and the growing cost of debt.

Our analysis also supports the view that CSR activities protect firms from downside risk. Managers of firms exposed to high climate risks who can develop successful CSR

strategies, for example, in terms of risk management, can generate tangible benefits for their firms in the form of better access to financing.

Our findings are also relevant for CRAs. Indeed, our results suggest that credit ratings do not reflect all the information related to physical climate risk over the period studied. These findings support the relevance of the strategy of several rating agencies that are developing their expertise in climate risks, notably through the acquisition of specialized agencies.

3.6. References

- Addoum JM, Ng DT, Ortiz Bobea A (2019) Temperature Shocks and Earnings News. *SSRN Electronic Journal*.
- Altman EI, Rijken HA (2004) How rating agencies achieve rating stability. *Journal of Banking & Finance* 28(11):2679–2714.
- Amiraslani H, Lins KV, Servaes H, Tamayo A (2019) A Matter of Trust? The Bond Market Benefits of Corporate Social Capital during the Financial Crisis. *SSRN Electronic Journal*.
- Andersson M, Bolton P, Samama F (2016) Governance and Climate Change: A Success Story in Mobilizing Investor Support for Corporate Responses to Climate Change. *Journal of Applied Corporate Finance* 28(2):29–33.
- Anginer D, Hrazdil K, Li J, Zhang R (2020) Adverse Climate Incidents and Bank Loan Contracting. *SSRN Electronic Journal*.
- Atanasova C, Schwartz E (2020) Stranded Fossil Fuel Reserves and Firm Value. *NBER working paper*, w26497.
- Baghai RP, Servaes H, Tamayo A (2014) Have Rating Agencies Become More Conservative? Implications for Capital Structure and Debt Pricing. *The Journal of Finance* 69(5):1961–2005.
- Baker M, Wurgler J (2002) Market Timing and Capital Structure. *The Journal of Finance* 57(1):1–32.
- Baldauf M, Garlappi L, Yannelis C (2020) Does Climate Change Affect Real Estate Prices? Only If You Believe In. *The Review of Financial Studies* 33(3):1256–1295.
- Bansal R, Kiku D, Ochoa M (2016) Price of Long-Run Temperature Shifts in Capital Markets. *NBER working paper*.
- Barrot JN, Sauvagnat J (2016) Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *The Quarterly Journal of Economics* 131(3):1543–1592.
- Baumeister C, Kilian L (2016) Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us. *Journal of Economic Perspectives* 30(1):139–160.
- Berkman H, Jona J, Soderstrom N (2021) Measurement and Market Valuation of Climate Risk. *SSRN Electronic Journal*.
- Bernstein A, Gustafson MT, Lewis R (2019) Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134(2):253–272.
- Bessembinder H, Jacobsen S, Maxwell W, Venkataraman K (2018) Capital Commitment and Illiquidity in Corporate Bonds. *The Journal of Finance* 73(4):1615–1661.
- Bingler JA, Kraus M, Leippold M, Webersinke N (2022) Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures. *Finance Research Letters*:102776.
- Bolton P, Kacperczyk M (2021) Global Pricing of Carbon-Transition Risk. *NBER working paper*, w28510.
- Born P, Viscusi WK (2006) The catastrophic effects of natural disasters on insurance markets. *Journal of Risk and Uncertainty* 33(1–2):55–72.
- Bradley M, Jarrell GA, Kim EH (1984) On the Existence of an Optimal Capital Structure: Theory and Evidence. *The Journal of Finance* 39(3):857–878.
- Brown JR, Gustafson MT, Ivanov IT (2021) Weathering Cash Flow Shocks. *The Journal of Finance* 76(4):1731–1772.
- Charpentier A (2008) Insurability of Climate Risks. *Geneva Pap Risk Insur Issues Pract* 33(1):91–109.
- Chava S, Roberts MR (2008) How Does Financing Impact Investment? The Role of Debt Covenants. *The Journal of Finance* 63(5):2085–2121.

- Chen HJ, Kacperczyk M, Ortiz-Molina H (2011) Labor Unions, Operating Flexibility, and the Cost of Equity. *Journal of Financial and Quantitative Analysis* 46(1):25–58.
- Chen Z, Harford J, Kamara A (2019) Operating Leverage, Profitability, and Capital Structure. *Journal of Financial and Quantitative Analysis* 54(1):369–392.
- Christensen P, Gillingham K, Nordhaus W (2018) Uncertainty in forecasts of long-run economic growth. *Proc. Natl. Acad. Sci. U.S.A.* 115(21):5409–5414.
- Correa R, He A, Herpfer C, Lel U (2021) The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters and Loan Pricing. *SSRN Electronic Journal*.
- Delis MD, de Greiff K, Ongena S (2019) Being Stranded on the Carbon Bubble? Climate Policy Risk and the Pricing of Bank Loans. *SSRN Electronic Journal*.
- Dell M, Jones BF, Olken BA (2014) What Do We Learn from the Weather? The New Climate–Economy Literature. *Journal of Economic Literature* 52(3):740–798.
- Engle RF, Giglio S, Kelly B, Lee H, Stroebel J (2020) Hedging Climate Change News. *The Review of Financial Studies* 33(3):1184–1216.
- Faiella I, Natoli F (2019) Climate change and bank lending: the case of flood risk in Italy. *Working paper, Bank of Italy*.
- Faulkender M, Petersen MA (2006) Does the source of capital affect capital structure? *The Review of Financial Studies* 19(1):45–79.
- Fiedler T, Pitman AJ, Mackenzie K, Wood N, Jakob C, Perkins-Kirkpatrick SE (2021) Business risk and the emergence of climate analytics. *Nat. Clim. Chang.* 11(2):87–94.
- Fischer EO, Heinkel R, Zechner J (1989) Dynamic capital structure choice: Theory and tests. *The Journal of Finance* 44(1):19–40.
- Flannery MJ, Rangan KP (2006) Partial adjustment toward target capital structures. *Journal of Financial Economics* 79(3):469–506.
- Florou A, Kosi U (2015) Does mandatory IFRS adoption facilitate debt financing? *Review of Accounting Studies* 20(4):1407–1456.
- Frank MZ, Goyal VK (2009) Capital Structure Decisions: Which Factors Are Reliably Important? *Financial Management* 38(1):1–37.
- Gostlow G (2020) The Materiality and Measurement of Physical Climate Risk: Evidence from Form 8-K. *SSRN Electronic Journal*.
- Graham JR, Harvey CR (2001) The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics* 60(2–3):187–243.
- Graham JR, Leary MT (2011) A review of empirical capital structure research and directions for the future. *Annual Review of Financial Economics* 3(1):309–345.
- Haraguchi M, Lall U (2015) Flood risks and impacts: A case study of Thailand’s floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction* 14:256–272.
- Hazra D, Gallagher (2022) Role of insurance in wildfire risk mitigation. *Economic Modelling* 108(105768).
- Helwege J, Wang L (2019) Liquidity and Price Pressure in the Corporate Bond Market: Evidence from Mega-Bonds. *SSRN Electronic Journal*.
- Hickey C, O’Brien J, Caldecott B, McInerney C, Ó Gallachóir B (2021) Can European electric utilities manage asset impairments arising from net zero carbon targets? *Journal of Corporate Finance* 70:102075.
- Hong H, Li FW, Xu J (2019) Climate risks and market efficiency. *Journal of Econometrics* 208(1):265–281.
- Hugon A, Law K (2019) Impact of Climate Change on Firm Earnings. *SSRN Electronic Journal*.
- Huynh TD, Xia Y (2022) Panic Selling When Disaster Strikes: Evidence in the Bond and Stock Markets. *Management Science*:mns.2021.4018.

- Huynh TD, Xia Y (2021) Climate Change News Risk and Corporate Bond Returns. *Journal of Financial and Quantitative Analysis* 56(6):1985–2009.
- Ilhan E, Krueger P, Sautner Z, Starks LT (2019) Institutional Investors' Views and Preferences on Climate Risk Disclosure. *SSRN Electronic Journal*.
- Ilhan E, Sautner Z, Vilkov G (2021) Carbon Tail Risk. *The Review of Financial Studies* 34(3):1540–1571.
- Jones BF, Olken BA (2010) Climate Shocks and Exports. *American Economic Review* 100(2):454–459.
- Jorion P, Shi C, Zhang S (2009) Tightening credit standards: the role of accounting quality. *Review of Accounting Studies* 14(1):123–160.
- Kahl M, Lunn J, Nilsson M (2019) Operating Leverage and Corporate Financial Policies. *SSRN Electronic Journal*.
- Kahle, K. M., Walkling, R. A. (1996) The impact of industry classifications on financial research. *Journal of Financial and Quantitative Analysis*, 31(3): 309-335.
- Keenan JM (2019) A climate intelligence arms race in financial markets. *Science* 365(6459):1240–1243.
- Kornfeld I (2019) Insurance coverage for droughts, due to climate change. *Arizona Journal Of Environmental Law & Policy* 10:151–186.
- Krueger P, Sautner Z, Starks LT (2020) The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies* 33(3):1067–1111.
- Kruttl MS, Roth Tran B, Watugala SW (2019) Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. *SSRN Electronic Journal*.
- Kunreuther H, Michel-Kerjan E (2007) Climate Change, Insurability of Large-scale Disasters and the Emerging Liability Challenge. *NBER working paper* w12821.
- Lehn K, Zhu P (2016) Debt, Investment and Production in the U.S. Oil Industry: An Analysis of the 2014 Oil Price Shock. *SSRN Electronic Journal*.
- Leland HE (1994) Corporate debt value, bond covenants, and optimal capital structure. *The Journal of Finance* 49(4):1213–1252.
- Lins KV, Servaes H, Tamayo A (2017) Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis: Social Capital, Trust, and Firm Performance. *The Journal of Finance* 72(4):1785–1824.
- Modigliani F, Miller MH (1958) The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review* 48(3):261–297.
- Moody's (2016) How Moody's Assesses the Physical Effects of Climate Change on Sovereign Issuers.
- Murfin J, Spiegel M (2020) Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *The Review of Financial Studies* 33(3):1217–1255.
- Myers SC, Majluf NS (1984) Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13(2):187–221.
- Ovtchinnikov AV (2010) Capital structure decisions: Evidence from deregulated industries. *Journal of Financial Economics* 95(2):249–274.
- Painter M (2020) An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics* 135(2):468–482.
- Pankratz N, Bauer R, Derwall J (2019) Climate Change, Firm Performance, and Investor Surprises. *SSRN Electronic Journal*.
- Pankratz NMC, Schiller C (2021) Climate Change and Adaptation in Global Supply-Chain Networks. *SSRN Electronic Journal*.
- Parsons C, Titman S (2008) Empirical Capital Structure: A Review. *Foundations and Trends in Finance* 3(1):1–93.
- Petersen MA (1994) Cash flow variability and firm's pension choice. *Journal of Financial*

- Economics* 36(3):361–383.
- Petersen MA (2009) Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies* 22(1):435–480.
- Reinartz SJ, Schmid T (2016) Production Flexibility, Product Markets, and Capital Structure Decisions. *The Review of Financial Studies* 29(6):1501–1548.
- Sautner Z, van Lent L, Vilkov G, Zhang R (2020) Firm-level Climate Change Exposure. *SSRN Electronic Journal*.
- Seltzer L, Starks LT, Zhu Q (2020) Climate Regulatory Risks and Corporate Bonds. *SSRN Electronic Journal*.
- Sharfman MP, Fernando CS (2008) Environmental risk management and the cost of capital. *Strategic Management Journal* 29(6):569–592.
- Standard and Poors, 2013. Corporate ratings criteria.
- Stocker M, Baffes J, Some YM, Vorisek D, Wheeler CM (2018) The 2014–16 Oil Price Collapse in Retrospect: Sources and Implications. *World Bank, Washington, DC*.
- Taylor KE, Stouffer RJ, Meehl GA (2012) An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society* 93(4):485–498.
- van Vuuren DP, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, Hurtt GC, et al. (2011) The representative concentration pathways: an overview. *Climatic Change* 109(1–2):5–31.
- Zerbib OD (2019) The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance* 98:39–60.

3.7. Main tables

Table 1

Descriptive statistics.

This table reports summary statistics. Panel A presents the descriptive statistics for the CRIS and the Four Twenty Seven climate variables. Each firm of the panel is covered by eight CRIS climate grades (an overall rating and seven subrisk ratings), and by five Four Twenty Seven climate grades (an overall rating and four subrisk ratings). In Panel B, descriptive statistics of various firm-year characteristics are reported for the full sample, the low climate risk (<40th percentile) and high climate risk (>60th percentile) observations. All variables are winsorized at the 1st and 99th percentiles, except for CreditRating. The statistics for CreditRating are presented for the firms that are credit rated. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999).

Panel A. Climate risks

	CRIS				Four Twenty Seven				
	N	Mean	SD	Median	N	Mean	SD	Median	
Climate risk	1,212	35.161	10.833	36.994	Climate risk	938	42.828	13.225	43.510
Heavy rainfall	1,212	37.305	15.796	36.382	OperationsRiskScore	938	38.247	10.146	36.210
Heat waves	1,212	31.828	10.562	30.511	Floods	938	23.615	7.946	22.330
Droughts	1,212	29.795	10.338	31.130	Sea level rise	938	11.130	9.114	8.790
Storms	1,212	44.197	15.096	46.349	HurricanesTyphoons	938	27.596	22.569	18.640
Sea level rise	1,212	41.663	13.984	46.943					
Temperature rise	1,212	23.873	8.940	23.735					
Rainfall patterns	1,212	16.168	6.989	16.569					

Panel B. Firm-year characteristics

	Total sample			Low climate risk firms, CRIS (<40 th percentile)	High climate risk firms, CRIS (>60 th percentile)	Difference in means between low and high climate risk firms	Low climate risk firms, 427 (<40 th percentile)	High climate risk firms, 427 (>60 th percentile)	Difference in means between low and high climate risk firms
	N	Mean	SD	Mean	Mean	T-statistic	Mean	Mean	T-statistic
BookLev	11,367	0.218	0.159	0.242	0.183	17.845	0.235	0.194	11.497
MarketLev	11,367	0.146	0.120	0.155	0.134	7.954	0.148	0.142	2.113
EBIT	11,367	0.092	0.070	0.101	0.083	11.774	0.099	0.080	12.194
Log Age	11,367	2.694	1.472	2.417	2.973	-18.716	2.443	3.471	-35.024
TobinQ	11,367	1.986	1.433	2.161	1.786	12.538	2.261	1.692	17.117
OpEx	11,367	0.691	0.529	0.773	0.629	12.888	0.762	0.624	11.313
R&DExp	11,367	0.020	0.036	0.013	0.029	-20.273	0.017	0.027	-10.018
PPE	11,367	0.297	0.236	0.255	0.323	-14.434	0.266	0.336	-12.883
LogTotAssets	11,367	9.376	1.214	9.267	9.458	-7.504	9.520	9.578	-2.059
Oil beta	11,367	0.019	0.152	0.003	0.030	-8.657	0.019	0.015	1.122
CreditRating	7,602	12.279	2.858	11.732	12.992	-17.092	11.954	13.001	-13.242
Log IntCoverage	11,058	2.689	1.717	2.512	3.040	-14.005	2.358	3.079	-18.004
WorkCap	11,367	0.131	0.172	0.105	0.166	-16.492	0.099	0.158	-14.691
CSR	8,598	3.273	1.572	3.221	3.369	-3.944	3.317	3.205	2.653
CDP A list	6,759	0.143	0.350	0.132	0.159	-2.864	0.149	0.154	-0.443

Table 2

Climate risk and long-term debt: book leverage.

This table presents estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable. Columns (1) to (5) report estimates using the CRIS measure of climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of climate risk. Columns (1), (2), (3), (6), (7), and (8) report OLS estimates. Columns (4), (5), (9), and (10) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2), (4), (6), (7), and (9) include country-industry and year fixed effects. Regressions (3), (5), (8), and (10) include firm and year fixed effects. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
	CRIS – OLS			CRIS – 2SLS		Four Twenty Seven – OLS			Four Twenty Seven – 2SLS	
EBIT	-0.204*** (-3.546)	-0.201*** (-3.485)	-0.327*** (-7.523)	-0.314*** (-7.786)	-0.328*** (-7.974)	-0.204*** (-3.292)	-0.201*** (-3.238)	-0.331*** (-6.561)	-0.322*** (-6.877)	-0.332*** (-6.964)
Log Age	-0.00177 (-0.501)	-0.00188 (-0.530)	0.00235 (0.313)	-7.20e-05 (-0.0157)	0.00391 (0.541)	-0.00576 (-1.461)	-0.00608 (-1.537)	0.00648 (0.738)	0.00203 (0.367)	0.00787 (0.931)
TobinQ	-0.00143 (-0.472)	-0.00153 (-0.504)	0.00637** (2.244)	0.00547** (2.096)	0.00632** (2.347)	0.000978 (0.279)	0.000858 (0.245)	0.00764** (2.209)	0.00714** (2.322)	0.00763** (2.322)
OpEx	-0.0444*** (-3.990)	-0.0445*** (-4.007)	-0.0414*** (-3.275)	-0.0416*** (-4.008)	-0.0414*** (-3.466)	-0.0448*** (-3.529)	-0.0453*** (-3.559)	-0.0536*** (-3.761)	-0.0533*** (-4.510)	-0.0535*** (-3.972)
R&DExp	-0.490*** (-4.292)	-0.494*** (-4.331)	-0.168* (-1.660)	-0.235*** (-2.618)	-0.165* (-1.723)	-0.362*** (-2.974)	-0.364*** (-2.985)	-0.143 (-1.322)	-0.190* (-1.957)	-0.142 (-1.381)
Log TotAssets	-0.000553 (-0.138)	-0.000900 (-0.225)	0.0212*** (3.045)	0.0173*** (3.481)	0.0217*** (3.307)	0.00108 (0.252)	0.00102 (0.239)	0.0231*** (2.946)	0.0183*** (3.159)	0.0236*** (3.186)
PPE	0.112*** (3.714)	0.112*** (3.721)	0.180*** (4.665)	0.170*** (5.464)	0.181*** (4.988)	0.0876** (2.360)	0.0876** (2.357)	0.210*** (5.003)	0.190*** (5.411)	0.211*** (5.320)
Oil beta	0.000972 (0.0645)	0.000738 (0.0489)	-0.0144 (-1.167)	-0.0145 (-1.252)	-0.0148 (-1.267)	-0.000173 (-0.0107)	-0.000459 (-0.0284)	-0.0100 (-0.782)	-0.0107 (-0.884)	-0.0106 (-0.869)
CreditRating	0.00218*** (3.337)	0.00217*** (3.320)	0.000417 (0.670)	-0.000630 (-0.766)	-0.000674 (-0.838)	0.00241*** (3.339)	0.00238*** (3.297)	0.000959 (1.431)	0.000175 (0.169)	8.64e-05 (0.0858)
Climate risk	-0.00154** (-2.304)	-0.000969 (-1.451)		-0.000658 (-1.005)		0.000625 (0.848)	0.00105 (1.417)		0.000790 (1.009)	
Climate risk*Post2015		-0.00139*** (-5.641)	-0.00134*** (-5.365)	-0.00140*** (-5.983)	-0.00136*** (-5.752)		-0.00104*** (-5.008)	-0.000904*** (-4.307)	-0.000964*** (-4.800)	-0.000915*** (-4.584)
Constant	0.125** (2.194)	0.109* (1.906)	-0.00256 (-0.0356)	-0.0931 (-1.273)	-0.00368 (-0.0545)	0.0327 (0.526)	0.0149 (0.239)	-0.0449 (-0.549)	-0.189** (-2.443)	-0.0466 (-0.604)
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.513	0.515	0.848			0.522	0.524	0.844		
Country-Industry Fixed Effects	Yes	Yes		Yes		Yes	Yes		Yes	
Firm Fixed Effects			Yes		Yes			Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3

Climate risk and long-term debt: market leverage.

This table presents estimates of the effects of overall climate risk on the level of long-term debt using MarketLev as the dependent variable. Columns (1) to (5) report estimates using the CRIS measure of climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of climate risk. Columns (1), (2), (3), (6), (7), and (8) report OLS estimates. Columns (4), (5), (9), and (10) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2), (4), (6), (7), and (9) include country-industry and year fixed effects. Regressions (3), (5), (8), and (10) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev	MarketLev
	CRIS – OLS			CRIS – 2SLS		Four Twenty Seven – OLS		Four Twenty Seven – 2SLS		
Climate risk	-0.00105** (-2.429)	-0.000804* (-1.842)		-0.000685 (-1.593)		0.000177 (0.354)	0.000381 (0.757)		0.000273 (0.553)	
Climate risk*Post2015		-0.000597*** (-3.588)	-0.000542*** (-3.203)	-0.000576*** (-3.624)	-0.000545*** (-3.388)		-0.000494*** (-3.338)	-0.000460*** (-2.928)	-0.000481*** (-3.250)	-0.000462*** (-3.091)
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.595	0.596	0.859			0.617	0.618	0.862		
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes	Yes		Yes		Yes	Yes		Yes	
Firm Fixed Effects			Yes		Yes			Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4

Difference-in-differences of leverage around the year 2015.

This table presents difference-in-differences estimates for the leverage before and after the year 2015. All regressions report estimates using as independent variables the interaction between Post2015 and a dummy variable equal to 1 if the climate risk indicator is above the 60th percentile and 0 if the climate risk indicator is below the 40th percentile. The dependent variable is BookLev in Columns (1) and (2), and MarketLev in Columns (3) and (4). The regressions are conducted on all firm-year observations except those between the 40th and the 60th percentiles of the climate risk indicator. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) MarketLev	(4) MarketLev
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
HighClimateRisk*Post2015	-0.0220*** (-3.723)	-0.0258*** (-3.826)	-0.00429 (-1.014)	-0.0134*** (-2.886)
Observations	9,080	7,136	9,080	7,136
R-squared	0.855	0.844	0.868	0.866
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 5

Climate risk, long-term debt, and fossil fuel dependency.

This table presents estimates of the effects of overall climate risk on long-term debt after accounting for fossil fuel dependency. Columns (1), (3), (5), and (7) report estimates using the CRIS measure of climate risk. Columns (2), (4), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (2) control for the interaction between Post2015 and Oil beta. Regressions (3) and (4) exclude firms belonging to Oil & Gas Extraction (SIC 1300-1399) and Petroleum & Coal Products (SIC 2900-2999) industries. Regressions (5), (6), (7), and (8) report estimates conducted on subsamples based on the values of Oil beta. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
	Control for Oil beta*Post2015		Exclude SIC13 & SIC29		Oil beta \geq 0		Oil beta < 0	
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Oil beta	-0.0280** (-1.965)	-0.0112 (-0.752)	-0.0157 (-1.219)	-0.00974 (-0.728)	-0.000692 (-0.0363)	-0.00106 (-0.0441)	-0.0199 (-0.673)	-0.0146 (-0.452)
Oil beta*Post2015	0.0392** (1.996)	0.00347 (0.170)						
Climate risk*Post2015	-0.00137*** (-5.474)	-0.000904*** (-4.307)	-0.00131*** (-5.153)	-0.000875*** (-4.017)	-0.00135*** (-3.884)	-0.000920*** (-3.060)	-0.000767* (-1.878)	-0.000743** (-2.010)
Observations	11,367	8,933	10,790	8,475	6,764	5,044	4,603	3,889
R-squared	0.848	0.844	0.850	0.846	0.863	0.860	0.890	0.885
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Credit rating and climate risk.

This table presents estimates of the effects of overall climate risk on credit rating. The regressions use CreditRating as the dependent variable for firm-year observations with a credit rating. Columns (1) to (3) report estimates using the CRIS measure of climate risk. Columns (4) to (6) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1), (2), (4), and (5) include country-industry and year fixed effects. Regressions (3) and (6) include firm and year fixed effects. All regressions exclude observations with missing Log IntCoverage. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	CreditRating	CreditRating	CreditRating	CreditRating	CreditRating	CreditRating
Climate risk measure	CRIS			Four Twenty Seven		
EBIT	6.872*** (4.021)	6.862*** (4.011)	3.667*** (4.201)	7.091*** (4.039)	7.087*** (4.034)	3.946*** (4.134)
Log Age	0.315*** (3.589)	0.315*** (3.590)	0.203* (1.708)	0.410*** (3.783)	0.410*** (3.781)	0.247* (1.789)
TobinQ	0.183** (2.138)	0.184** (2.145)	0.0950* (1.856)	0.138 (1.635)	0.139 (1.637)	0.108** (2.024)
OpEx	0.138 (0.613)	0.138 (0.613)	0.355** (2.229)	0.129 (0.465)	0.129 (0.466)	0.458** (2.557)
R&DExp	-2.140 (-0.805)	-2.121 (-0.796)	2.064* (1.954)	-3.937 (-1.514)	-3.924 (-1.505)	1.943* (1.827)
Log TotAssets	1.123*** (11.40)	1.124*** (11.39)	0.713*** (6.055)	1.122*** (10.37)	1.122*** (10.37)	0.816*** (5.942)
PPE	-0.224 (-0.378)	-0.225 (-0.379)	2.794*** (4.911)	0.407 (0.575)	0.407 (0.575)	3.664*** (5.910)
Oil beta	-1.781*** (-5.425)	-1.784*** (-5.424)	-0.390* (-1.860)	-1.689*** (-4.579)	-1.689*** (-4.578)	-0.336* (-1.716)
Log IntCoverage	0.458*** (5.510)	0.458*** (5.512)	0.0619 (1.440)	0.408*** (4.563)	0.408*** (4.564)	0.0474 (1.018)
WorkingCap	1.487* (1.914)	1.478* (1.899)	0.923** (2.201)	1.856** (2.218)	1.851** (2.206)	1.257*** (3.148)
Climate risk	0.00924 (0.734)	0.00781 (0.620)		-0.0255 (-1.560)	-0.0264 (-1.581)	
Climate risk*Post2015		0.00321 (0.692)	-0.00231 (-0.578)		0.00189 (0.492)	0.00289 (0.848)
Constant	-0.915 (-0.634)	-0.876 (-0.607)	2.876** (2.391)	0.250 (0.157)	0.287 (0.179)	1.473 (1.027)
Observations	7,602	7,602	7,602	6,326	6,326	6,326
R-squared	0.556	0.556	0.915	0.541	0.541	0.910
Country-Industry Fixed Effects	Yes	Yes		Yes	Yes	
Firm Fixed Effects	No	No	Yes	No	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7

Climate risk and equity issuances.

This table presents estimates of the effects of overall climate risk on the level of equity issuances, using NetEquityIssued as the dependent variable. Columns (1) and (2) report estimates using the CRIS measure of climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (3) include country-industry and year fixed effects. Regressions (2) and (4) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) NetEquityIssued	(2) NetEquityIssued	(3) NetEquityIssued	(4) NetEquityIssued
Climate risk measure	CRIS		Four Twenty Seven	
Climate risk	0.000148 (0.913)		0.000125 (0.816)	
Climate risk*Post2015	0.000231*** (2.963)	0.000177** (2.207)	0.000174*** (2.711)	0.0000978 (1.483)
Observations	11,367	11,367	8,933	8,933
R-squared	0.422	0.602	0.444	0.617
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes		Yes	
Firm Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 8

Climate risk, long-term debt, and corporate social responsibility (CSR).

Panel A reports OLS estimates of the effects of overall climate risk on long-term debt after controlling for CSR. Columns (1) and (2) report estimates using the CRIS measure of climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (3) use CSR Score as measure of CSR. Regressions (2) and (4) use the presence of the firm on the CDP A list as the measure of CSR. Panel B reports estimates of the effects of overall climate risk on long-term debt, for the analysis of subsamples based on the values of CSR variables. Columns (1) to (4) report estimates using the CRIS measure of climate risk. Columns (5) to (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1), (2), (5), and (6) report estimates conducted on subsamples based on the values of the CSR Score. Regressions (3), (4), (7), and (8) report estimates conducted on subsamples based on the presence of the firm on the CDP A list. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. Climate risk and long-term debt, when controlling for CSR

VARIABLES	(1)	(2)	(3)	(4)
	BookLev	BookLev	BookLev	BookLev
Climate risk measure	CRIS		Four Twenty Seven	
CSR Score	-0.000988 (-0.763)		-0.000995 (-0.712)	
CDP A list		0.00180 (0.554)		0.00311 (0.907)
Climate risk*Post2015	-0.00102*** (-4.203)	-0.00120*** (-3.944)	-0.000674*** (-3.233)	-0.000851*** (-3.188)
Observations	8,598	6,759	6,951	5,557
R-squared	0.879	0.887	0.875	0.877
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Climate risk and long-term debt, subsamples based on CSR variables

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
Climate risk measure	CRIS				Four Twenty Seven			
Subsamples	CSR Score above median	CSR Score below median	In CDP's A list	Not in CDP's A list	CSR Score above median	CSR Score below median	In CDP's A list	Not in CDP's A list
Climate risk*Post2015	-0.000345 (-1.139)	-0.00159*** (-4.301)	-0.000270 (-0.423)	-0.00136*** (-3.823)	-2.36e-05 (-0.0976)	-0.00136*** (-3.823)	0.000504 (0.993)	-0.00108*** (-3.474)
Observations	3,875	4,723	964	5,795	3,112	3,839	872	4,685
R-squared	0.901	0.887	0.930	0.891	0.898	0.885	0.928	0.882
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9

Climate risk and cost of bond loans.

This table presents OLS estimates of the effects of overall climate risk on the cost of bond loans, using Spread as the dependent variable. Columns (1) to (3) report estimates using the CRIS measure of climate risk. Columns (4) to (6) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (4) are conducted on the total sample. Regressions (2) and (5) cover the high risk companies with a climate risk rating above the 60th percentile and regressions (3) and (6) cover the low risk companies with a climate risk rating below the 40th percentile. All regressions include firm, loan characteristics (seniority, number of loans to the company on the same date, loan purpose, secured/unsecured status), and year fixed effects. Appendix A presents variable definitions. The total sample comprises all vanilla fixed-coupon bond loans over \$100 million with a maturity of more than 3 years granted to firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Spread	Spread	Spread	Spread	Spread	Spread
Climate risk measure	CRIS			Four Twenty Seven		
Sample	Total sample	High risk	Low risk	Total sample	High risk	Low risk
Log Amount	2.422 (0.682)	12.01*** (3.181)	-2.394 (-0.352)	4.982 (1.410)	10.06** (2.436)	-1.257 (-0.187)
Log Maturity	25.28*** (13.76)	21.11*** (6.533)	28.10*** (10.91)	26.06*** (15.02)	25.53*** (10.51)	28.56*** (10.55)
EBIT	-397.1*** (-5.049)	-519.2*** (-4.491)	-170.6 (-0.977)	-345.9*** (-4.722)	-420.5*** (-3.827)	-388.6** (-2.441)
Log Age	-34.04*** (-4.173)	-22.99 (-0.851)	-26.84*** (-3.702)	-36.70*** (-4.442)	-68.87 (-1.173)	-33.62*** (-4.022)
TobinQ	-5.218 (-0.767)	6.312 (0.865)	-12.85 (-0.926)	-4.553 (-0.746)	11.99* (1.818)	-8.464 (-0.735)
OpEx	-4.302 (-0.244)	-34.48 (-0.874)	5.846 (0.269)	-20.18 (-1.124)	-9.549 (-0.264)	-58.11*** (-2.764)
R&DExp	-175.5* (-1.894)	-336.7** (-2.088)	-65.99 (-0.340)	-140.5 (-1.586)	-286.4** (-2.186)	60.76 (0.303)
Log TotAssets	-32.67*** (-3.000)	-58.88*** (-3.358)	-14.42 (-0.995)	-28.64*** (-2.616)	-29.23* (-1.714)	-43.49** (-2.158)
PPE	-36.84 (-0.675)	-179.7 (-1.642)	52.93 (0.681)	-34.20 (-0.649)	-66.85 (-0.710)	-2.876 (-0.0337)
Oil beta	-26.53 (-1.127)	3.092 (0.138)	-71.24* (-1.811)	-12.45 (-0.705)	-2.619 (-0.0835)	-22.37 (-0.935)
CreditRating	-4.088** (-2.170)	-3.309 (-1.270)	-2.891 (-1.147)	-3.934** (-2.062)	-5.043** (-2.109)	-4.650 (-1.617)
Climate risk*Post2015	0.389 (1.231)	1.094** (2.181)	-0.980 (-1.195)	-0.0878 (-0.269)	1.266** (2.162)	-0.0202 (-0.0168)
Constant	519.8*** (3.324)	599.3** (2.538)	342.1 (1.401)	420.2*** (2.621)	441.1* (1.812)	759.5*** (2.719)
Observations	5,105	1,757	2,101	4,565	1,540	1,903
R-squared	0.836	0.848	0.834	0.806	0.854	0.809
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 10

Climate risk and cost of bank loans.

This table presents estimates of the effects of overall climate risk on the cost of bank loans using Spread as the dependent variable. Columns (1), (2), (3), and (7) report estimates using the CRIS measure of climate risk. Columns (4), (5), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (4) are conducted on the total sample. Regressions (2), (5), (7), and (8) cover the high risk companies with a climate risk rating above the 60th percentile and regressions (3) and (6) cover the low risk companies with a climate risk rating below the 40th percentile. Regressions (7) and (8) focus on US firms. All regressions include firm, loan characteristics (loan and repayment types, seniority, number of loans to the company on the same date, loan purpose, secured/unsecured status), and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, CreditRating, Log Amount, and Log Maturity. Appendix A presents variable definitions. Appendix A presents variable definitions. The total sample comprises all bank loans over \$100 million with a maturity of more than 3 years granted to firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread	(7) Spread	(8) Spread
Climate risk measure		CRIS			Four Twenty Seven		CRIS	Four Twenty Seven
Sample	Total sample	High risk	Low risk	Total sample	High risk	Low risk	High risk (USA only)	High risk (USA only)
Climate risk*Post2015	0.0779 (0.277)	4.245** (2.053)	-0.000824 (-0.00153)	0.0441 (0.163)	0.642 (0.561)	-0.639 (-1.271)	4.787*** (2.681)	1.640* (1.820)
Observations	3,388	1,009	1,467	2,873	879	1,317	663	751
R-squared	0.797	0.794	0.820	0.793	0.825	0.835	0.821	0.810
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11

Climate risk and long-term debt: alternative climate risk measure.

This table presents estimates of the effects of climate risk on the level of long-term debt, using the Sautner et al. (2020) climate risk measure. Columns (1), (2) and (3) report OLS estimates. Columns (4) and (5) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2) and (4) include country-industry and year fixed effects. Regressions (3) and (5) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	BookLev	BookLev	BookLev	BookLev	BookLev
	OLS			2SLS	
Climate risk	-0.0353** (-2.160)	-0.00207 (-0.0869)	0.0139 (0.952)	0.0137 (0.963)	0.0145 (1.058)
Climate risk*Post2015		-0.0560** (-2.083)	-0.0600** (-2.489)	-0.0607*** (-2.624)	-0.0604*** (-2.674)
Observations	8,770	8,770	8,770	8,770	8,770
R-squared	0.468	0.468	0.841		
Constant	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes	Yes	No		
Firm Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Appendix A. Variable Definitions

Variable	Description
BookLev	Ratio of long-term debt to book assets. DLTT/AT in Compustat.
CDP A list	Equals one if the company is rated A by CDP. Set to missing if the company was not questioned by CDP.
Climate risk	CRIS global risk grade for median scenario, 2050 time-horizon (except in Table IA5, where alternative horizons and scenarios are used), Four Twenty Seven global risk grade, or physical risk as measured by the variable $CCExposurePhy$ ($\times 10^3$) in Sautner et al. (2020). Sources Carbone 4, March 2018, Four Twenty Seven, November 2020, and Sautner et al. (2020).
CreditRating	This variable is based on the S&P Long-term Issuer Rating when available. If not available, we rely on Moody's Long-term Issuer Rating and eventually on the Fitch Long-term Issuer Default Rating if neither of the first two measures is available. Similar to Baghai et al. (2014), we linearize these ratings from 1 to 20, with 20 being the best rating. Missing ratings are coded as 0.
CSR Score	IVA Company Rating given in MSCI IVA ratings, converted from 0 for the worst grade (CCC) to 6 for the best grade (AAA).
Droughts	CRIS drought risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
EBIT	Ratio of EBIT to book assets. EBIT/AT in Compustat.
Floods	Four Twenty Seven flood risk grade. Source Four Twenty Seven, November 2020.
Heavy rainfall	CRIS heavy rainfall risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
Heat waves	CRIS heat wave risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
HighClimateRisk	Equals one for firms with climate risk above the 60 th percentile and 0 for firms below the 40 th percentile. Set to missing between the 40 th and 60 th percentiles.
HurricanesTyphoons	Four Twenty Seven hurricane and typhoon risks. Source Four Twenty Seven, November 2020.
Log Age	Natural logarithm of the difference between the year of observation and the initial public offering year (using IPODATE in Compustat). If the Names file ⁶⁵ indicates a higher age, we substitute the previous measure with the Names file number.
Log Amount	Natural logarithm of the amount borrowed, expressed in US dollars. Corresponds to Amount Issued (USD) in Thomson-Reuters and to Tranche Amount Converted (m)(USD) multiplied by 1 million in Dealscan.
Log IntCoverage	Natural logarithm of the ratio of EBIT to interest expenses. EBIT/XINT in Compustat.
Log Maturity	Natural logarithm of the maturity expressed in months. Corresponds to the number of months between issue date and maturity in Thomson-Reuters, and between tranche active date and tranche maturity date in Dealscan.
Log TotAssets	Natural logarithm of book assets (AT in Compustat). Book asset amounts are converted to US dollars using the year-end exchange rates from the OECD data portal ⁶⁶
MarketLev	Long-term debt divided by the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity. $DLTT/(AT-CEQ+PRCC_F*CSHO)$ in Compustat North America $DLTT/(AT-CEQ+PRCCD*CSHOC)$ in Compustat Global.
NetEquityIssued	Ratio of net equity issued to book assets. (SSTK-PRSTKC)/AT in Compustat.
Oil beta	Sensitivity of monthly stock returns to monthly oil (WTI) returns after controlling for monthly market (MSCI World) returns. Similar to Ilhan et al. (2021), we compute the sensitivity for each month with a rolling window of 60 months. For each firm i , the variable corresponds to the β_2 coefficient in the regression $Returns_{it} = Constant + \beta_1 Market\ returns_t + \beta_2 Oil\ returns_t$. The value of β_2 is then averaged over the year.
OperationsRiskScore	Four Twenty Seven operations risk grade. Source Four Twenty Seven, November 2020.
OpEx	Ratio of operational expenses to book assets. XOPR/AT in Compustat.
Post2015	Equals one for observations after 2015 and zero otherwise.
PPE	Ratio of net tangible assets to book assets. PPENT/AT in Compustat.
Rainfall patterns	CRIS rainfall pattern risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
R&DExp	Ratio of R&D expenses to book assets. XRD/AT in Compustat.
Regulatory risk	Climate regulatory risk as measured by the variable $CCExposureReg$ ($\times 10^3$) in Sautner et al. (2020).
Sea level rise	CRIS sea level rise risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used), or Four Twenty Seven sea level rise risk grade. Sources Carbone 4, March 2018, and Four Twenty Seven, November 2020.
Spread	For bonds: benchmark yield at issue in Bloomberg. For bank loans: Margin (Bps), in Dealscan.
Storms	CRIS storm risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
Temperature rise	CRIS rise in average temperature risk grade for median scenario, 2050 time-horizon (except in Table IA6, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
TobinQ	Ratio of the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity to book asset value. $(AT-CEQ+PRCC_F*CSHO)/AT$ in Compustat North America, $(AT-CEQ+PRCCD*CSHOC)/AT$ in Compustat Global.
WorkingCap	Ratio of working capital to book assets. WCAP/AT in Compustat

⁶⁵ https://wrds-web.wharton.upenn.edu/wrds/tools/variable.cfm?library_id=129&file_id=65815

⁶⁶ <https://data.oecd.org/conversion/exchange-rates.htm>

Appendix B. Description of the CRIS and Four Twenty Seven datasets

	CRIS	Four Twenty Seven
General overview	<p>CRIS ratings capture the increase in risk due to the increase in intensity or frequency of the climate-related hazards in the future due to global warming. They do not capture the absolute risk from future climate or weather.</p> <p>Scores range from 0 to 99. The higher the score, the higher the risk. Each company receives one rating, with the assumption that a company's climate exposure is stable over a few years.</p>	<p>Four Twenty Seven ratings capture both historical risks and the increase in intensity or frequency of the climate-related hazards in the future.</p> <p>Scores range from 0 to 100. The higher the score, the higher the risk. Each company receives one rating, with the assumption that a company's climate exposure is stable over a few years.</p>
Risks covered	<p>The climate risk score aggregates the scores of 7 subrisks:</p> <ul style="list-style-type: none"> • 4 acute risks <ul style="list-style-type: none"> ○ Increase in droughts ○ Increase in heatwaves ○ Increase in storms ○ Increase in heavy rainfalls • 3 chronic risks <ul style="list-style-type: none"> ○ Increase in average temperature ○ Changes in rainfall patterns ○ Increase in sea levels <p>The rating assigned to each subrisk is normalized to range between 0 and 99. The climate risk score is a weighted geometric mean of the 7 subrisks, with more weight given to acute risks.</p>	<p>The climate risk score aggregates the scores of 3 subrisks:</p> <ul style="list-style-type: none"> • Operations risk (70% of the total), including: <ul style="list-style-type: none"> ○ Historical and future floods ○ Increase in sea levels ○ Historical hurricane and typhoon risk • Supply chain risk (15%) • Market risk (15%) <p>The rating assigned to each subrisk is normalized to range between 0 and 100. The climate risk score is an arithmetic average of the 3 subrisks.</p>
Climate scenarios used	<p>All subrisks rely on the Representative Concentration Pathways (RCP) from the Intergovernmental Panel on Climate Change (IPCC):</p> <ul style="list-style-type: none"> • Low-emission scenario (RCP 4.5) • Medium-emission scenario (RCP 6.0) • High-emission scenario (RCP 8.5) 	<p>Historical data and high-emission scenario (RCP 8.5). Historical hurricane and typhoon risk is the only subrisk that does not rely on projections. All the other subrisks integrate a forward-looking approach and use the RCP 8.5 as a reference for projections. Four Twenty Seven considers that the impacts of the different RCPs are similar before 2050.</p>
Scoring principles	<p>For each company, CRIS identifies the industries and locations of the activities. This information is generally obtained from the firm's annual reports. Then, for each industry-location pair, CRIS assigns subrisk ratings by combining climate projections for the location with sectoral and sovereign vulnerability assessments. The subrisk rating is obtained by computing a weighted arithmetic average of the risk ratings for each industry-location pair, using the geographical and sectoral breakdown as weights. The geographic and sectoral breakdown of the activities is determined using revenues or fixed assets, depending on the sectoral capital intensity.</p>	<p>The sectoral breakdown of the activities is determined using revenues. For each climate hazard, Four Twenty Seven determines sector-specific sensitivity levels. The location of a firm's sites is primarily identified using Bureau van Dijk. Combining sector-specific sensitivities and climate information for the site's location, Four Twenty Seven assigns a rating to each site for each climate hazard. Then, for each climate hazard, the firm-level rating corresponds to the arithmetic average of the site-level ratings. Firm-level climate hazard ratings are then aggregated to form the Operations risk score. Supply chain and market risks depend on industry and country factors.</p>
Spatial resolution	<p>Climate hazards are modeled at the country level, except for 6 countries (Brazil, Canada, China, India, Russia, USA) that are further divided into 4 zones. To assess the exposure of each country/zone to each climate hazard, CRIS</p>	<p>The spatial resolution depends on the hazard:</p> <ul style="list-style-type: none"> • Historical and future floods <ul style="list-style-type: none"> ○ resolution of 25 x 25 km for rainfall

	relies on quantitative indicators, mostly the percentage of the population, land area, or Gross Domestic Product affected by the climate hazard.	<ul style="list-style-type: none"> ○ 90 x 90 m for flood frequency and severity ● Increase in sea levels, 90 x 90 m ● Historical hurricane and typhoon risks, 25 x 25 km
Time horizons and reference periods	The time horizons are 2050 and 2100 for all subrisks. The reference period is 1961-1990 for all subrisks except increase in storms and increase in sea levels (1985-2015).	<ul style="list-style-type: none"> ● Historical and future floods <ul style="list-style-type: none"> ○ time horizon: 2030-2040 ○ reference period: 1975-2005 ● Increase in sea levels <ul style="list-style-type: none"> ○ time horizon: 2040 ○ reference period: 1986-2005 ● Historical hurricane and typhoon risks <ul style="list-style-type: none"> ○ time horizon: no projections ○ reference period: 1980-2019
Correlation	The correlation between the CRIS climate risk score and the Four Twenty Seven climate risk score is 62.07%.	

The following table reports the five most-represented SIC2 industries and the five most-represented countries. For each industry and each country, the number in parentheses shows the percentage of observations with this affiliation in the total sample.

Rank	CRIS		Four Twenty Seven	
	Most represented industries (SIC2 industries)	Most represented countries	Most represented industries (SIC2 industries)	Most represented countries
1	28 – Chemical and Allied Products (11.3%)	USA (37.5%)	73 – Business Services (9.2%)	USA (41.0%)
2	73 – Business Services (9.0%)	Japan (22.9%)	49 - Electric, Gas, & Sanitary Services (7.4%)	Japan (24.2%)
3	49 - Electric, Gas, & Sanitary Services (7.7%)	Canada (5.9%)	35- Industrial Machinery & Equipment (6.0%)	Canada (4.8%)
4	35- Industrial Machinery & Equipment (5.5%)	UK (5.5%)	37 – Transportation Equipment (5.8%)	UK (4.8%)
5	37 – Transportation Equipment (5.5%)	France (4.9%)	38 - Instruments & Related Products (5.5%)	France (4.3%)

3.8. Internet Appendix

Section A of this Internet Appendix discusses the reasons why 2015 is a key year for climate risk awareness. Section B presents additional results that are discussed in the main text.

Figure 1. Leverage between 2010 and 2019 for high climate risk and low climate risk firms.

Table IA1. Bank loan, bond loan, and borrower characteristics.

Table IA2. Climate risk, long-term debt, and firm characteristics after 2015.

Table IA3. Climate risk and long-term debt: alternative specifications.

Table IA4. Climate subrisks and long-term debt.

Table IA5. Climate risks and long-term debt, alternative horizons and scenarios.

Table IA6. Climate subrisks and long-term debt, alternative horizons and scenarios.

Table IA7. Credit rating and climate risk, alternative horizons and scenarios.

Table IA8. Climate risk and long-term debt: exclusion of polluting industries.

Table IA9. Climate risk and long-term debt: regressions by industry groupings.

Table IA10. Physical climate risk, long-term debt, and regulatory risk.

IA. Section A. Why is 2015 a key year for climate risk awareness?

There are two reasons why 2015 can be considered a breakthrough year for climate risk. On the one hand, the Paris Agreement can be regarded as historic because of the extent of the commitment of countries and financial institutions; on the other hand, it is the launch of a standardization of disclosure of information related to climate risks through the TCFD.

1. COP21, the Paris Agreement

Although the United Nations Framework Convention on Climate Change (UNFCCC), which was adopted in 1992, establishes the general legal framework for international climate change action, it was not until 1997 that countries agreed on quantified emissions limits for developed countries for the first commitment period of the Kyoto Protocol (2008-2012). However, these top-down rules imposed on businesses by governments resulted in little progress in the field of climate change mitigation. In contrast, 2015 was a pivotal year in considering climate change, as economic actors decided to take up the issue. Furthermore, the Paris Agreement, which was signed in December 2015, applies for the first time to all countries, including major developing countries with large emissions, such as India and China.⁶⁷ The agreement confirms the objective of keeping global warming below 2°C and calls for continued efforts to limit it to 1.5°C. In advance of the Paris Climate Agreement, several private initiatives involving businesses declared their collective support for an effective climate change agreement to be reached at COP21.⁶⁸ One of the core aims of the Paris Agreement is to make all financial flows consistent with a pathway toward low emissions and climate-resilient development. The Agreement sends a signal that all finance, both public and private, needs to be directed toward

⁶⁷ On November 4, 2019, the US gave a formal notice of intention to withdraw from the Paris Agreement. The formal departure took effect on November 4, 2020. However, President Joe Biden recommitted the US to the Paris climate accord during his first day in office in January 2021.

⁶⁸ For example, CEOs of 79 large firms in 20 economic sectors with operations in over 150 countries and territories signed an open letter in favor of an ambitious deal; see [here](#).

the climate challenge. Several initiatives have since been developed to increase investors' and central banks' awareness of the climate risks to which they are exposed.⁶⁹ Between 2013 and 2017, the number of subnational and national-level policy and regulatory measures more than doubled (from 139 to 300),⁷⁰ with a substantial rise in system-level initiatives (finance regulations and guidelines and national-level roadmaps for green finance). In 2016, China adopted the "Guidelines for establishing a green financial system". In the same year, the European Union established the High-Level Expert Group on Sustainable Finance (HLEG), which led in 2018 to the European Commission's "Action Plan on Financing Sustainable Growth", including regulations on the establishment of a taxonomy to facilitate green investments not only on disclosures by institutional investors and asset managers but also on carbon-related benchmarks. Furthermore, according to its Climate Change Action Plan 2016-2020, the World Bank pledged to invest \$29 billion annually to fight against climate change, where \$13 billion comes from the private sector.

2. Climate risks financial disclosures

In April 2015, the G20 Finance Ministers and Central Bank Governors asked the Financial Stability Board (FSB) to review how the financial sector can take account of climate-related issues. Mark Carney, the former chair of the Financial Stability Board (FSB), underlined an urgent need for standard measures and disclosure of climate risks and established an industry-led group, the Task Force on Climate-related Financial Disclosures (TCFD), to design and

⁶⁹ For example, the United Nations' Principles for Responsible Investment (PRI) network indicated that in December 2021, \$121.3 trillion in assets were under management with 3,826 investors (compared to \$21 trillion in assets under management and 203 signatories in 2010). The CDP (carbon disclosure project) had 525 investors for \$96 trillion in assets, and climate action 100+ had 360 investors and more than \$34 trillion in assets under management (August 2019). The Network of Central Banks and Supervisors for Greening the Financial System (NGFS) was created in 2017 to enhance the role of the financial system to manage risks and to mobilize capital for green and low-carbon investments (108 members and 17 observers as of February 2022).

⁷⁰ See UN Environment (2018), "[Aligning the financial system with sustainable development](#)". For example, in 2015, Article 173 of France's Law on Energy Transition for Green Growth established new reporting requirements for financial firms to improve the quality of climate disclosure on their investment policy.

deliver these standards. Several initiatives providing information on climate issues already existed (Carbon Disclosure Project, Montreal Carbon Pledge, UN principles for Responsible Investment) but were fragmented and difficult to compare.

The Task Force divided climate-related risks into two categories: risks related to the transition to a lower-carbon economy and risks related to the physical impacts of climate change. Regarding physical climate risks, the framework recommends that organizations describe how resilient their strategies are to scenarios consistent with increased physical climate risks and describe their risk management processes related to the potential financial impacts of, in particular, transport difficulties, supply chain interruptions, damage to property and assets, increased insurance premiums and the potential for reduced availability of insurance on assets in high-risk locations.

The Task Force worked fast and released a preliminary report in March 2016, a draft report in December 2016 and the final report in June 2017. The public consultation received over 300 responses from commenters in 30 countries, and over 100 CEOs publicly supported the Task Force's recommendations (TCFD, 2017), indicating that the TCFD recommendations are largely the result of a collaborative process. Consequently, the TCFD framework has rapidly become the standard for the disclosure of climate risks. In addition, the process of developing the standards itself has led companies to recognize that they will be required to be transparent about climate risk. For example, starting in its 2016 annual report, Aviva, one of the largest insurance companies worldwide, has taken the TCFD framework as the guide for its own climate-related disclosure. In May 2018, ClimateWise's Chairman and Global Chairman of Aon Benfield Dominic Christian underlined that "In creating a universal disclosure framework the ambition of the TCFD is unparalleled and we regard the TCFD as a game-changer for the financial services sector in helping us to communicate our responses to the physical, transition and liability risks of climate change." The European Commission, in its 2018 action plan for a

greener economy, stated as a key feature of the plan the revision of “the guidelines on nonfinancial information to further align them with the recommendations of the Financial Stability Board's Task Force on Climate-related Financial Disclosures (TCFD).” In 2021, at least 120 governments, central banks, supervisors, and regulators formally expressed support for the TCFD recommendations, and more than 2,600 organizations endorsed them (TCFD report 2021). This rapid standardization of climate risk disclosure has allowed companies to investigate the extent of their own risks, of which they were not always aware, and investors, bankers and insurers to better measure their exposure to these risks.

Figure 1

Leverage between 2010 and 2019 for high climate risk and low climate risk firms.

This figure plots the median book leverage between 2010 and 2019 for high climate risk (>60th CRIS percentile) and low climate risk (<40th CRIS percentile) firms.



Table IA1

Bank loan, bond loan, and borrower characteristics.

This table reports summary statistics. Descriptive statistics of bank loans, bond loans, and borrower characteristics are reported for the full sample. All Compustat, Thomson-Reuters, Dealscan, and Bloomberg variables are winsorized at the 1st and 99th percentiles, except for CreditRating. The statistics for CreditRating are presented for the firms that are credit rated. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999).

	Bank loan and borrower characteristics			Bond loan and borrower characteristics		
	N	Mean	SD	N	Mean	SD
Climate risk (CRIS)	3,388	32.805	8.933	5,105	34.297	10.826
Climate risk (427)	2,873	40.263	10.295	4,565	41.144	11.729
Spread	3,388	157.882	85.617	5,105	164.264	126.003
Log Amount	3,388	20.620	0.904	5,105	20.231	0.690
Log Maturity	3,388	4.064	0.155	5,105	10.743	0.069
EBIT	3,388	0.091	0.060	5,105	0.090	0.063
Log Age	3,388	3.043	1.220	5,105	3.266	1.112
TobinQ	3,388	1.838	1.020	5,105	1.803	0.949
OpEx	3,388	0.597	0.544	5,105	0.603	0.580
R&DExp	3,388	0.012	0.026	5,105	0.014	0.025
PPE	3,388	0.321	0.268	5,105	0.341	0.267
Log TotAssets	3,388	9.708	1.127	5,105	10.477	1.123
CreditRating	3,007	11.283	2.691	4,789	12.991	2.937

Table IA2

Climate risk, long-term debt, and firm characteristics after 2015.

This table presents estimates of the effects of overall climate risk on the level of long-term debt after controlling for various firm characteristics after 2015. Panel A reports estimates using the CRIS measure of climate risk. Panel B reports estimates using the Four Twenty Seven measure of climate risk. Column (1) controls for the interaction between Post2015 and EBIT. Column (2) controls for the interaction between Post2015 and TobinQ. Column (3) controls for the interaction between Post2015 and OpEx. Column (4) controls for the interaction between Post2015 and LogTotAssets. Column (5) controls for the interaction between Post2015 and PPE. Column (6) controls for all these interaction terms. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: CRIS climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev
EBIT*Post2015	0.254*** (5.342)					0.246*** (3.404)
TobinQ*Post2015		0.00869*** (2.919)				0.00246 (0.599)
OpEx*Post2015			-0.00420 (-0.845)			-0.0102** (-1.972)
LogTotAssets*Post2015				-0.00386* (-1.661)		0.000473 (0.202)
PPE*Post2015					-0.00520 (-0.474)	0.00561 (0.505)
Climate risk*Post2015	-0.00113*** (-4.743)	-0.00120*** (-4.824)	-0.00136*** (-5.414)	-0.00134*** (-5.377)	-0.00132*** (-5.167)	-0.00117*** (-4.713)
Observations	11,367	11,367	11,367	11,367	11,367	11,367
R-squared	0.850	0.849	0.848	0.848	0.848	0.851
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Four Twenty Seven climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev
EBIT*Post2015	0.301*** (5.538)					0.314*** (3.458)
TobinQ*Post2015		0.00924** (2.578)				0.00105 (0.203)
OpEx*Post2015			-0.00153 (-0.273)			-0.0103* (-1.738)
LogTotAssets*Post2015				-0.00345 (-1.278)		0.00145 (0.567)
PPE*Post2015					-0.00973 (-0.815)	0.00201 (0.171)
Climate risk*Post2015	-0.000681*** (-3.418)	-0.000750*** (-3.506)	-0.000912*** (-4.326)	-0.000919*** (-4.350)	-0.000882*** (-4.123)	-0.000703*** (-3.347)
Observations	8,933	8,933	8,933	8,933	8,933	8,933
R-squared	0.848	0.845	0.844	0.844	0.844	0.848
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA3

Climate risk and long-term debt: alternative specifications.

This table presents estimates of the effects of climate risk on the level of long-term debt, using alternative specifications. Columns (1) to (5) report estimates using the CRIS measure of physical climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of physical climate risk. Regressions (1) and (6) include country, industry, and year fixed effects. Regressions (2) and (7) include country-year fixed effects. Regressions (3) and (8) include country-year and firm fixed effects. Regressions (4) and (9) include industry-year fixed effects. Regressions (5) and (10) include industry-year and firm fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev	(9) BookLev	(10) BookLev
	CRIS					Four Twenty Seven				
Climate risk	-2.30e-05 (-0.0382)	-0.00115** (-2.550)		-0.00297*** (-5.739)		0.00189*** (3.077)	0.000128 (0.267)		-0.00140*** (-3.175)	
Climate risk*Post2015	-0.00147*** (-5.899)	-0.000932*** (-3.231)	-0.000852*** (-3.010)	-0.00169*** (-5.023)	-0.00187*** (-5.681)	-0.00101***	-0.000939***	-0.000729**	-0.000731***	-0.000766***
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.368	0.299	0.857	0.321	0.860	0.367	0.284	0.856	0.308	0.858
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes			No		Yes			No	
Country-Year Fixed Effects	No	Yes	Yes	No	No	No	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Industry Fixed Effects	Yes	No				Yes				
Industry-Year Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Year Fixed Effects	Yes					Yes				

Table IA4

Climate subrisks and long-term debt.

This table presents estimates of the effects of climate subrisks on the level of long-term debt using BookLev as the dependent variable. Panel A reports estimates using the CRIS measures of climate subrisks. Panel B reports estimates using the Four Twenty Seven measures of climate subrisks. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: CRIS climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev
Droughts*Post2015	-0.00136*** (-5.142)						
Heat waves*Post2015		-0.000861*** (-3.304)					
Storms*Post2015			-0.000915*** (-5.184)				
Heavy rainfall*Post2015				-0.000968*** (-5.801)			
Temperature rise*Post2015					-0.000160 (-0.500)		
Rainfall patterns*Post2015						-0.000683* (-1.761)	
Sea level rise*Post2015							-0.000838*** (-4.040)
Observations	11,367	11,367	11,367	11,367	11,367	11,367	11,367
R-squared	0.848	0.847	0.848	0.848	0.846	0.846	0.847
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Four Twenty Seven climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev
OperationsRiskScore*Post2015		-0.00120*** (-4.736)		
Floods*Post2015			-0.00199*** (-5.985)	
Sea level rise*Post2015				-0.00105*** (-3.414)
HurricanesTyphoons*Post2015				-0.000561*** (-5.002)
Observations		8,933	8,933	8,933
R-squared		0.844	0.845	0.844
Constant		Yes	Yes	Yes
Firm Controls		Yes	Yes	Yes
Firm Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes

Table IA5

Climate risk and long-term debt, alternative horizons and scenarios.

This table presents estimates of the effects of climate risk on the level of long-term debt using alternative horizons and scenarios. Columns (1) and (3) report estimates using the CRIS low emission scenario measure of climate risk. Columns (2) and (5) report estimates using the CRIS high emission scenario measure of climate risk. Column (4) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) and (2) report estimates using the 2050 horizon measure of climate risk. Regressions (3), (4), and (5) report estimates using the 2100 horizon measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev
Climate risk measure	Low-emission scenario, 2050 horizon	High-emission scenario, 2050 horizon	Low-emission scenario, 2100 horizon	Medium-emission scenario, 2100 horizon	High-emission scenario, 2100 horizon
Climate risk*Post2015	-0.00135*** (-5.204)	-0.00132*** (-5.271)	-0.00105*** (-4.508)	-0.000943*** (-4.171)	-0.000856*** (-3.955)
Observations	11,357	11,357	11,357	11,357	11,357
R-squared	0.848	0.848	0.848	0.847	0.847
Constant	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA6

Climate subrisks and long-term debt, alternative horizons and scenarios.

This table presents estimates of the effects of climate subrisks on the level of long-term debt using alternative horizons and scenarios. The effect of each subrisk is estimated with a separate regression on the total sample, comprising 11,367 firm-year observations. Columns (1) and (3) report estimates using the CRIS low emission scenario measure of climate risk. Columns (2) and (5) report estimates using the CRIS high emission scenario measure of climate risk. Column (4) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) and (2) report estimates using the 2050 horizon measure of climate risk. Regressions (3), (4), and (5) report estimates using the 2100 horizon measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev
Climate risk measure	Low-emission scenario, 2050 horizon	High-emission scenario, 2050 horizon	Low-emission scenario, 2100 horizon	Medium-emission scenario, 2100 horizon	High-emission scenario, 2100 horizon
Droughts*Post2015	-0.00141*** (-5.133)	-0.00138*** (-5.220)	-0.00137*** (-5.155)	-0.00128*** (-5.200)	-0.00120*** (-5.373)
Heat waves*Post2015	-0.00114*** (-4.352)	-0.000944*** (-3.530)	-0.000970*** (-3.747)	-0.000664*** (-2.805)	-0.000529** (-2.419)
Storms*Post2015	-0.000915*** (-5.184)	-0.000915*** (-5.184)	-0.000677*** (-4.247)	-0.000677*** (-4.247)	-0.000677*** (-4.247)
Heavy rainfall*Post2015	-0.00100*** (-5.093)	-0.00101*** (-5.848)	-0.000951*** (-4.901)	-0.000792*** (-4.116)	-0.000777*** (-4.026)
Temperature rise*Post2015	-0.000195 (-0.647)	-0.000320 (-1.159)	-0.000299 (-1.109)	-0.000309 (-1.248)	-0.000256 (-1.343)
Rainfall patterns*Post2015	-0.000956*** (-2.601)	-0.000747** (-2.064)	-0.000804** (-2.279)	-0.000787** (-2.337)	-0.000618** (-2.327)
Sea level rise*Post2015	-0.000838*** (-4.040)	-0.000764*** (-3.821)	-0.000545*** (-3.245)	-0.000545*** (-3.245)	-0.000465*** (-2.962)

Table IA7

Credit rating and climate risk, alternative horizons and scenarios.

This table presents estimates of the effects of overall climate risk on credit rating, using alternative horizons and scenarios. The regressions use CreditRating as the dependent variable for firm-year observations with a credit rating. Columns (1), (2), (5), and (6) report estimates using the CRIS low emission scenario measure of climate risk. Columns (3), (4), (9), and (10) report estimates using the CRIS high emission scenario measure of climate risk. Columns (7) and (8) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) to (4) report estimates using the 2050 horizon measure of climate risk. Regressions (5) to (10) report estimates using the 2100 horizon measure of climate risk. Regressions (1), (3), (5), (7), and (9) include country-industry and year fixed effects. Regressions (2), (4), (6), (8), and (10) include firm and year fixed effects. All regressions exclude observations with missing Log IntCoverage. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, Log IntCoverage, and WorkingCap. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) CreditRating	(2) CreditRating	(3) CreditRating	(4) CreditRating	(5) CreditRating	(6) CreditRating	(7) CreditRating	(8) CreditRating	(9) CreditRating	(10) CreditRating
Climate risk measure	Low-emission scenario, 2050 horizon		High-emission scenario, 2050 horizon		Low-emission scenario, 2100 horizon		Medium-emission scenario, 2100 horizon		High-emission scenario, 2100 horizon	
Climate risk	0.00786 (0.607)		0.00745 (0.602)		0.000269 (0.0260)		-0.00327 (-0.335)		-0.00260 (-0.286)	
Climate risk*Post2015	0.00404 (0.843)	-0.00206 (-0.498)	0.00403 (0.868)	-0.00200 (-0.504)	0.00527 (1.234)	-0.000543 (-0.146)	0.00538 (1.280)	-8.92e-05 (-0.0247)	0.00471 (1.166)	-0.000273 (-0.0784)
Observations	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602
R-squared	0.556	0.915	0.556	0.915	0.556	0.915	0.556	0.915	0.556	0.915
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA8

Climate risk and long-term debt: exclusion of polluting industries.

This table presents OLS estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable, after exclusion of the most polluting industries. Columns (1) and (3) report estimates using the CRIS measure of climate risk. Columns (2) and (4) report estimates using the Four Twenty Seven measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Sample	Excluding Top5 polluting industries	Excluding Top5 polluting industries	Excluding Top10 polluting industries	Excluding Top10 polluting industries
Climate risk*Post2015	-0.00123*** (-4.656)	-0.000822*** (-3.533)	-0.00121*** (-4.505)	-0.000861*** (-3.602)
Observations	10,002	7,915	9,182	7,261
R-squared	0.835	0.832	0.838	0.835
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA9

Climate risk and long-term debt: regressions by industry groupings.

This table presents OLS estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable, for different industry groupings. Columns (1), (3), (5), and (7) report estimates using the CRIS measure of climate risk. Columns (2), (4), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (2) report estimates using observations in manufacturing (SIC 2000-3999). Regressions (3) and (4) report estimates using observations in transportation, communication, electric, gas, and sanitary services (SIC 4000-4999). Regressions (5) and (6) report estimates using observations in wholesale trade and retail trade (SIC 5000-5999). Regressions (7) and (8) report estimates using observations in services (SIC 7000-8999). All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
	SIC20-39		SIC40-49		SIC50-59		SIC70-89	
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Climate risk*Post2015	-0.00167*** (-4.391)	-0.000955*** (-2.660)	-0.00185*** (-3.447)	-0.000540 (-1.399)	-0.00174** (-2.022)	-0.00214*** (-2.750)	-0.00192** (-2.434)	-0.000863* (-1.762)
Observations	5,461	4,423	2,018	1,499	1,280	958	1,548	1,210
R-squared	0.791	0.779	0.879	0.866	0.881	0.881	0.854	0.875
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA10

Physical climate risk, long-term debt, and regulatory risk.

This table presents estimates of the effects of physical climate risk on the level of long-term debt, after controlling for regulatory risk. Columns (1) and (2) report estimates using the CRIS measure of physical climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of physical climate risk. Columns (5) and (6) report estimates using the Sautner et al. (2020) measure of physical climate risk. All regressions control for regulatory risk using the Sautner et al. (2020) measure of regulatory risk. Regressions (2), (4), and (6) control for the interaction between Post2015 and Regulatory risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
	CRIS		Four Twenty Seven		Sautner et al. (2020)	
Regulatory risk	0.00192 (0.529)	0.00852* (1.877)	0.00193 (0.485)	0.00868* (1.680)	0.00151 (0.408)	0.00990** (2.073)
Regulatory risk*Post2015		-0.0134** (-2.201)		-0.0135** (-1.985)		-0.0169*** (-2.659)
Climate risk					0.0134 (0.921)	0.00948 (0.654)
Climate risk*Post2015	-0.00111*** (-3.520)	-0.00105*** (-3.311)	-0.000628** (-2.230)	-0.000590** (-2.087)	-0.0599** (-2.490)	-0.0551** (-2.295)
Observations	8,762	8,762	6,994	6,994	8,762	8,762
R-squared	0.842	0.842	0.841	0.841	0.841	0.841
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Conclusion

La finance durable, marginale jusqu'aux années 1990, occupe maintenant une place incontournable dans la pratique de la finance. Cette thèse examine diverses problématiques contemporaines en finance durable.

Le premier chapitre explore le lien entre risque climatique et risque systémique pour les institutions financières. Nous proposons une nouvelle méthode de mesure du risque climatique extrême et nous l'appliquons aux institutions financières européennes sur la période 2005-2022. Ceci nous permet d'identifier les institutions les plus exposées aux risques physiques et de transition et de déterminer les caractéristiques associées à une plus grande exposition climatique. Nos résultats indiquent que les institutions financières les plus exposées au risque de transition ont des caractéristiques différentes de celles les plus exposées au risque physique, en particulier au niveau de la capitalisation boursière, du bêta des capitaux propres et des réserves de trésorerie. En revanche, dans le cas du risque de transition comme du risque physique, l'engagement dans la gestion des risques environnementaux et l'orientation à long terme des conseils d'administration sont associées à un moindre niveau de risque. De plus, nos résultats montrent que, contrairement au risque physique, le risque de transition est porteur de risque systémique. Enfin, nous trouvons que l'exposition au risque de transition est un déterminant du choix de divulguer ses émissions de CO₂.

Le deuxième chapitre analyse les effets informationnels des initiatives de développement durable très visibles. J'utilise pour cela deux cas d'initiatives très visibles de soutenabilité : les émissions d'obligations vertes et la signature de la déclaration de la Business Roundtable (par laquelle les entreprises signataires affirment leur engagement dans la responsabilité sociale). Je montre que les entreprises connaissent un accroissement du volume de recherches sur le moteur de recherche Google après avoir annoncé s'engager dans des

initiatives de soutenabilité, ce que j'interprète comme un surcroît d'attention des investisseurs individuels. A l'aide de données annuelles provenant de l'organisation non-gouvernementale CDP, je trouve que les participants de marché professionnels ne réagissent pas à la déclaration de la Business Roundtable, suggérant que cette classe d'agents économiques ne réagit pas aux initiatives purement déclaratives. De plus, les agences de notation environnementale tendent à réagir aux initiatives de soutenabilité très visibles, à travers des effets de transparence et d'attention. Les entreprises peuvent ainsi améliorer certaines de leurs notes environnementales via de simples déclarations d'intention ne s'ensuivant pas de résultats tangibles, probablement en raison de la difficulté d'interprétation d'informations molles et des ressources limitées dont disposent les agences de notation extra-financières.

Le troisième chapitre se focalise sur le lien entre risque climatique physique et choix de financement des entreprises. En utilisant de nouvelles données mesurant le risque physique de très grandes entreprises sur la période 2010-2019, nous trouvons que le risque climatique physique est devenu, sur la seconde moitié de la fenêtre d'étude, un déterminant important de la structure capitalistique des entreprises. Les entreprises les plus exposées au risque physique subissent une hausse des taux d'intérêt après 2015. Toutes choses égales par ailleurs, ces entreprises demandent moins de financement par dette que les entreprises peu risquées climatiquement. Toutefois, les entreprises les plus engagées dans la responsabilité sociale ne connaissent pas de baisse de leur ratio de dette, ce que nous interprétons comme un effet de substitution entre risque opérationnel et risque financier.

Au-delà des questions abordées dans le cadre de cette thèse, de nombreuses pistes de recherche en finance durable semblent fructueuses. Je présente ci-après deux idées pouvant donner lieu à des projets ultérieurs. Premièrement, le chapitre 1 analyse, dans le cas des institutions financières, les caractéristiques individuelles associées à l'exposition au risque climatique physique. Cette démarche est jusqu'à présent peu développée dans la littérature. La

mesure du risque climatique via des bases de données commerciales, ayant une couverture généralement limitée aux plus grandes entreprises et pour lesquelles les démarches d'ingénierie inverse tendent à être proscrites contractuellement, peut constituer un frein à la compréhension des facteurs influençant l'exposition à ce risque. A l'aide de données de marché, il serait par conséquent envisageable de développer un indicateur permettant de capter l'exposition des entreprises non-financières aux catastrophes naturelles climatiques et d'identifier les attributs ayant une association significative avec cette exposition. Deuxièmement, le lecteur notera que les chapitres 2 et 3 de ce travail mettent en lumière différents avantages associés à l'obtention d'une notation environnementale favorable et font écho à une large littérature documentant le moindre risque des entreprises démontrant leur responsabilité sociale. Il serait donc intéressant de déterminer quelles caractéristiques ou comportements des entreprises socialement responsables sont les sources de ce moindre risque.

Les différents acteurs professionnels de la finance pourront trouver dans ce travail des éléments de réflexion nourrissant leur pratique. Pour les organes de régulation, le premier chapitre suggère une prise en compte immédiate du risque de transition dans les pratiques de supervision prudentielle, alors que le deuxième chapitre pose la question de l'encadrement de la communication extra-financière. Pour les investisseurs professionnels, le troisième chapitre souligne que le risque climatique physique influence les demandes de financement des entreprises et le taux d'intérêt qui leur sont proposés. Pour les dirigeants d'entreprise, les trois chapitres soulignent l'importance de la gestion des risques climatiques, mais aussi les opportunités pouvant être créées par l'engagement dans la responsabilité sociale.

RÉSUMÉ

Cette thèse doctorale est composée de trois articles de recherche ayant trait à la finance durable. Le premier article propose une nouvelle méthode de mesure du risque climatique et l'applique aux institutions financières européennes. Ses résultats mettent en évidence que, contrairement au risque physique, le risque de transition est porteur de risque systémique. En analysant les caractéristiques corrélées avec nos indicateurs, cet article montre que les institutions financières exposées au risque de transition diffèrent des institutions exposées aux risques physiques. Le deuxième article étudie les effets informationnels des initiatives de soutenabilité dans lesquelles certaines entreprises s'engagent. Il montre que les entreprises arrivent à attirer l'attention des investisseurs individuels via ces initiatives, mais aussi l'attention des participants de marché professionnels et des agences de notation environnementale dans certains cas. Le troisième article analyse les choix de financement de très grandes entreprises sur un échantillon international couvrant la période 2010-2019. Ses résultats indiquent que le risque climatique physique est devenu un déterminant important de la structure financière des firmes sur les années récentes. Les entreprises les plus exposées au risque physique tendent en effet à se financer plus par capitaux propres et moins par dette après 2015.

MOTS CLÉS

Finance climatique, Responsabilité sociale d'entreprise, Structure financière, Finance d'entreprise

ABSTRACT

This doctoral thesis is composed of three research articles on sustainable finance. The first article proposes a new method for measuring climate risk and applies it to European financial institutions. The results show that, unlike physical risk, transition risk significantly contributes to systemic risk. By analyzing the characteristics correlated with our indicators, this article shows that financial institutions exposed to transition risk differ from institutions exposed to physical risks. The second article studies the informational effects of the sustainability initiatives in which certain companies engage. It shows that companies manage to attract the attention of individual investors through these initiatives, but also the attention of professional market participants and environmental rating agencies in some cases. The third article analyzes the financing choices of very large companies on an international sample covering the period 2010-2019. The results indicate that physical climate risk has become an important determinant of the financial structure of firms in recent years. The companies most exposed to physical risk tend to finance themselves more through equity and less through debt after 2015.

KEYWORDS

Climate finance, Corporate Social Responsibility, Capital structure, Corporate finance