



Three essays on the political economy of robot adoption and drought policies

Nourhan Hashish

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Three Essays on the Political Economy of Robot Adoption and Drought Policies

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Abstract

The first chapter aims at studying the impact of the robotization expansion that took place in South Korea on life satisfaction at the individual level. The life satisfaction of workers matters not only because it indicates their quality of life, but also because it is highly correlated with their productivity at the workplace. The empirical strategy consists of creating a robot exposure variable that measures the extent to which individuals in every occupation are being exposed to robots based on their characteristics such as age, gender and residential districts in an event study and a difference-in-difference (DiD) framework with multiple time periods. The two time periods account for both the early stages of robot adoption from 2005 to 2009 and the rapid-paced robot adoption following a major robotization policy in 2009. The treatment is a continuous variable consisting of the individual exposure score. The outcome variable would be the self-reported overall life satisfaction of the individuals. The data used for the project are the Korean Labor and Income Panel Survey (KLIPS) that provide a detailed individual and household level data about employment status, occupations, employment type, working hours, wages and other characteristics including life satisfaction in 273 districts. The results show that individuals more likely to work in highly exposed occupations tend to be less satisfied than those in low exposed occupations from 2005 to 2009, then as of 2009 onwards, being exposed to robotization positively impacts their life satisfaction. These results are driven by males aged 20 to 29 years old who have tertiary education and above due to an increase in their employment levels while their wages are not impacted at the aggregate. These results are robust to the 2008 financial crisis as well as the inclusion of additional fixed effects. The results indicate that the onset of robotization (years 2005 to 2009) had a negative impact on individual's life satisfaction then as of 2009, they self-adjust to the presence of robots at work. The labor market outcomes of the individuals by their education level help us disentangle the mechanisms driving the results in light of the displacement and productivity effects of robots at workplace. From 2005 to 2009, the low and the vocationally educated workers have been displaced from their work

leading to an increase in part-time employment and in firm switching. From 2009 onwards, the vocational and high educated individuals benefitted from the robotization manifested in a rise in their wages which is not the case for the low educated individuals. The enhanced wage of the highly educated workers signals the productivity effect in the occupations and sectors employing them. These results are persistent at the household level, when we look at the head of household and their spouse's life satisfaction as a result of robot exposure. The household level results indicate that the negative effect of robot exposure is mainly driven by the spouses whose husbands have low or vocationally educated workers due to the decrease in the total household income. A local labor market approach instrumented with Singapore and a replaceability instrumental variable is also used to examine the productivity effect at the regional level as well as possible psychological effects notably fear of being replaced by robots. The results of the local labor market approach do not show neither a productivity effect nor a psychological effect of robots on workers.

The second chapter further analyzes the impact of the robotization policy in South Korea on voting outcomes at the presidential and parliamentary elections levels. The rationale behind extending our analysis to the political economic implications pertains to potential public resentment towards threats to jobs is expressed through voting for the Right-wing parties. The empirical strategy employed consists of a shift-share instrumental variables approach where we instrument the adoption of robots in South Korean with that of Singapore. The outcome variable is the vote share for right, center or left wing parties at both the legislative as well as presidential elections level. The data used for the project are the Korean Labor and Income Panel Survey (KLIPS) and the International Federation of Robots data (IFR) as well as the presidential and legislative voting data at the district level from the South Korean National Election Commission. The results show that there exists a polarization in the voting behavior in the South Korean districts manifested in an increase in the vote share for both Right and Left wing parties and a decline in the vote shares for Centerist parties. This is more pertinent at the parliamentary election level than at the presidential election level. However, the presidential elections do exhibit a propensity to be polarized, manifested in the rise in Center-Left as well as the Right vote shares. In an attempt to understand the mechanisms driving our results, a number of heterogeneity analysis is conducted using the same regression specification to disentangle the groups of districts driving political polarization. The South Korean districts are divided into higher than the median level of age, education and employment level. The analysis shows that political polarization is driven primarily by generational conflict as robot adoption impacts older and younger generations differently. Older generations who have been disadvantaged from robotization at work tend

to favour voting for Right-wing parties.

The third chapter finds a causal link between a drought compensation policy change in Tunisia in 2016 and the results of the 2019 presidential elections. Droughts threaten countries' agricultural outputs, lead to food insecurity and conflicts as well as have implications on elections. Tunisia is a hybrid democratic regime with a multitude of political parties characterized by their weak influence and a wide ideological gap from the demands of the populace. The year 2019 marked the second presidential and parliamentary elections in Tunisia after the revolution and coincided with the removal of the drought declaration and compensation decrees that took place in 2016. Before 2016, the affected farmers were eligible for financial relief. However, as of 2016, this relief was no longer provided to farmers for three consecutive years of severe drought. I use the 2016 removal of drought declarations in Tunisia as a shock in a difference-in-differences framework where my treatment variable is continuous indicating the extent of agricultural land area damage caused by drought at the finest district level. My outcome variable is the vote share at the presidential elections level for the incumbent president. I use the drought decrees extracted from the Official Journal of Legal Announcements for the years 2015 and 2016 to build a novel dataset that includes the percentage of agricultural area damaged by drought as a proxy of drought damage at the district level. I couple these data with the voting data from the Instance Supérieure Indépendante pour les Élections (ISIE) for the presidential and parliamentary elections for the years 2014 and 2019. My results indicate that the removal of drought declaration decrees in Tunisia would decrease president Said's vote shares in favour of his opponent while voter turnout is not impacted. The mechanisms driving the results relate to people's general disapproval of the policy abandonment that manifested itself in the form of a rise of riots in the agricultural districts. These results highlight that despite the fact that democracy in Tunisia is hybrid meaning it has flaws, Tunisians still believe that democracy is the best way to govern. Therefore, the Tunisian people would rather punish the incumbent president - by voting for the opponent during presidential elections - than the incumbent party at the parliament if they deem governmental policies inefficient. Furthermore, the voters have not punished the incumbent parties in the parliamentary election; nor there has been any impact on trust in parties or closeness to them. These results highlight that under Tunisia's hybrid democratic regime, the public believes that policy accountability belongs to the president rather than the parliament. The results are robust to changing the main treatment variable to another variable proxy of drought damage as well as to changing the drought damage variable to a post treatment - for drought spells taking place in 2020 and 2021 - instead of the conventional pre-treatment variable.

Introduction

The rise of automation is a worldwide phenomena that lead to a lasting change in individuals' lives and their future prospects. Despite the difficulties in quantifying the effects of automation and robot adoption at work, there is some evidence that robot adoption can have two effects at work: a displacement or a productivity effect, which in turn affects employment and wages of workers ([Acemoglu and Restrepo, 2020](#); [Hirvonen et al., 2022](#); [Ford, 2015](#); [Brynjolfsson, Erik and McAfee, Andrew, 2014](#)). There are active debates in the literature concentrated on the primary effects of automation and artificial intelligence on individuals' employment, wages, fear of replacement if workers do not lose their jobs and the spread of poverty. The secondary effects of automation such as its impact on individuals subjective well-being and their political inclinations have recently become an important part of the debate.

The first chapter of this thesis evaluates a robot adoption policy initiated in South Korea on self-reported well-being through labor market outcomes. According to [Helliwell, J., Layard, R. and Sachs, J. \(2022\)](#), South Korea had a low happiness index compared to the OECD countries on average. South Korea ranked 59 among 146 countries in 2022, this low rank reflected the deterioration of Koreans' well-being ([Korea Times, 2022](#)). South Korea's low happiness rank coupled with the implementation of a robot adoption policy – that places it as the first country with the highest robotization at work rate¹ – was a main motivation to study a potential causal link between the two events in the first chapter.

The second chapter extends the first to study the implications of workplace robot adoption on voting outcomes, motivated by the worldwide rise in political divide and extreme political movements. In his paper, [Caselli et al. \(2021\)](#) emphasize how structural economic changes due to globalization, immigration and robot adoption are associated with Right-wing and populist parties' support. People's public discontent align with nationalistic sentiments and

¹As depicted in Figure 1.3

radical Right voting which lead to the rise of populism to more than 20% from 2011 to 2015 ([Rodrik, Dani, 2017](#)). Given that people differ in their interests and identities that evolve over time as a result of the interaction between historical legacies, socio-economic and institutional factors ([Shin and Agnew, 2007](#)), studying the South Korean context – with little immigration and a major robot adoption shock – was essential.

Aside from automation and artificial intelligence, climate shocks and natural disasters are worldwide concerns due to their detrimental effects on people’s livelihoods and high costs of combating and preventing. Droughts and water scarcity are expected to displace around 700 million people by 2030 ([UNICEF, 2024](#)). It is estimated that the cost of drought mitigation in Africa will be up to USD 30 billion per year ([PreventionWeb, 2009](#)). Tunisia has been suffering from consistent drought spells coupled with agricultural output losses.

The third chapter evaluates an unanticipated suspension of a drought information and compensation policy in Tunisia on voting behavior. Drought has been a major threat facing Tunisia, but with the help of governmental support, the negative consequences of drought were successfully managed. However, the suspension of the governmental support took place at a time where the country was transitioning to a multi-party democracy. The unpredictable drought policy abandonment and the aggravation of drought risks sparked people’s public discontent.

Each of the three chapters of this thesis contributes to a distinct literature. The research question, contribution, data, methodology, and results of each are detailed below.

Chapter 1: Robots, Labor Market Outcomes and Life Satisfaction: Evidence from South Korea

Co-authored chapter with Joop Adema and Jae Cho

As of 2005, the South Korean government embarked on a number of policies to increase robot adoption. These policies culminated in “the Intelligent Robots Development and Distribution Promotion Act” that was put in place in 2009 and successfully managed to enhance productivity through increasing robot adoption in different South Korean industries. The South Korean government was not only aiming at increasing the country’s overall productivity, but also at catching up with other developed economies such as the United States, Germany as well as some neighboring countries like Japan and Singapore.

The first chapter aims at studying the impact of the wave of robotisation that took place in South Korea on individuals’ life satisfaction. More precisely, the robotization onset was

from 2005 to 2009 and it continued to steeply increase from 2009 onwards. In this regard, the presumption to be tested is that the exposure of individuals to robots will lead to a decline in their life satisfaction both in the first period of the shock 2005 to 2009 and then will increase from 2009 onwards. We contribute to three streams of literature. The first one relates to the impacts of robots at work on workers' life satisfaction. [Hinks \(2021\)](#) and [Schwabe and Castellacci \(2020\)](#) report a negative correlation overtime between robots at work and workers' satisfaction, while [Gihleb et al. \(2020\)](#) analyze the labor market in the United States and find no relationship between life satisfaction and workers' exposure to robots.

A second stream of literature examines the labor market effects of robotization. [Acemoglu and Restrepo \(2020\)](#) and [Dauth et al. \(2021a\)](#) both employ a local labor market approach; the former finds a decline both in wages and employment while the latter confirms the adjustment of the labor market when robot adoption increases. In other papers, labor market effects are analyzed in a cross-country analysis context as in the work of [Graetz and Michaels \(2018\)](#) or at the firm level using an event study design by [Aghion et al. \(2021\)](#). The third stream of literature we add to is the societal effect of robotization; [Anelli et al. \(2019a\)](#) and [Anelli et al. \(2019a\)](#) study the impact of local and individual-level exposure to robots on voting behavior and find that higher exposure is associated with increased Right-wing voting.

The contribution to these three streams of literature is on four levels: first, we employ an individual level empirical strategy to study the impact of robotization on life satisfaction. This question has been addressed only using a local labor market approach. Second, this study moves one step further from the existing literature by leveraging labor market outcomes as mechanisms explaining the main outcomes. Third, using South Korea as a case study is a contribution to the literature given its different demographic feature than that of the United States and Germany that has been mostly the focus of the literature. The fourth contribution, is the fact that the analysis is extended to include the household effect; studying the impact of the exposure of the household head to robots at work on their spouses' life satisfaction.

The Korean Labor Income Panel Survey (KLIPS) is used for this study. It includes variables about wages, employment, and demographic characteristics as well as life satisfaction. The final KLIPS dataset comprises 325,112 individual-year observations covering the years 1998 to 2020 with a very low attrition rate. Following [Anelli et al. \(2019a\)](#), the exposure of individuals to robots is constructed using a multinomial logit probability of individuals to work in a given occupation k based on their age, gender, education and residential district

(before the start of robotization) multiplied by the replaceable hours at the occupation level following [Graetz and Michaels \(2018\)](#) and summed over all occupations. The rationale for using the probability of individuals to work in a given occupation enables the inclusion of both employed and unemployed individuals in the analysis. We use the constructed exposure measure at the individual level in an event study design.

Our results at the individual level show that robotization increases life satisfaction as of 2009. This increase in life satisfaction starting 2009 is due to a rise in employment levels but wages remain unchanged at the aggregate level. This is the case for males aged 20 to 29 years old with tertiary education. To disentangle our findings, we explore labor market mechanisms that could possibly drive the results by education level. The mechanisms are displayed at the low, vocational and high education levels as robotization is expected to have a different effect depending on the nature of the tasks. From 2005 to 2009, the low and the vocationally educated individuals have been displaced from their work in the form of a rise in part-time employment and switching of firms where they work. From 2009, we confirm that the vocationally and highly educated individuals benefit from robot adoption at work in the form of wage increases meanwhile, this is not the case for the low educated individuals.

In addition to the individual case, we also explore the life satisfaction changes of spouses owing to the increase in their husbands' exposure to robots. We use a difference-in-differences framework with multiple time periods to take into consideration the two waves of robot adoption, where the continuous treatment variable represents household heads' exposure to robots at work. Aligning with the outcome from the individual case, we confirm that the negative effect of robot exposure is mainly driven by the spouses whose husbands have either a low or a vocational education level due to the decrease in the total household wage. Our results indicate that the negative effect of robotization is not just limited to the individuals but it is amplified within the household when we consider their quality of lives.

A local labor market approach with a shift-share instrumental variable is used following the work of [Acemoglu and Restrepo \(2020\)](#) to explore the possibility of having a productivity effect at the district level and to test for the possible existence of a psychological impact as in the fear of workers being replaced by robots at the aggregated district level. We use Singapore as our reference country. From the results of the local labor market approach, we deduce that there is neither a productivity effect nor a psychological effect of robot adoption at the workplace on workers.

Chapter 2: Robots and Voting Outcomes: Evidence from South Korea

Co-authored chapter with Jae Cho

According to [Prysby and Scavo \(1993\)](#), voting behavior is a key determinant of government's performance as well as orientations on specific public policy issues. Alternatively stated, policy makers need to understand voters' drivers when casting their votes or making certain political decisions. There exists a large literature exploring the causes and changes in voting behavior. Recently, economists started to consider robot adoption at work as a potential factor affecting individuals' voting behavior. As robotization has countervailing effects on workers, its effect on voting behavior is puzzling. We attempt to scrutinize the causal effect of robotization at work on voting behavior by leveraging "the Intelligent Robots Development and Distribution Promotion Act" conducted by the South Korean government to promote domestic robot markets.

This chapter contributes to three strands of literature. The first contribution relates to the literature on the effect of automation on voting outcomes. [Caselli et al. \(2021\)](#); [Anelli et al. \(2019b\)](#) extensively explore the topic using Italian data and European data respectively. Their findings indicate a positive correlation between exposure to robot at work and support for the nationalistic ideologies of radical right parties. [Caselli et al. \(2021\)](#) provide evidence that automation positively affects the Italian populist movement. [Schöll and Kurer \(2024\)](#) use German labor market data at the county level in a two-way fixed effects model to show that robot adoption changed the workforce composition at the regional level in Germany. The composition effect is much larger than the expected political effect of robot adoption in the literature – that is the rise in extreme Right-wing voting – leading to a rise in vote shares for the progressive Left-wing parties.

[Frieden \(2018\)](#) finds a rise in populist movements when globalization becomes a threat to workers. [Abbondanza and Bailo \(2018\)](#) and [Autor et al. \(2020\)](#) also find that the influx of immigration coupled with the increase in trade exposure – that both threaten domestic labor market – are positively correlated with the rise in voting for extreme right parties. Our contribution to this literature is in many respects. First, we use a district-level panel data in a shift-share instrumental variable approach to study the effect of robotization on voting behaviors at a granular level in South Korea rather than at an aggregated country level. We add to this literature with our results that point at a rise in political polarization manifested in an increase in Left and Right-wing party vote shares simultaneously at both the parliamentary and the presidential elections level.

Another strand of literature, that our study is relevant to, is the intersection of political polarization and generational conflicts. There is a body of political economy literature that attribute the cause of political polarization to extreme divergence in old versus younger generations stance with regards to political ideologies hence, their support for political parties (Dalton, 1987; Philips, 2022; Moon et al., 2020; Jou and Endo, 2016; Stoker, Stoker). Dalton (1987) sheds light on generational differences in supporting Left versus Right-wing political parties. For instance, younger and older political activists have major roles in political polarization that reflect the interests of the different societal groups. Furthermore, Philips (2022) further investigates the effect of age, period and cohort effects on political polarization, partisanship and ideological sorting. The study discovers that age-related variables have a strong impact on political polarization. Our mechanisms overlap with the findings of this literature. As we attempt to explore a number of labor market heterogeneity analysis at the district level as our mechanisms, we show that younger generations tend to vote for Left-wing parties while older generations tend to favour Right-wing ones which ultimately leads to political polarization.

For the purpose of this study, 4 rounds of presidential elections are used covering the years 2002, 2007, 2012 and 2017. Presidential elections take place every 5 years with no consecutive terms. In addition, 6 rounds of legislative elections are used for the years 2000, 2004, 2008, 2012, 2016 as well as 2020. Parliamentary elections usually happen Every 4 years with possibilities of consecutive terms. We use the National Election Commission (NEC) data as our main source of South Korean voting data at the regional level. The Korean Labor Income Panel Survey (KLIPS) is also used for this study. It includes variables about wages, employment and demographic characteristics.

The KLIPS data are collapsed and weighted at the regional level to be further merged with the NEC data for more comprehensive regional level controls. The International Federation of Robot data (IFR) provide us with the industry level robot operational stock, installation data that are also merged with both the collapsed KLIPS and NEC data. The final dataset comprises 1,921 region-year observations covering 270 districts, 4 years of presidential elections and 6 years of parliamentary elections in total. The econometric approach will consist of a shift-share instrumental variables framework where we use Singapore’s robot exposure as an instrument for that of South Korea. The main motivation for using Singapore as an instrument in our specification is that it comes next in line in terms of rapid robot adoption following South Korea and strongly correlates with the latter’s robotization as a consequence. The exposure to the robot shock at the regional level is inspired by Dauth et al. (2021b).

The results show that robot adoption in South Korea led to an increase in both Left and Right vote shares at the parliamentary elections for the regions more exposed to robots at work. The same results were witnessed for the presidential elections but to a much lesser extent. These results indicate that there is a prevalence of political polarization in South Korea following the robotization wave that took place. Disentangling The mechanisms leading to these results entail a number of heterogeneity analysis to be able to distinguish between the group of individuals opting for Left-wing parties and those opting for Right-wing ones.

We follow the same empirical strategy on subsamples of the data to be able to find which subgroups of districts drive the political polarization. We specifically divide our observations into districts with higher (lower) than the median level of: employment share in manufacturing, employment in robot industry and age. Based on the district-level heterogeneity results and our individual as well as household level results from the first chapter, we conclude that the political polarization is driven by conflicts between generations as robotization impacts two generations differently. Workers from the older generation (above 40s) are more exposed to robotization than younger generation. Considering that the older (younger) group has a tendency to vote for Right (Left) parties, we confirm the negative effect of robot adoption on older generations. The older generations are the disadvantaged groups from robotization; therefore, they have an inclination to vote for Right-wing parties. The rationale behind this conjecture is in line with [Anelli et al. \(2019b\)](#) and [Anelli et al. \(2021\)](#) who find that public resentment towards possible threats to workers' jobs are expressed through a rise in Right-wing vote shares.

Chapter 3: Droughts and Voting Outcomes: Evidence from Tunisia

This chapter analyzes the impact of a drought policy change in 2016 on voting outcomes in Tunisia. Tunisia has been characterized by recurrent drought spells that cause crop losses on a yearly basis. To compensate the farmers for their losses, the Tunisian government published the percentage of agricultural area damage in drought decrees available for the farmers as well as the residents per district. The drought declaration decrees provide farmers with drought relief in the form of loan rescheduling while they provide the rest of the residents with the needed information to forecast possible food shortages they could face. The government has been releasing drought decrees until 2016. From 2016 to 2019, the decrees along with the relief have been suspended during years of intense drought spells.

I contribute to a literature on the political economy of climate change that links climate disasters' compensation policies and incumbents' vote share during election times. The

literature posits that having climate disaster compensation packages will encourage voters to reward the incumbent in elections ([Bastos and Miller, 2013](#)). [Bastos and Miller \(2013\)](#) use a three order polynomial regression of the relative margin of candidate's victory in elections to indicate that releasing drought compensations 2 years prior to holding elections in Brazil increases the reelection probability of the incumbent. [Fukumoto and Kikuta \(2024\)](#) use rainfall as an instrumental variable for a disaster compensation policy in Japan and find that providing compensation packages increase support for the incumbent political party as predicted by the "egotropic retrospective voting" theory.

The "egotropic retrospective voting" postulates that incumbents' vote share during elections is directly proportional to the provision of relief packages during election times ([Achen and Bartels, 2004](#); [Bovan et al., 2018](#)). I contribute to the literature with my results that overlap with that of the "egotropic retrospective" literature. Furthermore, the drought compensation policy suspension I study in this paper is another addition to the literature mostly focused on targeting drought relief around election times. I contribute to the literature with the data I am using. I constructed a novel dataset to proxy for drought damage from the percentage of agricultural land area damaged extracted from official Tunisian journals. The data used in the literature to study the impact of droughts on voting outcomes are either drought indices or rainfall average variation over a long period of time at least 30 years as in [Tarquninio \(2022\)](#). I abstract from using rainfall and resort to using a proxy for lack of rainfall closely reflecting Tunisia's main problem that is severe drought seasons that lead to agricultural output losses.

I contribute to the literature on how climate change can lead to conflict by stipulating that drought shocks coupled with drought declaration and compensation removals result in an increase in riots ([Decet and Marcucci, 2023](#); [Adhvaryu et al., 2021](#)). According to [Decet and Marcucci \(2023\)](#), droughts in Africa can amplify violent conflicts in rural areas prone to rainfall scarcity. In this chapter, I find that riots are ignited by both farmers and the rest of the residents living in districts where drought occurred and the associated compensation was removed because of citizens' general discontent. [Adhvaryu et al. \(2021\)](#) and [McGuirk and Burke \(2017\)](#) show that there exists a correlation between natural resources and conflicts in Africa. They develop a model predicting that economic prosperity is likely to happen in case of equilibrium conflict prevalence that depends on a region's own resources and those of their neighbors. They find that better institutional qualities minimize the incidence of a conflict equilibrium. The results of this chapter are in line with the findings of [Adhvaryu et al. \(2021\)](#) and [McGuirk and Burke \(2017\)](#), I provide evidence that democracy can work

efficiently when given a chance in channeling people’s public discontent during election times. This discontent is translated into a decrease in incumbent’s vote share rather than a rise in voter turnout. The focus of the literature on the determinants of voting behavior has been on either climate change mitigation or prevention policies specifically targeting election times to gain people’s support as in [Tarquinio \(2022\)](#). [Tarquinio \(2022\)](#) studies the impact of drought relief provided before election times on ruling party’s incumbency in India in a regression discontinuity design and an instrumental variables approach. This chapter studies the suspension of a drought compensation policy following a drought shock, which is considered a contribution to the literature that is focused on time-targeting compensation policies before elections rather than their complete removal.

The main data used in this study are the following: first, Instance Supérieure Indépendante pour les Élections (ISIE) for the presidential and parliamentary election results the years 2014 and 2019. Second, the drought governmental decrees that include the areas and the percentage of drought damage at the district level in 2015 and 2016. Third, the main source of covariates data is AidData for 1 km grid data on the GDP, distance to water, distance to road, population density in 2014 and 2019. The econometric approach will consist of a difference-in-differences framework where the treatment variable is continuous pre-removal indicating the percentage of damage caused by drought at the district level as per the drought declaration decrees. The outcome variable is the vote share for the incumbent president at the presidential election level while it is the vote share per political party at the parliamentary elections level.

The results indicate that the Tunisian people would rather vote less for the incumbent president to punish him during the presidential elections rather than the incumbent party at the parliamentary elections if they deem governmental policies inefficient. The voters have not punished the incumbent parties at the parliamentary election; nor there has been any impact on either trust in parties or closeness to them. These results indicate that under Tunisia’s hybrid democracy, the public holds the president rather than the parliament accountable for policies. I find that the abandonment of the drought declaration decrees in Tunisia led to an increase in riots by 2.8 percentage points following a 1 standard deviation increase in district-level damage after the policy removal. The results are robust to changing the main treatment variable to using a Normalized Difference Vegetation Index (NDVI) that is a proxy for drought damage and to changing the drought damage variable to a post-treatment one that covers drought spells in 2020 and 2021 instead of the pre-level variable.

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Chapter 1

Robots, Labor Market Outcomes and Life Satisfaction: Evidence from South Korea

Co-authored chapter with Joop Adema and Jae Cho

This paper investigates the impact of South Korea’s rapid robotization, driven by the country’s proactive robotization policies, on subjective well-being using individual and household-level panel data. We measure individual exposure to robotization by estimating the probability that individuals work in occupations susceptible to robotization. This approach allows us to study the effect of robotization at the individual level, including the unemployed and indirectly affected workers. Our findings indicate that the initial phase of automation adversely affected workers. However, this negative impact diminished during the subsequent phase of automation. This suggests that once workers adapt to an environment integrated with robots, they begin to experience the benefits of automation.

1.1 Introduction

Robot adoption is expected to significantly enhance firms productivity because they can perform increasingly complex tasks efficiently and at a rapid pace compared with human workers ([Bonfiglioli et al., 2024](#)). On the other hand, workplace robotization could raise concerns about the quality of lives of the workers manifested in their life satisfaction. Con-

sidering that a strong positive relationship between life satisfaction and job experience has been found (Heller et al., 2002), increasing robot adoption at work is expected to have an effect on workers’ life satisfaction. For example, a worker’s life satisfaction could be changed as a result of robotization directly impacting their labor market outcomes (e.g., workers may lose their jobs to robots and this loss can significantly impact their life satisfaction). Furthermore, due to the subjective nature of life satisfaction, the psychological effects of robotization (e.g., fear of losing their jobs in the future, feelings of incompetence when compared to robots, etc.) could also reduce a worker’s life satisfaction even if there is no actual impact on the workers wages or employment status.¹

With the rise of automation technologies, previous studies have extensively explored the changes in the labor market outcomes due to robotization. Economists have assessed the effects of robot technologies on labor market outcomes in a variety of settings and found evidence for two countervailing effects: a displacement effect and a productivity effect.

Acemoglu and Restrepo (2020) confirm that as specific tasks are transferred from workers to industrial robots, part of the workforce is displaced from their job. On the other hand, robotization enables workers who are not displaced to be more productive, or to produce novel products (Hirvonen et al., 2022). Furthermore, re-allocation of workers at the manufacturing sectors is witnessed in the case of Germany as the number of routine jobs in manufacturing sector decreases (Dauth et al., 2021). While evidence shows that there are pros and cons to robotization that can impact anyone (Acemoglu and Restrepo, 2020), multiple papers document that negative effects are more pronounced for young workers (Chiacchio et al., 2018) and labor market entrants (Dauth et al., 2021).

Amongst numerous studies evaluating the effect of robots on labor market outcomes, only a few of them were able to expand their scope of study to explore the effect of robotization on life satisfaction. This is primarily due to data limitations since the robot data sources used in previous studies are only defined at the sector or country level.² In addition, most of the literature examining the relationship between robotization and life satisfaction do not provide causal evidence. Instead, they rather focus their studies on countries with a relatively low density of industrial robots and much lower adoption rates (in terms of per 1000 workers) than South Korea (Gihleb et al., 2020; Schwabe and Castellacci, 2020).

¹If the displacement effect is stronger than the productivity effect then workers will lose their jobs and therefore life satisfaction will be negatively correlated with robotization.

²As the exposure measures are defined in the sector or country level, the previous studies, therefore, present the life satisfaction changes in an aggregated level. (Gihleb et al., 2020; Schwabe and Castellacci, 2020; Hinks, 2021)

In an attempt to overcome previous data limitations, we construct an individual-level exposure to robot, based on [Anelli et al. \(2021\)](#) and [Graetz and Michaels \(2018\)](#). Our exposure to robots measure is a proxy measure for distance to replaceable occupations. This proxy measure was chosen because both individuals working directly in replaceable occupations and those who are likely (based on demographic characteristics) to work in replaceable occupations may be affected by robotization. Additionally, we make a methodological contribution by adjusting the approach of [Anelli \(2019\)](#) to predict individual-level *replaceability* of employees in the base period, using occupation-level replaceability as is done in [Graetz and Michaels \(2018\)](#). This measure of replaceability is based on the overlap between occupational titles and robot application as defined by the International Federation of Robotics (IFR). Although it is a very simple approach, it predicts robot adoption well.³ Naturally, our robot exposure indicator allows us to investigate the life satisfaction of an individual by virtue of measuring robot exposure in an individual-occupation level.⁴

Information on individual’s life satisfaction is collected from the Korean Labor Income and Panel Study (KLIPS, hereafter). KLIPS provides us not only with individual level labor market outcomes, including employment and wage which allows us to observe the potential channels of the effect of robotization on worker’s life satisfaction, but also with the survey inquiring about individuals’ life satisfaction during our observation period. A linking of our exposure measure to the detailed individual level information from KLIPS, allows us to finally be able to provide a causal evidence of the effect of robotization on life satisfaction.

Our empirical strategy extends to the potentially most affected workers. Prior literature confirmed that the manufacturing sector is an industry that has the highest robot adoption rate as well as the highest male labor force participation rate; this is also applicable to the South Korean case.⁵ As robotization primarily affects the earnings and job security of the (male) household head, this in turn may affect the labour supply decisions made by the spouse. Therefore, we also study the labor market position and life satisfaction of spouses. These spouses are typically out of the labor force, work in part-time jobs, or work in low-paid occupations in South Korea. This is of particular interest, as previous work has shown that robots strengthen the position of incumbent laborers in firms (household heads or males in our study) ([Dauth et al., 2021](#)), and weakens that of potential entrants (spouses or females).⁶ Therefore, we believe we are the first to find to demonstrate the indirect effect

³[Graetz and Michaels \(2018\)](#) map the share of employment replaceable by robots to the country-industry level and use it as an Instrumental Variable for robot adoption across countries.

⁴For a detailed explanation, please refer to Section 4.

⁵See appendix

⁶Although a household head could be also female, in this paper we refer to the household head as male

of household head’s exposure to robotization on their spouse’s life satisfaction as well as economic activities.

The current research explores the South Korean case. In previous studies, the government’s role in fostering/controlling investments in robot-producing and robot-adopting industries was overlooked. This is simply because governments did not actively pursue policies specifically oriented towards industrial robots until recently. In 2005 the South Korean government launched the official support for intelligent and industrial robot industry, creating the systematic base for the industry in South Korea. The *Intelligent Robots Development and Distribution Promotion Act* introduced in 2009 gave the government wide-reaching abilities to spur robot development and adoption. The law aims at improving work conditions, increasing productivity and ultimately raising individuals’ life satisfaction. The statement of purpose of this law reads: “The purpose of this Act is to contribute to enhancing the quality of life of citizens and the national economy by establishing and promoting a policy on the sustainable development of the intelligent robot industry to facilitate the development and distribution of intelligent robots and lay down the foundation therefore.”⁷ This law entailed a wide set of measure, aimed at extending the use of robots in various industries. Therefore, the Korean government policies successfully led to the strong adoption of industrial robots over the past 15 years. In 2019, the number of industrial robots per thousand workers exceeded 10, which makes South Korea the country with the highest level of robot adoption in the world.⁸ In light of all these facts, we focus on two distinct time periods as our two exogenous shocks: between 2005 and 2009, when robot innovation (as measured by the number of patents) was strong and a new legislation was announced and after 2009, when the rate of robot adoption increased strongly due to the legislation.

Along with the fact that South Korea is a front-runner in robot adoption policy, the strong labor market challenges facing South Korea make the country an interesting set-up for the unprecedented adoption of robots during the past 15 years. South Korea has a rapidly declining workforce⁹, as strong increase in educational attainment of the available workforce¹⁰, an increase in flexible work arrangements¹¹, and a large gap in pay between men and women¹²

and the spouse as female, as coded in the Korean labor force survey which reflects the secondary position of women in the labor market. For a characterization of the South Korean labor market, see section 1.2

⁷For more on this law, we refer the reader to section 1.1.2 and the Act itself available at [Center \(2024\)](#).

⁸We elaborate on the adoption of robots in South Korea in section 1.1.2.

⁹The working age population in South Korea is expected to decrease by about 35% in the next 30 years ([Agency, 2022](#)).

¹⁰For further discussion, see section 1.1.2

¹¹In South Korea, the share of part time workers rose from below 2% in 2005 to 8% in 2019

¹²South Korea has an unconditional gender pay gap of 32.5%, the highest amongst the OECD countries.

which are the challenges that other developed countries also face (to a lesser extent).¹³ Considering that other countries followed the example of South Korea recently, strongly investing in automation technologies¹⁴, we expect that studying the South Korean case will teach the countries whose governments begin to allocate their investments in the field of robotics.

We find that the strong robotization of South Korea’s industries improved life satisfaction for workers at the aggregate level due to improvements in their employment status while it had no impact on their wages. The effect size we find between 2009 and 2019 is modest and statistically significant: a one standard deviation in individual-level robot exposure decreased life satisfaction by -0.04 points (on a scale of -1 to 1). This result is equivalent to that of a percentage increase in log wage that leads to a 0.023 unit increase in life satisfaction. We investigate heterogeneous labor market outcomes and work conditions channels conducive to the main results. We find that males aged 20-29 who have a tertiary education and above are the ones driving our main results. We disentangle the mechanisms further by education levels and find that the low and vocationally educated individuals are the ones prone to the displacement effect. This is due to the prevalence of part-time jobs (a proxy for low-quality jobs) and the firm switch variable respectively in the onset of robotization at work from 2005 to 2009.¹⁵

Since both the workers and their fellow household members are affected by robotization, we estimate the effect of the household head’s exposure to replaceable occupation on their spouse’s life satisfaction. In line with the individual-level findings, we find a negative effect on life satisfaction, but only in the period between 2005 and 2009. Importantly, we do not find a statistically significant effect on labor market outcomes for spouses. This incentivized us to explore two other potential channels 1) aggregated household wages and 2) the wage and working hours gap between household heads and spouses. We confirmed that the main negative effect of the household head’s vulnerability to robotization on their spouses’ life satisfaction is largely attributed to a decrease in the total household wage.

For more statistics on the position of women in the South Korean labor market ([“Organisation for Economic Co-operation and Development \(OECD\)”, 2025](#)). As many jobs amenable to robots are male-dominated, automation of these jobs may put downward pressure on male wages. Furthermore, since these individuals are likely to be at the low end of the wage distribution, this can also increase earnings inequality.

¹³See [Lee \(2020\)](#)

¹⁴For an overview of recent government-backed investments in robotics R&D, see [International Federation of Robotics \(IFR\) \(2025\)](#).

¹⁵We constructed the firm switch variable as a dummy equals zero if the individual stays in the same firm where he started working for the past 12 month following the initial date of the start of his job.

To explain our main findings, we dive into two main channels: labor market outcomes and psychological effects notably the fear of being replaced by robots at work. Specifically, we incorporate some fear of job loss mechanisms using a local labor market (LLM) approach that follows [Acemoglu and Restrepo \(2020\)](#) and [Dauth et al. \(2021\)](#). The local labor market approach accounts for broader productivity effects that are not related to one’s occupation. It also measures the local effects of robotization at the regional level rather than across the country. The local labor market approach can signal the psychological effect of robotization on life satisfaction. Unlike individual- and household-level results that show a decline in life satisfaction during the early phase of robotization, the LLM approach does not yield any positive or negative effects on life satisfaction. This is largely due to the productivity effects and the labor market improvements happening for all workers regardless of whether they work in a region likely to be replaced by a robot or not. Therefore, the fear mechanism is ruled out while labor market outcomes are the drivers of the decline in life satisfaction from 2005 to 2009 as well as its increase as of 2009.

This paper is structured as follows. Section 1.1.1 discusses the prior literature on the labor market effects of robotization and wellbeing and how we contribute to it. Section 1.1.2 discusses the South Korean governments’ policies to foster robots in the past two decades, and how this affected robotization in subsequent years. In section 1.2 we present the Korean labour force survey and how we construct a measure of robot exposure on an individual level. As we focus on both the effects of robotization on individuals as well as households we present comparable but distinct analyses in sections 1.3 and 1.4. Section 1.7 concludes.

1.1.1 Related Literature

Our work connects to several strands of literature. First of all, it relates to studies that aim to estimate the effects of robotization on labor markets. The workhorse of this literature is the data collected by the International Federation of Robots (IFR), which collects the number of robots installed in countries, by industry and by application. [Graetz and Michaels \(2018\)](#) use this data to document across industries in 17 countries that robots increased productivity between 1993 and 2007. Using the same data, [Acemoglu and Restrepo \(2020\)](#) study the labor market effects across US commuting zones between 1990 and 2007. By relying on sectoral robot adoption in more technologically advanced countries, they construct a shift-share IV to study causal effects. They find large negative effects on employment and wages, predominantly in manufacturing sectors. Similar approaches have been undertaken

by [Chiacchio et al. \(2018\)](#) and [Dauth et al. \(2021\)](#), who particularly document heterogeneity across workers and firms. Despite the fact that many of these studies find strong negative effects, they may have limited relevance to contemporaneous robot adoption, as most of these studies focus on the (late) 90s and early 2000s. A set of related studies has found that robotization may have contributed to the decreasing labor share in national income ([Guimarães and Gil, 2022](#)), and could attract jobs by reshoring ([Faber, 2020](#)). Using a survey of firms from Spain, [Koch et al. \(2021\)](#) find that larger and more productive firms adopt robots. Importantly, they document that job losses materialize in firms that do not adopt robots. This is consistent with [Hirvonen et al. \(2022\)](#), who find that within firms, adopting automation technologies does not preclude negative effects on labor market entrants and on firms not adopting robots. [Pavez, Luis R. Díaz and Martínez-Zarzoso, Inmaculada \(2023\)](#) employ a panel data of 16 economic sectors in 10 emerging countries from 2008 to 2014 to study the impact of foreign robot son labor market outcomes. They find that robot adoption has negatively impacted employment in sectors highly-exposed to robot adoption.

A key characteristic of whether industries expand employment depends on their exposure to international trade ([Aghion et al., 2020](#)). Firms can increase competitiveness by adopting robots, enabling the capture of larger shares of the world market. Moreover by performing a careful match of robot applications (as categorized by IFR) and occupations, [Caselli et al. \(2021\)](#) document positive employment effects on robot operators, but heterogeneous effects on other workers in Italy between 2011 and 2018. Specific to the South Korean context, [Kim \(2024\)](#) find that higher local concentration of industries suitable for robot adoption leads to a decrease in online job vacancies related to the manufacturing sector and routine occupations between 2010 and 2019.

We contribute to the literature on the labor market effects of robots, by studying the effects of robot adoption using a low-attrition longitudinal data representative of the South Korean labor force. The South Korean context is an important contribution to the literature that mostly focuses on automation and robot adoption either in Europe or in the United States. Unlike Europe and the United States, South Korea is characterized by very low inward migration flows coupled with an aging population, which explain their vital need for robots as means to compensate for the shortage in labor. The South Korean characteristics make it an ideal setting to study the effects of robot adoption on labor market outcomes and life satisfaction without the existence of any major confounders (notably having a large number of immigrants).

The second literature we contribute to is that on the relation between workplace and life satisfaction. First of all, employment, wages and job quality explain a large part of the variation in life satisfaction (Grün et al., 2010). Ochsen and Welsch (2012) show that labor market institutions with a positive effect on job security increase life satisfaction. Along similar lines, reduced job security by business cycle fluctuations reduce life satisfaction and impacts several mental health indicators (Avdic et al., 2020), even in the absence of actual effects of unemployment. Rose and Stavrova (2019) show that low levels of life satisfaction are correlated to lower re-employment probabilities, suggesting that there may be self-reinforcing effect. Furthermore, once in unemployment, the worse re-employment probabilities than before exacerbate the negative effects on life satisfaction (Green, 2011). Giuntella et al. (2024), using German data that spans 20 years in an event study and a difference-in-differences framework, find that workers exposed to artificial intelligence are less likely to be satisfied with their lives and jobs while they showed major concerns about their job security.

We contribute to this literature by showing that fear of job loss due to an important wave of automation may affect workers at risk of being affected by automation, directly or indirectly. Not only do we show this to be the case for workers directly exposed to robots through their current occupation, but also for workers likely to be substituted with those in exposed occupations. A related literature considers the dynamics of within-household life satisfaction: Powdthavee (2009) finds that there are strong spillover effects between partners. Therefore, we not only assess the effect on affected workers themselves, but also on the life satisfaction of their partners.

In this paper, we assess whether government’s policies achieved their ultimate objectives: improving well-being. We examine whether the life satisfaction of workers and their family members improved after robot adoption. South Korea poses a relevant setting: robot adoption was strongly encouraged by the central government, leading to an unprecedented adoption of industrial robots.

1.1.2 Institutional Background

As mentioned previously, the rapid automation in South Korea has been spurred by the national government. To thoroughly comprehend the political implementation by the state and its consequences on the labor market outcomes and workers’ life satisfaction, it is important to understand the impetus of the state’s involvement. Therefore, we introduce the

institutional background of automation in South Korea in this chapter.

After its history of colonization and Korean War (1950-1953), South Korea was not only suffering from drastic poverty but also lagged behind in terms of industrialization compared to developed countries. To avoid further recession, the government conducted an unprecedented process for improving its industrialization. According to Alice (1992), the process was “with subsidies to distort relative prices in order to stimulate economic activity.” Considering the high economic dependency of South Korea on the United States after World War II, the government’s strategy is more comprehensible. Between 1953 and 1961, the financial aid from the United States consisted of 70 percent of total imports and 75 percent of total fixed capital formation (Haggard et al., 1991). After the military coup led by Park, import-substituting economic strategy was fiercely executed. Under the new regime, the export-promotion program in the form of heavily subsidized credit and various institutional support was pronounced as a massive support for industrialization especially for the manufacturing sector. Taking the strong economic growth between the early 1960s and the mid-1990s into account, we can confirm that the strategy indeed worked to improve the economic conditions in South Korea. Furthermore, the export-oriented economy has established the base for the government and firms to rely on the efficiency of the manufacturing sector in order to keep up the growth rate and international competitiveness.

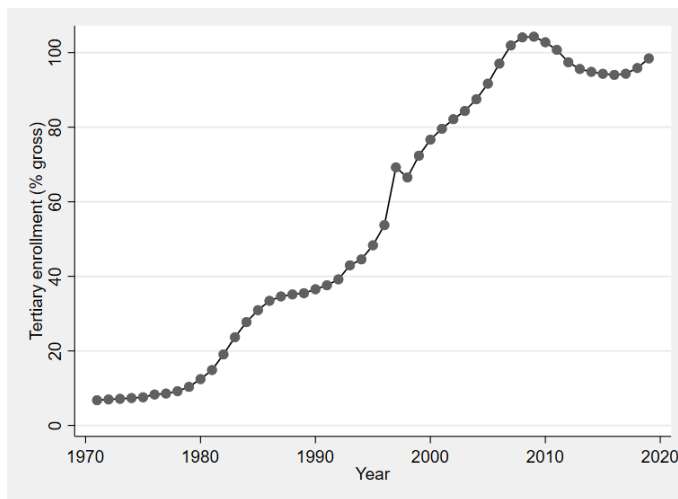


Figure 1.1: School enrollment at tertiary level, percentage of the population (World Bank 2021)

As Figure 1.1 illustrates, the population entering into tertiary education has been expanding since the mid 1980s; since higher education allows workers to have more bargaining power, it has lead to an increase in labor costs in South Korea by approximately 50% between 2000

and 2015 ([Jin, 2015](#)).

After the Asian financial crisis, the government used several methodical policies aimed at promoting robot adoption in the manufacturing sector even further.

From 2000 onwards, the government gradually started to allocate investment directly into the robot industry to foster the production of domestic robots in 2005, the state launched the very first official support for the intelligent and industrial robot industry in order to create a systematic base for the industry.¹⁶ After the introduction of these policies in 2005, approximately 486 million USD in government funds had flown into the robot related industry by 2007 ([Yoon, 2016](#)).

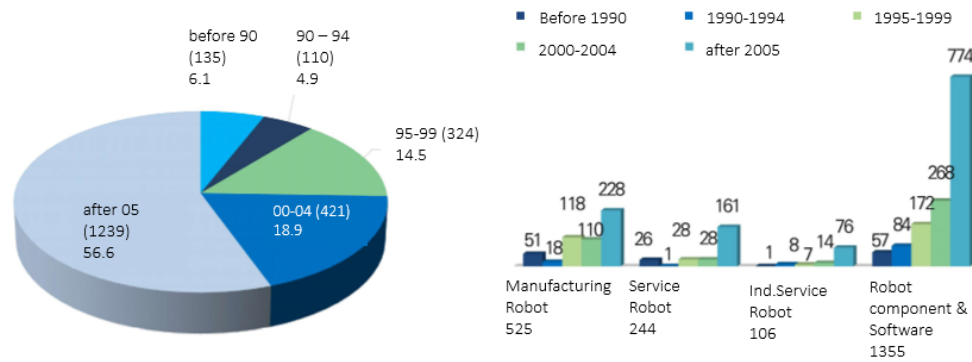


Figure 1.2: Number of newly added robot producers per year and per sector (Korea Robot Industry Promotion Institute 2011)

Between 2005 and 2019, 15.4% of all robotics patents were registered in South Korea, at the same time, South Korea contained less than 1% of the world's population.¹⁷ Prior to 2005, the share of robotics patents in South Korea was considerably smaller ([Keisner et al., 2015](#)).

Figure 1.2 demonstrates the number of robot related firms that were established after the 2005 policy. Approximately, 60 percent of robot enterprises were added after 2005. When we decompose the aggregated number of firms by sectors within the robot industry, we can confirm the conspicuous effect of the 2005 program. Furthermore, the effect of the state's

¹⁶For more information on this law, see [Korea National Science and Technology Information Service \(2025\)](#).

¹⁷For an overview of robotics patents until 2019, see [Center for Security and Emerging Technology \(CSET\) \(2023\)](#).

intervention in 2005 was visible in terms of robotics patents. South Korea occupied the third highest share of global robotics patents with 15.4% followed by the United States.¹⁸ After the emergency in the early 2000s, South Korea's robotics patents registered in the PATSTAT database accelerated and reached its peak in 2009.¹⁹

In 2008, the foundation for the Development and Distribution of Intelligent Robots Act was established in order to facilitate the development of intelligent robots and it finally led to the execution of the act from 2009.

The main difference between 2005 and 2009's policies is as follows. Previously, the government only supported the robot related industry; the *Development and Distribution of Intelligent Robots Act* was a package not only to promote the robot industry but also to encourage enterprises to adopt more automation in their production processes. Based on this act, a *Basic Robot Industry Plan* was and still is formulated every five years to stimulate the industrial robots market; for instance, according to article 24, firms investing in industry automation will obtain a tax deduction. As a result, from 2009 to 2018, the South Korean government invested over 17 billion US dollars to support the research and development of technologies related to the robotics industry.

To illustrate the massive adoption of robots in South Korea since 2009, the total number of industrial robots installed over time is shown in Figure 1.3. Specifically, Figure 1.3 shows the stock of robots as reported by IFR, divided by the total labor force, for a selected set of industrialized countries. Until 2009, South Korea's relative implementation of robots was comparable to Italy. In the period between 2005 and 2009, South Korea experienced the strongest increase in the number of robots per worker of all countries shown. After 2009, the number of robot installations in South Korea increased drastically. By 2019, the robot stock per worker exceeded 10, which trumps the countries with the next-highest stock of robots per worker (Germany and Japan) by more than a factor of two. In terms of net installations per worker (the slope in Figure 1.3), Korea exceeds all other countries shown. In the years between 2009 and 2019, South Korea installed on average 0.8 robots per 1,000 workers per year. In Germany, only 0.15 robots per 1,000 workers per years were installed.

¹⁸More detailed information can be found in [Asian Robotics Review \(2025\)](#).

¹⁹For more details, see [World Intellectual Property Organization \(WIPO\) \(2025\)](#), page 14.

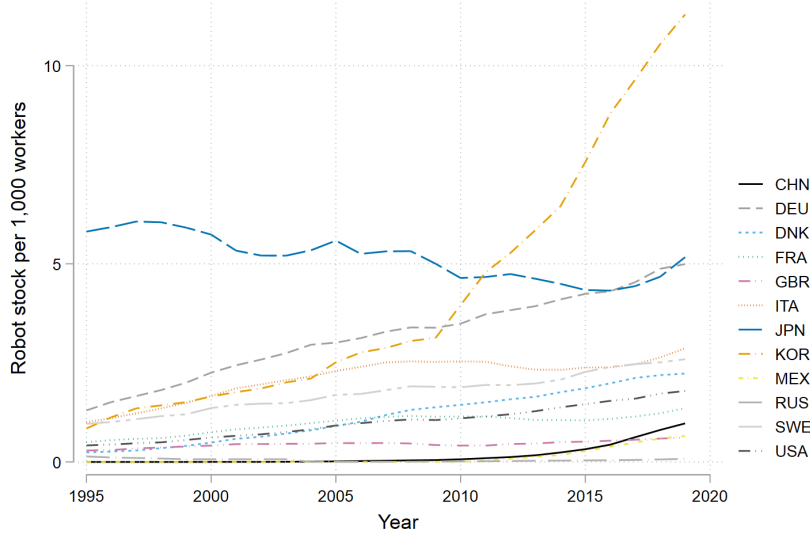


Figure 1.3: IFR (2020) and World Bank (2022)

1.2 Data Variable Description and Summary Statistics

1.2.1 KLIPS: a household-based labor force survey

Our main data provided by the Korean Labor Income and Panel Study (KLIPS). Conducted once a year, KLIPS is the only longitudinal income survey existing in South Korea. KLIPS collects information on consumption behavior, labor market participation, education, and social activities from about 5,000 households, including every member of these households. The data is available up to and including 2020. Our study observes the data from 1998 to 2020 based on the assumption that South Korea had a massive wave of automation during this period. We use an individual-level panel which is released for the annual conference held by KLIPS. The data contains information on gender; age; educational attainment; 3-digit occupation codes; 3-digit industrial affiliation codes; and labor market outcomes, such as employment, wages and working hours. The data contains the household's region of residence at an intermediate level of 225 divisions (these divisions comprise 3 types of units: Si (cities), Gun (counties) and Gu (districts)), which are nested in 17 larger geographic divisions (these divisions comprise 6 metropolitan cities, 1 special city, 1 special self-governing city, and 9 provinces). The comprehensive individual level information from KLIPS allows us to thoroughly understand the overall changes in average employment rate and the wage changes depending on workers' demographic information, occupations and working industry.

Furthermore, KLIPS comprises detailed questions on workers’ life quality, including their self-reported life satisfaction. Other information about the workers in the KLIPS include: Exposed rate of job training, job-status transition from permanent (regular) to temporary (part-time), preferred job training, reasons for leaving, smoking and drinking frequency, difficulties in obtaining a new job, etc. For the current study, we focus on the life satisfaction related questionnaire as a proxy of their life quality. KLIPS data provides us with the household identifier as well as each individual’s relationship with the household head. This allows us to study the effects of robotization through the labor market position of individuals and their household members.

KLIPS: Descriptive Statistics

The descriptive statistics in table 1.1 show the mean of the main variables of interest, their standard deviation in parentheses as well as the number of observations for the different samples used. Column (1) shows the main statistics for the overall sample of exposure used in the study while columns (2) and (3) represent the samples above and below the median exposure respectively. The median exposure of robotization is equal to 0.101. The above median exposure sample has a female mean of 0.38 which is much lower than that of the below median exposure of 0.68. The average age ranges between 40 and 45 years old in the three samples. The total number of observations for the above median exposure sample is 140,774 and the total number of observations for the below median exposure sample is 104,888. For the purpose of this study, the overall sample of exposure will be used in the main regression.

1.2.2 IFR: robot installations by industry and application

The International Federation of Robots (IFR) collects information on industrial robot adoption across countries, sectors, and applications. To harmonize the definition of a single robot across these dimensions, the following definition of a robot from IFR is used: a programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning. We use IFR data on the number of robots in use at the industry level in South Korea between 2004 and 2019. We merge the industry codes from IFR to the industry coding available throughout KLIPS (KSIC-8).

Local labor market approach

Table 1.1: Descriptives Statistics of the KLIPS Data

	(1) All	(2) Above Med. Exp.	(3) Below Med. Exp.
Life Satisfaction	0.32 (0.615)	0.28 (0.610)	0.37 (0.618)
Employed	0.66 (0.474)	0.68 (0.467)	0.63 (0.482)
Employed Manuf.	0.25 (0.432)	0.27 (0.446)	0.21 (0.408)
Log Monthly Wage	7.56 (0.668)	7.52 (0.620)	7.62 (0.730)
Log Hours	3.79 (0.380)	3.82 (0.369)	3.75 (0.391)
Work Satisfaction	3.33 (0.773)	3.27 (0.777)	3.42 (0.759)
Part-time	0.15 (0.356)	0.15 (0.361)	0.14 (0.348)
Log Hourly Wage	2.39 (0.677)	2.32 (0.632)	2.49 (0.728)
Education	3.79 (1.506)	3.40 (1.245)	4.31 (1.661)
Female	0.51 (0.500)	0.38 (0.486)	0.68 (0.465)
Age	42.53 (12.31)	40.44 (12.63)	45.35 (11.26)
5 years age bins	42.54 (12.43)	40.43 (12.75)	45.37 (11.39)
Observations	245 662	140 774	104 888

Using the distribution of industries across districts in 2004, as in [Acemoglu and Restrepo \(2020\)](#), we can proportionally distribute the adopted robots across the South Korean regions to generate a local exposure to robots. This regional-level robot exposure can be used to study the local labor market effects of robotization. One concern is that robot expansion within South Korea may be endogenous to local economic conditions. Therefore, our regional robot exposure is instrumented following [Acemoglu and Restrepo \(2020\)](#) using a shift-share instrument. In such a setting, the *shift* is robot adoption in more technologically advanced countries. Variation in temporal and regional robot exposure is driven by robot expansions in other countries, reflecting technological progress rather than local economic conditions in these countries.

1.2.3 Exposure Measure

Our exposure measure is a modification of the methodology of [Anelli \(2019\)](#). In this study, the authors constructed the exposure for 14 Western European countries from 1993 to 2016. Their measure enabled them to investigate the effect of robotization at an individual level. The measure is based on two main components: (i) an individual’s occupation is predicted using a multinomial logit (MNL) model (based on the following characteristics: age, gender, educational attainment and the district someone lives in) and (ii) an occupation’s exposure to robotization. Then, we can calculate an individual’s robot exposure in the following way by summing over all occupations:

$$Exposure_i = \sum_{k=1}^K \underbrace{Pr(o_i = k | age, gender, edu, region)}_{\text{Obtained by multinomial logit}} \times \theta_k \quad (1.1)$$

Here, θ_k is an occupation-level exposure to robots. [Anelli \(2019\)](#) use two distinct measures of robotization: the risk of computerization from [Frey and Osborne \(2017\)](#) and perceived threat (to workers) of automation from the International Social Survey Program in 1997. In our application, we use a different measure as we are interested in those most likely to be disadvantaged by robotization: low-skilled workers that are likely to work in occupations performing tasks that can be replaced by robots. Therefore, we use the simple occupation-level measure of [Graetz and Michaels \(2018\)](#). An occupation is coded as replaceable if the job title in the 1990 scheme contains a word that coincides with any of the applications mentioned in the IFR data. For example, welders are coded as replaceable because one

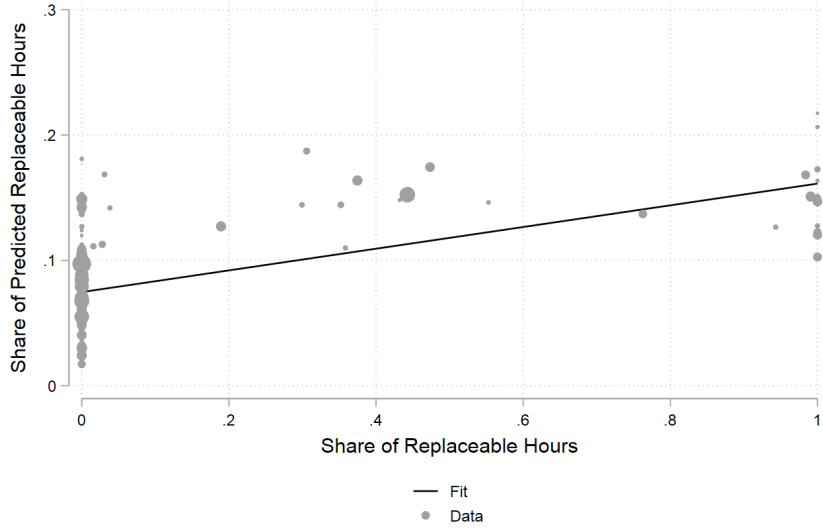


Figure 1.4: The Share of Replaceable Hours and the Predicted Share

of the applications of industrial robots is welding. We match the occupations in the 1990 US Census to the KSCO-5 classification. As this merging is not one-to-one, some KSCO-5 occupations also have fractional replaceability. We restrict our sample to all individuals present in the data prior to 2005. For this sample, we perform the multinomial logit and calculate $Exposure_i$ based on an individual's characteristics in the first available year. These results are robust to using earlier years, at the loss of precision.

Figure 1.4 shows that θ_k and the average of $Exposure_i$ by occupation are positively correlated, but show some variation. The size of each data point indicates the number of workers in that occupation in 2000. Notably, although some occupations are not replaceable (they lie on the y-axis), there is a strong residual variation in the predicted replaceability of the workers in some of these occupations. From Table 1.2, one can see that more exposed workers are likely to be low-skilled, male, young, and less likely to be located in the Seoul metropolitan region.

This exposure measures how exposed one is to occupations that can be replaced by robots. Therefore, this does not only measure direct effect through one's occupation, but also secondary labor market effects through the labor market effects of other household members as well as regional transformation.

Importantly, individuals' exposure is correlated with the exposure of other household members, through assortative mating and cohabitation. Therefore, we do not only consider one's

Table 1.2: Average Characteristics By Quartiles of Robot Exposure

	(1)	(2)	(3)	(4)
	Quartiles of Exposure _i			
	First	Second	Third	Fourth
Age	54.43	48.17	44.25	38.12
Share Female	0.81	0.51	0.59	0.18
Share High-skilled	0.61	0.44	0.06	0.00
Share in Seoul	0.21	0.27	0.22	0.12
Observations	81459	81123	81256	81274

own exposure in section 1.3, but also the exposure of other household members in 1.4.

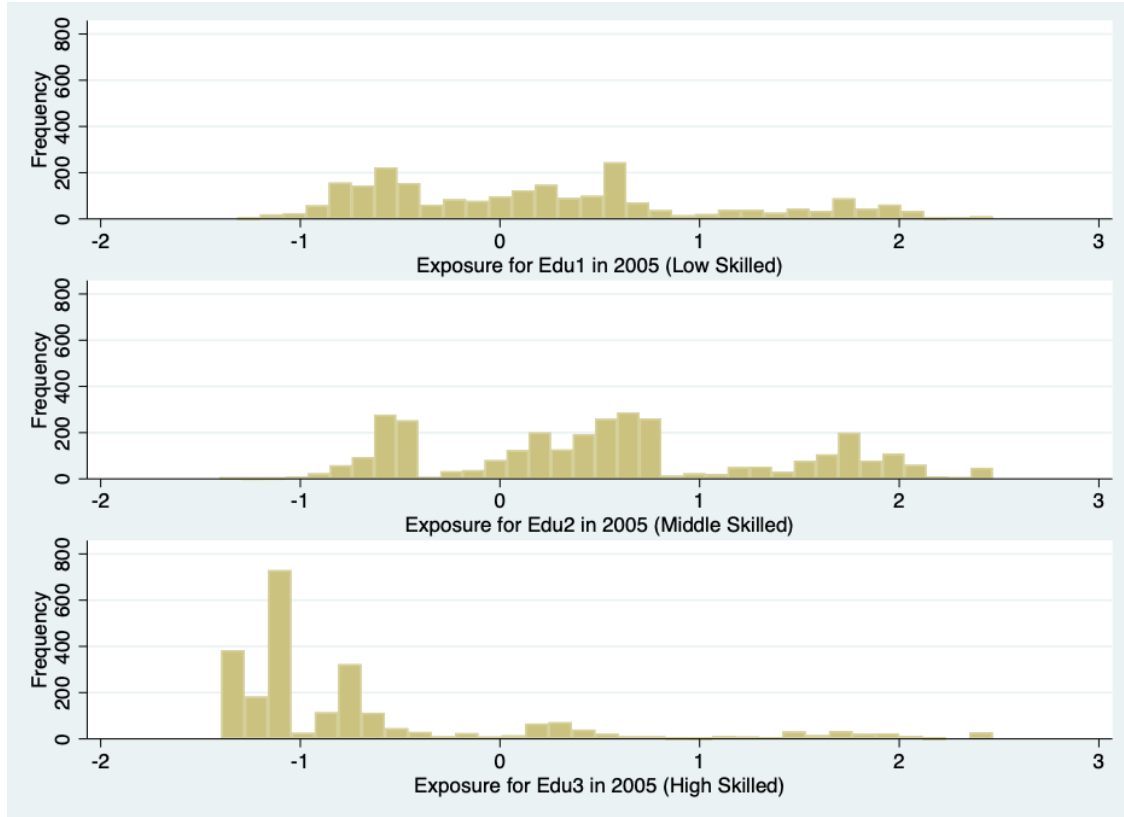


Figure 1.5: Histogram of the exposure variable by the three educational groups in 2005

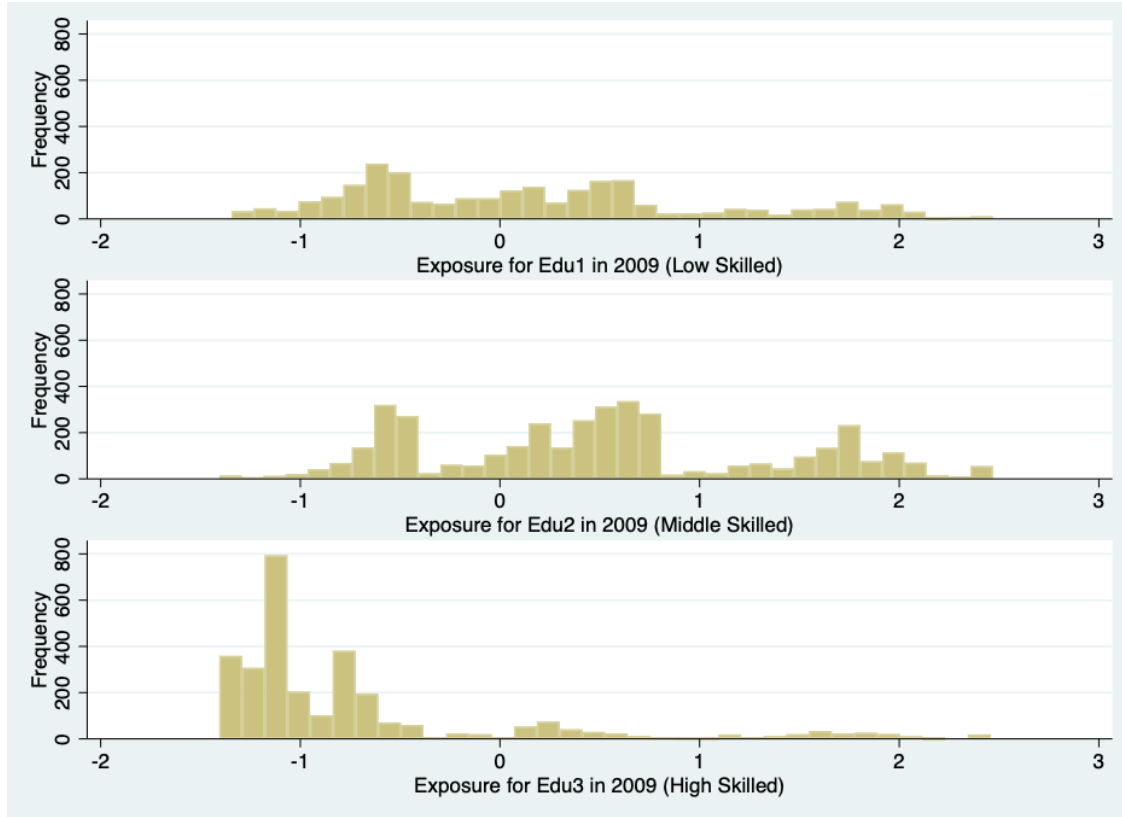


Figure 1.6: Histogram of the exposure variable by the three educational groups in 2009

Figure 1.5 and 1.6 show the distribution of the exposure to robotization measure in the years 2005 and 2009 respectively. According to the figures, there exists a lot of variation in the exposure measures to robots within the three education group.²⁰ The majority of the variation is coming from both the low education and the vocational education group. However, the high education group is the least varying of all the three. Exploring these within educational group exposure variation to robots is essential in further disentangling the results as well as the possible channels conducive to the main results.

²⁰We divide these three education (skill) group based on their final education level. High education group includes the workers who have certificates higher than college or university; vocational education group consists of the workers who have graduated from the vocational school after their high school education. Low education group contains the information of workers who received education lower than high school.

1.3 Individual Level

1.3.1 Empirical Specification: An Event Study Approach

As individuals with different levels of exposure to robotization may be affected differentially by shocks in productivity or export demand, it is important to assess whether the parallel trends assumption of the untreated potential outcomes. The event study design serves two purposes: first, it serves as a test for the parallel trend assumption prior to the widespread adoption of robotization, second, it sheds light on the dynamic path of outcomes.

$$Y_{idt} = \sum_k \beta_k 1(t = k) \times Exposure_i + \gamma X'_{it} + \phi_t + \theta_i + \epsilon_{idt} \quad (1.2)$$

Where Y_{idt} is the life satisfaction of individual i at time t in residential district d .²¹ $Exposure_i$ is the continuous measure of individual exposure level introduced in Equation 1.2. $\gamma X'_{it}$ captures individual-level time varying controls: such as education levels, 5 years age bins interacted with a female dummy. ϕ_t and θ_i are year and individual fixed effects respectively. These individual fixed effects capture any differences that may arise due to sample composition, which enables us to estimate within-individual effects. Finally, ϵ_{idt} is the error term. We cluster standard errors at the district and individual level.

β_k measures the relationship between robot exposure in year k relative to the base year 2004, the year before the robotization policies commenced. By utilizing a panel of individuals, we are able to account for individual fixed effects and year fixed effects to account for nationwide shocks. This methodology allows us to identify the differential impact of increased robot exposure over time on changes in life satisfaction within the same individuals.

There are several potential threats to identifying the β_k 's as the time-dependent causal effect of robotization. First, as we use demographic factors to predict individuals' occupations, shocks to these demographic factors unrelated to Korea's robot policy and exposure to robotization may confound the causal effect. To alleviate this concern, we add interactions between the demographic information and year fixed effects in robustness tests. Second, as the exposure of individuals within households may be positively correlated, we may capture the joint effect of exposure of both (or more) individuals in the household. By reverting to

²¹For the sake of simplicity, we construct a three-tier categorical variable to denote levels of life satisfaction: 1 for satisfied, 0 for neutral, and -1 for not satisfied.

a household-level regression, we can separately identify the effect of one's own exposure and spousal exposure.

1.3.2 Results

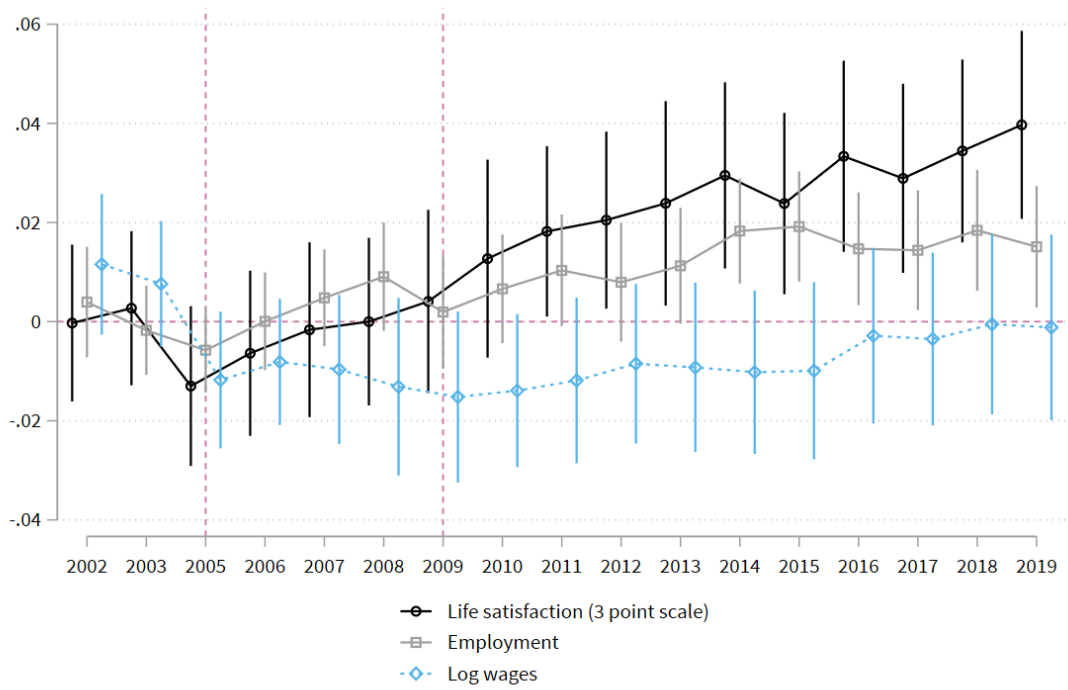
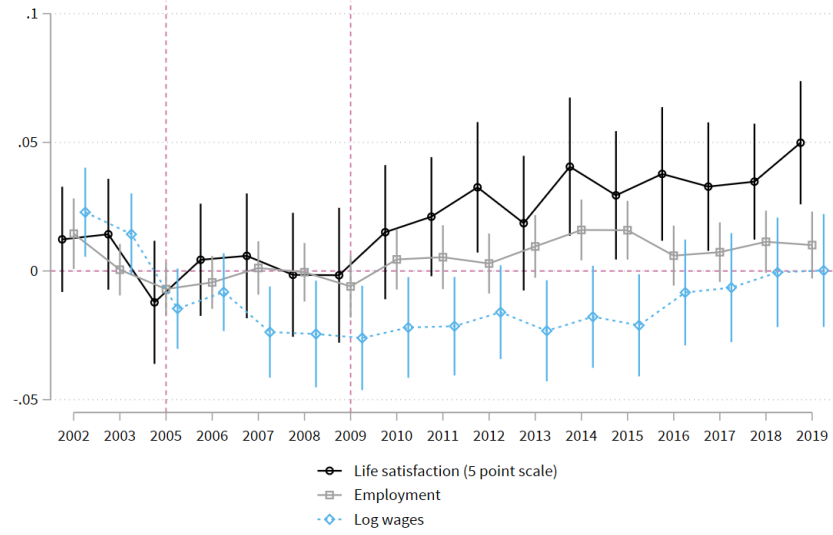
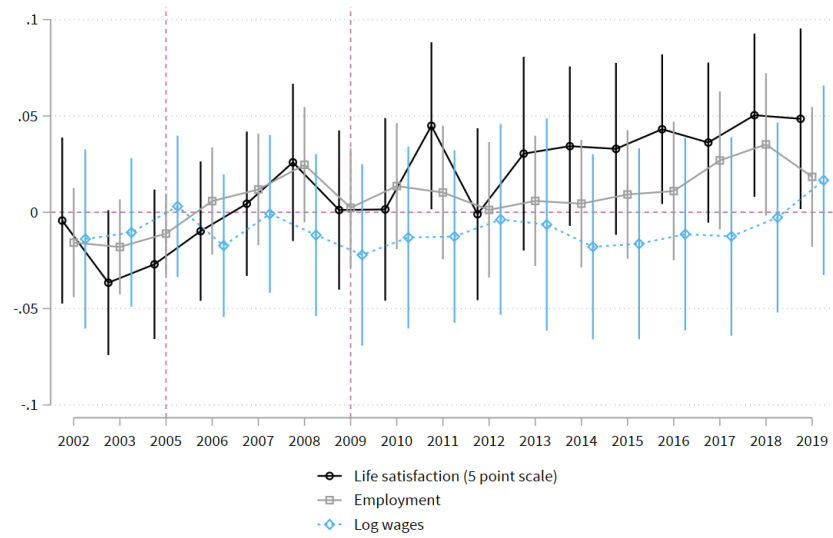


Figure 1.7: Event Study diagram of the effect of robotization exposure over time



(a) Male



(b) Female

Figure 1.8: Event Study diagram of the effect of robotization on life satisfaction by gender

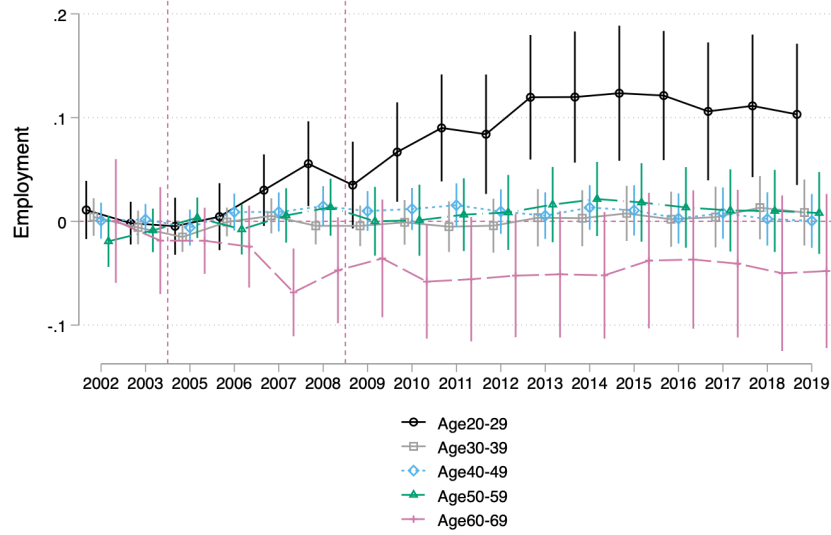


Figure 1.9: Event Study diagram of the effect of robotization exposure over time

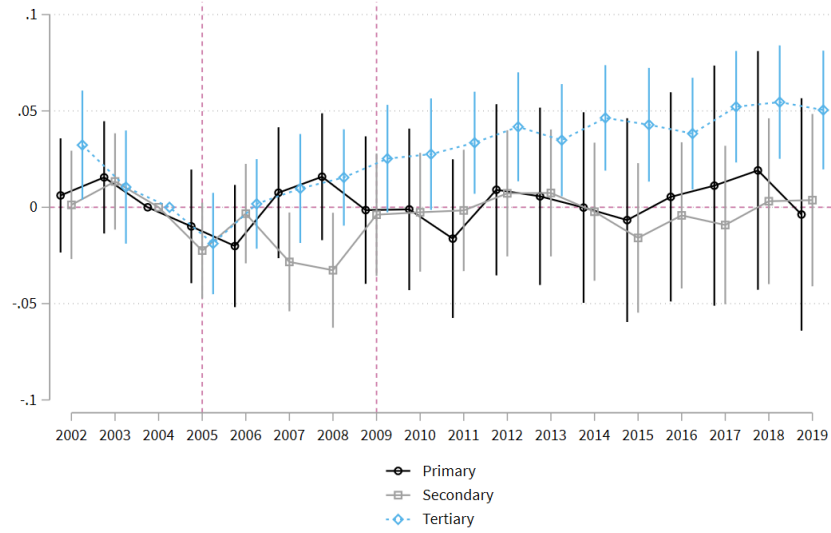


Figure 1.10: Event Study diagram of the effect of robotization on life satisfaction by the three main education levels

Figure 1.7 graphically shows the estimated β_k 's of equation 1.2. We find that after the introduction of the 2005 reform, life satisfaction (black) gradually increased among more exposed individuals. At the same time, there is no effect on wages, but slightly positive effects on employment probabilities up to 2 percentage points. Figure 1.11 shows that this is driven primarily by decreases in level 2 at the expense of level 4 of life satisfaction. At the

same time, job satisfaction increased considerably (Figure 1.12) after 2013.

This implies that robotization generally has a favorable impact on life satisfaction, yet a comprehensive analysis is essential due to the observed varying effects of robotization, contingent upon the initial levels of life satisfaction experienced. Additionally, it appears that the predominant portion of the positive influence of robotization can be attributed to its impact on employment opportunities rather than the wage enhancements resulting from automation in the workplace.

Figure 1.8 presents the analyzes from the event study on life satisfaction, employment and wage levels differentiated by gender. Initially, during the era of the first robot adoption initiative, male life satisfaction reflected the trend observed in wage reductions; a notable decline in log wages was observed immediately following the government’s inaugural robot adoption incentive. However, after the implementation of the second robot policy, male life satisfaction began to align more closely with employment trends, which were on an upward trajectory. It is also important to note that after experiencing a decline post-2005, wages did not exhibit any signs of increase.

For females, our analysis does not reveal statistically significant reductions either in wages or in employment. In terms of life satisfaction, an upward trend is observed following the second wave of automation, although this increase is not statistically significant. When these findings are juxtaposed with outcomes for males, it becomes evident that exposure to robot has a more pronounced impact on males than on females. However, for both genders, life satisfaction appears to increase a few years after the second wave of robotization, suggesting an adjustment period to a new working environment characterized by greater reliance on robots. Additionally, it is observed that males, who have greater exposure to robotization, begin to experience a statistically significant improvement in life satisfaction after this adjustment period, in contrast to their female counterparts.

Our investigation extends to an analysis of heterogeneity in age, aiming to discern variations in life satisfaction following the implementation of both the initial and subsequent robot promotion policies. Figure 1.9 elucidates our main event study segmented by age cohort. Before the initial wave of robotization, the division of our sample according to birth year does not yield statistically significant differences. However, after the first wave of automation, we can see that the oldest cohort (Age 60 - 69) has the highest negative effect, compared to the younger cohorts, particularly after the 2005 wave of robot adoption. This supports previous findings that older workers nearing retirement often face greater challenges in acquiring skills

that complement robotization (Fasbender and Gerpott, 2023; Asia et al., 2023). From around 2006 onward, the life satisfaction of the 60-69 age group seems to drop further, reaching the most negative levels between 2011 and 2015. The negative trend in life satisfaction among this older cohort suggests that the impact of robot adoption may have disproportionately affected workers nearing retirement, potentially due to the challenges they face in adaption new technologies, as seen in other studies on aging and automation (Asia et al., 2023).

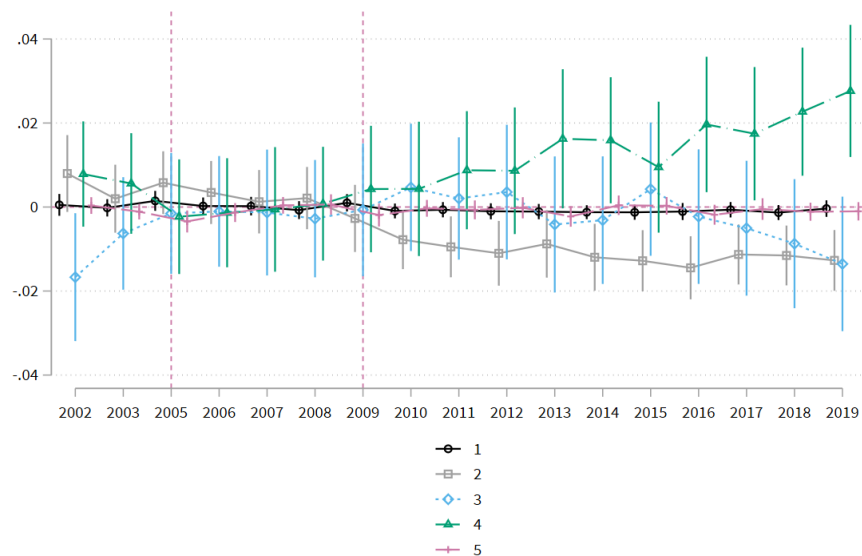


Figure 1.11: Levels of life satisfaction



Figure 1.12: Job satisfaction

1.3.3 Mechanisms

The econometric approach used for our mechanisms section consists of a difference-in-differences framework with multiple time periods, capturing the different stages of robot adoption in South Korea:

$$Y_{idt} = (\alpha + \delta Exposure_i) + \kappa Exposure_i \times 2005 - 2009 + \lambda Exposure_i \times Post_{2009} + \omega X'_{it} + \epsilon_{idt} \quad (1.3)$$

Where Y_{idt} is the life satisfaction of the individual i at time t in the residential district d . $Post_{2009}$ is a dummy equal to 1 if post 2009 is the year of the major robotization shock. The dummy $2005 - 2009$ equals 1 for the initial years 2005 and 2009, $Exposure_i$ is a continuous treatment variable representing the individual exposure level standardized. $Exposure_i \times 2005 - 2009$ captures the differential effect of high exposure between 2005 and 2009. $Exposure_i \times Post_{2009}$ is a second interaction term between the continuous treatment variable and the post 2009 dummy. In our baseline specification, we include year and individual fixed effects, which nest the first four terms of equation 1.3. By including individual fixed effects, we partial out all variation due to time-independent characteristics of individuals. $\omega X'_{it}$ captures time-varying individuals' characteristics such as education and gender interacted with 5 year age bins from 20 to 65 years old. This allows us to control for changes in outcomes over the life course for different demographic groups. Finally, ϵ_{idt} is the error term. The remaining identifying variation originates from a within-individual variation in exposure to robotization between 2005 and 2009 and beyond 2009. As errors may be correlated within regions, we cluster standard errors at the district level.

Given the absence of significant pre-trend indicators in the two years preceding the 2005 wave of robotization, particularly among the vocational and lower education groups, we proceeded with our study. Table 1.3 shows the average effects over the two time periods of interest. The most pronounced adverse impact of automation is observed among the lower-educated group, with a decrease in life satisfaction by 0.028 standard deviations with a high probability of exposure to robust at work. The vocational education group also exhibited a decline in satisfaction, though to a lesser extent than that observed in the lower-educated cohort. No discernible effect was identified within the highly educated group.

Additional examination of Table 1.3 suggests that the diminished life satisfaction before 2009

Table 1.3: Potential channels by Three education levels (individual level)

	Lower Educ.								Vocational Educ.								Tertiary							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Empl.	Emp.	Empl.	Firm	Empl.	Log	Work	Part-time	Log	Empl.	Emp.	Log	Firm	Empl.	Log	Work	Part-time	Empl.	Emp.	Log	Firm	Empl.	Log	Work	Part-time
2005-2009	-0.008	-0.004	0.013	0.009	-0.016	0.018	0.040**	0.009*	0.007	0.002	0.009	0.011***	-0.007	0.014**	-0.009	0.013	0.028***	0.027**	0.034***	-0.002	-0.003	0.016	-0.007	0.037***
Exposure × Post 2009	-0.006	(0.006)	(0.013)	(0.006)	(0.011)	(0.024)	(0.018)	(0.015)	(0.006)	(0.007)	(0.011)	(0.041)	(0.007)	(0.018)	(0.010)	(0.013)	(0.006)	(0.011)	(0.010)	(0.002)	(0.009)	(0.021)	(0.008)	(0.011)
Exposure × Post 2009	-0.013	-0.010	0.026	0.005	-0.009	0.036	0.028	0.027	0.002	0.003	0.011**	0.041**	-0.003	0.032**	0.001	0.012**	0.023**	0.019	0.050***	-0.001	-0.001	0.006	-0.018*	0.052**
Observations	4608	4608	2144	4608	25763	2118	1405	2187	7092	7092	2408	7092	4636	3718	2700	4240	5344	5328	3960	5328	4635	3212	3152	3840
Year DV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.85	0.614	0.673	0.786	0.421	0.308	0.626	0.580	0.377	0.604	0.696	0.816	0.428	0.312	0.588	0.638	0.84	0.628	0.732	0.848	0.490	0.333	0.771	0.692
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district and individual level.

among middle-educated workers could be linked to a shift from full-time to part-time employment. For those with secondary education, the increased frequency of changing employers post-robot adoption appears to be the primary factor contributing to their reduced life satisfaction. In contrast, the highly educated group experienced improvements in employment rates and wages.

The period from 2005 to 2009 marked a significant displacement of low and vocationally educated workers, driven by an increase in part-time work. Conversely, post-2009, vocational and highly educated individuals started to benefit from robotization through wage increments, a privilege not extended to their low-educated workers. This wage disparity underscored the varying capacities of these groups to adapt to the growing presence of robots. Furthermore, the analysis reveals that the negative implications of robot exposure are exacerbated for households with low or vocationally educated primary earners.

1.4 Household Level

In this chapter, we turn our focus to the effect of household heads' exposure to robots on their spouses' life satisfaction. Our main motivation of the current section is twofold. First, as we briefly mentioned above, manufacturing sector is the sector where robotization happens the most and is male dominated. As 90% of household heads in KLIPS are defined as males, we believe that if a household head has a high robot exposure, then this likely has certain effects on their spouses' life satisfaction. Second, according to the prior literature, there is a spillover effect in life satisfaction between household heads and their spouses (Powdthavee, 2009). Indeed, we also confirm it in our OLS regression 1.4. Based on this spillover effect, we posit that an exposure of household heads to robots at work could have a causal effect on the life satisfaction of their spouses. Drawing on our data construction, our conjecture is pertinent as we only sort couples who are not just married but also share their physical residential places. In other words, they interact with each other inevitably during our observation period; we believe this high intimacy will bring a high correlation between household heads' and spouses' life satisfaction. Table 1.4 validates our assumption.

Table 1.4: Spillover check: correlation between spouses' life satisfaction and husbands' life satisfaction

	(1)	(2)
Household head satisf.	0.617*** (0.006)	0.431*** (0.007)
Observations	59916.000	59540.000
Mean DV	0.31	0.31
sd DV	0.63	0.62
R ²	0.38	0.51
Controls	Yes	Yes
Year FE	No	Yes
HH.ID FE	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level.

1.4.1 Empirical Specification

We examine the effect of automation within the household level. Our empirical specification for the household level follows the multiple time periods difference-in-differences framework as well.

$$Y_{s,d,t} = \alpha + \beta Exposure_h + \sigma Exposure_h \times 2005 - 2009 + \lambda Exposure_h \times Post_{2009} + FE_s + \omega X'_{st} + \epsilon_{s,d,t} \quad (1.4)$$

$Y_{s,d,t}$ indicates life satisfaction of the spouse s at time t in district d . The time dummies are defined the same as with the individual specification. We have time dummies which are equal to 1 if the period is defined between 2005 and 2009; and 1 if it is any year beyond 2009. For the current specification, we employ the continuous treatment variable of household head's exposure to robotization to investigate the indirect effect within the household. Our variables of interest are the interaction terms of our exposure measure with time dummies, 2005 – 2009 and $Post_{2009}$. We control the education level of the spouse, the spouse's exposure to robotization and its interaction term with our time dummies. By including our control variables, we attempt to address a number of endogeneity issues in our model. First, the changes the labor supply of females which might affect our results. During our observation periods, the Korean government executed two significant education reforms which affected the changes in workers' average skill levels (Lee, 2020).²² As a consequence

²²The 6th (applied for the elementary and high school students who were registered in 1995-1998 school system) and 7th (applied for all primary and secondary students registered in 2000-2002 school system) reforms are conducted; one of the main consequences of those reforms was an increase in the female' entrance rate to tertiary education.

of those reforms, the female participation rate in the labor market increased; therefore, we expect changes in their life satisfaction. Furthermore, in order to attribute the results of our empirical specifications solely to robot exposure, we include a measure of spouses' exposure to robotization interacted with our time dummies. To allow our framework to capture the outcome changes of within-household variation in household head's exposure to robotization, we add the household identifier along with year fixed effects. Lastly, our error term is clustered at the district and household levels. To avoid confusion, the term household head is equivalent to husband; spouse indicates the household head (husband)'s wife.²³

1.4.2 Results

Our analysis starts with the spouses' overall life satisfaction changes. Table 1.5 demonstrates the life satisfaction changes when we regress it on their household heads' exposure to robotization. As previously explained, the exposure measure interacts with our time dummy variables. According to column 5, we confirm the negative effect of our variable of interest. The coefficient exhibits a 0.022 decrease in life satisfaction of spouses with a 1 standard deviation increase in their household heads' exposure to robotization; it is equivalent to the impact of decrease in log wage of 1 that leads to 0.135 increase in spouses' life satisfaction²⁴. This indicates that in the years between 2005 and 2009, the spouses became less satisfied than in the years before 2005 when their husbands had not yet been exposed to robotization. On the other hand, we don't confirm any compelling effect when we interact the exposure measure with Post 2009. The result is consistent regardless of the fixed effects and controls included.

²³In the KLIPS data, approximately 80% of household heads are defined as males. You can refer to the household descriptive statistics in the Appendix.

²⁴The OLS regression is added our Appendix

Table 1.5: The impact of householders' exposure to robotization on spouses' life satisfaction

	(1)	(2)	(3)	(4)	(5)
Exposure $\times$ 2005-2009	-0.025** (0.012)	-0.024** (0.012)	-0.021* (0.012)	-0.022* (0.012)	-0.022* (0.012)
Exposure $\times$ Post 2009	0.007 (0.012)	0.010 (0.012)	0.005 (0.013)	0.010 (0.011)	0.002 (0.013)
Observations	47811.000	47810.000	47576.000	47811.000	47575.000
Mean DV	0.25	0.25	0.26	0.25	0.26
sd DV	0.63	0.63	0.63	0.63	0.63
R ²	0.079	0.085	0.375	0.094	0.386
Controls	No	Yes	No	No	Yes
Year FE	No	No	No	Yes	Yes
HH.ID FE	No	No	Yes	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at the district and individual ID level. The exposure measure is standardized. Overall life satisfaction, the outcome of interest is a variable that has the following values: -1 indicating dissatisfaction, 0 indicating feeling neutral (neither satisfied nor dissatisfied) to 1 indicating feeling satisfied. The controls include education levels, and a female dummy interacted with 5 years age bins as well as spouses' exposure to robotization.

Table 1.6: The impact of household heads' exposure to robotization on life satisfaction of their spouses by three (household heads') education groups

	Lower Educ.		Vocational		High	
	(1)	(2)	(1)	(2)	(1)	(2)
Exposure $\times$ 2005-2009	-0.160*** (0.041)	-0.105*** (0.040)	-0.093*** (0.035)	-0.088** (0.037)	-0.090** (0.044)	-0.015 (0.043)
Exposure $\times$ Post 2009	-0.057 (0.044)	-0.011 (0.052)	-0.076* (0.042)	-0.070 (0.044)	-0.062 (0.050)	0.044 (0.051)
Observations	15754	15679	19788	19687	12266	12189
Mean DV	0.08	0.08	0.26	0.26	0.47	0.47
sd DV	0.62	0.62	0.62	0.62	0.59	0.59
R ²	0.093	0.357	0.066	0.348	0.054	0.361
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
HH.ID FE	No	Yes	No	Yes	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at the district and individual ID level. The exposure measure is standardized. Overall life satisfaction, the outcome of interest is a variable that has the following values: -1 indicating dissatisfaction, 0 indicating feeling neutral (neither satisfied nor dissatisfied) to 1 indicating feeling satisfied. The controls include education levels, and a female dummy interacted with 5 years age bins as well as spouses' exposure to robotization.

We also look at the spouses' life satisfaction changes in the three education level categories of their household heads as in the previous chapter. According to Table 1.6, we can confirm that the negative effect of automation at the household heads' working place on their spouses is mainly driven by the lower educated and vocational groups. In other words, as a spouse whose husband is highly educated is less affected by changes in her husband's exposure to robotization compared to a spouse whose husband works in low educated or vocational related occupations.

1.4.3 Mechanisms

To understand our main result, we explore the same potential mechanisms with the three education levels as in individual specification: low, vocational and high. Similar to the individual case, we expect that the indirect effect of exposure to robots will have a heterogeneous effect depending on the education level of the household heads. Starting with the 2005-2009 period, we confirm that none of the labor market related variables have significant coefficients to explain our main results refer to Table 1.7. Furthermore, the Post 2009 years do not exhibit any significant results either, except for a weak negative effect on manufacturing employment of the spouses. Considering that our main results demonstrate a negative effect of household heads' exposure to robotization on their spouses' life satisfaction, the coefficients of potential channels in 2005-2009 and Post 2009 cases are unexpected.

Therefore, it motivates us to investigate further channels to explain our findings in Section 1.5.

We attribute the negative effect of household heads' exposure to robots on the spouses' life satisfaction to the indirect effect of exposure to robots on within-household economic dynamics. To shed more light on this aspect, we regress the within-household total wages, wage gap and working hours gap of a married couple on the robot exposure of the household heads. The results are summarized in the Table 1.8. The first column demonstrates how the total income of the household will change when the household heads are more exposed to robotization. The strong negative sign of the 2005–2009 case underpins our assumption that the decrease in spouses' life satisfaction is driven by the negative effect of within household outcome changes. Interestingly, we do not have a significant coefficient for the wage and working hour gap between the household heads and spouses.²⁵ Contrariwise, we can see the household head's exposure attributes to the change in wage gap between the household head

²⁵For variable construction, we put household heads' observation before the spouses'.

Table 1.7: Potential channels driving the spouse's result by education level

	Lower Educ.								Upper Educ./ Vocational								Tertiary							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emp.	0.020	0.005	-0.015	-0.028	-0.057	-0.002	0.053	0.147	-0.039	-0.004	0.047	-0.002	-0.013	0.088	0.127	0.052	-0.014	0.000	-0.075	-0.005	-0.009	-0.012	-0.011	1.265
Exposure $\times$ 2005-2009	(0.033)	(0.004)	(0.054)	(0.088)	(0.047)	(0.074)	(0.078)	(0.971)	(0.035)	(0.003)	(0.080)	(0.011)	(0.041)	(0.073)	(0.081)	(0.758)	(0.038)	(0.003)	(0.075)	(0.02)	(0.043)	(0.075)	(0.044)	(1.233)
Emp.	0.018	0.007	0.036	-0.043	-0.058	0.019	0.040	0.848	-0.001	0.002	0.128	-0.014	0.040	0.004	0.100	1.072	-0.040	-0.004*	0.018	0.005	0.012	0.023	0.010	2.124
Exposure $\times$ Post 2009	(0.043)	(0.008)	(0.070)	(0.040)	(0.062)	(0.115)	(0.116)	(0.652)	(0.034)	(0.007)	(0.059)	(0.018)	(0.049)	(0.107)	(0.088)	(1.542)	(0.043)	(0.002)	(0.121)	(0.022)	(0.053)	(0.091)	(0.071)	(1.719)
Observations	15712.000	15712.000	5649.000	8234.000	8450.000	6058.000	3417.000	5654.000	19727.000	19727.000	7395.000	9748.000	9829.000	7683.000	5005.000	7395.000	12218.000	12218.000	4513.000	5256.000	5265.000	4286.000	3332.000	4516.000
Mean DV	0.55	0.01	6.90	2.61	3.85	-0.06	0.69	6.41	0.50	0.01	7.08	2.75	3.81	-0.21	0.72	8.25	0.44	0.00	7.50	2.71	3.69	-0.48	0.84	14.43
sd DV	0.50	0.12	0.58	0.46	0.47	0.67	0.46	5.41	0.50	0.13	0.60	0.27	0.42	0.66	0.45	8.55	0.50	0.07	0.70	0.32	0.44	0.62	0.37	15.03
R ²	0.590	0.064	0.042	0.024	0.045	0.314	0.031	0.412	0.557	0.080	0.632	0.591	0.106	0.319	0.551	0.414	0.598	0.061	0.753	0.901	0.193	0.360	0.668	0.379
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HHID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level.

and his spouse in *Post2009* case. Based on the definition of Log wage gap, the negative coefficient here indicates that the heads' exposure possibly affects the spouses' (heads') income positively (negatively); or simultaneously affects both of them.²⁶

Table 1.8: Effect of household exposure on the household dynamics

	Log Total Wage	Log Wage Gap	Log Hours Gap
Exposure $\times$ 2005-2009	-0.031*** (0.010)	-0.026 (0.029)	-0.004 (0.034)
Exposure $\times$ Post 2009	-0.039*** (0.014)	-0.074** (0.034)	-0.038 (0.040)
Observations	16318.000	12432.000	9829.000
Mean DV	8.22	6.99	7.08
sd DV	0.51	0.93	0.90
R ²	0.780	0.585	0.411
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at the district level.

1.5 Local Labour Market Approach

In the previous sections, we document how the South Korean population is affected by robotization through a proxy measure for proximity to affected occupations. We find that after an initial decrease in life satisfaction for those exposed to robotization, the effect of automation on life satisfaction fades out in the following years thereafter. However, this method does not capture the productivity effects accruing in the region of residence as well as the fear mechanism²⁷. In this section, therefore, we use two alternative approaches to shed light on labour market outcomes in the short and long run. This analysis is inspired by [Acemoglu and Restrepo \(2020\)](#), who posed the idea to use industry-level adoption of robots to predict robot adoption across regions in a country using the regional distribution of industries prior to the period of study. As robot adoption may be endogenous to local economic conditions, it can be instrumented with robot adoption in the same industries in another, ideally a technologically more advanced country. As robot adoption across industries

²⁶For further analysis on the changes in household dynamics, see appendix Table A8

²⁷We will discuss further in the following.

over the world is ultimately driven by technological progress, this alleviates any remaining concerns about the measure of robot exposure being affected by the local economy.

This approach differs from our previous methods in two important ways. First, the local labor market approach takes into account broader productivity effects as well, which are not directly related to one's occupation. This is significant in explaining our main results since productivity effects possibly have a positive effect on the life satisfaction of workers in the long term.

Second, it measures the local effects of robotization, rather than the effects across the country. In other words, the variation in robot exposure is measured at the regional level. This enables us to demonstrate possible psychological effects of robotization on life satisfaction, by comparing the changes of aggregated life satisfaction between regions and the actual changes in employment and wage at the aggregate level.

1.5.1 Local Labour markets approach

As the approach in Section 3 employs a difference-in-differences with multiple time periods, we are interested in the long- and short-run response to robot adoption in the regions most exposed. To study this, we use the following empirical strategy:

$$\Delta Y_d = \alpha + \beta \Delta robot_{t_1,d}^{t_2} + \gamma X'_{t_1,d} + \epsilon_d \quad (1.5)$$

where d index the region (Si, Gun, Gu)²⁸. The change in robot exposure $\Delta robot_{d,t=t_1}^{t_2}$ is the long-term difference in the predicted number of robots installed in the region d . X'_d is a vector of controls that includes the cohorts of 20 to 50 years of age, as well as high education, vocational education and gender shares per region. As we do not observe the number of robots installed in a specific region, we calculate it as follows:

$$\Delta robot_{t_1,d}^{t_2} = 1000 \times \frac{\Delta robot_{t_1,j}^{t_2}}{L_{t_1,j}} \times \frac{L_{t_1,jd}}{L_{t_1,d}} \quad (1.6)$$

where $\Delta robot_{t_1,j}^{t_2}$ denotes the total net installations in sector j between t_1 and t_2 . $L_{t_1,j}$

²⁸South Korea consists of upper and lower level local autonomy. Si, Gun, Gu are the three main types that belong to the lower local autonomy. There are 60 of Si(equivalent to city), 15 of specific Si(city), 82 Gun(county), 69 Gu(district)

denotes the total number of workers in t_1 in sector j , $L_{t_1,d}$ in region d and $L_{t_1,jd}$ in sector j and region d . We calculate the number of workers using KLIPS and the weights associated with each individual observation. We focus on the regions with at least 20 observations in the base year. This leaves us with 80 regions. For ease of interpretation, we multiply by 1000 to interpret $\Delta robot_{t_1,d}^{t_2}$ as the number of robots per 1000 workers. The average number of robots installed per 1,000 workers is N between 2005 and 2009 and N between 2009 and 2019

1.5.2 Shift-share Instrumental Variable

As the regional-level robot exposure correlates with beneficial local economic conditions, driven by sectors well suited for robotization, the results of Equation 1.6 could be suffer from omitted variable bias. This cannot be solved by controlling for local economic conditions, as these could also mediate the effect of robot adoption on life satisfaction and relevant labor market conditions. Therefore, we resort to the shift-share IV approach commonplace in the literature dealing with labor market effects of robotization. The instrument is calculated as follows:

$$\Delta robot_{t_1,dc}^{\hat{t_2}} = 1000 \times \frac{\Delta robot_{t_1,j}^{t_2}}{L_{t_1,jc}} \times \frac{L_{t_1,jd}}{L_{t_1,d}} \quad (1.7)$$

where c indexes the country (set) used as a reference. In our subsequent analysis, we use Singapore as a reference country. The use of such instruments is typically supported by the assumption that the reference country c is more technologically advanced than the country of interest. If this would not be the case, robot adoption in the reference country could be driven by local conditions in the country of interest (e.g. through development of new technologies amenable to the country of interest). As South Korea is at the forefront of robot development and adoption, this assumption is strong. To the best of our knowledge of our knowledge, this IV approach has not been used in the literature.

1.5.3 Replaceability Instrumental Variable

An alternative IV can be based on the replaceability of occupations in a region in a specific base period. Using the measure of replaceability (the share of hours worked that is

replaceable) developed by [Graetz and Michaels \(2018\)](#), θ_k (as discussed in Section 1.2.3), we construct a region-based measure of replaceability:

$$\hat{\theta}_d = \frac{\sum L_{dk}\theta_k}{\sum L_{dk}} \quad (1.8)$$

L_{dk} corresponds to the number of workers by occupation. This instrument, contrary to the shift-share instrument based on robot adoption in other countries, has no specific time dimension. However, the measure of replaceable hours from [Graetz and Michaels \(2018\)](#) is based on the matching of IFR applications and occupational titles in year t . Therefore, it is plausible that [Graetz and Michaels \(2018\)](#) find that this instrument is a strong predictor of subsequent robot adoption. This may suggest the matching of occupational titles to the functions of robots may generate a useful source of plausible exogenous variation ([Caselli et al., 2021](#)).

1.5.4 Results

To match our main empirical strategy temporally, we use long differences for two distinct time periods: 2005 to 2009 and 2009 to 2019. Table 1.9 shows the regression table of Equation 1.6.

We find that life satisfaction is unaffected by the local adoption of robots in both time periods. This can be reconciled with the negative initial and insignificant subsequent effects found in Section 1.3 in the following way. Our baseline result measures individuals' direct exposure to the jobs likely to be replaced by robots. However, this does not account for any productivity increases of high-skilled workers nor for improvements in the labor market conditions for those living in regions that undergo strong robotization through increased demand for labor unrelated to robot adopting industries. The only significant coefficient in table 1.9 is that of high-skilled wages between 2009-2019. An additional robot per 1000 workers is associated with a moderate increase in high-skilled wages of 0.4%.

However, the empirical strategy still face endogeneity problems because of the decision to adopt robots by industry. To overcome this issue, we employ an instrumental variable analysis in Equation 1.8 as well, using the IV based on replaceability for 2005-2009 and an IV using robot expansion in Singapore between 2009 and 2019. We use Singapore's data for the following reasons. First, during our observation period, Singapore was ahead of South

Table 1.9: Long Differences in a Local Labour Market Approach

2005-2009					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2005},d}^{t_{2009}}$	0.014 (0.022)	-0.015 (0.016)	-0.010 (0.020)	0.017 (0.022)	0.015 (1617.732)
Observations	85	85	83	85	85
R^2	0.20	0.35	0.16	0.26	0.22
2009-2019					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2009},d}^{t_{2019}}$	0.002 (0.002)	0.003 (0.003)	-0.000 (0.004)	0.001 (0.002)	0.004* (0.002)
Observations	85	85	83	85	85
R^2	0.27	0.22	0.28	0.27	0.25

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Korea in terms of robotization.

The results can be seen in Table 1.10. However, none of the coefficients are significant. The outcomes lead us to two suggestive conclusions. First, the productivity effect observed in a regional aggregated level on life satisfaction is small. This supports our results in section 1.3.2 and 1.4.2; the negative effect of automation is largely explained by the displacement effect.²⁹

Second, the changes in life satisfaction of workers are not due to the fear of being replaced by robots in the future but rather by the actual labor market outcome changes. The psychological fear of the robotization could be confirmed when diminishing life satisfaction is detected without any negative effect of robotization on labor market outcomes in the long term. As Table 1.10 demonstrates, the life satisfaction of workers is not significantly affected by robotization as the channels, employment and wage have not been impacted by exposure to robots. This shows that workers' life satisfaction is related to the labor market outcomes rather than other indirect channels.

²⁹Our previous exposure measure exhibits the replaceability of each occupation by robots

Table 1.10: Long Differences in a Local Labour Market Approach

2005-2009 (IV based on replaceability)					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2005},d}^{t_{2009}}$	0.064 (0.080)	-0.024 (0.087)	0.047 (0.071)	0.049 (0.110)	0.097 (0.093)
Observations	80	80	79	80	80
F-stat.	8.47	8.47	8.47	8.47	8.47
2009-2019 (IV using Singapore)					
	Life satisfaction	Log employment	log of LS wage	log of MS wage	log of HS wage
$\Delta robot_{t_{2009},d}^{t_{2019}}$	-0.001 (0.721)	-0.002 (0.885)	0.005 (0.012)	-0.001 (0.004)	-0.002 (0.006)
Observations	85	85	83	85	85
F-stat.	22.7	22.7	22.7	22.7	22.7

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6 Robustness Checks

1.6.1 The 2008 Financial Crisis

Table 1.11: Robustness checks for the 2008 Financial Crisis

Overall Life Satisfaction	(1)	(2)
Exposure $\times$ 2005-2007	-0.027*** (0.006)	-0.028*** (0.006)
Exposure $\times$ 2007-2009	-0.019*** (0.007)	-0.019*** (0.007)
Observations	173150	172161
Mean DV	0.28	0.28
R ²	0.087	0.393
Controls	Yes	Yes
Year FE	No	Yes
Individual FE	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at the district and individual level.

The main results of the impact of robotization on life satisfaction at the individual level are robust to the financial crisis shock in 2008. Table 1.11 illustrates the results of equation 1.3 with a minor change in the interaction terms to take into consideration the years 2005 to 2007 as well as 2007 to 2009. In other words, the early years of robotization 2005 to 2009 were subject to the 2008 shock. Therefore, two dummies were created: One for the years of robotization before the 2008 financial crisis and one for right after it from 2007 to 2009. The results in table 1.11 show that our main results are robust to the 2008 financial crisis. The interaction terms of exposure to robotization with the years 2005 to 2007 as well as with after the 2008 crisis (from 2007 to 2009) show a negative and significant impact on individuals' life satisfaction. This is in line with our main results which show a decline in the life satisfaction of individuals throughout the early robotization period from 2005 to 2009.

1.6.2 Adding More Fixed Effects

To enhance the robustness of our empirical strategy, we undertake a robustness check that incorporates an additional fixed effect into our analysis. Our previous investigation reveals that the impact of robot exposures exhibits considerable variation across different levels of education. In light of these findings, we investigate the application of a two-way fixed effects model, enriched with interaction terms, into our initial Equation 1.2. This refined approach allows for more control over the unique impacts attributable to each year and education level category, as well as the synergy effects arising at the confluence of these dimensions. By embedding this two-way fixed effects framework within our analysis, we attempt to capture not only the isolated influences of temporal and demographic factors but also the multifaceted effects emerging from their interplay. Echoing this methodology, we incorporate a two-way fixed effects models that employ the interaction term between the replaceability of each occupation (to robot exposure) and year as well as occupation and year. Our construct of replaceability draws on the foundational work of [Graetz and Michaels \(2018\)](#).³⁰

Figure 1.13 presents our results. Employing a two-way fixed effects model that integrates both education and year, we observe no significant impact from robot exposure following

³⁰Building on the methodology from [Graetz and Michaels \(2018\)](#), we align the IFR applications with occupational titles from the initial year of our study, 1998. This alignment strategy posits that matching occupational titles to robot functions could yield a valuable source of plausible exogenous variation, as suggested by ([Caselli et al., 2021](#)). This approach enhances our analysis by leveraging potential discrepancies between the intended functions of robots and the roles traditionally fulfilled by human labor, thereby offering a novel perspective on the impact of automation.

the implementation of two automation policies. This lack of significant effect persists even beyond the adaptation period post the second policy wave, starting from 2013. This outcome suggests that the annual variation in the education level of the workforce is a primary factor influencing our results, a finding corroborated by our heterogeneity analysis. Furthermore, our investigation employing a two-way fixed model that examines the interaction between occupation and time also fails to reveal any significant effects on our outcome variable. This indicates that the impact of robot exposure is subject to variation across different occupations. Given that our robot exposure measure is predicted on occupational data, we anticipated that our main outcome would reflect variations attributable to occupational characteristics. The absence of significant findings underscores the importance of our approach in capturing the occupation-dependent effects of robotization.

Our analysis, employing a two-way fixed effects model of job replaceability and year, reveals an intriguing trend: an increase in life satisfaction level post-2013. This finding suggests a key insight. Initially, it indicates that across occupations with uniform levels of replaceability, a unit increase in robot exposure correlates with enhanced life satisfaction following the second robotization wave. This observation suggests that the compatibility between a robot's capabilities and the job description does not solely determine worker satisfaction. Instead, the presence of robots appears to positively influence worker sentiments, irrespective of the direct applicability of robotics to their specific job tasks. This phenomenon hints at an indirect positive effect of robotization on workforce. Furthermore, this pattern holds true regardless of whether the job tasks are directly substitutable with robots; individuals in environments with higher robot exposure report greater satisfaction compared to those in less automated settings. This underscores an indirect beneficial impact of robotization, a conclusion that aligns with our previous findings from household-level analyses. In essence, our research illuminates the relationship between automation and worker well-being, highlighting the broader, positive ramifications of robotization beyond mere task substitution.

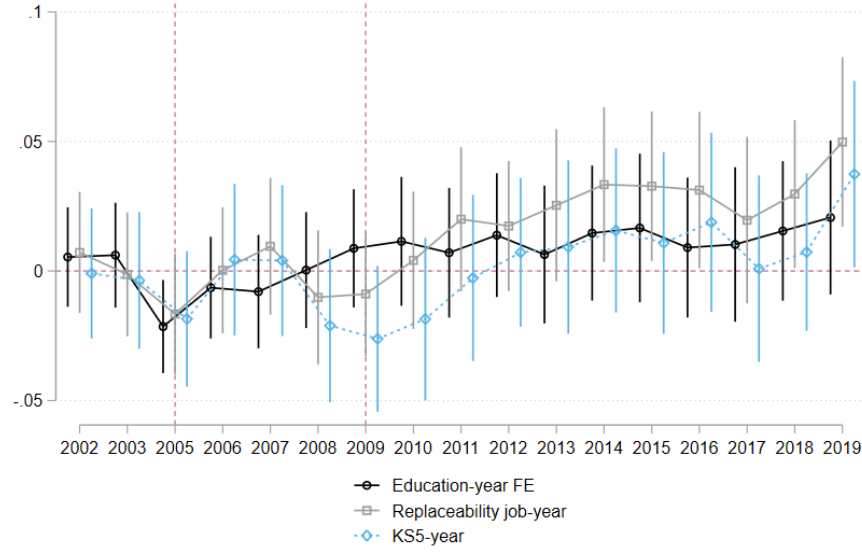


Figure 1.13: Robustness Check with Two-Way Fixed Effects

1.7 Conclusion

In South Korea, adopting robots was a two-step procedure that started in 2005 in the manufacturing sector followed by a sharp increase in robot adoption in all the sectors as of 2009. Our results at the individual level show that robotization before 2009 led to a decrease in the life satisfaction of individuals followed by an increase in life satisfaction due to a rise in employment levels. To disentangle our findings, we explore the labor market channels that could possibly drive the results. We find that these results are driven by young males aged 20 to 29 who happen to be highly educated.

The results are displayed at the low, vocational and high education levels as robotization is expected to have a different effect depending on these levels. The early wave of robot adoption from 2005 to 2009 witnessed a displacement effect of the low educated workers at the individual level. This indicates that the low educated individuals were the ones with the lowest life satisfaction as a result of being exposed to robots at work. The vocationally and highly educated individuals were not impacted.

The mechanisms leading to these results can be explained in light of the displacement of robots at workplace. From 2005 to 2009, the low and the vocationally educated individuals have been displaced of their work in the form of the rise in part-time employment and the

switching of their workplace. From 2009, we confirm that the vocational and high educated individuals benefitted from the robotization in the form of wage increases. This was not the case for the low educated individuals. The gap between the low and the other two educational groups in wages can be translated into differences in their ability to adjust to the increased volume of robots at their workplace. Additionally, the enhanced wage of the higher educated workers signals the productivity effect in certain occupations and sectors employing vocational and high educated workers.

In addition to the individual case, we also explored the life satisfaction change of spouses owing to the increase in their husbands' exposure to robots. Aligning with the outcome from the individual case, we confirm that the negative effect of robot exposure is mainly driven from the spouses whose husbands are low educated or vocational educated workers due to the decrease in the total household wage. Our result signifies that the negative effect of robotization is not just limited to the individuals but it is amplified within the household. This is especially true when we pay attention to their quality of lives.

Last but not least, we employed a local labor market approach instrumented with Singapore and a replaceability IV to exhibit the productivity effect of robotization as well as possible channels to proxy for psychological effects that were not explained by our exposure measure. Despite the confined sample size, our results show evidence of neither a productivity effect nor a psychological effect of robotization on workers.

The life satisfaction of workers matters not only because it indicates their quality of life, but also because it is highly correlated with the productivity of workers. As our study proves a general positive effect of robotization at the aggregate level and a specific negative effect for the low educated groups in the short term, it suggests that the government should design appropriate labor protection policies to promote low educated workers' ability to adjust to new working environments with newly-added robots instead of having them frequently switch their workplace.

Table A1: The impact of wages on individual life satisfaction

Overall Life Satisfaction	(1)	(2)
Log Wage	0.035*** (0.001)	0.023*** (0.001)
Observations	162995	161955
R ²	0.099	0.402
Controls	Yes	Yes
Year FE	No	Yes
Ind.ID FE	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district and individual ID level.

Table A2: Results by Subsample: Males over 40

Life Satisfaction	(1)	(2)
Exposure X 2005-2009	-0.024** (0.011)	-0.006 (0.011)
Exposure X Post 2009	-0.012 (0.012)	0.027** (0.013)
Observations	56413	56001
Mean DV	0.10	0.53
R ²	0.115	0.434
Controls	Yes	Yes
Year FE	No	Yes
Ind.ID FE	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level

Table A3: The Impact of Exposure to Robotization on Life Satisfaction by Age Groups

Life Satisfaction	(1)	(2)	(3)	(4)	(5)
	Age 20	Age 30	Age 40	Age 50	Age 60
Exposure X 2005-2009	-0.023 (0.020)	-0.038*** (0.009)	-0.018* (0.010)	-0.004 (0.014)	-0.026 (0.029)
Exposure X Post 2009	0.048 (0.061)	-0.012 (0.012)	0.013 (0.013)	0.020 (0.018)	-0.025 (0.038)
Observations	14017	43022	50989	41027	20226
Mean DV	0.22	0.34	0.29	0.26	0.24
R ²	0.436	0.475	0.501	0.495	0.560
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Ind.ID FE	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district and individual level

Table A4: Results by Subsample: Married males over 40 years old dummy

Life Satisfaction	(1)	(2)
Exposure X 2005-2009	-0.015 (0.012)	-0.010 (0.013)
Exposure X Post 2009	-0.026* (0.014)	0.017 (0.017)
Observations	26194	25773
Mean DV	0.10	0.52
R ²	0.144	0.506
Controls	Yes	Yes
Year FE Yes	No	Yes
Ind.ID FE	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district and individual level

Table A5: The impact of individual's exposure to robotization on life satisfaction by gender

Overall Life Satisfaction	Male		Female	
	(1)	(2)	(1)	(2)
Exposure $\times$ 2005-2009	-0.037*** (0.008)	-0.021*** (0.008)	-0.025* (0.014)	-0.017 (0.014)
Exposure $\times$ Post 2009	-0.017* (0.009)	0.011 (0.008)	-0.014 (0.014)	0.006 (0.015)
Observations	84759	84240	88391	87921
Mean DV	0.27	0.28	0.28	0.28
R ²	0.117	0.395	0.121	0.392
Controls	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Ind. FE	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district and individual level.

Table A6: The impact of householders' exposure to robotization on spouses' life satisfaction by satisfaction level

	Discontent	Neutral	Content
Exposure $\times$ 2005-2009	-0.072 (0.055)	0.369*** (0.096)	-0.297*** (0.090)
Exposure $\times$ Post 2009	-0.201*** (0.059)	0.293** (0.120)	-0.092 (0.106)
Observations	47734.000	47734.000	47734.000
Mean DV	0.10	0.54	0.36
sd DV	0.31	0.50	0.48
R ²	0.312	0.218	0.325
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HH.ID FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level.

Table A7: Household descriptive statistics

	Mean	SD	Min	Max	N
Average household size	2.365	0.189	2	2.6810625	245662
Householder age	53.172	13.975	15	100	319230
Spouse age	49.165	12.378	19	94	258750
Householder, average wage	295.582	246.837	1	18971.732	185654
Spouse, average wage	186.301	148.665	3	5099.1792	81851
%Householder, low education	0.234	0.000	0	.23437615	245662
%Householder, mid education	0.389	0.000	0	.38920099	245662
%Householder, high education	0.376	0.000	0	.37638614	245662
%Spouse, low education	0.287	0.000	0	.2874727	245662
%Spouse, mid education	0.414	0.000	0	.4144274	245662
%Spouse, high education	0.298	0.000	0	.29777962	245662
%Male householder	0.830	0.027	1	.88132823	108936
%Male spouse	0.028	0.009	0	.03810504	108936

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level.

Table A8: Effect of spouse exposure on the household dynamics

	Log Total Wage	Log Wage Gap	Log Hours Gap
Exposure $\times$ 2005-2009	-0.023** (0.010)	-0.070*** (0.026)	0.033 (0.036)
Exposure $\times$ Post 2009	-0.016 (0.013)	-0.056* (0.032)	-0.024 (0.035)
Observations	13585	10357	8585
Mean DV	8.17	6.97	2.66
sd DV	0.51	0.93	0.83
R ²	0.769	0.579	0.399
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HH.ID FE	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Standard errors are clustered at the district level. We confirm that the increase in spouses' robot exposure also negatively relates to the total household income; however, the declines in wage gap implies that it is spouses who receive relatively higher benefit from the robotization in regard to the wage raise. Interestingly, it is not detected from the table 1.8.

1.8 Appendix

1.8.1 Tables

1.8.2 Figures

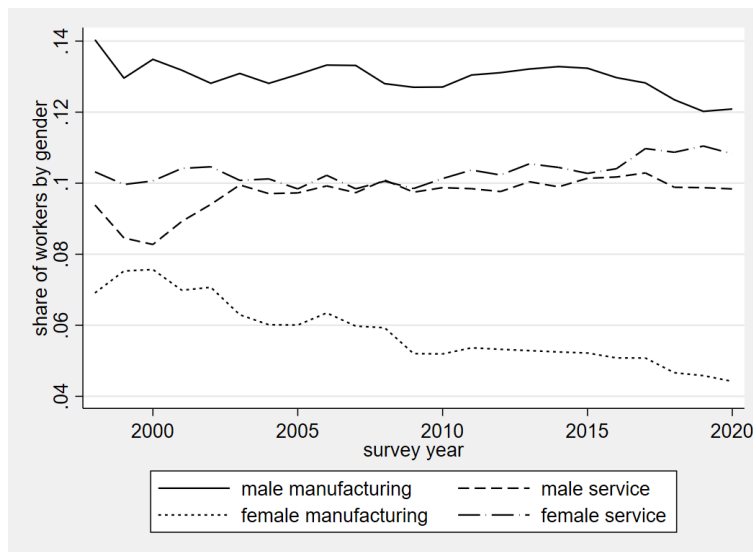


Figure A1: Labor participation rate by gender (KLIPS)

Note: The graph shows the labor participation rates of manufacturing and service sector by gender. As we mention in the main text, males' participation rate in manufacturing sector is dominant to the females.

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Chapter 2

Robots and Voting Behavior: Evidence from South Korea

Co-authored chapter with Jae Cho

In this paper, we find evidence that the South Korean districts with high robot adoption rates tend to be vote more for both Right and Left-wing parties at the parliamentary elections level. This result highlights the emergence of political polarization as a result of robot adoption. At the presidential election, districts with high levels of robotization tend to have an increase in the Right as well as the Center-Left vote shares. We attempt to disentangle the mechanisms behind these results at both the presidential and parliamentary levels through a series of heterogeneity analysis at the district level. We find that our results are driven by the divide between older and younger generations who have been differentially impacted by robot adoption.

2.1 Introduction

According to [Prysby and Scavo \(1993\)](#), government performance, policies and orientations on public policy issues are key determinants of people's voting behavior. In this regard, there is a vital need to understand voters' drivers when making certain political or voting decisions. There exists a large literature exploring the drivers of voting behavior. As labor market outcomes are highly correlated with voting decisions, previous studies analyzed different factors associated with workers' welfare. Several studies have closely examined the relation-

ship between labor market outcomes and voting behaviors. [Evgenia \(2020\)](#), for instance, demonstrates that voting rate for populist parties in 26 European countries increased as total unemployment rate rose between 2000 and 2017. [Brännlund \(2021\)](#) also demonstrates that fluctuations in unemployment rate alters electoral outcomes for certain parties. Recently, economists have started to pay attention to robot adoption as a possible contributing factor affecting workers’ voting decisions. Their attention on this subject has been driven by previous findings indicating that robotization at the workplace has an impact on labor market outcomes ([Acemoglu and Restrepo, 2020](#); [Aghion et al., 2021](#); [Anelli et al., 2024](#); [Cali and Presidente, 2022](#)). There are two main effects of robotization on workers: Displacement effect and productivity effect. The displacement effect indicates that adopting robots at work decreases the number of human workers who happen to be replaced by robots. On the other hand, the productivity effect predicts a reversed effect. Robots can expand labor demand by increasing industrial production (higher productivity) by robot adoption. Alternatively stated, the level of robot adoption is directly related to employment rate and income which affects public’s sentiments and voting decisions. Previous work highlighted that negative labor market outcomes direct voting outcomes in favour of Left-wing parties ([Dassonneville and Lewis-Beck, 2013](#); [Wright, 2012](#)).

To this end, we scrutinize the causal effect of robotization at workplace on voting behavior at the district level. Our robot exposure per district follows [Dauth et al. \(2021\)](#). We distribute the number of robots adopted per sector according to the ratio of workers working at this specific sector in a given district to the total population of this district. This measure suffers from endogeneity issues as the robot adoption is strongly correlated with the pre-economic condition of each sector. Therefore, we employ an instrumental variable approach in the same spirit of [Acemoglu and Restrepo \(2020\)](#) using Singapore’s high robot adoption rate. A particular attention is required to select the instrumental country as South Korea is a leading country in terms of robotization. We employ the case of Singapore for the following two reasons. First, Singapore is the only country whose robot adoption per employee is higher than that of South Korea during our observation period (2002-2020). We closely examine the fast pace of robot adoption rather than the adopted robot density. Admitting that this is not the canonical way of constructing the instrumental variable, our study is based on the assumption that Singapore’s rapid robot adoption contributes to the robot adoption of its neighboring countries. Second, Singapore is the only country who shares an equally high robot adoption trend per industry similar to that of South Korea. When we regress the robotization rate per robot we receive a positive linear relationship between both

countries.¹

Our study provides extensive outcomes on the effect of robotization on a five-level political spectrum in South Korea.² We present our main outcomes at the presidential and parliamentary elections levels.³ We synthesize each political party by ideology and finalize the spectrum.

Our parliamentary outcomes suggest that robotization affects voting behavior significantly; depending on the party, robotization displays heterogeneous effects on the changes in voting shares. During the four rounds of parliamentary elections, we find that the districts more exposed to higher robotization tend to diverge their voting shares towards Left and Right-wing parties. Consequently, the voting share for Central-Left and Central-Right parties decreased as their voters turned towards voting for Left and Right-wing parties instead. Interestingly, we find positive and stronger effect of robotization on the Central-Left and Right parties. Both outcomes suggest that there was a certain degree of susceptibility for polarization in parliamentary and presidential elections due to robotization exposure. The decline in abstention rate in both elections indicate that workers were more motivated to exercise their right to vote as they are more exposed to robotization.

To understand our main outcomes we advance our study to disentangle the mechanisms. We run the the same IV regression restricting the characteristics of individual within a same district. According to our heterogeneity analysis at the district level, we find that polarization caused by robotization is driven by the differential impact of robot adoption at work across generations. High share of workers aged between 20 and 30 tend to vote for Center-Right instead of voting for Right-wing parties for parliamentary elections. On the other hand, workers aged 50 tend to vote for Right-wing parties which leads to polarization at the parliamentary elections level. The vote share movement of presidential elections exhibit the same generational gap between young and old voters.

This project adds to three streams of literature. The first one relates to the effect of technology changes on voting behavior. [Caselli et al. \(2021\)](#); [Anelli et al. \(2019\)](#) explore the topic by employing Italian data and various European data as well; and find out a positive correlation between the exposure to robotization and support for nationalism and radical right parties. [Caselli et al. \(2021\)](#) also provides evidence that technology adoption positively affects the Italian populist movement. Our contribution to this literature is as follows: First,

¹Refer to Figure 5.

²The political spectrum includes: Left wing, Center-Left, Center, Center-Right and Right wing parties.

³Further description on each election is documented at Section 2.

based on our detailed panel database, we construct an exposure measure of robotization by region which allows us to look at the effect of robotization on voting behaviors at a more granular level in South Korea rather than an aggregated (country) level. Furthermore, owing to a shock happening in 2009 in South Korea, we are able to investigate the causal effect of robotization on voting behavior.⁴ [Schöll and Kurer \(2024\)](#) use German labor market data at the county level in a two-way fixed effects model to show that robot adoption changed the workforce composition at the regional level in Germany. The composition effect is much larger than the expected political effect of robot adoption in the literature – that is the rise in extreme Right-wing voting – leading to a rise in vote shares for the progressive Left-wing parties.

Our study is also built on [Frieden \(2018\)](#); [Abbondanza and Bailo \(2018\)](#); [Autor et al. \(2020\)](#) whose research examines the effect of economic instability on voting behavior. [Frieden \(2018\)](#) finds a rise in populist movements when globalization increases threat to workers. [Abbondanza and Bailo \(2018\)](#) and [Autor et al. \(2020\)](#) also find that the influx of immigration coupled with the increase in trade exposure – that both threaten domestic labor market – are positively correlated with the rise in voting for extreme right parties. Corroborating the aforementioned literature’s finding, we also confirm a correlation between unstable economic conditions caused by robot adoption and voting behavior. As we explore different labor market outcomes as our potential channels to explain our main outcomes, we provide further insights from the existing literature.

Last but not least, the literature strand that our study is relevant to is the intersection of political polarization and generational gaps. There is a body of literature mainly in political economic journals that scrutinize the cause of political polarization due to generation gaps ([Dalton, 1987](#); [Philips, 2022](#); [Moon et al., 2020](#); [Jou and Endo, 2016](#); [Stoker, Stoker](#)). [Dalton \(1987\)](#) sheds the light on generational differences in political parties. For instance, the role of younger and older political activists in political polarization that reflect the interests of the different societal groups. Furthermore, [Philips \(2022\)](#) investigates age, period and cohort effects on polarization, partisan strength, and ideological sorting. The study discovers that age-related variables increases political polarization.

The paper consists of the following order: Institutional background of our study in Section 2.2. This section includes the chronology, the main characteristics of the South Korean democracy, the ideologies of each party that are the basis of our five-level political spectrum.

⁴The shock here indicates the "the Intelligent Robots Development and Distribution Promotion Act" mentioned above.

Section 2.3 and 2.4 analyze our data and our IV specification respectively with our own robot exposure measure. In Section 2.5, we discuss our main results in terms of parliamentary and presidential results. Section 2.6 expands our study to explore the mechanisms driving our main results. Finally, Section 2.7 includes a number of robustness checks and 2.8 concludes.

2.2 Institutional Background

History and the Features of Korean Politics

South Korea is a democratic republic that includes a presidential, a parliamentary, and a semi-presidential system. According to article 66th of the Constitution of the Republic of Korea, the country is based on the presidential system. On account of the existence of a prime minister, South Korea's presidential system is considered to have some elements of a parliamentary government such as the presence of a prime minister. By the end of World War II, South Korea was bestowed colonial independence; however, the Korean war occurred during 1950-53. Due to this turmoil, the democracy in South Korea was established in a hasty manner. At the beginning of 20th century, the very first President Syngman Rhee managed to lead the country a step closer to democracy; by conducting illegal and violent incidents to amend the law in order to maintain his authority as a president. However, the latter's leadership was challenged by citizens' protests and demonstrations (Kim, 1996; Wilson, 2001)⁵. Despite the public's hope to have a stable political system, the citizens had to face long years of military dictatorship. The post dictatorship era was also suffering from the predominated authoritarianism under the cloak of democracy. In other words, the modern stabilized political system in South Korea is an outcome of continuous contest under the façade of democracy.

Drawing from the history of South Korea, its political history can be depicted by several features. First, authoritarianism is an outstanding one. There are multiple presidents who attempted to revise the law in favor of their elections or extending their terms, including President Rhee. Previous studies attribute certain bureaucratic authoritarianism to Korea's Confucian heritage which has developed a strong personalistic, so-called "imperial presidency" (Hellmann, 2011; Kil and Moon, 2001).

⁵For the detailed information on Syngman Rhee's fraudulent acts and protesting demonstration, refer to Appendix

Second, the public resistance is well demonstrated in the South Korean history. One of the main consequences of authoritarianism is resistibility in the political history of South Korea (Coke, 2006). As summarized above, the political vortex frequently came from the authorized party's desire to maintain their power or political decisions which is not concurred with public's longing; the main impetus bringing the democracy on the right track was the protests collaborated vast number of South Korean citizens against the ruling party. In modern history, the impeachment of President Park the 10th of March, 2017 by her wrongdoing⁶; this feature of Korean politics can even be traced back to its ancient dynasties.(Lee, 2003)

Third, the presence of political dichotomy is considered to be an outcome of authoritarianism. Alongside citizens' protests, the opposition party rarely converges with the ruling party's position on important policy stances. This setting has played a role in retaining democracy in South Korea while it hindered some of the ruling party's projects despite their expected positive results. According to Beak (2019), the Korean politics are defined as an ongoing competition between the ruling and the opposition parties without political harmonization.

Last but not least, the regionalism is an aspect of political circumstances in South Korea. As the congresswomen and congressmen are elected at the regional level, geographical location becomes the basis for interactions between the public and politicians (Agnew, 1987). Within South Korea, the confrontation between Gyeongsang-do (Yeongnam) and Jella-do (Honam), so-called East-West conflict (or Yeong-Honam conflict) is the most prominent.⁷ The root of the current regional conflict can also be detected in ancient dynasties as those two provinces were part of two different countries from the Three Kingdom periods.(Lee, 2009) The severity of certain conflicts, however, was intensively promoted in the 1960s by the ruling elites who utilized the main regional characteristics as major resources for gaining political power (Browne and Kim, 2003). Naturally, the political dichotomy was expressed by regionalism.⁸

As the plans for robotization at the workplace become a main element of the fourth industrialization implemented from the state, it can be considered as a vestige of the authoritarian political system. As a result of the resistivity of the Korean citizens in the past, we expect that the response to the imposed automation policy will be depicted by their behaviors. Also, it is important to understand how the ruling and the opposition parties will revise

⁶For an overview of the timeline of the current incident, see Reuters (2017).

⁷Do indicates the provinces; there are 9 provinces in South Korea. Gyeongsang-do and Jella-do are located adjacent to each other in South.

⁸If the ruling party is a party from Gyeongsang-do, the strong opposition against the ruling party comes from Jella-do; this particular circumstance give the casting vote to other provinces whose political color changes more diversely.

their policies related to robot adoption in response to the public's voting behavior in the following election periods alongside their main political ideas.

Voting System

South Korea follows the tripartite system, including the legislative, judicial, and administrative branches. The main purpose of power separation is to prevent power abuse by keeping each other in check. The chief Justice of the Supreme Court is appointed by the president with the approval of the National Assembly⁹ Accordingly, the public has opportunities to express political opinions to the legislative and administrative branches during election times at the presidential, national assembly and the regional elections level as well. Figure 4 showcases how the powers are distributed between the three branches and how the voting system corresponds to the branches.

Figures

Since 1948, the very first presidential election, South Korea has maintained universal, equal, direct, and secret suffrage ([Croissant and Gabriele, 2002](#)). Under the Article 5 of the Constitution, suffrage is granted for the South Korean citizens who are older than 18. Foreigners are also eligible only for the regional election if they maintain their stay for 3 years after obtaining permanent residency in South Korea. South Korean nationals residing in foreign countries are also qualified to vote for all elections if they verify their rights online in advance.

The presidential elections occur every 5 years. Candidates' registration ends on the 23 days before the designated election; the campaign can be initiated one day after the registration. There are two types of qualification conditions for the presidential candidates. If the candidate is enrolled in a party, the candidate should be recommended by the party. Otherwise, 500 recommendations of electorates from five different cities/states (total 5,000) qualify the candidate to register themselves to the system. All candidates should be South Korean citizens aged over 40. The selected candidate is not eligible for running their campaign for a second term.

⁹Since 1988, the judiciary structure has been divided into two components: the supreme court and constitutional court. Strictly speaking, there are two principals of the judicial branch: the Chief of Justice of Supreme Court and the President of the Constitutional Court. The candidates for the latter comes from the recommendation of the Chief of Justice of Supreme Court; the final appointment is decided by the President with the approval of the National Assembly.

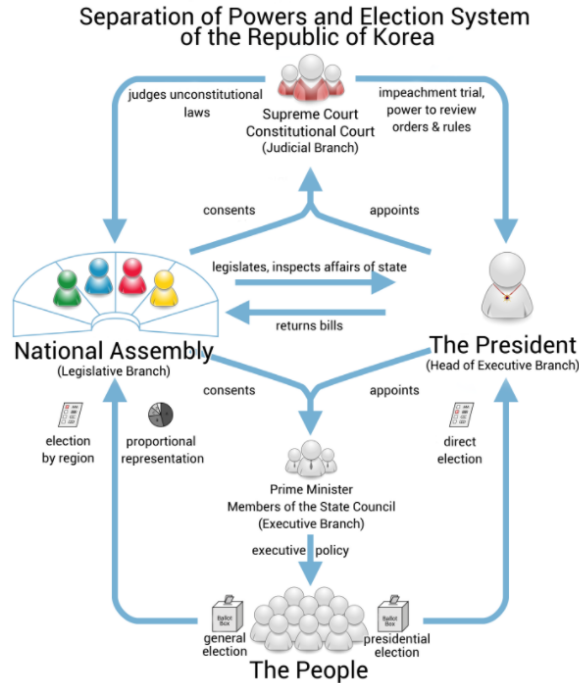


Figure 1: Separation of powers and election system (Dmthoth, 2017)

The legislative elections take place every 4 years. Contrary to the presidential elections, the legislators are able to serve consecutive terms without limit. According to Article 41 of the South Korean Constitution, the election of the National Assembly members is done through a direct universal and secret ballot by the citizens. For 14 days, the candidates are allowed to run their campaigns. The National Assembly is filled up based on two compatible methods: constituency election and proportional representation. The elected members of National Assembly are 253; 47 from the proportional representation. Similar to the presidential candidates, the legislative candidates are also required to be recommended by their parties. The election process is controlled by the National Election Commission (NEC) which is an independent institution focusing on the fair management of elections and referendums. (Kim, 2014) Under the supervision of the NEC, voters can vote at polling stations in the constituencies where they are registered. For each race, the electorates are given one ballot paper. Voters can mark ballot papers with a rubber stamp using red ink which are available in a voting booth. After the polls are closed, ballot boxes are sealed and transported to the constituency's counting; the ballot-counting is witnessed by the staffs from the NEC. Traditionally, ballots were hand-counted; since June 2002, the optical scanner has been adopted for the counting.

Evolution of Political Parties

We use a five political spectrum to indicate the political parties that we are investigating: Left, Central-Left, Center, Central-Right, and Right. This five-level spectrum is constructed based on each party's ideology. We start the current chapter by explaining the rationale behind the five-level grouping of the South Korean political parties. In the course of South Korea's history after the Korean war, the political parties have been extremely chaotic in terms of their formulation and amalgamation amongst them. It is difficult to discern the early political parties not only as they have been changing their names frequently but also as they split their parties into either new parties with different political inclinations or joined other political parties with different ideologies.

	Left	Mid-Left	Mid	Mid-Right	Right
1996	Saejeongchi (Progressivism)				
2000		Saecheonnyeon (Social Liberalism)			
2005	Minju Yeolyin (Progressivism)	Saecheonnyeon (Social Liberalism)			
2008		Tonghab Minju (Social Liberalism)			
2011.7		Minju (Social Liberalism)			
2011.12	Minju Tonghab (Progressivism)				
2013.9				Minju (Conservative Liberalism)	
2014		Saejeonchi-Minju (Social Liberalism)			
2015		Deobuleh (Social Liberalism)			

Figure 2: Evolution of Deobuleh Party

Figure 2 describes how one party could change its ideology and name over the course of 19 years.¹⁰ On the 11th of September 1995 Seajeonchi (that means new politics) party was established. In 1997, Seajeonchi won the presidential election, boosting its promising future. However, from the following years, members of the party started to have conflicts over the different political ideas. In the end, they dispersed the party by establishing a new one called Seacheonnyeon Minju (meaning a new millennium democracy) and eliminated the partial members. After 5 years of relatively solid achievements, Seacheonnyeon Minju had to split the party as there was fissures emerging in it once again. After the dispersion,

¹⁰The Figure 2 demonstrates the complexity of each party's evolution. In the following section, we explain the definition of five-level spectrum used in this study.

Seacheonnyeon Minju changed its name to cover their on-going fissures between the party members. The splitting and merging with other parties continue currently for similar reasons. Such chronology is not only applicable to Saejeongchi but to all parties in South Korea. Alternatively stated, due to their complex history and ideology changes, it is difficult to study the changes of voting shares per parties. To enable the analysis on heterogeneous political beliefs, therefore, we construct the five-level political spectrum to embrace all parties and their political nuances.¹¹ In the following section, we illustrate how we construct the spectrum.

2.3 Data and Political Variable Measurement

2.3.1 Data

KLIPS: a household-based labor force survey

Our main data is provided by the Korean Labor Income and Panel Study (KLIPS). Conducted once a year, KLIPS is a comprehensive longitudinal income survey existing in South Korea. KLIPS collects information on consumption behavior, labor market participation, education, and social activities from about 5,000 households, including every member of these households. The data is available up to and including 2020. Our study observes the data from 1998 to 2020 given that South Korea had a massive wave of automation during this period. We use an individual-level panel which is released for the annual conference held by KLIPS. The data contains information on gender, age, educational attainment, 3-digit occupation codes, 3-digit industrial affiliation codes and labor market outcomes, such as employment, wages and working hours. The data contains household's region of residence at an intermediate level of 225 divisions (these divisions comprise 3 types of units: Si (cities), Gun (counties) and Gu (districts)), which are nested in 17 larger geographic divisions (these divisions comprise 6 metropolitan cities, 1 special city, 1 special self-governing city, and 9 provinces). The individual level data from KLIPS allow us to thoroughly understand the overall changes in average employment rate and the wage changes depending on workers' demographic information, occupations and working industry. Furthermore, KLIPS comprises detailed questions on workers' life quality, including their current life satisfaction. Other information about workers in the KLIPS include: Exposed rate of job training, job-status

¹¹A mapping demonstrating how each party has evolved is included in Appendix.

transition from permanent (regular) to temporary (part-time), preferred job training, reasons for leaving, smoking and drinking frequency, difficulties in obtaining a new job, etc. For the purpose of our study, we focus on the life satisfaction related questionnaire as a proxy of their quality of life. KLIPS data provides us with the household identifier as well as each individual’s relationship with the household head. This allows us to study the effects of robotization through the labor market situation of individuals within the household.

IFR: robot installations by industry and application

The International Federation of Robots (IFR) collects information on industrial robot adoption across countries, sectors, and applications. The following definition of a robot from IFR is used: a programmed mechanism with a degree of autonomy to perform locomotion, manipulation or positioning. We use IFR data on the number of robots in use at the industry level in South Korea between 2004 and 2019. We merge the industry codes from IFR to the industry coding available throughout KLIPS’s industrial codes.¹² We, then, distribute the number of robots per sector following the work of [Acemoglu and Restrepo \(2020\)](#) and [Dauth et al. \(2021\)](#).¹³

NEC: Voter turnout data at district level

We collect information on voting outcomes of each election from the National Election Commission (NEC) which is an independent constitutional institution in South Korea. The primary purpose of establishing NEC is to manage fair elections and other administrative affairs regarding political parties and funds. Since 1963, NEC has archived and released the outcome of each and every referendum. By virtue of NEC’s input to digitize election outcomes, all information on elections and their outcomes are easily accessible via their website. The election returns are recorded at the district level. To conduct our research, we include 4 presidential elections (2002, 2007, 2012, and 2017) and 6 legislative elections (2000, 2004, 2008, 2012, 2016, 2020). During our different observation periods, several districts (dis)appeared or were combined with other districts. To take this into consideration, we fix districts used in our study according to the most recent definition which gives us a total number of 270 districts.

¹²We convert the KSIC (Korean industrial codes) into SIC codes.

¹³Our robot exposure measure is explained in the following chapter.

Final Panel Data Set

We combine all our datasets using our 3-digit district codes. Table 1 demonstrates a general overview of individuals in our final data.¹⁴ As previously mentioned, we have 270 districts. For our empirical study, we compute the mean values of individuals' characteristics at the district level.

Table 1: Descriptives Statistics of the Final Data Set

	(1) Presidential	(2) Parliamentary
Δ Left	-0.01 (0.0179)	-0.08 (0.181)
Δ Center left	-0.0037604 (0.385)	0.08 (0.323)
Δ Center	-.00186 (0.00492)	-.0021742 (0.0258)
Δ Center Right	0.18 (0.265)	0.10 (0.279)
Δ Right	-0.16 (0.255)	-0.09 (0.188)
Δ Nullified	-.0026391 (0.00910)	0.000147 (0.0102)
Δ Abstention	-0.04 (0.315)	0.0014717 (0.467)
Δ Robot Korea	0.0124 (0.0760)	0.0043615 (0.0140)
Δ Robot Singapore	0.0008583 (0.00689)	0.0001535 (0.000419)
Δ HS Employment Rate	0.76 (0.168)	0.77 (0.168)
Δ MS Employment Rate	0.60 (0.184)	0.59 (0.149)
Δ Robot Industry Employment Rate	0.10 (0.119)	0.09 (0.105)
Δ LS Employment Rate	0.62 (0.188)	0.61 (0.182)
Δ HS Rate	0.29 (0.167)	0.28 (0.162)
Δ MS Rate	0.44 (0.142)	0.43 (0.132)
<i>Observations</i>	2836	2836

This descriptive statistics table shows the mean of the variables. The standard errors are between parentheses.

¹⁴An overview of individuals at the district level is included in our Appendix.

2.3.2 Political Variable Measurement

Five-level Spectrum

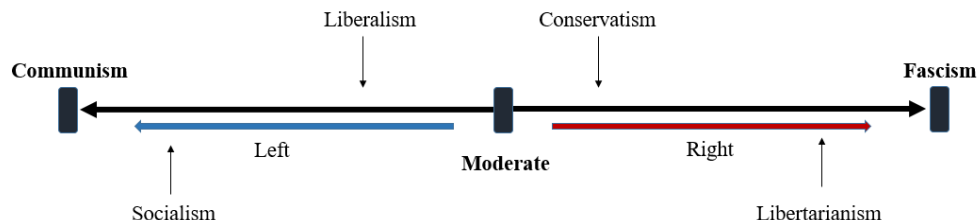


Figure 3: One-dimension Political Spectrum

The political parties in South Korea have been frequently and regularly modified. For this reason, we construct a synthesized measure that combines parties into clusters that share either similar ideologies or political movements. Our five-level spectrum strategy is built on the most common and long-standing “single-dimension” political spectrum since the French Revolution (1789-99) as it delineates the political spectrum in South Korea.

Figure 3 describes the basic idea of the political spectrum on a single dimension. Accordingly, each party exhibiting political movements inclining towards liberalism will be categorized as a Central-Left in our specification. To minimize the subjectivity of our party-clustering into five categories, we analyze the parties’ political ideologies and movements: attitudes toward private property, wealth redistribution as well as their policies regarding workers’ welfare (Gindler, 2020). Figure 4 exemplifies our clustering process. Departing from (Gindler, 2020), we also include the political parties’ policy stances when it comes to technology developments when clustering the parties into five levels.

It is worth mentioning that our measures are not *absolute* but *relative* ones. In other words, depending on the election years, one party can change clusters in our spectrum. For example, in the Figure 4, Kukmin party appears two times in *Center* and *Center-Right*. It is because in year 2002 Parliamentary election, there were more extreme parties to Left and Right than previous years which causes Kukmin to be more inclined towards a moderate ideology. In the following Parliamentary elections, however, the ballot was crowded by parties with ideologies of Left which permits us to classify Kukmin into Center-Right.

Merging Procedure

Spectrum	Example Parties	Ideology	Tech Policies
Left	Nodong, Jinbo	A system that puts the state at the center rather than individualism. Breaking down the class inequality	weak support
Center Left	Deobuleh, kukmin	Emphasis on social equality and welfare. Put some restrictions on the economic part	Enhance the new technology sector for increasing jobs for the youth
Center	Deobuleh, Kukmin, Sidae	In between center left and center right	Based on AI and big data, launching E-Government, sustainable technology
Center Right	Kukmin, KukmineuiHim	Pursues market economy principles, but has a conservative tendency in social order	Based on the new technology, improving the education system
Right	Chinpark, Kukmineui Him	Preservation of the existing system is a priority. center of wealth accumulation	Depending on the parties, different policies toward technologies

Figure 4: Different Ideologies of the Parties in terms of Technological Policies

Departing from previous studies, our study includes results at both the presidential and the legislative elections level. In this section, we describe how we combine the presidential and legislative elections according to the five-level spectrum. For each election, we first append all election results by district and year. We eliminate independent candidates as their political ideologies cannot be classified under our constructed five-level political spectrum. Each election has 5 political parties according to our measurement. In our observation period, from 2000 to 2017, the year 2012 is the only year where both presidential and legislative elections were held simultaneously.

2.4 Empirical Strategy

2.4.1 Instrumental Variable

This paper aims at studying the impact of robot adoption that took place in South Korea on voting outcomes at the regional level. For the purpose of this study, 4 rounds of presidential elections are used covering the years 2002, 2007, 2012 and 2017. Presidential elections take place every 5 years with no consecutive terms. In addition, 6 rounds of legislative elections are also used to cover the years 2000, 2004, 2008, 2012, 2016 as well as 2020. Parliamentary elections usually happen Every 4 years with possibilities of consecutive terms. We use the National Election Commission (NEC) data as our main source of South Korea’s regional level voter turnout data. The Korean Labor Income Panel Survey (KLIPS) is also be used for this study. It includes variables about wages, employment and demographic characteristics as well. The KLIPS data is collapsed and weighted at the regional level to be further merged with the NEC data for more comprehensive regional level controls. The International Federation of Robot data (IFR) provides us with the industry level robot operational stock, installation data that is also merged with both the collapsed KLIPS and the NEC data and that will be considered our main exposure variable for our empirical specification. The final presidential elections dataset comprises around 1,581 observations while that of the parliamentary elections has 1,252 district-year observations covering 270 districts, 4 years of presidential and 6 years of parliamentary elections in total.

The econometric approach will consist of a shift-share instrumental variables (IVs) framework ([Jaravel, 2024](#)). This approach help us overcome a number of endogeneity concerns that we could otherwise not overcome such as the correlation that exists between our dependent variable that is vote shares for the different levels of our constructed political spectrum might be correlated with unobserved shocks at the district level not captured in our dataset. In addition to having an omitted variable bias problem; the set of controls used in the regression can miss capturing some of the confounding factors such as district or national level policies impacting either the local economy or voting outcomes. Robot adoption happens to be procyclical which could be further reflected in citizen’s voting behavior ([Caselli et al., 2021](#); [Anelli et al., 2019](#)). Therefore, our IV regression aims at capturing the exogenous factors influencing robot adoption rather than demand-driven elements potentially affecting both robotization and voting behavior. The main regression will follow the below specification :

$$\Delta VoteShare_{i,d,t} = \sigma_1 \widehat{\Delta Robot Exposure}_{South Korea,d,t} + \omega_1 X'_{d,t0} + \epsilon_{i,d,t} \quad (2.1)$$

Where $\Delta VoteShare_{i,d,t}$ is the vote share for political spectrum i at district d time t minus that of time $t-1$. The year $t0$ refers to the base year of both the presidential and parliamentary elections in our data: for the presidential election, it is the year 2002 and for the parliamentary election, it is the year 2000. $X'_{d,t0}$ comprises district level controls at time $t0$ such as night light density, high skilled workers rate, middle skilled workers rate, 50 and 60 age cohort rates per district. The error $\epsilon_{i,d,t}$ is clustered at the district level.

$$\widehat{\Delta Robot Exposure}_{South Korea,d,t} = \sigma_2 \Delta Robot Exposure_{Singapore,d,t} + \omega_2 X'_{d,t0} + \tau_{i,d,t} \quad (2.2)$$

We use Singapore's robot exposure as an instrument for that of South Korea's as per equation (2) above. The main motivation for using Singapore as an IV is that it comes next in line in terms of rapid robot adoption following South Korea and highly correlates with the latter's robotization as a consequence.

The exposure to the robot shock at the regional level is inspired by [Dauth et al. \(2021\)](#) and is calculated as follows for South Korea and Singapore respectively:

$$\Delta Robot Exposure_{South Korea,d,t} = \ln \sum_{j=1}^J \left(\frac{emp_{j,d}^{t0}}{emp_d^{t0}} \times \frac{\Delta Robot_{j,t}}{emp_j^{t0}} \right) \quad (2.3)$$

$$\Delta Robot Exposure_{Singapore,d,t} = \sum_{j=1}^J \ln \left(\frac{emp_{j,d}^{t0}}{emp_d^{t0}} \times \frac{\Delta Robot_{j,t}}{emp_j^{t0}} \right) \quad (2.4)$$

Where the district is the unit of analysis. The second term $\frac{\Delta Robot_{j,t}}{emp_j^{t0}}$ measures the national robot adoption as the number of robots per industry j relative to its labor force size in year $t0$. This is being multiplied by $emp_{j,d}^{t0}$ that is the employment level at year $t0$ in industry j district d . For each district d , the exposure of industries are summed up to industry J and scaled by the district's total employment emp_d^{t0} for the base year $t0$ ¹⁵. The rationale

¹⁵The national number of robots data ranges from 1993 to 2020. The regional exposure is per 1000

for using this exposure measure is to allocate the industry-level exposure to districts based on the industry employment shares across these districts in order to overcome the lack of availability of precise district-level robot adoption data. For the robot exposure of Singapore in equation 2.4, we follow the same specification of the South Korean robot exposure in equation 2.3 in terms of employment shares except for the $\Delta Robot_{j,t}$ part that is changed to signal the use of Singapore's robot adoption as our shift-share IV.

2.4.2 Instrumental Variable: Singapore

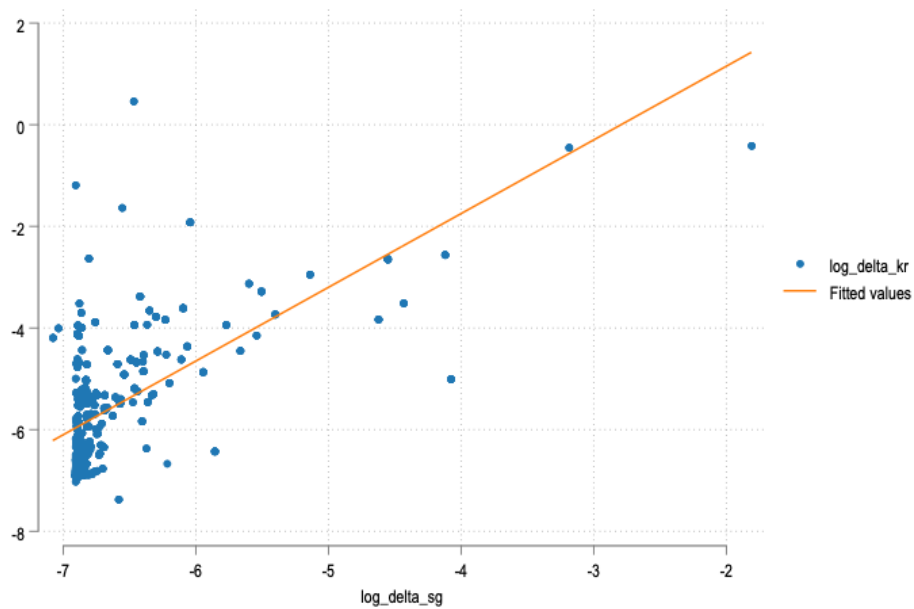


Figure 5: Correlation between robot adoption rate in South Korea and Singapore

workers before being plugged in the main regression

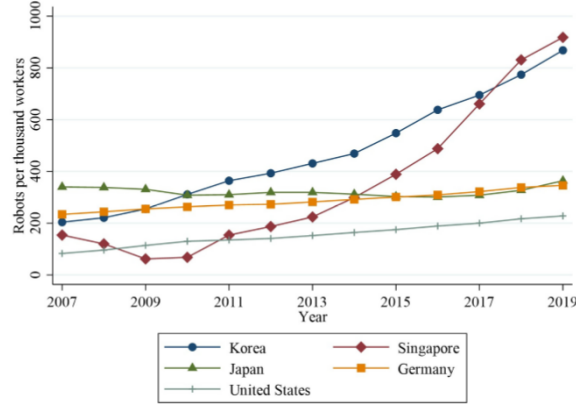


Figure 6: Robot density by country, 2015 per 10,000 employees in the manufacturing industry (Source:)

Our predicted robot exposure of South Korea (equation 2.3) possibly suffers from endogeneity issue due to the exposure of some industries to more robots than others. In other words, the variables related to the voting patterns of the workers in a district could be affected by domestic industry-specific demand shocks. To avoid this endogeneity concern, we employ robot adoption of Singapore as an instrumental variable for robot exposure measure in South Korea in the spirit of [Acemoglu and Restrepo \(2020\)](#). Based on the assumption that robot adoption of each industry is exogenous as the domestic pattern follows that of the leading country, we cautiously select Singapore as an anchor country for South Korea. A number of studies rely on an instrumental variables approach for their specification by employing multiple countries' number of robots to construct their instrumental variable ([Anelli et al., 2019, 2021](#); [Dauth et al., 2021](#)). The assumption that industries in their observing countries follow robot adoption trends per industry as their instrumental countries that happen to be the leading countries in terms of robot adoption. For South Korea, the pool of countries who are as advanced in terms of robotization is relatively narrow as South Korea is the leading country. Therefore, combining multiple countries to construct our IV will not help us overcome our endogeneity issue in our study; we specifically choose Singapore for the following reasons. First, Singapore has similar trends to that is South Korea in terms of robot density. Table 5 supports our argument that Singapore and South Korea share has a very similar robot density rate computed by sectors.

Second, Singapore is the only country who has higher robot adoption during our observation period. This is crucial as it indicates a strong evidence that South Korea has followed the robot adoption trend in the different sectors in Singapore. To provide evidence that our empirical strategy doesn't suffer from weaknesses despite the fact that we are employing

only one country as our IV, graph 6 demonstrates that Singapore has accelerated its number of robots faster than South Korea since 2013. However, South Korea has higher absolute robot density, the development rate is much higher for Singapore. In other words, our study is based on the assumption that higher velocity of robotization in Singapore affected South Korea's robot adoption.

2.5 Results

Table 2: Parliamentary Election Results

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	0.0450*** (0.0130)	-0.0341** (0.0173)	-0.00429*** (0.000915)	-0.0581*** (0.0119)	0.0404*** (0.00901)	0.00193 (0.00120)	-0.0949** (0.0429)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	89.76	89.76	89.76	89.76	89.76	89.76	89.76
First stage Coeff.	2.582***	2.582***	2.582***	2.582***	2.582***	2.582***	2.582***
First stage SE.	(0.272)	(0.272)	(0.272)	(0.272)	(0.272)	(0.272)	(0.272)

The standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts. The dependent variables presented in each column refer to the percentage point change. The mean of the dependent variables is for the variables in levels rather than in deltas. The 2SLS refers Singapore's robot exposure that is used as a the shift-share instrument used as a first stage regression. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors in parentheses.

The results of our main IV regressions are presented in table 2. Each column shows the impact of robot exposure on the five main political spectrum in South Korea at the district level. The first column highlights that a 1 percentage point increase in the $\Delta RobotExposure$ in South Korea leads to 4.5 percentage points increase in $\Delta Left$ vote shares. The second, third and fourth column show a decline in $\Delta CenterLeft$, $\Delta center$ and $\Delta CenterRight$ vote shares by 3.4, 0.4 and 5.8 percentage points respectively. $\Delta Right$ vote share increases by 4.4 percentage points at the 1 percent significance level as $\Delta RobotExposure$ increases by 1 percentage point. The Kleibergen-Paap F statistics indicate that the instrument used for our endogeneous variable is robust. On one hand, these results point at a shift away from the Center political spectrum towards both the Right and Left vote shares. We consider this

Table 3: Presidential Elections Results

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	0.000202 (0.00119)	0.0776*** (0.0262)	0.000598* (0.000319)	-0.0442* (0.0242)	0.0416** (0.0175)	0.000781 (0.000744)	-0.0777*** (0.0262)
Observations	1,252	1,252	1,252	1,252	1,252	1,252	1,252
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	61.85	61.85	61.85	61.85	61.85	61.85	61.85
First stage Coeff.	1.28***	1.28***	1.28***	1.28***	1.28***	1.28***	1.28***
First stage SE.	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)

The standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts. The dependent variables presented in each column refer to the percentage point change. The mean of the dependent variables is for the variables in levels rather than in deltas. The 2SLS refers Singapore’s robot exposure that is used as a the shift-share instrument used as a first stage regression. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors in parentheses.

result to be indicative of the rise of political polarization. On the other hand, the results also suggest that there is a decline in abstention by 0.09 percentage points which feeds in the rise of the vote share towards both the Right and Left vote parties. We extend our results to the presidential elections presented in table 3. We deduce from the results that there is some susceptibility for polarization at the presidential elections level as well. A one percentage point increase in $\Delta RobotExposure$ in South Korea decreases abstention by 0.07 percentage points. This decline feeds in the rise of both the right as well as the Center-Left vote shares by 0.04 and 0.07 percentage points respectively.

Despite the fact that no similar studies exist neither for South Korea in particular nor for Asia in general, these results are considered as novel to the literature. [Frey et al. \(2018\)](#) found evidence that supporting the former US President Trump was higher in the local labour markets more exposed to robots adoption, and [Anelli et al. \(2019\)](#) found a positive correlation between exposure to robot adoption at the individual level and Right-wing party voting. According to our results, there is a rise in both Right-wing and Left-wing parties happening simultaneously. Recent research related to the impact of robotization on labour market outcomes (such [Acemoglu and Restrepo, 2020](#); [Acemoglu et al., 2020](#); [Chiacchio et al., 2018](#); [Dauth et al., 2017](#)), show that possible mechanisms at play are likely related to the displacement effect of automation on workers. However, the literature related to the impact of automation on political outcomes does not attempt to explore the mechanisms at play. This is primarily due either to the difficulty in attributing the actual drivers of voting

behavior to being exposed to automation at the individual level and to data limitation issues. We believe that we are among the first to attempt to disentangle some of the mechanisms possibly driving the polarization in the results that we got. The mechanisms for each of the presidential and parliamentary outcomes are discussed under the channels section.

In order to disentangle the mechanisms driving the results, we run a number of heterogeneity analysis at the district level. More precisely, we rerun the same IV regressions after restricting the districts to the ones that have a higher than the *median* level of individuals i) for the low, middle, high skilled degree or, ii) those working in manufacturing, services, employed in robot industry or, iii) those whose employment level of age cohorts range from 20 to 60 years old. The rationale behind this heterogeneity analysis is that the districts with a more prevalent group of the aforementioned people who are typically impacted by the presence of robot adoption would give us an idea about their tendencies towards a given political spectrum rather than the other. This would in turn help us decipher the group of individuals who are potentially driving the results. The heterogeneity analysis is being done both at the parliamentary and the presidential levels separately.

2.5.1 Parliamentary

Table 4: The Parliamentary Elections IV for Districts with an Above Median Employment Share age 20

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00147 (0.00143)	-0.00373 (0.0197)	-0.00695*** (0.00182)	0.0874*** (0.0314)	-0.0555** (0.0242)	0.00273** (0.00132)	-0.130*** (0.0340)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	34.38	34.38	34.38	34.38	34.38	34.38	34.38
First stage Coeff.	2.923***	2.923***	2.923***	2.923***	2.923***	2.923***	2.923***
First stage SE.	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)

The standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts. The dependent variables presented in each column refer to the percentage point change. The mean of the dependent variables is for the variables in levels rather than in deltas. The 2SLS refers Singapore's robot exposure that is used as a the shift-share instrument used as a first stage regression. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors in parentheses.

Table 5: The Parliamentary Elections IV for Districts with an Above Median Employment Share age 50

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00230 (0.00148)	0.0249 (0.0166)	-0.00283** (0.00137)	-0.0252 (0.0195)	0.0226** (0.00941)	0.00269* (0.00139)	-0.0830*** (0.0288)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	36.55	36.55	36.55	36.55	36.55	36.55	36.55
First stage Coeff.	2.793***	2.793***	2.793***	2.793***	2.793***	2.793***	2.793***
First stage SE.	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 6: The Parliamentary Elections IV for Districts with an Above Median Manufacturing Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00180 (0.00178)	0.0267 (0.0165)	-0.00587*** (0.00135)	0.0172 (0.0255)	-0.0217* (0.0131)	0.00493*** (0.00164)	-0.105*** (0.0377)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	33.41	33.41	33.41	33.41	33.41	33.41	33.41
First stage Coeff.	3.07***	3.07***	3.07***	3.07***	3.07***	3.07***	3.07***
First stage SE.	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 7: The Parliamentary Elections IV for Districts with an Above Median Employment Share in Robot Industry

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00619 (0.00509)	0.0354* (0.0199)	-0.00412*** (0.00128)	-0.0262 (0.0255)	0.0123 (0.0172)	0.00233** (0.00109)	-0.104*** (0.0369)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	57.27	57.27	57.27	57.27	57.27	57.27	57.27
First stage Coeff.	2.871***	2.871***	2.871***	2.871***	2.871***	2.871***	2.871***
First stage SE.	(0.379)	(0.379)	(0.379)	(0.379)	(0.379)	(0.322)	(0.379)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

The polarized results we got at the parliamentary level raise an important question: who could possibly be the group of individuals voting for the Right-wing parties and who are the ones voting for the Left wing parties? In an attempt to answer this question, the tables below focus on the districts with an above median level of a certain group of individuals. On one hand, Table 2.6.1 considers the impact of robot exposure on the voting outcomes at the different South Korean political spectrum levels for districts with a prevalent rate of young workers who happen to be of 20 years old of age. The results show that they tend to move away from Right-wing parties (decline by 0.05 percentage points in the Right-wing vote shares) towards more Center-Right parties (increase in the vote shares by 0.08 percentage points). They exhibit a decline in their abstention shares by 0.13 percentage points meaning that they tend to participate in the voting process. These results are significant at the 5 percent significance level.

On the other hand, table 14 considers the impact of robot exposure on voting outcomes at the different South Korean political spectrum levels for districts with a high rate of old-aged workers of 50 years of age. The table shows that these districts tend to have a rise in Right-wing vote share by 0.02 percentage points. This rise in Right-wing voting is stemming from the decline in the center vote share by 0.002 percentage points and mostly by the decline in abstention share by 0.08 percentage points significant at the 5 percent level. The results highlight that that older workers tend to increase their participation in the political scene. However, looking at the results of both tables and that of 14, we find that there exists a gap between the younger and older generation in terms of how they believe political

parties could cater for their demands. It is indeed the case that older generations are more susceptible to be replaced by robots once robots are set in place at work,¹⁶ they buy in the Right-wing parties rhetoric and believe that the Right-wing parties are better able to offer them compensations and favourable solutions for their degrading situations.¹⁷ Districts with a high number of workers in both the manufacturing sector and the robot industry as per tables 15 and 16 tend to have a decline in both abstention and Center vote shares at the 5 percent levels as well as an increase in the nullified vote shares by 0.004 and 0.002 percentage points respectively.

2.5.2 Presidential

Table 8: Instrumental Variables of the Presidential Elections: Above Median Low Skilled Employment The Parliamentary Elections IV for Districts with an Above Median Employment Share in Robot Industry

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta Robot Exposure_{d,t}$	-0.00491* (0.00283)	0.0749** (0.0298)	-0.000261*** (6.79e-05)	0.0220*** (0.00520)	-4.05e-05 (3.18e-05)	-0.000746*** (0.000178)	-0.0339* (0.0198)
Observations	159	159	159	159	159	159	159
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	104.6	104.6	104.6	104.6	104.6	104.6	104.6
First stage Coeff.	1.342***	1.342***	1.342***	1.342***	1.342***	1.342***	1.342***
First stage SE.	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

¹⁶See table 2 of the first chapter.

¹⁷Older generations who are worse off due to robot adoption at the workplace favour Right-wing parties who call for economic stability without having to endure drastic social changes or having to resort to opening South Korea to foreign migrants. However, younger workers cast their vote for Left-wing parties for the different measures they implement to ensure the mitigation of adverse effects of robot adoption on vulnerable population (Shimbun, 2022; Harrison et al., 2023; Shin and Jeon, 2022).

Table 9: Instrumental Variables of the Presidential Elections: Above Median Manufacturing Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00298** (0.00150)	0.0656*** (0.0242)	-0.000159 (0.000147)	0.0128 (0.00969)	-6.12e-06 (1.18e-05)	-0.000675*** (0.000140)	-0.0289* (0.0152)
Observations	136	136	136	136	136	136	136
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	263.9	263.9	263.9	263.9	263.9	263.9	263.9
First stage Coeff.	1.373***	1.373***	1.373***	1.373***	1.373***	1.373***	1.373***
First stage SE.	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 10: Instrumental Variables of the Presidential Elections: Above Median Services Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00410** (0.00159)	0.0675*** (0.0187)	-0.000121 (0.000116)	0.0156** (0.00676)	-1.79e-05 (1.65e-05)	-0.000508*** (0.000171)	-0.0396*** (0.0149)
Observations	237	237	237	237	237	237	237
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	144.9	144.9	144.9	144.9	144.9	144.9	144.9
First stage Coeff.	1.357***	1.357***	1.357***	1.357***	1.357***	1.357***	1.357***
First stage SE.	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 11: Instrumental Variables of the Presidential Elections: Above Median Employment Age 20

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.0165*** (0.00520)	0.222*** (0.0714)	-9.13e-05 (0.000119)	0.0335** (0.0137)	-0.000127* (7.04e-05)	-0.000557 (0.000721)	-0.152*** (0.0373)
Observations	118	118	118	118	118	118	118
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	7.542	7.542	7.542	7.542	7.542	7.542	7.542
First stage Coeff.	1.349***	1.349***	1.349***	1.349***	1.349***	1.349***	1.349***
First stage SE.	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 12: Instrumental Variables of the Presidential Elections: Above Median Employment Age 30

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00378*** (0.00143)	0.0906*** (0.0231)	-0.000202 (0.000332)	0.00158 (0.00638)	-1.17e-05 (3.69e-05)	-0.000705** (0.000288)	-0.0284* (0.0156)
Observations	132	132	132	132	132	132	132
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	193.5	193.5	193.5	193.5	193.5	193.5	193.5
First stage Coeff.	1.579***	1.579***	1.579***	1.579***	1.579***	1.579***	1.579***
First stage SE.	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

We repeat the same heterogeneity analysis for the same set of groups of individuals per districts for the presidential elections. The main results of the impact of robot adoption on the presidential elections show a rise in the Right-wing vote shares as well as the Center-Left vote shares. We do not consider these results to be hinting at polarization at the presidential elections level but rather as a very susceptible case for polarization in the future.

Table 17 shows an increase in Center-Left vote shares by 0.07 percentage points following an increase in robot exposure by 1 percentage points in districts with a high fraction of low

skilled workers. The same results are consistent in table 18 and 19 in districts with high shares of manufacturing as well as services sector workers, these districts witness an increase in Center-Left vote shares by 0.065 and 0.067 percentage points respectively. Given that the manufacturing sector is the most exposed to robot adoption followed by the services sector, it is believed that the vote shares of individuals working in these sectors would be more towards the Right-wing parties according to the literature mostly studying European contexts. However, we see different results in the South Korean case and we believe it has to do with parties belonging to the Center-Left and what they propose as policies.

Districts with high shares of young workers aged 20 and 30 are depicted in table 20 and 21 respectively. The results show an increase in Center-Left vote shares and a decline in Left-wing vote shares.¹⁸ These results highlight that younger workers who are not exposed to robot adoption prefer the Center parties, specifically the Center-Left parties. In South Korea, there is a trend that older workers are more exposed to robotization rather than younger ones. Connecting this with our results, our heterogeneity analysis provide evidence that there is a possible negative effect of robotization on labor market outcomes. Therefore, the group more exposed to robotization (older generation) expresses their resentment via their votes for Right-wing parties.

2.6 Mechanisms

In order to disentangle the mechanisms driving the results, we run a number of heterogeneity analysis at the district level. More precisely, we rerun the same IV regressions after restricting the districts to the ones that have a higher than the *median* level of individuals i) for the low, middle, high skilled degree or, ii) those working in manufacturing, services, employed in robot industry or, iii) those whose employment level of age cohorts range from 20 to 60 years old. The rationale behind this heterogeneity analysis is that the districts with a more prevalent group of the aforementioned people who are typically impacted by the presence of robot adoption would give us an idea about their tendencies towards a given political spectrum rather than the other. This would in turn help us decipher the group of individuals who are potentially driving the results. The heterogeneity analysis is being done both at the parliamentary and the presidential levels separately.

¹⁸Additional tables of the heterogeneity analysis by age cohorts are available in the appendix. No significant results are present for 40, 50 and 60 years old age cohorts.

2.6.1 Parliamentary

Table 13: The Parliamentary Elections IV for Districts with an Above Median Employment Share age 20

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00147 (0.00143)	-0.00373 (0.0197)	-0.00695*** (0.00182)	0.0874*** (0.0314)	-0.0555** (0.0242)	0.00273** (0.00132)	-0.130*** (0.0340)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	34.38	34.38	34.38	34.38	34.38	34.38	34.38
First stage Coeff.	2.923***	2.923***	2.923***	2.923***	2.923***	2.923***	2.923***
First stage SE.	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)

The standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts. The dependent variables presented in each column refer to the percentage point change. The mean of the dependent variables is for the variables in levels rather than in deltas. The 2SLS refers Singapore's robot exposure that is used as a the shift-share instrument used as a first stage regression. Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses.

Table 14: The Parliamentary Elections IV for Districts with an Above Median Employment Share age 50

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00230 (0.00148)	0.0249 (0.0166)	-0.00283** (0.00137)	-0.0252 (0.0195)	0.0226** (0.00941)	0.00269* (0.00139)	-0.0830*** (0.0288)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	36.55	36.55	36.55	36.55	36.55	36.55	36.55
First stage Coeff.	2.793***	2.793***	2.793***	2.793***	2.793***	2.793***	2.793***
First stage SE.	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)	(0.462)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 15: The Parliamentary Elections IV for Districts with an Above Median Manufacturing Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00180 (0.00178)	0.0267 (0.0165)	-0.00587*** (0.00135)	0.0172 (0.0255)	-0.0217* (0.0131)	0.00493*** (0.00164)	-0.105*** (0.0377)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	33.41	33.41	33.41	33.41	33.41	33.41	33.41
First stage Coeff.	3.07***	3.07***	3.07***	3.07***	3.07***	3.07***	3.07***
First stage SE.	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)	(0.461)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 16: The Parliamentary Elections IV for Districts with an Above Median Employment Share in Robot Industry

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00619 (0.00509)	0.0354* (0.0199)	-0.00412*** (0.00128)	-0.0262 (0.0255)	0.0123 (0.0172)	0.00233** (0.00109)	-0.104*** (0.0369)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	57.27	57.27	57.27	57.27	57.27	57.27	57.27
First stage Coeff.	2.871***	2.871***	2.871***	2.871***	2.871***	2.871***	2.871***
First stage SE.	(0.379)	(0.379)	(0.379)	(0.379)	(0.379)	(0.322)	(0.379)

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

The polarized results we got at the parliamentary level raise an important question: who could possibly be the group of individuals voting for the Right-wing parties and who are the ones voting for the Left wing parties? In an attempt to answer this question, the tables below focus on the districts with an above median level of a certain group of individuals. On one hand, Table 2.6.1 considers the impact of robot exposure on the voting outcomes at the different South Korean political spectrum levels for districts with a prevalent rate of young workers who happen to be of 20 years old of age. The results show that they tend to move away from Right-wing parties (decline by 0.05 percentage points in the Right-wing vote shares) towards more Center-Right parties (increase in the vote shares by 0.08 percentage

points). They exhibit a decline in their abstention shares by 0.13 percentage points meaning that they tend to participate in the voting process. These results are significant at the 5 percent significance level.

On the other hand, table 14 considers the impact of robot exposure on voting outcomes at the different South Korean political spectrum levels for districts with a high rate of old-aged workers of 50 years of age. The table shows that these districts tend to have a rise in Right-wing vote share by 0.02 percentage points. This rise in Right-wing voting is stemming from the decline in the center vote share by 0.002 percentage points and mostly by the decline in abstention share by 0.08 percentage points significant at the 5 percent level. The results highlight that that older workers tend to increase their participation in the political scene. However, looking at the results of both tables and that of 14, we find that there exists a gap between the younger and older generation in terms of how they believe political parties could cater for their demands. It is indeed the case that older generations are more susceptible to be replaced by robots once robots are set in place at work,¹⁹ they buy in the Right-wing parties rhetoric and believe that the Right-wing parties are better able to offer them compensations and favourable solutions for their degrading situations.²⁰ Districts with a high number of workers in both the manufacturing sector and the robot industry as per tables 15 and 16 tend to have a decline in both abstention and Center vote shares at the 5 percent levels as well as an increase in the nullified vote shares by 0.004 and 0.002 percentage points respectively.

¹⁹See table 2 of the first chapter.

²⁰Older generations who are worse off due to robot adoption at the workplace favour Right-wing parties who call for economic stability without having to endure drastic social changes or having to resort to opening South Korea to foreign migrants. However, younger workers cast their vote for Left-wing parties for the different measures they implement to ensure the mitigation of adverse effects of robot adoption on vulnerable population (Shimbun, 2022; Harrison et al., 2023; Shin and Jeon, 2022).

2.6.2 Presidential

Table 17: Instrumental Variables of the Presidential Elections: Above Median Low Skilled Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00491* (0.00283)	0.0749** (0.0298)	-0.000261*** (6.79e-05)	0.0220*** (0.00520)	-4.05e-05 (3.18e-05)	-0.000746*** (0.000178)	-0.0339* (0.0198)
Observations	159	159	159	159	159	159	159
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	104.6	104.6	104.6	104.6	104.6	104.6	104.6
First stage Coeff.	1.342***	1.342***	1.342***	1.342***	1.342***	1.342***	1.342***
First stage SE.	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 18: Instrumental Variables of the Presidential Elections: Above Median Manufacturing Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00298** (0.00150)	0.0656*** (0.0242)	-0.000159 (0.000147)	0.0128 (0.00969)	-6.12e-06 (1.18e-05)	-0.000675*** (0.000140)	-0.0289* (0.0152)
Observations	136	136	136	136	136	136	136
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	263.9	263.9	263.9	263.9	263.9	263.9	263.9
First stage Coeff.	1.373***	1.373***	1.373***	1.373***	1.373***	1.373***	1.373***
First stage SE.	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 19: Instrumental Variables of the Presidential Elections: Above Median Services Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00410** (0.00159)	0.0675*** (0.0187)	-0.000121 (0.000116)	0.0156** (0.00676)	-1.79e-05 (1.65e-05)	-0.000508*** (0.000171)	-0.0396*** (0.0149)
Observations	237	237	237	237	237	237	237
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	144.9	144.9	144.9	144.9	144.9	144.9	144.9
First stage Coeff.	1.357***	1.357***	1.357***	1.357***	1.357***	1.357***	1.357***
First stage SE.	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 20: Instrumental Variables of the Presidential Elections: Above Median Employment Age 20

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.0165*** (0.00520)	0.222*** (0.0714)	-9.13e-05 (0.000119)	0.0335** (0.0137)	-0.000127* (7.04e-05)	-0.000557 (0.000721)	-0.152*** (0.0373)
Observations	118	118	118	118	118	118	118
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	7.542	7.542	7.542	7.542	7.542	7.542	7.542
First stage Coeff.	1.349***	1.349***	1.349***	1.349***	1.349***	1.349***	1.349***
First stage SE.	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)	(0.491)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 21: Instrumental Variables of the Presidential Elections: Above Median Employment Age 30

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
$\Delta RobotExposure_{d,t}$	-0.00378*** (0.00143)	0.0906*** (0.0231)	-0.000202 (0.000332)	0.00158 (0.00638)	-1.17e-05 (3.69e-05)	-0.000705** (0.000288)	-0.0284* (0.0156)
Observations	132	132	132	132	132	132	132
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	193.5	193.5	193.5	193.5	193.5	193.5	193.5
First stage Coeff.	1.579***	1.579***	1.579***	1.579***	1.579***	1.579***	1.579***
First stage SE.	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

We repeat the same heterogeneity analysis for the same set of groups of individuals per districts for the presidential elections. The main results of the impact of robot adoption on the presidential elections show a rise in the Right-wing vote shares as well as the Center-Left vote shares. We do not consider these results to be hinting at polarization at the presidential elections level but rather as a very susceptible case for polarization in the future.

Table 17 shows an increase in Center-Left vote shares by 0.07 percentage points following an increase in robot exposure by 1 percentage points in districts with a high fraction of low skilled workers. The same results are consistent in table 18 and 19 in districts with high shares of manufacturing as well as services sector workers, these districts witness an increase in Center-Left vote shares by 0.065 and 0.067 percentage points respectively. Given that the manufacturing sector is the most exposed to robot adoption followed by the services sector, it is believed that the vote shares of individuals working in these sectors would be more towards the Right-wing parties according to the literature mostly studying European contexts. However, we see different results in the South Korean case and we believe it has to do with parties belonging to the Center-Left and what they propose as policies.

Districts with high shares of young workers aged 20 and 30 are depicted in table 20 and 21 respectively. The results show an increase in Center-Left vote shares and a decline in Left-wing vote shares.²¹ These results highlight that younger workers who are not exposed to robot adoption prefer the Center parties, specifically the Center-Left parties. In South

²¹Additional tables of the heterogeneity analysis by age cohorts are available in the appendix. No significant results are present for 40, 50 and 60 years old age cohorts.

Korea, there is a trend that older workers are more exposed to robotization rather than younger ones. Connecting this with our results, our heterogeneity analysis provide evidence that there is a possible negative effect of robotization on labor market outcomes. Therefore, the group more exposed to robotization (older generation) expresses their resentment via their votes for Right-wing parties.

2.7 Robustness Checks

Table 22: The Impact of Robot Adoption on Parliamentary Elections: Using a synthetic Instrumental Variable that includes Germany, Japan and Singapore.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	7.794 (5.315)	-2.653 (14.09)	-0.525 (0.651)	-14.62 (21.03)	10.25 (14.19)	-0.0963 (0.139)	-14.75 (20.85)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	6.327	6.327	6.327	6.327	6.327	6.327	6.327
First stage Coeff.	0.083**	0.083**	0.083**	0.083**	0.083**	0.083**	0.083**
First stage SE.	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 23: The Impact of Robot Adoption on Parliamentary Elections: Using an Instrumental Variable that includes Germany.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-53.91 (81.07)	75.46 (110.7)	-0.344 (0.645)	-27.59 (39.91)	19.28 (28.87)	0.254 (0.432)	-34.53 (42.77)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	0.698	0.698	0.698	0.698	0.698	0.698	0.698
First stage Coeff.	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
First stage SE.	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 24: The Impact of Robot Adoption on Parliamentary Elections: Using an Instrumental Variable that includes Japan.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.288 (4.908)	7.912 (14.49)	-0.516 (0.554)	-16.92 (19.90)	11.88 (13.69)	-0.0614 (0.112)	-17.97 (17.49)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	1.669	1.669	1.669	1.669	1.669	1.669	1.669
First stage Coeff.	0.097	0.097	0.097	0.097	0.097	0.097	0.097
First stage SE.	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 25: The Impact of Robot Adoption on Presidential Elections: Using a synthetic Instrumental Variable that includes Germany, Japan and Singapore.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.0130 (0.0287)	0.578 (0.552)	0.00376 (0.00338)	0.136 (0.301)	0.261 (0.229)	0.0156 (0.0144)	-0.692 (0.836)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	4.24	4.24	4.24	4.24	4.24	4.24	4.24
First stage Coeff.	1.160**	1.160**	1.160**	1.160**	1.160**	1.160**	1.160**
First stage SE.	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 26: The Impact of Robot Adoption on Presidential Elections: Using an Instrumental Variable that includes Germany.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.0614* (0.0339)	1.649 (1.558)	0.00847 (0.0166)	0.315 (1.739)	-0.364 (1.609)	0.0142 (0.0315)	-1.938 (2.338)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	7.044	7.044	7.044	7.044	7.044	7.044	7.044
First stage Coeff.	0.270***	0.270***	0.270***	0.270***	0.270***	0.270***	0.270***
First stage SE.	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 27: The Impact of Robot Adoption on Presidential Elections: Using an Instrumental Variable that includes Japan.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.0116 (0.0293)	0.499 (0.563)	0.00326 (0.00262)	0.133 (0.266)	0.324 (0.223)	0.0187 (0.0191)	-0.512 (0.757)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	4.24	4.24	4.24	4.24	4.24	4.24	4.24
First stage Coeff.	0.479***	0.479***	0.479***	0.479***	0.479***	0.479***	0.479***
First stage SE.	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Tables 28 and 31 present the results of running the main instrumental variables regression after having changed the IV to a synthetic one that includes Germany, Japan and Singapore's industrial and regional employment shares. In Tables 29, 30, 32 and 33, we replace Singapore – that is our main IV in the regression specification – with Germany and Japan respectively. We find no significant impact of any of these IVs of Tables 28 to 33 on our main outcome variable that is voting outcome for the five-level political spectrum at both the presidential and the parliamentary elections levels. The fact that using a synthetic IV and other country IVs doesn't yield significant results is evidence supporting the plausibility of our main IV that is Singapore. The rationale behind using Singapore as the main IV is that their robot adoption was a shock similar to the South Korean case. In Germany and Japan however, the robot adoption process was a gradual process as per Figure 6. In this case, we consider our main results in Section 2.7 to be robust to using other IVs.

Table 28: The Impact of Robot Adoption on Parliamentary Elections: Using a synthetic Instrumental Variable that includes Germany, Japan and Singapore.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	7.794 (5.315)	-2.653 (14.09)	-0.525 (0.651)	-14.62 (21.03)	10.25 (14.19)	-0.0963 (0.139)	-14.75 (20.85)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	6.327	6.327	6.327	6.327	6.327	6.327	6.327
First stage Coeff.	0.083**	0.083**	0.083**	0.083**	0.083**	0.083**	0.083**
First stage SE.	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 29: The Impact of Robot Adoption on Parliamentary Elections: Using an Instrumental Variable that includes Germany.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-53.91 (81.07)	75.46 (110.7)	-0.344 (0.645)	-27.59 (39.91)	19.28 (28.87)	0.254 (0.432)	-34.53 (42.77)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	0.698	0.698	0.698	0.698	0.698	0.698	0.698
First stage Coeff.	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
First stage SE.	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 30: The Impact of Robot Adoption on Parliamentary Elections: Using an Instrumental Variable that includes Japan.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.288 (4.908)	7.912 (14.49)	-0.516 (0.554)	-16.92 (19.90)	11.88 (13.69)	-0.0614 (0.112)	-17.97 (17.49)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.06	0.35	0.006	0.34	0.12	0.015	0.743
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	1.669	1.669	1.669	1.669	1.669	1.669	1.669
First stage Coeff.	0.097	0.097	0.097	0.097	0.097	0.097	0.097
First stage SE.	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 31: The Impact of Robot Adoption on Presidential Elections: Using a synthetic Instrumental Variable that includes Germany, Japan and Singapore.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
$\Delta RobotExposure_{d,t}$	-0.0130 (0.0287)	0.578 (0.552)	0.00376 (0.00338)	0.136 (0.301)	0.261 (0.229)	0.0156 (0.0144)	-0.692 (0.836)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	4.24	4.24	4.24	4.24	4.24	4.24	4.24
First stage Coeff.	1.160**	1.160**	1.160**	1.160**	1.160**	1.160**	1.160**
First stage SE.	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)	(0.612)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 32: The Impact of Robot Adoption on Presidential Elections: Using an Instrumental Variable that includes Germany.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
<i>$\Delta RobotExposure_{d,t}$</i>	-0.0614* (0.0339)	1.649 (1.558)	0.00847 (0.0166)	0.315 (1.739)	-0.364 (1.609)	0.0142 (0.0315)	-1.938 (2.338)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	7.044	7.044	7.044	7.044	7.044	7.044	7.044
First stage Coeff.	0.270***	0.270***	0.270***	0.270***	0.270***	0.270***	0.270***
First stage SE.	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table 33: The Impact of Robot Adoption on Presidential Elections: Using an Instrumental Variable that includes Japan.

VARIABLES	$\Delta Left$ (1)	$\Delta CenterLeft$ (2)	$\Delta Center$ (3)	$\Delta CenterRight$ (4)	$\Delta Right$ (5)	$\Delta Nullified$ (6)	$\Delta Abstention$ (7)
<i>$\Delta RobotExposure_{d,t}$</i>	-0.0116 (0.0293)	0.499 (0.563)	0.00326 (0.00262)	0.133 (0.266)	0.324 (0.223)	0.0187 (0.0191)	-0.512 (0.757)
Observations	1,584	1,584	1,584	1,584	1,584	1,584	1,584
Mean DV level	0.016	0.37	0.002	0.35	0.16	0.009	0.37
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	4.24	4.24	4.24	4.24	4.24	4.24	4.24
First stage Coeff.	0.479***	0.479***	0.479***	0.479***	0.479***	0.479***	0.479***
First stage SE.	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Tables 28 and 31 present the results of running the main instrumental variables regression after having changed the IV to a synthetic one that includes Germany, Japan and Singapore's industrial and regional employment shares. In Tables 29, 30, 32 and 33, we replace Singapore – that is our main IV in the regression specification – with Germany and Japan respectively. We find no significant impact of any of these IVs of Tables 28 to 33 on our main outcome variable that is voting outcome for the five-level political spectrum at both the presidential

and the parliamentary elections levels. The fact that using a synthetic IV and other country IVs doesn't yield significant results is evidence supporting the plausibility of our main IV that is Singapore. The rationale behind using Singapore as the main IV is that their robot adoption was a shock similar to the South Korean case. In Germany and Japan however, the robot adoption process was a gradual process as per Figure 6. In this case, we consider our main results in Section 2.7 to be robust to using other IVs.

2.8 Conclusion

This paper investigates the impact of robotization on the voting behavior of the workers in South Korea. Departing from previous works which mainly focused on the shift of voting outcome towards extreme parties (Anelli et al., 2019), we explore all political parties in South Korea, synthesizing them into five-political clusters. By doing so, our study provides more precise information on how voters' political inclination has changed. Furthermore, to increase the precision of our analysis, we construct an instrumental variable based on the robot adoption rate in Singapore. As South Korea is a leading country in terms of robotization, we pay particular attention on our IV construction. Acemoglu and Restrepo (2020) and Dauth et al. (2021) employ the *number* of robots that are adopted by the more advanced robotized countries as for their IV construction. In our study, we more focus on the *trend* of robot adoption of Singapore based on the circumstance that Singapore has sharply accelerated its robotization (steeper than South Korea during our observation period); and finally exceeded the number of installed robots of South Korea.

Our empirical results confirm that robotization causes political polarization in South Korea. Our results from parliamentary elections demonstrate that the parties closer the Center have been less popular; the voters have moved toward Right and Left-wing votes. The presidential election outcomes show a certain degree of susceptibility for polarization as well. In both elections, we verify that higher robot adoption causes reduction of voting abstention. We believe that this implies a possible negative effect of robotization on labor market outcomes; it promotes workers' desire to express their resentment against robot adoption at their workplace. Our following analysis on mechanisms supports this conjecture.

To comprehend the impetus of our main outcome, we conduct a number of heterogeneity analysis. We run the same IV regression for a multitude of sub-samples to see which sub-group drives the political polarization strongly. We divide our observations into higher

(lower) than the median level of: skill level, sectors, and employment level of ages. Based on the analysis, we conclude that the political polarization is mainly driven by conflicts between generations as robotization impacts two generations differently. Workers from the older generation (above 40s) are more exposed to robotization than from younger generation. Considering that more aged (younger) group has a tendency to vote for Right (Left) parties, we deduce the possible negative effect of robotization on the older generation. Our rationale behind of this conjecture is based on the finding from [Anelli et al. \(2019\)](#) and [Anelli et al. \(2021\)](#) in which the authors discover that public resentment towards possible threats to their jobs is expressed through voting for the Right-wing parties. We believe that older generations are the groups who have been disadvantaged from robotization; therefore, they have an inclination to vote for Right-wing parties.

Our finding suggests two main political implications. First, our study provides an evidence of possible causes of polarization. In the context of our study, the generational conflict is expressed as a political polarization. Particularly, this generation conflict is attribute to robotization. In other words, the South Korean society has a major problem embedded in its younger versus older generations due to robotization at the workplace. As a country that accelerates its technology abruptly, the generation gap regarding a new technology is expected. The issue is that the assistance from the government to close this generational gap lacks in South Korea. We believe that once this technological gap between generations is filled, then the political polarization should be less present.

Second, our study demonstrates a possible negative effect of robotization particularly on older generations. We expect that this negative effect aligns with the *displacement effect* of automation.²² This finding implies that the South Korean government needs to take into consideration the possible unemployment problem caused by robotization, especially for the older generations. Considering that South Korea is an aging-population country, the senior public's unemployment problem should be paid enough attention for its future labor market. There are two possible limitations of the current study. First, our specification is at the district level, not at the individual level. As voting decisions are often an individual decision rather than a collective decision, our aggregated outcomes at the district level might underestimate the impact of robotization on individuals' voting behavior. Second, despite our constructed robot exposure measure in the spirit of [Acemoglu and Restrepo \(2020\)](#) and [Dauth et al. \(2021\)](#), we do not have information on the number of adopted robots at the firm level which will be the ideal set up for our study. We believe that our stable instrumental

²²Refer to [Acemoglu and Restrepo \(2020\)](#); [Dauth et al. \(2021\)](#)

variable reduces possible endogeneity issues and renders our results robust. However, using a more detailed data on robot adoption at the firm level could be an avenue for future research.

2.9 Appendix

2.9.1 Tables

Parliamentary Heterogeneity analysis

Table A1: Instrumental Variables of the Parliamentary Elections: Above Median Low Skilled Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	2.491*** (0.436)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00236 (0.00224)	-0.0220 (0.0251)	-0.00844*** (0.00206)	0.0647* (0.0365)	-0.0287 (0.0232)	0.00285 (0.00204)	-0.148*** (0.0461)
Observations	188	188	188	188	188	188	188
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	32.61	32.61	32.61	32.61	32.61	32.61	32.61

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A2: Instrumental Variables of the Parliamentary Elections: Above Median Middle Skilled Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	2.546*** (0.469)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	0.000223 (0.00141)	-0.0183 (0.0147)	-0.00505*** (0.00185)	0.0121 (0.0338)	-0.0134 (0.0144)	0.00146 (0.00114)	-0.0791** (0.0321)
Observations	176	176	176	176	176	176	176
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	29.38	29.38	29.38	29.38	29.38	29.38	29.38

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A3: Instrumental Variables of the Parliamentary Elections: Above Median High Skilled Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	2.414*** (0.443)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00422 (0.00295)	0.0159 (0.0129)	-0.00484*** (0.00161)	0.0108 (0.0287)	-0.0188 (0.0124)	0.00146* (0.000824)	-0.0731*** (0.0170)
Observations	180	180	180	180	180	180	180
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
idstat	5.178	5.178	5.178	5.178	5.178	5.178	5.178
Kleibergen-Paap Wald F stat.	29.58	29.58	29.58	29.58	29.58	29.58	29.58

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A4: Instrumental Variables of the Parliamentary Elections: Above Median Services Share

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	2.99*** (0.308)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00503* (0.00281)	0.0186** (0.00867)	-0.00532*** (0.000894)	0.0239 (0.0175)	-0.0176 (0.0122)	0.00240** (0.00108)	-0.118*** (0.0192)
Observations	281	281	281	281	281	281	281
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	94.35	94.35	94.35	94.35	94.35	94.35	94.35

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A5: Instrumental Variables of the Parliamentary Elections: Above Median Employment Share age 30

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	-0.00511 (0.00372)	0.00190 (0.0202)	-0.00504*** (0.00104)	0.0391 (0.0284)	-0.0270 (0.0183)	0.000907 (0.000908)	-0.0957*** (0.0155)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	82.29	82.29	82.29	82.29	82.29	82.29	82.29

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A6: Instrumental Variables of the Parliamentary Elections: Above Median Employment Share age 40

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	-0.00511 (0.00372)	0.00190 (0.0202)	-0.00504*** (0.00104)	0.0391 (0.0284)	-0.0270 (0.0183)	0.000907 (0.000908)	-0.0957*** (0.0155)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	82.29	82.29	82.29	82.29	82.29	82.29	82.29

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A7: Instrumental Variables of the Parliamentary Elections: Above Median Employment Share age 60

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	2.852*** (0.287)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00946* (0.00560)	0.0303 (0.0224)	-0.00701*** (0.00160)	-0.00717 (0.0278)	-0.00944 (0.0138)	0.00331 (0.00245)	-0.142*** (0.0437)
Observations	163	163	163	163	163	163	163
Mean DV	0.017	0.372	0.0017	0.397	0.103	0.008	0.408
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	98.77	98.77	98.77	98.77	98.77	98.77	98.77

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Presidential Heterogeneity analysis

Table A8: Instrumental Variables of the Presidential Elections: Above Median Middle Skilled Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.237*** (0.121)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00403 (0.00267)	0.0444 (0.0428)	0.000106 (6.77e-05)	0.0214* (0.0121)	1.17e-05 (3.64e-05)	-0.000438** (0.000206)	-0.0448** (0.0220)
Observations	153	153	153	153	153	153	153
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	103.0	103.0	103.0	103.0	103.0	103.0	103.0

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A9: Instrumental Variables of the Presidential Elections: Above Median High Skilled Employment

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.317*** (0.109)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00422 (0.00295)	0.0159 (0.0129)	-0.00484*** (0.00161)	0.0108 (0.0287)	-0.0188 (0.0124)	0.00146* (0.000824)	-0.0731*** (0.0170)
Observations	180	180	180	180	180	180	180
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	29.58	29.58	29.58	29.58	29.58	29.58	29.58

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A10: Instrumental Variables of the Presidential Elections: Above Median Employment in Robot Industry

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.344*** (0.173)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.000657 (0.00129)	0.0502* (0.0267)	-0.000292 (0.000243)	-0.0101** (0.00489)	-7.10e-06 (2.83e-05)	-0.000374 (0.000259)	-0.00859 (0.0114)
Observations	134	134	134	134	134	134	134
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	59.78	59.78	59.78	59.78	59.78	59.78	59.78

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A11: Instrumental Variables of the Presidential Elections: Above Median Employment Age 40

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.183*** (0.135)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00145 (0.00223)	-0.00308 (0.0402)	6.81e-06 (6.07e-05)	0.0210* (0.0123)	1.97e-05 (3.47e-05)	9.93e-05 (0.000259)	-0.0238 (0.0186)
Observations	142	142	142	142	142	142	142
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	76.31	76.31	76.31	76.31	76.31	76.31	76.31

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A12: Instrumental Variables of the Presidential Elections: Above Median Employment Age 50

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.596*** (0.152)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00238 (0.00161)	0.0398* (0.0238)	9.65e-05* (5.32e-05)	-0.00303 (0.00697)	3.10e-06 (2.15e-05)	-1.07e-05 (0.000188)	-0.0225* (0.0134)
Observations	128	128	128	128	128	128	128
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	110.3	110.3	110.3	110.3	110.3	110.3	110.3

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

Table A13: Instrumental Variables of the Presidential Elections: Above Median Employment Age 60

VARIABLES	$\Delta Left$	$\Delta CenterLeft$	$\Delta Center$	$\Delta CenterRight$	$\Delta Right$	$\Delta Nullified$	$\Delta Abstention$
<i>First Stage</i>							
$\Delta RobotExposure_{Singapore,t}$	1.145*** (0.298)						
<i>Second Stage</i>							
$\Delta RobotExposure_{d,t}$	-0.00731 (0.00529)	0.0879 (0.0629)	-7.85e-05 (0.000210)	0.00892 (0.0123)	-7.70e-05 (8.26e-05)	-0.000402 (0.000411)	-0.0567 (0.0372)
Observations	134	134	134	134	134	134	134
Mean DV	0.066	0.339	0.007	0.343	0.141	0.0140	0.827
2SLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald F stat.	14.77	14.77	14.77	14.77	14.77	14.77	14.77

Note:*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Standard errors are clustered at the district level. The district controls include night light density, high skilled rate, middle skilled rate, 50 and 60 age cohorts

2.9.2 Figures

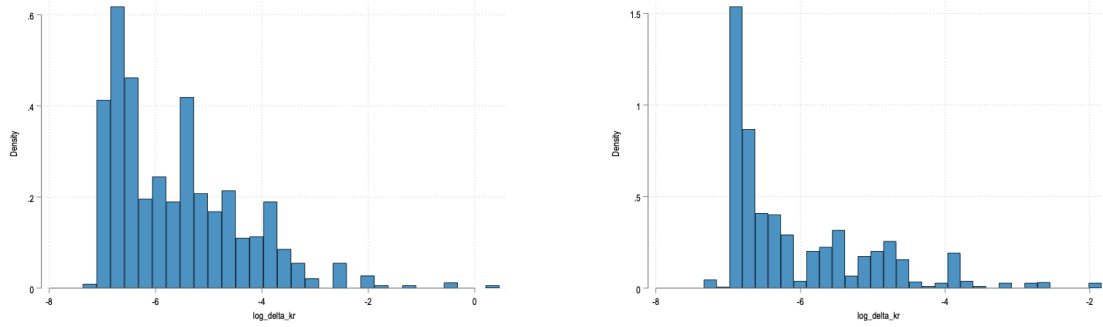


Figure A1: Delta Robot Exposure distribution for Presidential elections on LHS - Parliamentary on RHS

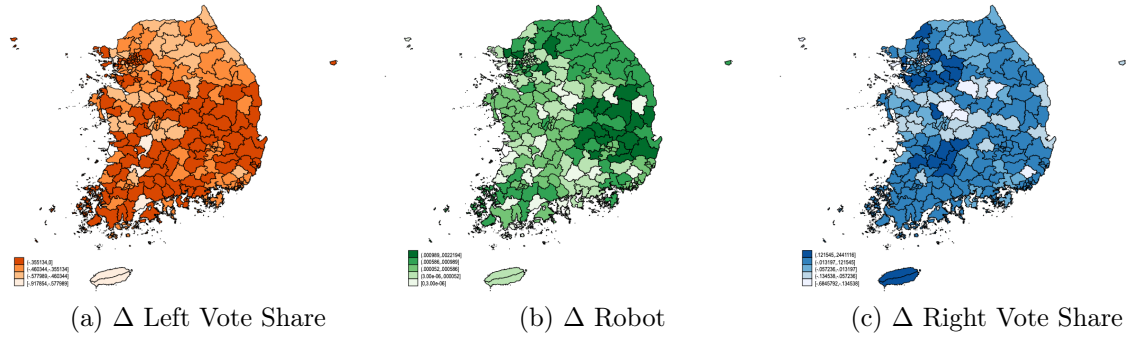


Figure A2: The 2000-2004 Parliamentary Elections Delta Vote Shares

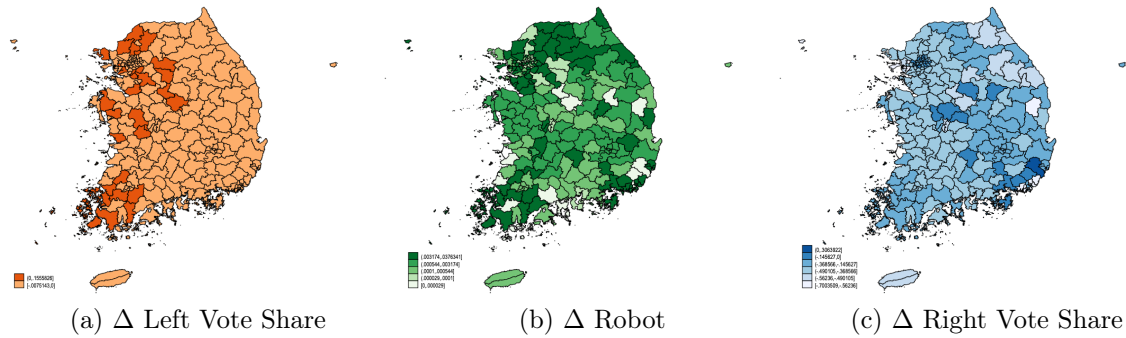


Figure A3: The 2004-2008 Parliamentary Elections Delta Vote Shares

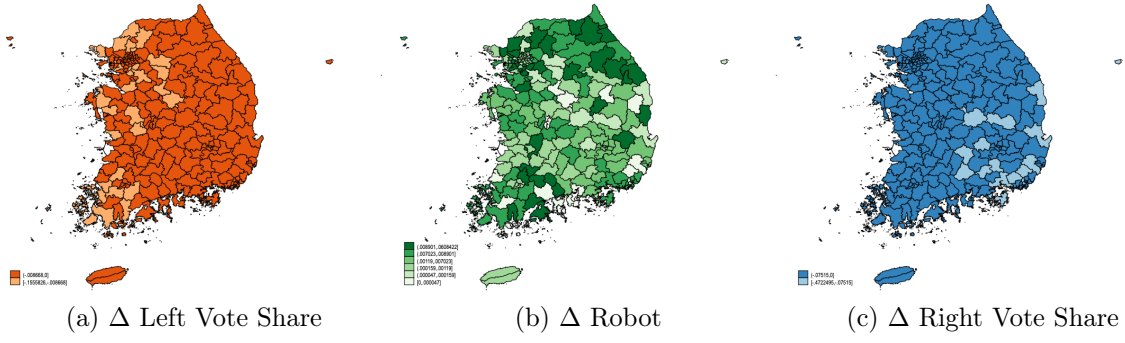


Figure A4: The 2008-2012 Parliamentary Elections Delta Vote Shares

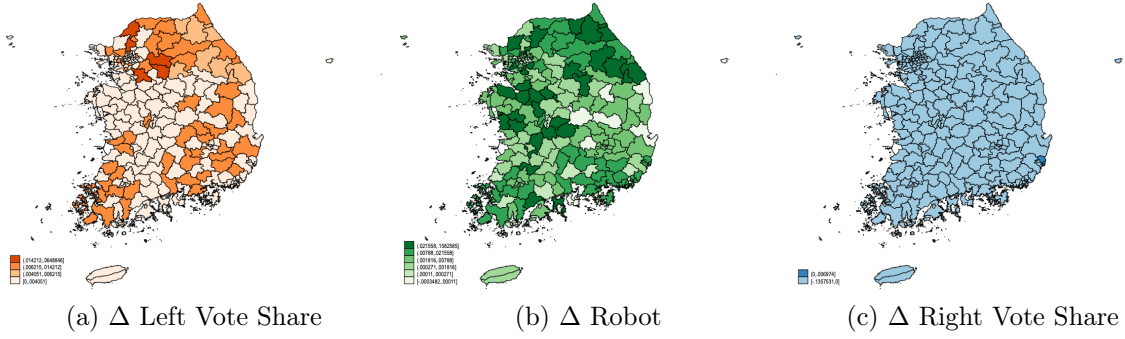


Figure A5: The 2012-2016 Parliamentary Elections Delta Vote Shares

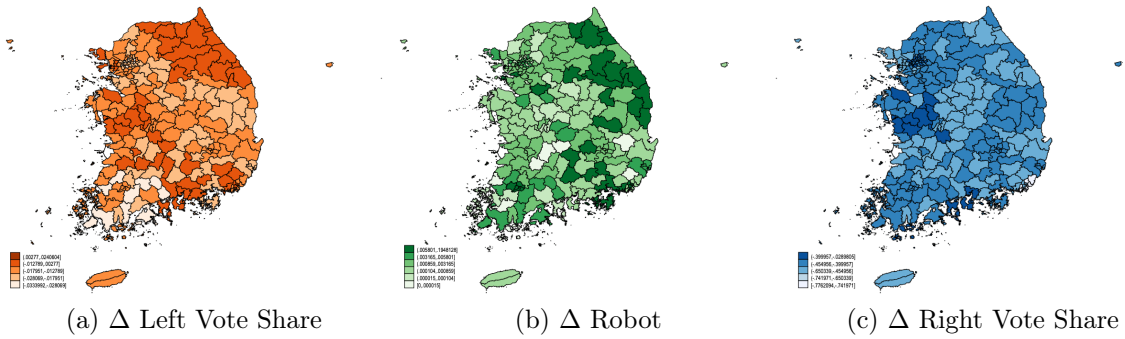


Figure A6: The 2002-2007 Presidential Elections Delta Vote Shares

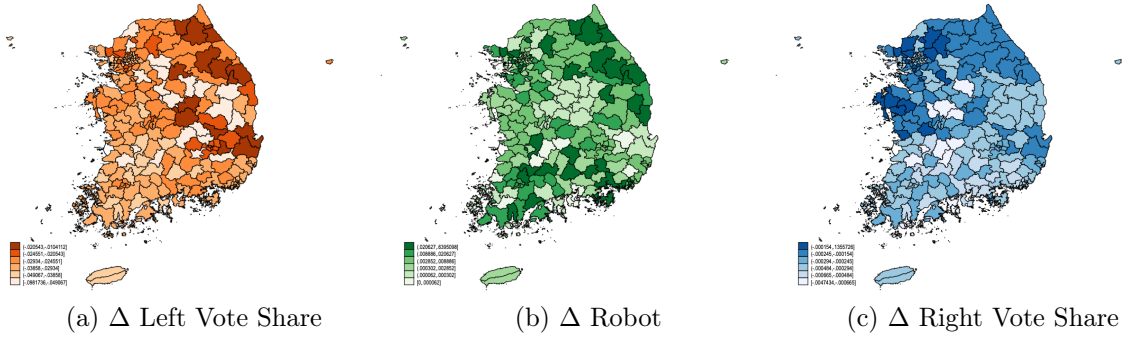


Figure A7: The 2007-2012 Presidential Elections Delta Vote Shares

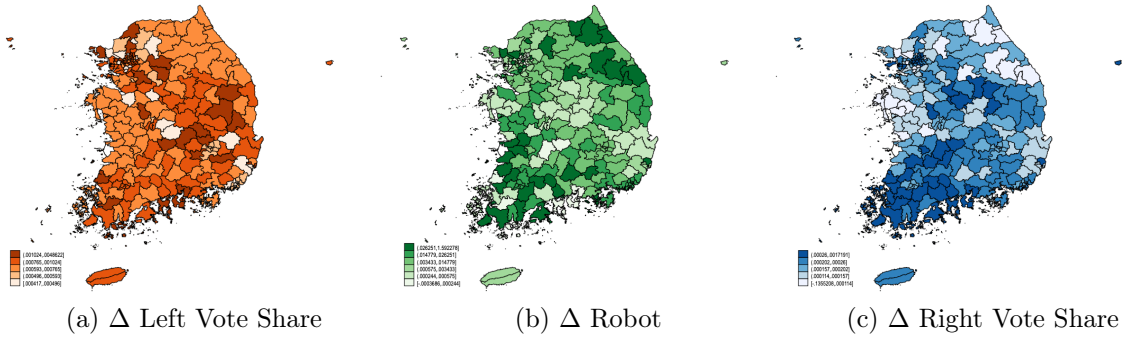


Figure A8: The 2012-2017 Presidential Elections Delta Vote Shares

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Chapter 3

Droughts and Voting Behavior: Evidence from Tunisia

Using a novel dataset in a difference-in-differences framework, I study the political implications of the change in policies protecting drought-impacted communities in Tunisia in 3088 districts. In 2016, the Tunisian government had drastically reduced support to farmers affected by droughts. I show that this resulted in lower vote share for the incumbent candidate in the second round of the 2019 presidential elections. The magnitudes are substantial: a one standard deviation increase in the district-level damage caused by droughts after the policy change leads to a decline in the incumbent's vote share by 10 percentage points. I show that the likely mechanism is the rise of public discontent: the drought-affected districts had a higher number of riots or violent protests relative to the policy change. I find no significant effects either on voter turnout, closeness to incumbent party at the parliamentary elections or on trust in political parties at the parliament.

3.1 Introduction

Climate change and environmental challenges have long been a topic of intense debate for researchers and policymakers in developed countries, but more so in developing countries that face the negative effects while lacking the necessary natural disasters coping and prevention mechanisms.¹ A major climate change issue, characterized by its gradual-onset is drought

¹According to the World Health Organization [WHO \(2023\)](#), around 2 billion people don't have access to drinking water and 600 million are subject to foodborne diseases on a yearly basis, with 30% children under

(rainfall deficiency occurring over an extended period of time, ([NASA Earth Observatory, 2024](#)). Droughts are considered to be the most serious threat negatively affecting 55 million people worldwide on a yearly basis ([WHO, 2024](#)). It is true that droughts are exogenous shocks in nature, but their heavy economic disturbances spark an immediate call – from the citizens side – for governmental interventions.

Tunisia serves as a notable example of a country that has been grappling with recurrent droughts for decades. Despite the severity of the Tunisian drought phases, the Tunisian government has implemented measures since the 1980s that have helped in managing and mitigating their negative effects. One of the key forms of government support is the issuance of drought declaration decrees, which are officially published in government journals. These decrees are essential as they provide a formal acknowledgment of the extent to which agricultural lands in various districts have been impacted by drought. For farmers, these declarations are particularly critical. They provide access to government assistance aimed at alleviating the financial burdens that drought impose. Specifically, farmers who are directly affected by these drought conditions benefit from a favorable rescheduling of their existing loans. The government provides large banks in Tunisia with the needed resources. This process is facilitated by these banks, which extend the repayment period of these loans up to five years, while maintaining the original interest rates.²

This financial relief is vital for farmers, as it provides them with the necessary breathing space to recover from the losses incurred by prolonged periods of insufficient rainfall. Through these measures, the Tunisian government has played a pivotal role in helping its agricultural sector cope with recurring challenges posed by drought. As for the rest of the Tunisian districts' residents, they are indirectly benefiting from the governmental drought declarations given that this allows for an estimate of districts' degree of exposure to drought. If the residents of the districts know the degree of exposure of their districts to droughts (i.e. the detrimental effects of drought on their districts), they would be able to keep track of the food shortages they will face thus, will be able to anticipate the needed imports and can prevent potential price hikes as a result.

From 2016 to 2019, Tunisia has experienced severe drought spells; that is lack of rainfall leading to losses in agricultural production. This severe drought was coupled with the suspension of drought declaration decrees due to government's financial constraints, leading

⁵ bearing more prone to foodborne fatalities. It is estimated that in 2020, 770 million people faced famine in Africa and Asia. Climate change has a negative impact on food availability, quality leading to nutrition and health crises.

²This is a case by case situation that depends on the profile of the farmer at the bank.

to a rise in discontent among the Tunisian people, that manifests itself in the form of violent protests and a decline in incumbent vote share during the presidential elections. However, the government resumed the release of drought decrees as of 2020. The reason for the removal of the drought decrees during the three consecutive years prior to 2020 was unannounced to the people. In other words, the removal of drought decrees is considered to be an unexpected event facing the inhabitants of the Tunisian districts – farmers and the rest of the inhabitants alike – despite the severe drought that hit Tunisia during these years.³

Furthermore, the removal of the drought declaration policy coincided with a pivotal transitional period towards democracy. Tunisia held the second parliamentary and presidential elections in 2019. Following the Arab Spring wave in the Middle East, Tunisia held the first elections in 2014. While the first elections were being held in Tunisia in 2014, the drought declarations were still available to the public and compensations were granted to farmers. In 2019 however, drought declarations and relevant compensations were already cut as of the year 2016. This setting provides an ideal opportunity for the public to hold their political leaders accountable for the consequences of drought neglect through voting at the polls during elections.

Therefore, I study in this paper the impact of the abandonment of a drought declaration policy – an unanticipated policy change at the district level – on the within district within period change in presidential elections results in Tunisia. I extract from the drought declaration decrees the percentage of damage happening to agricultural land areas in order to create an intensive margin drought damage variable, as a proxy of drought at the district level indicating the percentage of agricultural area damage. The drought damage variable is my main explanatory variable in a difference-in-differences framework where incumbent’s vote share is the main outcome variable.

For the purpose of this study, I use a novel dataset on drought declarations from Tunisia’s official journals along with l’Instance Supérieure Indépendante pour les Élections (ISIE) for the voting data for the years 2014 and 2019. I further use geospatial datasets for district level characteristics from AidData’s geospatial data repository. The channels explaining the results consist of looking at the impact of the removal of drought declaration on citizens’ public discontent.

³Serrano (2023), Al-Estiklal Newspaper (2022) and Gafrej (2021) shed light on the on-going debates in the media on the severity of droughts, the role of the government in producing drought declarations, people’s discontent with the removal of these declarations and blaming the president for the negligence of drought issues in Tunisia.

I use riots as a proxy of people’s discontent. Datasets on riots in Tunisia are from the Armed Conflict Location and Events data (ACLED). The results are robust to changing the drought damage variable – that is the main continuous treatment variable in the diff-in-diff framework – from a pre-removal variable to a post-removal variable. Moreover, the results are robust to changing the drought damage treatment variable altogether to using the Normalized Difference Vegetation Index (NDVI) variable that is another proxy of drought damage.

I find that a one standard deviation increase in drought damage following the policy removal would lead to a decline in incumbent’s vote share by 10.24 percentage points in districts more prone to drought spells compared with the less prone ones. The mechanisms driving the results pertain to people’s public discontent with the performance of the government with regards to drought management. I use riots as a proxy for public discontent and find that drought damage leads to a rise in riots by all residents per district by 3 percentage points as well as a rise in farmers’ riots by 6 percentage points. The results are in line with the premise that in a hybrid democracy, the president is held accountable for the performance of the government.⁴

Using the parliamentary elections as a placebo, I find no impact of drought declarations removal on parliamentary elections results. I further investigate the impact of the drought declaration removal on whether the Tunisians perceive people to be trustworthy⁵ and their satisfaction with the performance of the government. I find no impact of the policy removal shock on perceptions of interpersonal trust. However, I find that a one standard deviation increase in drought damage post policy removal reduces satisfaction with the incumbent government’s performance by 2.2 percentage points in districts more likely to have droughts compared with the ones with less frequent droughts.

The results are robust to using drought damage post shock - extracted from official drought decrees for the years 2020 and 2021.⁶ Some important policy implications of this study relate to the importance of ensuring information transparency especially when a governmental support policy such as the drought compensation policy is being removed. In addition, the role of the private sector, when it comes to drought compensations and insurance, needs to be increased under the auspices of the government.

⁴This may be due to the weakly-performing and unrepresentative political parties that push voters towards punishing the incumbent at the presidential elections level, disregarding the parliamentary one as in [Conconi et al. \(2024\)](#).

⁵More information on cabinet change can be found in Section 6.

⁶More information on the NDVI variable can found in Section 8.

The rest of the paper is organized as follows: Section 3.2 summarizes the related literature and the contribution of this paper to it, Section 3.3 describes the institutional context: mainly the political situation in Tunisia, the drought situation and the governmental policies to support drought-impacted communities. Section 3.4 and Section 3.5 present the empirical strategy and data sources respectively, Section 3.6 discusses the results, analyzes the mechanisms driving the results and provides a number of robustness checks. Finally, Section 3.7 concludes.

3.2 Literature Review

There is a growing body of research focused on understanding the relationship between natural disasters compensation policies and election outcomes, particularly how experiencing a climate-related event influences the vote share of incumbents. Studies have produced varying results, with some suggesting that natural disasters can significantly impact electoral outcomes, while others find the effects to be minimal or inconsistent. This lack of agreement highlights the complexity of the issue and the numerous factors that can influence how voters perceive and respond to their government’s handling of climate-related challenges. A number of papers show results on voters favouring the incumbent in some cases, while they can also be against him in others.

The political economy literature on climate change shows that following a natural disaster and conditional on having disaster relief, voters tend to reward the incumbent in elections as in (Cavalcanti, Francesco, 2018; Bastos and Miller, 2013). In their paper, Bastos and Miller (2013) use a parametric framework, where they add a three order polynomial on the regression of the relative margin of candidate’s victory in elections. They show that releasing drought declarations 2 years before elections in Brazil leads to a higher probability of the incumbent being reelected. Using rainfall as an instrumental variable for a disaster compensation policy in Japan, Fukumoto and Kikuta (2024) find that disaster compensation increases support for the political party in power in line with the “egotropic retrospective voting” behavior. According to Achen and Bartels (2004) and Bován et al. (2018) “egotropic retrospective voting” stipulates that incumbents’ vote share increase (decline) during elections because the voters benefiting (suffering) from the provision (removal) of climatic events relief packages tend to reward (punish) them during election times. In other words, the phenomena of “egotropic retrospective voting” fuels a general satisfaction (dissatisfaction) with the incumbent and occurs when the governmental response is deemed efficient (inefficient)

in compensating the losers following a natural disaster. [Ashworth et al. \(2018\)](#) further highlights that this is the case given that voters tend to vote less for the incumbent when facing exogenous climate shocks. My results overlap with that of the “egotropic retrospective” literature. Furthermore, the drought declaration policy removal studied in this paper is another addition to the literature that has mostly been focusing on targeting drought relief around election times.

My contribution to the literature extends to the data that I am using for this study; I use a novel dataset as a proxy for drought damage using drought declaration decrees extracted from official Tunisian journals. In particular, I use the percentage of agricultural land damage due to drought before the policy removal as my main continuous treatment variable. The data used in the literature to study the impact of droughts on voting outcomes are either drought indices or rainfall average variation over a long period of time at least 30 years as in [Tarquinio \(2022\)](#). I abstract from using rainfall and resort to using a proxy for lack of rainfall closely reflecting Tunisia’s main problem that is severe drought spells that negatively impact agricultural output.

To the best of my knowledge, this is the first paper that attempts to look at possible mechanisms linking a climate policy shock with voting outcomes. I show that the lack of adequate policy response to droughts results in public discontent (which I proxy for by riots). I contribute to the literature on climate and conflict stipulating that drought shocks coupled with drought declaration removals result in the rise of riots or violent protests as in the work of [Decet and Marcucci \(2023\)](#) and [Adhvaryu et al. \(2021\)](#). In this paper, riots increase from both the farmers and the rest of the residents living in the districts impacted by drought because of citizen’s general public discontent with the persistence of drought spells while drought relief is no longer provided for them. According to [Decet and Marcucci \(2023\)](#), droughts in Africa are correlated with violent conflicts in rural areas due to precipitation scarcity that renders river and lake water access essential.

In addition, strong developed democratic institutions are capable of mitigating such conflicts by developing the needed water redistribution and infrastructure. [Adhvaryu et al. \(2021\)](#) and [McGuirk and Burke \(2017\)](#) provide evidence from Africa that presents the correlation between natural resources and conflicts. They provide a model that explains that economic prosperity is only possible in case of equilibrium conflict prevalence depending on a region’s own resources and those of their neighboring regions. The better the institutional qualities, the less likely there will be a conflict equilibrium. The results of this paper confirm the findings of [Adhvaryu et al. \(2021\)](#) and [McGuirk and Burke \(2017\)](#) by showing that democracy

can channel people’s public discontent – riots also increase – during election times. This discontent manifests itself in the form of a decline in incumbent’s vote share. It is expected that the better the democratic institutions are, the less likely that riots or conflicts occur.

The literature on the determinants of voting attitudes has focused on either climate change mitigation or prevention policies specifically designed around election times to gain people’s support as in [Tarquinio \(2022\)](#). [Tarquinio \(2022\)](#) studies the impact of drought relief targeting on ruling party incumbency and electoral competition in a number of Indian states using a regression discontinuity design and an instrumental variables approach. This paper studies the removal of a compensation policy following a drought shock, which is considered as a contribution to the literature mostly focused on time-targeting drought policies before elections rather than their complete removal.

3.3 Institutional Background

3.3.1 Political Situation

Table 1: Tunisian Presidential Elections in 2014 and 2019

Pres. Election Year	2014	2019
Winning Candidate’s Name	Beji Caid Essebsi	Kaies Saied
Winning Candidate’s Party	Nidaa Tounes	Non-partisan
Winning Candidate’s Pol. Spectrum	Center to Center-left	Center to Center-left
Opponent’s Name	Moncef Marzouki	Nabil Karoui
Opponent’s Party	Congress for the Republic	Heart of Tunisia
Opponent’s Pol. Spectrum	Center-left to Left	Center

Tunisia’s democratic transition started with the revolution triggered by a young street vendor’s self-immolation on December 27, 2010. This pivotal moment in history rippled across the Middle East, inspiring people to demand better living conditions. On the macroeconomic level, the Tunisian economy was performing well right before the revolution thanks to improved harvests, an increase in exports and investments. However, the economics gains were highly concentrated among the upper and upper-middle classes of the capital Tunis as well as some other coastal regions, leaving a large group of population of different regions and

classes behind ([World Bank, 2023](#); [Observatoire National de l'Emploi et des Qualifications \(ONEQ\), 2013](#)).

Agriculture policies were aimed at Coastal crops while leaving the south with little investment creating major disparities between the Coastal and Southern regions in terms of public services and infrastructure ([Masri, 2017](#)). Additionally, unemployment rates were above 30 percent in the decade prior to the revolution; an unprecedented level compared with Tunisia's average that is around 14 percent. It is estimated that around 50 percent of the unemployed hold either master's degrees or technical degrees, 31 percent were engineers and 70 percent were technicians ([Honwana, 2013](#)).

Following the revolution, Tunisia turned into a semi-presidential regime where the president is the head of state and the prime minister is responsible for the government. Tunisia is a pioneer country in the region in embracing political pluralism resulting in the creation of more than 70 parties belonging to a representative range of political spectrum.⁷

According to the Economist Democracy Index 2022, Tunisia is classified as a "hybrid regime" indicating that it is a democracy with weaknesses pertaining to the state capacity, the rule of law and the strength of political parties.⁸

Tunisia's presidential elections take place every five years. The president is elected by universal suffrage for a five year term. A first round of elections is being held and if no candidate gets more than 50% of the vote in the first round, then there would be a second-round for the top two finishers. A president can only serve two terms. The parliamentary elections are also held every five years using party-list proportional representation on closed lists and seats are distributed on the constituencies on the basis of the largest remainder method ([The Elecoral Knowledge Network, 2014b,a](#)). The first fair presidential and parliamentary elections were held in 2014.

The 2014 presidential elections consisted of two rounds; none of the candidates got more than 50% of the vote shares. In the first round, the two candidates who got the majority of the votes were: Beji Caid Essebsi and Moncef Marzouki, with 39% and 33% vote shares respectively. In the second round, Essebsi got 55.7% of the vote shares to become the president of Tunisia until 2019.⁹ This paper focuses on the presidential elections of 2014 and

⁷Following the 2011 revolution, political parties started to develop at a high pace. The parties formed were either small in size and fragmented or big parties with structural and leadership issues deeming the functioning of the parties below the expectations of the citizens ([Ottaway, 2021](#)).

⁸This is explained in further details in [Gherib \(2012\)](#).

⁹[Markey et al. \(2023\)](#) provide the details of the events surrounding the elections.

2019 in Tunisia. The president from 2014 to 2019, Beji Caid Essebsi, was a prominent figure from the political party *Nidaa Tounes*, which is positioned from the center to the center-left on the political spectrum.

Essebsi's tenure was marked by policies and ideologies aligned with this centrist stance. His opponent Moncef Marzouki was part of the *Congress for the Republic* party that is a secular leftist party. The political landscape shifted in 2019 with the election of Kais Saied, an independent, non-partisan candidate. Despite his independence from any political party, Saied's policies and rhetoric indicate a continuation of the center to center-left political spectrum, similar to his predecessor. Saied's references are drawn from leftist ideologies of Councilism as well progressive populist movements in the west and South America according to [Nafti \(2024\)](#).

Saied's priorities have been further reflected on his policy decisions and public statements, signaling his alignment with the broader principles of social justice and equity that characterized his predecessor's administration. The president's political inclinations are evident in his consistent advocacy for workers' rights and his strong commitment to preserving social equality following his predecessor. A number of social protection policies have been carried out under the incumbency of Essebsi and continued to do so under that of president Saied. A prominent example is the social assistance program aiming at supporting the vulnerable groups in Tunisia as well as poverty alleviation. The social assistance program involves health care, pension schemes and food subsidy provisions ([Carnegie Endowment for International Peace, 2022](#)).

In addition, Essebsi and Saied both carried out policies that enhance public sector employment as a main priority to overcome the rise of unemployment in Tunisia ([International Monetary Times, 2023](#)). Therefore, the main outcome variable in this paper is based on the alignment of Saied's political spectrum with that of Essebsi, it represents the vote share for the convergence of the political spectrum of both the 2014 and the 2019 presidents in Tunisia. It is worth noting that the opponent to president Saied, Nabil Karoui, was part of the *Heart of Tunisia* party that is of a centrist nature.

Following the death of Essebsi in 2019, presidential elections had to take place within 90 days after his death as per the Constitution. In the second round of the newly called elections, Kais Saied won to become president with a 72.7% while Nabil Karoui got 27.3% of the total vote shares. Kais Saied was running for the 2019 presidential elections as an independent candidate; he was not part of any political party at the time of the elections.

Table 1 provides a comparison between the 2014 and the 2019 incumbent as well as opponent presidents in terms of their political parties and political spectrum. As for the first round of the 2019 presidential elections, there were 26 candidates, belonging to different political parties, running for the first round of the 2019 presidential elections. 8 candidates out of the 26 were independent – were not part of any political party – Kais Said is one of them. Among the 8 independent candidates, 2 were supported by some political parties: Safi Said who was supported by *the People’s movement* party and Abbdelkrim Zbidi who was backed up by *Nidaa Tounes* (Fanack, 2019; Wikipedia, 2019).¹⁰

3.3.2 Droughts in Tunisia and Drought Declaration Decrees

Tunisia is a North-African country, covering around 16 million hectares or 63,170 square miles. Its North-East side overlooks the Mediterranean sea, with Libya and Algeria are located on its South and East sides respectively. Rainfall is an essential factor for Tunisia’s agricultural sector. It is estimated that on average, precipitation is below 100 millimeters a year in the Southern parts while it is above 1000 millimeters a year in the Northern regions. Tunisia’s summer weather is hot and dry while in the winter, it is cool and humid (Thabet et al., 1994; Kayouli, 2000).

According to the International Fund for Agricultural Development (IFAD), agriculture remains a pivotal sector, contributing nearly 10% to GDP and providing employment for around 16% of the workforce in Tunisia. However, agriculture remains a core sector in the economy. An agricultural land area that is considerably small (less than 10 percent of the total area) of a given crop would lead to around 35% of agricultural production, 20% exports and a workforce not less than 27% according to Mansour and Hachicha (2014). Agricultural land in Tunisia is divided by crop type where grains such as wheat and barley as well as olives together cover around 87% of the total: grains with 43% and olives with 44%. The remaining 17% is allocated between forage crops, vegetable crops, legumes that have 7%; 3% and 2.5% respectively.

Projections indicate that by 2025, drought is expected to decrease crop cultivation by approximately 30 percent. Drought conditions in Tunisia have recently worsened, affecting

¹⁰The most recent presidential elections took place on October 6th, 2024. There were 3 main candidates: Kais Said (independent candidate), Zouhair Maghzaoui (People Mouvement paty) and Ayachi Zammel (Azimou party and a strong opponent of Kais Said). Kais Said won the elections with a 90,69% vote share followed by Ayachi Zammel who got 7,35% and Zouhair Maghzaoui with a 1,97% vote share (Wikipedia, 2024; ISIE, 2024).

the entire country with increasing severity. The Food and Agricultural Organization (FAO) reports a particularly high frequency of severe droughts in the Northern-Central regions of Tunisia. Severe drought is defined as a prolonged period of insufficient rainfall that results in significant agricultural output losses. In other words, Tunisia's agriculture sector is impacted by drought but at varying degrees depending on the region where the agricultural land is located and on the cultivated crop's dependency on rainfall. Agricultural land area where grains are cultivated is heavily dependent on rainfall and is mostly concentrated in the Northern-Central regions of Tunisia where 47% of the total land area cultivated is located in the Northern regions, while 53% is in the Central ones. As for the cultivation of olives, it is located in the Central and Southern regions of Tunisia contributing to 87% of the total cultivated land area ([Atlas, 2024](#)).

Since the 1980s, the Tunisian Ministry of Agriculture has addressed these droughts by issuing official drought declaration decrees, that are published in the country's Official Journal. These decrees are made accessible to the public both online and in print copies. When the government declares a drought through these decrees, it formally identifies the total agricultural areas within each district that have been adversely affected by drought spells. This declaration indicates government intervention aimed at mitigating the economic impact on farmers. The primary form of support comes from banks, which restructure the loans of farmers whose lands have been damaged by drought. The restructuring extends the loan repayment period by five years, while maintaining the original interest rates. A sudden removal of the drought declaration decrees took place for three consecutive years that happened to be years of severe drought from 2016 to 2019. Severe drought spells are recurrent and government support in the form of drought declarations are provided to alleviate their negative impact. However, the 2016-2019 severe drought spells were unexpectedly not covered by the governmental financial relief.¹¹

This financial relief is crucial for farmers, helping them cope with the significant challenges posed by recurrent drought spells.

Some local Tunisian newspapers have been complaining about this unexpected abandonment of the policy when it was needed the most due to the persistence of drought.¹² Meanwhile, there are a few private insurance companies to substitute for these governmental interventions. On one hand, the removal of this policy constitutes a shock to farmers, who cannot

¹¹[Serrano \(2023\)](#) further highlights people's discontent with the removal of the policy.

¹²[Gafrej \(2021\)](#) highlights this drought management problem that culminated in the sudden removal of the drought declaration decrees without providing the beneficiaries with either alternative compensations or the reason for the unexpected shift in this particular governmental policy.

quantify the extent of agricultural losses they are incurring. On the other hand, this is a shock to all the inhabitants of the district given that there will be difficulties in quantifying the extent of damage caused by drought at the district levels. This would result in food shortages and eventually price hikes. Thus, the removal of drought declarations was an unanticipated event to both the farmers and locals per district.

3.4 Empirical Strategy

This paper aims at studying the impact of the drought declaration removal in 2016 in Tunisia on the 2019 presidential election outcomes. More precisely, I test the hypothesis that the exposure of districts to low rainfall coupled with a removal of drought declarations will lead to a greater decline in incumbent's vote share.

There are several endogeneity concerns. First, the dependent variable might be correlated with unobserved shocks at the district level. An example of such shocks would be internal immigration. Internal immigration happening across Tunisian districts is likely to be due to droughts; district inhabitants might move across districts to escape drought consequences – Thus, impacting voting outcomes at the district level.

A second endogeneity problem would be the omitted variable bias; the data might not be capturing all the confounding factors impacting voting behavior at the district level. Among the relevant confounders not accounted for in the data, there is the varying governance quality per district that differentially impacts the structure of the local economy as well as its performance. Another important confounder may be the influence of access to internet and social media platforms which may have an impact on citizens' perception of their government, thus on their voting behavior, see [Guriev et al. \(2021\)](#).

In order to address these endogeneity issues, I use a standard difference-in-differences framework where the treatment variable is the pre-shock percentage of agricultural land area damage at the district level in Tunisia as a drought proxy. Other diff-in-diff specifications include district and year fixed effects akin to a two-way fixed-effects model as in [Callaway et al. \(2024\)](#).

The empirical strategy is as follows:

$$Y_{d,t} = \alpha + \beta_1 DroughtDamagePre2016_d \times Post2016_t + \gamma_d + \delta_t + X_{d,t} + \epsilon_{d,t} \quad (3.1)$$

The unit of observation is the district level. $Y_{d,t}$ is incumbent's vote share in district d at time t (Essebsi's in 2014 and Saied's in 2019). $DroughtDamagePre2016_d$ is a standardized continuous treatment variable indicating the extent of damage driven by drought at the district level, using data from before 2016 as decreed in the drought declarations. The treatment variable is standardized to be able to interpret the results, however, it does not have an impact on the structure of the treatment variable. Figure A1 is a histogram of the drought damage at the finest district level in Tunisia variable before and after standardization. The figure shows a high frequency of the districts with ones and zeros as percentage of damage and a lot of variation in the frequency of exposure among the rest of the districts between one and zero. $Post2016_t$ is a dummy equals 1 if the year is 2019 given that the study includes 2 election years: 2014 and 2019. $X_{d,t}$ is a vector of controls including the GDP per 1km grid cell, distance to road and water, the precipitation level and the population count all at the grid cell level. The total number of observations is 3,088.

In some specifications, γ_d and δ_t , that are district and year fixed effects respectively, are added which absorbs $DroughtDamagePre2016_d$ as well as $Post2016_t$. In other specifications, no fixed effects are added which allows to estimate the impact of each of $DroughtDamagePre2016_d$ and $Post2016_t$ on vote share before interacting them. Finally, $\epsilon_{d,t}$ is the error term clustered at the district level. The maps presented in Figure A2 compare the districts voting for Kaies Saied and the extent of drought damage per district, a slight negative correlation exists. In order to test the mechanisms driving the result, we use the same regression with a different dependent variable, namely, riots as a measure of public discontent.¹³

3.5 Data

The voting data are from the Instance Supérieure Indépendante pour les Élections (ISIE). ISIE is a Tunisian autonomous public body responsible for all operations related to the organization, management and supervision of elections following the Tunisian electoral legislations. ISIE is responsible for vote counting, announcing preliminary and final election results. In compliance with Tunisian electoral laws and constitution mandates, ISIE also provides and oversees election calendars, in addition to other administrative roles aiming at preserving fair elections.

The ISIE data consist of the number of votes per president for the presidential elections

¹³See more details in the data and mechanisms sections.

and the number of votes per political party for the parliamentary elections. I use these data for the years 2014 and 2019 to build a voting share variable that will be the outcome variable. The final dataset includes 3088 observations at the finest district level available. A timeline of the voting data is presented in Figure A3 in the Appendix, showing that the first presidential elections took place in 2014. This is followed by the drought declaration removal, the main event of this paper that spans the years 2016 to 2019 then, the 2019 presidential elections were held.

The drought decrees are extracted from the “ Official Journal of Legal Announcements" for the years 2015 and 2016 to build a novel dataset that includes the percentage of agricultural areas damaged by drought as a proxy of drought damage at the district level. The Journal has as a main aim to publish legal texts. It is available in an online version and in a pdf format downloadable from the official website ([Tunisia Government, 2024](#)). Figure A4 in the appendix provides an example of a drought decree. It includes the names of the districts exposed to droughts at the finest level as well as the percentage of agricultural area damage caused by drought.

The ministry of agriculture declares the percentage of areas damaged per district in these drought decrees. Consequently, the farmers living on the damaged areas will be eligible for a governmental intervention consisting of easing their financial constraints. Banks mediate the governmental funds by rescheduling loans for farmers whose lands are impacted by drought. The rescheduling allows farmers to have loans at the initial interest at which they were granted. This is a case by case process only concerning farmers living in areas impacted by droughts.

I couple this dataset with AidData. AidData is a research lab that provides precise spatial data not only on aid projects but also on practical applications and on investment development. The sources of AidData’s geospatial data are: Population Density and Counts (CIESIN), Precipitation and Temperature (UDEL) and Gross Domestic Product (CIRES) as indicated in [Goodman \(2019\)](#). I use the data for the years 2014 and 2019 which include 1 km grid cell data on precipitation, GDP at the grid cell level (proxied by nighttime lights using the methodology of Goodman 2019), distance to water, distance to road as well as population density. The average number of grid cells per district in Tunisia is 20.

The Armed Conflict Location and Event Data Project (ACLED) is another data source used for this project. According to [Raleigh et al. \(2010\)](#), the data consist of a geospatial mapping of political events and conflict. The ACLED data include the location of the events and the

dates of their occurrence, the participants and whether violent events lead to fatalities. For the purpose of this project, I use the “riots” variable as a proxy of people’s public discontent at the district level. According to [ACLED \(2019\)](#) the variables’ definition of ACLED, riots refer to events where conflict is prevalent among their demonstrators. I make use of the riots variable along with the “actors” variable that refers to the category of individuals involved in the riots. The actors of the riots are the residents per district that happen to be workers or farmers.

I use the ArabBarometer data, that provide individual level cross-sectional public opinion surveys in the Middle East and North Africa (MENA) region, to explore the impact of the policy removal on the general public opinion of the Tunisian people. In particular, I use the third, fourth and fifth waves of the ArabBarometer data for the years 2013, 2016 and 2018 respectively. I collapse the data to get averages of variables at the district-year level. My focus is on two main variables trust in parliament and closeness to incumbent party at the parliamentary level. Table A1 provides the descriptive statistics of the variables used to produce Table 2.

The average drought damage is around 52% in the South regions while it is around 23% in the Northern-Central regions. In addition, the mean log precipitation in the Northern-Central regions is 3.49 slightly less than in the Southern regions that is 3.52. Furthermore, Figure A5 shows a weak and negatively significant correlation of -0.15 between declared drought damage and rainfall. This correlation indicates that the declared drought damage is not only a function of rainfall but also agricultural losses per district.

3.6 Results

3.6.1 Main Results

Table 2: The impact of drought declaration removal on the second round of the presidential elections

Vote Share	(1)	(2)	(3)
Drought Damage $\times$ Post	-0.129*** (0.023)	-0.163*** (0.025)	-0.163*** (0.025)
Observations	3088	3088	3088
Mean DV	0.64	0.64	0.64
R ²	0.348	0.592	0.597
Controls	No	No	Yes
Year FE	No	Yes	Yes
District FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was subject to by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per grid cells (1 km each), the distance of grid cells to roads and water as well as the population count at the grid cell level. The standard errors are clustered at the district level.

Table 3: The impact of drought declaration removal on voter turnout rate

Voter Turnout	(1)	(2)	(3)
Drought Damage $\times$ Post	0.051 (0.048)	-0.022 (0.015)	-0.020 (0.016)
Observations	2145	2140	2140
Mean DV	0.62	0.62	0.62
R ²	0.161	0.712	0.713
Controls	No	No	Yes
District FE	No	Yes	Yes
Year FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was subject to by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per grid cells (1 km each), the distance of grid cells to roads and water as well as the population count at the grid cell level. The standard errors are clustered at the district level.

Table 2 presents the results of estimating equation (3.1). Column 1 depicts the results without any controls, district or year fixed effects. The results of column (1) indicate that a one standard deviation increase in drought damage post 2016 lead to a decline in incumbent vote share by 8.3 percentage points that is 64% of the mean vote share in districts more likely to have droughts compared with the ones less likely to experience them. Column (2) presents the results with district fixed effects aiming at capturing unobserved characteristics not accounted for in the dataset at the district level. Column 3 includes controls, district and year fixed effects which translates into a higher R-squared compared to the other two columns. The results of columns 2 and 3 are the same. Both columns have a result with a magnitude of -0.163 indicating that a one standard deviation increase in drought damage post the 2016 shock leads to 10.24 percentage points decrease in Saied's vote share in districts that are more damaged compared with the ones that are less damaged due to drought, that is 64% of the dependent variable mean.¹⁴

It is important to note that the only difference between column (2) and (3) is that column (3) includes a year fixed effect and the dataset has only 2 years: 2014 and 2019. The results of Table 2 confirm the correlation depicted in Figure A6, that is an attempt to find if there

¹⁴Table A2 illustrates the impact of rainfall on vote results at the presidential elections level. Column(3) shows that there are no significant results after adding year and district fixed effects. These results indicate that the presence of rainfall in itself is not a driver of voting outcomes and that the results of Table 2 are rather caused by the removal of drought declarations not by precipitation levels.

exists a correlation between declared drought damage and delta incumbent vote share – where incumbent here refers to the winning candidate in the 2019 presidential elections, Kaies Saied. This figure does show a weak and negative correlation of -0.31, significant at the 5% significance level.

Column 3 of Table A3 in the appendix presents the coefficients of the controls added in the regression, log GDP per grid cell and log precipitation are both positively and significantly impacting Kaies Saied’s vote share. Table 3 investigates if the drought declaration removal would impact voter turnout. Voter turnout is calculated as the number of signing voters on the day of the election over that of registered voters. I find no significant results on voter turnout at the district level. Table A4 shows that none of the controls have a significant impact on voter turnout either.

3.6.2 Additional Results: Trust in Government and Parliamentary Parties.

Table 5 further looks at the impact of the removal of the drought declarations on people’s perception of the performance of the government. The results indicate that a one standard deviation increase in drought damage post-2016 leads to a decline in the perceived to be satisfactory government performance by 2.2 percentage points in the highly susceptible districts to droughts compared with the less susceptible ones. Drought decrees are usually publicly declared within the months between August and November every year. It is as of the year 2016 that drought decrees were not produced for the year 2016 and the three years to follow. The reason for the removal was not publicly declared to the people. This unanticipated abandonment of the drought policy coincided with the 2016 cabinet change.

Table 4: The impact of drought declaration removal on government performance

Government Performance	Unsatisfactory	Satisfactory
Drought Damage $\times$ Post	0.041 (0.095)	-0.132** (0.063)
Observations	2994	2994
Mean DV	2.46	1.70
R ²	0.186	0.090
District FE	Yes	Yes
Year FE	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level.

In August 2016, a new government was formed under the prime minister Youssef Chahed.¹⁵ Chahed's predecessor, Habib Essid, was dismissed because of the government's inability to deliver economic reforms ([France 24, 2016](#)). I rerun the main regression on Tunisian people's trust in the government formed post-2016 as presented in Table 5. Column 3 includes controls and district fixed effects and highlights that a 1 standard deviation increase in drought declarations post removal leads to an increase in Tunisian people's trust in the 2016 government by 4 percentage points. This result reflects people's high expectations of the new government formed. The results of Table 4 and 5 highlight the negative performance of the government in power prior to the 2016 governmental change, lead to an increase in people's trust in the newly established government post-2016. However, it is important to note that despite the high trust in the post-2016 government, the decline in Saied's vote share in the 2019 presidential elections in Table 2 indicates that the performance of the new government was still not up to the expectations of the people.

¹⁵The prime minister stated that his top priority would be to tackle security issues and to fight corruption. In addition to merging the ministry of Environment with that of Local Affairs but no details on drought management under this new government were stated according to [Business News \(2016\)](#).

Table 5: The impact of drought declaration removal on trust in the post-2016 government

Trust in the post 2016 Government	(1)	(2)	(3)
Drought Damage $\times$ Post	0.138*** (0.046)	0.154*** (0.052)	0.153*** (0.051)
Observations	2994	2994	2994
Mean DV	2.80	2.80	2.80
R ²	0.055	0.127	0.128
District FE	No	Yes	Yes
Controls	No	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was subject to by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per grid cells (1 km each), the distance of grid cells to roads and water as well as the population count at the grid cell level. The standard errors are clustered at the district level.

Table 6: The Impact of the drought declaration removal on interpersonal trust

Interpersonal Trust	High Trust	Little to No Trust
Drought Damage $\times$ Post	0.015 (0.016)	-0.018 (0.016)
Observations	2994	2994
Mean DV	0.15	0.15
R ²	0.098	0.105
District FE	Yes	Yes
Year FE	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level.

Table 6 presents the results for interpersonal trust. The aim of running this regression is to check if citizens' discontent against the government has been affecting trust between the people themselves, not only their trust in their government. The removal of drought declarations has no significant impact on trust between people. Regression 3.1 is run on the parliamentary elections sample to check if voters would punish political parties at the parliamentary elections. Some of the prominent political parties among others are Ennahda, Nidaa Tounes and Popular front. Ennahda is a non-secular Right-wing party emphasizing

religious references for democratic rule. Ennahda won the majority of seats in the 2019 parliamentary elections, while it was the second party to win seats in the 2014 parliamentary elections.

Table 7: The impact of drought declaration removal on parliamentary elections

Vote Share	Ennahda		Nidaa		P.Front	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought Damage $\times$ Post	-0.062 (0.044)	-0.040 (0.032)	-0.019 (0.012)	-0.010 (0.009)	0.003 (0.004)	0.005* (0.003)
Observations	2740	2734	2741	2735	2664	2658
Mean DV	0.19	0.19	0.13	0.13	0.02	0.02
R ²	0.134	0.174	0.280	0.415	0.173	0.226
District FE	No	yes	No	Yes	No	Yes
Year FE	No	yes	No	Yes	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year.

Table 8: The impact of the removal of drought declarations on parliament trust and closeness to incumbent

Outcome Variable	Parliam. Trust	Close to Incumbent
Drought Damage $\times$ Post	-0.005 (0.095)	-0.007 (0.020)
Observations	1432	1961
Mean DV	2.45	0.10
R ²	0.118	0.116
Controls	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level.

Table 7 shows the results of the regression on the vote share for Ennahda, Nidaa Tounes, and the Popular front that constitute around 39% of the vote shares in the 2019 parliamentary elections. The rest of the vote shares are distributed among the other existing and emerging political parties, as well as the independent lists. Each of these parties and lists received a vote share ranging from 0.20% to 4.5%, not exceeding the 5% shares.¹⁶ There is no impact

¹⁶The International Foundation for Electoral Systems (2023) extensively shows the share and seats of votes per party in the 2019 parliamentary elections.

of the removal of the drought policy on parliamentary elections. This result reinforces the idea that the incumbent president is the one to blame in case of an inadequate government response to a climate shock in a context where political parties are institutionally weak. Table 8 repeats the regression 3.1 to check if the removal of drought declarations has an impact on trust in parliament or closeness to the incumbent party at the parliamentary level. The drought declaration policy removal shock does not have a significant impact on either of them. Therefore, it can be deduced that the impact of the policy shock is only relevant at the presidential election level.

3.6.3 Mechanisms

Table 9: The impact of drought declaration removal on riots

Riots	(1)	(2)	(3)	(4)
Drought Damage $\times$ Post	0.094** (0.038)	0.149** (0.068)	0.267** (0.133)	0.081 (0.092)
Observations	1793	660	363	295
Mean DV	0.28	0.40	0.39	0.42
R ²	0.712	0.766	0.831	0.704
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Farmers riots	No	Yes	Yes	Yes
Region	All	All	North-Center	South

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level. All regressions include log rainfall, distance to water, distance to road and mean GDP per capita at the grid cell levels as controls.

In this section, I study the mechanism driving the impact of the policy change on presidential elections. Table 9 presents the results for riots as a proxy of public discontent. Column 1 illustrates the impact of dropping the drought declarations on the prevalence of riots in all Tunisian regions; a one standard deviation increase in drought damage post the 2016 abandonment of the policy leads to an increase in riots by 2.6 percentage points, accounting for 28 percent of the mean dependent variable, in the districts highly-exposed to droughts. It is important to note that column 1 focuses on riots driven by not only farmers but the different sectors of the population within the districts.

The rioters are groups of individuals or mobs not belonging to any organization but who engage in violent demonstrations in a spontaneous way. Column 2 limits the sample to farmers' riots in all the Tunisian regions, the results indicate that a one standard deviation increase in drought damage post removal in the drought-prone regions leads to an increase in farmers' riots by 6 percentage points, that is 40 percent of the mean dependent variable. Column 3 further restricts the sample to riots driven by farmers in the Northern-Central regions; the results of column 1 and 2 are maintained with a much stronger impact in the Northern-Central regions that are more agriculture as well as more densely-populated than their Southern counterparts.¹⁷ Other variables that impact riots are shown in column 4 Table A5, where log grid cell GDP as well as log distance to road both negatively and significantly impact riots per district.

¹⁷To reconcile these results with that of Table 11, the high prevalence of agricultural lands in the Northern-Central Tunisian districts coupled with the high density of population living there increases riots events. In the Southern Tunisian regions, the negative impact of drought spells on cultivated crops are more prevalent than in the Northern-Central regions but it does not spark enough riots because of the low population density. According to [the Institut National de la Statistique \(INS\) \(2022\)](#), the Center-Eastern and North-Eastern Tunisian regions had around 2.8 million and 1.7 million inhabitants respectively in 2022 that is around 40% of the total population.

3.6.4 Robustness Checks

Table 10: The impact of drought declaration removal on voting outcomes: using a drought damage treatment post removal and a pre-period variable

Vote Share	(1)	(2)	(3)
Damage2020 $\times$ Pre	0.080*** (0.028)	0.075*** (0.028)	0.074** (0.029)
Damage2020	-0.042*** (0.010)	- -	- -
Pre	-0.186*** (0.026)	-0.219*** (0.030)	- -
Observations	2910	2910	2830
Mean DV	0.64	0.64	0.64
R ²	0.268	0.523	0.532
Controls	Yes	Yes	Yes
Year FE	No	No	Yes
District FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations covering the agricultural years 2020 and 2021. "Pre" is a dummy equals 1 if the year of election is 2014. The standard errors are clustered at the district level.

Table 11: The impact of drought declaration removal on vote share in round 2 of the presidential elections after restricting the sample to the Northern-Central areas.

Vote Share	North-Center			South		
	(1)	(2)	(3)	(4)	(5)	(6)
Drought Damage $\times$ Post	-0.082*** (0.029)	-0.132*** (0.034)	-0.132*** (0.034)	-0.255*** (0.020)	-0.258*** (0.023)	-0.258*** (0.023)
Observations	1414	1414	1414	1674	1674	1674
Mean DV	0.66	0.66	0.66	0.63	0.63	0.63
R ²	0.127	0.437	0.439	0.709	0.800	0.800
Controls	No	No	Yes	No	No	Yes
District FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is post the year 2016 (the last drought declaration year). The controls include yearly precipitation per district, the GDP per grid cells (1 km each), the distance of grid cells to water and the population count at the grid cell level. The standard errors are clustered at the district level.

Table 12: Impact of Normalized Difference Vegetation Index (NDVI) on Incumbent Vote Share

Vote Share	(1)	(2)	(3)
NDVI pre $\times$ Post	-0.206*** (0.022)	-0.212*** (0.030)	-0.212*** (0.030)
Observations	2581	2581	2581
Mean DV	0.63	0.63	0.63
R ²	0.528	0.679	0.680
Controls	No	No	Yes
District FE	No	Yes	Yes
Year FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level. The NDVI variable is created by aggregating daily data to monthly ones by taking the maximum value. The average of the monthly maximum value is used to calculate the yearly values. The NDVI negative values are truncated to 0 according to aiddata's description of the NDVI variable.

Table 10 presents the results of running regression (3.1) after changing the treatment variable to have it as a post-treatment instead of a pre-treatment as well as having a pre-period variable instead of a post one. I use drought declaration decrees for the years 2020 and 2021

to create the continuous treatment variable. The results of this table are comparable with that of Table A3 in the appendix. The interaction term of this table would be translated as the impact of drought damage in the years 2020 and 2021 during the pre-period (that are years before the policy removal takes place) on vote share for president Essebsi, the 2014 winning presidential candidate. The magnitude of interaction term means that a one standard deviation increase in drought damage post removal would lead to 5.1 percentage points increase in vote share for Essebsi. The interaction term in the first column shares the same magnitude of drought damage of Table A3 which means that the results are robust to changing the years of the drought declarations policies. The overlap of the magnitude of the interaction term with that of this table with that of A3 supports the pre-trends assumption deemed necessary for differences-in-differences regressions.¹⁸

Tunisia's agriculture is mostly concentrated in the country's Northern-Central regions. For this reason, I rerun the main regression after splitting the sample into two: the Northern-Central regions and the Southern regions. Table 11 column 3 and 6 show that an increase in damage caused to agricultural land by 1 standard deviation post the 2016 removal shock, is likely to cause a decrease in Saied's vote share by 8.5 and 16.5 percentage points respectively in the Northern-Center and Southern districts. Despite the fact that agricultural lands are more prevalent in the Northern-Central districts than in the Southern ones, the impact of the policy removal in the Southern districts is more pronounced than in the Northern-Central counterparts. This is likely the case given that the Northern-Central regions have more agricultural lands and more densely-populated therefore, the drought mitigation is more concentrated in this region rather than the Southern ones.

Table 12 is an additional attempt to check if having the Net Vegetation Index (NDVI), as a treatment variable - proxy of drought - replacing the main drought damage, would change the results we get. The NDVI variable is created by aggregating daily data to monthly ones by taking the maximum value. The average of the monthly maximum value is used to calculate the yearly values. The NDVI is used to assess the vegetation greenness and density as well as to monitor plant health. For this reason, the NDVI is considered to be a proxy of drought damage. The results are consistent with the main results in Table 2, where a one standard deviation increase in NDVI pre-shock would lead to a decrease in Saied's vote share by 14.4 percentage points. It is worth noting that the results support the claim that drought declarations were not targeting specific districts or farmers but they were actually

¹⁸The dataset used for this paper consists of two main data points that hinder a testing of the pre-trends assumption. However, this table serves as a possible pre-trends test in the same spirits of the robustness checks regression of [Akhmedov and Zhuravskaya \(2004\)](#).

targeting the districts that were facing drought spells that led to agricultural output losses at the district level.

3.7 Conclusion

Droughts pose a threat to countries in terms of agricultural output losses, food insecurity, conflicts and has implications on elections as well. Inability to protect vulnerable communities may have political implications. This paper establishes a causal link between a drought policy change in Tunisia in 2016 and the results of 2019 presidential elections in a diff-in-diff framework. Tunisia suffers from severe droughts which lead to significant crop losses. Before 2016, the affected farmers were eligible for financial relief. However, as of 2016, this relief was no longer provided to farmers for three consecutive years of severe drought. The damage induced by drought not only concerns farmers but extends to Tunisian residents in the different districts prone to drought. These residents can no longer quantify the extent of agricultural output losses they incurred thus, are unable to track potential food shortages.

Furthermore, Tunisia's political landscape is characterized by a hybrid democratic regime with a multitude of political parties that exert relatively weak influence and exhibit a wide ideological gap from the demands of the populace. The year 2019 marked the second presidential as well as parliamentary elections in Tunisia's history after the revolution and coincided with the removal of the drought declaration and compensation decree. Following the removal of the drought declaration decrees in Tunisia, people's general disapproval of the policy abandonment manifested itself in the rise of riots in the agricultural districts by 2.8 percentage points following a 1 standard deviation increase in district-level damage following the policy change. This general disapproval is partly-driven by farmers who are no longer eligible for compensations of their agricultural losses, while the rest of residents per district cannot keep track of the impact of drought thus, cannot anticipate potential food shortages they are likely to face. Tunisians discontent went beyond rioting in districts to polling centers during election times; by punishing the presidential candidate politically-aligned with his predecessor. These results highlight that despite the fact that democracy in Tunisia is flawed to a great extent. However, Tunisians still believe that democracy is the best way to govern.

Therefore, the Tunisian people would rather punish the incumbent president - by voting for the opponent during presidential elections - than the incumbent party at the parliament if

they deem governmental policies inefficient. Interestingly, the voters have not punished the incumbent parties in the parliamentary election; nor there has been any impact on trust in parties or closeness to them. These results show that in Tunisia's hybrid democratic regime, the public believes that the real policy accountability belongs to the president rather than to the parliament.

Additional findings indicate that the drought policy removal shock did not affect voter turnout or interpersonal trust. However, it did erode trust in the post-2016 government, with a one standard deviation increase in drought damage after the policy change leading to a 4 percentage points decline in trust in the newly-formed government. This decline in trust helps explain the reduction in incumbent's vote share during the presidential elections. It is worth noting that this result explains to a great extent the decline in incumbent's vote share at the presidential elections level. Furthermore, the results are robust to changing the main treatment variable to another variable proxy of drought damage as well as to changing the drought damage variable to a post treatment - for drought spells taking place in 2020 and 2021 - instead of the conventional pre-variable. The study highlights important policy implications, emphasizing the need to ensure information transparency in case of removing government policies that target vulnerable groups of the population such as drought relief policies as well as strengthening the role of the private sector in drought relief provisions.

3.8 Appendix

3.8.1 Tables

Table A1: Descriptive Statistics

	(1) All	(2) North-Center	(3) South
Kais Saied V.S.	0.64 (0.189)	0.66 (0.140)	0.62 (0.221)
Voter turnout	1.09 (1.713)	1.26 (2.083)	0.95 (1.329)
Log precipitation	3.50 (0.438)	3.49 (0.436)	3.52 (0.439)
Percentage of drought damage	38.67 (39.12)	22.98 (31.75)	51.93 (39.86)
Log grid cell GDP	-0.06 (1.523)	0.18 (1.549)	-0.25 (1.473)
Log grid cell population	10.60 (0.649)	10.70 (0.624)	10.52 (0.657)
Log distance to road	7.99 (0.812)	7.79 (0.673)	8.15 (0.878)
Log distance to water	10.13 (1.335)	9.82 (1.187)	10.39 (1.396)
Drought dec. dummy	0.60 (0.490)	0.47 (0.499)	0.71 (0.453)
<i>Observations</i>	3088	1414	1674
mean coefficients; sd in parentheses			
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			

Table A2: The impact of rainfall on voting outcomes at the presidential elections level

Vote Share	(1)	(2)	(3)
Log Rainfall	-0.015 (0.012)	-0.055 (0.047)	-0.051 (0.036)
Observations	3088	3088	3088
Mean DV	0.64	0.64	0.64
R ²	0.001	0.222	0.470
Year FE	No	No	Yes
Ind. FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per 1km grid cell, the distance of grid cells to water and the population count at the grid cell level. The standard errors are clustered at the district level. Log grid cell GDP, log distance to water, log distance to road and log grid cell population are not absorbed by the district fixed effects because these are cell-level variables.

Table A3: The impact of drought declaration removal on vote share in round 2 of the presidential elections

Vote Share	(1)	(2)	(3)
Drought Damage $\times$ Post	-0.129*** (0.023)	-0.163*** (0.025)	-0.163*** (0.025)
Drought Damage	0.074*** (0.017)	- -	- -
Post	0.173*** (0.022)	- -	- -
Log grid cell GDP			-0.189*** (0.067)
Log distance to water			0.037 (0.044)
Log distance to road			-0.171* (0.096)
Log grid cell population			0.058 (0.086)
Log precipitation			0.091*** (0.030)
Observations	3088	3088	3088
Mean DV	0.64	0.64	0.64
R ²	0.348	0.592	0.597
Controls	No	No	Yes
Year FE	No	Yes	Yes
District FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per 1km grid cell, the distance of grid cells to water and the population count at the grid cell level. The standard errors are clustered at the district level. Log grid cell GDP, log distance to water, log distance to road and log grid cell population are not absorbed by the district fixed effects because these are cell-level variables.

Table A4: The impact of drought declaration removal on voter turnout rate

Voter Turnout	(1)	(2)	(3)
Drought Damage $\times$ Post	-0.021 (0.069)	-0.062 (0.083)	-0.066 (0.080)
Drought Damage	-0.034 (0.056)	- -	- -
Post	-0.410*** (0.062)	- -	- -
Log grid cell GDP			-6.784*** (0.227)
Log population			-10.006*** (0.141)
Log distance to road			0.194** (0.081)
Log distance to water			-7.991*** (0.172)
Log precipitation			-0.069 (0.186)
Observations	2458	2453	2453
Mean DV	0.63	0.63	0.63
R ²	0.019	0.177	0.179
Controls	No	No	Yes
District FE	No	Yes	Yes
Year FE	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The controls include yearly precipitation per district, the GDP per grid cells (1 km each), the distance of grid cells to water and the population count at the grid cell level. The standard errors are clustered at the district level. Log grid cell GDP, log distance to water, log distance to road and log grid cell population are not absorbed by the district fixed effects because these are cell-level variables.

Table A5: The impact of drought declaration removal shock on riots

Riots	(1)	(2)	(3)	(4)
Drought Damage $\times$ Post	0.061 (0.058)	0.100** (0.040)	0.045 (0.049)	0.094** (0.038)
Drought Damage	-0.041 (0.055)	- -	-0.025 (0.046)	- -
Post	-0.219*** (0.065)	-0.231*** (0.037)	- -	- -
Log rainfall	-0.119** (0.056)	0.034 (0.044)	-0.133** (0.053)	0.015 (0.038)
Log grid cell GDP	0.024 (0.025)	0.339*** (0.066)	0.029 (0.023)	0.370*** (0.119)
Log grid cell population	0.033 (0.035)	-0.454** (0.179)	0.022 (0.034)	-0.263 (0.280)
Log distance to road	-0.043 (0.043)	0.517*** (0.134)	-0.034 (0.042)	0.526** (0.237)
Log distance to water	0.076*** (0.026)	-0.140*** (0.050)	0.070*** (0.023)	-0.159 (0.097)
Observations	1793	1793	1793	1793
Mean DV	0.28	0.28	0.28	0.28
R ²	0.101	0.642	0.249	0.712
Controls	Yes	Yes	Yes	Yes
District FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The regression includes vote shares for the second round of the presidential elections years 2014 and 2019. "Drought Damage" is a standardized continuous treatment variable indicating the percentage of damage a district was affected by drought, as decreed in the drought declarations. "Post" is a dummy equals 1 if the year is the 2019 election year. The standard errors are clustered at the district level. All regressions include log rainfall, distance to water, distance to road and mean GDP per capita at the grid cell levels as controls. Log grid cell GDP, log distance to water, log distance to road and log grid cell population are not absorbed by the district fixed effects because these are cell-level variables.

3.8.2 Figures

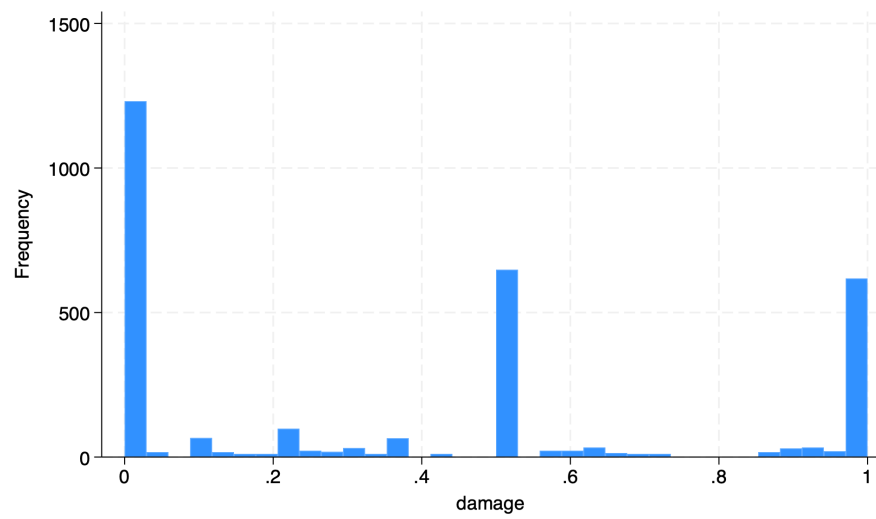
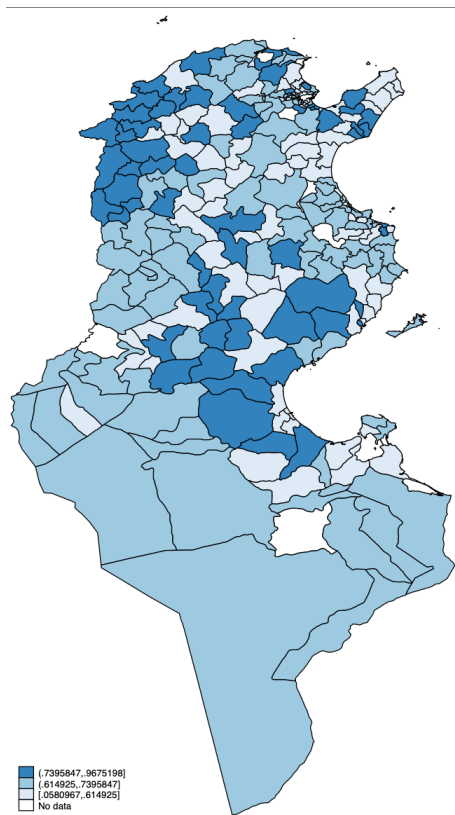
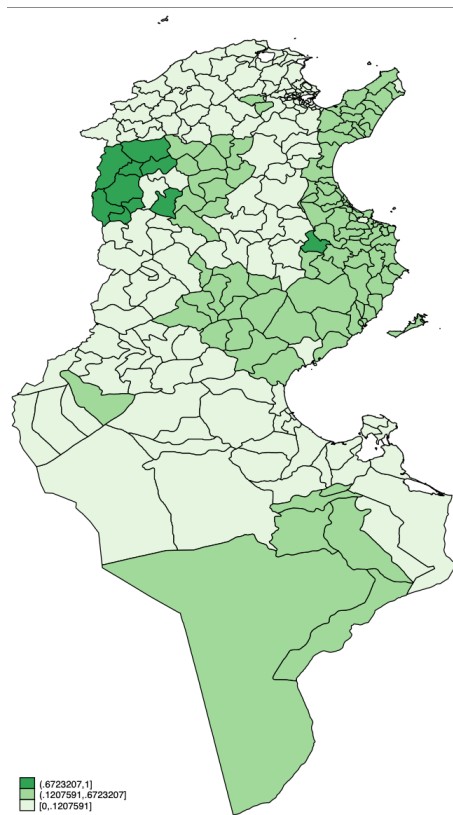


Figure A1: Histogram of drought damage prior to its standardization.



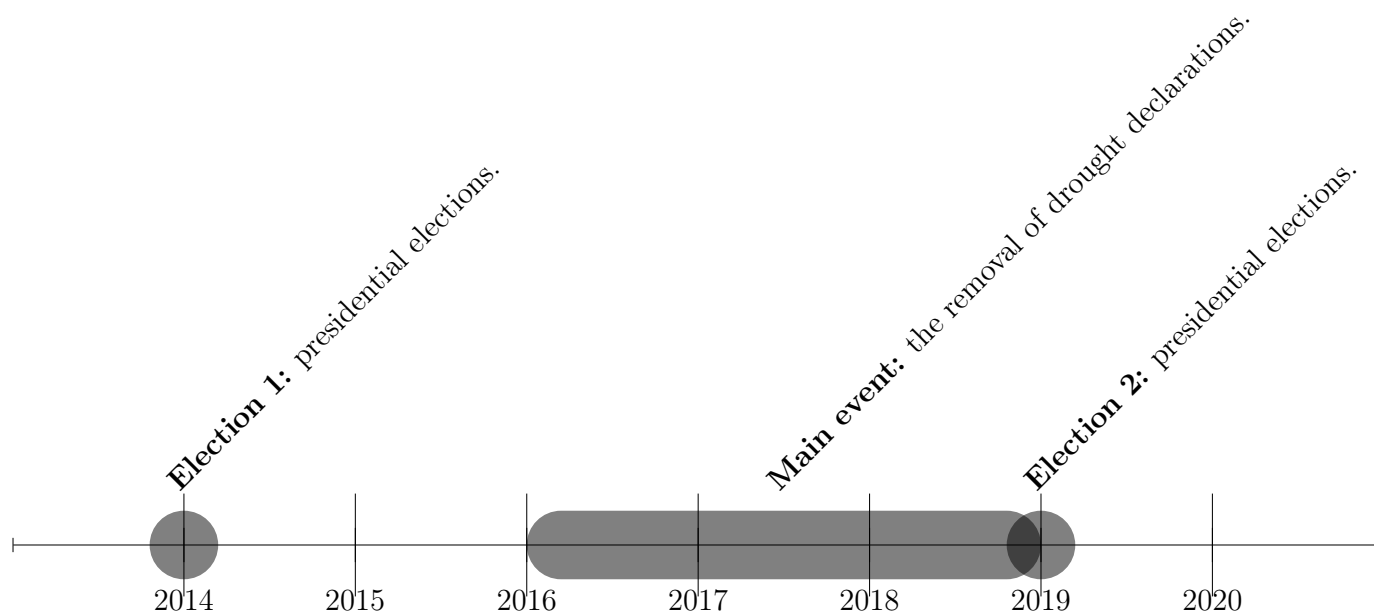
(a) The 2019 Presidential Vote Share



(b) The Percentage of Drought Damage

Figure A2: Vote Share and Drought Damage Maps

Figure A3: Timeline of the Voting Data and Main Event



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Sommaire

Lois

Loi n° 2015-27 du 18 août 2015, portant approbation de la lettre de garantie de l'Etat relative au prêt objet de la convention conclue entre la société tunisienne de l'air et un groupe de banques étrangères pour l'acquisition d'un avion « AIRBUS A330-300 » 1862

Loi n° 2015-28 du 18 août 2015, portant approbation de la lettre de garantie de l'Etat relative au prêt objet de la convention conclue entre la société tunisienne de l'air et un groupe de banques étrangères pour l'acquisition d'un avion « AIRBUS A320-214 » 1862

Loi n° 2015-29 du 18 août 2015, portant approbation de la lettre de garantie de l'Etat relative au prêt objet de la convention conclue entre la société tunisienne de l'air et un groupe de banques étrangères pour l'acquisition d'un avion « AIRBUS A330-300 » 1863

(a) The First Page of the Journal

BEN AROUS	MORNAG	SIDI SALEM EL Garsi	75
		EL KABOUTTI	87
		EL KANA	100
		AIN RKAD	62
		ELKSIBI	47
		OUDNA	57
	MHAMDYA	ERRISALA	20
		JBEL ERSASS	38
		SIDI FREJ	45
		MONJI SLIM	85
		CITE SAADA	100
		CITE NASSIM	100
	FOUCHANA	NAASSEN	80
		DOUAR EL HOUGH	88
		CHBEDDA	56
		EL MGHIRA	71
	BOUMHEL	FOUCHANA	100
		BOUMHEL	100
	HAMMAN CHATT	HAMMAN CHATT	100

(b) The Percentage of Agricultural Area Damage at the finest District Level

Figure A4: The Tunisian Official Journal of Legal Announcements

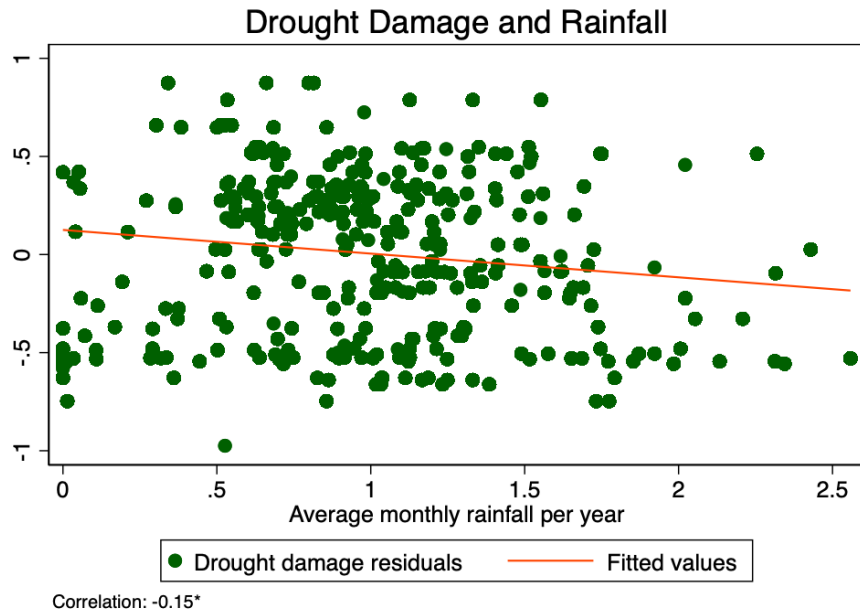


Figure A5: Correlation between Drought Damage and Rainfall

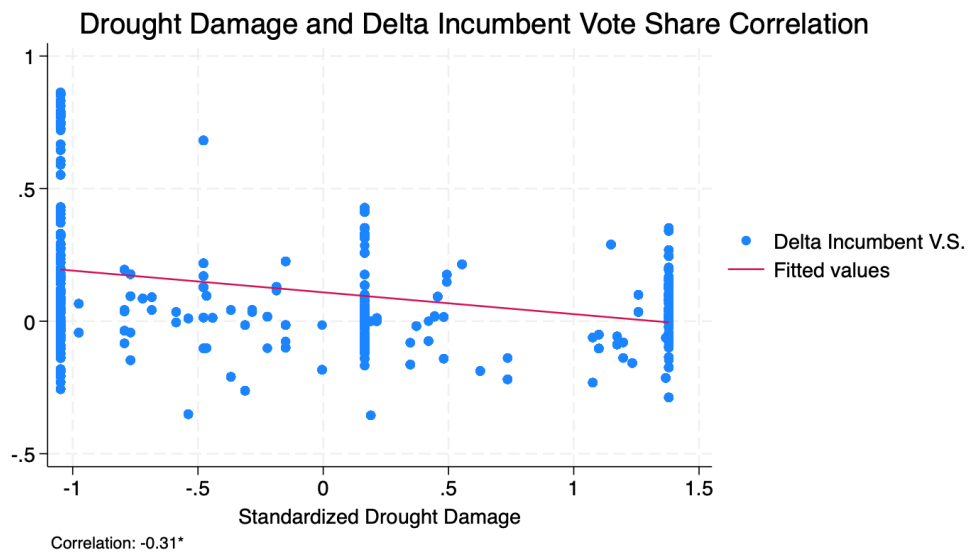


Figure A6: Correlation between the Standardized Drought Damage and Delta Incumbent Vote Share.

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Trois Essais sur l'Economie Politique de l'Adoption des Robots et des Politiques de Lutte Contre la Sécheresse

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Résumé

L’automatisation est devenu un phénomène mondial qui mène aux changements durables dans les vies des gens ainsi que leurs futurs. Malgré les difficultés quantitatives liés aux études des effets de l’adoption des robots au travail, la plupart de ces études présente des preuves de deux effets des robots au travail: soit un effet de remplacement, soit un effet de production, ce qui a un impact notamment sur l’emploi et les salaires des travailleurs ([Acemoglu and Restrepo, 2020](#); [Hirvonen et al., 2022](#); [Ford, 2015](#); [Brynjolfsson, Erik and McAfee, Andrew, 2014](#)).

Le premier chapitre de cette thèse porte sur l’évaluation d’une politique d’adoption des robots mise en place au Corée du Sud sur le bien-être autodéclaré à travers des mécanismes des performances générales du marché du travail. Selon [Helliwell, J., Layard, R. and Sachs, J. \(2022\)](#), l’indice du bonheur la Corée du Sud est plus bas que la moyenne des pays de l’OCDE. Le rang de la Corée du Sud est le 59 parmi les 146 pays étudiés en 2022, ce rang reflète la dégradation du bien-être des Coréens ([Korea Times, 2022](#)). Le fait que la Corée du Sud soit mal classé dans les rangs de l’indice du bonheur en même temps que l’adoption des politiques des robots au travail – ce qui fait que la Corée du Sud devient le premier pays au niveau de robotisation mondial au travail ¹⁹ – a été la motivation pour laquelle on examine dans ce premier chapitre des liens causals potentiels entre ces deux événements.

Le deuxième chapitre développe le premier tout en étudiant les enjeux de l’existence des robots au travail sur le résultat des votes, motivé par l’augmentation mondiale des divisions politiques et des mouvements politiques extrêmes. Dans son article, [Caselli et al. \(2021\)](#) explique comment les changements économiques et structurelles causés par la globalisation, l’immigration and les robots mènent au soutien des partis de droite et populistes durant les élections. En effet, cette association existe à cause du Coût élevé de l’ajustement au différents chocs au niveau local, sectoriel et individuel ([Holm et al., 2017](#)). Le mécontentement

¹⁹comme indiqué sur la Figure 1.3

général du peuple est aligné avec des tendances nationalistes ainsi que le vote pour l'extrême droite, ce qui a augmenté le support des partis populistes de plus de 20% de 2011 au 2015 (Rodrik, Dani, 2017). Il existe des différences entre les peuples d'un même pays dans leurs identités et leurs intérêts qui évoluent avec le temps en raison des interactions entre leurs héritages historiques, des facteurs institutionnels et socio-economiques (Shin and Agnew, 2007).

Le troisième chapitre porte sur l'évaluation de la suspension imprévue d'une politique d'information et de compensation des effets néfastes de la sécheresse en Tunisie sur les résultats des élections. La sécheresse est un grand menace pour la Tunisie mais avec le support du gouvernement, ses effets négatives pouvaient être gérer avec succès.??

Cependant, la suspension du support gouvernemental a eu lieu durant un temps où la Tunisie était en train de transitionner vers un régime démocratique ayant plusieurs partis politiques. La suspension inattendue de cette politique liés à la sécheresse ainsi que la détérioration des conséquences de la dernière à mener à l'augmentation du mécontentement des peuples.

Cette thèse est formé de trois chapitre. Chaque chapitre contribue à une littérature distincte. La question de recherche, contribution, base de donnée, méthodologie, et résultats de chacun des trois chapitres est détaillés ci-dessous.

Chapitre 1: Robots, Résultats sur le Marché du Travail et Satisfaction de la vie: Évidence de la Corée du Sud

Coauteur du chapitre avec Joop Adema and Jae Cho

En 2005, le gouvernement de la Corée du Sud à entamer des politiques ayant pour but d'augmenter le nombre de robot adopté au travail. Ces politiques ont abouti à la "Loi sur la promotion du développement et de la distribution des robots intelligents" mise en place en 2009. Cette loi à réussi à améliorer la productivité au travail en augmentant le taux des robots adoptés dans les différents industries de la Corée du Sud. Le but de cette loi était d'élérer la productivité du pays ainsi que rattraper les autres pays développés comme les États Unis, L'Allemagne et d'autres pays voisins comme le Japon et Singapour.

Le premier chapitre évalue l'impact des vagues de robotisation à la Corée du Sud sur la satisfaction de vie des individus. La première vague d'adoption des robots a eu lieu de 2005 à 2009 suivi par une deuxième beaucoup plus élevée en 2009. Dans ce contexte, l'hypothèse testé est que l'exposition des individus aux robots entraînera une baisse de leur satisfaction de vie au cours de la première période du choc, de 2005 à 2009, puis augmentera à partir

de 2009. Nous contribuons à trois courants de littérature. Le premier concerne l'impact des robots au travail sur la satisfaction des travailleurs. [Hinks \(2021\)](#) et [Schwabe and Castellacci \(2020\)](#) signalent une corrélation négative entre les robots au travail et la satisfaction des travailleurs, tandis que [Gihleb et al. \(2020\)](#) analyse le marché du travail aux États-Unis et ne trouve aucune relation entre la satisfaction de la vie et l'exposition des travailleurs aux robots.

Un deuxième courant de littérature examine les effets de la robotisation sur le marché du travail. [Acemoglu and Restrepo \(2020\)](#) et [Dauth et al. \(2021a\)](#) emploient tous deux une approche au niveau du marché du travail local; le premier constate une baisse des salaires et de l'emploi, mais le second confirme l'ajustement du marché du travail lorsque l'adoption des robots augmente. Dans d'autres articles, les effets sur le marché du travail sont analysés dans le cadre d'une analyse transnationale, comme dans les travaux de [Graetz and Michaels \(2018\)](#), ou au niveau de l'entreprise en utilisant un modèle d'étude d'événement par [Aghion et al. \(2021\)](#). Le troisième courant de littérature que nous ajoutons est l'effet sociétal de la robotisation; [Anelli et al. \(2019a\)](#) et [Anelli et al. \(2019a\)](#) étudient l'impact de l'exposition locale et individuelle aux robots sur le résultat électoral et constatent qu'une plus grande exposition est associée à une augmentation du vote en faveur des partis de droite.

La contribution aux différents courants de littérature est sur quatre niveaux: premièrement, on utilise une stratégie empirique individuelle pour étudier l'effet de la robotisation sur la satisfaction de vie. Cette question n'a été abordé qu' à travers une approche du marché du travail local. Deuxièmement, cette étude exploite les résultats au niveau du marché de travail local comme des mécanismes expliquant les résultats principaux. Troisièmement, le fait de présenter la Corée du Sud comme une étude de cas est une contribution à la littérature grâce aux caractéristiques de la dernière au niveau de la démographie complètement différente de celle des États Unis et de l'Allemagne qui sont le plus étudié dans la littérature. La quatrième contribution est l'inclusion de l'effet du ménage; on étudie l'impacte de l'exposition du chef de ménage aux robots au travail sur la satisfaction de vie de leurs époux.

l'Enquête coréenne en panel sur les revenus du travail est la base de donnée fondamentale de cette étude. Cette base de données comprend des variables sur les salaires, l'emploi, des caractéristiques démographiques ainsi que la satisfaction de vie. La version finale de l'ensemble de données consiste de 325, 112 observations annuelles individuelles sur les années 1998 à 2020, avec un faible taux d'attrition. La construction de la mesure d'exposition individuelle aux robots suit la méthode de [Anelli et al. \(2019a\)](#) en employant une probabilité logit multinomiale des individus de travailler dans une profession donnée k en fonction de

leur âge, de leur genre, de leur niveau d'éducation et de leur quartier de résidence (avant le début de la robotisation) multipliée par les heures remplaçables au niveau de la profession conformément à [Graetz and Michaels \(2018\)](#) et calculée sur l'ensemble des professions. À l'aide du modèle de la probabilité logit multinomiale des individus de travailler dans une profession donnée, on prends en compte les employés en plus les chômeurs dans notre analyse. On utilise ce modèle dans le cadre d'une étude d'événements.

Au niveau individuel, nos résultats montrent que les robots au travail ont eu un impacte positive sur la satisfaction de vie à partir de 2009. Cela est grâce à l'augmentation du niveau d'emploi à partir du 2009 mais les salaires restent inchangées au niveau agrégé. C'est le cas des hommes âgés de 20 à 29 ans ayant suivi un enseignement supérieur. Afin de décrypter nos résultats, on emploie une approche du marché de travail local dans le but d'explorer les mécanismes par les différents niveaux d'enseignement qui contribuent aux résultats principaux. Les mécanismes sont présentés au niveau de l'enseignement bas, spécialisé et supérieur car l'adoption des robots au sein du travail a des effets variés selon la nature des tâches de chaque occupation.

Entre 2005 et 2009, les individus qui ont un niveau d'enseignement bas et spécialisé ont été déplacé du travail sous la forme soit d'une augmentation de l'emploi à temps partiel soit d'un changement d'entreprise où ils travaillent. Dès 2009, nos résultats confirment que les individus qui ont un niveau d'enseignement spécialisé et supérieur bénéficient de l'adoption des robots au travail sous la forme d'une hausse des salaires, ce qui n'est pas le cas pour les individus qui ont un niveau d'enseignement bas. En plus des résultats individuels, on examine les changements de la satisfaction de vie des épouses dans le cas où leurs conjoints sont exposés aux robots au travail. Nous utilisons un système de différences dans les différences avec plusieurs périodes pour prendre en compte les deux vagues d'adoption des robots. Le traitement est une variable continue qui représente l'exposition des chefs de ménage aux robots au travail. Conformément avec les résultats au niveau individuel, nous confirmons que l'effet négatif de l'exposition aux robots est principalement causé par la baisse des salaires totales des ménages pour les femmes des ménages dont le chef a eu un niveau d'enseignement bas ou spécialisé. Ces résultats indiquent que l'effet négatif des robots ne concerne pas seulement les individus touchés au travail par l'existence des robots mais aussi leurs qualités de vies et celles de leurs ménages.

Nous utilisons l'approche du marché du travail local avec une variable instrumentale de type shift-share suivant [Acemoglu and Restrepo \(2020\)](#) pour vérifier si un effet productif existe au niveau régional ainsi que pour tester la possibilité d'existence d'un effet psychologique comme

la crainte de la substitution des travailleurs par des robots au niveau régional agrégé. On emploie Singapour comme un pays de référence. D’après les résultats de cette approche, on constate qu’il n’existe ni d’effet sur la productivité ni d’effet psychologique sur les travailleurs.

Chapitre 2 : Robots et Résultats du Vote : L’Expérience de la Corée du Sud

Coauteur du chapitre avec Jae Cho

Selon [Prysby and Scavo \(1993\)](#), le comportement électoral est un élément clé qui détermine la performance du gouvernement ainsi que les orientations du peuple sur des questions spécifiques de politique publique. Les décideurs politiques ont besoin de comprendre les motivations des électeurs lorsqu’ils votent ou prennent certaines décisions politiques. Il existe une littérature importante qui explore les causes et les changements dans le comportement électoral. Récemment, les économistes ont commencé à considérer l’adoption de robots au travail comme un facteur potentiel affectant le comportement électoral des individus. La robotisation ayant des effets diverses sur les travailleurs, son effet sur le comportement électoral est déconcertant. Nous tentons d’examiner l’effet causal de la robotisation au travail sur le comportement électoral en tirant parti de la « loi sur la promotion du développement et de la distribution des robots intelligents » adoptée par le gouvernement sud-coréen pour promouvoir les marchés nationaux des robots.

Ce chapitre contribue aux trois volets de littérature. La première contribution est étroitement liée à la littérature sur l’effet de automatisation sur les résultats du vote. [Caselli et al. \(2021\)](#); [Anelli et al. \(2019b\)](#) abordent ce sujet tout en utilisant des données italiennes et européenne. Leurs résultats montrent une corrélation positive entre être exposé aux robots et le soutien des idéologies nationalistes des partis de la droite radicale. Les résultats de [Caselli et al. \(2021\)](#) prouvent que l’automatisation a un effet positif sur les mouvements populistes Italiens. Dans son article, [Schöll and Kurer \(2024\)](#) emploient des données du marché du travail allemand au niveau du pays dans un modèle à effets fixes à deux voies pour montrer que l’adoption de robots a changé la composition de la main-d’œuvre au niveau régional en Allemagne. L’effet de la composition est beaucoup plus pertinent que l’effet politique de l’adoption des robots dans la littérature – notamment l’augmentation du vote pour l’extrême droite – ce qui augmente le vote pour les partis de gauche.

[Frieden \(2018\)](#) montre que la mondialisation qui menace les travailleurs cause une hausse des mouvements populistes. [Abbondanza and Bailo \(2018\)](#) and [Autor et al. \(2020\)](#) constatent que l’afflux d’immigrants et l’augmentation des échanges commerciaux, qui menacent tous deux le marché du travail national, sont positivement corrélés à l’augmentation de votes en

faveur des partis d'extrême droite.

Notre contribution à cette littérature est sur plusieurs axes. Le premier est notre appui sur des données de panel au niveau du district dans une approche de variable instrumentale shift-share pour étudier l'effet de la robotisation sur les comportements de vote à un niveau granulaire en Corée du Sud plutôt qu'à un niveau agrégé au niveau du pays. La deuxième contribution est à travers nos résultats qui indiquent une augmentation de la polarisation politique sous forme d'une hausse des votes aux partis droites et gauches en même temps sur le deux niveaux présidentiels et parlementaires.

Cette étude est comparable à un autre domaine de la littérature sur l'intersection de la polarisation politique et le conflit entre les générations. Il existe une littérature d'économie politique qui attribue la cause de la polarisation politique à une divergence extrême entre les positions des anciennes et des jeunes générations dans les idéologies politiques, d'où leur soutien aux partis politiques. [Dalton \(1987\)](#) met l'accent sur les différences générationnelles dans le soutien aux partis politiques de gauche et de droite. Par exemple, les militants politiques plus jeunes et plus âgés jouent un rôle majeur dans la polarisation politique qui reflète les intérêts des différents groupes sociaux. En outre, [Philips \(2022\)](#) étudie l'effet de l'âge, de la période et de la cohorte sur la polarisation politique, l'orientation partisane et le tri idéologique. L'étude révèle que les variables liées à l'âge ont un impact important sur la polarisation politique. Nos mécanismes se recoupent avec les résultats de cette littérature. Comme nous tentons d'explorer un nombre d'analyses de l'hétérogénéité du marché du travail au niveau régional comme nos mécanismes, nous montrons que les jeunes générations ont tendance à voter pour des partis de gauche tandis que les générations plus âgées ont tendance à favoriser les partis de droite, ce qui conduit à la polarisation politique.

On emploie également quatre tours d'élections présidentielles couvrant les années 2002, 2007, 2012 et 2017. Les élections présidentielles ont lieu tous les 5 ans sans mandats consécutifs. En outre, 6 tours d'élections législatives sont utilisés pour les années 2000, 2004, 2008, 2012, 2016 ainsi que 2020. Les élections parlementaires ont généralement lieu tous les 4 ans avec la possibilité de mandats consécutifs. Nous utilisons les données de la Commission électorale nationale (NEC) comme principale source de données sur le vote en Corée du Sud au niveau régional. L'enquête coréenne sur le panel des revenus du travail est également utilisée pour cette étude. Elle comprend des variables relatives aux salaires, à l'emploi et aux caractéristiques démographiques.

Les données panel des revenus sont regroupées et pondérées au niveau régional afin d'être fu-

sionnées avec les données NEC pour des contrôles plus complets au niveau régional. Les données de la Fédération internationale des robots (IFR) nous fournissent le stock opérationnel de robots au niveau de l'industrie, les données d'IFR qui sont également fusionnées avec celle des revenus et NEC. L'ensemble final de données comprend 1, 921 observations région-année couvrant 270 districts, 4 années d'élections présidentielles et 6 années d'élections parlementaires au total. L'approche économétrique consiste en un cadre de variables instrumentales de type shift-share dans lequel l'exposition de Singapour aux robots est instrument pour celle de la Corée du Sud. La principale motivation pour utiliser Singapour comme instrument dans notre spécification est qu'elle vient après la Corée du Sud en termes d'adoption rapide de robots et qu'elle est fortement corrélée avec la robotisation de cette dernière. L'exposition au choc robotique au niveau régional est inspirée par [Dauth et al. \(2021b\)](#).

Les résultats montrent que l'adoption de robots en Corée du Sud a entraîné une augmentation de vote de gauche et de droite aux élections législatives dans les régions les plus exposées aux robots au travail. Les mêmes résultats ont été observés pour les élections présidentielles, mais dans une moindre mesure. Ces résultats indiquent qu'il existe une prévalence de la polarisation politique en Corée du Sud suite à la vague de robotisation qui s'est produite. Démêler les mécanismes conduisant à ces résultats implique un certain nombre d'analyses d'hétérogénéité afin de pouvoir distinguer le groupe d'individus optant pour les partis de gauche de ceux optant pour les partis de droite.

Nous suivons la même stratégie empirique sur des sous-échantillons de données afin de pouvoir déterminer quels sous-groupes de districts sont à l'origine de la polarisation politique. Nous divisons spécifiquement nos observations en districts dont le niveau de la part de l'emploi dans l'industrie manufacturière, de l'emploi dans l'industrie robotique et de l'âge est supérieur (ou inférieur) au niveau médian. Sur la base des résultats de l'hétérogénéité au niveau des districts et des résultats au niveau des individus et des ménages présentés dans le premier chapitre, nous concluons que la polarisation politique est due à des conflits entre les générations, la robotisation ayant un impact différent sur les deux générations. Les travailleurs de la génération plus âgée (plus de 40 ans) sont plus exposés à la robotisation que la jeune génération. Étant donné que le groupe le plus âgé (le plus jeune) a tendance à voter pour des partis de droite (de gauche), nous confirmons l'effet négatif de l'adoption des robots sur les générations plus âgées. Les générations plus âgées sont les groupes désavantagés par la robotisation ; elles ont donc tendance à voter pour des partis de droite. Le raisonnement qui sous-tend cette conjecture est conforme à [Anelli et al. \(2019b\)](#) et [Anelli et al. \(2021\)](#), qui constatent que le ressentiment de l'opinion publique à l'égard des menaces éventuelles

pesant sur les emplois des travailleurs s'exprime par une augmentation des parts de voix de la droite.

Chaptire 3: Les Sécheresses et les Résultats du Vote : Preuves tirées de la Tunisie

Ce chapitre analyse l'impact d'un changement d'une politique liée à la sécheresse en 2016 sur les résultats du vote en Tunisie. La Tunisie est caractérisée par des périodes de sécheresse récurrentes qui causent des pertes de récoltes chaque année. Afin d'indemniser les agriculteurs pour leurs pertes, le gouvernement tunisien a publié le pourcentage de la surface agricole endommagée dans des décrets sur la sécheresse, disponibles pour les agriculteurs ainsi que pour les résidents par région. Les décrets de déclaration de sécheresse garantissent aux agriculteurs une aide sous la forme d'un rééchelonnement des prêts, tandis qu'ils fournissent au reste des résidents les informations nécessaires pour prévoir les pénuries alimentaires auxquelles ils pourraient être confrontés. Le gouvernement a publié les arrêtés de sécheresse jusqu'en 2016. De 2016 à 2019, les décrets et les mesures d'aide ont été suspendus pendant des années d'intense sécheresse.

Je contribue à la littérature sur l'économie politique du changement climatique qui établit un lien entre les politiques d'indemnisation des catastrophes climatiques et la part de voix des candidats sortants en période électorale. La littérature postule que l'existence de programmes d'indemnisation des catastrophes climatiques encouragera les électeurs à récompenser le candidat sortant lors des élections ([Bastos and Miller, 2013](#)). ([Bastos and Miller, 2013](#)) utilise une régression polynomiale de trois ordres de la marge relative de la victoire du candidat aux élections pour indiquer que la mise en place de compensations pour la sécheresse deux ans avant les élections au Brésil augmente la probabilité de réélection du candidat sortant. [Fukumoto and Kikuta \(2024\)](#) utilise la pluviométrie comme variable instrumentale pour une politique d'indemnisation en cas de catastrophe au Japon et constate que l'octroi d'indemnités augmente le soutien au parti politique en place, comme le prévoit la théorie du "vote rétrospectif égotropique".

Le "vote rétrospectif égotropique" postule que la part de vote des titulaires pendant les élections est directement proportionnelle à la fourniture de paquets d'aide pendant les périodes électorales ([Achen and Bartels, 2004](#); [Bovan et al., 2018](#)). Je contribue à la littérature avec mes résultats qui se recoupent avec ceux de la littérature « rétrospective égotropique ». En outre, la suspension de la politique d'indemnisation de la sécheresse que j'étudie dans cet article est un autre ajout à la littérature principalement axée sur le ciblage de l'aide à la

sécheresse autour des périodes électorales. Je contribue à la littérature par les données que j'utilise. J'ai construit un nouvel ensemble de données pour évaluer les dommages causés par la sécheresse à partir du pourcentage de terres agricoles endommagées extraites des journaux officiels tunisiens. Les données utilisées dans la littérature pour étudier l'impact des sécheresses sur les résultats des votes sont soit des indices de sécheresse, soit des variations moyennes des précipitations sur une longue période de temps, au moins 30 ans, comme dans [Tarquinio \(2022\)](#). Je renonce à utiliser les précipitations et je me contente d'utiliser une variable de substitution pour le manque de précipitations, qui reflète étroitement le principal problème de la Tunisie, à savoir les graves saisons de sécheresse qui entraînent des pertes de production agricole.

Je contribue à la littérature sur la façon dont le changement climatique peut conduire aux conflits en stipulant que les chocs de sécheresse couplés à la suppression des déclarations de sécheresses et ses compensations entraînent une augmentation des émeutes ([Decet and Marcucci, 2023](#); [Adhvaryu et al., 2021](#)). Selon ([Decet and Marcucci, 2023](#)), les sécheresses en Afrique peuvent amplifier les conflits violents dans les zones rurales où les précipitations sont rares. Dans ce chapitre, je constate que les émeutes sont déclenchées à la fois par les agriculteurs et par le reste des habitants des régions où la sécheresse a sévi et où les compensations associées ont été supprimées en raison du mécontentement général des citoyens. La présence d'institutions démocratiques joue un rôle essentiel dans l'atténuation des conflits en développant la redistribution de l'eau et les infrastructures nécessaires. [Adhvaryu et al. \(2021\)](#) et [McGuirk and Burke \(2017\)](#) montrent qu'il existe une corrélation entre les ressources naturelles et les conflits en Afrique. Ils développent un modèle prévoyant que la prospérité économique est susceptible de se produire en cas d'existence d'un point d'équilibre de la prévalence des conflits qui dépend des ressources propres d'une région et de celles de ses voisins. Ils constatent que de meilleures qualités institutionnelles minimisent l'incidence d'un équilibre conflictuel. Les résultats de ce chapitre sont conformes aux conclusions de [Adhvaryu et al. \(2021\)](#) et [McGuirk and Burke \(2017\)](#), je prouve que la démocratie peut fonctionner efficacement lorsqu'on lui donne une chance de canaliser le mécontentement public pendant les périodes électorales. Ce mécontentement se traduit par une diminution de la part de voix du candidat sortant plutôt que par une augmentation de la participation électorale.

La littérature sur les déterminants du comportement électoral s'est concentrée sur soit l'atténuation du changement climatique soit sur les politiques de prévention ciblant spécifiquement les périodes électorales pour gagner le soutien de la population, comme dans [Tarquinio \(2022\)](#). [Tarquinio \(2022\)](#) étudie l'impact de l'aide apportée aux victimes de la

sécheresse avant les élections sur le mandat du parti au pouvoir en Inde, en utilisant un modèle de discontinuité de la régression et une approche de variables instrumentales. Ce chapitre étudie la suspension d’une politique d’indemnisation de la sécheresse à la suite d’un choc de sécheresse, ce qui est considéré comme une contribution à la littérature qui se concentre sur les politiques d’indemnisation ciblées dans le temps avant les élections plutôt que sur leur suppression complète.

Les principales données utilisées dans cette étude sont les suivantes : premièrement, l’Instance Supérieure Indépendante pour les Élections (ISIE) pour les résultats des élections présidentielles et parlementaires des années 2014 et 2019. Deuxièmement, les décrets gouvernementaux sur la sécheresse qui incluent les zones et le pourcentage de dommages causés par la sécheresse au niveau du district en 2015 et 2016. Troisièmement, la principale source de données de covariables est AidData pour les données de grille de 1 km sur le PIB, la distance à l’eau, la distance à la route, la densité de population en 2014 et 2019. L’approche économétrique consistera en un cadre de différence dans les différences où la variable de traitement est continue avant le retrait indiquant le pourcentage de dommages causés par la sécheresse au niveau des régions selon les décrets de déclaration de la sécheresse. La variable de résultat est le pourcentage de vote pour le président sortant au niveau de l’élection présidentielle, tandis qu’elle est le pourcentage de vote par parti politique au niveau des élections parlementaires.

Les résultats indiquent que les Tunisiens préfèrent voter moins pour le président sortant dans le but de le punir lors des élections présidentielles plutôt que pour le parti sortant lors des élections législatives s’ils jugent les politiques gouvernementales inefficaces. Les électeurs n’ont pas sanctionné les partis sortants lors des élections législatives ; il n’y a pas eu non plus d’impact sur la confiance dans les partis ou la proximité avec eux. Ces résultats indiquent que, dans le cadre de la démocratie hybride tunisienne, le public considère le président plutôt que le parlement responsable des politiques et leurs conséquences. Je trouve que l’abandon des décrets de déclaration de sécheresse en Tunisie a conduit à une augmentation des émeutes de 2,8 points de pourcentage suite à une augmentation d’un écart type des dommages au niveau du district après la suppression de la politique. Les résultats sont robustes si l’on change la principale variable de traitement en utilisant un indice de végétation par différence normalisée (NDVI) qui est une approximation des dommages causés par la sécheresse et si l’on change la variable des dommages causés par la sécheresse en une variable post-traitement qui couvre les périodes de sécheresse en 2020 et 2021 au lieu de la variable pré-traitement.

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