Robotization and the Political Response of Politicians

Maria Petrova[1], Gregor Schubert[2], Bledi Taska[3], and Pinar Yildirim[*4]

[1]UPF, Barcelona IPEG, BSE

[2]UCLA

[3]SkyHive

[4]Wharton School, University of Pennsylvania and NBER

November 15, 2024

[*]Authors are listed alphabetically. This study was initially part of the working paper titled Automation, Career Values and Political Preferences by the same authors. Petrova is an ICREA Professor at the Universitat Pompeu Fabra. Schubert is an Assistant Professor at the UCLA Anderson School of Management. Taska is the Head of Analytics at SkyHive. Yildirim is an Associate Professor at the Wharton School of the University of Pennsylvania. We are grateful to Burning Glass Technologies for providing the data used in the analyses. We thank Daron Acemoglu, Christian Dustmann, John Friedman, Sergei Guriev, Rafael Lalive, Guy Michaels, Joan Monras, Giacomo Ponzetto, Piero Stanig, Daniel Sturm, Marco Tabellini, Ekaterina Zhuravskaya, the audiences at Aarhus, Berkeley, Berlin, Bologna, Carlos III, CEPR Labour Symposium 2024, CREI, Dortmund, Hamburg, Harvard, HEC, LISER, Northwestern, Padua, Paris School of Economics, Pompeu Fabra, Schwartz Reisman Institute, Sciences Po, Stanford, Autonoma Barcelona, UCL, and "Studying Critical Junctions" Conference in Munich and Resek Conference at UIUC for their extremely valuable feedback. We thank Felipe Barbieri, Nikita Belyi, Fedor Boboshin, Felipe Brugues, Mario Carillo, Sebastian Ellingsen, Gregori Galofre-Vila, Adilzhan Ismailov, Shreya Mathur, Elisa Mougin, Milan Quentel, Gianluca Russo, Juan Andres Russy, Nikita Varyoshkin, Yihao Yuan, and Georgii Zherebilov for excellent research assistance. Maria Petrova thanks funding from the European Research Council (ERC) under the European Union Horizon 2020 research and innovation program (Grant Agreement 803506), the Plan Nacional project PID2020-120118GBI0, and the Severo Ochoa Programme for Centres of Excellence in R&D (Barcelona School of Economics CEX2019-000915-S), funded by MCIN/AEI/10.13039/501100011033. Yildirim thanks the Mack Institute and the Dean's Research fund at the Wharton School for their research support. Correspondence can be sent to Pinar Yildirim at Wharton School, 3730 Walnut St. Philadelphia, PA, 19104, e-mail: pyild@wharton.upenn.edu.

1 Introduction

Technology is a powerful force shaping individuals' experiences in the labor market, significantly impacting both their short- and long-term economic outcomes (Acemoglu and Restrepo, 2018). Among recent technological shifts, the rapid rise in robotization has arguably had the most profound effect on the workforce over the past two decades. According to the International Federation of Robotics, the number of robots installed annually more than doubled between 2013 and 2023, increasing from 13,000 to over 44,000 per year.[1] As of September 2024, there are over 4 million robots operating worldwide.

Parallel to the growth in robotization, numerous studies have documented its negative impact on labor markets. Acemoglu and Restrepo (2019) found that robots have led to job displacement and loss in the short term. Within individual firms, wage effects have been mixed: higher-skilled workers have seen wage increases, while lower-skilled workers have experienced declines (Acemoglu and Restrepo, 2024). This wage inequality extends beyond individual firms, with studies reporting increased wage disparity in U.S. commuting zones experiencing higher levels of robotization (Kambourov and Manovskii, 2009).

Income declines resulting from job loss and wage reductions have been documented as significant sources of economic shocks, which, in turn, shape individuals' political responses (Guriev and Papaioannou, 2022; Panunzi et al., 2024). Politicians who understand how their constituents react to these economic shocks may seek to leverage these fluctuations to their advantage. However, the literature has yet to fully explore or document how politicians respond to labor market changes driven by automation and the resulting waves of unemployment.

In this paper, we examine the supply-side political response to robotization, focusing specifically on how politicians respond to increasing automation. To achieve this, we conduct an analysis using data from the International Federation of Robotics, examining how robotization evolved in the U.S. between 2000 and 2016. We investigate various political responses, such as the campaign visits of presidential candidates in 2016 and the policy positions of elected officials, inferred from their roll call votes.

Robot adoption affects both people's electoral preferences and, in response, politicians' behavior in multiple ways. Research indicates that robotization has contributed to rising unemployment, greater inequality (Acemoglu and Restrepo, 2022), and diminished opportunities for upward mobility (Petrova et al., 2024). In theory, such negative economic shocks can drive support for politicians on both extremes of the political spectrum (Margalit, 2019). Studies suggest that recent economic transformations, especially skill-biased technological change and globalization, have led to future income losses and, consequently, increased support for right-wing and populist

[1] `https://ifr.org/ifr-press-releases/news/u.s-companies-invest-heavily-in-robots`

politicians. Frey et al. (2018) and Petrova et al. (2024) suggest that in the United States, robot adoption has bolstered electoral support for Donald Trump, viewed as the most populist of recent Republican presidential nominees. Additionally, Anelli et al. (2021) and Gallego et al. (2022) argue that robot adoption and digitalization have pushed individuals further toward right-leaning political preferences.

There are theoretical foundations for these effects. Guiso et al. (2017) and Di Tella and Rotemberg (2018) argue that income loss and feelings of betrayal can foster anti-elite sentiments. Similarly, Panunzi et al. (2024) presents a theory in which income dissatisfaction resulting from economic loss makes disillusioned voters more risk-tolerant in their political choices, ultimately increasing support for populist candidates.

We construct a dataset using pre-existing industry shares weighted by U.S. robot adoption rates within corresponding industries. We examine how robot exposure in commuting zones—geographic areas where people are likely to work—affects certain political behaviors. Specifically, we analyze campaign visits during the 2016 presidential election, distinguishing between all campaign visits, and those late in the campaign, in October and November. To account for potential endogeneity, we use robot adoption in select EU countries (Denmark, Italy, Sweden, Finland, France, Germany, and the UK) as an instrument for U.S. robot adoption, following the approach of Acemoglu and Restrepo (2020) and Faber et al. (2022).

We find that the Republican candidate, Donald Trump, was more likely to visit areas with higher robot exposure, particularly in October (on average) and in November within the high-manufacturing commuting zones (those with manufacturing employment above the median). Our findings indicate that each additional robot per 1,000 workers increased campaign visits by an average of 1.03 visits in October and 0.7 visits in November. We do not observe a similar effect for the Democratic candidate in 2016, Hillary Clinton.

We also examine the effect of robot adoption on the policy positions of Congressional representatives, as inferred from their roll call votes. Specifically, we utilize NOMINATE scores from Poole and Rosenthal (2011) and McCarty et al. (2006), along with similar roll call-based scores from Nokken and Poole (2004). Our findings indicate that in areas with greater exposure to robots, politicians were more likely to shift their policy preferences to the right.

Our results indicate that the effects of labor-displacing technologies, such as robot adoption, extend beyond shifts in electoral preferences; they also lead politicians to adjust their behavior. Specifically, our findings show that politicians modify both their campaign strategies and their roll call voting patterns once elected.

The paper is organized as follows: Section 2 provides a summary of the data (subsection 2.1) and outlines the methodology (subsection 2.2), Section 3 presents the empirical results, and Section 4 concludes.

2 Empirical Strategy

2.1 Data

We use several data sources in this paper. We will detail them here before we describe the empirical specification. We aggregate all data at the level of commuting zones based on 1990 boundaries.

Robot Stock Data. To measure exposure to robots, we follow the literature and gather data from the International Federation of Robotics (IFR), an association that reports annual statistics on the number of robots installed and in operation for a number of North American and European countries (Acemoglu and Restrepo, 2019). To see more details on this dataset, please refer to Petrova et al. (2024). To summarize, the dataset contains data from various industries, as codified according to the International Standard Industrial Classification (ISIC) code. We map these codes to the North American Industrial Classification to be able to map the labor market shares to relevant industries. IFR's historical data provides information about nearly 50 countries and dates back to 1993, and is claimed to cover roughly 90% of the robot market. However, it is only after 2004 that the data contains a mapping between the robot data and the industries. For more details on this data set, please see Petrova et al. (2024).

Campaign Visit Data Data on campaign visits are from Devine (2019). Devine collects and reports data for the campaign visits of the 2016 presidential candidates, and we aggregate it to the commuting zone level. We were not able to obtain similar data for 2012 or 2008.

From an anecdotal perspective, looking at data on the content of campaign speeches demonstrates that it is not unusual for political candidates to directly address job losses, often with specific examples from manufacturing. Anecdotally, speeches tend to put the blame on "Capitol Hill" or elite politicians, who forgot about the working class. For instance, on June 28, 2016, during a campaign in Monessen, PA, presidential candidate Donald Trump made a stop at Alumisource, a metals recycling facility and made the following statement:

> *"Our politicians have aggressively pursued a policy of globalization - moving our jobs, our wealth and our factories to Mexico and overseas. Globalization has made the financial elite who donate to politicians very wealthy. But it has left millions of our workers with nothing but poverty and heartache. For years, they watched on the sidelines as our jobs vanished and our communities were plunged into depression-level unemployment. Our politicians took away from the people their means of making a living and supporting their families. Skilled craftsmen and tradespeople and factory workers have seen the jobs they loved shipped thousands of miles away. Many Pennsylvania towns once thriving and humming are now in a state despair."*

Political Ideology of Politicians We measure political ideologies by using NOMINATE and Nokken and Poole scores for the US House of Representatives for the year 2016 available via VoteView (voteview.com).

Demographic Characteristics of a Region. We also use several Census-based variables, primarily as commuting zone-level controls, including the population, the share of females, age characteristics, such as the share of population above 65 years; education characteristics like the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; as well as the racial characteristics like the shares of Whites, Blacks, Hispanics, and Asians in a commuting zone. We use data from the 2000 Census in the US.

Labor Market Characteristics of a Region. We also control for the general labor market characteristics by including the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing (e.g., textile industry and the paper, publishing, and printing industry from probably another source).

2.2 Empirical Estimation

We are interested in establishing the causal relationship between robotization and the response of politicians to the changes that followed robotization. The overall empirical strategy in this chapter is detailed in Petrova et al. (2024), and we refer the readers to this study. More specifically, we would like to run regressions of the following form:

$$Political\_Response_{c,t} = \beta_1 + \beta_2 Exposure\_to\_robots_{c,(t_0,t_1)} + \beta \mathbf{X}_c + \varepsilon^{\ell}_{c,t}, \tag{1}$$

where $Political\_Response_{c,t_1}$ is the observed political response by a politician at time t in a commuting zone (CZ from here on) c. This response is triggered by the economic and labor market outcomes that come as a result of labor market exposure to robotization in CZ c over period (t_0, t_1), $Exposure\_to\_robots_{c,(t_0,t_1)}$.

To address potential confounders at the level of commuting zones, we include a rich set of control variables which are common in the robotization literature (e.g., Acemoglu and Restrepo, 2019; Faber et al., 2019; Petrova et al., 2024), and also use an instrumental variables approach that is explained in detail further below. More specifically,$\mathbf{X}_c$ will include the controls for region c from 1990, including the log of population, share of females (in total population), share of population above 65 years, share of population with high school, some college, college and postgraduate education, share of Whites, African Americans, Hispanics, and Asians (in total population), share of employment in manufacturing, share of female employment in manufacturing, share in light manufacturing (textile industry and the paper, publishing, and printing industry), share of employment in routine occupations and change in exposure to imports from China from 1990 to 2007, using data from the American Community Survey and County Business Patterns. This specification follows Petrova et al. (2024), which builds on Acemoglu and Restrepo (2020). For the analysis, we focus on the period of 2000 to 2016, over which we have detailed outcome data.

The right-hand-side variable here is measured as the exposure to new robots introduced in a commuting zone CZ c in period (t_0, t_1), $Exposure\_to\_robots_{c,(t_0,t_1)}$, as in (Acemoglu and Restrepo, 2019; Faber et al., 2019; Petrova et al., 2024). This measure combines an exposure due to local industry employment shares with a "shifter" in the form of a change in the robot stock impacting a particular industry code. Specifically, exposure to robots in commuting zone c over the period (t_0, t_1), denoted as $\text{Exposure\_to\_robots}_{c,(t_0,t_1)}$, is calculated as the product of the local industry employment share and the average of the change in robot stock within a given industry, following the approach of Acemoglu and Restrepo (2019) and Faber et al. (2019):

$$\text{Exposure\_to\_robots}_{c,(t_0,t_1)} = \sum_{i \in \iota} l_{ci} \Delta APR_{i,(t_0,t_1)},$$

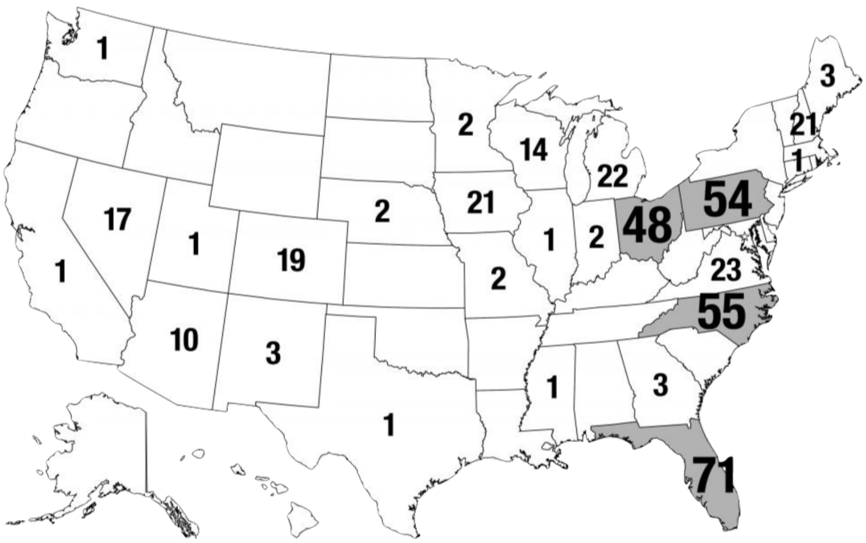
where $\Delta APR_{i,(t_0,t_1)}$ represents the change in adjusted robot penetration in industry i between t_0 and t_1, and l_{ci} is the share of industry i employment in total employment in commuting zone c.

The above specification is subject to endogeneity concerns. Local labor market shares may be influenced by unobserved factors that simultaneously drive both employment patterns and the adoption of robots, introducing potential bias in the estimates. To address this issue, we adopt an instrumental variables (IV) approach, consistent with Acemoglu and Restrepo (2019) and Petrova et al. (2024). Specifically, we instrument robot adoption in the U.S. using data on robots installed in a subset of European countries (Denmark, Italy, Sweden, Finland, France, Germany, and UK). This strategy exploits variation in robot adoption driven by industry-level dynamics in Europe while minimizing the influence of local U.S. labor market conditions, thereby providing a more robust estimate of the causal impact of robot exposure.

3 Results

In this subsection, we study whether the economic shocks generated through robotization demand for populism, as identified in the previous literature Guriev and Papaioannou (2022); Panunzi et al. (2024), triggered some changes in the behavior of politicians. To illustrate the deliberate campaigning patterns of presidential candidates, Figure 1, sourced from nationalvote.com, shows the number of campaign visits by Donald Trump when he was a presidential candidate in 2016, for each state. The figure demonstrates Trump's campaign visits were more heavily concentrated in the East Coast of the United States. More than half of these visits are in states considered to be part of the Rust Belt: Illinois, Indiana, Michigan, Missouri, New York, Ohio, Pennsylvania, West Virginia, and Wisconsin.

Figure 1: Number of Campaign Visits by Donald Trump by Each State, 2016 Presidential Campaign



Notes. The figure is reprinted from Nationalvote.com. The counts represent the number of campaign visits by Donald Trump to each state when he was a presidential candidate in 2016.

In Table 1, we check if the automation exposure of a CZ is correlated with the number of campaign visits to that location, looking separately at the visits by the Republican and Democratic Presidential candidates while campaigning for the 2016 Presidential Election. We find no significant evidence of Democratic candidate's more frequent campaign visits to CZs with higher automation exposure. Still, we find a positive association for the Republican candidate. One standard deviation increase in robot exposure is associated with 0.83 additional visits to a CZ for the Republican candidate in October 2016 and 0.45 additional visits in November. When we split the commuting zones as high-manufacturing and low-manufacturing based on the median share of labor force in manufacturing occupations, Panel B shows that this increase is guided exclusively by a significant increase in the number of visits of Republican candidate in the high manufacturing CZs, and that this effect is concentrated in the last months of the campaign (Column (1) and (4) include visits from July to November 2016). Panel C indicates no significant association between campaign visits and robot exposure in areas with a low proportion of manufacturing, though this finding comes with wide confidence intervals because the instrument is weaker for this subgroup of geographies, as indicated by the F-statistics.

Table 1: Robot Adoption and Campaign Visits, 2016. IV

	Republicans			Democrats		
	All	November 2016	October 2016	All	November 2016	October 2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Commuting Zones						
U.S. Robot Exposure '04-'16	1.216	0.454**	0.835*	-0.693	-0.470	-0.214
	(1.105)	(0.206)	(0.457)	(1.677)	(0.379)	(0.715)
Mean of D.V.	1.924	0.293	0.823	1.708	0.334	0.655
KP F-stat.	1327.910	1327.910	1327.910	1327.910	1327.910	1327.910
Observations	722	722	722	722	722	722
Panel B: High-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.918	0.617***	0.532	-0.818	-0.647	-0.068
	(1.257)	(0.137)	(0.561)	(1.852)	(0.572)	(0.752)
Mean of D.V.	2.767	0.329	1.283	2.221	0.454	0.857
KP F-stat.	615.721	615.721	615.721	615.721	615.721	615.721
Observations	362	362	362	362	362	362
Panel C: Low-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	1.774	4.495	0.803	24.006	4.822	11.784
	(15.029)	(8.150)	(2.222)	(44.375)	(6.923)	(19.910)
Mean of D.V.	1.076	0.257	0.361	1.193	0.213	0.452
KP F-stat.	9.544	9.544	9.544	9.544	9.544	9.544
Observations	360	360	360	360	360	360
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry; the share of employment in routine occupations; and change exposure to imports from China from 1990 to 2007 using data from the American Community Survey and County Business Patterns). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, and UK in the same periods. Observations are weighted by commuting zone population.

We also ask whether exposure to automation and robotization translated into differential policies. Table 2 presents roll call votes by politicians as well as the Nokken and Poole scores for the US House of Representatives for the year 2016 (Nokken and Poole, 2004; Lewis et al., 2023). Here, a score of -1 indicates a far-left ideology, a score of 1 indicates a far-right ideology, and 0 represents moderate ideologies. Panel A in the table finds no correlation on average between a CZ's robot exposure and the score of the candidates representing it in the House of Representatives. Panels B and C break down the CZs by high and low manufacturing labor shares. In Column (1) and

(2), we see that in CZs with higher manufacturing intensity, greater exposure to automation is associated with a more conservative record of the politician representing the CZ, whereas there is no statistically significant relationship in low manufacturing-intensity regions. Specifically, in high manufacturing areas, a one-unit increase in automation exposure of labor is associated with a 0.030 p.p. increase in the roll call score, controlling for the score in 2012. This implies a more conservative roll-call voting behavior.

In columns (3), (4), (7), and (8), we consider the effect on *absolute* changes in ideology scores, and find that exposure to robotization is related to an increase in the absolute level of scores. This suggests a rise in *extreme* political views. This effect is evident in both high- and low-manufacturing CZs, with the largest effect observed in low-manufacturing CZs. Together with the smaller and statistically not significant change in the *average* political bias of local politicians' votes, this implies that some politicians in low-manufacturing CZs became more left-leaning in ideology, even as others may have moved to the right. This change in absolute levels of ideology is consistent with the perception of increasing polarization in the country, and may indicate that the differential effects of automation exposure could be one of its main drivers.

4 Conclusion

In this study, we report a few key findings regarding the political response to automation. While a number of studies document the demand side of political response to robotization (Petrova et al., 2024), how politician's rhetoric changes in response to growing robotization has been under-documented.

Our findings demonstrate that increased exposure to robots in high-manufacturing areas is associated with politicians' campaign strategies, and likely contributed to the observable shifts in the policy positions of elected officials. Specifically, the analysis of the 2016 presidential election reveals that the Republican candidate, Donald Trump, targeted regions with high robot adoption in his campaign visits during the critical months of October and November, and in commuting zones with higher share of higher manufacturing workers. This campaign focus is likely to capitalize on the economic concerns and sense of disenfranchisement among voters in these areas (Guriev and Papaioannou, 2022), where income loss and economic insecurity heighten anti-elite and populist sentiments (Rodrik, 2021).

Moreover, effects of robotization and politicians' respond extend beyond the electoral period to longer-term effects, including the Congressional representativesâ voting behaviors. We observe a rightward shift in policy preferences in response to robotization, as measured by the NOMINATE and Nokken and Poole scores Nokken and Poole (2004). Therefore, it is possible that the economic

Table 2: Automation and Roll Call Votes. IV

	Nominate Scores (House of Representatives)				Nokken Poole (House of Representatives)			
	2016 Score	2016 Score	2016 Abs Score	2016 Abs Score	2016 Score	2016 Score	2016 Abs Score	2016 Abs Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Commuting Zones								
U.S. Robot Exposure '04-'16	0.016	0.014	0.011	0.011	0.012	0.010	0.008	0.007
	(0.025)	(0.024)	(0.014)	(0.014)	(0.027)	(0.026)	(0.016)	(0.015)
Ideology '12		-0.091		-0.052		-0.096		-0.099
		(0.127)		(0.106)		(0.131)		(0.113)
Mean of D.V.	0.311	0.313	0.351	0.353	0.317	0.319	0.359	0.362
SD of D.V.	0.240	0.240	0.176	0.175	0.253	0.253	0.188	0.187
F-stat.	1325.554	1209.609	1325.554	1249.453	1325.554	1216.215	1325.554	1245.910
Observations	719	714	719	714	719	714	719	714
Panel B: High-Manufacturing Commuting Zones								
U.S. Robot Exposure '04-'16	0.034*	0.030*	0.027**	0.026**	0.032	0.027	0.026**	0.025**
	(0.018)	(0.016)	(0.011)	(0.011)	(0.020)	(0.018)	(0.013)	(0.012)
Ideology '12		-0.271*		-0.129		-0.295*		-0.182
		(0.157)		(0.118)		(0.162)		(0.124)
Mean of D.V.	0.287	0.288	0.334	0.335	0.291	0.292	0.342	0.343
SD of D.V.	0.243	0.243	0.173	0.172	0.256	0.256	0.183	0.182
F-stat.	615.721	672.406	615.721	630.442	615.721	658.642	615.721	618.481
Observations	362	361	362	361	362	361	362	361
Panel C: Low-Manufacturing Commuting Zones								
U.S. Robot Exposure '04-'16	-0.267	-0.225	0.362*	0.386**	-0.337	-0.304	0.331*	0.370**
	(0.227)	(0.235)	(0.192)	(0.181)	(0.233)	(0.235)	(0.200)	(0.189)
Ideology '12		0.007		0.226		-0.014		0.225
		(0.097)		(0.184)		(0.094)		(0.196)
Mean of D.V.	0.336	0.338	0.369	0.372	0.342	0.346	0.377	0.381
SD of D.V.	0.235	0.235	0.178	0.176	0.248	0.247	0.191	0.189
F-stat.	10	8	10	9	10	7	10	9
Observations	357	353	357	353	357	353	357	353
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry; the share of employment in routine occupations; and change exposure to imports from China from 1990 to 2007 using data from the American Community Survey and County Business Patterns). We also control for the scores from 2012 in columns (2), (4), (6) and (8). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany and UK in the same time periods. Observations are weighted by commuting zone population.

concerns of the electorate, influenced by robotization, reflect onto the political attitudes and decision-making among legislators. This trend might be partly because the profile and the party of the elected representatives change as robotization alters the political preferences of the electorate (Petrova et al., 2024), or because the politicians themselves start to take different policy positions in response.

Altogether, our findings underscore the impact of automation, penetrating the political arena. Robotization has repercussions of political shifts, and a potential for increased polarization, which puts pressure on representatives to adopt positions that resonate with the impacted constituencies.

Overall, our research points to the need for comprehensive studies addressing the economic and political challenges posed by automation and the consequences of labor market disruptions on policymakers.

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