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Abstract

This paper examines the impact of the large structural shocks – automation and import competition – on voter turnout during US federal elections from 2000 to 2016. Although the negative income effect of both shocks is comparable, we find that political participation decreases significantly in counties more exposed to industrial robots. In contrast, the exposure to rising import competition does not reduce voter turnout. A survey experiment reveals that divergent beliefs about the effectiveness of government intervention drive this contrast. Our study highlights the role of beliefs in the political economy of technological change.

Keywords: automation, trade, labor demand, voter turnout
JEL Classification: J23,F16,D72

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1 Introduction

Structural changes such as globalization and automation drastically affect labour markets (among others, Acemoglu and Restrepo 2020; Autor et al. 2013; Graetz and Michaels 2018) and have far reaching implications a number of other domains (Adda and Fawaz 2020; Autor et al. 2019). Yet, such structural changes are not “a fate to be divined rather than an expedition to be undertaken” (Autor 2022). That is, their pace and direction as well as consequences might be shaped by political actions.

Some structural changes affect political preferences (Anelli et al. 2019; Autor et al. 2020; Schöll and Kurer 2023). Yet, regardless of electoral outcomes as such, it is crucial that preferences for parties and candidates expressed through elections are representative of the preferences of the whole population and not only of certain groups who are more likely to vote (Fowler 2015; Lijphart 1997). Indeed, high voter turnout is essential for the functioning of democracies (e.g., Dahl 1989). Differences in voter turnout can affect the overall legitimacy of the government and its actions (Grillo 2019), and, ultimately, the public policies that are implemented (Fowler 2013; Horiuchi and Saito 2009).

We study how structural changes to the economy affect political participation in the long run. Structural changes due to increased trade competition or automation have distributional consequences with sharp drops in income for the affected groups (Dauth et al. 2014, 2021). The effect of income on voter turnout is a focus of a large, yet inconclusive literature: empirical evidence documents both its positive association with political participation as well as no association (for overviews, Cancela and Geys 2016; Smets and Ham 2013). Several recent studies that aim to identify a causal relationship between changes in income and voter turnout document contradictory results as well (e.g., Bellettini et al. 2023; Charles and Stephens Jr 2013; Jungkunz and Marx 2022; Schafer et al. 2022). In contrast to temporary shocks to income, structural changes are all the more important to consider because they can create persistent feedback loops of missing political representation and distorted public policy that fails to consider the concerns of adversely affected citizens and at worst amplifies the consequences of structural change (extending the argument of Lijphart 1997)

In this paper, we study the effect of the two large structural changes to the US economy — long-run labor market adjustment to industrial robots and Chinese imports — on voter turnout at federal elections across US counties between 2000 and 2016. We follow the methodology by Acemoglu and Restrepo (2020) and Autor et al. (2013) to construct measures of local exposure to industrial robots as well as to import competition from China. To establish the validity of our approach, we first estimate the causal effect of both structural shocks on employment and income applying the same shift-share instrumental variable strategy. We confirm the established finding that both automation and import competition from China lead to lower employment growth and comparable declines in average household income at the level of US local labor markets.[1] We then estimate the effect of commuting-zone exposure to industrial robots and to Chinese imports on long-term changes in county-level voter turnout at both US presidential and US House of Representative elections over two 8-year election cycles between 2000 and 2016.[2]

We document a significant negative relationship between a commuting-zone exposure to industrial robots and changes in county-level turnout at both types of federal elections. We find that a one standard deviation increase in exposure to robots reduced the voter turnout at presidential elections by 1 percentage point or that one robot per thousand workers reduced the voter turnout by about 13 voters. Given the average increase in the US stock of robots during 8-year period, our estimates suggest increasing exposure to robots reduced voter turnout at the presidential elections by about 1 million voters.

In contrast, we find that the exposure to rising imports from China does not affect turnout at presidential elections and positively affects turnout at US House of Representative elections. The finding of the differential response of political participation to robots and Chinese import penetration is robust to controlling for differences in the net migration rate, the swing state status or the intensity of political campaigning at the

[1] While the average decrease in income is comparable between the two shocks, they are not identical. For instance, the effect of the trade competition was found to be more concentrated in the manufacturing employment (Faber et al. 2019). See Section 4 for the discussion on the potential differences and their implications for our results.

[2] The reference years in 2000, 2008 and 2016 cover critical elections in which two-term incumbents (Bill Clinton, George W. Bush, Barack Obama, respectively) were stepping down from office and long-run political directions were set.

county-level.

Further analyses corroborate this main result and shed light on the underlying mechanisms. By considering individual-level data from *General Social Survey*, we establish that the decrease of voter turnout is concentrated among people most at risk of automation. To elaborate on the mechanisms behind the differential effects, we probe various motivations of absenteeism in an online survey experiment. While both shocks are perceived to be equally important, respondents found layoffs due to automation to be more inevitable and federal government to be less able to tackle it than in the import competition scenario. This result is consistent with the nature of the shock affecting the expected utility of voting. Finally, the complimentary analysis of political campaigns corroborates the link between lower voter turnout and lower attention of political parties. Regions exposed to automation are targeted by fewer and cheaper advertisements during political campaigns. In addition, we document a mismatch: In the regions affected by automation, political advertisements are more likely to focus on unemployment due to increased trade competition and less likely to touch upon issues of social security. The latter findings might explain why political parties are reluctant to campaign on technology related topics and instead divert voters attention to other political issues (Gallego and Kurer 2022).

The contribution of our paper is threefold. First, we extend the literature on political and social consequences of structural changes (Autor et al. 2020; Caprettini and Voth 2020; Feigenbaum and Hall 2015) by studying a new margin through which technological change affects its own long-term trajectory, voter turnout. Second, we contribute to the literature on the economic determinants of political participation (Cancela and Geys 2016; Markovich and White 2022; Smets and Ham 2013) by providing a causal analysis of the effect of the two recent labor market shocks on political participation in the US. Our framework allows us show that the relationship between them is not uniform, i.e., negative income shocks do not always affect political participation in the same way. Third, we extend work on the underlying mechanisms that link structural economic change and individual political behavior and empirically test several of the mechanisms (for overview, Gallego and Kurer 2022). We establish that a more nuanced approach to considering political participation is needed. Namely, not only the change in income matters for political participation but the reason for this change too.

The rest of the paper proceeds as follows: In Section 2, we outline the empirical strategy for both the regional and the individual level analyses. In Section 3 we present the data and in Section 4 the results of the regional analysis. In Section 5 we consider why the nature of the shock may matter for its effect on political participation and present the evidence from the survey experiment. Section 6 concludes.

2 Empirical Strategy

2.1 Aggregate level

We apply a difference-in-differences framework pioneered by seminal studies on the local labour market effects of trade (Autor et al. 2013) and automation (Acemoglu and Restrepo 2020). This approach captures the long-run general equilibrium adjustment to differential exposure to exogenous shocks to labour demand in US local labour markets and therefore considers changes in employment over periods of 7 years or more at the level of 722 continental US commuting zones (CZ).[3].

We follow this approach to identify the long-run effect of automation and Chinese import competition on political participation at US federal elections and estimate the following model:

$$\Delta log(Y_{j,c,t}) = \beta^r \begin{pmatrix} \text{US Exposure} \\ \text{to Robots} \end{pmatrix}_{c,t} + \beta^c \begin{pmatrix} \text{US Exposure} \\ \text{to Chinese} \\ \text{Imports} \end{pmatrix}_{c,t} + \mathbf{X'}_{c,2000}\,\gamma + \mathbf{Z'}_{j,t}\,\delta + \epsilon_{j,c,t} \quad (1)$$

where, in our main result, $Y_{j,c,t}$ stands for the number of votes at US federal elections in county j in commuting-zone c at time t. We estimate the model by stacking log differences over two 8-year periods: 2000-2008 and 2008-2016.[4] We control for unobserved period-specific regional trends by interacting census division with period indicators. Hence,

[3]Commuting zones are groups of counties that constitute local labour markets in which workers seek employment to adjust to changes in labour demand (see Tolbert and Sizer 1996)

[4]Each period covers two four-year terms of US Presidents and four two-year terms of the US House of Representatives. We consider the number of votes at the beginning and the end of each 8-year period.

our main regression identifies the coefficients β^r and β^c from variation in exposure to labour market shocks between CZs in a given time-period and census division. Following Borusyak et al. (2022), we add lagged manufacturing shares interacted with period indicators to control for any unobserved shocks specific to the manufacturing sector overall in each period.

We also include $\mathbf{X'}_{c,2000}$, a vector of commuting-zone baseline characteristics in 2000, to allow for differential trends due to observable differences in demographics (age, education, gender and ethnic composition) or in the exposure to offshoring (share of routine employment, offshorability index) as in Faber et al. (2019). At last, we account for a series of potential contemporaneous confounds $\mathbf{Z'}_{j,t}$, such as the period-specific net migration rate, changes in the share of college-educated adults, the swing state status and the average spending on TV campaign ads per household in 2008 and 2016.

Exposure to robots: Following Acemoglu and Restrepo (2020) we construct a shift-share measure of commuting zone exposure to industrial robots in each period, mapping changes in the stock of industrial robots per workers in 19 US industries into the 1990 employment structure of US commuting zones. Accordingly, in each period for each commuting zone we compute the sum of changes in the stock of industrial robots R_i^{US} in industry i relative to the total number of workers in industry i in 1990, subtracting the growth of the robot stocks due to real output growth $g_{i,t:t+1}^{US}$ over the period, weighted by $l_{c,i,1990}$, the share of industry i in total employment in commuting zone c in 1990:

$$\begin{array}{c}\text{US Exposure to}\\ \text{Robots}_{c,t}\end{array} \equiv \sum_{i\in I} l_{c,i,1990}\left(\frac{R_{i,t+1}^{US}-R_{i,t}^{US}}{L_{i,1990}^{US}} - g_{i,t:t+1}^{US}\frac{R_{i,t}^{US}}{L_{i,1990}^{US}}\right) \tag{2}$$

When regressing the US exposure to robots on various measures of political participation, there are reasons to believe that the exposure measure could be correlated with the error term. For instance, it is possible that both the adoption of industrial robots and political participation are a function of unobserved changes in the US local labour market conditions, such as changes in the strength of unions. If unions are less able to organize workers and bargain for higher wages due to changes in legislation in certain states (e.g. right-to-work laws), firms could face lower incentives to introduce labour-saving technologies while workers are becoming less politically engaged. Therefore, we construct an instrumental variable as in Acemoglu and Restrepo (2020) using changes in the penetration of robots in industry i in five European countries ahead of the US in terms of the adoption of robot technology (Denmark, Finland, France, Italy, Sweden) and the lagged share of industry i in total employment in commuting zone c in 1970 to predict US adoption of robots only due to exogenous improvements in technology:

$$\begin{matrix}\text{Exposure to} \\ \text{Robots}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} l_{ci,1970} \, \frac{1}{5} \sum_{j \in EU5} \left(\frac{R^{EU5}_{i,t+1} - R^{EU5}_{i,t}}{L^{EU5}_{i,1990}} - g^{EU5}_{i,t:t+1} \frac{R^{EU5}_{i,t}}{L^{EU5}_{i,1990}} \right) \tag{3}$$

The identifying assumption of this strategy is that there are no differential shocks or trends affecting voting in commuting zones with greater exposure to robots relative to those with less exposure.

Exposure to Chinese imports: In addition, we construct the commuting zone exposure to Chinese imports for each period following Autor et al. (2013) as the sum of changes of merchandise imports from China to the US relative to the total number of workers in industry i weighted by the share of each manufacturing industry i in total commuting zone employment in c at the beginning of each period:

$$\begin{matrix}\text{US Exposure to} \\ \text{Chinese Imports}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} l_{ci,t} \left(\frac{M^{CN-US}_{i,t+1} - M^{CN-US}_{i,t}}{L^{US}_{i,t}} \right) \tag{4}$$

Also this second explanatory variable could be correlated with the error term, for instance when an exogenous increase in income, e.g. the fracking boom, leads to higher demand for imported consumer products but also affects the likelihood of citizens to engage with politics. To mitigate the possible bias from omission and simultaneity, we construct an instrumental variable as in Autor et al. (ibid.) using imports of Chinese goods by eight high-income as well as lagged employment shares $l_{ci,t-1}$ in order to isolate the export supply shock stemming from China's accession to the WTO and its marketoriented reforms in the 2000s.[5]

$$\begin{array}{c}\text{Exposure to Chinese}\\ \text{Imports}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} l_{ci,t-1} \left(\frac{M_{i,t+1}^{CN-OT} - M_{i,t}^{CN-OT}}{L_{i,t}^{US}} \right) \quad (5)$$

Section 3 in the Appendix provides a detailed description of the data sources used to construct all measures of commuting zone exposure to robots and Chinese imports.

2.2 Individual level

To refine our main set of results and to test the relationship between the exposure to different labor market shocks and political participation at the individual level, we study micro-data from the General Social Survey on political behavior and attitudes and estimate the following regression model at the individual level:

$$\begin{aligned} GSS_{i,c,d,t} = {} & \text{Ind. exposure to Robots}_{i,t} + \text{Ind. exposure to Chinese Imports}_{i,t} + \\ & \text{US exposure to Robots}_{c,t-1:t} + \text{US exposure to Chinese Imports}_{c,t-1:t} + \alpha_{d,t} + \epsilon_{i,c,d,t} \end{aligned} \quad (6)$$

where, for each GSS survey question, $GSS_{i,c,d,t}$ corresponds to the answer of respondent i, in commuting zone c, in a census division d in year t. We estimate this regression using data from all nine biannual waves of the GSS from 2000 to 2016 and restrict the sample to individuals with age between 18 and 65. This yields a baseline sample of more than 12,000 individuals that provided information on their participation at the last presidential election. [6]

Individual exposure to robots: We build a novel measure of individual exposure to automation over the period 2000 to 2016 using a data by Webb (2019) who gauges the exposure of an occupation to automation by measuring the overlap between the text of job task descriptions and the text of robotic patents. Yet, to correctly attribute automatability scores to individuals according to their occupation, one has to take into account that

[5] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

[6] The number of observations for each question varies across questions and is lower than the overall sample size, as some questions are not asked to all survey participants and not in every wave.

an individual's observed occupation is endogenous to the automation process itself (Anelli et al. 2019). Indeed, the observed occupation might be a worker's occupational choice after being replaced by technology. To account for it, we use data from the GSS from 1980 and 1989, the decade before the automation shock, to estimate a multinomial logit model of occupational choice conditional on age, education, gender, father's occupation and degree and census region when 16 years old (9000 observations, Pseudo-R2=0.1759). This allows us to predict out-of-sample occupational choice probabilities for each individual in the years 2000 to 2016, as a set of counter-factual occupational choice less likely to be endogenous to automation. Figures SM1 and SM3 in the Supplementary Online Materials show the out-of-sample prediction accuracy. Then we compute an individual's exposure to automation as the sum of the automatability score θ_o taken from Webb (2019) on the 2-digit census occupation level weighted by the predicted choice probability to work in occupation o:

$$\begin{matrix}\text{Individual} \\ \text{Exposure to} \\ \text{Robots}_{i,t}\end{matrix} = \sum_{o=1}^{14} \left(\hat{Pr}(Occ = o | age_i, gender_i, educ_i, paocc_i, padeg_i, reg16_i) \times \theta_o \right) \tag{7}$$

Individual exposure to Chinese imports: To capture an individual's exposure to merchandise imports from China, we follow Colantone et al. (2019) using log changes in merchandise imports from China in an individual's 3-digit SIC 1987 industry i over the preceding 8 year period.

$$\begin{matrix}\text{Individual Exposure to} \\ \text{Chinese Imports}_{i,t}\end{matrix} = ln(M_{i,t}^{CN-US}) - ln(M_{i,t-8}^{CN-US}) \tag{8}$$

3 Data description

3.1 Political participation

To study political participation at the county-level, we use data from Dave Leip's Atlas of U.S. Elections (Leip 2021) on the total number of votes at US presidential and House of Representative elections by county in years 2000, 2008 and 2016. This data source provides county-level election results based on official reports for all states. With this data we compute the log changes in the total number of votes as a measure of political participation at the county-level. To control for the contemporaneous change in a county's underlying population of eligible voters that might explain differential growth in voting, we use US Census estimates for the total number of adult citizens (citizen voting age population, CVAP). This is our preferred measure of voting population as it is available for counties in all US states and is unaffected by unobserved differences and changes in voter registration or the share of foreign residents.[7] For robustness, we also consider estimates of the total number of adult residents (voting age population, VAP) per county provided by the US Census. Yet, this measure comes with the disadvantage of hiding important regional differences in the share of foreign residents in the adult population.[8] Finally, we also consider the number of registered voters per county as provided by Leip (ibid.). Yet, this measure comes with the disadvantage of being affected by regional differences in voter registration practice as well as policy changes regarding voting registration. Apart from it, voter registration is not available for all states.[9] For these reasons, we use changes in the citizen voting age population as our preferred measure of contemporaneous changes in the underlying population of eligible voters.

[7]Data for the year 2000 comes from the decennial census. Data for years 2008 and 2016 are 5-year estimates over the period 2006 to 2010 and 2014 to 2018 based on the American Community Survey. Citizen voting age data is only available from year 2000 on.

[8]The share of non-US citizens in the adult population is highest in coastal and border regions, e.g. 49% in Los Angeles county in 2017, and has changed continuously over the past 20 years.

[9]Dave Leip's Atlas does not provide full coverage in terms of voter registration data, since some states do either not have voter registration, e.g., North Dakota, or reported the number of voters inconsistently, e.g., Wisconsin, Florida, Mississippi.

3.2 Local labor markets

We compute local labor market variables in each commuting zone using 5% samples from the US Decennial Census for the years 1970, 1990 and 2000 as well as samples from the American Community Survey in 2006, 2007 and 2008 as well as 2014, 2015 and 2016 all provided by the *Integrated Public Use Microdata Series* (IPUMS). This data has the advantage of providing detailed information on individual characteristics (age, sex, education, ethnicity, birthplace) as well as their labor market situation (employment status, occupation, industry, income by source). Using the crosswalks by Autor and Dorn (2013), we can map geographies provided in the IPUMS data to 722 continental commuting zones.[10] This allows us to aggregate data at the commuting zone level and construct a rich set of labor market variables.

As outcomes we compute the change in the log count in total, manufacturing and non-manufacturing employment. Since census data is collected for all individuals of a household, we also compute changes in the dollar change in the commuting-zone average household income per adult defined as the sum of individual incomes of all working-age household members (age 16–64), divided by the number of household members of that age group.

As regression controls we consider baseline characteristics of commuting zones in terms of demographics (log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), the industry composition (shares of employment in agriculture, mining, construction, manufacturing) and the exposure to offshoring (share of routine jobs, average offshorability index) following Autor et al. (2013).

[10]The lowest geographic units in the IPUMS census data are either county groups (1970) or Public Use Microdata Areas (PUMA). Both of them are groups of counties that contain at least 250,000 (1970) or 100,000 people and often intersect with multiple commuting zones. Therefore, we employ the crosswalks used by Autor et al. (2013). We perform a probabilistic assignment of individual observations in the census data into multiple commuting zones based on crosswalks publicly available at https://www.ddorn.net/data.htm

3.3 Other contemporaneous controls

Migration: Recent studies have pointed at the role of internal migration of workers to adjust to changing labor market conditions due to exposure to robots or rising imports from China (Faber et al. 2019; Greenland et al. 2019). To account for the potentially confounding factor of out-migration on changes in voter turnout, we use county-to-county migration counts from the SOI Migration Database. This data is constructed from annual tax return filings of the Internal Revenue Service (IRS). The IRS computes the total number of in- and out-migrating taxpayers by tracking changes in taxpayers' addresses reported between years since 1990.[11]. For each county we compound in- and out-migration flows reported in the data over each 8-year period from 2000 to 2008 and from 2008 to 2016. To compute the net migration rate, we scale the net inflow of migrants per period by the total county population at the beginning of each period. County population estimates for the years 2000 and 2008 are taken from the US Census.

Political campaigning: A second potential confounding factor is localized political campaigning before elections that might be different by region and therefore affect mobilization of voters. [12] To account for it, we use data on political television advertisements (hereafter "ads") from the Wesleyan Media Project (WMP, previously called the Wisconsin Advertisement Project). This database provides a full coverage of political ads broadcasted in the year leading up to congressional (house and senate), gubernatorial, and presidential elections across all 210 US media markets in the years 2008 and 2016.[13] For each broadcast, the database provides detailed information on broadcasting time, ad length, TV channel, political affiliation as well as a large set of issue categories, for example "taxes", "healthcare" or "gun control".[14] Importantly, the database provides cost estimates for each ad which allows us to estimate the total spending on political

[11]Following the migration literature, we use the number of reported tax exemptions on returns with address changes as proxy for the number of migrating individuals (see Gross 2003)

[12]As we discuss in the Conclusion, the party's decision to allocate resources to different areas might be endogenous and depend on the anticipated voter turnout.

[13]Media markets or "Designated Market Areas" are historical broadcasting regions in the US where residents receive the same radio and television signals. These areas are widely used for commercial research on media audiences in the US. Each media market has an exact mapping into US counties which is provided by Nielsen Media Research.

[14]Appendix Figure C3 shows an illustrative example of the story boards collected for each ad.

advertisement per media market in 2008 and 2016. We combine the WMP data with US Census data on the number of households per county to construct a measure of television campaigning intensity by dividing the total spending on political ads by the total number of households of all counties in a given media market area in 2008 or 2016.

4 Results

Local Labor Markets: In a first step, we validate our data set by replicating established findings of the negative employment and income effect of exposure to robots and Chinese imports across US local labor markets. To compare our estimates more closely to the existing literature we construct all outcome variables as stacked differences over three time periods between 1993, 2000, 2007 and 2015 at the commuting zone level. We control for the full set of 1990 baseline commuting zone characteristics and find employment effects similar to those documented in Faber et al. (2019). In Table A2 we find that a standard deviation increase in the exposure to robots and Chinese imports reduced manufacturing employment growth by about 1 and 5 percentage points, respectively. We also find the employment effect of exposure to rising Chinese imports to be limited to manufacturing employment, while there seems to be a significant negative effect for increasing exposure to robots outside of manufacturing. Despite the differences in the extent of the employment effect, we can show that both shocks had a statistically comparable effect on the average annual household income per adult. Table A3 shows that a standard deviation increase in the exposure to robots decreased the change in the average annual household income per adult by 571 dollars, while an equivalent increase in the exposure to Chinese imports reduced income by 762 dollars. Decomposing household income we can show that both shocks lead to reductions in the wage income of households as well as to increased reliance on social security and income from welfare programs. Across all our specifications the Kleibergen-Paap F-Statistic of the first stage is larger than the threshold value of 10 across which fulfills the requirement of instrument relevance. Overall, Tables A2 and A3 confirm previous findings on the negative effect of both shocks on employment and the economic situation of households and working adults living in more exposed commuting zones.

Political Participation: In a second step, we employ the local labor market framework to test the effect of both structural (and as just demonstrated income) shocks on county-level changes in political participation at federal elections between 2000, 2008 and 2016. In Table 1 we report the results of two-stages least squares regressions of both exposure measures on changes in the log number of voters at presidential elections. Controlling for baseline controls, we find that a standard deviation increase in the exposure to robots reduced the growth in the number of votes by 1.8 percentage points, while exposure to Chinese imports had a largely insignificant effect on voting. In specification (2), we control for contemporaneous change in the underlying population of eligible voters in terms of the citizen voting age population, the net in-migration rate and changes in the share of college-educated adults. In addition, we control for swing state status of each county as well as difference in political campaigning intensity at the 2008 and 2016 elections. All controls significantly predict growth in voting and substantially reduce the effect size of robot exposure but without affecting the significance level. In this full specification, we estimate that a standard deviation increase in robot exposure reduced voting by 1 percentage point, while Chinese imports do not affect the growth in the number of votes at presidential elections in any specification. Wald tests at conventional significance levels consistently reject the null hypothesis that the difference of the estimated coefficients is zero. As a one standard deviation change in robot exposure corresponds to an increase of roughly 0.51 robots per thousand workers, our estimate implies that one more robot per thousand workers caused voting growth to fall by about 2 percentage points. This magnitude has to be compared with an average growth in the number of votes per 8-year election cycle of about 7.9 percent.

Table 1: Effect of exposure to robots and Chinese imports on voting at U.S. federal elections elections: county-level stacked differences 2000-2016 (2SLS)

	Δ log(votes) × 100			
	US President		US House of Representatives	
	(1)	(2)	(3)	(4)
US Exposure to Robots	-1.841***	-1.006***	-2.130***	-1.308**
	(0.384)	(0.265)	(0.669)	(0.584)
US Exposure to Chinese Imports	0.470	0.561	2.232*	1.846*
	(0.848)	(0.581)	(1.218)	(0.999)
Δ log(citizen voting age population)		0.721***		0.690***
		(0.0440)		(0.0911)
Net in-migration rate		20.34***		40.10***
		(4.327)		(9.422)
Δ share of college educated		-27.60**		4.411
		(13.45)		(25.68)
Perennial swing state		1.266***		2.978***
		(0.488)		(0.836)
TV campaign ads, USD per HH		0.110***		0.164*
		(0.0232)		(0.0984)
Kleibergen-Paap F-Stat	31.99	33.01	28.32	29.49
R^2	0.65	0.84	0.44	0.57
Observations	6172	6136	5483	5432
Wald Test [R=C] p-Value	0.008	0.010	0.002	0.005
Region × Period	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Pre-trend		✓		✓

Note: The dependent variable is the change in the log count of votes multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). Regressions in column (2) and (4) also account for pre-trends controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

To corroborate this finding, we further study voting at US House of Representative elections between the same reference years. In Table 1, we find a more pronounced negative effect of robot exposure and a significantly positive effect of exposure of Chinese imports on voting at US House elections. In our full specification, we estimate that one standard deviation increase in exposure to robots leads to a -1.6 percentage points decrease and and Chinese imports to a 2.2 percentage point increase at House of Representative elections. These results broadly confirm differential voting response to comparable income shocks at the local labor market level. Our finding is also robust to using alternative measures for changes in the population of eligible voters (see Table B7).

To assess the magnitude and political significance of our finding, we run an additional regression using not changes in the number of votes, but in voter turnout as an outcome variable (Table SM3). We compute voter turnout as the number of votes relative to the citizen voting age population and therefore do not control for changes in the eligible population as a an independent variable. Similar to studies on the employment effect of both shocks (Acemoglu and Restrepo 2020; Autor et al. 2013), looking at the outcome relative to a baseline population allows to translate the observed effects into individual equivalents (workers, or in our case voters). For both types of elections, we estimate the fully specified model and find that a standard deviation increase in the exposure to robots reduces voter turnout by about 0.5 percentage points, while increased exposure to Chinese imports has a statistically insignificant and at best positive effect on voter turnout. Our estimate implies that one more robot per thousand workers is associated with a 1 percentage point lower *voter turnout*. Given the average increase in the stock of robots of about 80,000 robots per electoral 8-year period, it can be estimated that automation has reduced turnout by about 1 million voters per 8-year period. [15] The results of Acemoglu and Restrepo (2020) suggest that one more robot per thousand workers reduces employment by 6 workers. Our estimates suggest an even larger effect on political participation

[15]For the year 2000, we count 212 million US adult residents, 196 million adult citizen residents, 127 million employed workers and 105 million voters. The average national turnout at the presidential election was at 53%. This means that for 1000 workers there were on average 1500 citizen residents and 803 voters. The reduction in voters due to one more robot per thousand workers is then equivalent to $13 \approx 803 - (0.5367 - 0.01) \times 1500$.

with one more robot per thousand workers reducing turnout by about 13 voters. This result suggests that the effect of automation on political participation goes beyond those people that are directly affected.

Table 2: Individual exposure to robots and imports from China and individual political participation: pooled OLS

	Heavy lifting	Forceful hand movement	Likely to lose job	Voted in last election	General trust
	(1)	(2)	(3)	(4)	(5)
Individual exposure	0.118***	0.074***	0.056***	-0.117***	-0.050***
to robots	(0.019)	(0.020)	(0.012)	(0.011)	(0.013)
Individual exposure	0.022***	0.023***	0.008	-0.005	-0.008
to Chinese Imports	(0.008)	(0.008)	(0.005)	(0.005)	(0.007)
US Exposure to Robots	0.033*	0.040***	0.022***	-0.003	-0.039**
	(0.018)	(0.015)	(0.007)	(0.014)	(0.015)
US Exposure to Chinese	-0.004	-0.007	0.000	0.000	0.016***
Imports	(0.005)	(0.007)	(0.003)	(0.003)	(0.006)
Observations	3733	3734	5260	9163	5649
R2	0.17	0.11	0.06	0.15	0.13
Sample mean	0.45	0.48	0.09	0.71	0.39
Individual controls	Yes	Yes	Yes	Yes	Yes
Year x Census Division	Yes	Yes	Yes	Yes	Yes

Note: Pooled sample consists of cross-sectional survey from years 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014 and 2016. All outcome variables are coded binary: (1) Respondent's work implies heavy lifting (2) R's work implies forceful hand movements (3) R believes job loss within next 12 months to be likely (4) R voted at last presidential election (5) R believes that people can be trusted in general. All specifications control for the following individual characteristics: age, years of schooling, gender and income. Standard errors are clustered at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Individual Exposure to Automation and Trade: To elaborate on why the effect of automation on political participation potentially might go beyond those directly affected, we study micro-level data of the *General Social Survey* (GSS) for the years 2000 to 2016 (see Section 2.2 for details on the data and empirical strategy). It contains detailed information on the labour market situation of US residents as well as their political attitudes and beliefs. We build a measure of individual exposure to automation using data by Webb (2019) who gauges the exposure of an occupation to automation by measuring the overlap between the text of job task descriptions and the text of robotic patents. In addition, we compute a measure of individual exposure to imports from China following Colantone et al. (2019) by computing the log change in imports in an individual's industry over the previous 8 years. To be able to distinguish individual exposure to both shocks from the exposure from living in an exposed region, we add the two commuting zones measures of exposure to robots and Chinese imports over the past 8 years as well. Our main regressions are repeated cross-sections of biannual waves from the GSS between the years 2000 to 2016. We also control for confounding individual characteristics such as age, education, gender and income.

Table 2 documents how individual and regional exposure to the shocks affects the outcome variables of interests. First, in columns 1 and 2 we validate that the constructed measures of individual exposure to robots and Chinese imports are meaningful by confirming that more exposed individuals are also more likely to engage in manual work that involves forceful hand movements and heavy lifting. Next, column 3 shows that individuals that are more exposed to robots are also more likely to fear job loss in the next 12 months, which is in line with the labour market effects reported in Table A2. For individuals exposed to Chinese imports, expectations of job loss do not seem to be affected on average.[16] Column (4) presents the central result of this part of the analysis. It documents that one standard deviation increase in an individual's exposure to robots reduced the likelihood of having voted at the past presidential election by 12 percent. Unlike individual exposure to robots, individual exposure to Chinese imports or regional effects do not appear to affect the likelihood to abstain. The results of the GSS analysis suggest that people who are generally exposed to automation are less likely to cast their votes. The effect does not seem to be mediated by potential change of economic conditions in the region. This confirms the finding of the differential effect on voter turnout at presidential elections at the county-level reported in Table 1.

Although, as shown in Table A3, the income effects of both shocks are comparable, the shocks are not identical. One documented difference is that the consequences of an

[16] This might be since the individual exposure to Chinese imports is non-zero for workers that are working in manufacturing industries at the moment of survey and zero for all service sector workers which constitute the majority of workers.

intensified trade with China are more confined to manufacturing employment, while an increase in automation generates negative employment spillovers outside manufacturing (Faber et al. 2019). People employed in different sectors might have different propensity to vote, which might explain the differential voter turnout following the two shocks that we observe. Yet, this difference is unlikely to explain the observed result. First, the parts of the difference between the affected groups are likely to be captured by the demographic characteristics that we control for. Second, even under the assumption that there is some sector specific determinant of the voter turnout orthogonal to established demographic determinants of voter turnout and specific to non-manufacturing employment (Smets and Ham 2013), the fact that we find no effect among the affected in manufacturing sector and a negative effect in mixed sample of affected in both manufacturing and non-manufacturing employment, it would have to hold that the affected in non-manufacturing employment are the sole drivers of the fairly large effect that we observe. As it does not appear feasible, we proceed by considering what possible mechanisms by trigger differential effects on political participation between the two structural changes by means of an online survey experiment.

5 Evidence from the Online Survey Experiment

5.1 Hypotheses

Voting is the fundamental act of civic engagement in a democracy and therefore received a lot of academic attention. A number of theories attempted to answer why people turn out to polls and how they vote (see e.g., Dhillon and Peralta 2002, for an overview of theories). Given that we do not aim at predicting the outcomes of the elections and what candidates are preferred but solely the voter turn out, we can simplify and adjust the existing models to guide our further analysis.

From a rational voter perspective, citizens decide to vote if the utility from voting outweights the utility from abstaining. Therefore, in this framework, the differential effect of the two shocks on the voter turn out is due to the fact that they deferentially affect the expected utility of the individual voters.

The simplest model of calculus of voting (following Dhillon and Peralta 2002) is

$$U_j(voting) = B_j P_j + D_j + c_j \tag{9}$$

where B_j is the benefit expected to be derived from success of one's favorite candidate, which is the difference in utility of voter j if his favorite candidate is elected and the utility if the opponent does, P_j is the perceived likelihood that one's vote will make a difference, D_j is the expressive benefit that voter j gets from the act of voting and c_j are costs of voting.[17]

For simplicity, we leave out the probability of being a pivotal voter and costs of voting (e.g., getting to the poll etc.), as probability of being pivotal is negligible in the nation-wide US elections and costs of voting are unlikely to vary depending on the shock. These simplifications lead to:

$$U_j(voting) = B_j + D_j \tag{10}$$

which means that the utility of voting is a sum of instrumental and expressive utilities. Without the ambition of contributing to political theory, we posit that a number of factors may differ depending on the nature of the labor shock, hence, affecting the instrumental and expressive value. Below we elaborate what factors may affect the instrumental and expressive value of potential voters.

The expressive value of voting typically includes factors that are not affected by the outcome of the vote. In the earlier models, D_j represented utility from civic duty, but it was then extended to include the utility gained from voting according to one's party affiliation (Fiorina 1976). One may, therefore, assume that if a political party actively uses one of the shocks in its agenda, potential voters may gain utility from expressing support to the party in addition to the instrumental value.

[17]While both automation and increased trade competition are issues and therefore it may be suggested that issue voting models are more appropriate, it does not appear to be the case as the issue voting models (e.g., Macdonald et al. 1995; Rabinowitz and Macdonald 1989) consider the candidate choice and not participation choice of voters.

The instrumental value (B_j) appears to be more complex. As both of our shocks are labor shocks, we assume that the ideal outcome for a voter in response to the shock is preventing negative economic consequences. Several factors might affect the instrumental value of voting depending on the labor market shock. First, if a voter perceives one shock to be more important and have larger consequences, he might expect higher instrumental benefits if the issue is addressed. Importantly, the perceptions of potential voters and not *de facto* consequences of the shocks matter. Second, while the voters expect to benefit if the issue is addressed, voting in elections is a tool of influencing the government and governmental policies. Therefore if voters do not believe that the issue may be addressed through governmental action or policy they may expect less instrumental utility. Furthermore, going beyond governmental ability to address the shocks, one might perceive one shock to be in general more inevitable and irreversible which may affect the willingness to vote. Third, if there is no candidate or political party who advocates an agenda to address the shock, voting may cast less instrumental utility. Additionally, the instrumental value of voting may be affected by global preferences such as time or risk preferences. For example, a present-biased voter may discount any utility that would come from addressing the issue in the future and not immediately. If the shocks trigger a shift in these preferences, they might translate into differential voting response.

5.2 Survey Experiment: Design and Procedures

To consider what factors might contribute to the observed aggregate differences in the political participation, we conduct an online survey experiment. In February-March 2021, we recruited 835 of US residents via Prolific to take part in the study. Prolific is a platform similar to mTurk, but it offers the advantage of reaching to more diverse and naive respondents (Peer et al. 2017). The respondents were on average 36 years old, about 60% of the respondents were males. We attempted to exclude students (0.6% of total sample) who might not have labor market experience yet. We over-sampled industries that might be considered as affected by automation (manufacturing, mining, logistics and warehousing), which constitute ca. 30% of the sample. The respondents took on average

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to invest in automation and other labour-saving technologies. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and introducing new technologies is the way forward. As a result of shutting down some of the production lines that become automated, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by developments in labour saving technologies and automation of processes. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

Figure 1: Newspaper article for automation condition. Highlights added. The highlighted parts varied depending on the treatment.

less than 9 minutes (median 7,5 min) to answer the survey and were reimbursed with a flat payment of 1 GBP.

In our study we followed the approach of Di Tella and Rodrik (2020). After answering basic demographic questions, respondents saw a piece of text formatted as a newspaper article (for example, see Fig 1). The article reported that a manufacturing plant announced layoffs. Depending on the treatment, the reason for the layoffs varied. We conducted three treatments: In Automation treatment the layoffs were due to the introduction of labor saving technologies. In Trade treatment the layoffs were due to increased trade competition with other countries and in particular with China. Additionally, we run a control treatment in which layoffs were due to restructuring and new managerial practices. In the last treatment, neither automation nor trade was mentioned.[18]

Under the text the respondents saw 3 comprehension questions. Two of the questions had to be answered correctly in order to proceed with the study. The questions referred to the information in the articles and ensured careful reading.

[18]The texts of the news pieces from Trade and Control conditions, as well as further survey materials can be found in the Appendix G.

After that the respondents answered questions about their perceptions of consequences of different scenarios (individual for unemployed workers and more general for the society as a whole), desired actions by the government, voting and political attention to the issue, emotional responses towards different kinds of unemployment (following Granulo et al. 2019), a version of preference survey module of Falk et al. (2016) to consider time, risk, altruism, trust as well as locus of control.

Since we expect heterogeneities in responses along the lines of the party affiliation, apart from self-reported measure of political position, we elicited attitudes on the role of competition, government involvement and role of luck in success in the US to validate if the self-reported measure was meaningful. Precise wording of questions as well as their sequence can be found in the Supplementary Online Materials G.2.

5.3 Survey Experiment: Results

For most questions, respondents express their agreement or disagreement to provided statements on a 7 point Likert scale that ranges from strongly disagree (1) to strongly agree (7) where 4 represents the indifference point. First, we conclude that all three suggested stories are equally believable as we do not detect difference in how much the respondent can relate to the described event (Kruskal-Wallis H test, $\chi^2(2) = 2.721, p = 0.26$).

All three reasons for unemployment are perceived to be equally damaging both for individuals in the short term (ease of finding the next employment) as well as in the long term (long lasting consequences of the shock, its effect on inequality in the future and opportunities in the future).[19] Yet, the respondents perceive some consequences of the shocks differently. For instance, they believe that in case of layoff due to automation, employees are less likely to find a position within the same occupation. Moreover, optimal search strategies seem to differ. While in all three scenarios, the respondents most often recommend to start searching for a new job directly (42% of respondents in Automation,

[19] Unless otherwise specified, the statements are based on the results of the two-tailed t-tests. For robustness we have replicated our analysis using the OLS regression and controlling for main demographic variables. The results remained qualitatively similar. The reader can find the mean scores as well as p-values of the t-tests not mentioned in the main text in the Supplementary Online Materials G.2.

53% in Trade and 60% in Control), the share of respondents choosing this option is significantly lower in Automation than in the two other conditions (Automation and Control p=0.000, Automation and Trade p=0.007). However, in case of unemployment due to automation, the respondents more often recommend gaining additional qualifications or retraining into a new occupation before searching for a new job [20]. Taken together, while unemployment due to different shocks appears to affect the recommended job search strategy, we do not detect the differences in main variables that relate to consequences of the shocks. Therefore, it appears unlikely that different perceptions of the consequences and importance of the shocks can drive the differential effect observed in the aggregate data.

As outlined above, the second factor that might affect the instrumental value of voting and thus the voter turnout is if the issue can be addressed and ultimately solved by the government. Our data suggests that the government is seen as less helpful in coping with automation as compared to trade shock. When asked who could have prevented the job loss, more respondents in the Trade condition highlighted the role of the federal government (21% in Trade vs 6% in Automation (p=0.000) and 3% in Control (p=0.000)). For the same question a largest share of respondents stated that the job losses were inevitable (see Figure 2): 49.5% in Automation treatment as compared to 36.8% in Control (p=0.0025) and 30.3% in Trade (p=0.000). In a separate question if there is anything the society can do to prevent job losses due to technological advances and intensified trade[21], participants in all treatments were more likely to agree that technological unemployment represents a bigger challenge to society. The average score is 3.35 for trade unemployment and 3.79 for technological one (p=0.000). While the respondents rather disagree with the grim statement, they are more pessimistic about automation.

Another question, that may lend additional support to the hypothesis that governmental involvement is perceived to be more useful in case of Trade as opposed to Automation

[20] Additional qualifications: Automation 18%, Trade 13% and Control 11%, p=0.09 and p=0.01 for respective comparisons. Retraining into new occupation: Automation 28%, Trade 20% and Control (17%), p=0.04 and p=0.002.

[21] The question was asked separately for technological advances and intensified trade. Both questions were presented in all treatments at the very end of the survey.

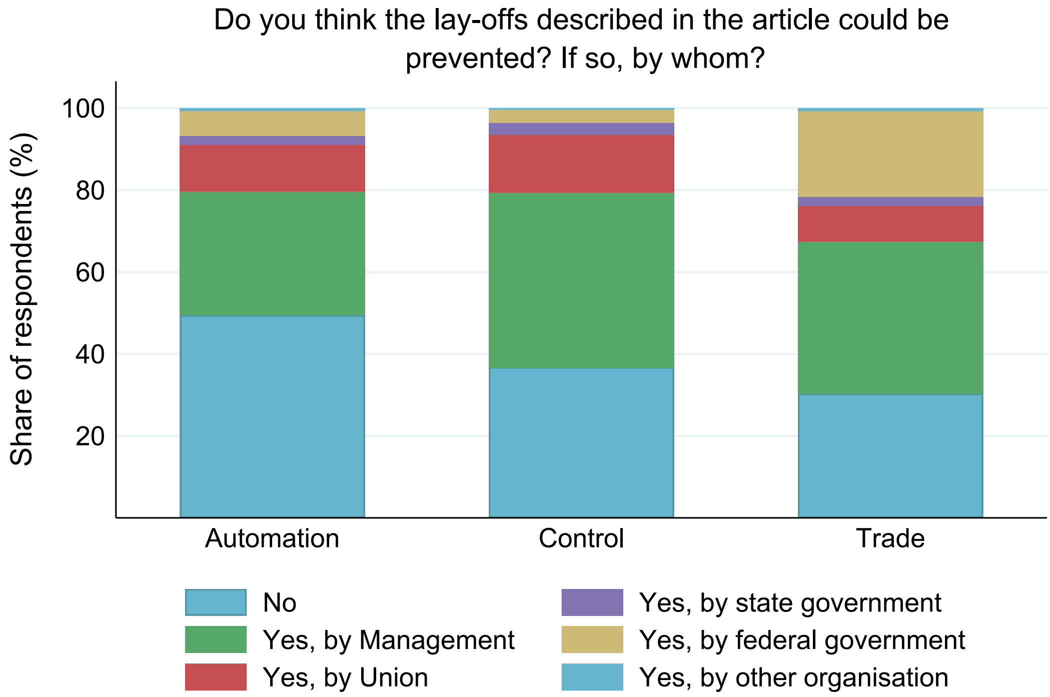

Figure 2: Exact wording of the answer options: No, the lay-offs are inevitable; Yes, by the company management; Yes, by the union or other professional organisation; Yes, by the state government; Yes, by the federal government; Yes, by other organisation.

or Control scenario, replicated the approach of Di Tella and Rodrik (2020) with slight adjustments to the answer options available to the respondents. The respondents were asked what should the government do in each scenario and could choose one of the four options: nothing, administer direct transfers to affected parties, introduce import tariffs and introduce automation taxes. Three out of four options imply that the government needs to engage. The smallest share of respondents indicated that the government should do nothing in Trade condition (only 5%) as compared to 9% in Automation ($p=0.055$) and 11% in Control ($p=0.008$) (see Figure 3). That is, government involvement is more demanded in Trade condition.

Based on the survey responses, we conclude that the government engagement may be seen as most helpful against the consequences of the trade shock. Additionally, the unemployment due to Automation seems to be perceived as more inevitable in general.

We also asked several questions related to voting and political attention towards the issues. In all treatments, the respondents overwhelmingly agree that voting in general

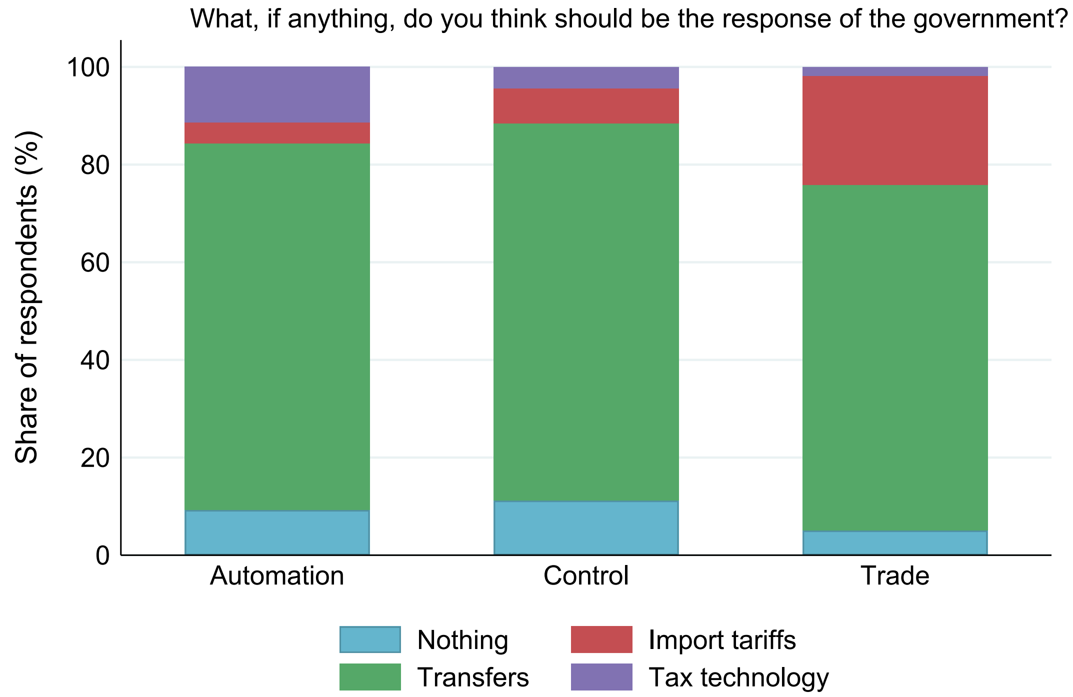

Figure 3: Exact wording of the answer options: Government should do nothing; Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance); Government should restrict imports from overseas, by placing import tariffs on such imports for example; Government should impose higher taxes on labour-saving technology and regulate automation more strictly.

is important with average score of 6.3 points out of 7. Moreover, in all treatments respondents tend to agree that it is important to draw attention of public and politicians to the issues. However, in Automation condition respondents express stronger agreement (5.36) with the statement that not enough political attention is dedicated to the issue than in Trade (5.06, p=0.01). The Control condition falls in between.

As questions about voting and political attention might relate to ongoing political discussion in the US, we expected that the observed responses might depend on political attitudes of the respondents. Before exposing respondents to the treatment manipulation, we asked where would they place themselves on a 7 point scale between extremely liberal (1) and extremely conservative (7)[22]. We intentionally chose not to mention specific political parties in order to avoid attitudes towards party leaders and rather focus

[22] About 1% of respondents answered "I do not know", they are excluded from this part of the analysis

on ideological positions. Additionally, we asked several questions that relate to one's ideological position (the role of the government, role of luck and effort in success and attitudes towards competition). The self-reported measure strongly and significantly correlates with responses to the ideological statements in the expected direction[23], which reconfirms that self-reported measure of political attitudes can be used to consider heterogeneities along the lines of political affiliation. On average our sample is slightly liberal (3.1 with 4 corresponding to "moderate") with no significant differences among treatments (Kruskal-Wallis test, $\chi^2(2) = 0.362, p = 0.83$).

To consider the role of political affiliation, we run an OLS regression with answers to different statements as a dependent variable and the continuous measures of the political position and thetreatment as well as the interaction of the two as independent variables. Additionally, we control for age, level of education, gender, if the respondent is white, if the respondent works in the affected industry (see list above). While the political affiliation of the respondent does not significantly interact with treatment for questions on the importance and consequences of the shocks (both individual and societal), the interaction term of political attitudes and Trade condition has large (ca. a third of a point) and significant coefficient on both questions related to political attention toward the shocks (see Table SM5). That is, more conservative respondents in the Trade condition tend to express stronger agreement with the statements that not enough political attention is dedicated to the problem and that it is important to draw attention to it. In line with the argument that voting along own party preference may yield additional expressive utility, this results supports the idea that the more conservative voters may gain additional utility of expressive voting in the Trade condition.

In our survey responses we do not detect any differences in global preferences such as risk, trust and time preferences as well as altruism and locus of control. Also, contrary to some findings of Granulo et al. (2019), we do not find differences in emotional responses to different types of unemployment (see results of the t-tests in the Supplementary Online

[23] Higher values stand for more conservative position and stronger agreement with the statement: *Competition is harmful. It brings out the worst in people*, Pearson's correlation= -0.3, p=0.000; *The government should take more responsibility to ensure that everyone is provided for*, Pearson's correlation=-0.6 p=0.000; *In the US, people become successful because they got lucky*, Pearson's correlation=-0.57, p=0.000

Materials G.2).

We additionally considered heterogeneity of responses by age, by being employed in the affected industry (Manufacturing and Transportation and Warehousing, ca. 30% of the sample) and if the respondent is at risk of automation where the risk of automation score is calculated following the methodology used above for GSS respondents. This analysis did not provide additional insights into mechanisms behind the patterns documented with the regional data. Although each of the factors had significant coefficients for some variables, there are no notable interaction effects with treatment conditions.

To sum up, our survey evidence suggests that the automation shock is seen as more inevitable and governmental interventions to address it as less helpful. These two factors might have negatively affected the utility from voting and therefore led to lower voter turnout. On the contrary, in the case of Trade shock a more conservative groups of voters might have gained additional utility from expressing the party loyalty. From our survey it does not appear that one shock is perceived as more important than another.

6 Discussion and Conclusion

In this paper, we consider if structural changes affect political participation by reallocating income. Answering a question put forward as one of the most pressing in the review of Gallego and Kurer (2022), we study the effect of the two largest structural changes to the economies of the past decades — long-run labor market adjustment to industrial robots and Chinese imports — on voter turnout in the US between 2000 and 2016. First, we confirm the established finding that both automation and import competition from China lead to comparable in magnitudes declines in employment and average household income at the level of local labor market. We document a significant negative relationship between a commuting-zone exposure to industrial robots and changes in county-level turnout at both types of federal elections. In contrast, the exposure to rising imports from China does not affect turnout at presidential elections and positively affects turnout at US House of Representative elections. In an online survey experiment we consider several potential driving factors. While both shocks are perceived to be equally important, respondents found layoffs due to automation to be more inevitable and federal government to be less able to tackle it than in the import competition scenario.

By considering the effect of the two structural shocks we can show that the relationship between labor market conditions and political participation is not uniform, i.e. negative income shocks do not always affect political participation in the same way, which appears to be an implicit assumption in the literature on the economic determinants of political participation (Burden and Wichowsky 2014; Charles and Stephens Jr 2013; Rosenstone 1982). It is not solely change in economic condition that matters but the reasons behind the shock and the role of the government in addressing it. With the message similar to Di Tella and Rodrik (2020) and Gallego and Kurer (2022), our results suggest that the reasons behind the income shocks are crucial for how reduction of income affects political engagement.

One can argue that the differential effect of these particular shocks on the voter turnout is even more important to consider as they offer two alternative ways of reducing labor costs of production and policies aimed to slow the pace of one process may accelerate the other. For instance, to reduce labor costs one could either buy cheaper supplies abroad instead of producing them in the country or introduce labor saving technologies and thus produce with less labor. Because citizens who care about intensified trade vote, the politicians might be more likely to champion their agenda and introduce measures that impede trade and consequently prompting firms to more actively invest into the labor saving technologies, further disadvantaging those at risk of automation.

Our data also allows to elaborate how political parties react to the decrease in voter turnout. On one hand, they might attempt to capture the votes of the affected individuals and thus counteract the decrease in voter turnout by intensified political campaigning. On the other hand, they might reduce the intensity of political campaigning in response to the decreased voter turn out. Our data supports the latter hypothesis. In our main specification (Table 1) we control for the level of political campaigning and the results suggest that even if political parties attempt to capture the votes of the voters affected by automation, they do not appear to be able to offset it. Yet, considering the intensity of political campaigning in more detail, it also appears more likely that political parties anticipate the decrease in voter turnout and in response reduce the number and budget on the political ads in the affected regions. Table B8 reports that for the presidential campaign fewer and cheaper ads were shown in the regions affected by automation. There is no significant change in the number or costs of ads in the regions affected by Chinese imports. For those ads that were shown in the regions affected by automation, the topics appear to be ill tailored: We document a significant increase in ads that mention jobs and trade, but decrease in those mentioning jobs without connection to trade[24] and social security issues, that based on our survey experimental evidence, are of particular importance in case of automation. This mismatch may be interpreted as a manifestation of a diversion hypothesis that suggests that political parties might divert voters into thinking that the cause of economic transformations that they experience as undesirable is international trade or immigration (Gallego and Kurer 2022).

Further rigurous investigations are need to consider if *politicians* respond to the structural shocks differently. Feigenbaum and Hall (2015) show that legislators in the US House of Representatives adjusted their roll-call behavior and vote in favor or more protectionist trade bills when their districts was more affected by Chinese import competition. This result suggest that legislators are sensitive to shocks to local labor markets. Yet, it remains unclear whether legislators tried to address the concerns of local workers or the interests of local company owners seeking trade protection. As Bartels (2009) demonstrates that US Senators tend to be more responsive to the interests of the most affluent constituents, it is possible that legislators only address local labor market shocks when the interests of workers and company owners align, which is more likely to be the case for import competition than for increased levels of automation. Differential response by politicians may, therefore, be an important root to the differences in perceived government efficacy and might trigger the disparities in political participation levels that we document.

[24]Our ads data does not have a topic "automation" or comparable and therefore does not allow to construct a direct equivalent to the number of ads that mention jobs and China or trade. We compare this category to the number of the ads that mention jobs and do not mention China or trade.

Our evidence corroborates the concerns about the reinforcing feedback loop that is likely to ignore the interests of those who do not vote (Lijphart 1997). Our results suggest that the ignored voices belong to those affected by automation.

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Appendix A Commuting-zone level analysis

Table A1: Descriptive statistics for commuting zone analysis, 1990-2015

	(1)	(2)	(3)	(4)	(5)	(6)
		Exposure to robots	Exposure to China	Relative exposure to robots vs. China		
Quartiles	All	Q4	Q4	Q1	Q4	Q4-Q1
Observations	722	180	180	181	180	361
Changes in outcomes, 1990-2015:						
Log manufacturing employment	-16.3	-27.3	-29.5	-22.9	-18.3	4.5
Log non-manufacturing employment	21.9	19.8	21.6	23.3	17.6	-5.7***
Annual household income/adult	2,973.5	1,639.0	1,816.3	2,607.2	2,156.9	-450.2*
...from wages and salaries	3,039.1	1,736.8	1,808.6	2,562.7	2,358.5	-204.2
...from business investment	-475.8	-582.7	-506.6	-428.6	-615.8	-187.2***
...from social security and welfare	410.3	484.9	514.4	473.1	414.3	-58.8**
Log number of adults in poverty	27.8	35.5	35.2	32.2	30.0	-2.1
Share of population, 1990 (in %):						
Above 65 years old	13.4	13.7	13.5	13.4	13.8	0.4
Female	51.1	51.5	51.4	51.1	51.3	0.2***
Less than college	71.4	73.7	74.2	71.8	72.7	0.9
Some college or more	25.4	23.2	22.9	25.1	24.3	-0.8
White	87.0	90.4	87.4	86.1	90.6	4.5***
Black	7.8	8.0	10.5	9.8	6.2	-3.6***
Asian	0.1	0.1	0.1	0.1	0.1	-0.1**
Hispanic	5.8	1.4	1.9	4.2	3.8	-0.4
Share of employment, 1990 (in %):						
Agriculture	6.6	4.6	4.9	6.1	6.0	-0.1
Mining	1.8	0.7	0.8	1.0	1.7	0.7***
Construction	6.4	6.1	6.3	6.5	6.2	-0.3*
Manufacturing	16.9	24.5	25.4	19.9	19.7	-0.2
Routine employment	35.7	38.4	39.8	37.0	36.9	-0.1
Index, 1990:						
Offshorability Index	-0.1	-0.0	-0.0	-0.0	-0.1	-0.0*

Note: Column's (1) to (5) display unweighted means of changes in outcomes between 1990 and 2015 as well as unweighted means of commuting zone characteristics in 1990. For each commuting zone we compute the average exposure to robots and China over the periods 1990 to 2000, 2000 to 2007 and 2007 to 2015. Columns (2) and (3) display unweighted means of the commuting zones in the highest quartiles of the average exposure to robots and China, respectively. We compute a measure of relative exposure to robots vs. China by standardizing both exposure measures to have a mean of zero and a standard deviation of 1 and take the difference between the standardized measures of exposure to robots and China. Column (6) displays the difference in the mean commuting zone characteristics between the forth and the first quartile of relative exposure and reports statistical significance of the underlying ttest. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A2: Effects of exposure to robots and Chinese imports on changes in employment: stacked differences (1990-2015) 2SLS

	Δ log(employment)		
	Total	Manufacturing	Non-manufacturing
	(1)	(2)	(3)
US Exposure to Robots	-1.21***	-1.12***	-1.20***
	(0.22)	(0.34)	(0.24)
US Exposure to Chinese Imports	-0.89	-5.69***	0.80
	(1.25)	(1.72)	(1.08)
Kleibergen-Paap F-Stat	32.77	32.13	32.79
Observations	2166	2166	2166
R^2	0.33	0.16	0.30
Region × time	✓	✓	✓
Demographics	✓	✓	✓
Industry shares	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓
Pre-trends	✓	✓	✓

Note: N=2,166 (3×722 Commuting Zones) The dependent variables in columns (1), (2) and (3) is the change in the log of total, manufacturing and non-manufacturing employment respectively, multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Specifications (1) to (3) control for the change of the respective outcome variable between 1970 and 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A3: Effects of exposure to robots and Chinese imports on changes in household income per working-age adult, by source: stacked differences (1990-2015) 2SLS

	Δ Average HHI/adult			
	Total	Wage-salary	Business-invest	SocSec + Welfare
	(1)	(2)	(3)	(4)
US Exposure to robots	-571.19***	-572.12***	-25.88*	26.80***
	(86.23)	(79.12)	(10.42)	(2.61)
US Exposure to Chinese Imports	-765.18**	-764.31***	-13.13	12.26
	(236.76)	(217.77)	(37.05)	(12.32)
Kleibergen-Paap F-Stat	32.32	32.32	32.32	32.32
Observations	2166	2166	2166	2166
R^2	0.14	0.17	0.03	0.22
Region × time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓

Note: N=2,166 (3×722 Commuting Zones) The dependent variable in column (1) is the ten-year equivalent real dollar change in the commuting-zone average household income per adult which is defined as the sum of individual incomes of all working-age household members (age 16–64), divided by the number of household members of that age group. Following Autor et al. (2013) total income is split up into wage and salary income in column (2); self-employment, business, and investment income in column (3); social security and welfare income in column (4). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Appendix B County-level analysis

Table B4: Descriptive statistics for county-level analysis, 2000-2016

	(1)	(2)	(3)	(4)	(5)	(6)
		Exposure to robots	Exposure to China	Relative exposure to robots vs. China		
Quartiles	All	Q4	Q4	Q1	Q4	Q4-Q1
Observations	3066	761	765	771	759	1543
Changes in county-level outcomes, 2000-2016:						
Log voters at presidential elections	15.9	13.9	15.1	16.7	13.4	-3.2***
Log voters at house elections	16.5	14.5	15.9	18.4	13.3	-5.1***
Voter turnout at presidential elections	4.7	4.5	5.2	5.0	4.3	-0.7***
Voter turnout at house elections	4.7	4.5	5.2	5.4	4.0	-1.4***
Share of commuting-zone population, 2000 (in %):						
Above 65 years old	13.4	13.7	13.5	13.4	13.8	-0.4
Female	51.1	51.5	51.4	51.1	51.3	-0.2***
Less than college	71.4	73.7	74.2	71.8	72.7	-0.9
Some college or more	25.4	23.2	22.9	25.1	24.3	0.8
White	87.0	90.4	87.4	86.1	90.6	-4.5***
Black	7.8	8.0	10.5	9.8	6.2	3.6***
Asian	0.1	0.1	0.1	0.1	0.1	0.1**
Hispanic	5.8	1.4	1.9	4.2	3.8	0.4
Share of commuting-zone employment, 2000 (in %):						
Agriculture	6.6	4.6	4.9	6.1	6.0	0.1
Mining	1.8	0.7	0.8	1.0	1.7	-0.7***
Construction	6.4	6.1	6.3	6.5	6.2	0.3*
Manufacturing	16.9	24.5	25.4	19.9	19.7	0.2
Routine employment	35.7	38.4	39.8	37.0	36.9	0.1
Commuting-zone index, 2000:						
Offshorability Index	-0.1	-0.0	-0.0	-0.0	-0.1	0.0*

Note: Columns (1) to (5) display unweighted means of changes in county-level outcomes between 2000 and 2016 and of counties' commuting-zone characteristics in 2000. For each county, we compute the average exposure to robots and China if its commuting-zone over the periods 2000 to 2008 and 2008 to 2016. Columns (2) and (3) display unweighted means of counties in the highest quartiles of the average commuting zone exposure to robots and China, respectively. We compute a measure of relative exposure to robots vs. China by standardizing both exposure measures to have a mean of zero and a standard deviation of 1 and take the difference between the standardized measures of exposure to robots and China. Column (6) displays the difference in means between the forth and the first quartile of relative exposure and reports statistical significance of the underlying ttest. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B5: Effects on voting at US presidential elections: county-level stacked differences 2000-2016 (2SLS)

	Δlog(votes) $\times$ 100				
Panel A. US President	(1)	(2)	(3)	(4)	(5)
US Exposure to Robots	-1.841***	-0.722***	-0.859***	-1.013***	-1.006***
	(0.384)	(0.240)	(0.250)	(0.262)	(0.265)
US Exposure to Chinese Imports	0.470	0.538	0.569	0.535	0.561
	(0.848)	(0.592)	(0.591)	(0.581)	(0.581)
Δ log(citizen voting age pop.)		0.940***	0.753***	0.750***	0.721***
		(0.0249)	(0.0422)	(0.0413)	(0.0440)
Net in-migration rate			23.25***	23.18***	20.34***
			(4.247)	(4.202)	(4.327)
Δ share of college educated			-23.87*	-26.72**	-27.60**
			(12.87)	(13.35)	(13.45)
Perennial swing state				1.452***	1.266***
				(0.484)	(0.488)
TV campaign ads, USD per HH				0.114***	0.110***
				(0.0232)	(0.0232)
Kleibergen-Paap F-Stat	31.99	32.18	32.38	32.97	33.01
R^2	0.65	0.83	0.83	0.84	0.84
Observations	6172	6172	6168	6136	6136
Wald Test [R=C] p-Value	0.008	0.039	0.022	0.012	0.010
Region $\times$ Period	✓	✓	✓	✓	✓
Lagged mfg. share $\times$ Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine jobs & Offshorability	✓	✓	✓	✓	✓
Pre-trend					✓

Note: The dependent variable is the change in the log count of votes at US presidential elections multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). Regressions in column (2) to (5) control for the contemporaneous change in the log count of the citizen voting age population (CVAP) multiplied by 100. Specifications (4) and (5) control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Specification (5) accounts for pre-trends controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B6: Effects on voting at US House of Representatives elections: county-level stacked differences 2000-2016 (2SLS)

	Δlog(votes) $\times$ 100				
Panel B. US House of Rep.	(1)	(2)	(3)	(4)	(5)
US Exposure to Robots	-2.130***	-1.218*	-1.378*	-1.634**	-1.308**
	(0.669)	(0.721)	(0.720)	(0.732)	(0.584)
US Exposure to Chinese Imports	2.232*	2.114**	2.048*	2.188**	1.846*
	(1.218)	(1.059)	(1.062)	(1.093)	(0.999)
Δ log(citizen voting age pop.)		0.784***	0.530***	0.527***	0.690***
		(0.128)	(0.155)	(0.155)	(0.0911)
Net in-migration rate			31.00***	31.08***	40.10***
			(7.245)	(7.434)	(9.422)
Δ share of college educated			3.098	0.118	4.411
			(24.66)	(25.38)	(25.68)
Perennial swing state				2.176***	2.978***
				(0.721)	(0.836)
TV campaign ads, USD per HH				0.163	0.164*
				(0.101)	(0.0984)
Kleibergen-Paap F-Stat	28.32	28.47	28.68	29.39	29.49
R^2	0.44	0.53	0.54	0.54	0.57
Observations	5483	5483	5479	5448	5432
Wald Test [R=C] p-Value	0.002	0.011	0.010	0.005	0.005
Region $\times$ Period	✓	✓	✓	✓	✓
Lagged manufct. share $\times$ Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓	✓
Pre-trend					✓

Note: The dependent variable is the change in the log count of votes at elections of the US House of Representatives multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). Counties in congressional districts with uncontested races are excluded from the sample. Regressions in column (2) to (5) control for the contemporaneous change in the log count of the citizen voting age population (CVAP) multiplied by 100. Specifications (4) and (5) control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Specification (5) accounts for pre-trends controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B7: Robustness of effect on voting at U.S. federal elections elections to different measures of voting population: county-level stacked differences 2000-2016 (2SLS)

	Δ log(votes) $\times$ 100					
	US President			US House of Representatives		
	(1)	(2)	(3)	(4)	(5)	(6)
US Exposure to Robots	-1.013***	-0.992***	-1.643***	-1.634**	-1.636**	-2.302***
	(0.262)	(0.278)	(0.251)	(0.732)	(0.754)	(0.663)
US Exposure to Chinese	0.535	0.763	0.761	2.188**	2.505**	2.401*
Imports	(0.581)	(0.597)	(0.701)	(1.093)	(1.117)	(1.267)
Net in-migration rate	23.18***	17.96***	45.63***	31.08***	26.31***	40.56***
	(4.202)	(4.338)	(5.153)	(7.434)	(7.335)	(9.416)
Δ Share of College	-26.72**	-16.13	-32.94**	0.118	8.926	-13.01
Educated	(13.35)	(13.25)	(14.96)	(25.38)	(25.43)	(27.11)
Perennial swing state	1.452***	1.424***	2.453***	2.176***	2.182***	2.915***
	(0.484)	(0.473)	(0.465)	(0.721)	(0.729)	(0.682)
TV campaign ads,	0.114***	0.115***	0.0818***	0.163	0.151	0.0961
USD per HH	(0.0232)	(0.0239)	(0.0310)	(0.101)	(0.102)	(0.0907)
Δ CVAP	0.750***			0.527***		
	(0.0413)			(0.155)		
Δ VAP		0.773***			0.562***	
		(0.0395)			(0.155)	
Δ Reg			0.422***			0.374***
			(0.0340)			(0.0464)
Kleibergen-Paap F-Stat	32.97	31.94	33.47	29.39	28.82	30.26
Observations	6136	5939	5660	5448	5284	4973
Wald Test [R=C] p-Value	0.012	0.006	0.001	0.00461	0.003	0.002
Region $\times$ Period	✓	✓	✓	✓	✓	✓
Lagged mfg. share $\times$ Period	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Routine Jobs & Offshor.	✓	✓	✓	✓	✓	✓

Note: The dependent variable is the log change in the number of voters at elections of the US President and the US House of Representatives, respectively, multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Counties with uncontested races are excluded from the sample in specifications (4), (5) and (6). Specifications (1) and (4) control for the same set of controls specification (5) of both B5 and B6 and weight by the initial citizen voting-age population of each county in the year 2000. Specifications (2) and (5) control for log changes in the voting-age population multiplied by 100 and weight by the initial voting-age population of each county in the year 2000. Specifications (3) and (6) control for log changes in the number of registered voters multiplied by 100 and weight by the initial number of registered voters of each county in the year 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B8: Effect of robots and imports from China on political advertising at US presidential elections in 2008 and 2016: county-level (2SLS)

	Spending on Political Ads / HH			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel A:	(1)	(2)	(3)	(4)
US Exposure to Robots	-1.312***	0.0553***	-0.149*	-0.0142*
	(0.359)	(0.0114)	(0.0794)	(0.00850)
US Exposure to Chinese Imports	0.670	0.00120	0.110	0.0109
	(0.619)	(0.0101)	(0.104)	(0.0135)
Kleibergen-Paap F-Stat	32.17	32.17	32.17	32.17
Observations	6140	6140	6140	6140
Wald Test [R=C] p-Value	0.0011	0.0000	0.0151	0.0755
	Number of Political Ads			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel B:	(5)	(6)	(7)	(8)
US Exposure to Robots	-1116.4*	89.15***	-85.69	-3.010
	(621.6)	(11.56)	(135.3)	(13.98)
US Exposure to Chinese Imports	810.4	3.197	87.35	23.46
	(808.1)	(14.89)	(130.7)	(22.40)
Kleibergen-Paap F-Stat	32.17	32.17	32.17	32.17
Observations	6140	6140	6140	6140
Wald Test [R=C] p-Value	0.0260	0.0000	0.258	0.262
Region × time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share × time	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Swing State	✓	✓	✓	✓

Note: The dependent variables are the estimated dollar value of spending on political ads per household (Panel A) and the total number of political ads in the designated market area a county belongs in the election year 2008 and 2016. All specifications include census division dummies interacted with a time period dummy as covariates, control for 2000 demographic characteristics of the commuting zone (i.e., log population, share of women, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians), the 10-year lagged share of manufacturing employment interacted with a time period dummy as well as the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). All specifications also control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's share in the national number of households in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B9: Effect of robots and imports from China on political advertising at US House of Representatives elections in 2008 and 2016: county-level (2SLS)

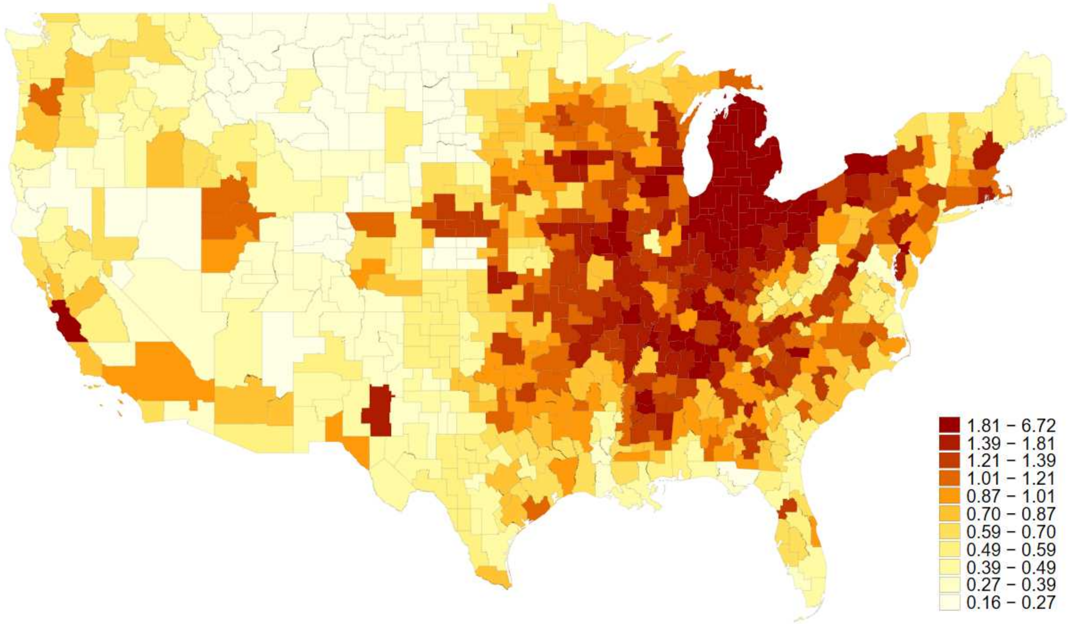
	Spending on Political Ads / HH			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel A:	(1)	(2)	(3)	(4)
US Exposure to Robots	-0.395	0.0108	-0.00707	-0.130**
	(0.301)	(0.00719)	(0.0446)	(0.0544)
US Exposure to Chinese Imports	-0.350	-0.0305	-0.0741	-0.0501
	(0.284)	(0.0203)	(0.0680)	(0.0406)
Kleibergen-Paap F-Stat	30.06	30.06	30.06	30.06
Observations	5560	5560	5560	5560
Wald Test [R=C] p-Value	0.909	0.0893	0.387	0.252
	Number of Political Ads			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel B:	(5)	(6)	(7)	(8)
US Exposure to Robots	-463.6	15.12*	-21.19	-209.8**
	(516.6)	(8.969)	(74.66)	(98.20)
US Exposure to Chinese Imports	-245.0	-38.92	-84.61	-32.00
	(465.3)	(23.81)	(102.0)	(63.78)
Kleibergen-Paap F-Stat	30.06	30.06	30.06	30.06
Observations	5560	5560	5560	5560
Wald Test [R=C] p-Value	0.735	0.0506	0.587	0.147
Region × time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share × time	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Swing State	✓	✓	✓	✓

Note: The dependent variables are the estimated dollar value of spending on political ads per household (Panel A) and the total number of political ads in the designated market area a county belongs in the election year 2008 and 2016. All specifications include census division dummies interacted with a time period dummy as covariates, control for 2000 demographic characteristics of the commuting zone (i.e., log population, share of women, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians), the 10-year lagged share of manufacturing employment interacted with a time period dummy as well as the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). All specifications also control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnsota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virgina, Wisconsin). Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's share in the national number of households in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

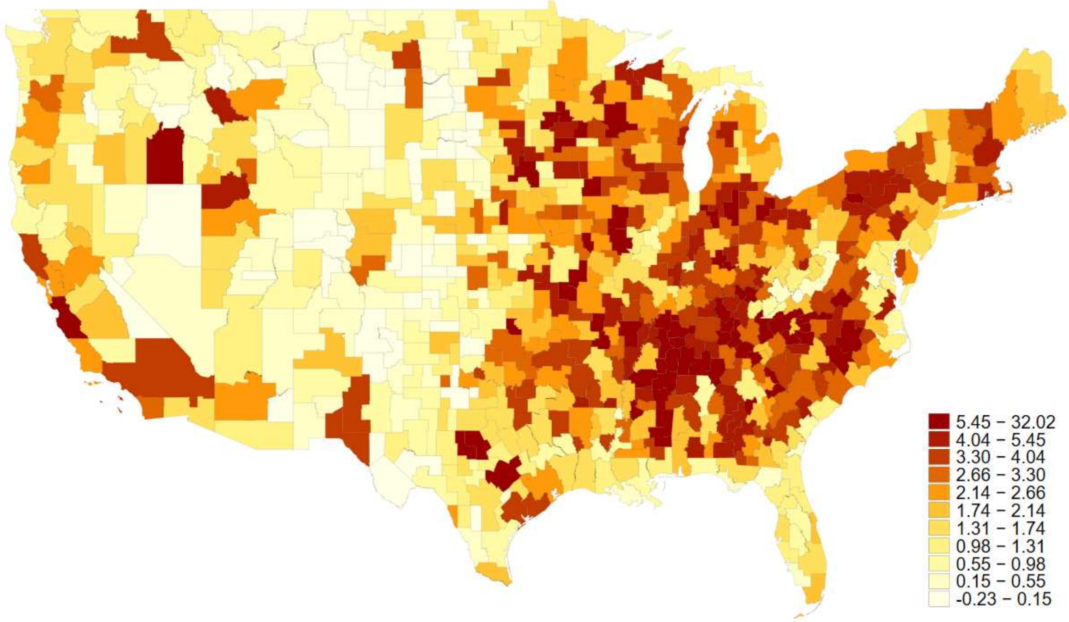
Appendix C Figures

Figure C1: Geographical variation in commuting-zone exposure to robots and Chinese imports between 2000 and 2015

(a) US exposure to robots

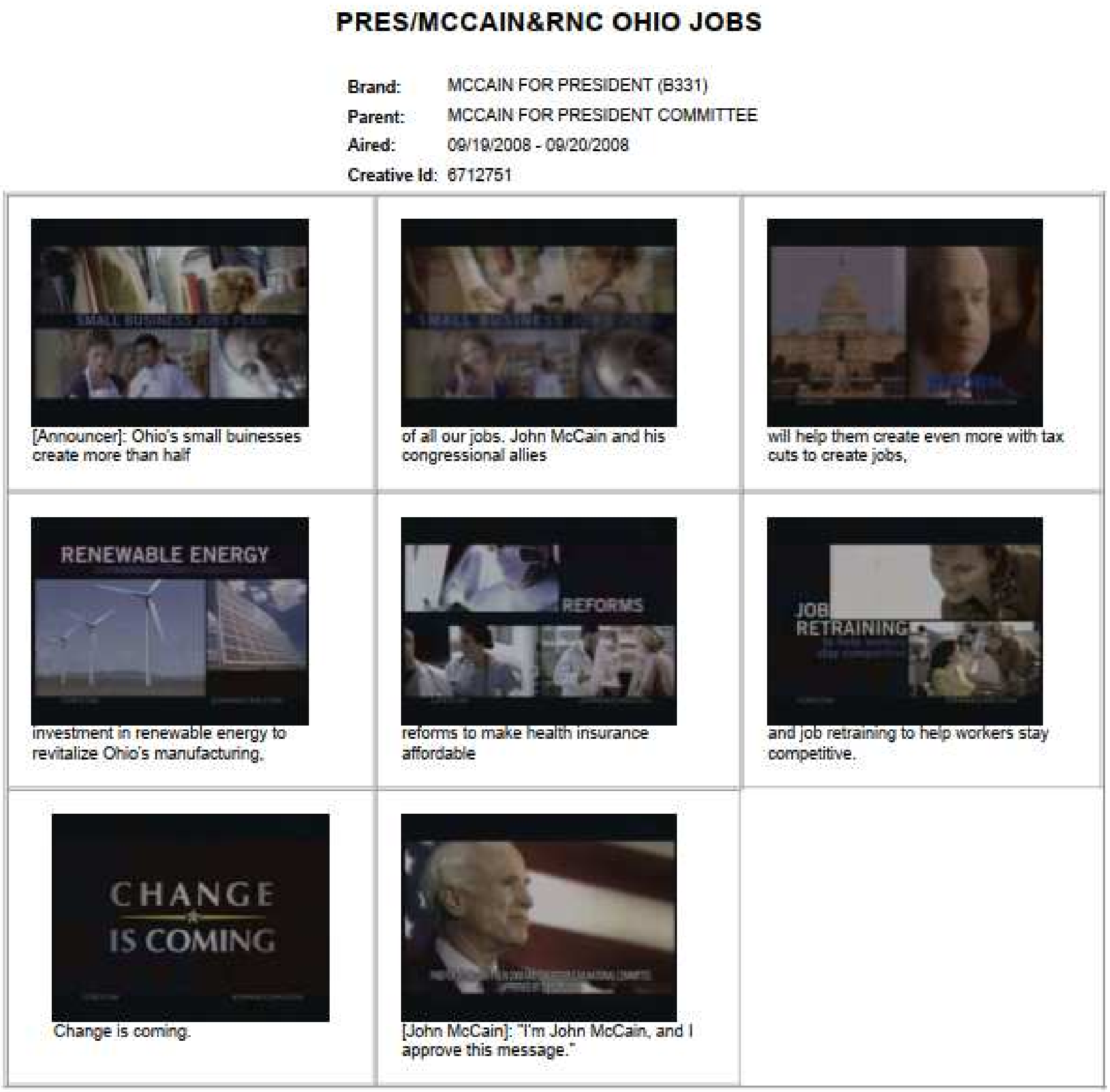


(b) US exposure to Chinese imports



Note: Figures show variation in exposure across 11 bins with the same number of commuting-zones each.

Figure C3: Example of campaign ad storyboard from Wesleyan Data Project



For Online Publication: Supplementary Online Materials

Appendix D Data

D.1 Exposure to Robots

We follow Acemoglu and Restrepo (2020) and construct a measure of commuting zone exposure using the following data sources:

Industrial robots: We use data on operational stock of industrial robots from the International Federation of Robotics (IFR) for the United States and six European countries (Denmark, Finland, France, Italy, Sweden, Germany) from 1993 to 2016.[25] We classify the IFR data into 13 manufacturing industries, and 6 broad industries outside manufacturing.[26] To obtain the 19 IFR industries as in Acemoglu and Restrepo (ibid.), we perform the following adjustments to the original data: First, we keep the industry "all other manufacturing branches" and label it as "Miscellaneous manufacturing". Second, "All other non-manufacturing branches" are considered as "Services". Third, the residual category "Metal (unspecified)" is allocated proportionally to all industries in the "Metal industries" (Basic Metals, Metal Products, Electronics, Industrial Machinery) and 4.) the residual "Unspecified", which is allocated proportionally over all 19 IFR industries. The IFR data comes with two drawbacks: first, it groups the US together with Canada as Northern America before 2011 and second, it doesn't provide a split-up by industries for the Northern America before 2004. Given that the US accounts for about 90 percent of the North American robot stock, we accept the first limitation. To deal with the second limitation, we apply an algorithm that attributes the total stock in each year before 2004 according to an industry's share in the total stock in 2004, the first year with disaggregated information on the industry level. We apply this solution also to Denmark, which similarly lacks data by industry before 1996.

[25]These selected European countries exhibit levels and an evolution of the number of robots per 1000 workers that mirror the US over the sample period from 1993 to 2015 and will be used to construct an instrumental variable.

[26]Manufacturing industries include Food and Beverages, Textiles, Wood and Furniture, Paper and Printing, Plastics and Chemicals, Minerals, Basic Metals, Metal Products, Electronics, Industrial Machinery, Automotive, Shipbuilding and Aerospace, Miscellaneous Manufacturing; Non-Manufacturing industries include Agriculture, Mining, Utilities, Construction, Education and Research, Services.

Industry employment and output: Furthermore, we use data on employment and output from the 2007 and 2019 EU KLEMS releases (Stehrer et al. 2019; Timmer et al. 2007).[27] As in Acemoglu and Restrepo (2020), we translate the numbers of persons employed in each European country-industry in 1990 into "US equivalent workers" by dividing the total number of hours worked in a European industry by the hours per worker in the corresponding US industry. This is to account for the fact that European workers work on average less hours and to make employment numbers comparable. To adjust for the growth in robot stock due to output growth, we compute an output growth rate and use the output deflators provided by EU KLEMS to correct for inflation.

Commuting zone employment: Finally, we compute industry employment shares in each commuting zone using data from the US Decennial Census for the years 1970, 1990 and 2000 as well as from the American Community Survey in 2006, 2007, 2008 and 2009 and 2014, 2015, 2016 and 2017 provided by the *Integrated Public Use Microdata Series* (IPUMS). We use the crosswalks by Autor and Dorn (2013) to map geographies provided in the IPUMS data to 722 continental commuting zones. To compute the industry employment in each commuting zone in a given year, we sum over working individuals between 15 and 64 by industry using person weights from IPUMS multiplied with probability weights from the geographical crosswalks. We calculate the total commuting zone employment simply as the sum of employment across all industries.[28].

D.2 Exposure to Chinese Imports

To construct a measure of commuting zone exposure to Chinese imports as in Autor et al. (2013), we use the following data:

International trade: We obtain data on merchandise imports from China to the US as well as to Australia, Denmark, Germany, Finland, Japan, New Zealand, Spain and Switzerland from 1990 to 2016 at the HS 1996 6-digit product level from *Uncomtrade*. We map this data to SIC 1987 4-digit codes using a crosswalk provided by Autor et al. (ibid.) and adjusted trade values to 2007 US$ prices using the personal consumption

[27]We use both releases as the 2019 release in NACE 2 only covers the period 2000 to 2018, while the 2007 NACE1 release only provides data from 1970 to 2005. To obtain industry employment and output data for multiple countries from 1990 to 2016 we do therefore need to combine both the 2007 NACE 1 and the 2019 NACE 2 releases. The mapping of NACE 1/2 to IFR industries is available upon request.

[28]The mapping of 1990 Census Bureau industry classes to corresponding IFR industries is also available upon request.

expenditure deflator provided by the Federal Reserve Bank of St. Louis.

Industry employment: We obtain employment counts by SIC 1987 industry for each commuting zone in 1980, 1990 and 2000 using an algorithm by David Dorn that assigns employment counts to employment brackets reported in the establishment data of the US Census Bureau's *County Business Patterns*. For years after 2007, we make use of industry employment imputations by Eckert et al. (2021) also based on the *County Business Patterns* dataset.[29] This data allows us to compute a measure of exposure to Chinese imports for each commuting zone as the sum of changes in Chinese imports per worker in each industry at the national level weighted by an industry's share in total commuting zone employment.

[29]Industry crosswalks from NAICS 2007 to SIC 1987 necessary to use the data from Eckert et al. (2021) for our purpose are available upon request.

Appendix E Tables

Table SM1: First stage regressions for commuting zone analysis, stacked differences (1990-2015)

	US Exposure to robots	US exposure to Chinese imports
	(1)	(2)
Exposure to Robots	0.80***	-0.02*
	(0.11)	(0.01)
Exposure to Chinese Imports	0.00	0.53***
	(0.04)	(0.06)
Observations	2166	2166
R^2	0.65	0.42
Region × time	✓	✓
Demographics	✓	✓
Industry shares	✓	✓
Routine Jobs & Offshorability	✓	✓

Note: N=2,166 (3×722 Commuting Zones) The dependent variable in columns (1) and (2) is the US exposure to robots and the US exposure to Chinese imports, respectively. Explanatory and dependent variables are all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table SM2: First stage regressions for county-level analysis, stacked differences (2000-2016)

	US Exposure to robots	US exposure to Chinese imports
	(1)	(2)
Exposure to Robots	0.45***	-0.04***
	(0.02)	(0.01)
Exposure to Chinese Imports	-0.09	0.49***
	(0.09)	(0.06)
Observations	6136	6136
R^2	0.61	0.49
Region × Period	✓	✓
Lagged mfg. share × Period	✓	✓
Demographics	✓	✓
Routine Jobs & Offshorability	✓	✓

Note: The dependent variables in columns (1) and (2) is the US exposure to robots and the US exposure to Chinese imports, respectively. Exposure measures are computed for 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Explanatory and dependent variables are all standardized to have a mean of zero and a standard deviation of 1. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table SM3: Effect on voter turnout at U.S. federal elections elections: county-level stacked differences 2000-2016 (2SLS)

	Δ Voter Turnout × 100	
	US President	US House of Representatives
	(1)	(2)
US Exposure to Robots	-0.515***	-0.533*
	(0.168)	(0.297)
US Exposure to Chinese Imports	0.168	0.358
	(0.324)	(0.648)
Net in-migration rate	3.788***	6.425***
	(1.125)	(2.047)
Δ Share of College Educated	-19.26**	0.898
	(7.500)	(15.55)
Perennial swing state	1.142***	1.320***
	(0.291)	(0.362)
TV campaign ads, USD per HH	0.0693***	0.0446
	(0.0144)	(0.0634)
Kleibergen-Paap F-Stat	32.78	30.75
Observations	6136	5556
Wald Test [R=C] p-Value	0.0466	0.155
Region × Period	✓	✓
Lagged mfg. share × Period	✓	✓
Demographics	✓	✓
Routine Jobs & Offshorability	✓	✓

Note: The dependent variable is the change in voter turnout (votes per citizen voting-age population) at elections of the US President and the US House of Representatives, respectively, multiplied by 100. Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Counties with uncontested races are excluded from the sample in specifications (2). Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

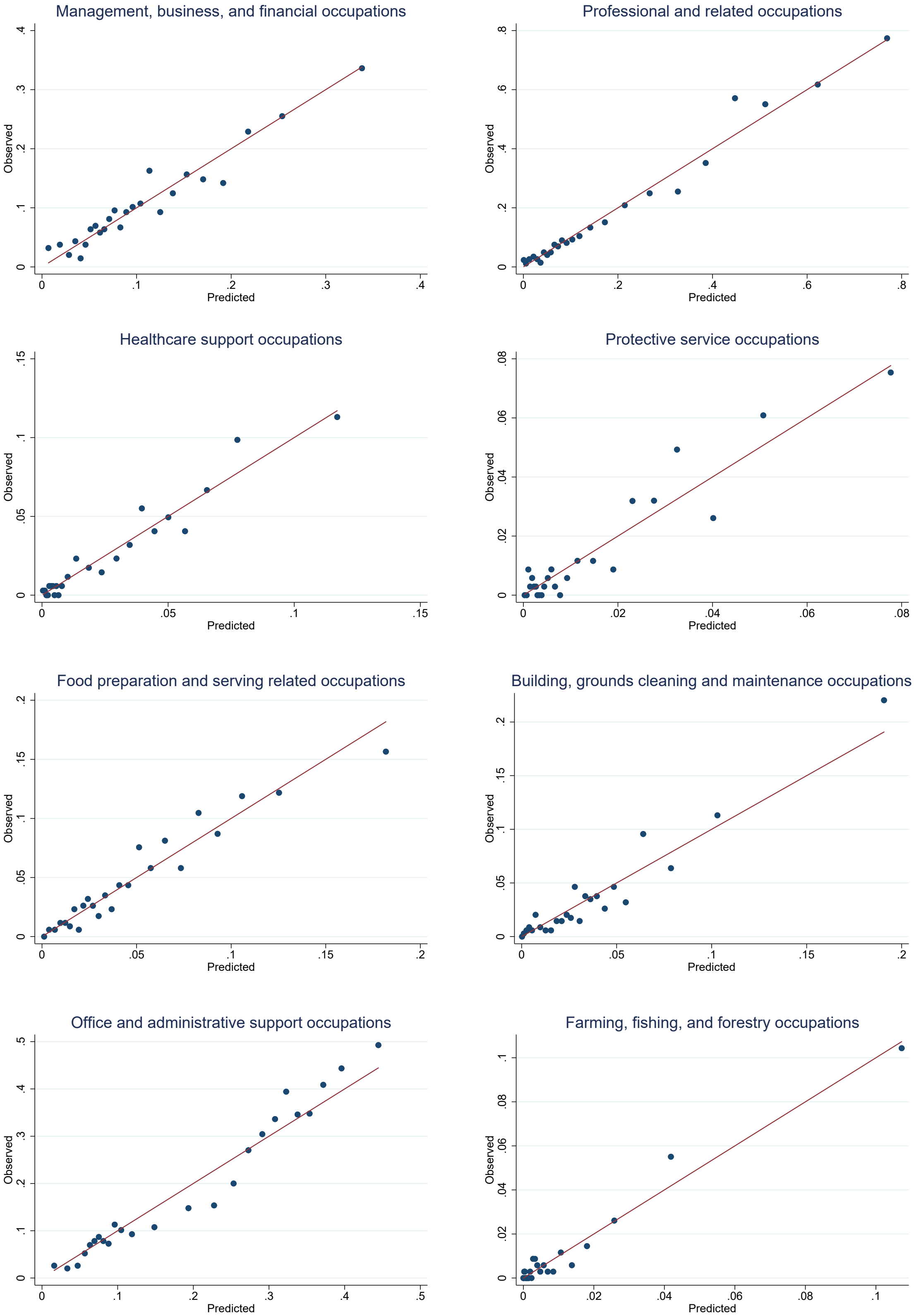
Table SM4: Effect of exposure to robots and Chinese imports on county-level employment: stacked differences 2000-2016 (2SLS)

	Δ log(employment)$\times$ 100		
	Total (1)	Manufacturing (2)	Non-manufacturing (3)
US Exposure to Robots	-1.267***	0.965	-1.667***
	(0.449)	(0.679)	(0.452)
US Exposure to Chinese Imports	-1.254	-7.452***	0.846
	(1.247)	(2.393)	(1.262)
Kleibergen-Paap F-Stat	36.57	36.31	36.67
R^2	0.28	0.10	0.25
Observations	6170	6170	6170
Region $\times$ time	✓	✓	✓
Demographics	✓	✓	✓
Industry shares	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓
Pre-trends	✓	✓	✓

Note: Table reports 2SLS estimates from a stacked difference regression over two 8-year election periods, from 2000, 2008, to 2016. The dependent variables in columns (1), (2) and (3) is the change in the log count of employment in total, manufacturing and non-manufacturing employment respectively, multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 2000 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force); shares of employment in broad industries in 2000 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

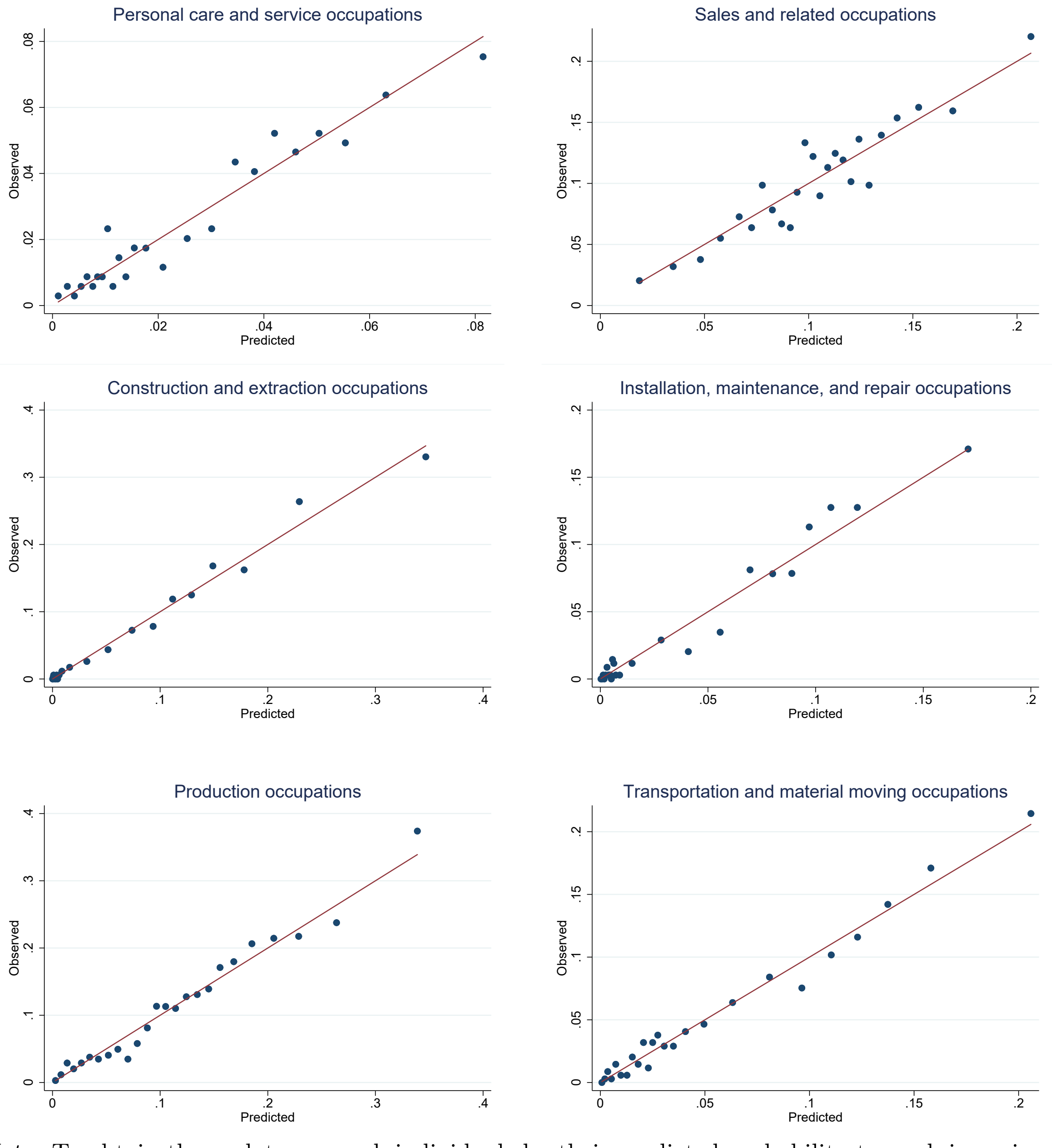
Appendix F Figures

Figure SM1: Predicted vs. observed shares of individuals working in an occupation group



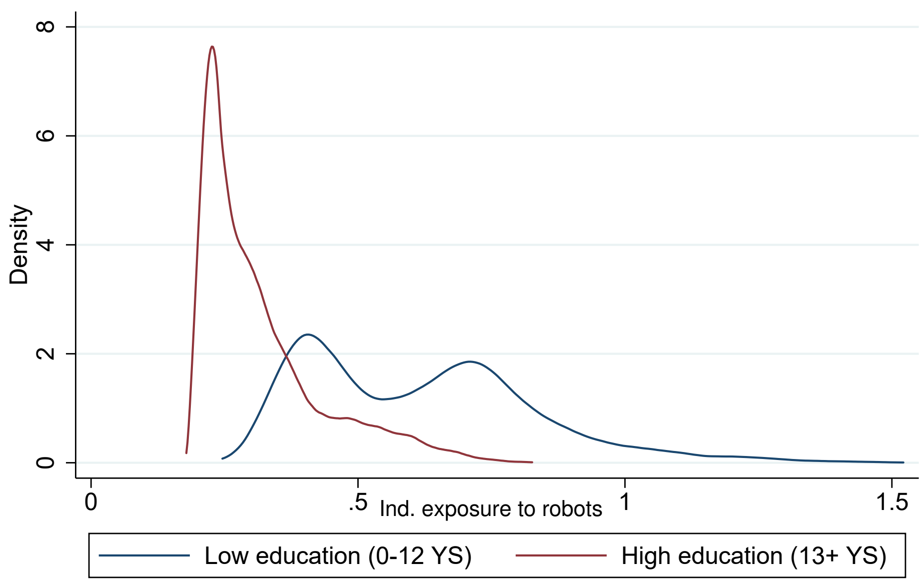
Note: To obtain these plots, we rank individuals by their predicted probability to work in a given occupation and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that occupation.

Figure SM3: Predicted vs. observed shares of individuals working in an occupation group (continued)



Note: To obtain these plots, we rank individuals by their predicted probability to work in a given occupation and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that occupation.

Figure SM4: Distribution of individual exposure to robots by years of schooling



Appendix G Survey materials

G.1 Vignettes

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to discontinue the production of goods that face strong competition from producers abroad, in particular from China. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and discontinuing the production of items where we can't compete with manufacturers from China and focusing on our most competitive products is the way forward. As a result of shutting down some of the production lines that used to produce those goods, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by greater ease of trading with other nations. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

Figure SM5: Trade condition. The highlighted text varied depending on the treatment. Highlights are added.

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to restructure the company and optimize the organization of the production lines. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and restructuring and optimizing our production processes is the way forward. As a result of shutting down some of the production lines that are not needed in the new streamlined production flow, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by developments in new organizational practices. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

Figure SM6: Control condition. The highlighted text varied depending on the treatment. Highlights are added.

G.2 Results of t-tests

Manipulation check

I can relate to the story described in the article.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.107	1.642	t(556) = -1.312 p = 0.190	t(556) = -1.550 p = 0.122	t(552) = -0.212 p = 0.832
Control	277	4.289	1.636			
Trade	277	4.318	1.572			

Consequences for workers and search strategies

I believe the employees who are about to lose their jobs will find another job easily.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	2.911	1.166	t(556) = -0.708 p = 0.479	t(556) = -1.313 p = 0.190	t(552) = -0.579 p = 0.563
Control	277	2.982	1.199			
Trade	277	3.040	1.149			

I believe the employees who are about to lose their jobs will be able to find a position in the same occupation.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	3.288	1.349	t(556) = -2.563 p = 0.011	t(556) = -2.923 p = 0.004	t(552) = -0.347 p = 0.728
Control	277	3.581	1.351			
Trade	277	3.621	1.339			

If one is in the position of the workers to be laid off due to introduction of new technologies/ increased competition with China/ the company reorganization, there is nothing one can do.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.562	1.480	t(556) = -1.060 p = 0.289	t(556) = 1.457 p = 0.146	t(552) = 2.415 p = 0.016
Control	277	4.700	1.595			
Trade	277	4.372	1.607			

I believe automation/ increased trade competition/ the introduction of new organisational practices has long lasting consequences.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.630	1.388	t(556) = -1.264 p = 0.207	t(556) = -0.156 p = 0.876	t(552) = 1.279 p = 0.201
Control	277	5.765	1.129			
Trade	277	5.646	1.062			

I believe the best that the laidoff employees can do is: (*with answer*: to retrain into a new occupation)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.285	0.452	t(556) = 3.152 p = 0.002	t(556) = 2.066 p = 0.039	t(552) = -1.079 p = 0.281
Control	277	0.173	0.379			
Trade	277	0.209	0.408			

I believe the best that the laidoff employees can do is: (*with answer*: to get additional qualifications that would be beneficial for the worker's current occupation)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.181	0.386	t(556) = 2.463 p = 0.014	t(556) = 1.679 p = 0.094	t(552) = -0.786 p = 0.432
Control	277	0.108	0.311			
Trade	277	0.130	0.337			

I believe the best that the laidoff employees can do is: (*with answer*: to start looking for another position right away)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.420	0.494	t(556) = -4.210 p = 0.000	t(556) = -2.717 p = 0.007	t(552) = 1.457 p = 0.146
Control	277	0.596	0.492			
Trade	277	0.534	0.500			

Is job loss preventable and what should the government do?

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: No, the layoffs are inevitable)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.495	0.501	t(556) = 3.034 p = 0.003	t(556) = 4.698 p = 0.000	t(552) = 1.620 p = 0.106
Control	277	0.368	0.483			
Trade	277	0.303	0.460			

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the state government)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.021	0.145	t(556) = -0.568 p = 0.570	t(556) = -0.025 p = 0.980	t(552) = 0.541 p = 0.589
Control	277	0.029	0.168			
Trade	277	0.022	0.146			

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the federal government)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.060	0.239	t(556) = 1.570 p = 0.117	t(556) = -5.273 p = 0.000	t(552) = -6.622 p = 0.000
Control	277	0.032	0.178			
Trade	277	0.209	0.408			

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the company management)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.302	0.460	t(556) = -3.052 p = 0.002	t(556) = -1.734 p = 0.083	t(552) = 1.301 p = 0.194
Control	277	0.426	0.495			
Trade	277	0.372	0.484			

What, if anything, do you think should be the response of the government? (*with answer*: Government should do nothing)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.093	0.290	t(556) = -0.755 p = 0.451	t(556) = 1.925 p = 0.055	t(552) = 2.656 p = 0.008
Control	277	0.112	0.316			
Trade	277	0.051	0.219			

What, if anything, do you think should be the response of the government? (*with answer*: Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance))						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.751	0.433	t(556) = -0.600 p = 0.549	t(556) = 1.151 p = 0.250	t(552) = 1.745 p = 0.081
Control	277	0.773	0.420			
Trade	277	0.708	0.456			

What, if anything, do you think should be the response of the government? (*with answer*: Government should restrict imports from overseas, by placing import tariffs on such imports for example)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.043	0.203	t(556) = -1.499 p = 0.135	t(556) = -6.533 p = 0.000	t(552) = -5.134 p = 0.000
Control	277	0.072	0.259			
Trade	277	0.224	0.418			

What, if anything, do you think should be the response of the government? (*with answer*: Government should impose higher taxes on laboursaving technology and regulate automation more strictly)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.114	0.318	t(556) = 3.113 p = 0.002	t(556) = 4.627 p = 0.000	t(552) = 1.726 p = 0.085
Control	277	0.043	0.204			
Trade	277	0.018	0.133			

Voting and Political Attention

I believe it is important to always vote in elections.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	6.327	1.121	t(556) = 1.729 p = 0.084	t(556) = 0.103 p = 0.918	t(552) = -1.633 p = 0.103
Control	277	6.148	1.323			
Trade	277	6.318	1.113			

I believe it is important to draw the attention of the public and of politicians to the fact that people lose jobs due to automation/ due to increased trade competition with China/ due to modern organisational practices.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.480	1.389	t(556) = 0.938 p = 0.348	t(556) = 0.977 p = 0.329	t(552) = -0.032 p = 0.975
Control	277	5.368	1.435			
Trade	277	5.372	1.232			

I believe politicians do not pay enough attention to the unemployment due to automation/ due to increased trade competition with China/ due to the introduction of new organisational practices.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.356	1.430	t(556) = 1.209 p = 0.227	t(556) = 2.457 p = 0.014	t(552) = 1.113 p = 0.266
Control	277	5.202	1.570			
Trade	277	5.061	1.401			

Emotional responses

If I were laid off due to automation/ due to increased competition with China/ as a part of the reorganisation, as described in the article, I would be very angry.						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.463	1.386	t(556) = -0.782 p = 0.434	t(556) = -1.058 p = 0.291	t(552) = -0.263 p = 0.792
Control	277	5.552	1.322			
Trade	277	5.581	1.259			

If I were laid off due to automation/ due to increased competition with China/ as a part of the reorganisation, as described in the article, I would be very frustrated.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.964	1.127	t(556) = -0.806 p = 0.420	t(556) = -0.907 p = 0.365	t(552) = -0.081 p = 0.935
Control	277	6.040	1.078			
Trade	277	6.047	1.019			

If I were laid off due to automation, as described in the article/ due to increased competition with China/ as a part of the reorganisation, I would be very worried about my future.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	6.053	1.171	t(556) = -0.193 p = 0.847	t(556) = 0.219 p = 0.827	t(552) = 0.421 p = 0.674
Control	277	6.072	1.137			
Trade	277	6.032	1.081			

Risk, Trust, Time, Altruism, Locus of Control

In general, how willing or unwilling you are to take risks.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.324	2.305	t(556) = -0.415 p = 0.678	t(556) = -1.006 p = 0.315	t(552) = -0.551 p = 0.582
Control	277	5.408	2.475			
Trade	277	5.520	2.299			

Trust How well does the following statement describe you as a person? As long as I am not convinced otherwise, I assume that people have only the best intentions.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.217	2.430	t(556) = 0.867 p = 0.386	t(556) = 0.215 p = 0.830	t(552) = -0.662 p = 0.509
Control	277	5.036	2.500			
Trade	277	5.173	2.379			

Time In comparison to others, are you a person who is generally willing to give up something today in order to benefit from it in the future or are you not willing to do so?						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	7.060	1.865	t(556) = -0.781 p = 0.435	t(556) = 0.629 p = 0.529	t(552) = 1.355 p = 0.176
Control	277	7.188	1.982			
Trade	277	6.957	2.030			

How willing are you to give to good causes without expecting anything in return?						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	7.053	2.181	t(556) = 0.593 p = 0.553	t(556) = 0.782 p = 0.434	t(552) = 0.188 p = 0.851
Control	277	6.942	2.243			
Trade	277	6.906	2.265			

When you think about the course of your life, to what extent do you think you have control over the direction it is taking?						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	6.530	2.007	t(556) = 1.618 p = 0.106	t(556) = 0.104 p = 0.917	t(552) = -1.514 p = 0.130
Control	277	6.249	2.097			
Trade	277	6.513	1.997			

Perception of consequences for society

There will be more opportunities for the next generation.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.214	1.562	t(556) = -0.188 p = 0.851	t(556) = 0.865 p = 0.387	t(552) = 1.056 p = 0.291
Control	277	4.238	1.549			
Trade	277	4.101	1.507			

In the future, people will be sharply separated into haves and havenots						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.826	1.469	t(556) = 0.080 p = 0.937	t(556) = -0.039 p = 0.969	t(552) = -0.121 p = 0.904
Control	277	4.816	1.419			
Trade	277	4.830	1.384			

I do not believe there is anything that the society can do to prevent job losses due to technological progress.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	3.740	1.688	t(556) = -0.321 p = 0.748	t(556) = 1.556 p = 0.120	t(552) = 1.842 p = 0.066
Control	277	3.787	1.755			
Trade	277	3.520	1.656			

I do not think there is something that the society can do to prevent job losses due to intensfied trade with other countries.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	3.423	1.467	t(556) = 0.599 p = 0.549	t(556) = 1.959 p = 0.051	t(552) = 1.300 p = 0.194
Control	277	3.347	1.566			
Trade	277	3.177	1.506			

G.3 Additional regressions

Table SM5: Heterogeneity along respondents' political ideology

VARIABLES	Not Enough Political Attention (1)	Important to Draw Attention (2)
Control	-0.271	-0.0911
	(0.261)	(0.238)
Trade	-1.363***	-1.207***
	(0.243)	(0.233)
Age	0.00715	0.00798*
	(0.00507)	(0.00439)
Edu	-0.141***	-0.0863*
	(0.0540)	(0.0462)
DV: Male	0.161	0.0499
	(0.104)	(0.0953)
DV: White	-0.0863	0.0256
	(0.150)	(0.134)
DV: Aff industry	-0.0729	-0.0224
	(0.117)	(0.104)
More Conservative	-0.205***	-0.239***
	(0.0524)	(0.0540)
Control#More Conservative	0.0111	-0.0205
	(0.0809)	(0.0762)
Trade#More Conservative	0.349***	0.357***
	(0.0706)	(0.0680)
Constant	6.276***	6.222***
	(0.312)	(0.291)
Observations	812	812
R-squared	0.060	0.077

Note: Attitudes towards the statement: (1) "I believe politicians do not pay enough attention to the unemployment due to [the introduction of new organizational practices/increased trade competition with China/automation].". (2) "I believe it is important to draw the attention of the public and of politicians to the fact that people lose jobs [due to modern organizational practices / due to automation / due to increased trade competition with China]". The variable "More Conservative" is continuous with higher values corresponding to a more conservative political position. Robust standard errors given in parentheses. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.