

Robots, China and Polls: Structural Shocks and Political Participation in the US*

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10 March 2022

Abstract: What is the effect of labour market adjustment to automation on political participation? We study the consequences of the introduction of industrial robots across US commuting zones on voter turnout in US counties between 2000 and 2016. We first replicate prior results showing negative effects of exposure to robots on employment and household incomes at local labour markets and then show that an increase in the exposure by one robot per thousand workers leads to a 0.5 percentage point lower voter turnout at US presidential elections. We contrast this result with the effect of the exposure to Chinese imports, for which we do not find a negative effect on political participation. The effect persists despite controlling for migration responses to labor market changes and intensity of political campaigning in the region. To understand why the effect is not uniform, we conduct an online survey experiment. We find that the nature of the shock matters beyond the mere economic consequences. While the government is seen as instrumental in addressing the trade shock, it is perceived less effective in the case of automation. Our findings highlight an important behavioral aspect of the political economy of technological change.

Keywords: automation, trade, labor demand, voter turnout

JEL Classification: J23, F16, D72

*We thank seminar audiences at IESE, Max Planck Institute for Innovation and Competition, EARIE 2021 for helpful comments.

1 Introduction

High voter turnout is essential for the functioning of democracies. Scholars have shown that differences in voter turnout can affect the degree to which election results reflect the preferences of the citizenry (Fowler, 2015), who wins elections (Fowler, 2013; Hansford and Gomez, 2010), and the public policies that are implemented (Fowler, 2013; Horiuchi and Saito, 2009). At the same time, scholars have identified changes in economic conditions to be a key determinant of an individual's propensity to vote (see Blais, 2006; Cancela and Geys, 2016; Smets and Ham, 2013, for literature reviews).

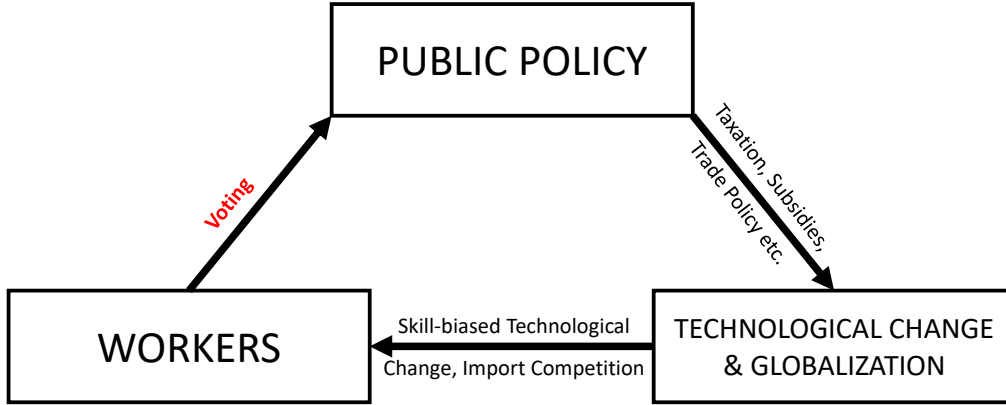
Existing empirical work mostly considered the effect of transient income shocks on turnout, such as oil price spikes (Charles and Stephens Jr, 2013), business cycles (Burden and Wichowsky, 2014) or extreme weather events (Horiuchi and Saito, 2009) and has yielded inconclusive results. Yet, little attention has been paid to the effect on political participation of long-term structural changes due to labor market adjustment to increasing industrial automation (e.g., Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018) or import competition (e.g., Abraham and Kearney, 2020; Autor, Dorn, and Hanson, 2013; Autor and Dorn, 2013; Autor, Dorn, Hanson, and Song, 2014). Did the local job losses caused by these structural changes lead to higher or lower voter turnout?

Considering such effects is all the more important, since structural changes to the economy are themselves a function of public policy that, in turn, is endogenous to the electoral process (see Figure 1). Hence, if long-term changes in income due to technological change or globalization lead to lower turnout, they can create important feedback loops of missing political representation and distorted public policy that fails to consider the concerns of adversely affected citizens and at worst reinforces the direction of structural change.¹ Conversely, higher turnout can lead to a different feedback loop with increasing demand for populist politics (Guiso et al., 2017).

In this paper we contribute to the nascent and growing literature on political and

¹This is plausible since marginal voters are found to differ strongly in their preferences from habitual voters (Fowler, 2015), to be ignored by politicians (e.g. Griffin and Newman, 2005; Martin, 2003) and because election results have long-term consequences due to incumbent advantage at the next electoral race.

Figure 1: The endogenous political economy of trade and technology



social consequences of structural changes (Caprettini and Voth, 2020; Dorn et al., 2020). We estimate the effect of long-run labour market adjustment to industrial robots and Chinese imports on political participation in the US between 2000 and 2016. We study this relationship in two steps:

First, we follow Acemoglu and Restrepo (2020) and construct a measure of exposure to industrial robots at the commuting-zone level using the growth in robot penetration by industry and taking the ex-ante industry composition of commuting-zone employment.². As in Acemoglu and Restrepo (ibid.) we build an instrumental variable using the plausibly exogenous increases in robot penetration in other high-income countries and the lagged industry employment shares. In a similar vein, we build a measure of commuting-zone exposure to imports from China following the instrumental variable approach pioneered by Autor, Dorn, and Hanson (2013). First, we confirm the established finding that both automation and import competition from China lead to declines in employment and average household income at the commuting-zone level. Then, we use an instrumental variable approach to causally estimate the effect of commuting-zone exposure to industrial robots and to Chinese imports on long-term changes in voter turnout at the county-level. To this end, we consider changes in turnout at both US presidential and House

²Commuting 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)

of Representative elections over two 8-year election cycles between 2000 and 2016.³ We document a significantly 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, voter turnout at the presidential elections was reduced by about 1 million voters due to automation. We compare this with the effect of exposure to rising imports from China which we find to not affect turnout at presidential elections and to positively affect turnout at US House of Representative elections. The finding of the differential voting response 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 county-level. By looking at the micro-level data from the General Social Survey, we find that the decrease of voter turnout is not due to region wide changes in economic conditions, but is driven by people at risk of automation. Individuals that are one standard deviation more exposed to industrial robots were 15 percent less like to have voted in the last presidential election

The staggering discrepancy in the political reaction to automation relative to trade motivates the second part of the empirical analysis. To better understand what drives the differential response to both shocks, we design an online survey experiment with US residents. We expose the respondents to hypothetical cases of company layoffs that depending on the condition were attributed to increased import competition, introduction of labour saving technologies or changes in the organization. We probe into different explanations why individuals may want to abstain in case of automation but not in case of exposure to trade. We consider how respondents perceive the consequences of the shocks (both individual for workers who were affected as well as for the society in general), the ability of the government to deal with the shocks and emotional responses.

³The 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.

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 deal with it than in the import competition scenario. The results of the survey suggest that the shock may affect the voter turnout differently because the nature of the shock affected the expected utility of voting. Yet, we do not find support for the hypothesis that lower voter turnout might be driven by their disappointment in the political system as such: respondents in the automation condition were more likely to agree with the statement that not enough political attention is dedicated to the problem and that it is important to draw the attention of public and politicians to it.

To sum it up, the contribution of our paper is threefold. First, we contribute to the literature on the political economy of technological change 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 by providing a causal analysis of the effect of two recent labour market shocks, automation and Chinese imports, on political participation in the US. Our framework allows us show that the relationship between labour market conditions and political participation is not uniform, i.e. negative employment shocks do not always affect political participation in the same way. Third, we attempt to understand why the effects of the two shocks are different and establish that a more nuanced approach that considers behavioral motives for voting is needed. For the two shocks in question, we find that workers' perceptions of the inevitability as well as of the government's efficacy to solve the economic issue differ significantly between the shocks. That is, different reasons of economic hardship might differentially affect if people resort to political means for addressing it or not. As political participation is an important part of the feedback loop between citizens and the government, distortions in political participation may result in public policies that shape the direction of technological change without considering the grievances of displaced workers, therefore reinforcing a vicious circle.

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 A 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

We apply a difference-in-differences framework pioneered by seminal studies on the local labour market effects of trade (Autor, Dorn, and Hanson, 2013) and automation (Acemoglu and Restrepo, 2020). This approach intends to capture 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).

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:

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

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, 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

⁴Each 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.

(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 confounders $\mathbf{Z}'_{j,t}$, 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:

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

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 (ibid.) 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:

$$\begin{aligned} \text{Exposure to} \\ \text{Robots}_{c,t:t+1} &\equiv \sum_{i \in I} l_{ci,1970} \frac{1}{5} \sum_{j \in EU5} \left(\frac{R_{i,t+1}^{EU5} - R_{i,t}^{EU5}}{L_{i,1990}^{EU5}} - g_{i,t:t+1}^{EU5} \frac{R_{i,t}^{EU5}}{L_{i,1990}^{EU5}} \right) \end{aligned} \quad (3)$$

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, Dorn, and Hanson (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:

$$\begin{aligned} \text{US Exposure to} \\ \text{Chinese Imports}_{c,t:t+1} &\equiv \sum_{i \in I} l_{ci,t} \left(\frac{M_{i,t+1}^{CN-US} - M_{i,t}^{CN-US}}{L_{i,t}^{US}} \right) \end{aligned} \quad (4)$$

Also this second explanatory 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, Dorn, and Hanson (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 market-oriented reforms in the 2000s.⁵

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

Section A 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.

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

3 Data description

3.1 Local labour 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.⁶ 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 of employment in manufacturing and non-manufacturing industries. 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. Finally, we compute the percentage change of the number of working-age adults with family income less than the poverty threshold as defined by the US Census for each individual.

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,

⁶The 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, Dorn, and Hanson (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>

mining, construction, manufacturing) and the exposure to offshoring (share of routine jobs, average offshorability index) following Autor, Dorn, and Hanson (2013).

3.2 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.

⁷Data 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.

⁸The 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.

⁹Dave 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.

3.3 Other contemporaneous controls

Migration: Recent studies have pointed at the role of internal migration of workers to adjust to changing labour 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 1990.¹⁰ 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 are differences in localized political campaigning before elections. That is, voter turnout might be linked to how actively the parties campaigned in a certain region. 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 2016.¹¹ 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”.¹² Importantly, the database provides cost estimates for each ad which allows us to estimate the total spending on political advertisement per media market in 2008 and 2016. We combine the

¹⁰Following 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)

¹¹Media 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

¹²Appendix Figure F3 shows an illustrative example of the story boards collected for each ad.

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 Labour 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 C1 we find that one standard deviation increase in exposure to robots and Chinese imports reduced manufacturing employment growth by about 1 and 5 percentage point, 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 C1 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. To gauge the importance of each shock for extreme economic insecurity, we additionally estimate the effect of both shocks on changes in the number of adults with family incomes below the poverty threshold as defined by the US Census. We find a significant and positive ef-

fect for both shocks, yet more pronounced for increasing import competition from China. Across all our specifications our 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, Table C1 confirms 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 labour market framework to test the effect of both income shocks on county-level changes in political participation at federal elections between 2000, 2008 and 2016. In C2 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 the full set of baseline controls, we find that a standard deviation increase in robots reduced voting growth by 1.8 percentage points, while exposure to Chinese imports had a largely insignificant effect on voting. In specification (2), we add the contemporaneous change in the underlying population of eligible voters in terms of the citizen voting age population, which reduces the effect size of robot exposure by more than half without affecting the significance level. To control for the risk of confounding labor market adjustment through migration, we continue by controlling for differences in the net migration rate as well as changes in the share of college-educated adults. Finally, we consider the swing status of each county as well as difference in political campaigning intensity. Both controls seem to be positive predictors of growths in voting, yet they do not affect the significance of the negative effect of robot exposure. In our full specification, we estimate that a standard deviation increase in robot exposure reduced voting by 1 percentage point, while Chinese imports do not affect voting in any specification. Wald tests at conventional significance levels consistently reject the null hypothesis that the difference of the estimated coefficients is zero.

To corroborate this finding, we further study voting at US House of Representative elections between the same reference years. Here, we find a more pronounced negative effect of robot exposure and a significantly positive effect of exposure of Chinese imports

on voting. In our full specification, we estimate that one standard deviation increase in exposure to robots leads to a -1.6 percentage points decrease and Chinese imports to a 2.2 percentage point increase at House of Representative elections. Although the estimates are less precise than for presidential elections¹³, the 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 C4).

To assess the magnitude and political significance of our finding, we run an additional regression reported in C5 using not changes in the number of votes, but in voter turnout as an outcome variable. 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, Dorn, and Hanson, 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. To put this in perspective, an increase in one 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.¹⁴ The results of Acemoglu and Restrepo (2020) suggest that one robot per thousand workers reduces employment by 6 workers. The magnitude of the effect of robots adoption on political participation is larger with one robot per thousand workers being equivalent to

¹³This might partly be due to the fact that we exclude about 10 percent of counties that held elections with only 1 candidate for the House of Representatives.

¹⁴For 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 $13 \approx 803 - (0.5367 - 0.01) \times 1500$.

reducing turnout by about 13 voters. This result suggests that not only people directly affected by automation might abstain.

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 Appendix B 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. As in the regional regressions we control for census divisions dummies interacted by period, but no individual characteristics as they are already used to predict occupational choice probabilities. Table C8 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 reconfirming that more exposed individuals are also more likely to engage in work that involves forceful hand movements and heavy lifting. Next, column 3 and 4 show that individuals that are more exposed to robots are more likely to fear job loss in the next 12 months and are more likely to be already unemployed, which is in line with the labour market effects reported in Table C1. For individuals exposed to Chinese imports, both current employment and expectations of job loss do not seem to be affected.¹⁵ Column

¹⁵This 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.

5 presents the central result of this part of analysis. It documents that one standard deviation increase in an individuals exposure to robots reduced the likelihood of having voted at the past presidential election by 15 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 ?? . Now, given that the underlying shocks to income seem comparable but the voting response not, we explore possible mechanisms 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 outweighs 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 *ibid.*) is

$$U_j(voting) = B_j P_j + D_j + c_j \tag{6}$$

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.¹⁶

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 nationwide US elections and costs of voting are unlikely to vary depending on the shock. These simplifications lead to:

$$U_j(\text{voting}) = B_j + D_j \quad (7)$$

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.

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

¹⁶While 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.

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 go to the polls. 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 this preferences, they might translate into differential voting response.

5.2 An Online 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 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

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

article (for example, see Fig 2). 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.¹⁷

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 of the provided article.

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.,

¹⁷The texts of the news pieces from Trade and Control conditions, as well as further survey materials can be found in the Appendix D.

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 text of questions as well as their sequence can be found in the Appendix D.2.

5.3 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).¹⁸ 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 treatments, the respondents most often recommend to start searching for a new job directly (42% of respondents in Automation, 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

¹⁸Unless 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 Appendix D.2.

retraining into a new occupation before searching for a new job ¹⁹. 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 3): 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 trade²⁰, 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 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

¹⁹Additional 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 $p=0.002$.

²⁰The question was asked separately for technological advances and intensified trade. Both questions were presented in all treatments at the very end of the survey.

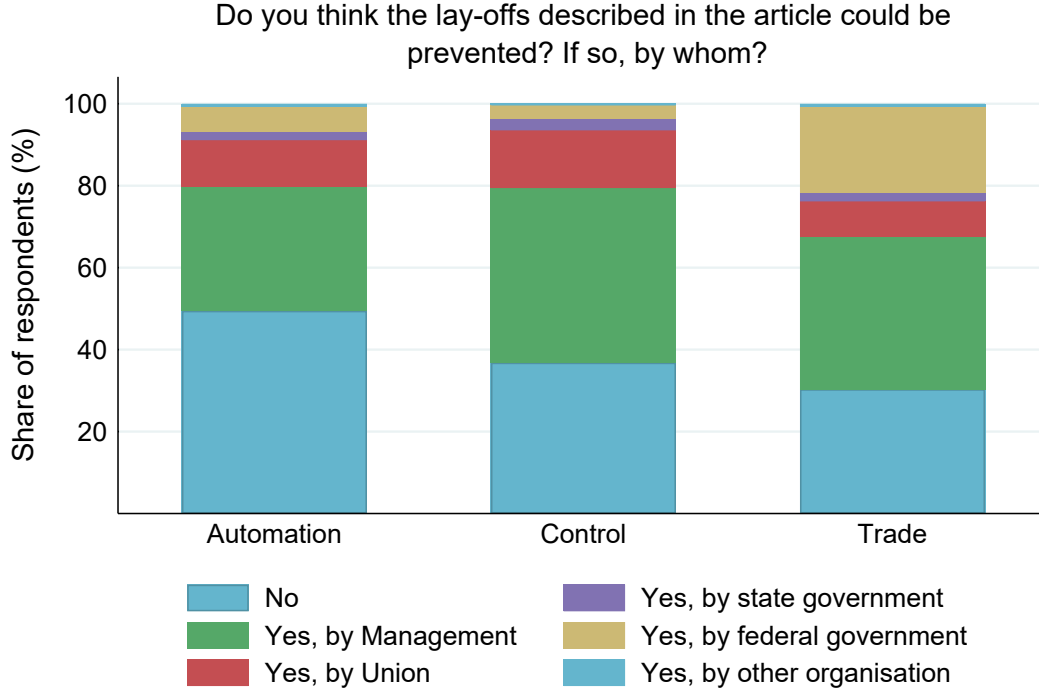


Figure 3: Exact wording of the answer options: No, the lay-offs are inevitable; Yes, by the company management; Yes, by the union or other professional organisation; Yes, by the state government; Yes, by the federal government; Yes, by other organisation.

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 4). 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 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

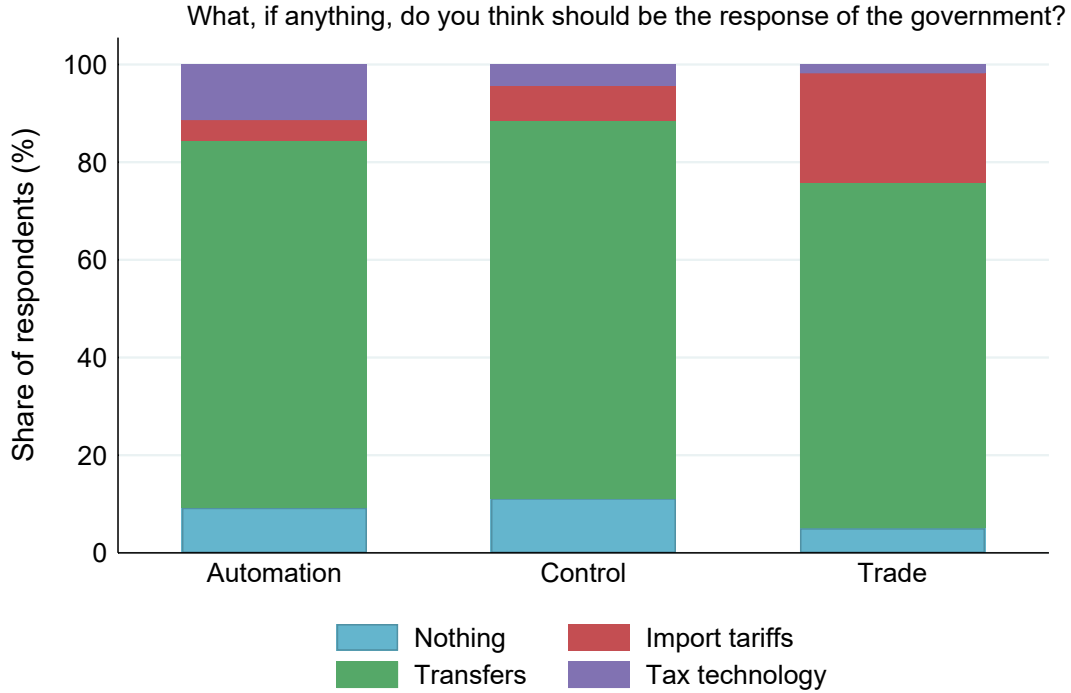


Figure 4: Exact wording of the answer options: Government should do nothing; Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance); Government should restrict imports from overseas, by placing import tariffs on such imports for example; Government should impose higher taxes on labour-saving technology and regulate automation more strictly.

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)²¹. We intentionally chose not to mention specific political parties in order to avoid attitudes towards party leaders and rather focus 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 direction²², which

²¹About 1% of respondents answered "I do not know", they are excluded from this part of the analysis

²²Higher values stand for more conservative position and stronger agreement with the statement: *Com-*

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 measure of political position and treatment 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 (manufacturing or transport and warehousing). 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 E9). 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 Appendix D.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 anal-

petition 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

ysis 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 it up, our survey evidence suggests that the fact that the automation shock is seen as more inevitable and governmental interventions to address it are considered to be less helpful 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 study how technological change may affect its own long-term trajectory through its effect on voter turnout. To do so, we estimate the effect of long-run labour market adjustment to industrial robots on participation at federal elections in the US. We replicate prior results showing negative effects of exposure to robots on employment and household incomes at local labour markets and then show that the exposure to robots significantly reduced voting at the elections of both the US President and the US House of Representatives. This result extends the general finding of Caprettini and Voth (2020), who using historic data on the Swing Riots demonstrate that unemployment due to automation could lead to social unrests and warn against political consequences of rapid and regionally concentrated job losses. While abstaining in the elections is a different and perhaps more subtle form of protest, it may be more relevant in the modern world. Our approach of comparing two negative income shocks also reveals that it is not the effect of economic hardship as such: intensified trade with China which also resulted in lower income did not affect the voter turn out in the same way. To look into the differences we run an online survey experiment that allows to shed light on potential mechanism at play. The effect may depend on workers perceptions of the efficacy of a political response.

Our framework allows to show that the relationship between labour market conditions and political participation is not uniform, i.e. negative employment 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). Our findings also might offer a way to reconcile a longstanding debate between “withdrawal” and “mobilization” theories in political science that argue for opposite effects of economic conditions on voting (Brody and Sniderman, 1977; Gamson, 1968; Radcliff, 1992; Rosenstone, 1982; Schlozman and Verba, 1979; Southwell, 1988; Verba et al., 1995; Wilkes, 2004). 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), 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 labour costs of production and policies aimed to slow the pace of one process may accelerate the other. For instance, to reduce labour costs one could either buy cheaper supplies abroad instead of producing them in the country or introduce labour saving technologies and thus produce with less labour. 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 labour 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 ??) 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 C6 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 trade²³ and social security issues. Following the results of the survey experiment, the latter topic appears to be of particular importance in case of automation.

This evidence corroborates the concerns about the reinforcing feedback loop that is likely to ignore the interests of those who do not vote. Our results suggest that the ignored voices belong to those affected by automation. Moreover, the current state of political system may be an equilibrium: as citizens believe that the government has no means of addressing the issue of automation, this topic is rarely touched upon in the public discussions (see the frequency of mentions of the topics in the New York Times in Figure F4). Vice versa, because the topic is rarely touched in public discussions and no approaches are offered, citizens continue to believe that the government has no means of addressing the issue. Therefore, our work can offer an important applied insight: to restore the distorted feedback loop and attract the voters affected by the automation to the polls, it might be necessary to encourage the public discussion about alternative policies that may remedy changes triggered by automation. As politicians are unlikely to do so, this may fall on other public actors.

²³Our 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.

References

- Abraham, Katharine G and Melissa S Kearney (2020). “Explaining The Decline in the US Employment-to-Population Ratio: A Review of the Evidence”. In: *Journal of Economic Literature* 58.3, pp. 585–643.
- Acemoglu, Daron and Pascual Restrepo (2020). “Robots and jobs: Evidence from US labor markets”. In: *Journal of Political Economy* 128.6, pp. 2188–2244.
- Anelli, Massimo, Italo Colantone, and Piero Stanig (2019). “We Were the Robots: Automation and Voting Behavior in Western Europe”. In: *BAFFI CAREFIN Centre Research Paper* 2019-115.
- Autor, David, David Dorn, and Gordon H Hanson (2013). “The China syndrome: Local labor market effects of import competition in the United States”. In: *American Economic Review* 103.6, pp. 2121–68.
- Autor, David H and David Dorn (2013). “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market”. In: *American Economic Review* 103.5, pp. 1553–97.
- Autor, David H, David Dorn, Gordon H Hanson, and Jae Song (2014). “Trade Adjustment: Worker-Level Evidence”. In: *The Quarterly Journal of Economics* 129.4, pp. 1799–1860.
- Blais, André (2006). “What Affects Voter Turnout?” In: *Annual Review of Political Science* 9, pp. 111–125.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022). “Quasi-experimental shift-share research designs”. In: *The Review of Economic Studies* 89.1, pp. 181–213.
- Brody, Richard and Paul Sniderman (1977). “From Life Space to Polling Place: The Relevance of Personal Concerns for Voting Behavior”. In: *British Journal of Political Science* 7.3, pp. 337–360.
- Burden, Barry C and Amber Wichowsky (2014). “Economic discontent as a mobilizer: unemployment and voter turnout”. In: *The Journal of Politics* 76.4, pp. 887–898.
- Cancela, Joao and Benny Geys (2016). “Explaining Voter Turnout: A Meta-Analysis of National and Subnational Elections”. In: *Electoral Studies* 42, pp. 264–275.
- Caprettini, Bruno and Hans-Joachim Voth (2020). “Rage against the machines: Labor-saving technology and unrest in industrializing England”. In: *American Economic Review: Insights* 2.3, pp. 305–20.
- Charles, Kerwin Kofi and Melvin Stephens Jr (2013). “Employment, wages, and voter turnout”. In: *American Economic Journal: Applied Economics* 5.4, pp. 111–43.
- Colantone, Italo, Rosario Crino, and Laura Ogliari (2019). “Globalization and Mental Distress”. In: *Journal of International Economics* 119, pp. 181–207.
- Dhillon, Amrita and Susana Peralta (2002). *Economic theories of voter turnout*.

- Di Tella, Rafael and Dani Rodrik (2020). “Labour Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys”. In: *The Economic Journal* 130.628, pp. 1008–1030.
- Dorn, David, Gordon Hanson, Kaveh Majlesi, et al. (2020). “Importing political polarization? The electoral consequences of rising trade exposure”. In: *American Economic Review* 110.10, pp. 3139–83.
- Eckert, Fabian, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang (2021). *Imputing Missing Values in the US Census Bureau’s County Business Patterns*. Tech. rep. National Bureau of Economic Research.
- Faber, Marius, Andres Sarto, and Marco Tabellini (2019). “The impact of technology and trade on migration: Evidence from the US”. In: *Harvard Business School BGIE Unit Working Paper* 20-071.
- Falk, Armin, Anke Becker, Thomas J Dohmen, David Huffman, and Uwe Sunde (2016). “The preference survey module: A validated instrument for measuring risk, time, and social preferences”. In:
- Fiorina, Morris P (1976). “The voting decision: instrumental and expressive aspects”. In: *The journal of politics* 38.2, pp. 390–413.
- Fowler, Anthony (2013). “Electoral and Policy Consequences of Voter Turnout: Evidence from Compulsory Voting in Australia”. In: *Quarterly Journal of Political Science* 8, pp. 159–182.
- (2015). “Regular Voters, Marginal Voters and the Electoral Effects of Turnout”. In: *Political Science Research and Methods* 3.2, pp. 205–219.
- Gamson, William A (1968). “Stable unrepresentation in American society”. In: *American Behavioral Scientist* 12.2, pp. 15–21.
- Graetz, Georg and Guy Michaels (2018). “Robots at Work”. In: *Review of Economics and Statistics* 100.5, pp. 753–768.
- Granulo, Armin, Christoph Fuchs, and Stefano Puntoni (2019). “Psychological reactions to human versus robotic job replacement”. In: *Nature human behaviour* 3.10, pp. 1062–1069.
- Greenland, Andrew, John Lopresti, and Peter McHenry (2019). “Import competition and internal migration”. In: *Review of Economics and Statistics* 101.1, pp. 44–59.
- Griffin, John D and Brian Newman (2005). “Are voters better represented?” In: *The Journal of Politics* 67.4, pp. 1206–1227.
- Gross, Emily (2003). “US population migration data: Strengths and limitations”. In: *Internal Revenue Service Statistics of Income Division, Washington, DC*. http://www.irs.gov/pub/irs-soi/99gross_update.doc.
- Guiso, Luigi, Helios Herrera, Massimo Morelli, Tommaso Sonno, et al. (2017). *Demand and supply of populism*. Centre for Economic Policy Research London, UK.
- Hansford, Thomas and Brad Gomez (2010). “Estimating the Electoral Effects of Voter Turnout”. In: *American Political Science Review* 104.2, pp. 268–288.

- Horiuchi, Yusaku and Jun Saito (2009). “Rain, elections and money: the impact of voter turnout on distributive policy outcomes in Japan”. In: *Asia Pacific Economic Paper* 379.
- Leip, David (2021). *Dave Leip’s Atlas of U.S. Presidential Elections*. URL: <http://uselectionatlas.org>.
- Macdonald, Stuart Elaine, George Rabinowitz, and Ola Listhaug (1995). “Political sophistication and models of issue voting”. In: *British Journal of Political Science* 25.4, pp. 453–483.
- Martin, Paul S (2003). “Voting’s rewards: Voter turnout, attentive publics, and congressional allocation of federal money”. In: *American journal of political science* 47.1, pp. 110–127.
- Peer, Eyal, Laura Brandimarte, Sonam Samat, and Alessandro Acquisti (2017). “Beyond the Turk: Alternative platforms for crowdsourcing behavioral research”. In: *Journal of Experimental Social Psychology* 70, pp. 153–163.
- Rabinowitz, George and Stuart Elaine Macdonald (1989). “A directional theory of issue voting”. In: *American political science review* 83.1, pp. 93–121.
- Radcliff, Benjamin (1992). “The Welfare State, Turnout, and the Economy: A Comparative Analysis”. In: *American Political Science Review* 86.2, pp. 444–454.
- Rosenstone, Steven J. (1982). “Economic Adversity and Voter Turnout”. In: *American Journal of Political Science* 26.1, pp. 25–46. ISSN: 00925853, 15405907. URL: <http://www.jstor.org/stable/2110837>.
- Schlozman, Lehman and Sidney Verba (1979). *Injury to Insult: Unemployment, Class, and Political Response*. Harvard University Press.
- Smets, Kaat and Carolien van Ham (2013). “The Embarrassment of Riches? A Meta-Analysis of Individual-Level Research on Voter Turnout”. In: *Electoral Studies* 32.2, pp. 344–359.
- Southwell, Priscilla (1988). “The Mobilization Hypothesis and Voter Turnout in Congressional Elections, 1974-1982”. In: *Political Research Quarterly* 41.2, pp. 273–287.
- Stehrer, Robert, Alexandra Bykova, Kirsten Jäger, Oliver Reiter, and Monika Schwarzhappel (2019). “Industry level growth and productivity data with special focus on intangible assets”. In: *Vienna Institute for International Economic Studies Statistical Report* 8.
- Timmer, Marcel P, Mary O Mahony, Bart Van Ark, et al. (2007). “EU KLEMS growth and productivity accounts: an overview”. In: *International Productivity Monitor* 14, p. 71.
- Tolbert, Charles M and Molly Sizer (1996). *US commuting zones and labor market areas: A 1990 update*. Tech. rep.
- Verba, Sidney, Kay Lehman Schlozman, and Henry E Brady (1995). *Voice and equality: Civic voluntarism in American politics*. Harvard University Press.

- Webb, Michael (2019). "The Impact of Artificial Intelligence on the Labor Market". In: *Available at SSRN 3482150*.
- Wilkes, Rima (2004). "First nation politics: Deprivation, resources, and participation in collective action". In: *Sociological Inquiry* 74.4, pp. 570–589.

Appendix A Data

A.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 2016.²⁴ We classify the IFR data into 13 manufacturing industries, and 6 broad industries outside manufacturing.²⁵ 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.

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).²⁶ As in Acemoglu and Restrepo (2020), we translate the numbers of persons

²⁴These 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.

²⁵Manufacturing 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.

²⁶We 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

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.²⁷

A.2 Exposure to Chinese Imports

To construct a measure of commuting zone exposure to Chinese imports as in Autor, Dorn, and Hanson (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, Dorn, and Hanson (ibid.) and adjusted trade values to 2007 US\$ prices using the personal consumption 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

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.

²⁷The mapping of 1990 Census Bureau industry classes to corresponding IFR industries is also available upon request.

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.²⁸ 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.

Appendix B Empirical Strategy and Data for the Individual Level Analysis

To test the relationship between the exposure to different labour 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:

$$\begin{aligned} GSS_{i,c,d,t} = & \text{Individual exposure to Robots}_{i,t} + \text{Individual exposure to Chinese Imports}_{i,t} + \\ & \text{US exposure to Robots}_{c,t-1:t} + \text{US exposure to Chinese Imports}_{c,t-1:t} + \alpha_{d,t} + \epsilon_{i,c,d,t} \end{aligned} \quad (8)$$

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 16 and 65. This yields a baseline sample of more than 12,000 individuals that provided information on their participation at the last presidential election.²⁹

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

²⁸Industry crosswalks from NAICS 2007 to SIC 1987 necessary to use the data from Eckert et al. (2021) for our purpose are available upon request.

²⁹The 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=.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. 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 :

$$\begin{aligned} \text{Individual} \\ \text{Exposure to} \\ \text{Robots}_{i,t} \end{aligned} = \sum_{o=1}^{14} \left(\hat{Pr}(Occ = o | age_i, gender_i, educ_i, paocc_i, padeg_i, reg16_i) \times \theta_o \right) \quad (9)$$

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.

$$\begin{aligned} \text{Individual Exposure to} \\ \text{Chinese Imports}_{i,t} \end{aligned} = \ln(M_{i,t}^{CN-US}) - \ln(M_{i,t-8}^{CN-US}) \quad (10)$$

Appendix C Tables

Table C1: Effects on changes in employment, household incomes per working-age adult and poverty, stacked differences (1990-2015)
2SLS

	Employment			Average HHI/adult		Poverty
	Manufacturing (1)	Non- Manufacturing (2)	Total (3)	Wage- salary (4)	Business- invest (5)	SocSec + Welfare (6)
US Exposure to Robots	-1.126*** (0.338)	-1.204*** (0.242)	-571.2*** (86.23)	-572.1*** (79.12)	-25.88* (10.42)	26.80*** (2.612)
US Exposure to Chinese Imports	-5.685*** (1.722)	0.825 (1.081)	-765.2** (236.8)	-764.3*** (217.8)	-13.13 (37.05)	12.26 (12.32)
Kleibergen-Paap F	32.10	32.76	32.32	32.32	32.32	32.32
R ²	0.155	0.298	0.138	0.167	0.0277	0.222
Region × time	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓	✓	✓
Pre-trends	✓	✓				

Note: $N=2,166$ (3×722 Commuting Zones) The dependent variables in columns (1) and (2) is the change in the log count of employment in manufacturing and non-manufacturing industries respectively, multiplied by 100 (i.e., $[\ln(yt+1)-\ln(yt)] \times 100$). The dependent variable in column (3) 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 (4); self-employment, business, and investment income in column (5); social security and welfare income in column (6); and income from other non-specified sources. The dependent variable in column (7) is the ten-year equivalent percentage change of the number of working-age adults with family income less than the poverty threshold as defined by the US Census for each individual. 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.

Table C2: Effects on voting at US presidential elections: county-level stacked differences 2000-2016 (2SLS)

	$\Delta \ln(\text{votes}) \times 100$				
Panel A. US President	(1)	(2)	(3)	(4)	(5)
US exposure to robots	-1.841*** (0.384)	-0.722*** (0.240)	-0.859*** (0.250)	-1.170*** (0.265)	-1.013*** (0.262)
US exposure to Chinese imports	0.470 (0.848)	0.538 (0.592)	0.569 (0.591)	0.607 (0.597)	0.535 (0.581)
Δ Citizen voting age population		0.940*** (0.0249)	0.753*** (0.0422)	0.754*** (0.0424)	0.750*** (0.0413)
Net in-migration rate			23.25*** (4.247)	23.28*** (4.267)	23.18*** (4.202)
Δ Share of college educated			-23.87* (12.87)	-27.67** (13.50)	-26.72** (13.35)
Perennial swing state				2.170*** (0.492)	1.452*** (0.484)
TV campaign ads, USD per HH					0.114*** (0.0232)
Kleibergen-Paap F-Stat	31.99	32.18	32.38	33.29	32.97
Observations	6172	6172	6168	6168	6136
Wald Test [R=C] p-Value	0.00836	0.0391	0.0225	0.00439	0.0117
Region $\times$ Period	✓	✓	✓	✓	✓
Lagged mfg. share $\times$ Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine jobs & Offshorability	✓	✓	✓	✓	✓

Note: The dependent variable is the change in the log count of votes at US presidential elections multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \times 100$). 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). 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 C3: Effects on voting at US House of Representatives elections: county-level stacked differences 2000-2016 (2SLS)

	$\Delta \ln(\text{votes}) \times 100$				
Panel B. US House of Rep.	(1)	(2)	(3)	(4)	(5)
US exposure to robots	-2.130*** (0.669)	-1.218* (0.721)	-1.378* (0.720)	-1.695** (0.743)	-1.634** (0.732)
US exposure to Chinese imports	2.232* (1.218)	2.114** (1.059)	2.048* (1.062)	2.116** (1.077)	2.188** (1.093)
Δ Citizen voting age population		0.784*** (0.128)	0.530*** (0.155)	0.529*** (0.155)	0.527*** (0.155)
Net in-migration rate			31.00*** (7.245)	31.10*** (7.404)	31.08*** (7.434)
Δ Share of college educated			3.098 (24.66)	-1.038 (25.00)	0.118 (25.38)
Perennial swing state				2.294*** (0.729)	2.176*** (0.721)
TV campaign ads, USD per HH					0.163 (0.101)
Kleibergen-Paap F-Stat	28.32	28.47	28.68	29.57	29.39
Observations	5483	5483	5479	5479	5448
Wald Test [R=C] p-Value	0.00212	0.0113	0.00975	0.00490	0.00461
Region $\times$ Period	✓	✓	✓	✓	✓
Lagged manufact. share $\times$ Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓	✓

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., $[\ln(yt+1)-\ln(yt)] \times 100$). 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). 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 C4: Robustness of effect on voting at U.S. federal elections elections to different measures of voting population: county-level stacked differences 2000-2016 (2SLS)

	$\Delta \ln(\text{votes}) \times 100$					
	US President			US House of Representatives		
	(1)	(2)	(3)	(4)	(5)	(6)
US Exposure to Robots	-1.013*** (0.262)	-0.992*** (0.278)	-1.643*** (0.251)	-1.634** (0.732)	-1.636** (0.754)	-2.302*** (0.663)
US Exposure to Chinese Imports	0.535 (0.581)	0.763 (0.597)	0.761 (0.701)	2.188** (1.093)	2.505** (1.117)	2.401* (1.267)
Net in-migration rate	23.18*** (4.202)	17.96*** (4.338)	45.63*** (5.153)	31.08*** (7.434)	26.31*** (7.335)	40.56*** (9.416)
Δ Share of College Educated	-26.72** (13.35)	-16.13 (13.25)	-32.94** (14.96)	0.118 (25.38)	8.926 (25.43)	-13.01 (27.11)
Perennial swing state	1.452*** (0.484)	1.424*** (0.473)	2.453*** (0.465)	2.176*** (0.721)	2.182*** (0.729)	2.915*** (0.682)
TV campaign ads, USD per HH	0.114*** (0.0232)	0.115*** (0.0239)	0.0818*** (0.0310)	0.163 (0.101)	0.151 (0.102)	0.0961 (0.0907)
Δ CVAP	0.750*** (0.0413)			0.527*** (0.155)		
Δ VAP		0.773*** (0.0395)			0.562*** (0.155)	
Δ Reg			0.422*** (0.0340)			0.374*** (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	0.0117	0.00553	0.000903	0.00461	0.00256	0.00157
Region $\times$ Period	✓	✓	✓	✓	✓	✓
Lagged mfg. share $\times$ Period	✓	✓	✓	✓	✓	
Demographics	✓	✓	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓	✓	✓

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., $[\ln(yt+1)-\ln(yt)] \times 100$). 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 C2 and C3 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 C5: Effect on voter turnout at U.S. federal elections elections:
county-level stacked differences 2000-2016 (2SLS)

	Δ Voter Turnout $\times 100$	
	US President (1)	US House of Representatives (2)
US Exposure to Robots	-0.515*** (0.168)	-0.533* (0.297)
US Exposure to Chinese Imports	0.168 (0.324)	0.358 (0.648)
Net in-migration rate	3.788*** (1.125)	6.425*** (2.047)
Δ Share of College Educated	-19.26** (7.500)	0.898 (15.55)
Perennial swing state	1.142*** (0.291)	1.320*** (0.362)
TV campaign ads, USD per HH	0.0693*** (0.0144)	0.0446 (0.0634)
Kleibergen-Paap F-Stat	32.78	30.75
Observations	6136	5556
Wald Test [R=C] p-Value	0.0466	0.155
Region $\times$ Period	✓	✓
Lagged mfg. share $\times$ 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 C6: Effect of robots and imports from China on political advertising at US presidential elections in 2008 and 2016: county-level (2SLS)

	<i>Spending on Political Ads / HH</i>			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
<i>Panel A:</i>	(1)	(2)	(3)	(4)
US Exposure to Robots	-1.312*** (0.359)	0.0553*** (0.0114)	-0.149* (0.0794)	-0.0142* (0.00850)
US Exposure to Chinese Imports	0.670 (0.619)	0.00120 (0.0101)	0.110 (0.104)	0.0109 (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
<i>Number of Political Ads</i>				
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
<i>Panel B:</i>	(5)	(6)	(7)	(8)
US Exposure to Robots	-1116.4* (621.6)	89.15*** (11.56)	-85.69 (135.3)	-3.010 (13.98)
US Exposure to Chinese Imports	810.4 (808.1)	3.197 (14.89)	87.35 (130.7)	23.46 (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 $\times$ time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share $\times$ 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 C7: Effect of robots and imports from China on political advertising at US House of Representatives elections in 2008 and 2016: county-level (2SLS)

	<i>Spending on Political Ads / HH</i>			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
<i>Panel A:</i>	(1)	(2)	(3)	(4)
US Exposure to Robots	-0.395 (0.301)	0.0108 (0.00719)	-0.00707 (0.0446)	-0.130** (0.0544)
US Exposure to Chinese Imports	-0.350 (0.284)	-0.0305 (0.0203)	-0.0741 (0.0680)	-0.0501 (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
	<i>Number of Political Ads</i>			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
<i>Panel B:</i>	(5)	(6)	(7)	(8)
US Exposure to Robots	-463.6 (516.6)	15.12* (8.969)	-21.19 (74.66)	-209.8** (98.20)
US Exposure to Chinese Imports	-245.0 (465.3)	-38.92 (23.81)	-84.61 (102.0)	-32.00 (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 $\times$ time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share $\times$ 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 C8: Exposure to robots and imports from China and individual-level labour market outcomes: 2000-2016

	Heavy lifting	Forceful hand movement	Unemployed	Likely to lose job	Voted in last election
	(1)	(2)	(3)	(4)	(5)
Individual Exposure to Robots	0.1920*** (0.0081)	0.1466*** (0.0088)	0.0138*** (0.0035)	0.0465*** (0.0053)	-0.1498*** (0.0050)
Individual Exposure to Chinese Imports	0.0161** (0.0075)	0.0198** (0.0078)	-0.0048** (0.0023)	0.0062 (0.0049)	0.0034 (0.0046)
US Exposure to Robots	0.0322* (0.0166)	0.0441** (0.0179)	-0.0029 (0.0044)	0.0201** (0.0080)	-0.0020 (0.0110)
US Exposure to Chinese Imports	-0.0036 (0.0054)	-0.0038 (0.0065)	0.0008 (0.0019)	0.0007 (0.0035)	0.0006 (0.0028)
Observations	4,296	4,295	10,978	6,169	12,457
R ²	.1455297	.094614	.010725	.0509463	.1074814
Sample mean	.4557728	.4796275	.3700971	1.773068	.7022558
Year x Census Division	Yes	Yes	Yes	Yes	Yes

Note: All outcome variables are coded binary: (1) Respondent's work implies heavy lifting (2) Respondent's work implies forceful hand movements (3) Unemployed vs. Employed (4) Respondent believes job loss within next 12 months to be likely (5) Did R vote at last presidential election. Standard errors in parentheses. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Appendix D Survey materials

D.1 Vingettes

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 D1: 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 D2: Control condition. The highlighted text varied depending on the treatment. Highlights are added.

D.2 Results of t-tests

Manipulation check

I can relate to the story described in the article.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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: (<i>with answer:</i> to retrain into a new occupation)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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: (<i>with answer:</i> to get additional qualifications that would be beneficial for the worker's current occupation)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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: (<i>with answer:</i> to start looking for another position right away)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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 the government should do?

Do you think the layoffs described in the article could be prevented? If so, by whom? (<i>with answer: No, the layoffs are inevitable</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Yes, by the state government</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Yes, by the federal government</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Yes, by the company management</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Government should do nothing</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance)</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Government should restrict imports from overseas, by placing import tariffs on such imports for example</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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? (<i>with answer: Government should impose higher taxes on laboursaving technology and regulate automation more strictly</i>)						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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?

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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?

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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?

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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 intensified trade with other countries.						
Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
				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			

Appendix E Selected regressions: Heterogeneity along political ideology.

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

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

More Conservative: higher values correspond to more conservative political position

Table E9: Attitudes towards the statement: (1) "I believe politicians do not pay enough attention to the unemployment due to [the introduction of new organisational 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 organisational practices / due to automation / due to increased trade competition with China]

Appendix F Figures

Figure F1: Commuting zone exposure to robots (2000-2015)

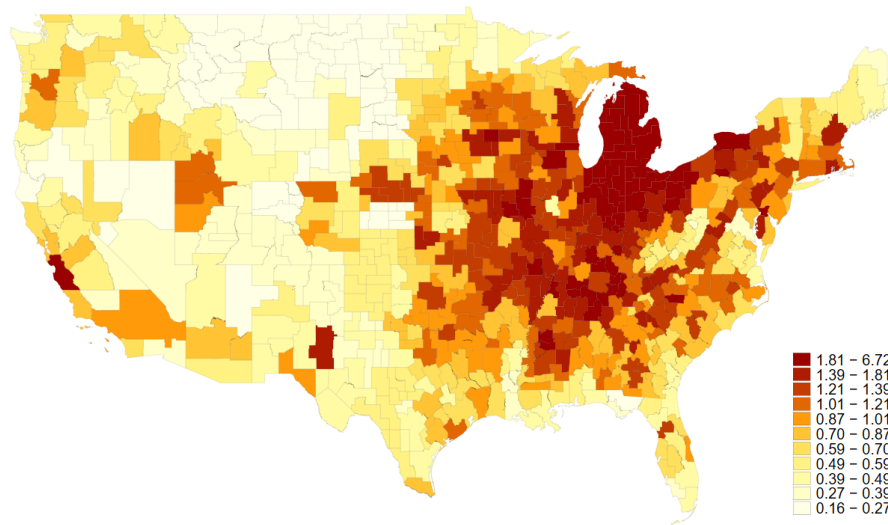


Figure F2: Commuting zone exposure to Chinese imports (2000-2015)

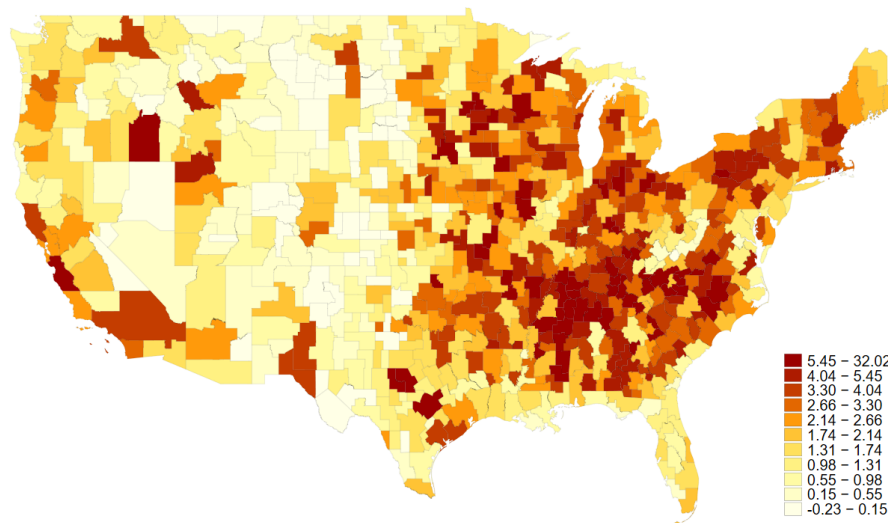


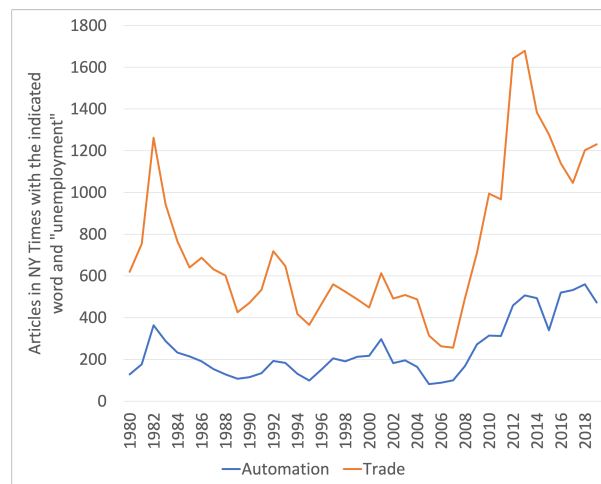
Figure F3: Example of campaign ad storyboard from Wesleyan Data Project

PRES/MCCAIN&RNC OHIO JOBS

Brand: MCCAIN FOR PRESIDENT (B331)
Parent: MCCAIN FOR PRESIDENT COMMITTEE
Aired: 09/19/2008 - 09/20/2008
Creative Id: 6712751

 SMALL BUSINESS JOBS PLAN [Announcer]: Ohio's small businesses create more than half	 SMALL BUSINESS JOBS PLAN of all our jobs. John McCain and his congressional allies	 SMALL BUSINESS JOBS PLAN will help them create even more with tax cuts to create jobs,
 RENEWABLE ENERGY investment in renewable energy to revitalize Ohio's manufacturing,	 REFORMS reforms to make health insurance affordable	 JOB RETRAINING to help workers stay competitive. and job retraining to help workers stay competitive.
 CHANGE IS COMING Change is coming.	 JOHN MCCAIN FOR PRESIDENT [John McCain]: "I'm John McCain, and I approve this message."	

Figure F4: Media Attention to Automation vs. Trade



Notes: Annual count of articles in the New York Times mentioning either automation or trade and unemployment. Data from Factiva. Exact search strings: "(automation or robot* or technolog*) and (unemployment or job loss*)" and "(trade or outsourcing or import*) and (unemployment or job loss*)".