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

Marina Chugunova
Max Planck Institute for Innovation and Competition

Arnau Juanmarti
IESE Business School

Klaus Keller
Max Planck Institute for Innovation and Competition

Sampsa Samila
IESE Business School

3 September 2021

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 0.64 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. Using individual level data we document that people at risk of automation are 15% percent more likely to abstain. 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

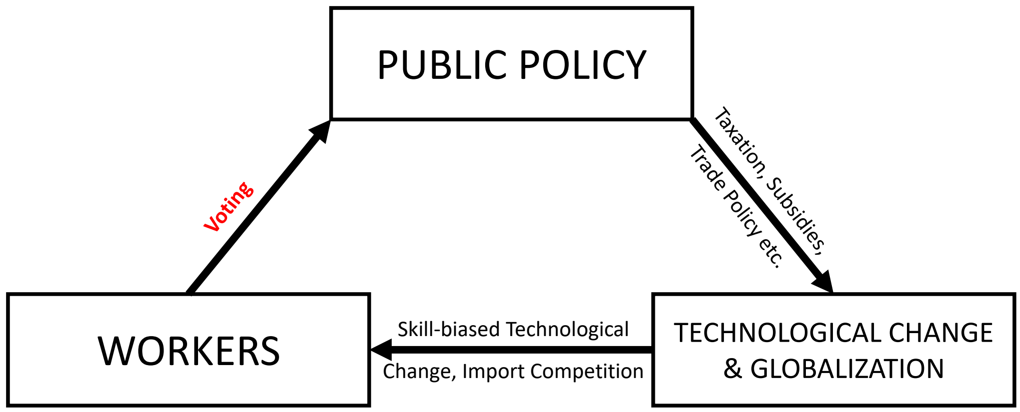
High voter turnout is essential for the functioning of democracies. Scholars have shown that differences in voter turnout can affect the degree to which election results reflect the preferences of the citizenry (Fowler, 2015), who wins elections (Fowler, 2013; Hansford and Gomez, 2010), and the public 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).

While 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), 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 increased voter turnout (Burden and Wichowsky, 2014) or reduced turnout (Rosenstone, 1982)?

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).

[1]This 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



In this paper we contribute to the nascent and growing literature on political and 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 on political participation in the US between 2000 and 2016. We study this relationship in three 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). After confirming the established finding that both automation and import competition lead to declines in employment and average household income at the commuting-zone level, we use the 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

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

this end, we consider changes in turnout at both US presidential and House 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, leading us to the conclusion that a one standard deviation increase in exposure to robots leads to a 0.32 percentage point lower voter turnout. This means that an increase in exposure by one robot per thousand workers over 8 years reduced turnout by about 9 voters. The total increase in the stock of robots of about 80,000 robots per electoral 8-year period is then predicted to have reduced national turnout by 720,000 voters per cycle. We compare this with the effect of exposure to import competition from China which we find not to affect the voter turn out, or affect it positively at best, depending on the specification.

In a second step, we use micro-level data from the General Social Survey to check whether the differential effect of the exposure to robots and Chinese imports on turnout can also be observed at the individual-level. To this end, we construct a measure of individual exposure to industrial robots using data on the automatability of occupations based on the text similarity of robotic patents and occupation descriptions developed by Webb (2019). To account for the endogeneity of an individual's observed occupation to automation, we apply the method developed by Anelli et al. (2019) that computes individual exposure as the sum of automatability scores of occupations weighted by a worker's probability to work in that occupation based on an individual based on individual characteristics. In addition, we measure individual exposure to import competition as the growth of Chinese imports in a worker's industry over the previous 8 years. Using data from the General Social Survey conducted every second year between 2000 and 2016, we estimate the effect of both measures on several factors related to individuals' labour market situation, voting behavior, political attitudes and beliefs. We find evidence that higher individual exposure to robots is significantly associated with a higher probability of unemployment as well as perceived higher likelihood of losing a job. Importantly,

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

the individual-level analysis documents that individuals that are one standard deviation more exposed to industrial robots were 11 percent less like to have voted in the last presidential election and exhibit lower levels of trust. As in the county-level analysis, we do not find evidence for a negative effect of the exposure to Chinese imports on individual turnout, although we find that individuals more exposed to import competition have lower confidence in the US Congress.

The staggering discrepancy in the political reaction to automation relative to trade motivates the third part of the empirical analysis. To better understand the behavioral mechanisms that drive 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 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. 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. While both shocks are perceived to be equally important, respondents found automation shock to be more inevitable and consider the federal government to be less able to deal with it. 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 one needs to employ a more nuanced approach that considers behavioral motives. 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 both 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 and present the results in Section 3. In Section 4 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 5 concludes.

2 Empirical Strategy

2.1 Regional Analysis

[4]

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. We follow this

[4] Section A in the Appendix reports on the used data sources.

approach to identify the long-run effect of automation and Chinese import competition on political participation in the US and estimate the following model:

$$\Delta Y_{j,c,t} = \beta^r \begin{array}{c}\text{US Exposure to} \\ \text{Robots}\end{array}_{c,t:t+1} + \beta^c \begin{array}{c}\text{US Exposure to} \\ \text{Chinese Imports}\end{array}_{c,t:t+1} + \mathbf{X'}_{c,t0}\gamma + \epsilon_{j,t} \quad (1)$$

where, in our main result, $Y_{j,c,t}$ stands for the percentage-point change in voter turnout at US presidential elections in county j in commuting-zone c over period t. Following the presidential election cycle, we estimate the model by stacking differences over two 8-year periods: 2000-2008 and 2008-2016. We include $\mathbf{X'}_{c,t0}$, a vector of commuting-zone baseline characteristics in 2000, to allow for differential trends due to observable differences in demographics (age, education, gender and ethnic composition), industry shares and exposure to offshoring (share of routine employment, offshorability index), as documented by Faber et al. (2019). In addition, we control for unobserved period-specific regional trends by interacting the periods and census regions. 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 region.

Exposure to robots: For each period we construct a shift-share measure of commuting zone exposure to industrial robots following Acemoglu and Restrepo (2020), 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 over period t to $t+1$ relative to the total number of workers in industry i in 1990, minus the growth of the robot stocks due to real output growth $g_{i,t:t+1}^{US}$ over the period, weighted by $l_{c,i,1990}$, the share of industry i in total employment in commuting zone c in 1990:

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

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. To make sure that changes in robot penetration are only driven by exogenous improvements in technology and avoid biased estimates, we therefore construct an instrumental variable as in Acemoglu and Restrepo (2020) using changes in the penetration of robots in industry i in five European countries ahead of the US in terms of the use of robot technology (Denmark, Finland, France, Italy, Sweden) and the lagged share of industry i in total employment in commuting zone c in 1970.

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

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 industry i in total manufacturing employment in commuting zone c at the beginning of each period:

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

Also this second explanatory 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]

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

2.2 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:

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

where, for each GSS survey question, $GSS_{i,c,d,t}$ corresponds to the answer of respondent i, in commuting zone c, in a census divsion 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. [6]

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

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

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

an individual's observed occupation is endogenous to the automation process itself (Anelli et al., 2019). Indeed, the observed occupation might be a worker's occupational choice after being replaced by technology. To account for it, we use data from the GSS from 1980 and 1989, the decade before the automation shock, to estimate a multinomial logit model of occupational choice conditional on age, education, gender, father's occupation and degree and census region when 16 years old (9000 observations, Pseudo-R2=.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:

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

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

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

3 Results

In a first step, we validate our data set by replicating the established finding of the negative effect of both labour market shocks on changes in employment over three time periods between 1993, 2000, 2007 and 2015. Our findings are similar to the employment effects documented by Faber et al. (2019), showing a negative effect of both shocks on manufacturing employment but only a negative employment effect outside manufacturing for the case of automation. Despite the concentration of the import shock on manufacturing industries, we show that the effect of both shocks on the average annual household income per adult were comparable. Table A1 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 total 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 effect for both shocks, yet more pronounced for increasing import competition from China. Overall, Table A1 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.

In a second step, we test the effect of both income shocks on political participation at the regional level. For this aim, we use county-level data by Dave Leip's Atlas of US elections that reports the total number of voters that turned out at US presidential and US House of Representatives elections in 2000, 2008 and 2016. For this analysis we remove the time period between 1992 and 2000 due to data limitation. We compute three standard measures of voter turnout as share of the potential electorate. First, we use the number of registered voters as reported by Dave Leip's Atlas of US Elections as denominator. This measure has the advantage of being a precise count but also bears the disadvantage of being affected by regional differences in the management of voter registers as well as policy changes. Beyond, voter registration is not available for all states. To improve on both points, we compute a second measures using US Census estimates for the adult voting age population by county. Though it is available for all counties in all states, it comes with the disadvantage of hiding important regional differences in the share of foreign residents in the adult population[7]. Thus, we compute a third measure using US Census estimates for the citizen voting age population as denominator. This is our preferred measure 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. Table A2 reports the results of two-stages least squares regressions of changes in the voter turnout relative to citizen voting age population on the exposure to robots and Chinese imports. We make use of the two-period panel structure of our data and account for unobserved regional trends in each period by including census division by period dummies. The F-Statistic of the first stage is larger than the threshold value of 10 across all four specifications which fulfills the requirement of instrument relevance. To make the effect of the two labour market shocks comparable we standardized all explanatory variables to have a mean of zero and a standard deviation of 1. In the fully specified model in column (4), we estimate that a standard deviation increase in the exposure to robots reduced the change in voter turnout by 0.32 percentage points. An increase in robot exposure by two standard deviations corresponds to an increase in one robot per thousand workers over 8 years, or 0.66 robots per thousand voting age citizens. Following specification (4) this increase lead to a 0.64 percentage points lower voter turnout, which is equivalent to reducing turnout by about 9 voters. Hence, the total increase in the stock of robots of about 80,000 robots per electoral 8-year period is predicted to have reduced turnout by 720,000 voters per cycle.[8] At the same time, Table A2 reports a statistically insignificant and at best positive effect of increased exposure to Chinese imports on voter turnout. We repeat the estimation for turnout at US house of representative elections in Panel B. Though the effect of robot exposure is again negative and statistically different from the exposure to Chinese imports, we cannot reject the null hypothesis at conventional significance levels. Tables A3 and A4 repeat the exercise using turnout over registered

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

[8]For the year 2000, we count 212 million US adult residents, 196 million adult citizen residents, 127 million employed workers and 105 million voters. The average national turnout at the presidential election was at 53%. This means that for 1000 workers there were on average 1500 citizen residents and 803 voters. The reduction in voters due to one more robot per thousand workers is then equivalent to 9 $\approx 803 - (0.5367 - 0.0064) * 1500$.

voters or voting age population as alternative measures. Both confirm the negative effect of increased robot exposure on presidential election turnout with comparable effect sizes and varying statistical significance. For the reasons of lower coverage and reliability of these alternative measures, we consider that these robustness checks that broadly confirm our finding but are less precise than our estimates in Table A2.

To test whether the differential political response to both income shocks can actually be observed at the individual-level, we study micro-level data of the *General Social Survey* (GSS) for the years 2000 to 2016 that 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 A5 documents how individual and regional exposure to the shocks affects labour market situation of the respondents. First, we validate that our individual exposure to robots and Chinese imports measure predict manual work as we find that more exposed individuals are also more likely to engage in work that involves forceful hand movements and heavy lifting. Next, Table A5 shows 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 A1. For individuals exposed to Chinese imports, both current employment and expectations of job loss do not seem to be affected.[9] We turn to the effect on political outcomes in Table A6. Strikingly, we find 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. This goes along with lower levels in general trust as well as a preference for a bigger government and its stronger engagement in reducing in inequality. At the same time, we observe that a higher individual exposure to Chinese imports was related to lower levels of trust in the US congress as well as a preference for reduction in inequality but did not affect turnout at presidential elections. This confirms the finding of the differential effect on voter turnout at presidential elections at the county-level reported in Table A2. Overall, we find individual-level exposure to matter more than community exposure at the commuting-zone level. To understand why the two shocks deferentially affect the voter turnout and shed light on potential mechanisms, we conduct an online survey experiment.

4 Evidence from the Online Survey Experiment.

4.1 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 go to the poll if the utility from voting outweights the utility from abstaining. Therefore, in this framework, the differential effect of the two shocks on the voter turn out is due to the fact that they deferentially affect the expected utility of the individual voters.

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

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

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

where B_j is the benefit expected to be derived from success of one's favorite candidate, which is the difference in utility of voter j if his favorite candidate is elected and the utility if the opponent does, P_j is the perceived likelihood that one's vote will make a difference, D_j is the expressive benefit that voter j gets from the act of voting and c_j are costs of voting.[10]

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

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

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

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

The instrumental value (B_j) appears to be more complex. As both of our shocks are

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

labor shocks, we assume that the ideal outcome for a voter in response to the shock is preventing negative economic consequences. Several factors might affect the instrumental value of voting depending on the labor market shock. First, if a voter perceives one shock to be more important and have larger consequences, he might expect higher instrumental benefits if the issue is addressed. Importantly, the perceptions of potential voters and not *de facto* consequences of the shocks matter. Second, while the voters expect to benefit if the issue is addressed, voting in elections is a tool of influencing the government and governmental policies. Therefore if voters do not believe that the issue may be addressed through governmental action or policy they may expect less instrumental utility. Furthermore, going beyond governmental ability to address the shocks, one might perceive one shock to be in general more inevitable and irreversible which may affect the willingness to 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.

4.2 An Online Survey Experiment: Design and Procedures

To consider what of the above parameters 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 the Prolific Academic to take part in the study. Prolific Academic 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 under 9 minutes (median 7,5 min) to answer the survey and were reimbursed with a flat payment of 1 GBP.

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

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

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

Figure 2: An example of the text presented during the survey. Automation condition. Highlights added. The highlighted text varied depending on the treatment.

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 news article (for example, see Fig 2). In the article, it was reported that a manufacturing plant announced layoffs. Depending on the treatment, the reason for the layoffs was different. 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.[11]

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 were supposed to ensure that the participants read the text carefully.

After that the respondents answered questions about their perceptions of consequences

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

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

Since we expect heterogeneities in responses along the lines of the party affiliation, apart from self-reported measure of political position, we elicited attitudes on the role of competition, government involvement and role of luck in success in US to be able to see if the self-reported measure was meaningful. Precise text of questions as well as their sequence can be found in the Appendix C.1.

4.3 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 representing the indifference point. We conclude that all three suggested stories were 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).[12] 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

[12]Unless otherwise specified, the statements are based on the results of the two-tailed t-tests. For robustness we have replicated our analysis using the OLS regression and controlling for main demographic variables. The results remained qualitatively similar. The reader can find the mean scores as well as p-values of the t-tests in the Appendix C.1.

and Control p=0.000, Automation and Trade p=0.007). Instead of searching for a new position directly, in case of automation unemployment gaining additional qualifications or retraining into a new occupation are more recommended strategies[13]. 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 indeed suggests that the government is seen as less helpful in coping with automation shock 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 trade[14], 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

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

[14]The two questions were asked in all treatments at the very end of the survey.

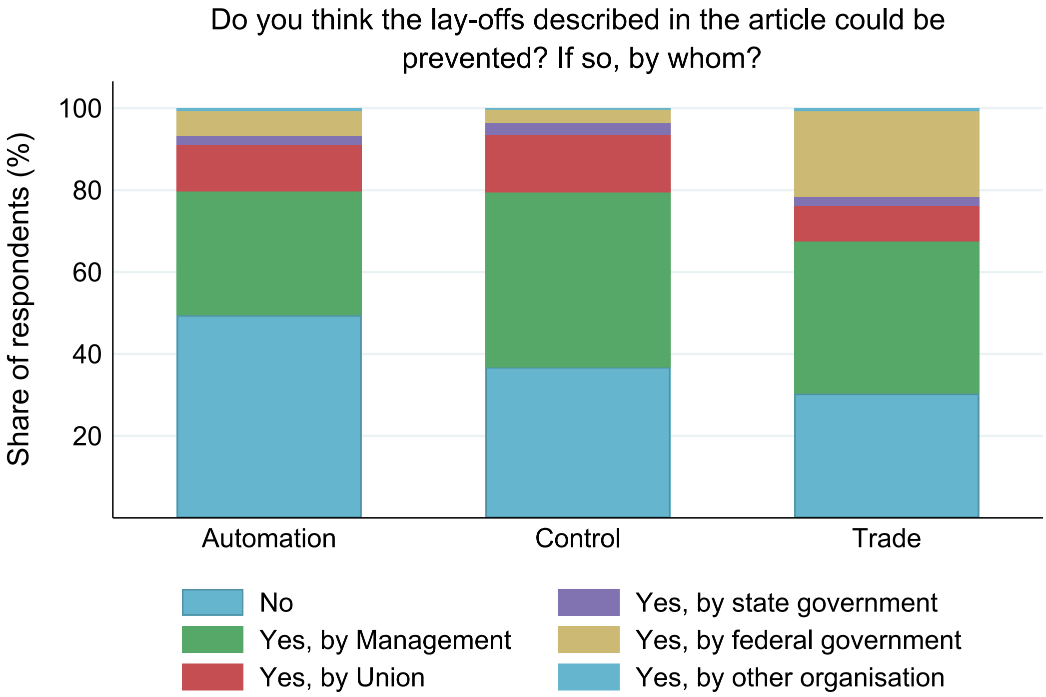


Figure 3: Exact wording of the answer options was: No, the lay-offs are inevitable; Yes, by the company management; Yes, by the union or other professional organisation; Yes, by the state government; Yes, by the federal government; Yes, by other organisation.

asked what should the government do in each scenario and could choose one of the four options: nothing, administer direct transfers to affected parties, introduce import tariffs and introduce automation taxes. Three out of four options imply that the government needs to engage. The smallest share of respondents indicated that the government should do nothing in Trade condition (only 5%) as compared to 9% in Automation (p=0.055) and 11% in Control (p=0.008) (see Figure 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 for 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

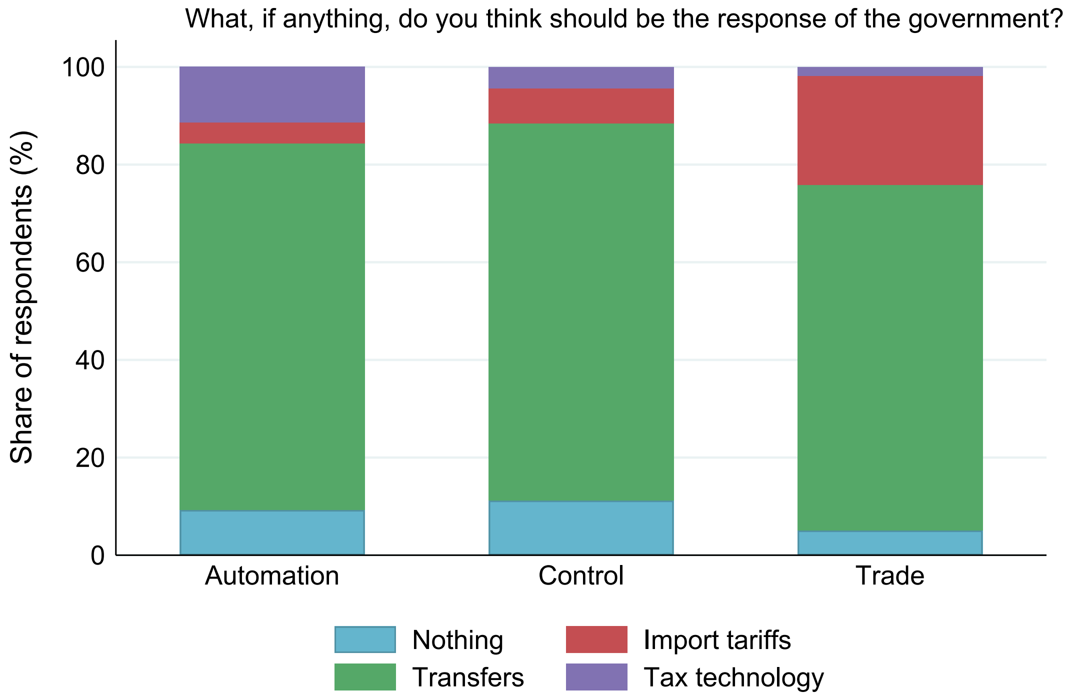


Figure 4: Exact wording of the answer options was: Government should do nothing; Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance); Government should restrict imports from overseas, by placing import tariffs on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

to the issues. However, in Automation condition respondents express stronger agreement (5.36) with the statement that not enough political attention is dedicated to the issue than in Trade (5.06, p=0.01). The control condition falls in between.

As questions about voting and political attention might relate to current 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)[15]. 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

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

attitudes towards competition). The self-reported measure strongly and significantly correlates with responses to the ideological statements in the expected direction[16], which reconfirms that self-reported measure of political attitudes can be used to consider heterogeneities along the lines of political affiliation. On average our sample is slightly liberal (3.1 with 4 corresponding to "moderate") with no significant differences among treatments (Kruskal-Wallis H test, $\chi^2(2) = 0.362, p = 0.83$).

To consider the role of political affiliation, we run an OLS regression with agreements 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 A8). 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 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 C.1).

We additionally considered heterogeneity of responses by age, by being employed in the affected industry (Manufacturing and Transportation and Warehousing, ca. 30% of

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

the sample) and if the respondent is at risk of automation where the risk of automation score is calculated following the methodology used above for GSS respondents. This analysis did not provide additional insights into mechanisms behind the patterns documented with the aggregated 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.

5 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 political participation 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 leads to lower voter turnout at the US presidential elections. Individual level data reconfirms this finding and additionally documents that it is individuals at risk of automation who abstain. This result suggests that the feedback loop between the affected voters and the government may be suppressed in case of automation: the voters who are affected are less likely to vote and therefore less likely to have their interests represented in public policies that shape the direction of technological change. 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). 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 are 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. Interestingly, 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 7). 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.

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.

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.

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.

Griffin, John D and Brian Newman (2005). "Are voters better represented?" In: *The Journal of Politics* 67.4, pp. 1206–1227.

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.

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.

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.

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.

Webb, Michael (2019). "The Impact of Artificial Intelligence on the Labor Market". In: *Available at SSRN 3482150*.

Appendix A Data

A.1 Political Participation

Regional data: To study political participation at the regional level, we leverage two types of measures.

Our first variable of interest is the change in county-level voter turnout at presidential and congressional elections which captures changes in political participation of citizen residents. We use data from Dave Leip's Atlas of U.S. Elections (Leip, 2021) on the total number of voter that turned out at US presidential and House of Representative elections in 2000, 2008 and 2016. To derive turnout as a share of actual voters relative to a county's citizenry, we compute turnout using different potential voting populations as denominators: 1.) the number of registered voters per county as provided by Leip (2021) [17] 2.) the estimated number of adult residents (Voting age population = VAP) 3.) the estimated number of adult citizen population per county (Citizen voting age population = CVAP). For the latter two denominators we use estimates provided by the US Census Bureau for years 2000, 2009 and 2016.

Individual data: To study the relationship between political participation at the individual level, we additionally leverage micro-data on political behavior and attitudes from all biannual waves of the *General Social Survey* (GSS) from 2000 to 2016. The survey questions of interest for our study pertain to general trust, confidence in the executive branch of the U.S. federal government, confidence in U.S. Congress and voting at the last U.S. presidential election. In addition the data set provides information on individual characteristics, such as age, gender, ethnicity, education and county of residence as well as on an individual's current employment stats, occupation, industry and expectations of job loss. Beyond, it contains information on an individual's upbringing, such as the region of residence at the age of 16, father's education and father's occupation.

A.2 Exposure to Robots

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

[17] North Dakota, Wisconsin, Florida and Mississippi do have inconsistent data on voter registration and hence are excluded when considering turnout by registered voters.

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.[18] We classify the IFR data into 13 manufacturing industries, and 6 broad industries outside manufacturing.[19] To obtain the 19 IFR industries as in Acemoglu and Restrepo (2020), 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).[20] As in Acemoglu and Restrepo (2020), we translate the numbers of persons employed in each European country-industry in 1990 into "US equivalent workers" by dividing the total number of hours worked in a European industry by the hours per worker in the corresponding US industry. This is to account for the fact that European workers work on average less hours and to make employment numbers comparable. To

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

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

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

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.[21] We report the fit of the replication in the Appendix.

Individual exposure to robots: To compute a measure of individual exposure to automation we use novel data by Webb (2019). This data gauges the exposure of 4-digit census occupations to automation by measuring the overlap between the text of job task descriptions provided by the O*Net database of occupations and tasks by the US Department of Labor, and the text of robotic patents from 1990 to 20.. retrieved from Google Patents. For the purpose of our study we build aggregate exposure scores for 14 2-digit occupations weighted by each 4-digit occupation's employment share.

A.3 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.

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

Industry employment: We obtain employment counts by SIC 1987 industry for each commuting zone in 1980, 1990 and 2000 using an algorithm by David Dorn that assigns employment counts to employment brackets reported in the establishment data of the US Census Bureau's *County Business Patterns*. For years after 2007, we make use of industry employment imputations by Eckert et al. (2021) also based on the *County Business Patterns* dataset.[22] 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.

Individual exposure to Chinese imports: To measure the exposure of individual's to Chinese imports, we make use of the same data sources and consider past changes in Chinese imports in the SIC 1987 industry an individual is observed to be working in.

A.4 Controls

We construct start-of-period economic and demographic characteristics of each commuting zone using micro-data from the US Census in 1970, 1980, 1990 and 2000, as well as from the three-year samples of the American Community Survey after 2000, all provided by IPUMS.

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

Appendix B Tables

Table A1: Effects on changes in employment, household incomes per working-age adult and poverty, stacked differences (1990-2015) 2SLS

	Employment		Average HHI/adult				Poverty
	Manufacturing	Non-Manufacturing	Total	Wage-salary	Business-invest	SocSec + Welfare	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
US Exposure to Robots	-1.126***	-1.204***	-571.2***	-572.1***	-25.88*	26.80***	2.255**
	(0.338)	(0.242)	(86.23)	(79.12)	(10.42)	(2.612)	(0.875)
US Exposure to Chinese Imports	-5.685***	0.825	-765.2**	-764.3***	-13.13	12.26	7.012***
	(1.722)	(1.081)	(236.8)	(217.8)	(37.05)	(12.32)	(1.692)
Kleibergen-Paap F	32.10	32.76	32.32	32.32	32.32	32.32	32.32
R^2	0.155	0.298	0.138	0.167	0.0277	0.222	0.132
Region × time	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓	✓	✓
Contemp. changes	✓	✓	✓	✓	✓	✓	✓
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)] x 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 A2: Effect of robots and imports from China on county-level electoral participation: stacked differences, 8-year periods from 2000-2016 (2SLS)

	Change in Turnout/Citizen Voting Age Population			
Panel A: US Presidential Elections	(1)	(2)	(3)	(4)
US Exposure to robots	-0.128	-0.329***	-0.422***	-0.318**
	(0.171)	(0.127)	(0.152)	(0.154)
US Exposure to Chinese imports	0.198	0.429	0.217	0.205
	(0.270)	(0.287)	(0.375)	(0.364)
Kleibergen-Paap F Statistic	83.55	128.1	43.51	43.90
R^2	0.756	0.760	0.764	0.768
Observations	6172	6172	6172	6172
Wald Test [R=C] p-Value	0.356	0.0189	0.0778	0.141
Panel B: US House of Rep. Elections	(5)	(6)	(7)	(8)
US Exposure to robots	-0.189	-0.391	-0.328	-0.269
	(0.315)	(0.267)	(0.304)	(0.316)
US Exposure to Chinese imports	0.535	0.840*	0.809	0.805
	(0.428)	(0.453)	(0.644)	(0.646)
Kleibergen-Paap F Statistic	83.55	128.1	43.51	43.90
R^2	0.329	0.335	0.339	0.340
Observations	6172	6172	6172	6172
Wald Test [R=C] p-Value	0.233	0.0405	0.0832	0.102
Region × time	✓	✓	✓	✓
Demographics		✓	✓	✓
Industry shares			✓	✓
Routine Jobs & Offshorability				✓

Note: The dependent variable is the percentage point change of voter turnout at US presidential elections (columns (1) to (4)) and at the US House of Representative Elections (columns (5) to (8)). Differences are computed over 8-year election cycles, from 2000 to 2008 and from 2008 to 2016. Column (1) and (5) include census division dummies interacted with time period dummies as covariates. Column (2) and (6) also control for 2000 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column (3) and (7) also include shares of employment in broad industries in 2000 (i.e., agriculture, mining, construction, manufacturing). And column (4) and (8) also include the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). 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 A3: Effect of robots and imports from China on electoral participation: stacked differences 2000-2016 (2SLS)

	Change in Turnout/Registered Voters			
Panel A: US Presidential Elections	(1)	(2)	(3)	(4)
US Exposure to robots	-0.292	-0.362**	-0.425*	-0.368
	(0.191)	(0.183)	(0.235)	(0.243)
US Exposure to Chinese imports	1.271***	1.342***	1.246**	1.278**
	(0.396)	(0.423)	(0.561)	(0.566)
Kleibergen-Paap F Statistic	122.3	168.2	44.73	42.96
R^2	0.479	0.485	0.486	0.487
Observations	5598	5598	5598	5598
Wald Test [R=C] p-Value	0.000487	0.000399	0.00158	0.00216
Panel B: US House of Rep. Elections	(5)	(6)	(7)	(8)
US Exposure to robots	-0.401	-0.503	-0.548	-0.549
	(0.329)	(0.354)	(0.409)	(0.424)
US Exposure to Chinese imports	1.580***	1.680**	1.526*	1.561*
	(0.594)	(0.666)	(0.921)	(0.945)
Kleibergen-Paap F Statistic	122.3	168.2	44.73	42.96
R^2	0.134	0.136	0.139	0.139
Observations	5598	5598	5598	5598
Wald Test [R=C] p-Value	0.00667	0.00872	0.0245	0.0252
Region × time	✓	✓	✓	✓
Demographics		✓	✓	✓
Industry shares			✓	✓
Routine Jobs & Offshorability				✓

Note: The dependent variable is the percentage point change of voter turnout at US presidential elections (columns (1) to (4)) and at the US House of Representative Elections (columns (5) to (8)). Differences are computed over 8-year election cycles, from 2000 to 2008 and from 2008 to 2016. Column (1) and (5) include census division dummies interacted with time period dummies as covariates. Column (2) and (6) also control for 2000 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column (3) and (7) also include shares of employment in broad industries in 2000 (i.e., agriculture, mining, construction, manufacturing). And column (4) and (8) also include the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). 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 number of registered voters in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A4: Effect of robots and imports from China on county-level electoral participation: stacked differences, 8-year periods from 2000-2016 (2SLS)

	Change in Turnout/Voting Age Population			
Panel A: US Presidential Elections	(1)	(2)	(3)	(4)
US Exposure to robots	-0.0621	-0.268**	-0.308**	-0.228
	(0.168)	(0.128)	(0.156)	(0.158)
US Exposure to Chinese imports	0.364	0.609**	0.469	0.471
	(0.240)	(0.270)	(0.360)	(0.359)
Kleibergen-Paap F Statistic	83.69	128.1	42.20	42.41
R^2	0.740	0.743	0.747	0.750
Observations	5972	5972	5972	5972
Wald Test [R=C] p-Value	0.204	0.00605	0.0302	0.0509
Panel B: US House of Rep. Elections	(5)	(6)	(7)	(8)
US Exposure to robots	-0.135	-0.362	-0.252	-0.208
	(0.330)	(0.288)	(0.328)	(0.339)
US Exposure to Chinese imports	0.725*	1.073**	1.101*	1.111*
	(0.410)	(0.456)	(0.655)	(0.664)
Kleibergen-Paap F Statistic	83.69	128.1	42.20	42.41
R^2	0.305	0.310	0.314	0.314
Observations	5972	5972	5972	5972
Wald Test [R=C] p-Value	0.159	0.0218	0.0465	0.0541
Region × time	✓	✓	✓	✓
Demographics		✓	✓	✓
Industry shares			✓	✓
Routine Jobs & Offshorability				✓

Note: The dependent variable is the percentage point change of voter turnout at US presidential elections (columns (1) to (4)) and at the US House of Representative Elections (columns (5) to (8)). Differences are computed over 8-year election cycles, from 2000 to 2008 and from 2008 to 2016. Column (1) and (5) include census division dummies interacted with time period dummies as covariates. Column (2) and (6) also control for 2000 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column (3) and (7) also include shares of employment in broad industries in 2000 (i.e., agriculture, mining, construction, manufacturing). And column (4) and (8) also include the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). 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 voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A5: Exposure to robots and imports from China and individual-level labour market outcomes: 2000-2016

	Employed	Unemployed	Likely to lose job	Heavy lifting	Forceful hand movement
	(1)	(2)	(3)	(4)	(5)
Individual Exposure to Robots	-0.0028	0.0138***	0.0465***	0.1920***	0.1466***
	(0.0040)	(0.0035)	(0.0053)	(0.0081)	(0.0088)
Individual Exposure to Chinese Imports	0.0025	-0.0048**	0.0062	0.0161**	0.0198**
	(0.0039)	(0.0023)	(0.0049)	(0.0075)	(0.0078)
US Exposure to Robots	-0.0146*	-0.0029	0.0201**	0.0322*	0.0441**
	(0.0077)	(0.0044)	(0.0080)	(0.0166)	(0.0179)
US Exposure to Chinese Imports	-0.0037	0.0008	0.0007	-0.0036	-0.0038
	(0.0035)	(0.0019)	(0.0035)	(0.0054)	(0.0065)
Observations	13,208	10,978	6,169	4,296	4,295
R^2	.0092275	.010725	.0509463	.1455297	.094614
Sample mean	.7597668	.0858991	.0987194	.4557728	.4796275
Year x Census Division	Yes	Yes	Yes	Yes	Yes

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

Table A6: Exposure to robots and imports from China and individual-level political participation: 2000-2016

	Voted in last election	General trust	Trust in federal govt	Trust in Congress	Govt should do more	Govt should reduce inequality
	(1)	(2)	(3)	(4)	(5)	(6)
Individual Exposure	-0.1498***	-0.1070***	-0.0052	0.0324***	0.1162***	0.1979***
to Robots	(0.0050)	(0.0049)	(0.0071)	(0.0078)	(0.0138)	(0.0233)
Individual Exposure	0.0034	0.0090	-0.0114	-0.0279***	-0.0206	-0.0580**
to Chinese Imports	(0.0046)	(0.0066)	(0.0087)	(0.0085)	(0.0136)	(0.0226)
US Exposure	-0.0020	-0.0311***	-0.0053	0.0055	-0.0195	0.0126
to Robots	(0.0110)	(0.0111)	(0.0142)	(0.0144)	(0.0808)	(0.0530)
US Exposure	0.0006	0.0124**	-0.0117	-0.0098	-0.0122	0.0224
to Chinese Imports	(0.0028)	(0.0063)	(0.0073)	(0.0069)	(0.0170)	(0.0198)
Observations	12,457	7,725	7,738	7,736	7,606	7,805
R^2	.1074814	.0734139	.0375427	.064101	.0325902	.0280419
Sample mean	.7022558	.3700971	1.773068	1.682265	2.901525	4.256246
Year x Census Div.	Yes	Yes	Yes	Yes	Yes	Yes

Note: GSS questions (Yes/No): (1) Did R vote at last presidential election? (2) Can people generally be trusted?; GSS questions (Likert scale 1-5): (3) Would you say you have confidence in people in the executive branch of the federal government? (4) Would you say you have confidence in people in Congress? (5) Should government generally do more or less? (6) Should government reduce income differences? Standard errors in parentheses. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively

Table A7: Effects on public health and addictive behavior, commuting-zones (2007-2012) 2SLS

	Changes of Share of Population Reporting, 2007 - 2012				
	Fair-Poor Health	Physical Problems	Mental Problems	Currently Smoking	Binge Drinking
US Exposure to Robots	0.000	0.008	0.010	0.024**	0.033***
	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)
US Exposure to Chinese Imports	0.004	0.009	-0.001	-0.015	0.002
	(0.003)	(0.006)	(0.004)	(0.010)	(0.010)
Observations	607	607	607	607	605
R2	.017294	-.0598606	.0782619	.0732413	.1223016
Kleibergen-Paap	6.235	6.235	6.235	6.235	6.230
Sample mean dep. var. in 2007	0.056	0.124	0.105	0.475	0.302
Census Division	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Industry Shares	Yes	Yes	Yes	Yes	Yes
Routine Employment	Yes	Yes	Yes	Yes	Yes

Appendix C Survey materials

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 5: 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 6: Control condition. The highlighted text varied depending on the treatment.Highlights are added.

C.1 Results of t-tests

Manipulation check

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

Consequences for workers and search strategies

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

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

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

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

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

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

I believe the best that the laidoff employees can do is: (*with answer*: to start looking for another position right away)						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				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? (*with answer*: No, the layoffs are inevitable)

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? (*with answer*: Yes, by the state government)

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? (*with answer*: Yes, by the federal government)

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? (*with answer*: Yes, by the company management)

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? (*with answer*: Government should do nothing)

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? (*with answer*: Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance))

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? (*with answer*: Government should restrict imports from overseas, by placing import tariffs on such imports for example)

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? (*with answer*: Government should impose higher taxes on laboursaving technology and regulate automation more strictly)

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.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				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.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				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.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				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.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.463	1.386	t(556) = -0.782 p = 0.434	t(556) = -1.058 p = 0.291	t(552) = -0.263 p = 0.792
Control	277	5.552	1.322			
Trade	277	5.581	1.259			

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

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

Risk, Trust, Time, Altruism, Locus of Control

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

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

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

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

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

Perception of consequences for society

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

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

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

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

Appendix E Figures

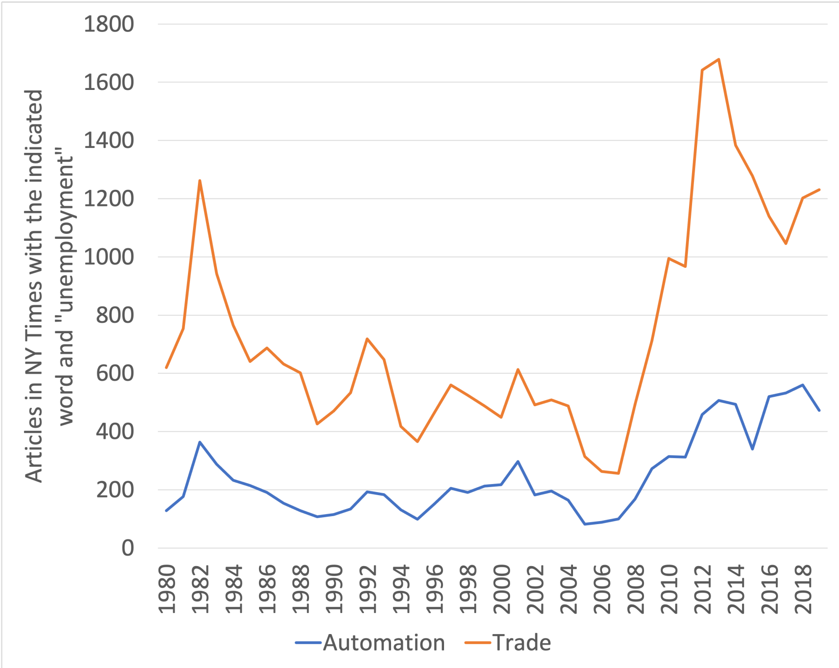
Appendix D Selected regressions: Heterogeneity along political ideology.

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

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 A8: 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]

Figure 7: 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*)".

Figure 8: Commuting Zone Exposure to Robots (1993-2007): Replication vs. Acemoglu et al. (2020)

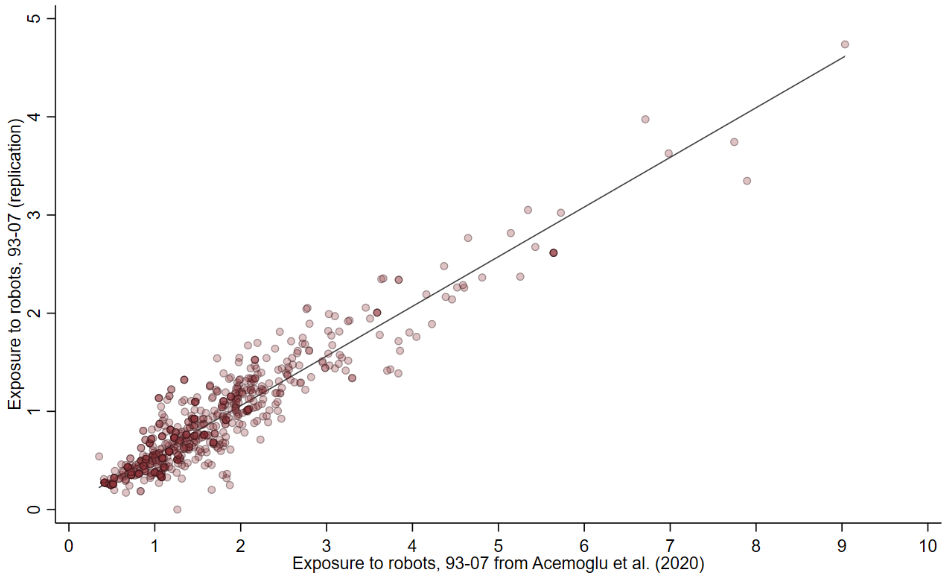


Figure 9: Commuting Zone Exposure to Robots (1993-2007): Replication