Industrial Automation and Political Polarization:
The Electoral Impact of the Rise of the Robots

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Abstract

Has increased industrial automation contributed to the widening political divide? In this paper we explore the impact of industrial automation on political outcomes and polarization in the United States from the early 1990s to 2016. In particular, we attempt to estimate the causal effect of the change in the stock of industrial robots on both congressional elections, and presidential elections, as well as the ideological positions of members elected to the House of Representatives. We accomplish this using the change in the national stock of industrial robots for fifteen broad industries and the composition of employment in local labor markets to construct a Bartik-like instrument referred to in this paper as *exposure to robots*. Our results suggest that commuting zones with high levels of exposure to industrial roboticization saw increases in political competition that align with polarization, with our most clear results between the 2011-2016 period. We also find that their support for the more liberal party eroded over the period observed, culminating in their increased support for the Republican nominee for President between the 2008 and 2016 election cycles. However, we find no measurable effect between our measure of industrial automation and political polarization for members elected to the House of Representatives.

∮ Thanks to my advisor Professor Barry Eichengreen for his encouragement and guidance; to my brother and editor Matthew Williams for his poetic influence; and to my group of friends for always making sure I would leave the library at some point.

∞ Special thanks to my partner Evelyn Li for her loving support and patience throughout this process.

† To the Unknowns and my Sentinel brothers; *Line Six*.

1 Introduction

The first industrial robot was Unimate, which worked on the General Motors assembly line in 1961. It performed a dangerous task in place of laborers, transporting die castings from an assembly line and welding them to auto bodies. By the 1980s, new and far more sophisticated industrial robots were being designed and mass produced. As newer models became increasingly intelligent, their ability to perform tasks without human intervention grew exponentially. In 1984, this translated into a twenty-three percent reduction in employment in the automotive manufacturing sector in Detroit. However, this decline in employment accompanied a two percent increase in production compared to 1979. “There’s no doubt in our mind that much of that job loss is related to automation,” a United Auto Workers spokesperson said at the time. Despite this observed displacement effect within early adopting industries, these early waves of automation did not alarm laborers in the United States. Automation was seen as another way to improve quality and remain competitive in an increasingly globalized market place (Brown and Schrage, 1984).

This stands in stark contrast to the uprising of textile workers in the early years of the Industrial Revolution in Great Britain. The Luddites, as they came to be known, rose in revolt against new factories implementing textile innovations in stockings that reduced the number of workers needed and production time. These innovations dramatically reduced the wages for these artisans and even left many without work entirely. The tension between the laborers with the skills they had crafted over a lifetime, and the factory owners with machines that were beginning to fuel industry, eventually culminated in the Luddites storming factories and smashing machines all across Northern England. These clashes became increasingly violent, with deaths accumulating on both sides. Eventually, the government in London flooded the Luddite communities with thousands of soldiers, executing and imprisoning many of those involved in the conflict as well as passing laws prohibiting the destruction of industrial machinery.

Today’s post-industrial societies seem far from storming firms and stifling reforms meant to automate tasks once performed by laborers. However, since the introduction of advanced robotics into the U.S. economy, real wages for the average American worker have barley kept up with inflation and labors share of national income has dropped precipitously over the past four decades; Figure 1. As a result of skills-based technological change, the amount of middle-income jobs in the United States has largely been hollowed out (Autor and Dorn. 2013, [4]), pushing many former or would-be manufacturing workers into lower-pay service-sectors occupations. Meanwhile, the returns to educated and highly-skilled workers have outpaced their lesser-skilled peers, splitting the U.S. labor market as those middle-income occupations have either disappeared or have been automated.

Yet, this is not only an economic phenomenon, as the economics and politics of technological innovation cannot be separated. Several newly published papers seem to confirm what these trends in the U.S. work force already suggest. In particular, it has been shown that increased exposure to industrial robots negatively impacts wages and employment in local labor markets (Acemoglu and Restrepo. 2017 [2]), and that innovations in automation reduce wages and labors share of national income over the long run (Acemoglu and Restrepo. 2017[1]). These social costs of workplace automation will cause laborers to seek non-market forms of resistance to automation, such as political activism. However, technological change's tendency to exacerbate income inequality produces disparities in who the political system tends to serve, with the more affluent class gaining the reigns of policy making. This rift in economic fortunes accompanies a widening political divide, causing the median of the two major political parties to shift away from the ideological center, while simultaneously moving legislatures to the right (Voorheis, McCarty and Shor. 2015[19]). Our analysis relies on these relationships between technology and inequality, and through them we will will study the impact of automation, in the form of industrial robotics, on political outcomes and ideological polarization in the United States.

Taking a dataset collected by the International Federation of Robotics (IFR) we construct a variable, *exposure to robots*, as our primary variable of interest. In order to measure political outcomes and party polarization, we use a combination of vote shares for House congressional races and Presidential races, along with the Poole and Rosenthal DW-Nominate Scores for members of Congress between the 103^{rd} and 115^{th} Congressional sessions. Our empirical strategy is to regress the changes in these outcome variables on our *exposure to robots* variable, along with several demographic, economic, trade competition, and political controls. We do this for changes observed within the last three decennial census periods to avoid issues of political Gerrymandering, and to measure the time heterogenous effects of the rising stock of robots. Our findings suggest that commuting zones whose industrial structures are most vulnerable to increases in the national stock of industrial robots displayed increased political competition typical in polarized politics, and party preference transitions for both congressional representatives and Presidential nominees. However, these changes have not translated into measurable effects on the ideological polarization of members in the House of Representatives.

The remainder of this paper is structured as follows. We will begin by discussing some of the previous studies on income inequality's connection with both technology and political polarization. We then turn to describe and examine the data we use in our empirical analysis and document the construction of our measure of exogenous technology shocks. Continuing on, we examine the relationship between these shocks and our various measures of political outcomes. Finally, we take up issue with our own analysis and provide concluding remarks. Additional considerations for the interaction of technology and trade are provided in addendum.

2 Previous Literature

It is widely believed that rising economic inequality is being driven in large part by rapid technological change and increasing globalized trade. The growth in labor market polarization since the 1980s is hypothesized to be the result of the falling costs of automating routine tasks (Autor and Dorn, 2013[4]). The adoption of information technology creates rapid employment and wage growth at the lower and upper tails of the skill and wage distribution. It has also been shown that

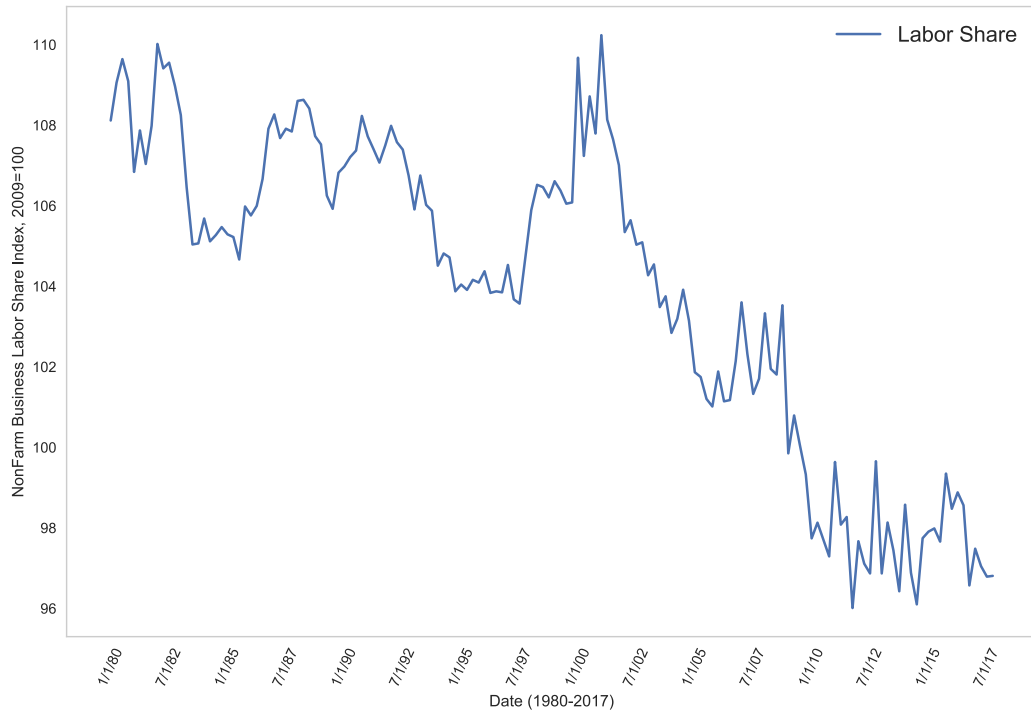

Figure 1: Labor Share of National Income, 1980-2017

industries facing a sudden increased exposure to import competition see falling levels of employment and depressed wages for a prolonged period following such shocks, and that these shocks are more exaggerated in local labor markets where the import competing industries are concentrated (Autor, Dorn and Hanson, 2016[6]). Combined, these two factors have made workplace automation a force for reducing labor's share of national income (Acemoglu and Restrepo, 2017[1]) and increasing polarization of labor markets since the 1980s, all reinforced by trade shocks that further depressed employment and wages in the affected industries.

There is additional evidence that labor markets for men, who would represent a disproportionate portion of workers in the affected industries, have been experiencing some unique trends over this same period. Writing in his 2016 book *Men Without Work*[9], Nicholas Eberstadt finds that one in every six prime working-age males in the United States is without paid work, and one in eight have completely dropped out of the civilian labor force. These findings contribute to the narrative that men who once could have been employed in a thriving manufacturing industry have been relegated to the sidelines in favor of highly-advanced and adaptable robotics, creating a surplus of low-skill male laborers, which has put downward pressure on their wage rates.

The American public's attitude towards workplace automation has also gone through rapid change since the 2000s. In a 2006 *Social Trends*[18] report by the Pew Research Center, the public rendered a split verdict in an up or down vote on the impact of job automation on American working life with forty-two percent saying it hurt working life and forty-six percent saying it helped working life. By 2016[16] and 2017[17], another set of Pew surveys found that two thirds of Americans (65%)

expected the majority of jobs currently performed by humans to be done by robots or computers in fifty years. They were also twice as likely (72%) to express worry rather than enthusiasm (33%) over such a future. In the same 2017 survey, 58 percent of Americans said there should be limits on the number of jobs business can replace with machines, even if they are better and cheaper than humans. These numbers recall a recent quote by MIT Economist Daron Acemoglu regarding automation when he said, "Anxiety could take the place of reasonable action" when it comes to policy decisions by elected officials. The recent steel and aluminum tariffs imposed by the current administration, an ill conceived response to political pressure from those impacted by global trade, suggests we take the possibility of a political backlash to automation seriously.

The mechanism by which inequality increases polarization are somewhat obscure. Economic inequality appears to cause the median position of both political parties to shift within states, with Democrats becoming more liberal and Republicans more conservative (Voorheis et al., 2015[19]). Inequality simultaneously pulls the median ideology of legislatures to the right by ousting moderates and replacing them with representatives who lean more heavily to the right ideologically. With both parties moving away from the ideological center, legislatures tend to face more gridlock, further entrenching the status quo. This ultimately creates a feedback loop where increases in wealth inequality increase political polarization, which in turn constrains legislatures from enacting policy solutions in response to inequality, leading to more inequality. This research suggests that mechanisms that increase inequality would lead to increased political polarization.

2.1 Evolution of the Partisan Ideological Drift

We next take steps to examine the expanding partisan divide that has emerged over the last thirty years. While it is generally agreed that there are multiple causal variables that have contributed to this divide, the specific underlying forces, be they economic shocks or cultural shifts, remain tentative in the prevailing literature. While the contributions of the evolving media culture, surges in legal and illegal immigration, and the downsides to increasing globalization all have their parts to play in this process, the magnitude of their contributions remains uncertain.

Using the first dimension of DW-Nominate Scores (Poole and Rosenthal, 1985[15]; McCarty, Rosenthal, and Poole, 2006[14]), a typical measure of polarization in the federal legislature, we plot the spread of ideological scores between the two major political parties from the mid-1980s to the present, as well as the difference between these parties ideological centers over the same period[1]. Figure 2 displays both of these plots side by side. The figure on the left displays the minimum, median, and maximum of the distribution of nominate scores for the two parties, and the figure on the right shows the difference between the parties distribution median and means. By the mid 1980s the two were already somewhat polarized with a difference between their centers of approximately 0.65. During the 99th Congress, that came to session in January of 1985, the members of the House of Representatives from minority Republican party had an average ideological score of 33.37

[1] This plots polarization on a binary axis between 100 and -100, with positive movements being more conservative and negative ones more liberal. The ideological center would sit at zero.

with a standard deviation of 14.82. By the 115th Congress, the one now ending in 2018, the party had an average ideological score of 49.14 and a standard deviation of 15.14. The Democratic Party experience a similar shift away from the political center, party average -30.95 in 1985 to -39 in 2016, and a narrowing standard deviation, 16.64 in 1985 to 11.68 in 2016. We also observe that by the early 2000s the two parties no longer have any overlap in their ideological scores, the minimum of the GOP no longer crosses the maximum score of the Democrats. While these figures show that the prevailing trend has been toward more polarization it does not reveal any meaningful information about why such a process is occurring.

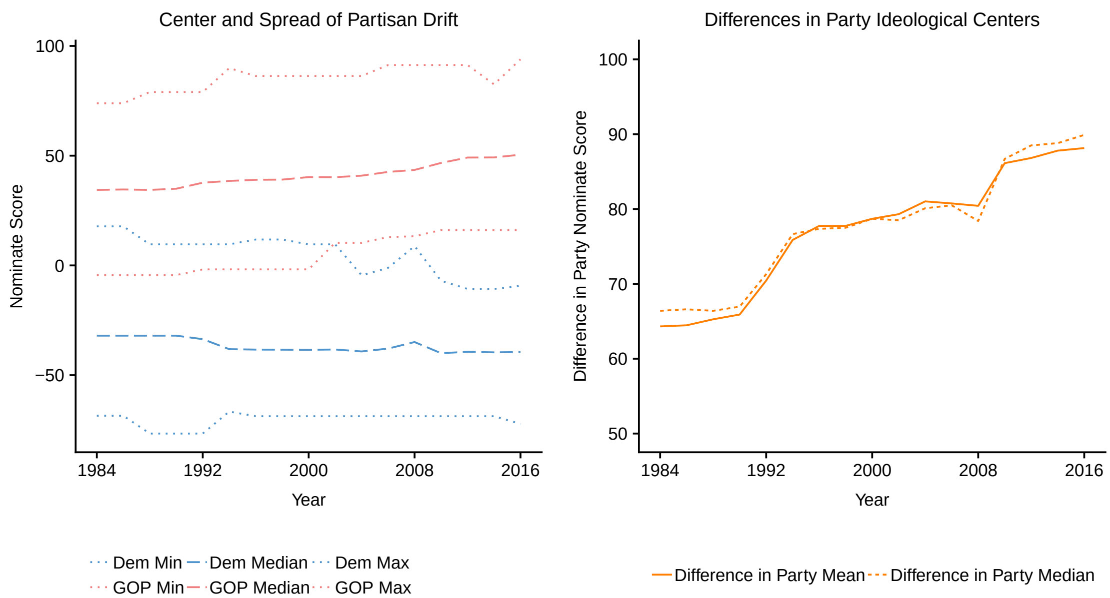

Figure 2: Nominate Scores 1982-2016

The ‘why’ that is asked when we observe this trend in polarization usually comes with a variety of answers. In Poole and Rosenthal’s *Polarized America* [14], they observe that the trend in polarization is tightly connected to trends in wage and income inequality; with increasing income inequality starting in 1969 being closely followed by the sudden rise in polarization in 1977. They argue that inequality feeds directly into polarization: individuals at the top allocate more resources toward political parties that resist policy proposals for redistribution. Once this sort of policy agenda becomes the status quo it becomes exceedingly difficult to alter. This can be attributed to the structure of the US legislative process where minority parties can obstruct new legislation with relative ease. The complementary polarizing trends in American politics and the US labor market would then not appear coincidental. It is estimated that over half of the distance between the median American workers wages and those in the 10th percentile is due to failures in the legislature to increase the minimum wage (David Lee, 1999[13]). Increases in polarization have been accompanied by stagnant real median wages, reductions in top marginal tax rates and estate taxes, and the strong body of evidence that voting patterns and policy outcomes are less responsive to the views of low-income constituents relative to high-income ones (Bartels 2002[7]). Left to its own devices, the status quo will perpetuate the circumstances that paralyze the political process rendering it incapable of redressing the sources of inequality that stem from outside the political sphere such as: shifts in executive compensation practices, wage premiums put on higher education, increased global competition in manufactured goods, and advancements in technology.

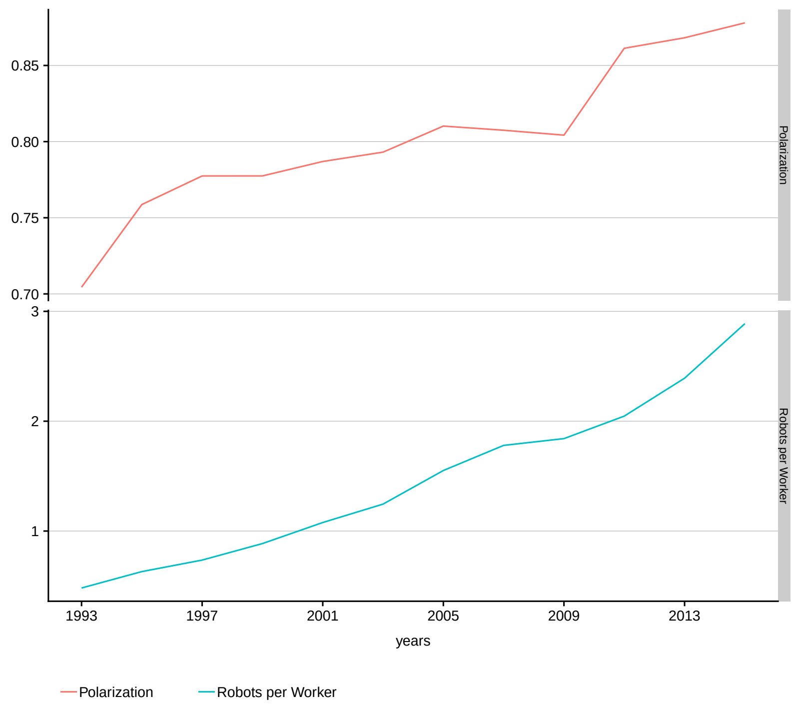

Figure 3: Party Polarization and Robots per Worker 1993-2016

The top panel is the difference in mean Nominate Score between the two major political parties. The bottom the the total number of robots per thousand workers in 1990.

How closely do rising inequality and political polarization mirror the rapid growth in technological advancements? The process of creative destruction allows for some earnings instability in market based economies. However, periods of rapid skill-biased technological change tend to generate greater earnings instability during the transition period. If we assume that the shifts in political partisan positions and the wage distribution precede the period of rapid technological shocks, then the initial forces driving these trends would simply be exacerbated. If we speculate that rapid advancements in technological progress shift the relative demand among skill groups we would then expect to see the sort of bifurcation of the labor market as has been documented (Autor and Dorn, 2013[4]). This contribution to rising inequality would then manifest itself outside the market and likely in the political and social space. Figure 3 gives us our first visual indication of a possible relationship between rising partisan polarization and the relatively recent advancements in robotics technology.

The competition over political resources does not happen exclusively between the wealthy and the poor. Current research suggests that economic anxiety, such as stagnant wages and pressures on employment, allows for politicians that appeal to more nativist policies to gain traction (Inglehart and Norris, 2016[12]). Because some side effects of skills-based technological change are short-term losses for labor's share of national income, such as reduced wages and employment, there is likely to be a decrease in state and local tax revenues coupled with an increase in government transfers in the form of welfare assistance programs(Feler and Senses, 2016[10]). Competition over public funds could intensify the political positions of the two parties, who increasingly represent the increasing class divide in the country. Areas drifting toward the conservative party would then reflect a response to tightening budgets and falling revenue, often casting those being impacted by competition with robots as as taking advantage of the welfare system.

Considering this causal relationship between political polarization and economic inequality, along with the fact that sudden import shocks also contribute to declines in workforce participation and low-wage growth,(Autor, Dorn and Hanson, 2016[6]), it is then unsurprising that current research links increases in political polarization with exogenous import shocks to local labor markets (Autor, Dorn, Hanson and Majlesi, 2017[3]). This effect is accompanied by increasing political competition reflected as reductions in incumbent party vote shares and tighter congressional victory margins. Given this, we surmise that a similar polarizing effect will be linked to some sort of technology shock where we see corroborating impacts on labor markets.

Attempting to assess the impact that all workplace automation has on political polarization proves difficult due to the various sorts of automation that can take place. One particular form of automation has already been shown to have significant impacts on labor. Looking at industrial robot use between 1990 and 2007, it has been shown by linear regression that, in a model where robots compete with human labor, robots can lower employment and wages (Acemoglu and Restrepo, 2017[2]). Connecting this with political outcomes, a recent study found that that the support for then Presidential nominee Donald J. Trump was significantly higher in local labor markets more exposed to the adoption of robots between the 2012 and 2016 election cycle (Frey, Berger, and Chen, 2017[11]).

Our contribution is to expand the scope of the analysis already performed connecting both inequality and workforce automation with political outcomes. This analysis accomplishes this by taking a similar variable that measures a labor market's exposure to robots and regress it on measures of political competition and polarization for various time periods between the early 1990s and 2016 that have not yet been examined. We hope that this provides additional material for current research in the area of political economy connecting trade and technology to forces driving inequality and political outcomes in the United States.

3 Description of Data Sources

For data measuring a legislature's political ideology, we use one hundred times the first dimension of the Poole- Rosenthal DW-Nominate scores (Poole and Rosenthal, 1985[15]; McCarty, Rosenthal, and Poole, 2006[14]), or Nominate Score. This measure assesses the roll call votes of a representative over the course of their political career and places them on a binary ideological scale from negative one to positive one[2]. Movements toward negative one are a sign of a more liberal politician and movements toward positive one distinguish the more conservative. The ideological center would be the center of this axis at zero with more polarized positions being further away from this measure of political center. Our estimates using changes in vote share data were collected from the CQ Press Voting and Elections Collection. Congressional election data consists of historical data from the 1992 to the 2016 congressional election cycles and provides congressional-district-level vote shares for the Democratic and Republican party candidates. Historical Presidential election data provides these same party vote shares, but held at the county level.

The data on our technology shocks was acquired from the International Federation of Robotics (IFR), which defines industrial robots as "automatically-controlled, reprogrammable machines" that can perform a wide range of labor intensive tasks capable of replacing labor. The dataset includes measures of the national stock of industrial robots by industry, country and year starting from 1993. Industry level data is reliably reported for seven broad industries at roughly the two-digit level, and for thirteen subsectors within manufacturing. These broad industries correspond roughly to paper, plastic and chemicals, food and beverages, glass and ceramics, basic metals, metal products, metal machinery, textiles, wood and furniture, electronics, transportation, and other manufacturing industries. The data show that roughly *80%* of the stock of robots are designated as being utilized in manufacturing subsectors. Industry-level breakdowns for the United States are not available until 2004. We impute these missing data using an IV estimator and the the stock of industrial robots by industry for a subset of countries for which industry breakdowns are available through the 1990s: Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the United Kingdom[3]. We combine this instrument with 1995 industry employment data collected from the EUKLEMS dataset to measure the number of industrial robots per thousand workers by country and industry[4].

There is no doubt that several other factors contribute greatly to the ideological position of elected representatives. We introduce a series of economic, political, and demographic controls in an attempt to address some of the omitted variable bias we will undoubtably be presented with. Start-of-period political controls include the Nominate score of the representative originally holding the congressional seat, the share of votes cast for the winning candidate at the beginning of the period, an indicator for if the candidate ran unopposed, all interacted with an indicator for if the seat was held by a Republican at the beginning of the period. Economic controls include the share of manufacturing employment, the share of routine jobs, and an offshorability index used in other related papers[3], all measured for the 722 commuting zones in the continental United States[5]. Be-

[2]Since we use 100 times the Nominate Score our extreme values move toward -100 and 100.

[3]Roughly 28 percent of the robot data were not classified into one of the 15 broad industries. We reallocate these unclassified robots proportional with the distribution of classified robots for each year

[4]The 1990 data was not available in the public EUKLEMS data. We assume that the 1990 level data follow a typical population growth trend, making our robot to worker ratios lower than they would otherwise be.

[5]County to Commuting Zone crosswalk was provided from David Dorns public data page.

cause political loyalties are often drawn along racial lines, we have included controls in our analysis accounting for the distribution of the four most common racial groups in relation to whites. Counties that are more or less racially homogenous may drift further away from the ideological center. Additional demographic controls include the proportion of four age categories, the proportion of females, and the proportion of university degree holders, all at the county level. Commuting-zone total employment and manufacturing-specific shares were gathered from the County Business Patterns (CBP) as well as the Inter-university Consortium for Political and Social Research (ICPSR), and aggregated to the commuting-zone-level[6]. Missing values and employment flag identifiers were imputed with estimates using the fixed-point imputation strategy developed by Autor, Dorn and Hanson (2013[6])[7]. County-level demographic characteristics were provided by the Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS).

The data gathered for these variables come from three primary sources. Data on imports and exports were acquired from the UN Comtrade website and were downloaded with their six-digit Harmonized Commodity Codes. These codes were then crosswalked to their Standard Industrial Classification (SIC 1987) equivalents using a file provided on David Dorns public data page. Data for industry shipments were acquired from the NBER-CES Manufacturing Industry Database, which is a joint effort between the National Bureau of Economic Research (NBER) and the Center for Economic Studies (CES), as well as the Census Bureaus Manufacturers' Shipments, Inventories, and Orders (M3) survey. This data provides the value of shipments at the four-digit SIC 1987 industrial level. This data was then used to construct a variable measuring a commuting zone's exposure to Chinese import penetration[8]. For additional robustness, we instrument our Chinese import penetration variable with one constructed with Chinese import values from seven other countries that experienced a similar level of trade with China[9].

4 Measuring Local Labor Market Exposure to Robots

Our analysis calls for measuring the effects of industrial robots on political outcomes. Our review of the relevant literature suggests that if any relationship exists between the two it will be manifested in effects industrial robots have on local labor markets. Previous studies use a shift-share variable design to estimate the effects of the increased national stock of industrial robots on wages and

[6]Data to crosswalk congressional districts and counties was also provided from ICPSR using the Census of Population and Housing: Congressional District Equivalency Files.

[7]These Stata Do files were only available for the 1980, 1990, and 2000 CBP tables. For the 2010 CZ manufacturing shares we replace missing data with the lower bound designated by the indicated employment flags.

[8]This variable was constructed as in Autor, et al. 2016 [3]: Import penetration is defined here as $\Delta IP_c = \sum_{i \in \mathcal{I}} l_{ic}^{1990} \left(\frac{M_{i,\tau_2} - M_{i,\tau_1}}{Y_{i,\tau_1} - X_{i,\tau_1} + M_{i,\tau_1}} \right)$ where $M_{i,\tau_2} - M_{i,\tau_1}$ is the change in Chinese imports for industry i between time periods τ_1 and τ_2, the denominator $Y_{i,\tau_1} - X_{i,\tau_1} + M_{i,\tau_1}$ is the initial absorption (US industry shipments plus net exports) at the start of the period τ_1, and l_{ic}^{1990} is the share of employment for industry i in CZ c.

[9]We take the average change in imports from China within each industry across the economies of Australia, Denmark, Finland, Japan, New Zealand, Spain, and Switzerland. The industry CZ weights used are replaced by their 10-year lag, while initial absorption in the expression for industry-level import penetration is replaced by its 3-year lag

unemployment in commuting zones(Acemoglu and Restrepo, 2017[]). The goal of our analysis is to use this same approach to estimate the impact of the rising stock of industrial robots on political outcomes in the United States. Our first step is to reconstruct the exogenous *exposure to robots* variable described in the these papers.

A growing number of empirical studies employ a quasi experiment identification strategy that implements what has been dubbed as Bartik or Bartik-like estimators (Bartik, 1991[]). In this strategy, industry shocks for specific-geographic-location are imputed by combining the local shares of industry compositions with the national level shocks in these industries. For our specification, each "shock" of industrial robots in a particular industry is weighted by a commuting zone's share of total employment for that industry. Then, the sum of these weighted shocks is taken across industries for each commuting zone to create our geographic specific technology shock primary variable of interest. Thus our *exposure to robots* variable is designated as

$$\Delta Exposure\ to\ Robots\ US = \sum_{i \in \mathcal{I}} l_{ic}^{1990} \left(\frac{R_{i\tau_2}^{US}}{L_{i,1990}} - \frac{R_{i\tau_1}^{US}}{L_{i,1990}} \right) \tag{1}$$

where $R_{i,\tau}$ is the stock of robots in industry i between time periods τ_1 and τ_2 over $L_{i,1990}$ the national employment in industry i in 1990, weighted by l_{ic}^{1990}, which is the share of employment in industry i for commuting zone c. The consistency of this estimator when used in OLS relies on the additional assumption that industry shocks are not correlated with additional shocks that impact commuting zones whose industrial structures are highly dependent on those industries(Borusyak, Hull, and Jaravel, 2018[8]).

A prevailing concern in quasi experimental studies is that our model specification suffers from sources of endogeneity. In our framework, we would be concerned that the adoption of robots for any specific U.S. industry could be correlated with unobserved trends affecting these industries or possibly to other economic conditions impacting the labor markets that specialize in those industries. To identify the technology driven component of a commuting zone's exposure to robots, we use the spread of robots at the industry-level in fourteen advanced economies in Europe to instrument the U.S. variable in equation (1)[10].

$$\Delta Exposure\ to\ Robots\ EU = \sum_{i \in \mathcal{I}} l_{ic}^{1980} \left(q_{75} \left(\frac{R_{i\tau_2'}}{L_{i,1995}} \right) - q_{75} \left(\frac{R_{i\tau_1'}}{L_{i,1995}} \right) \right) \tag{2}$$

where $q_{75}\left(\frac{R_{i\tau'}}{L_{i,1995}}\right)$ is the 75^{th} quantile of the distribution of robots per worker in industry i across the fourteen European economies in our sample[11], and is l_{ic}^{1980} the share of labor for industry i in commuting zone c in 1980 and is used to focus on persistent variations in the specialization of commuting zones in different industrial sectors, and to mitigate any simultaneity bias that may arise.

[10] Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the United Kingdom are used for estimates prior to the year 2000. After this period Austria, Belgium, Czechoslovakia, the Netherlands, Slovakia, and Slovenia were added to the sample.

[11] See description below Figure 4 for explanation on the selection of this quantile

4.1 Constrained by Gerrymandering

Because our analysis requires the use of political data that is directly dependent on the assignment of geographical areas to congressional districts, our analysis must be contained to time periods where these geographical units remain relatively intact. This requirement puts additional strain on what time periods in American politics we can compare and take differences over.

Each Congressional District in the House of Representatives must represent as equal a portion of the states population as possible, currently at 435 seats at approximately 711,000 people each. A state's apportionment of congressional seats is determined by its corresponding share of the aggregate population of the 50 states, which is based on decennial census population counts. By federal law, redistricting must follow each census for two reasons: states gain or lose congressional districts as a result of the apportionment of seats, and districts must be redraw so that each has approximately equal populations. Each states government determines how these boundaries will then be redrawn to reflect these changes. However, while some states leave their redistricting to impartial and non-partisan committees and organizations, others allow politicians and hired outside consultants to set the new district boundaries for political purposes. This has led to the creating of so called "safe seats" for the competing political parties to hold when the voting demographics shift away from their favor in a process known as Gerrymandering. This has resulted in dramatic reallocations of district boundaries in a wild variety of shapes.

Because of this, our empirical strategy must account for the instability in a districts geographic location and its ability to reflect changes in voter preferences across periods in which a decennial census occurred. Each portion of our analysis for congressional race outcomes will then use the differences in the inter-census periods; 1993-2000, 2001-2010, and 2011-2016.

4.2 First-Stage

Our 2SLS strategy has two purposes. The first is to address issues of enogeneity that may arise from unobserved characteristics that may correlate roboticization with commuting zones that specialize in these industries. The second is that the data for the United States reaches back to 1993, but does not contain industry breakdowns until 2004. In order to measure the effects of robots on employment and wages prior to 2004 previous studies have taken a subset of European countries that provide industry breakdowns dating back to the 1990's and use this instrumental strategy to impute the U.S. distribution over the same time period[12]. Figure 5 gives us some indication of the relationship between European and U.S. changes in industry robots utilization for the period we wish to compare and impute values. For the majority of industries we examine, those that introduced more robots between 1993 and 2000 in Europe also did so in the United State between 2004 and 2010. The same relationship holds true for common period covering the early 2000 and 2010.

Our first stage equation takes the following form:

[12] See Acemoglu and Restrepo 2017 [2].

$$\sum_{i \in \mathcal{I}} l_{ic}^{1990} \left(\frac{R_{i\tau_2}^{US}}{L_{i,1990}} - \frac{R_{i\tau_1}^{US}}{L_{i,1990}} \right) = \pi \sum_{i \in \mathcal{I}} l_{ic}^{1980} \left(q_{75} \left(\frac{R_{i\tau_2'}}{L_{i,1995}} \right) - q_{75} \left(\frac{R_{i\tau_1'}}{L_{i,1995}} \right) \right) + W_{j\tau}' \Gamma + v_{j\tau} \quad (3)$$

Our instrument is the first explanatory variable, defined as the change in the 75th quantile of the spread of robots per worker across each industry, taken from the subset of European industries with a high rate of roboticization. A set of political, economic, trade, and demographic controls $W_{j\tau}$ for each county-congressional district cell j at the beginning of period are also included τ[13]. Figure 6 shows the residual plot of US exposure to robots against the exposure to robots in Europe between each of the three inter-census periods we identified and after the economic, demographic, and exogenous trade covariates have been partialled out. The figure signals that there is a sufficient level of correlation between the usage of robots by European industries and U.S. industries for us to proceed with our analysis[14].

4.3 County-Cogressional District Cells

In order to map our political data at the congressional district level with economic and demographic data at the commuting zone and county level, we will will define our unit of analysis as the county-congressional district cell (Autor et al, 2017[3]). Counties are assigned the Nominate score of the congressional district they belong to, and commuting zone (CZ) level data is assigned to each county within its commuting zone. To make it so each congressional district holds equal weight in our analysis, we weigh our commuting-zone level data by each county's proportion of the voting age population within its congressional district.

5 Main Results

We examine the political consequences of increased use of industrial robots by measuring the effect of a constructed variable, *exposure to robots* in three phases: beginning with changes in congressional vote shares; followed by changes in political beliefs and polarization; and finally, estimating the impact on Presidential voting. All three phases deploy an equation of the following form:

$$\Delta Y_{j\tau} = \gamma + \beta \Delta X_{j\tau} + W_{j\tau}' \theta + \epsilon_{j\tau} \quad (4)$$

where the dependent variable $\Delta Y_{j\tau}$ is the change in political outcome for time period τ corresponding to county-congressional district cell j. Our primary variable of interest $\Delta X_{j\tau}$ is the change in (exogenous) *exposure to robots* for county-congressional district cell j over period τ, for

[13] For estimates involving congressional data the demographic and economic controls are taken from the most recent decennial census measures.

[14] A similar relationship exists for the differences take in our Presidential voting analysis. The first-stage F-statistics are reported in each summary regression table in the appendix. These F-statistics are suspiciously high and persist when including or excluding various combinations of our covariates. This, despite that our measure of European robot exposure used different employment data in its ratio to robots and ten-year lagged local industry shares.

which has been instrumented in all regressions with the variable defined in (2). The full set of control variables $W_{j\tau}$ measures start of period political and economic conditions, as well as a range of demographic controls for county-congressional district cell j for period τ.

5.1 Impact of Exposure to Robots on Congressional Vote Shares

The following analysis of the effect of increased *exposure to robots* on congressional race elections is an attempt to illustrate how industrial automation?s adverse impact on local labor markets materializes in the political space. With the expansive literature describing the influence of economic conditions on political incumbency in mind, we set out to determine the impact of *exposure to robots* on the change in votes shares for the incumbent party for each major political party, as well as its impact on the margins of electoral victories.

5.1.1 Changes in Incumbent Party Vote Shares

Since increased *exposure to robots* has been shown to reduce wages and employment in local labor markets, the party initially holding political power in these labor markets is hypothesized to experience a reduction in their vote shares over the period the changes occurred. Table C.1 displays the results of the initial OLS and proceeding 2SLS estimating the effect of increased *exposure to robots* on incumbent vote shares. Panel A applies a stacked-differences specification, which enables the inclusion of direct controls for regional trends at the Census Division level, while Panels B,C, and D examine long-difference estimates in the time heterogeneity of the effect covering the inter-census time periods.

The results in Panel B of Table C.1 show the effect of changes in our exogenous technology shocks are positive and statistically significant during the period between 1993 and 2000. Districts with a high *exposure to robots* seem to reward the incumbent party across this earlier period. These estimates are persistently positive across this time period and enter into the analysis as statistically significant when including Census Division dummies. The significance is robust when controlling for beginning of period political conditions and the change in Chinese import penetration. The inclusion of the exogenous component of the change in Chinese import penetration increases the magnitude of the estimated coefficient and increases precision. The inclusion of our demographic controls increases the magnitude of the coefficient and increases its statistical significance. When controlling for commuting-zone-level economic conditions, the size of the coefficient increases again, along with the standard error, behind the point of statistical significance.

These estimated positive effects of changes in *exposure to robots* on incumbent party vote shares during this initial period require further explanation. The 1990s was a period of notable economic expansion. Perpetually low unemployment and average annual GDP growth rates nearing 4% may have offset any negative political effects we would expect to see associated with increasing industrial automation. It is also possible that those commuting zones going through these initial waves or roboticization are disproportionately benefiting from policies enacted by their political representatives over this period. Furthermore, this earlier period contains relatively low ratios of robots to the number of workers in the total economy (less than one robot for every thousand workers). It is then likely that our *exposure to robots* variable is capturing other associated political and economic circumstances that are arising in the same regions most exposed to these technology shocks. Further investigation to control for these factors should be carried out to see if these positive effects can be corrected.

Panel C demonstrates how this positive relationship breaks down across the 2001-2010 time period, the effect of exposure to robots on incumbent vote shares reduced to virtually nothing. These estimates correspond with the total stock of industrial robots per worker crossing its first integer in the aggregate of all industries; Figure 4. We can see that nearly all estimated coefficients are now negative for both OLS and 2SLS, though none of the estimates appear to be precise. The lack of a meaningful impact across this period may seem surprising at first, but the two elections cycles in this sample both come on the heals of the two most recent economic recessions: the early 2000 recession partly triggered by the Dot-Com Bubble bursting, and the housing and financial crisis that lead to the Great Recession in 2008. These significant economic events likely influenced voters discontent with the state of the economy already, and any impact the growing stock of labor-replacing technologies had on political outcomes has been washed away by these other closely related but distinct concerns.

We further estimate the evolution of the relationship moving into the 2011-2016 period. This period is marked by sluggish economic growth, historically low interest rates, and stubbornly high levels of unemployment. Our results in Panel D are now persistently negative and statistically significant when including all covariates, suggesting that congressional districts that experienced a higher change in their exposure to these technology shocks delivered an electoral rebuke to the incumbent political party. Column (7) of Panel D shows that, when comparing congressional districts at the $25th$ and $75th$ percentile of the exogenous exposure to the increased national stock of industrial robots, the more exposed district would see a 0.057 ($0.8253 \times 1.018/14.8$) further standard deviation decrease in support for the incumbent party over this period[15]. While these impacts are small as we control for all other covariates, these consistently negative estimated results and standard errors suggest an asymmetric effect of *exposure to robots* on incumbent party vote shares during this period[16]. Figure 4 demonstrates that these effects coincide with the observed trend in the overall roboticization of the US economy, taking a slight digression only only to resume what appears to be stronger growth in the years immediately preceding the Great Recession.

That we see these estimated effects during the recovery suggest that firms responded to the downturn by dramatically reducing the size of their workforces and substituting capital in the form of industrial robots. The long recovery in employment in these regions could have been caused in part by this process of roboticizing industries, which could have then, in turn, manifested itself at the ballot box. This explanation becomes more plausible once we examine the almost immediate recovery in manufacturing output, with total manufacturing output reaching to almost its pre-

[15]The standard deviation of the change in incumbent party vote share between 2011 and 2016 is 14.8

[16]Estimates for the effect of CZ manufacturing shares are positive and significant for the 2011-2010 observation period for both OLS and 2SLS specifications when including all covariates.

recession level by 2011, coupled with the anemic recovery of manufacturing employment. This mismatch between manufacturing employment and output, while an enduring trend throughout the early and mid 2000's, takes on a sharper contrast in this later period when compared with the observed surge in robots per worker following the financial recession (Figure 7).

The results from Table C.1 suggest that regions most exposed to these technology shocks initially supported the party holding office, but this support eroded over the proceding periods with estimated negative effects of this exposure by the current decade. Panel A attempts to estimate the effect the increasing national robot stock had on those regions with industries most exposed using the entirety of observed changes employing a stacked-differences specification[17]. The increment of controls on our measure of exogenous technology shocks continues to estimate negative effects on incumbent party vote shares throughout the period specified, with significance given to the estimates that control for Chinese import penetration[18]. The inclusion of demographic controls significantly reduces the magnitude of our point estimate behind the point of statistical significance. The inclusion of the economic controls causes the standard error to jump some, yet it does not greatly alter the size of the the coefficient[19].

While there is only a suggestion of reduced support for political incumbents in the 2010 census period, much of the variation in changes in incumbent vote shares appears to be caused by variations in demographic and beginning-of-period economic conditions across the three decades in our sample. The question of how these changes may have effected either of the main political parties in these regions within each period and across them should be examined. We turn to this analysis in the proceeding section.

5.1.2 Changes in Democratic and Republican Party Vote Shares

As we estimate the impact of exogenous technology shocks in a political space, we first look to how the shift away from incumbents has operated in terms of each political party's vote-shares in congressional races for House seats as shown on Table C.2[20]. On Panel C, the effects of high exposure to the increasing robotic stock on votes shares for the Democratic Party, during the period between 1993 and 2000, are estimated to be positive. However, these results prove to be the opposite for Republicans, during this same period, evincing negative changes in voter support [21]. Using these estimates — which include all other covariates, however imprecise, along with

[17] This stacked differences specification excludes the 1993-2000 time period to account for the unresolved associations during this time period. However, the fully inclusive estimates produce much of the same results with stronger suggestions of a null effect when controlling for demographics and economic conditions.

[18] Chinese import penetration comes in as negative for both the local and exogenous measures with a high rate of statistical significance for all estimates in Table C.1.

[19] The increase in standard errors when economic controls are included is a pattern observed throughout this analysis. The inclusion of commuting zone manufacturing shares specifically is the culprit. The expected high level or correlation between commuting zone manufacturing shares and the variable of interest, exposure to robots, is apparent and expected. Further analysis of this relationship should be considered.

[20] Estimates between the Democratic and Republican parties are opposites of each other, with some noise in a few cases due to third party candidate shares.

[21] Estimates for Chinese import competition enter as negative and statistically significant for Democratic vote shares, and maintain this specification until the inclusion of our economic controls in which the sign is flipped and

the interquartile range of the exogenous change in *exposure to robots* — congressional districts with a relatively higher exposure would have seen a 0.1828 ($10.49 \times 0.3851676/22.10686$) standard deviation increase in support for the Democratic Party. This suggests that the regions most exposed to this particular form of industrial automation are initially held Democratic and where the party has strengthened its support, or where they have realigned toward the Democratic Party during this early wave of roboticization[22].

The evidence that in this early period of industrial automation exposed labor markets oriented toward the Democratic Party provides further context for our estimated effects on political incumbents in Table C.1 Panel B. The successful economy that was presided over by the Democratic Clinton administration could have translated into stronger support for incumbent Democrats in Congress. The development of this relationship when the national stock of industrial robots is considerably higher in the proceeding periods follows a similar pattern as the one observed in Table C.1. Panel D of Table C.2 shows that, as technological advancements diffused further into the economy, the once positive orientation of these regions toward the more liberal political party becomes almost non-existent. Only the OLS point estimate shows a positive impact of greater roboticization on Democratic vote shares. The 2SLS estimates now all show a persistent negative relationship between these regions and support for Democratic congressional candidates[23]. This null to negative estimated effect continues on to Panel E of Table C.2, which contains the same estimates for this relationship between the period of 2011 and 2016.

The time heterogenous relationship between party vote shares and local labor markets most exposed to roboticization suggest that, as the stock of industrial robots increased, voter preferences in these regions shifted away from Democratic candidates. The lack of a clear directional estimate for either party in this later period indicate that political competition increased, benefiting the GOP over the Democrats, although the effects in the intermediate period are imprecisely estimated[24]. We can see this transition occur across census periods by examining the subset of congressional districts in 90^{th} percentile of changes in *exposure to robots* from 1992 through 2016. Figure 10 displays how the composition of seats held for this group changes by party over this time. Of the 137 congressional districts that sustained high levels of roboticization through our sample, 78 were held by Democrats and 59 were held by Republicans in 1992. By the year 2010, 99 or the nearly 73% of these seats were held by the GOP. While these changes at the higher end of the distribution of exposure to industrial roboticization seem to suggest a strong relationship, the standard errors

the estimates become highly insignificant.

[22]The positive orientation toward Democratic candidates connected with our analysis in Table C.1 indicate that our measure of exogenous technology shocks are picking up the effect of some other variable occurring during the period between 1993 and 2000.

[23]Estimates of the coefficient for Chinese import competition on Democratic vote shares produce primarily negative point estimates that are not statistically significant. The only estimate that enters with a positive sign is when demographic controls are introduced. Commuting Zone shares of manufacturing employment also enter into the equation negatively, but not precisely estimated.

[24]The stronger negative and relatively more precise estimates in the period between 2001-2010 over the later period of 2011-2016 could signal that the initial shift in voter preference largely took place in the earlier period, and that proceeding elections already reflect this realignment.

of our estimates do not allow us to make a strong causal argument here. However, an additional inference we can take away with these observations is that the reduction in incumbent vote shares caused by the rise in robot exposure between 2011 and 2016 occurs after the party composition of the most exposed regions switches from primarily Democratic to Republican.

Yet, there appears to be sparse evidence of a direct effect of the increases in exogenous industrial robotics utilization on the vote shares of either major political party, despite associations between these regions and changes in party preferences that are observed. The same confounding factors dealing with the selection of our samples and other macroeconomic changes could be overshadowing any direct impact roboticization had, those being the recessions that preceded both election cycles. The rise of Republican political dominance in the highly exposed regions coincides with the sharp decline in manufacturing employment seen at the national level, and Figure 9 shows that these aggregate national trends match those seen in the manufacturing subsectors most prone to roboticization. Given these economic conditions, we would expect to see the rival political party make electoral gains. However, if the newly dominant party fails to provide economic relief for these newly acquired constituents, the same political forces that drove these voters toward the current party in power could reverse. This increase in political competition can be seen in the narrowing of electoral victory margins over our sample period. Considering this, we will pivot and begin our investigation of the relationship between *exposure to robots* and changes in electoral victory margins.

5.1.3 Changes in Winning Vote Share Margins

As economic pressures caused by the competition between technology and labor intensify within our sample, we see a procession of changes in the political landscape. The suggestion of a possible punitive impact of roboticization on incumbent party vote shares following the observed change in party preferences toward the more conservative political party may be translated as an intensifying of political competition in these regions. If the economic pressures hypothesized to be caused by automating manufacturing production are indeed reverberating as heightened political competition between the two major parties, any one party successfully capturing congressional seats would be subject to thinning victory margins.

Table C.3 regresses the change in the winning vote share margins on *exposure to robots* in order to measure these effects. Panel's B and C give long difference estimates for the periods covering 1993-2000 and 2001-2010, respectively. Following the same observed pattern in the tables from the preceding two sections, these estimates lack statistical significance and show a null relationship[25]. Panel D covering the period between 2011 and 2016 shows negative effects on winning vote share margins for congressional election outcomes, with significance given to the estimates that include all covariates[26]. These estimates further contribute to the apparent time heterogenous trend in the

[25] Estimates for Chinese import competition show negative and significant effects when all covariates are included. Manufacturing shares are positive but insignificant.

[26] In this particular regression the sign for manufacturing shares is positive and significant, and Chinese import competition covariate has an estimated null effect.

impact changes in roboticization have had on political outcomes we have seen so far in our analysis.

As the aggregate national stock of robots has grown, the regions most vulnerable exhibit clearer influences between them and increased political competition. Applying the point estimate on Panel D column (7), the estimated difference in impact between the interquartile range of the distribution of commuting zones *exposure to robots* is a reduction of roughly 0.056 ($0.825 \times 1.896/28.117$) of a standard deviation or 1.564 percentage points[27]. Estimates using stacked-differences produce somewhat larger estimated effects but lack significance. Still, the direction of these coefficients suggest that a more precisely estimated effect would still be negative[28].

The apparent relationship between estimated effects on incumbent party vote shares in Table C.1 for Panels A and D corroborate with the estimates on Table C.3 for the same pair of Panels. As economic pressures caused by the competition between technology and labor intensifies over our sample we see a procession of changes in the political landscape. That the sustained decline in manufacturing employment across the subsectors identified as being prone to heavy roboticization also experience sustained increases in output indicates that a driving force of the increasing imbalance in economic fortunes is being driven by this process of automation; Figures 9 and 8. While these same industries were already shedding workers prior to the emergence of a clearer negative estimated impact of this process on the political landscape, the overall decline in the national economy after the Great Recession may have impacted these manufacturing communities more acutely. The trends in employment prior to the financial crisis suggest manufacturing shares were headed in this direction, regardless. Parts of this decline are explained by the documented impacts of global trade competition. However, the increasing output observed in these industries indicates that while increasing competition may have reduced employment, these manufacturing subsectors carried on production while leaving their former workers behind. This suggests that the inevitable consequences of industrial automation would have produced similar political effects had these trends been left to run their course.

This combination of signals pointing to increased competition for voters in these regions indicates that commuting zones with a high exposure to growing roboticization are expressing these economic pressures at the ballot box. The question of how this is impacting the ideological makeup of elected politicians is unclear, assuming it is having an impact at all. The increased political competition is unlikely to be the result of more robust political coalitions and the broadening of political support through the advocation of more moderate policies, as these changes are occurring over the period of policy divergence. More likely that could be the result of more polarizing political debates being had in congressional districts that reside in labor markets vulnerable to roboticization.

[27] The std. of the change in electoral victory margins between 2011 and 2016 was 28.117

[28] Estimates for Chinese imports and manufacturing shares show a null effect in the stacked-regression.

5.2 Impact of Exposure to Robots on Nominate Scores

Moving on to the primary analysis, here we examine the impact of the growth in *exposure to robots* on the ideological composition and polarization of elected members to the House of Representatives. We are interested to see if the possible effects being measured on changes in vote share are having an impact on the aggregated policy positions of elected representatives. To do this, we attempt to to measure the impact the processes of industrial roboticization has on changes in 100Nominate scores and absolute scores of representatives.

Columns (1)-(7) on Table C.4 presents the estimated coefficients for changes in Nominate Scores or changes in the ideological composition of the House. Panel B compares the voting behavior of representatives elected to the 103^{rd} Congress with those elected to the same seat in the 107^{th} or from 1993 to 2000. The estimates show no relationship between exogenous technology shocks and changes in the position of newly elected officials[29]. The estimated positive incumbent vote share relationship for Democrats between 1993 and 2000 does not seem to have translated into a shift in the ideological position of these seats. Panel C's left column does the same for officials from the 108^{th} against those in the 112^{th} Congressional sessions (or years 2001-2010). The estimates for this period show a null effect, which corresponds with the null effects we found on changes in vote shares during the same period[30]. The left side of Panel D again estimates this same relationship for our most recent observations and show null effects for our OLS and 2SLS estimates for all increments of our controls. The stacked-differences estimates largely correspond with this null effect, but provide estimates that point toward a reduction in 100×Nominate scores for those regions most exposed to industry roboticization[31]. Columns (8)-(14) of Table C.4 examines these same effects on changes in the absolute 100×Nominate scores as our measure of political polarization. The estimates all show a rather strong null effect, both in the long-difference and stacked-difference specifications[32].

The null relationship estimated in Table C.4 indicates that while industrial roboticization's pressures on wages and employment may have produced a political response in vote shares, there is no indication of a significant impact on national legislature ideological positions and policy polarization. Much of the turnover in congressional representatives takes place across the sample period

[29]Chinese import penetration enters as positive and highly significant in the 2SLS for both the local and exogenous variables, but is reduced to a null effect when economic controls are introduced.

[30]The estimates for Chinese imports follow the same pattern as in Panel B, but turn to null effects with the addition of demographic controls instead.

[31]This lone estimate carries a p-value of 0.118, but is not in agreement with the rest of the estimates. Chinese import penetration shows a strong null effect in the OLS estimate, but enters the 2SLS estimate as positive a significant for the local and exogenous measures. The inclusion of economic controls greatly reduces the size of this coefficient while increases the standard error producing a null effect. Manufacturing shares are positive and highly significant in both OLS and 2SLS.

[32]In the stacked-differences estimates, Chinese import penetration enters as negative and highly insignificant in the OLS estimate. Both the local and exogenous estimates enter as positive and highly significant in the 2SLS estimates, but become null with the addition of demographic covariates. Manufacturing shares in the economic controls show positive and significant effects. Panel B shows a similar pattern, with a Chinese import estimate showing as insignificance with the inclusion of economic controls. Panel C shows null effect for Chinese imports and manufacturing shares. Panel D shows Chinese imports as negative and manufacturing share as positive, both at a high level of significance in each model they enter.

confounded by the two most recent recessions[33]. Additionally, the inflection points in Figure 2 and the progression in Figure 10 reveal the sharpest increases in party polarization due to representative turnover takes place during election cycles not included in our sample. This is particularly acute for our 2011-2016 estimates since the changes in congressional representatives primarily happen prior to these election cycles.

An additional confounding factor to be considered is elected representatives that occupy the same space along the spectrum of Nominate scores do not necessarily advocate for the same policy prescriptions, nor do these changes reflect the relative ideological positions alternative candidates in each congressional district offer to voters.

5.3 Impact of Exposure to Robots on Presidential Voting

Because the implied impacts of the growing robot stock on political outcomes appear to be small, changes in vote shares seem to be an appropriate approach in estimating their possible causal impact. In a further attempt to estimate this causal effect, we turn to analyzing the relationship between these exogenous technology shocks and Presidential election vote shares. Because Presidential elections offer an opportunity for us to observe all entities in our sample making a selection from the same pool of candidates, where realizations of these choices coincide, we can resolve issues surrounding how different regions may be making different choices based on the relative positions of other candidates. It also offers an opportunity to measure political changes as well as period of growth in the robot stock. Since the geographic unit of analysis for Presidential elections are held at the county-level our analysis in no longer constrained by the process of redistricting that occurs at each incident of the ten year census.

Before delving into the statistical analysis, it's worth taking a look at the various policy positions of the various Presidential candidates party platforms during each period[34]. By 1992 manufacturing employment was already in decline, off of its high in 1979 by roughly 2 million, with a ratio of about 0.48 robots per thousand US workers. The concerns facing some manufacturing workers were already present and had accelerated by the year 2000 when the ratio crosses one robot for every thousand workers. This period is also significant in that it is prior to the ascension of China to the WTO. A crude measure of the degree to which the competing political parties reflect the concerns of laborers suffering under the pressures of roboticization is how they place an emphasis on manufacturing in these documents.

In the 2000 Democratic Party Platform, the document specifically refers to the preservation of manufacturing jobs three times. In contrast, the Republican Party Platform document of the same era makes no mention of manufacturing or manufacturing jobs. The party platforms for 2008 resemble a similar contrast in messaging around manufacturing. The Republican document mentions manufacturing twice: once in reference to protecting gun manufacturers and another

[33] The 2001-2010 samples coincide with the most recent economic recessions, as well as reflect the most amount of turnover in highly roboticized regions seen in Figure 10

[34] This information was gathered from the UC Santa Barbara *American Presidency Project*

mention as a consequence of plans to build new nuclear power plants. In contrast, the Democratic Party document outlines a broad plan for rejuvenating manufacturing at all levels using the word eleven times with language specifically identifying the loss of manufacturing sector jobs. The platforms in the 2016 election reveal the weakness in this association. While the Democratic party platform designates a section dubbed *Fostering a Manufacturing Renaissance* and outlines the intent to create well paying manufacturing jobs at length, the Republican document makes no real mention of the plight of manufacturing jobs, aside from condemning a tax imposed as part of the Affordable Care act. This reveals the weakness in our association as this recent election stands out clearer, and it is known that the Republican candidate for President put a great amount of emphasis on the loss of manufacturing jobs. Still, this crude association provides some additional context to our analysis below.

Table C.5 presents the results of estimating the impact of a change in exposure to industrial roboticization on the change in vote shares cast at the county level for the Republican Party nominee for President. The left hand side (Panels A, B, and C) displays the long-difference estimates for changes that occurred between the 1992 election of Bill Clinton, a challenger to an incumbent Republican George H. W. Bush, and three other presidential elections (the elections of George W. Bush, Barack Obama, and Donal J. Trump). Panel A shows negative effects for the exogenous exposure to roboticization, using the 2SLS specification, on Republican candidate vote shares, though these estimates are imprecise[35]. The estimates in Panel A for columns (1)-(7) appear in agreement with the presumption that the historic economic expansion presided over by a Democratic Executive branch in the 1990's delivered substantial benefits to the commuting zones most prone to roboticization, despite the observed declines in manufacturing employment over this period.

These imprecisely measured, negative effects carry over the 1992-2008 differences shown in Panel B. The introduction of our demographic controls produce a significant estimate, but the further inclusion of the controls for start of period economic conditions reduce the coefficient dramatically and increase the precision of the estimate to a null effect. Panel C presents the results of our longest set of differences spanning 1992-2016. The estimates here show a strong null effect on changes in GOP vote shares. These long difference estimates may face issues of endogeneity due to the violation of assumptions necessary for these estimators consistency[36]. Despite this, we can surmise that the political platform of the 2008 Democratic candidate provided favorable policy solutions for the regions most impacted by the process of industrial roboticization[37]. This comparison carries over to Panel D, with measurements between the 2000-2008 elections. We have here, again, negative and imprecise estimates, with the exception of a highly significant and negative effect when exploiting the variation of in vote share changes within our demographic measures. The inclusion of CZ

[35]The OLS estimates for these regressions use the 2004-2008 changes in a given industries robot stock since the IFR data does not report these figure before the beginning of this period. Focus should instead be given the the 2SLS estimates.

[36]Difference-in-Difference estimators assume endogenous factors arise from fixed entity unobserved characteristics. Longer estimates are at greater risk of violating this assumption.

[37]The 2008 election cycle also coincides with the housing and financial crisis, which may act as a confounding factor in our analysis.

manufacturing and routine occupations shares, and the occupations offshorability index reduces the size of the coefficient to a null effect once again[38]. This indicates that the process of roboticization has had political ramifications during the 2000-2010 period, somewhat contrary to our estimates in the previous sections. Our estimated impact on congressional elections gave less precise estimates, but these results suggest additional analysis should be conducted to examine the changes that occurred between 2000-2008.

So far, we have seen that congressional districts within commuting zones vulnerable to roboticization have consistently oriented themselves towards the Democratic nominee for President. That we estimated this relationship even for the 1992-2000 election shows that our estimates are not just capturing trends that determine the election victor[39]. Panel F displays the estimates for the most recent long-differences specification (the changes observed between the years of 2008 and 2016). All 2SLS estimates measuring the exogenous component of increased industrial roboticization produce positive and statistically significant coefficients. The incremental inclusion of our additional covariates gradually reduces the estimated magnitude, but a positive and significant link remains present[40]. The switch in the direction of the coefficients in Panel F (and to some extent Panel E) indicates that our *exposure to robots* variable is reflecting changes toward political candidates that establish policy positions central to the concerns of those afflicted by the employment and wage pressures typical from exogenous technology shocks. While the emphasis the Republican Party nominee placed on manufacturing mainly dealt with those subsectors in direct competition with Chinese imports, the overall message of taking extreme measures to rejuvenate the manufacturing base seems to have resonated with a broader coalition that includes those whose employment and wages were threatened by the process of industrial automation.

6 Discussion of Results

Several patterns emerge from the estimates in our analysis. Some of these patterns seem to support the causal story of political consequences in response to rising growth in robotics utilization among industries. However, some issues arise due to the constraints in how the data can be used and associated. Possible confounding factors with the above analysis also require further explanation.

The prevailing pattern is in the progression of heterogenous effects between our given dependent variable and exogenous *exposure to robots*. Our primary interpretation for this general pattern is that as the stock of industrial robots has risen, the political impacts have become more acute. These impacts are seen repeatedly at the end of our sample period, but does not arise prior. Part of this may be do to the election cycles selected in our sample. We based our selection on the longest period that could be accurately measured within each iteration of the decennial period. The intention was to produce magnitudes large enough to be observed in our primary variable

[38]Chinese import penetration is persistently estimated as positive and statistically significant for these set of regressions. Positive effects for this covariate is also persistent in the Panel E estimates, but the addition of other covariates makes these estimates imprecise.

[39]George Bush was the victor in the 2000 election, though he lost the popular vote.

[40]Estimates for Chinese import penetration came in an remained both positive and statistically significant.

of interest. The omission of periods within and between these periods poses a problem in our analysis. Estimates for the inter-census periods can be constructed and taken. However, much of the changes in political behaviors seem to occur in the transition between census periods. Because we cannot regress the 2000-2001 or 2010-2011 changes due to redistricting, we cannot make valid statistical inferences as to whether the turnover observed between these periods was at all induced by increasing economic pressures from roboticization. This poses a particular problem for our measure of political polarization.

Our assumption that robots are having an impact on political polarization through their effect on labor markets assumes that the growth in industrial robots has been large enough to sufficiently impact commuting zones to generate a sense of economic anxiety, independent of all other sources of labor market shocks during this time period. There are still relatively few robots in the United States, although their locations appear to be concentrated. Further analysis very well may find that any negative effects born out of identifying these industries offer up some other unappreciated causal factor affecting either employment and wages or political attitudes in regions associated with these industries.

Our decision to estimate the polarizing effect of industrial automation by using measures of polarization in congressional representatives relies on incumbents being removed from office or stepping down. This means that even if we can observe signs of increased political competition that coincides with periods in which the Congress became more polarized, we rely on there being a change in representative to estimate a polarizing effect we assume to be taking place in the population. Additionally, because the impacts on changes in congressional vote shares appear to be small, too small to swing or even significantly influence elections even at the highest end of the distribution of our *exposure to robots* variable, it should then not be surprising that the measured impact on representative ideologies are null even if these voters do support more divisive candidates.

That we see our most convincing estimates reflected in those taken on Presidential elections lends more credence to the imprecise estimates regarding impacts on congressional vote shares. The general direction of these coefficients tend to agree across these tables. If these results are correct, they would fall in line with the model that asserts that industrial robots compete with labor to reduce national income, increasing inequality during transition periods of faster automation (Acemoglu and Restrepo, 2017[1]). Through this mechanism of increasing inequality we can further correlate the effects of rising inequality with political polarization (Voorheis, McCarty and Shor, 2015[19]). These results indicate that there are indeed political consequences being had and our ability to measure their impacts on polarization may yet be there to uncover. Possible approaches to tease out this relationship would be to use survey data to estimate this relationship at the micro data level.

There is also the chance that our model is reflecting existing trends that appear to be correlated, but have no real causal relationship. For instance, in Figure 2 we see that there was indeed an increase in political polarization across our sample periods, particularly for Republicans. However, this is a continuation from the early 1980's and likely has several other causal factors occurring at the regional and national level unrelated to roboticization. The same can be observed when examining the upward trend in the implementation of technological innovation of all kinds, including improvements in industrial robotics. Our results could be catching these trends that already exist.

Several aspects in our technical specifications should be considered when interpreting these estimates. When using long-difference estimators to deal with endogenous measurement errors of the causal effect, there is the implicit assumption that these unobserved factors are fixed over the period in during which we take the difference. The longer the differences we take the more likely that our entity-specific characteristics are not fixed over these longer time periods. This makes our longer estimates less reliable in producing consistent and precisely estimated coefficients. Our shortest estimate in Table C.5 crosses a period of eight years, and the longest, from 1992 to 2016, crosses 24 years. Over that time period several political changes have occurred as has been described in the previous sections. This may help explain why we see the hypothesized effects across some time periods, but not others.

7 Concluding Remarks

The widening political divide in the United States no doubt has several causal factors. The nation has been changing rapidly as its moral trends are redirected and demographic makeup shifts. Aside from the cultural upheaval that has contributed to the sorting of citizens into more culturally and racially distinct political parties, the country has also experienced a dramatic shift in its distribution of national income. These economic trends seem tightly correlated with the ever-widening political divide we continue to observe in our national politics. At least some of this virulence seems to stem from increasing pressures on labor in the form of import competition.

Our contribution to this still growing body of work has been to demonstrate that workplace automation in the form of industrial robots may also be contributing to this partisan wrangling at the national level. We have been able to demonstrate that these technology shocks exhibit effects that have been the tell-tale sign of political polarization in previous studies. Our results suggest that as the stock of industrial robots has expanded, districts and counties located in local labor markets at a disadvantage in the race against technology have experienced more political competition during an age of rising polarization. Increased use of advanced robotics in manufacturing has been shown to reduce employment and wages in labor markets where they've been installed. Additionally, the majority of robots are located in areas now dominated by the Republican Party.

While the total amount of robots within the U.S. remains relatively low, forecasts suggest they will be increasingly used in forms of production outside those already identified. If we are to take these findings as germane, we must then contend with the possibility that the arrival of these waves of industrial automation will be accompanied by ever more divisive political rhetoric and policy posturing. Awareness of these findings should motivate further investigation and analysis, and proposals for an adequate policy response should be taken up by the invested parties. For, previous literature and history suggests that if the causal dance between inequality and polarization is left unchecked it could result in reactionary policy decisions with both social and economic consequences.

References

[1] Acemoglu, D. and P. Restrepo (2017a). The race between machine and man: Implications of technology for growth, factor shares and employment. *SSRN Electronic Journal*.

[2] Acemoglu, D. and P. Restrepo (2017b). Robots and jobs: Evidence from us labor markets. *SSRN Electronic Journal*.

[3] Autor, D., D. Dorn, G. Hanson, and K. Majlesi (2016, September). Importing political polarization? the electoral consequences of rising trade exposure. Working Paper 22637, National Bureau of Economic Research.

[4] Autor, D. H. and D. Dorn (2013, August). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review 103*(5), 1553–97.

[5] Autor, D. H., D. Dorn, and G. H. Hanson (2013, May). The geography of trade and technology shocks in the united states. *American Economic Review 103*(3), 220–25.

[6] Autor, D. H., D. Dorn, and G. H. Hanson (2016, Oct). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics 8*(1), 205–240.

[7] Bartels, L. M. (2002). Economic inequality and political representation. *Larry M. Bartels*.

[8] Borusyak, K., P. Hull, and X. Jaravel (2018). Quasi-experimental shift-share designs. *Working Paper*.

[9] Eberstadt, N. (2016). *Men Without Work: America's Invisible Crisis*. Templeton Press.

[10] Feler, L. and M. Z. Senses (2017, November). Trade shocks and the provision of local public goods. *American Economic Journal: Economic Policy 9*(4), 101–43.

[11] Frey, C. B., T. Berger, and C. Chen (2018). Political machinery: did robots swing the 2016 us presidential election? *Oxford Review of Economic Policy*.

[12] Inglehart, R. and P. Norris (2016). Trump, brexit, and the rise of populism: Economic have-nots and cultural backlash. *SSRN Electronic Journal*.

[13] Lee, D. S. (1999). Wage inequality in the united states during the 1980s: Rising dispersion or falling minimum wage? *The Quarterly Journal of Economics*.

[14] McCarty, N., K. T. Poole, and H. Rosenthal (2006). *Polarized America: The Dance of Political Ideology and Unequal Riches*. MIT Press.

[15] Poole, K. T. and H. Rosenthal (1985). A spatial model for legislative roll call analysis. *American Journal of Political Science*.

[16] Smith, A. (2016). Public predictions for the future of workforce automation. *Pew Research Center*.

[17] Smith, A. and M. Anderson (2017). Automation in everyday life. *Pew Research Center*.

[18] Taylor, P., C. Funk, and P. Craighill (2006). Public says american work life is worsening, but most workers remain satisfied with their jobs. *Pew Research Center*.

[19] Voorheis, J., N. McCarty, and B. Shor (2015). Unequal incomes, ideology and gridlock: How rising inequality increases political polarization. *SSRN Electronic Journal*.

Appendices

A Instrumental Variable Approach

Quantile Selection

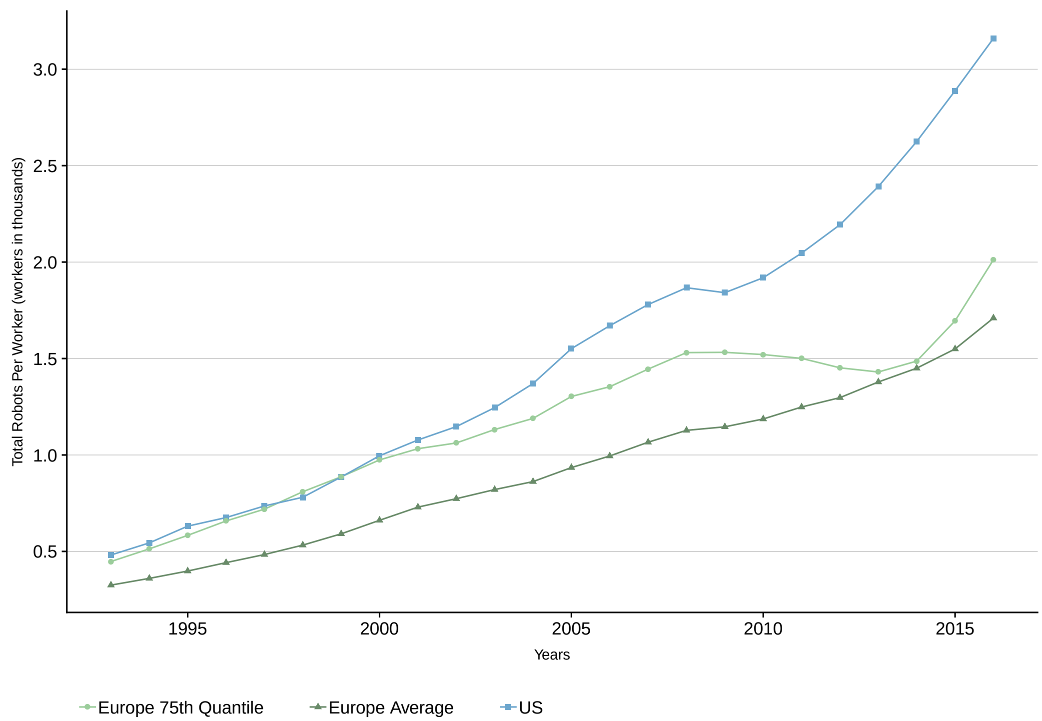

Figure 4: Robots Per Worker (thousands), 1990-2017

In determining how to contruct the exogenous component, we followed in the path of the previous authors and compare the evolution of robots per worker in the United States with the average and a selected quantile across the subset of European countries in our sample displayed in Figure 4. To construct robots per worker in Europe we combined the IFR datasets with employment data by industry from the EUKLEMS public use data. The employment data provided by EU KLEMS only goes back to 1995 for most of the countries in our analysis, and so we can expect the ratio of robots to workers to be lower than we would otherwise expect if we had employment figures from 1990. This has lead us to select a much higher quantile of the distribution of robots per workers across our subset of European countries (75th quantile) when compared to the quantile selected by Acemoglu and Restrepo in their analysis (30th quantile). However, we have decided that the disparity is within reason and proceed forward with our analysis.

First-Stage Relationships

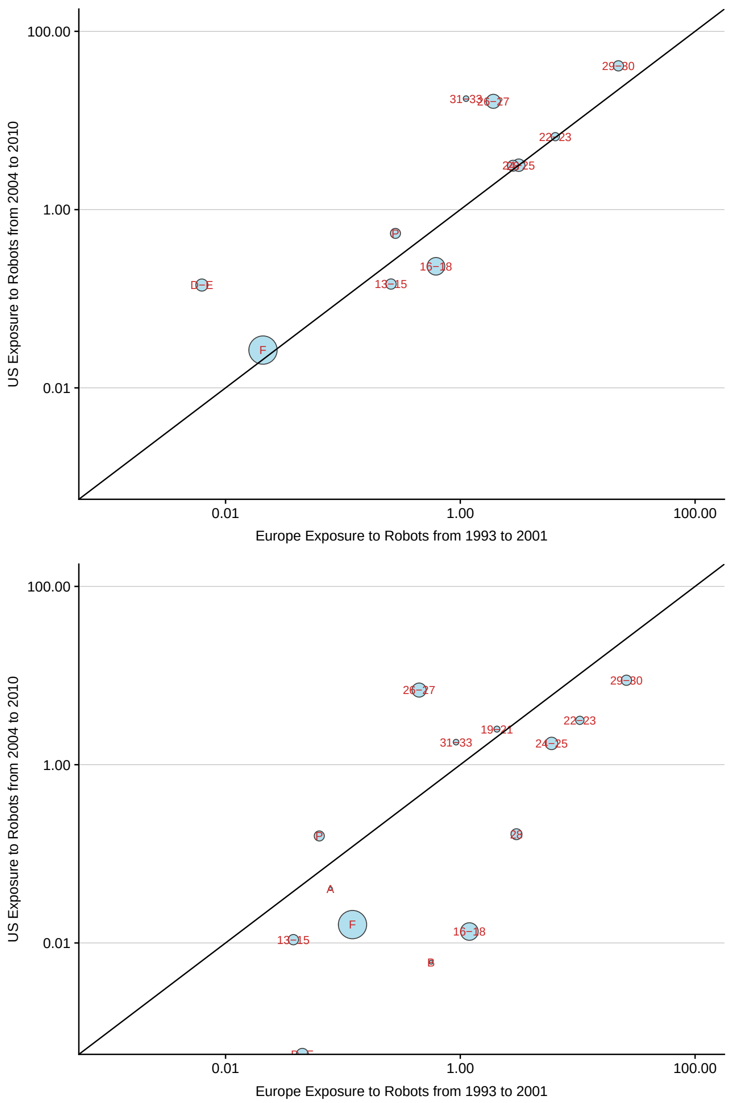

Figure 5: The relationship between robot adoption in Europe and the United States.

Notes: The top panel gives the scatter plot of the change in the number of robots per thousand workers in Europe between 1993 and 2000 and in the United States between 2004 and 2010. The bottom panel shows the same relationship using the change in the number of robots per thousand workers in Europe between 2001 and 2010. The solid line corresponds to the 45 degree line. Marker size indicates the share of U.S. employment in the corresponding industry. Industries are labeled according to their ISIC Rev. 4 two-digit designations.

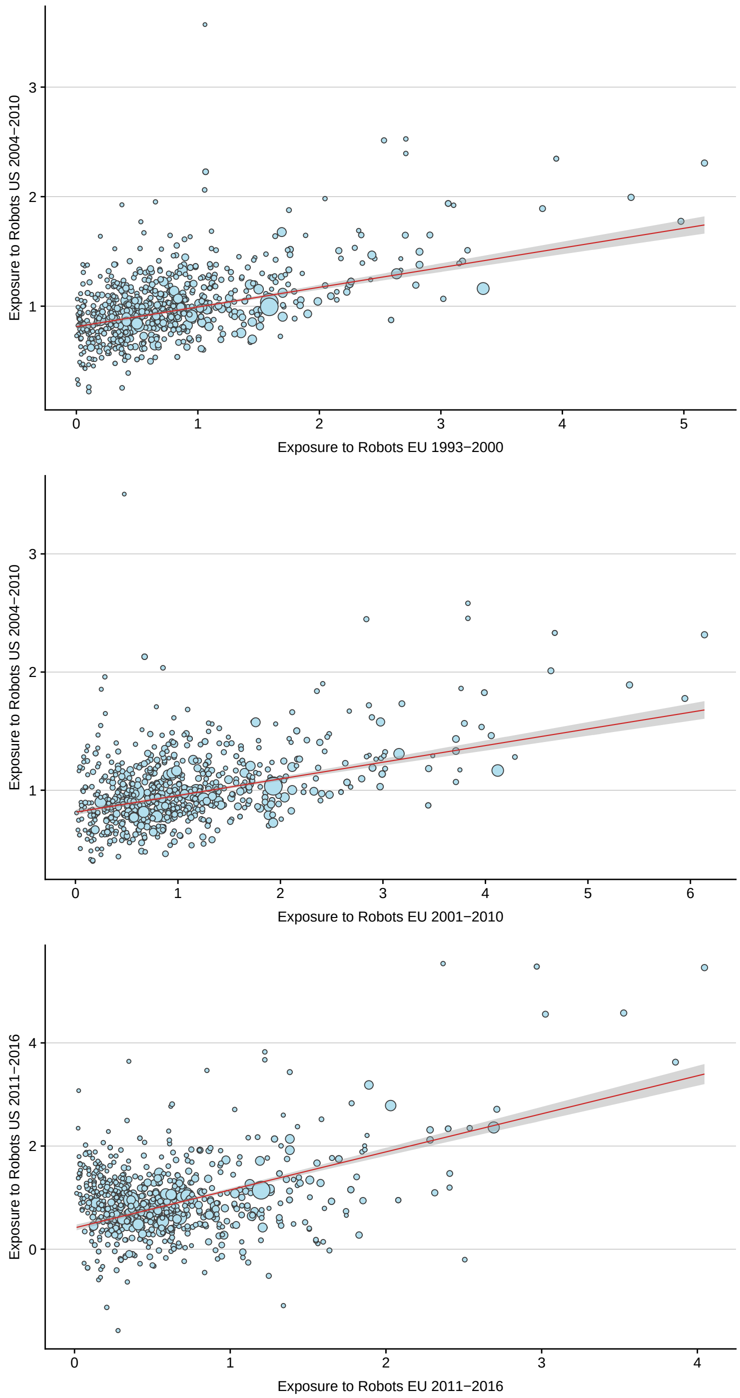

Figure 6: First-Stage Relationship

Notes: The figure shows the residual plot of US exposure to robots against the exposure to robots in Europe between the years designated after the economic, demographic, and exogenous trade covariates have been partialled out. The solid line shows the regression coefficient from a weighted regression with commuting zone total population as weights. Marker size indicates the share of the start of period US working age population in the corresponding commuting zone.

B Industrial Robots & Chinese Imports: Competing on Polarization

Much of the current literature maintains that skill-based technological change and trade competition due to increasing globalization are working hand in hand to reduce labor's share of national income. If that is correct we would face having omitted a variable that measures import penetration within these regions, which would also cause an ideological shift from the center and impact our various measured changes in vote shares. There is some discussion whether the regions that are impacted by these two forces overlap to any significant degree or not. One such paper found that regions affected by trade and technological exposure were only slightly correlated (Autor, Dorn and Hanson, 2013[5]) at roughly -0.02 to 0.01 depending on the period observed. However, their definition of technological exposure was much more broad, and it is possible that a tighter positive correlation exists between the regions affected by import competition and robticization.

Table B.1: Regression of Change in Exposure to Robots on Select Covariates

	1993-2000		*2001-2010*		*2011-2016*	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
[1em] IP China	4.776	-6.804*	-0.675	-0.359	100.7***	86.94***
	(3.182)	(3.837)	(0.793)	(0.876)	(15.05)	(17.09)
% CZ Routine Jobs	0.215	-0.466	-0.903	-0.872	6.870***	6.849***
	(1.039)	(1.146)	(1.376)	(1.353)	(2.612)	(2.638)
Offshorability Index	0.222**	0.412***	0.379***	0.372***	0.226	0.241
	(0.103)	(0.133)	(0.143)	(0.140)	(0.279)	(0.283)
% CZ Manufacturing Emp.	0.102***	0.124***	0.182***	0.178***	5.693***	5.673***
	(0.0307)	(0.0300)	(0.0379)	(0.0386)	(1.302)	(1.298)
Cragg-Donald F-statistic		287.6		1022.0		272.1
N	755	755	755	755	755	755

Dependent variables are the change in exposure to robots for each decennial census period. Columns (1) and (2) cover the period between 1993 and 2000. Columns (3) and (4) cover between 2001 and 2010. Columns (5) and (6) are for the change between 2011 and 2016. 2SLS estimates instrument the change in Chinese import penetration using the change in other developed countries' imports from China. All estimates control for county level demographics defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. Dummies for the 9 Census Divisions are included, and standard errors are clustered by CZ's.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In order to distinguish between the impact of increased import competition and the process of industrial automation on political outcomes we regress the change in growth in our *exposure to robots variable* on the change Chinese import penetration over changes in the past three decades cover the periods between the decennial census. The results in Table B.1 show the change in Chinese import penetration on the corresponding time periods change in *exposure to robots.* The regression controls for beginning of period economic conditions, a range of demographic characteristics, and includes nine dummies for each of Census Divisions to control for regional level differences. Columns (1) and (4) of Table reftable:china show that for the period from the early 1990's through 2010 labor markets that experienced a high growth of Chinese import penetration were either either negatively of not significantly correlated with those most exposed to competition from industrial robots. However, going into the most recent decennial census period starting in 2010, the relationship switches.

This reversal may be explained by other research showing that industries responding to import competition do so through increased innovation and investment in R&D ([]). It could be determined if the sudden positive correlation between roboticization and import competition has to do with this response. Another explanation could be that the composition of Chinese imports has changed to one in more direct competition with those industries most prone to roboticization in the United States. Given the point estimates for the exogenous growth in Chinese imports in column (6) commuting zones Further investigation could be warranted to explore why such a reversal in trends has occured, if in fact it has. The confounding relationship between changes in Chinese import competition and increases in industrial robots use in 2010 present an issue.

C Regression Tables & Supporting Figures

Table C.1: Exposure to Robots Effect on Change in Vote Shares Cast for Incumbent Party

	Δ*Incumbent Vote Share*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A, Stacked-Differences: 2001-2010,2011-2016						
[1em] Δ Exposure to Robots	0.0497	-8.748***	-6.420***	-4.316***	-3.847***	-0.823	-0.417
	(0.442)	(2.465)	(1.613)	(1.192)	(1.081)	(0.714)	(0.714)
Cragg-Donald F-statistic		33.07	37.15	44.27	24.99	42.14	41.77
N	10816	7268	7268	7268	7268	7268	7268
	Panel B: 1993-2000						
[1em] Δ Exposure to Robots	4.041*	2.574	4.063	4.578*	4.639*	6.870**	6.758**
	(2.168)	(3.052)	(2.657)	(2.720)	(2.691)	(2.796)	(3.096)
Cragg-Donald F-statistic		710.5	759.2	931.9	436.9	415.3	401.8
N	3548	3548	3548	3548	3548	3548	3548
	Panel C: 2001-2010						
[1em] Δ Exposure to Robots	-1.399	-1.662	-1.035	-0.942	-0.941	0.265	0.606
	(1.608)	(2.897)	(1.968)	(1.985)	(1.987)	(1.898)	(2.118)
Cragg-Donald F-statistic		667.7	694.9	700.6	348.3	364.5	246.0
N	3623	3623	3623	3623	3623	3623	3623
	Panel D: 2011-2016						
[1em] Δ Exposure to Robots	-0.773	-0.598	-0.998*	-0.867	-0.790	-0.629	-1.018*
	(0.511)	(0.605)	(0.550)	(0.548)	(0.527)	(0.532)	(0.592)
Cragg-Donald F-statistic		716.8	770.1	724.1	291.3	290.7	390.7
N	3645	3645	3645	3645	3645	3645	3645
Additional Covariates:							
Census Division Dummies	✓	✓	✓	✓	✓	✓	✓
Political	✓		✓	✓	✓	✓	✓
Δ Chinese Import Penetration	✓			✓			
Exogenous Δ Chinese Import Penetration					✓	✓	✓
Demographic	✓					✓	✓
Economic	✓						✓

Notes: Panels A presents the stacked-differences estimates of the exposure to robots on incumbent party vote share changes. Panels B through D present long-differences estimates of the exposure to robots on incumbent party vote share changes. Standard errors are triple clustered on congressional districts, commuting zones, and census period, and double clustered on congressional districts and commuting zones respectively. The dependent variable is the linear change in incumbent party vote shares for political candidates in congressional House races. Political controls include a dummy for the election of a Republican candidate in the start of period election, the vote share of the winning party, a dummy for unopposed elections, the Nominate score of the start of period election winner based on votes shares during the start of the period, where each of those variable is interacted with the dummy for a Republican election victory. Controls for the impact of Chinese import competition are defined as the change in import penetration of the period observed. Economic controls include the share of manufacturing in total employment from the NBER-CES Manufacturing Industry Database, as well as share of routine occupations and offshorability of occupations, all measured at the commuting zone level. County demographic cells are defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. All cells are weighted by the share of the total district population as measured at the beginning of the census period.

Standard errors in parentheses

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

Table C.2: Exposure to Robots Effect on Change in Party Vote Shares

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) OLS	(9) 2SLS	(10) 2SLS	(11) 2SLS	(12) 2SLS	(13) 2SLS	(14) 2SLS
	Panel A, Stacked-Differences: 1993-2000,2001-2010,2011-2016													
	Democrat							*Republican*						
[1em] Δ Exposure to Robots	0.414	0.0599	-1.433	-0.768	-0.208	0.762	0.100	-0.453	-0.287	1.085	0.493	0.0788	-0.745	-0.0263
	(0.423)	(1.483)	(1.165)	(1.054)	(0.990)	(0.859)	(0.873)	(0.415)	(1.485)	(1.142)	(1.043)	(0.989)	(0.859)	(0.871)
Cragg-Donald F-statistic		60.97	67.03	73.55	43.96	79.65	61.73		60.97	67.03	73.55	43.96	79.65	61.73
N	10816	10816	10816	10816	10816	10816	10816	10816	10816	10816	10816	10816	10816	10816
	Panel B, Stacked-Differences: 2001-2010,2011-2016													
	Democrat							*Republican*						
[1em] Δ Exposure to Robots	0.158	-1.466	-2.962**	-2.121*	-2.234**	-0.555	-0.846	-0.201	1.155	2.481*	1.791*	1.914*	0.512	0.873
	(0.430)	(1.776)	(1.338)	(1.113)	(1.061)	(0.731)	(0.752)	(0.416)	(1.767)	(1.269)	(1.075)	(1.025)	(0.719)	(0.737)
Cragg-Donald F-statistic		33.07	37.15	44.27	24.99	42.14	41.77		33.07	37.15	44.27	24.99	42.14	41.77
N	7268	7268	7268	7268	7268	7268	7268	7268	7268	7268	7268	7268	7268	7268
	Panel C: 1993-2000													
	Democrat							*Republican*						
[1em] Δ Exposure to Robots	1.979	3.991	2.554	3.175	3.220	5.665**	5.366*	-2.100	-3.991	-2.554	-3.175	-3.220	-5.665**	-5.366*
	(2.089)	(3.167)	(2.815)	(2.846)	(2.811)	(2.887)	(3.151)	(2.255)	(3.167)	(2.815)	(2.846)	(2.811)	(2.887)	(3.151)
Cragg-Donald F-statistic		710.5	759.2	931.9	436.9	415.3	401.8		710.5	759.2	931.9	436.9	415.3	401.8
N	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548
	Panel D: 2001-2010													
	Democrat							*Republican*						
[1em] Δ Exposure to Robots	-0.137	-0.618	-2.403	-2.351	-2.397	-1.273	-1.892	-0.453	0.618	2.403	2.351	2.397	1.273	1.892
	(1.533)	(3.620)	(1.945)	(1.945)	(1.956)	(1.751)	(2.048)	(0.415)	(3.620)	(1.945)	(1.945)	(1.956)	(1.751)	(2.048)
Cragg-Donald F-statistic		667.7	694.9	700.6	348.3	364.5	246.0		667.7	694.9	700.6	348.3	364.5	246.0
N	3623	3623	3623	3623	3623	3623	3623	10816	3623	3623	3623	3623	3623	3623
	Panel E: 2011-2016													
	Democrat							*Republican*						
[1em] Δ Exposure to Robots	0.591	-0.941	-0.232	-0.290	-0.422	0.212	0.554	-0.453	0.635	0.0659	0.135	0.216	-0.250	-0.367
	(0.471)	(0.604)	(0.603)	(0.611)	(0.586)	(0.526)	(0.585)	(0.415)	(0.600)	(0.579)	(0.579)	(0.558)	(0.495)	(0.563)
Cragg-Donald F-statistic		716.8	770.1	724.1	291.3	290.7	390.7		716.8	770.1	724.1	291.3	290.7	390.7
N	3645	3645	3645	3645	3645	3645	3645	10816	3645	3645	3645	3645	3645	3645
Additional Covariates:														
Census Division Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Political	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Δ Chinese Import Penetration	✓			✓				✓			✓			
Exogenous Δ Chinese Import Penetration					✓	✓	✓					✓	✓	✓
Demographic	✓					✓	✓	✓					✓	✓
Economic	✓						✓	✓						✓

Notes: Panels A and B present the stacked-differences estimates of the exposure to robots on winning candidate vote share margins. Panels C through E present long-differences estimates of the exposure to robots on winning candidate vote share margins (standard errors double clustered on congressional districts and commuting zones). The dependent variable is the linear change in winning vote share margins for political candidates in congressional House races. Political controls include a dummy for the election of a Republican candidate in the start of period election, the vote share of the winning party, a dummy for unopposed elections, the Nominate score of the start of period election winner based on votes shares during the start of the period, where each of those variable is interacted with the dummy for a Republican election victory. Controls for the impact of Chinese import competition are defined as the change in import penetration of the period observed. Economic controls include the share of manufacturing in total employment from the NBER-CES Manufacturing Industry Database, as well as share of routine occupations and offshorability of occupations, all measured at the commuting zone level. County demographic cells are defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. All cells are weighted by the share of the total district population as measured at the beginning of the census period.

Standard errors in parentheses

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

Table C.3: Exposure to Robots Effect on Change in Winning Vote Share Margin

	Δ *Winning Vote Share Margin*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A, Stacked-Differences: 1993-2000,2001-2010,2011-2016						
[1em] Δ Exposure to Robots	-0.196	-9.998***	-6.932***	-4.618**	-7.493***	-2.209	-1.747
	(0.821)	(3.075)	(2.155)	(1.885)	(1.955)	(1.469)	(1.483)
Cragg-Donald F-statistic		60.97	67.03	73.55	43.96	79.65	61.73
N	10816	10816	10816	10816	10816	10816	10816
	Panel B: 1993-2000						
[1em] Δ Exposure to Robots	-1.845	-0.976	-1.124	-1.272	-1.100	0.121	0.286
	(2.974)	(4.597)	(3.827)	(3.912)	(3.872)	(3.971)	(4.301)
Cragg-Donald F-statistic		710.5	759.2	931.9	436.9	415.3	401.8
N	3548	3548	3548	3548	3548	3548	3548
	Panel C: 2001-2010						
[1em] Δ Exposure to Robots	-2.261	0.569	-1.100	-0.995	-0.946	-0.245	-1.032
	(3.053)	(5.924)	(4.086)	(4.136)	(4.151)	(3.885)	(4.401)
Cragg-Donald F-statistic		667.7	694.9	700.6	348.3	364.5	246.0
N	3623	3623	3623	3623	3623	3623	3623
	Panel D: 2011-2016						
[1em] Δ Exposure to Robots	-1.793**	-0.801	-1.484	-1.239	-1.114	-1.114	-1.896*
	(0.883)	(1.122)	(1.037)	(1.051)	(1.009)	(1.001)	(1.087)
Cragg-Donald F-statistic		716.8	770.1	724.1	291.3	290.7	390.7
N	3645	3645	3645	3645	3645	3645	3645
Additional Covariates:							
Census Division Dummies	✓	✓	✓	✓	✓	✓	✓
Political	✓		✓	✓	✓	✓	✓
Δ Chinese Import Penetration	✓			✓			
Exogenous Δ Chinese Import Penetration					✓	✓	✓
Demographic	✓					✓	✓
Economic	✓						✓

Notes: Panels A presents the stacked-differences estimates of the exposure to robots on winning candidate vote share margin changes. Panels B through D present long-differences estimates of the exposure to robots on winning candidate vote share margin changes. Standard errors are triple clustered on congressional districts, commuting zones, and census period, and double clustered on congressional districts and commuting zones respectively. The dependent variable is the linear change in congressional House race candidate vote share victory margins. Political controls include a dummy for the election of a Republican candidate in the start of period election, the vote share of the winning party, a dummy for unopposed elections, the Nominate score of the start of period election winner based on votes shares during the start of the period, where each of those variable is interacted with the dummy for a Republican election victory. Controls for the impact of Chinese import competition are defined as the change in import penetration of the period observed. Economic controls include the share of manufacturing in total employment from the NBER-CES Manufacturing Industry Database, as well as share of routine occupations and offshorability of occupations, all measured at the commuting zone level. County demographic cells are defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. All cells are weighted by the share of the total district population as measured at the beginning of the census period.

Standard errors in parentheses

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

Table C.4: Exposure to Robots Effect on Change in 100×Nominate Scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A, Stacked-Differences: 1993-2000,2001-2010,2011-2016													
	Δ*Nominate*							Δ*Absolute Nominate*						
[1em] Δ Exposure to Robots	0.395	1.308	0.134	-0.848	-1.697	-1.215	-1.404	0.683*	1.229	3.089	1.119	1.400	0.853	0.267
	(0.633)	(2.442)	(2.118)	(1.992)	(1.900)	(1.680)	(1.688)	(0.363)	(1.795)	(2.710)	(0.945)	(2.241)	(2.272)	(2.367)
Cragg-Donald F-statistic		60.97	67.03	73.55	43.96	79.65	61.73			710.5	73.55	759.2	436.9	415.3
N	10816	10816	10816	10816	10816	10816	10816	10816	3548	3548	10816	3548	3548	3548
	Panel C: 1993-2000													
	Δ*Nominate*							Δ*Absolute Nominate*						
[1em] Δ Exposure to Robots	-0.454	5.121	1.124	0.0289	-0.0872	-2.515	-3.862	1.229	3.089	1.400	0.895	0.853	0.267	0.590
	(3.783)	(5.618)	(4.869)	(5.033)	(4.988)	(5.302)	(5.932)	(1.795)	(2.710)	(2.241)	(2.302)	(2.272)	(2.367)	(2.582)
Cragg-Donald F-statistic		710.5	759.2	931.9	436.9	415.3	401.8		710.5	759.2	931.9	436.9	415.3	401.8
N	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548	3548
	Panel D: 2001-2010													
	Δ*Nominate*							Δ*Absolute Nominate*						
[1em] Δ Exposure to Robots	-0.761	-4.308	-3.082	-3.339	-3.311	-3.113	-2.703	2.010	2.090	1.805	1.767	1.797	1.976	0.925
	(3.556)	(5.155)	(4.649)	(4.702)	(4.704)	(4.444)	(5.067)	(1.966)	(2.239)	(2.187)	(2.208)	(2.207)	(2.180)	(2.621)
Cragg-Donald F-statistic		667.7	694.9	700.6	348.3	364.5	246.0		667.7	694.9	700.6	348.3	364.5	246.0
N	3623	3623	3623	3623	3623	3623	3623	3623	3623	3623	3623	3623	3623	3623
	Panel E: 2011-2016													
	Δ*Nominate*							Δ*Absolute Nominate*						
[1em] Δ Exposure to Robots	-0.144	-0.827	-0.415	-0.0360	0.565	0.248	-0.346	-0.0662	-0.284	-0.0248	0.250	0.490	0.331	-0.0678
	(0.555)	(0.623)	(0.585)	(0.627)	(0.646)	(0.654)	(0.720)	(0.350)	(0.473)	(0.387)	(0.423)	(0.416)	(0.397)	(0.468)
Cragg-Donald F-statistic		716.8	770.1	724.1	291.3	290.7	390.7		716.8	770.1	724.1	291.3	290.7	390.7
N	3645	3645	3645	3645	3645	3645	3645	3645	3645	3645	3645	3645	3645	3645
Additional Covariates:														
Census Division Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Political	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Δ Chinese Import Penetration	✓			✓				✓			✓			
Exogenous Δ Chinese Import Penetration					✓	✓	✓					✓	✓	✓
Demographic	✓					✓	✓	✓					✓	✓
Economic	✓						✓	✓						✓

Notes: Panels A and B present the stacked-differences estimates of the exposure to robots on winning candidate vote share margins. Panels C through E present long-differences estimates of the exposure to robots on winning candidate vote share margins (standard errors double clustered on congressional districts and commuting zones). The dependent variable is the linear change in winning vote share margins for political candidates in congressional House races. Political controls include a dummy for the election of a Republican candidate in the start of period election, the vote share of the winning party, a dummy for unopposed elections, the Nominate score of the start of period election winner based on votes shares during the start of the period, where each of those variable is interacted with the dummy for a Republican election victory. Controls for the impact of Chinese import competition are defined as the change in import penetration of the period observed. Economic controls include the share of manufacturing in total employment from the NBER-CES Manufacturing Industry Database, as well as share of routine occupations and offshorability of occupations, all measured at the commuting zone level. County demographic cells are defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. All cells are weighted by the share of the total district population as measured at the beginning of the census period.

Standard errors in parentheses

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

Table C.5: Exposure to Robots Effect on Change in Republican Party Presidential Candidate Vote Shares

	Δ *GOP Vote Share*													
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) OLS	(9) 2SLS	(10) 2SLS	(11) 2SLS	(12) 2SLS	(13) 2SLS	(14) 2SLS
	Panel A:1992-2000							*Panel D*: 2000-2008						
[1em] Exposure to Robots	0.993	0.0882	-0.924	-1.195	-0.997	-1.064	-1.270	1.230**	-0.733	-0.632	-0.739	-0.745	-1.947***	-0.0792
	(0.745)	(1.502)	(1.057)	(1.060)	(1.078)	(0.848)	(1.259)	(0.586)	(0.729)	(0.753)	(0.729)	(0.729)	(0.600)	(0.660)
Cragg-Donald F-statistic		494.7	546.0	649.2	453.1	640.6	212.5		533.3	690.5	687.8	342.1	397.3	260.8
N	2966	2966	2966	2966	2966	2966	2966	2966	2966	2966	2966	2966	2966	2966
	Panel B:1992-2008							*Panel E*: 2000-2016						
[1em] Exposure to Robots	2.712**	-0.856	-1.715	-2.132	-2.045	-2.991**	-0.313	0.130	0.785*	0.840**	0.676*	0.673*	-0.123	0.112
	(1.067)	(1.864)	(1.463)	(1.400)	(1.414)	(1.169)	(1.595)	(0.219)	(0.427)	(0.424)	(0.404)	(0.405)	(0.205)	(0.269)
Cragg-Donald F-statistic		495.5	557.3	607.8	305.3	399.9	334.5		586.6	714.0	668.4	337.9	385.8	271.5
N	2966	2966	2966	2966	2966	2966	2966	3018	3018	3018	3018	3018	3018	3018
	Panel C:1992-2016							*Panel F*: 2008-2016						
[1em] Exposure to Robots	0.737**	0.677	0.419	0.0858	0.145	-0.409	0.156	0.0943	1.538***	1.600***	1.295***	0.747*	0.421**	0.606**
	(0.318)	(0.594)	(0.525)	(0.487)	(0.494)	(0.282)	(0.357)	(0.181)	(0.409)	(0.411)	(0.420)	(0.392)	(0.187)	(0.241)
Cragg-Donald F-statistic		564.5	611.6	593.0	311.7	395.8	349.0		590.9	654.4	530.3	227.9	156.2	28.27
N	3018	3018	3018	3018	3018	3018	3018	3011	3011	3011	3011	3011	3011	3011
Additional Covariates:														
Census Division Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Political	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Δ Chinese Import Penetration	✓			✓				✓			✓			
Exogenous Δ Chinese Import Penetration					✓	✓	✓					✓	✓	✓
Demographic	✓					✓	✓	✓					✓	✓
Economic	✓						✓	✓						✓

Notes: Controls for the impact of Chinese import competition are defined as the change in import penetration of the period observed. Economic controls include the share of manufacturing in total employment from the NBER-CES Manufacturing Industry Database, as well as share of routine occupations and offshorability of occupations, all measured at the commuting zone level. County demographic cells are defined by 5 age groups, the percent that is female, percentage of university degree holders, and the percentage of 4 racial groups. All cells are weighted by the counties total voting age population as measured at the beginning of the census period.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: National Manufacturing Output and Employment1990-2017

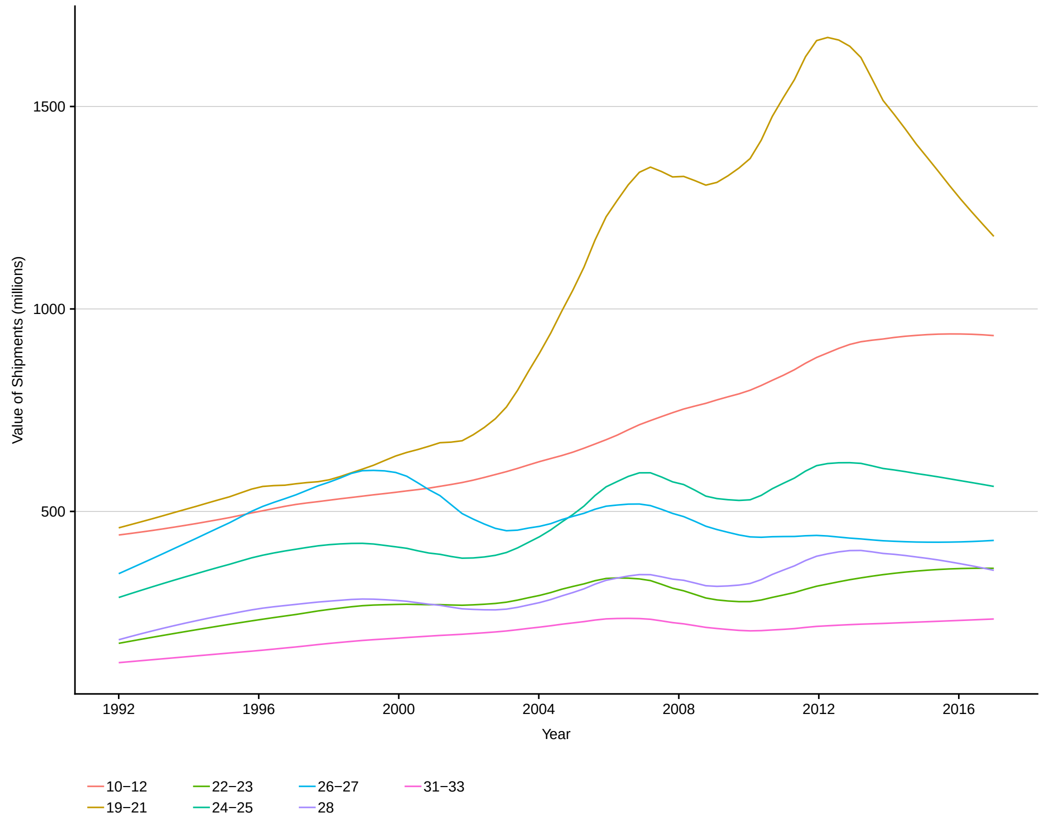

Figure 8: Output of Heavily Roboticized Manufacturing Subsectors (ISIC Rev. 4)

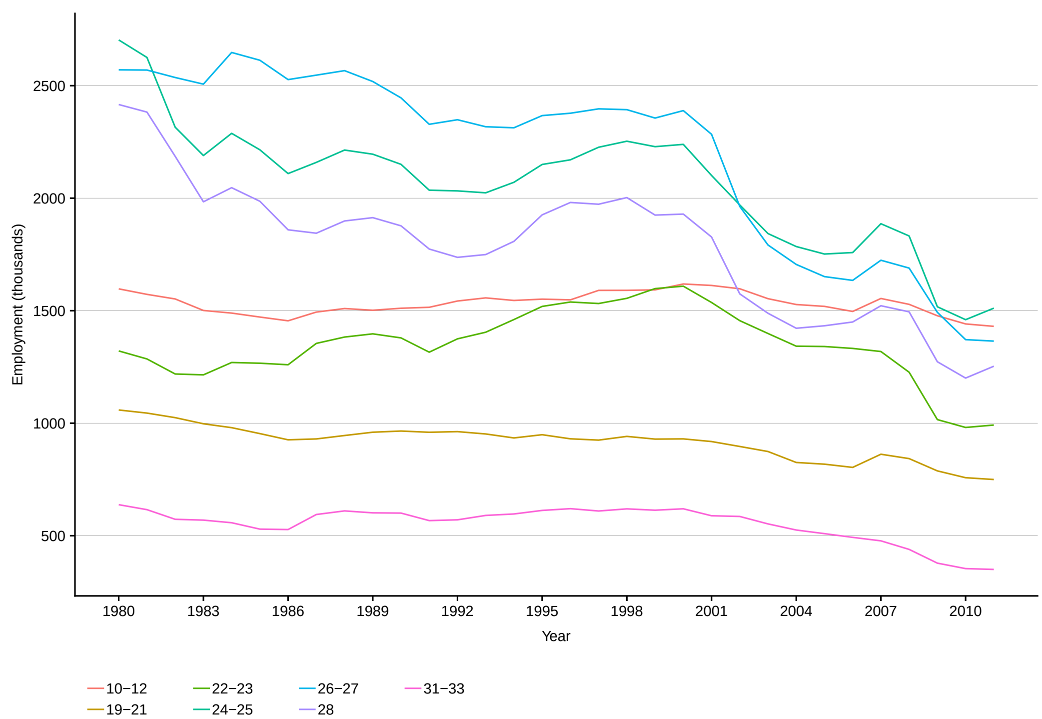

Figure 9: Manufacturing Employment by Subsector (ISIC Rev. 4)

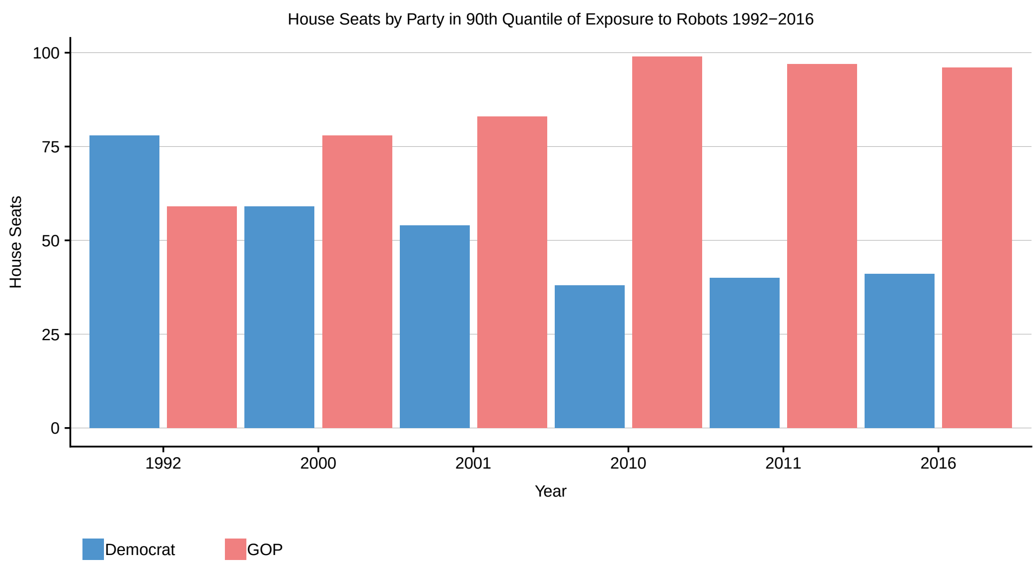

Figure 10: 90th Percentile Exposure to Robots Congressional Seat Party Transition

D Summary Statistics

Table D.1: Congressional Summary Statistics, 1993-2000

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change Nominate	3548	15.36807	(33.29023)	-109.2	0	0	0	109.3
Change Absolute Nominate	3548	6.894504	(17.32014)	-46.3	0	0	0	76.6
Δ Exposure to Robots	3548	.5275402	(.3308563)	.0032919	.3011474	.4798117	.4798117	2.864146
IP China	3548	.0114797	(.0099439)	.0001471	.0052971	.0084907	.0084907	.0666057
EU Exposure to Robots	3548	.8769839	(.7250589)	.0017054	.4152728	.6914179	.6914179	5.169586
eu_mu_deltaip	3548	.0048816	(.0049819)	.0000403	.001815	.0031142	.0031142	.0308708
Beg. Nominate	3548	.0165259	(.347891)	-.766	-.277	-.084	-.084	.79
Winning Candidates Vote Share	3548	66.32583	(12.87538)	50.11	57.49	63.39	63.39	100
GOP Win	3548	.4086809	(.4916594)	0	0	0	0	1
Unopposed	3548	.0901917	(.2864965)	0	0	0	0	1
% Age 18-25	3548	.1048727	(.0364714)	.0376344	.0873245	.1004403	.1004403	.4929748
% Age 26-35	3548	.1573391	(.0262107)	.0775974	.1403874	.1525263	.1525263	.4473868
% Age 36-45	3548	.1409834	(.0169763)	.0739809	.1303168	.1402997	.1402997	.2592834
% Age 45-64	3548	.1880034	(.0218259)	.0357269	.1753895	.1896505	.1896505	.2679083
% Age 65+	3548	.143436	(.0433265)	.0138774	.1152278	.1393183	.1393183	.3408993
% Black non-hisp	3548	.1079703	(.154888)	0	.0033652	.0319973	.0319973	.8586617
% White hisp	3548	.0239985	(.051224)	0	.0016011	.0039274	.0039274	.4428548
% Asian/Pac.	3548	.0089042	(.0184589)	0	.0015028	.0030448	.0030448	.2841128
% Other race	3548	.0004961	(.0006611)	0	.0000914	.0002734	.0002734	.0108696
% College Deg.	3548	.1519402	(.0683115)	.0362749	.1037144	.136492	.136492	.5901951
% Female	3548	.5109103	(.0160372)	.3207123	.5044029	.5123491	.5123491	.5596684
% CZ Routine Jobs	3548	.3006885	(.0327392)	.2130913	.278543	.301114	.301114	.3774758
Offshorability Index	3548	-.253823	(.3076674)	-1.110316	-.4700438	-.2523004	-.2523004	.7147169
% CZ Manufacturing Emp.	3548	1.406192	(.828628)	.0117919	.7752471	1.265517	1.265517	4.109715

Table D.2: Congressional Summary Statistics, 2001-2010

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change Nominate	3623	11.79075	(30.98748)	-82.7	0	0	0	100.6
Change Absolute Nominate	3623	6.963704	(16.18367)	-45.4	0	0	0	60
Δ Exposure to Robots	3623	.5383886	(.3409675)	.0032919	.3059938	.4777429	.4777429	2.864146
IP China	3623	.0305471	(.0322222)	.0004452	.012232	.0200043	.0200043	.2314125
EU Exposure to Robots	3623	1.192124	(.8888971)	.011088	.5944721	.9702214	.9702214	6.137131
eu_mu_deltaip	3623	.0026812	(.0030459)	9.82e-06	.0009029	.0015318	.0015318	.0192822
Beg. Nominate	3623	.1655705	(.3649212)	-.687	-.204	.303	.303	.863
Winning Candidates Vote Share	3623	72.73492	(16.13076)	50.04	61.44	68.81	68.81	100
GOP Win	3623	.6273806	(.4835687)	0	0	1	1	1
Unopposed	3623	.2188794	(.4135437)	0	0	0	0	1
% Age 18-25	3623	.0901302	(.0335457)	.0342599	.0740265	.0837797	.0837797	.4604101
% Age 26-35	3623	.1261453	(.0225675)	.0627341	.1120751	.1254972	.1254972	.2572618
% Age 36-45	3623	.154824	(.0156426)	.0684433	.1449299	.1536705	.1536705	.2260467
% Age 45-64	3623	.2311146	(.0258435)	.0549657	.2164413	.2313483	.2313483	.4050179
% Age 65+	3623	.1423884	(.0404207)	.0180083	.1153712	.1393021	.1393021	.3471584
% Black non-hisp	3623	.1027506	(.1463161)	0	.0051686	.0345393	.0345393	.8596509
% White hisp	3623	.03813	(.0611433)	0	.0048272	.0121721	.0121721	.4305603
% Asian/Pac.	3623	.0126323	(.0253932)	0	.0021875	.0041318	.0041318	.3112717
% Other race	3623	.0119515	(.0089965)	0	.0066062	.0093983	.0093983	.1125084
% College Deg.	3623	.188034	(.0844629)	.051278	.127725	.1685867	.1685867	.7117427
% Female	3623	.5057984	(.0184704)	.3274737	.5006018	.5083626	.5083626	.5743638
% CZ Routine Jobs	3623	.3013256	(.0281391)	.2222687	.2812656	.3025121	.3025121	.3537765
Offshorability Index	3623	-.5240879	(.3024795)	-1.383358	-.7501884	-.5259056	-.5259056	.5437161
% CZ Manufacturing Emp.	3623	1.083334	(.6257099)	0	.5934642	1.032332	1.032332	3.130271

Table D.3: Congressional Summary Statistics, 2011-2016

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change Nominate	3645	3.011632	(16.75071)	-83	0	0	0	82.6
Change Absolute Nominate	3645	1.90716	(10.58393)	-55.4	0	0	0	49.9
Δ Exposure to Robots	3645	1.060006	(.8870836)	.0075727	.511293	.8076079	.8076079	7.191508
IP China	3645	.0016464	(.0032571)	-.0208112	.0006776	.001891	.001891	.0136667
EU Exposure to Robots	3645	.6982867	(.5677177)	.0132704	.3440414	.5501488	.5501488	4.045628
eu_mu_deltaip	3645	-.0015601	(.0021018)	-.013716	-.0016835	-.0006569	-.0006569	.0001347
Beg. Nominate	3645	.2937492	(.3801778)	-.687	.222	.424	.424	.913
Winning Candidates Vote Share	3645	68.31857	(14.33083)	0	58.42	63.98	63.98	100
GOP Win	3645	.7615912	(.4261688)	0	1	1	1	1
Unopposed	3645	.1262003	(.3321205)	0	0	0	0	1
% Age 18-25	3645	.0900667	(.0345096)	.0169903	.0728231	.0830419	.0830419	.4669064
% Age 26-35	3645	.1188527	(.0214195)	.0594955	.1048421	.1159078	.1159078	.2764669
% Age 36-45	3645	.1245647	(.0157648)	.0589321	.1145042	.1243691	.1243691	.1977
% Age 45-64	3645	.2771267	(.0305267)	.1030443	.2605812	.2788113	.2788113	.4213483
% Age 65+	3645	.1527593	(.0405074)	.037277	.1248763	.1492919	.1492919	.4338471
% Black non-hisp	3645	.1074893	(.1505337)	0	.0064481	.0357942	.0357942	.8543878
% White hisp	3645	.0449277	(.0571789)	0	.0085	.020778	.020778	.3654047
% Asian/Pac.	3645	.0170247	(.0319297)	0	.0031787	.0057604	.0057604	.3338504
% Other race	3645	.0156722	(.0096947)	0	.0096799	.013609	.013609	.0977384
% College Deg.	3645	.2139599	(.092746)	.0416803	.1463311	.1944953	.1944953	.7762864
% Female	3645	.5023667	(.0207543)	.278894	.4986212	.5060031	.5060031	.5677769
% CZ Routine Jobs	3645	.30154	(.0278325)	.2222687	.2823171	.3025121	.3025121	.3537765
Offshorability Index	3645	-.5262359	(.3033549)	-1.383358	-.7526562	-.5298724	-.5298724	.5437161
% CZ Manufacturing Emp.	3645	.1248747	(.071837)	0	.0744416	.1093037	.1093037	.4814495

Table D.4: Presidential Summary Statistics, 1992-2000

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change GOP Vote Share	2968	17.51579	(7.728321)	-9.77	12.53	17.14	17.14	45.79
Exposure to Robots	2968	.4489292	(.3384745)	.000641	.2162794	.3917165	.3917165	2.3587
IP China	2968	.0111688	(.0098508)	.0000373	.0048463	.0084422	.0084422	.0666057
EU Exposure to Robots	2968	.8074993	(.7053448)	.0013719	.3592164	.6530784	.6530784	5.169586
eu_mu_deltaip	2968	.0029382	(.0035437)	0	.0008179	.0015699	.0015699	.0220367
GOP Win	2968	.5181941	(.4997531)	0	0	1	1	1
Winning Candidate Vote Share	2968	46.85135	(7.342391)	25.13	41.67	45.67	45.67	82.8
% Age 18-25	2968	.0998186	(.0352211)	.0376344	.0813373	.0963369	.0963369	.3559768
% Age 26-35	2968	.1527512	(.0250369)	.0798747	.1379222	.1485259	.1485259	.4473868
% Age 36-45	2968	.1392075	(.0168057)	.0816085	.1286069	.1382435	.1382435	.2592834
% Age 45-64	2968	.1901501	(.0219524)	.0357269	.1782581	.1912546	.1912546	.2679083
% Age 65+	2968	.150202	(.0435653)	.0138774	.1215534	.1466158	.1466158	.3408993
% Black non-hisp	2968	.0848036	(.1426777)	0	.0014659	.0145198	.0145198	.8586617
% White hisp	2968	.019893	(.0472504)	0	.0012923	.0032333	.0032333	.4428548
% Other race	2968	.0056628	(.012175)	0	.0013063	.0024273	.0024273	.2841128
other	2968	.0004009	(.0005964)	0	.0000516	.000211	.000211	.0108696
% College Deg.	2968	.1429414	(.0595005)	.0362749	.1017992	.1325466	.1325466	.567508
females	2968	.5096909	(.0161737)	.3207123	.5038344	.511438	.511438	.5523187
% CZ Routine Jobs	2968	.2924444	(.0333459)	.1999184	.2699105	.2928887	.2928887	.3774758
Offshorability Index	2968	-.293276	(.3008823)	-1.110316	-.5133449	-.2872784	-.2872784	.7147169
% CZ Manufacturing Emp.	2968	1.30367	(.8412619)	.0070581	.6265907	1.187562	1.187562	4.109715

Table D.5: Presidential Summary Statistics, 2000-2008

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change GOP Vote Share	2968	17.5478	(10.92373)	-24.73	9.81	17.185	17.185	52.53
Exposure to Robots	2968	.4489292	(.3384745)	.000641	.2162794	.3917165	.3917165	2.3587
IP China	2968	.049195	(.0460341)	.0003296	.0206981	.0347085	.0347085	.3005815
EU Exposure to Robots	2968	1.956	(1.735926)	.0082293	.8349024	1.537284	1.537284	12.68172
eu_mu_deltaip	2968	.009732	(.0106628)	0	.0031225	.0061123	.0061123	.0658838
GOP Win	2968	.5181941	(.4997531)	0	0	1	1	1
Winning Candidate Vote Share	2968	46.85135	(7.342391)	25.13	41.67	45.67	45.67	82.8
% Age 18-25	2968	.0998186	(.0352211)	.0376344	.0813373	.0963369	.0963369	.3559768
% Age 26-35	2968	.1527512	(.0250369)	.0798747	.1379222	.1485259	.1485259	.4473868
% Age 36-45	2968	.1392075	(.0168057)	.0816085	.1286069	.1382435	.1382435	.2592834
% Age 45-64	2968	.1901501	(.0219524)	.0357269	.1782581	.1912546	.1912546	.2679083
% Age 65+	2968	.150202	(.0435653)	.0138774	.1215534	.1466158	.1466158	.3408993
% Black non-hisp	2968	.0848036	(.1426777)	0	.0014659	.0145198	.0145198	.8586617
% White hisp	2968	.019893	(.0472504)	0	.0012923	.0032333	.0032333	.4428548
% Other race	2968	.0056628	(.012175)	0	.0013063	.0024273	.0024273	.2841128
other	2968	.0004009	(.0005964)	0	.0000516	.000211	.000211	.0108696
% College Deg.	2968	.1429414	(.0595005)	.0362749	.1017992	.1325466	.1325466	.567508
females	2968	.5096909	(.0161737)	.3207123	.5038344	.511438	.511438	.5523187
% CZ Routine Jobs	2968	.2924444	(.0333459)	.1999184	.2699105	.2928887	.2928887	.3774758
Offshorability Index	2968	-.293276	(.3008823)	-1.110316	-.5133449	-.2872784	-.2872784	.7147169
% CZ Manufacturing Emp.	2968	1.30367	(.8412619)	.0070581	.6265907	1.187562	1.187562	4.109715

Table D.6: Presidential Summary Statistics, 2008-2016

	N	Mean	Standard Deviation	Min	25^{th} Percentile	Median	75^{th} Percentile	Max
Change GOP Vote Share	3020	24.24544	(14.04639)	-45.29	14.81	25.64	25.64	59.61
Exposure to Robots	3020	1.62588	(1.284917)	.0132247	.7789809	1.383062	1.383062	10.23439
IP China	3020	.0618221	(.0538931)	.0004159	.0272529	.0463629	.0463629	.3506716
EU Exposure to Robots	3020	2.866012	(2.421484)	.0256101	1.345951	2.290871	2.290871	17.9398
eu_mu_deltaip	3020	.0088591	(.0088945)	0	.003205	.0059013	.0059013	.0546138
GOP Win	3020	.5145695	(.4998705)	0	0	1	1	1
Winning Candidate Vote Share	3020	46.85841	(7.283826)	25.13	41.72	45.71	45.71	82.8
% Age 18-25	3020	.100028	(.0352134)	.0376344	.0815917	.096657	.096657	.3559768
% Age 26-35	3020	.1528517	(.0255251)	.0798747	.1379222	.1485906	.1485906	.4473868
% Age 36-45	3020	.1390925	(.0167842)	.0816085	.1284762	.1381211	.1381211	.2592834
% Age 45-64	3020	.1899057	(.0219194)	.0357269	.177916	.1909679	.1909679	.2679083
% Age 65+	3020	.1497975	(.0434379)	.0138774	.1212806	.146271	.146271	.3408993
% Black non-hisp	3020	.0886638	(.1453574)	0	.0015146	.0156567	.0156567	.8586617
% White hisp	3020	.0196189	(.0468886)	0	.0013078	.0032459	.0032459	.4428548
% Other race	3020	.0056296	(.0120804)	0	.0012914	.0024146	.0024146	.2841128
other	3020	.0004014	(.0005964)	0	.0000516	.0002112	.0002112	.0108696
% College Deg.	3020	.1424578	(.0593347)	.0362749	.1013946	.1319626	.1319626	.567508
females	3020	.509753	(.0165402)	.3207123	.5038836	.5115968	.5115968	.5523187
% CZ Routine Jobs	3020	.2922483	(.0332298)	.1999184	.2692124	.2926619	.2926619	.3774758
Offshorability Index	3020	-.2993729	(.302735)	-1.110316	-.522402	-.2973118	-.2973118	.7147169
% CZ Manufacturing Emp.	3020	1.298962	(.8359444)	.0070581	.6326191	1.185109	1.185109	4.109715