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MINIMUM WAGES AND RISE OF THE ROBOTS

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We have received helpful comments from seminar participants at the 2025 FSRDC Conference at Cornell. The research was conducted while the authors were Special Sworn Status researchers at the Federal Statistical Research Data Center. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release. DRB Approval Number: CBDRB-FY25-P2315-R12475. Erik Brynjolfsson is the Director of the Stanford Digital Economy Lab which is partially funded by a variety of industry, government and nonprofit organizations. He has given over 400 talks, some of which were compensated. He is also a co-founder of Workhelix, Inc.

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ABSTRACT

This paper studies how minimum wage policy affects firms' adoption of automation technologies. Using both state-level measures of robot exposure and novel plant-level data on industrial robot imports linked to U.S. Census microdata from 1992–2021, we show that increases in minimum wages raise the likelihood of robot adoption in manufacturing. Our preferred identification exploits discontinuities at state borders, comparing otherwise similar firms exposed to different wage floors. Across specifications, a 10 percent increase in the minimum wage increases robot adoption by roughly 8 percent relative to the mean.

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1 Introduction

This paper investigates the relationship between state-level labor policies and the adoption of industrial robots by U.S. manufacturing firms. We find evidence that increases in minimum wages are associated with subsequent increases in the probability of robot adoption. While existing literature has studied the impact of minimum wage increases on employment, wages, and firm survival, less attention has been paid to how such policies may influence capital-labor substitution through automation. Industrial robots represent a salient form of labor-replacing capital, particularly in routinized production settings where higher minimum wages can raise effective labor costs and induce capital-labor reallocation.

We study the link between minimum wage and robot adoption in two ways. First, we disaggregate national data on robots to the state level, creating a state-level robot exposure measure similar to that in (Acemoglu and Restrepo, 2020), and then consider how changes in state-level robot exposure correlate with changes in state-level minimum wages.

Second, create a novel panel dataset of robot adoption at the plant level, and study how changes in robot adoption at the plant level correlate with changes in minimum wages in the state in which the plant is located. More specifically, for this second approach, we use protected microdata from the U.S. Census Bureau, including the Longitudinal Business Database (LBD) and Longitudinal Firm Trade Transactions Database (LFTTD), to construct a panel dataset of robot adoption among U.S. manufacturing firms from 1992 to 2021. Firms are identified as robot adopters by linking import records of industrial robots to firm identifiers in the LBD, an approach similar to that taken by (Dixon et al., 2021) in their study of Canadian firms adopting robots. We mainly focus on single-unit manufacturing firms (i.e., plants) to reduce complications from intra-firm adjustments and to better isolate exposure to local labor market policies. Our preferred specifications compare single-unit firms located in border counties of adjacent U.S. states with differing minimum wage laws, allowing us to exploit geographic discontinuities in policy exposure (Holmes, 1998; Dube et al., 2010).

We find that firms subject to higher minimum wages are more likely to adopt robots, even after controlling for observable firm and local economic characteristics. Moreover, the estimated effect of the minimum wage on industrial robot adoption is economically meaningful and highly consistent across the two approaches: a 10% increase in the minimum wage is associated with an approximately 8% increase in the likelihood of robot adoption, relative to the sample mean.

These results contribute to the literature on technology adoption and labor market institutions. They provide evidence that wage policy can influence firms' technological investment decisions, with potential implications for productivity, employment composition, and regional economic dynamics.

2 Background and Related Literature

Previous research has documented both positive and negative effects of automation on labor market outcomes. In a study of 17 OECD countries over a 15-year time period, Graetz and Michaels (2018) find that robot adoption contributed to national GDP growth. Firm-level studies from several countries (Acemoglu et al., 2020; Dixon et al., 2021; Koch et al., 2021) have shown that robots are associated with increased employment and productivity growth. However, findings at the industry or regional level have been more mixed, with some studies reporting job losses (Acemoglu and Restrepo, 2020).

The U.S. evidence base remains limited. Brynjolfsson et al. (2023b) use cross-sectional establishment-level data recently collected by the U.S. Census Bureau to document a number of characteristics of manufacturing establishments with robots. These include that robot adopters tend to be larger, and that robot adoption tends to cluster in certain areas, which they call “Robot Hubs”. Their data is cross-sectional, however, which does not allow for a comprehensive study of the drivers of adoption as we are able to do with panel data in this study.

There is a large literature on the labor effects of minimum wage (Clemens, 2021; Dube and Lindner, 2024). The literature on firm responses to minimum wage is comparatively smaller (Clemens, 2021). There is some evidence of minimum wage increases leading to increased substitution between labor and capital (Harasztosi and Lindner, 2019; Hau et al., 2020). (Lordan and Neumark, 2018) find that increases in minimum wages decreases the share of automatable employment held by low-skilled workers, particularly in manufacturing. Keum (2025) develops a novel measure of automation using text analysis of investment disclosures for U.S. publicly traded firms and finds a positive link between minimum wages and automation. There are a small handful of papers that explicitly study the link between minimum wage increases and robot adoption.

There are several other papers that investigate the link between labor policies and robot adoption in other countries. Fan et al. (2021) investigates the relationship between rising minimum wages and robot investment in China using a paired-city approach, exploiting variation in minimum wages across metropolitan areas that straddle city or provincial boundaries. While no effect is observed between 2004–2007, a 10% minimum wage increase from 2008–2012 raises the probability of robot adoption by 0.11%, against an average adoption rate of 0.19%. The effects are more pronounced among high-productivity firms, private firms, coastal firms, and those employing high-skilled labor. The study attributes weaker effects in state-owned enterprises to noneconomic mandates, such as employment guarantees, suggesting the effect that labor protections have in limiting these effects.

Akgündüz et al. (2024) studies the impact of a sharp 33.5% minimum wage hike in Turkey in 2016 on firm-level robot adoption. They find that medium and large firms responded by increasing robot use along both extensive and intensive margins, especially those firms with high shares of routine work and blue-collar labor. They find that a 1% increase in minimum wage employment share is associated with a 0.4% rise in robot adoption probability for medium firms and a 2.7% rise for large firms. Adoption was also more likely among R&D-intensive firms and those in competitive industries. Despite these firm-level effects, the overall impact is muted due to the dominance of small firms, which were largely unaffected.

Plümpe (2024) studies the effect of Germany's minimum wage introduction in 2015 on robot adoption using plant-level survey data from the IAB Establishment Panel combined with administrative labor market data. She finds a positive effect of minimum wage exposure on robot adoption overall, with plants affected by the wage floor increasing their probability of robot adoption between 2015 and 2018. However, the mechanism operates entirely through plants' workforce composition. Plümpe demonstrates that the minimum wage effect is concentrated among plants with high shares of simple manual workers performing routine, easily replaceable tasks, with negligible effects on robot adoption in plants dominated by workers in non-routine occupations.

3 Aggregate Evidence

To motivate our econometric analysis, we first explore the relationship between a state-level measure of robot exposure and changes in the minimum wage. Following (Acemoglu and Restrepo, 2020), we construct state-level long-difference measures of exposure to industrial robots by combining robot installation information from the International Federation of Robotics (IFR), U.S. state-industry employment decomposition from County Business Patterns (CBP), and industry-level value added measure from the NBER-CES database:[1] [2]

$$\text{Exposure to robots}_{s,(2004,2016)} = \sum_{i \in I} l_{si,2000} \times \left(\frac{M^{US}_{i,2016} - M^{US}_{i,2004}}{L^{US}_{i,2000}} - g^{US}_{i,(2004,2016)} \frac{M^{US}_{i,2004}}{L^{US}_{i,2000}} \right) \times 100,$$

[1] The start and ending year of the long-difference exposure is selected based on data availability.

[2] We focus on the manufacturing sector only for two reasons. First, it offers a cleaner concordance between IFR industry classifications and NAICS codes. Second, manufacturing has been the primary adopter of industrial robots.

where $l_{si,2000}$ is the employment share of industry i in state s in the baseline year (2000); $(M^{US}_{i,2016} - M^{US}_{i,2004})$ is the change in total U.S. robot stock in industry i which captures the growth in robot deployment nationally; $L^{US}_{i,2000}$ is U.S. employment in industry i in the baseline year which normalizes robot change by workforce size and yields a measure of robots per base year worker; $g^{US}_{i,(2004,2016)}$ is the log growth in value added in industry i from 2004 to 2016; and $\frac{M^{US}i,2004}{L^{US}i,2000}$ is the robot stock per worker in 2004 capturing the pre-existing automation in industry i relative to the baseline population, and the interaction of the two work as a detrending factor that adjusts for the growth in baseline robot levels. The initial baseline employment shares work to allocate national robot adoption across states based on initial industry composition. The exposure measure gives us a state-level measure of weighted sum of industry-specific excess robot adoption in industry i after controlling for the expected growth given the initial levels of adoption and national value added growth (demand side) in the industry.

We combine this with a measure of the minimum wage changes observed at the state level over the 2003-2015 period.[3] The state-level minimum wage data is obtained from the Department of Labor. We use federal minimum wage for states that have not adopted a state minimum wage, such as Alabama, Louisiana, Mississippi, South Carolina and Tennessee. Several states, including Georgia, Oklahoma, and Wyoming, maintain statutory minimum wages below the federal rate. Then we construct the minimum wage change measure using the symmetric midpoint (DHS) growth rate proposed by Davis et al. (1996):

$$\Delta\text{DHS Minimum Wage}_{s,(2003,2015)} = \frac{\text{Minimum Wage}_{s,2015} - \text{Minimum Wage}_{s,2003}}{0.5 \times (\text{Minimum Wage}_{s,2015} + \text{Minimum Wage}_{s,2003})}.$$

Figure 1a displays our robot exposure measure as defined above. The map reveals significant geographic variation in robot exposure across U.S. states, with the color gradient ranging from light blue (minimal change, min ≈ 0.01) to dark navy (maximum change, max ≈ 0.13). States in the Southwest (Arizona, New Mexico, California), Midwest (Michigan, Indiana, Kansas), and Northwest (Washington) show the highest concentrations of robot exposure, reflecting strong manufacturing sectors – Automotive production, Aerospace manufacturing, Industrial machinery production, and Electronics/semiconductors; and states in the Mountain West, parts of the South, and Northern regions, show minimal robot exposure consistent with less dependence on manufacturing.

Figure 1b displays state-level minimum wage changes covering the period 2003–2015 using Davis et al. (2007) growth rates (DHS). The map again reveals substantial geographic variation in minimum wage policy exposure across U.S. states, with the gradient ranging from

[3] We lag the minimum wage measure by one year relative to robot exposure.

light blue (minimal change, ΔDHSmin = 0.00) to dark navy (maximum change, ΔDHSmax $\approx$ 0.9). Kansas stands out as having the darkest shading, indicating the largest growth over the study period. Most states cluster in the medium-to-dark purple range (0.50–0.75), reflecting the widespread increases in state minimum wages during this period. Wyoming and Georgia appear among the lightest-colored states, indicating minimal minimum wage adjustments between 2003 and 2015.

Finally, figure 1c displays a strong positive correlation in the relationship between the state-level robot exposure and the minimum wage measures. A regression line summarizes the unweighted correlation between the two, with a coefficient of 0.056. The correlation implies that a 10% increase in the minimum wage is associated with an approximately $0.056 \times 10\% = 0.0056$ increase in robot exposure, which is about 8% of the sample mean (0.07).

4 Evidence from Census Microdata

While the aggregate, state-level measures provide suggestive evidence on the relationship between minimum wage and robot adoption, they overlook important within state-industry variations. As pointed out by Brynjolfsson et al. (2023a,b), industrial robot distribution is geographically skewed towards a few "robot hubs", even after controlling for the industry composition effects. Thus, we turn to firm- and establishment-level micro data which allows us to precisely identify the time and location of robot adoption, and furthermore allows us to utilize sharp differences in minimum wages across state borders as our econometric research design, ala (Holmes, 1998; Dube et al., 2010).

4.1 Data and Sample Construction

The construction of our firm level sample is comprised of two steps. First, we use the LFTTD, which provides firm-level trade records, to identify firms that import industrial robots in 1992-2021, based on U.S. International Trade Commission (USITC) 10-digit Harmonized System (HS) codes for industrial robots. Second, we use the LBD to create a matched sample of robot importing and non-importing firms over 1992-2021, based on firm age, employment size, and industry.

According to an USITC Executive Briefings on Trade, most industrial robots installed in the U.S. are imported from companies based in foreign countries such as Japan, Germany, and Switzerland.[4] Thus, to capture robot adoption, we compile the relevant HS codes from

[4] `https://www.usitc.gov/publications/332/ebotindustrialrobots5-14-14.pdf`

the USITC and rely on granular firm-level trade transaction data to identify firms that import robots. Specifically, we first scrutinize all 10-digit HS codes in Harmonized Tariff Schedule of the United States (HTS) documents from 1992 to 2021, and identify all products that are classified as industrial robots. We also monitor changes in code and definitions, incorporating both robots and robot parts. The detailed HS codes and definitions are presented in Table 1.

A central limitation of using firm-level robot import records to proxy for robot adoption is that this measure omits robots produced domestically in the U.S. To assess the validity of our approach, we compare the aggregate time-series patterns of robot imports from U.S. customs data and robot installations data from the International Federation of Robotics (the same data source as in Section 3 with all industries included). We extract 10-digit HS level import data from the USA Trade Online maintained by the U.S. Census for the set of industrial robot products identified in Table 1, and aggregate the annual import value of these products by year.[5] We then construct a comparable U.S. national robot installation measure (aggregated from industry decompositions) by taking the product of number of robot installations and average unit price of industrial robot (extracted from Klump et al. (2021)) each year. In Figure 2, we plot the aggregated trend of the two measures from 1993 to 2016. Although the two series do not coincide in levels, their movement trends track each other closely over time. Both series exhibit pronounced dips around the Dot-com bubble burst and the financial crisis recession, both followed by sustained growth thereafter. The similarity in cyclical patterns between robot imports and IFR robot installation provides useful evidence that our import-based measure captures meaningful variation in robot adoption dynamics.

Using the 10-digit HS codes for industrial robots, we identify robot importing firms in the LFTTD, which provides detailed transactions level data on imports and exports of U.S. firms in the Census Bureau's Business Register.[6] The LFFTD allows us to track the quantity, value, country of origin, destination firm, and types of robots at both shipping and delivery time. We define a firm as adopting robots if it imports robots in a given year. To improve the precision of our adoption measure, we exclude firms in wholesale, finance, insurance, real estate, and professional services (NAICS codes 42, 52 and 53, and 5413-5416), which are more likely to act as robot integrators rather than end users. Our overall approach adapts (Dixon et al., 2021), which uses Canadian data, to the U.S. context.

Our second source of data is the LBD, which is a panel dataset of all establishments in the U.S., covering all industries in the private non-farm economy (Jarmin and Miranda, 2002;

[5] We use value rather than quantities, as quantities may reflect parts and components of robots.

[6] The Census Bureau Business Register covers all tax paying businesses in the U.S. Information on the Business Register and the LFTTD can be found in Walker (1997) and Kaman and Ouyang (2020).

Chow et al., 2021). The LBD contains information on the establishment's age, employment, industry, and location. It also includes establishment and firm identifiers allowing us to identify the ownership structure between firms and establishments. For all our analyses, we restrict our attention to single-unit firms – firms that have a single establishment – which simplifies the analysis of local policy effects by precisely locating the firm.

To create a matched sample of robot importing and non-importing firms, we start with firms identified as robot importing in 1992-2021 from the LFTTD. We use the LBD to extract the age, employment, and 6-digit NAICS industry for the longitudinal history of these robot importing firms over 1992-2021, and restrict the sample to single-unit firms in manufacturing industry. We create age group (0-5, 6-10, 11-15, 16-25, 26+) and employment size group (0-4, 5-9, 10-19, 20-49, 50-99, 100-499, 500+) as categorical variables, so all robot importing firm-year observations can be classified into cells fully interacted by year, age group, employment size group, and 6-digit NAICS industry. The matched sample is constructed to include all firms (robot importing and non-importing) in these cells defined for robot importing firms.

To identify the impact of state-level policy variations on robot adoption, we merge minimum wage data obtained from the Department of Labor with LBD sample by firm location. This approach yields two samples of analysis as shown in Table 2.

4.2 Empirical Strategy

First, we run firm-level OLS regressions on an indicator for whether the firm adopts a robots:

$$\text{Adopt}_{it} = \alpha + \beta \ln\left(MW_{st}\right) + X_{it} + \psi_i + \tau_t + \epsilon_{it}, \tag{1}$$

where Adopt_{it} is a binary indicator for whether firm i adopts a robot in year t, and $\ln(MW_{st})$ is the natural log of state-level minimum wage in state s at year t. We also include employment size, previous importer dummy as controls (X_{it}) and firm (ψ_i) and year (τ_t) fixed effects. This linear probability model (LPM) approach allows us to estimate how changes in the minimum wage are associated with within-firm changes in the likelihood of robot adoption.

Our preferred empirical strategy exploits cross-state policy variation by exploiting firms located in adjacent counties that share one state border. Our regression function is as follows:

$$\text{Adopt}_{ipt} = \alpha + \beta \ln\left(MW_{st}\right) + X_{it} + \xi_j + \phi_p + \tau_t + \epsilon_{ipt} \tag{2}$$

where Adopt_{ipt} is a binary indicator for whether firm i located in adjacent country pair p adopts a robot in year t, the definition of $\ln(MW_{st})$ remains the same as in equation 1, and

X_{it} includes firm-level controls such as age, employment size, and previous robot importer dummy. Furthermore, we include a rich set of fixed effects to capture time (τ_t) and industry trends (ξ_j), as well as adjacent country pair fixed effects (ϕ_p) to compare firms on either side of the state borders but adjacent counties.[7] This geographic discontinuity allows for better control of unobserved regional shocks, and is a strategy that has been used in a number of other papers studying the effects of labor policies (Holmes, 1998; Dube et al., 2010).

For our sample of single units in county pairs at state borders, a single firm may appear multiple times as it can be located in a county that is along multiple state-borders and in multiple county-pairs. To account for this mechanical correlation in the residuals, we two-way cluster our standard error terms by county and state-border pair.

4.3 Results

Table 2 provides summary statistics for the variables used in our regressions, broken out across the two sets of data samples that we use in this study. Sample 1 includes data for all single-unit manufacturing firms. Sample 2 includes only those single-unit manufacturers that are in counties at state borders that are paired with a county in a neighboring state. Note that because many counties abut more than one other county in a neighboring state, there are many repeated observations for this sample (these repeated observations get addressed via county and state border pair fixed effects in the regressions that follow).

We note that not many firms adopt robots. Of the approximately 240,000 single-unit firms in the full sample, only 2,600 of them ever adopt a robot (mean = 0.0034). In comparison, Brynjolfsson et al. (2023a), which uses data from the U.S. Census Bureau's Annual Survey of Manufacturers, finds that in 2018, approximately 9.8% of firms had robots, and larger firms were more likely than smaller firms to have robots.

The low numbers we find are not surprising for two reasons. First, whereas Brynjolfsson et al. (2023a) use data from 2018, the data we use in our sample goes much further back in time and covers 1992–2019. We know from the International Federation of Robotics (IFR) data that robot adoption increased dramatically during this time period. Given that our sample includes many observations from earlier time periods, when robot adoption was a very rare event, it makes sense that our mean adoption rate is so low. Second, we are identifying robot adoption using import data records. This is likely an undercount as we will miss any firms that adopted robots not by importing them directly but via a third party which acquired and/or resold robots to them.

[7] Our set of fixed effects may vary based on the regression sample but the main specification restricts the sample to border-county firms.

Table 3 provides results on robot adoption for single-unit firms (columns 1 and 2). These results are from linear probability regressions (Equation 1) of robot adoption in year t on log minimum wage in year $t-1$, log firm age in year t, log employment in year t, a dummy variable indicating if the firm has previously imported robots, year fixed effects, and firm fixed effects. Column 2 in addition includes a dummy variable indicating if the state is a right to work state in year $t-1$. Standard errors are clustered at the firm level for all the results reported in the Table.

First focusing on Sample 1 for all single-unit firms, we observe that the coefficient on log minimum wage in year $t-1$ is positive and similar in magnitude in both columns 1 and 2. Column 2 introduces a dummy variable for whether a state is a right to work (RTW) state, which we include to rule out that the coefficient on log minimum wage is driven by contemporaneous changes in RTW policies. The coefficient on the dummy variable indicating if the state is a right to work state in year $t-1$ is positive and significant in this specification.

We next turn to more stringent specifications that focus on firms located close to state borders (sample 2). The goal of this exercise is to control for similar socio-economic or local demand or other unobserved local factors which we assume are similar in counties neighboring each other across state borders. But, the labor policy environment firms face differs depending on the state in which they are based.

Table 3, Sample 2, presents results from a series of "state border" analyses (Equation 2). In columns 3 and 4 we replicate the analyses performed on Sample 1, but focusing on state border pairs of firms, and include state border-pair fixed effects (column 3) and further include a RTW dummy (column 4). For these regressions we see that the coefficient on minimum wage remains positive, statistically significant, but slightly smaller in magnitude to the coefficient in column 2. In contrast, the coefficient on right to work states flips signs but is not statistically significant. For these regressions, standard errors are two-way clustered at the county and state border pair. Columns 5 and 6, include country-pair fixed effects. The results are very similar in magnitude to the results in columns 3 and 4.We take the results of Table 3 to suggest that there is a strong relationship between increasing minimum wage and the subsequent probability of adopting a robot.

To quantify the effects of minimum wage on robot adoption, we take the coefficients from Table 3 columns 2 and 6. Under sample 1 column 2, when minimum wage is 10% higher, the probability of robot adoption increases by 11.6% ($= 0.00394 \times 10\%/0.00341$) of the average adoption rate in the sample. Similarly, under our preferred specification in sample 2 column 6, a 10% increase in minimum wage leads to an 8.4% rise in robot adoption relative to the sample average ($= 0.00255 \times 10\%/0.00304$). These effects are economically meaningful, and their magnitudes closely align with the aggregate-level estimate reported in Section 3 (approximately 8%).

5 Conclusion

Using detailed administrative data from the U.S. Census Bureau, we provide new evidence that higher minimum wages are associated with a greater likelihood of robot adoption among U.S. manufacturing firms. Our findings suggest that wage policy can accelerate the adoption of robots. This has implications for debates on the minimum wage, particularly with respect to employment effects and firm adjustment margins. While robots may enhance productivity, they may also alter the structure of employment, especially in low-wage sectors as typically found in manufacturing.

Our study does not consider labor outcomes, such as employment. Nevertheless, policymakers may wish to consider complementary strategies to mitigate potential displacement effects, such as retraining programs or targeted support for small firms. Future research could examine how robot adoption interacts with labor market institutions, worker outcomes, and firm performance over longer time horizons.

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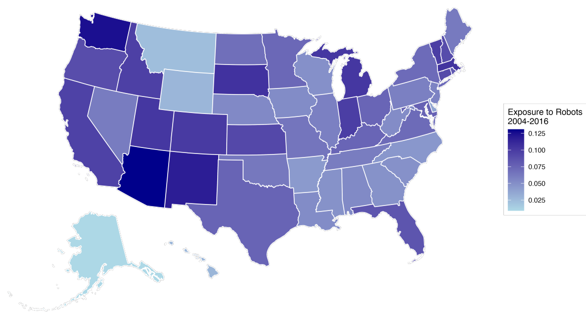
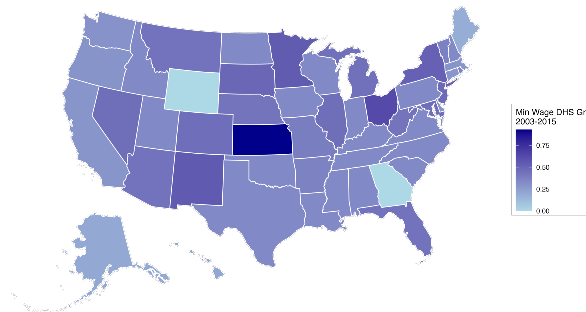
Appendix A: Figures and Tables

Figure 1: State-Level Exposure to Robots and Minimum Wage



(a) Exposure to Robots, 2004-2016



(b) Minimum Wage DHS Growth, 2003-2015

(c) Relationship between Exposure to Robots and Minimum Wage

Figure 2: IFR Aggregate Robot Installation vs Robot Imports in the U.S.

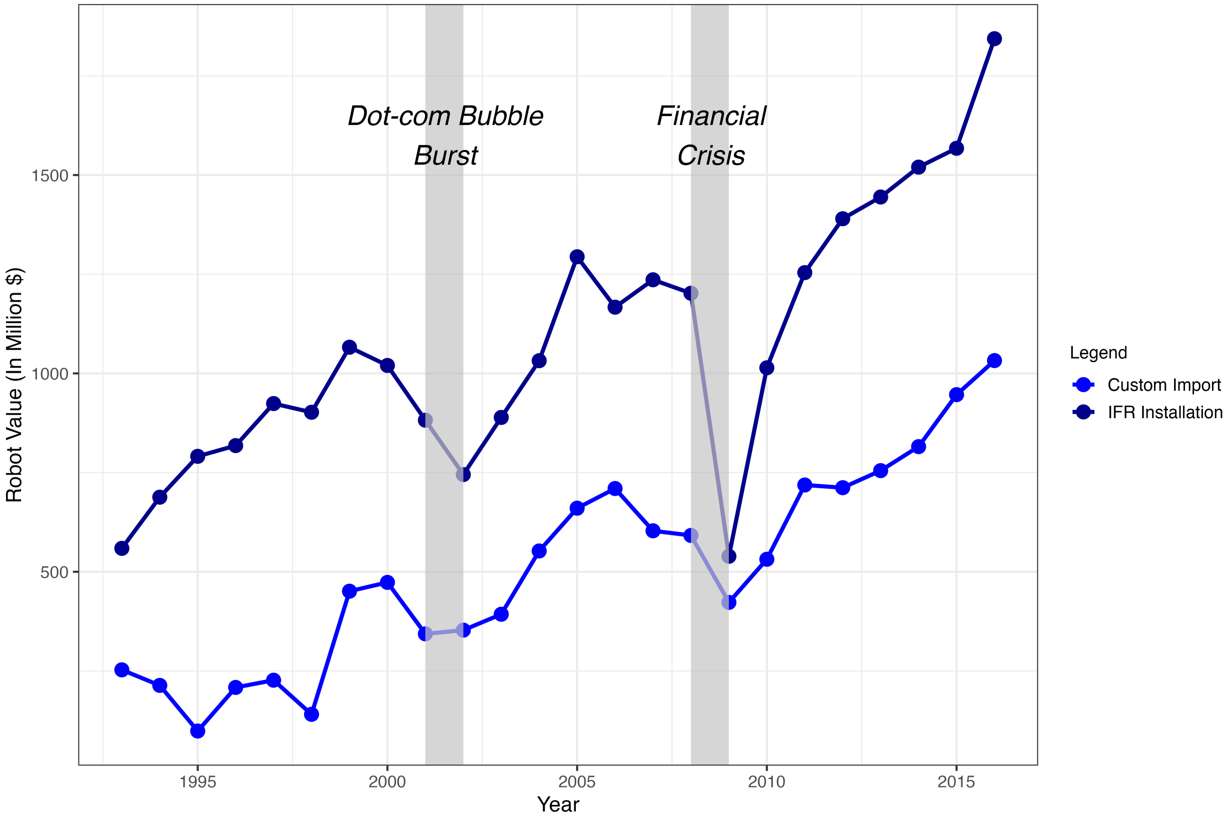


Table 1: Identified Harmonized System (HS) Codes for Industrial Robots

HS10 code	Time Period	Description
Other lifting, handling, loading or unloading machinery (for example, elevators, escalators, conveyors, teleferics):		
8428900010	1992-1997, 1999-2006	
8428900120	2007-2011	Other machinery: industrial robots
8428900220	2012-2021	
8428908015	1997-1998	Other: industrial robots
Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter; parts thereof:		
8479500000	1996-2021	Industrial robots, not elsewhere specified or included
8479899040	1992-1994	Other machines and mechanical appliances (con.): industrial robots
8479899540	1995	
8479908040	1992-1993	Parts, other: industrial robots
8479909440	2002-2021	
8479909540	1994-1997, 1999-2001	Parts, other: of industrial robots
8479909740	1997-1998	

Table 2: Summary Statistics across Two Samples

Sample	1 Single Unit Manufacturers Only		2 Single Units in County Pairs at State Borders	
Variable	Mean	St. Dev.	Mean	St. Dev.
Robot Adoption Dummy	0.00341	0.0583	0.00304	0.0550
log Min Wage (t-1)	1.812	0.272	1.807	0.272
RTW (t-1)	0.289	0.453	0.200	0.400
log Employment	2.274	1.382	2.324	1.375
Number of observations	1544000		1387000	
Number of firms	240000		87000	
Number of robot-importing firms	2600		900	

Table 3: The Impact of Minimum Wage on Robot Adoption

	Robot Adoption					
	Sample 1		Sample 2			
	(1)	(2)	(3)	(4)	(5)	(6)
log Min Wage (t-1)	0.00365***	0.00394***	0.00275**	0.00257*	0.00280**	0.00255*
	(0.00110)	(0.00110)	(0.00135)	(0.00145)	(0.00135)	(0.00143)
RTW (t-1)		0.00207***		-0.000278		-0.000494
		(0.000784)		(0.000488)		(0.000608)
log Employment	0.00274***	0.00275***	0.00216***	0.00216***	0.00215***	0.00215***
	(0.000186)	(0.000186)	(0.000202)	(0.000202)	(0.000196)	(0.000197)
Previous Importer Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects			Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes				
log Firm Age			Yes	Yes	Yes	Yes
Border-pair Fixed Effects			Yes	Yes		
County-pair Fixed Effects					Yes	Yes
SE Clustering	Firm	Firm	County and State Border-pair Two-way	County and State Border-pair Two-way	County and State Border-pair Two-way	County and State Border-pair Two-way
Observations	1544000	1544000	1387000	1387000	1387000	1387000
Firms	240000	240000	87000	87000	87000	87000
Adjusted R-squared	0.19	0.19	0.089	0.089	0.09	0.09