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Abstract

In recent years, the use of industrial robots has witnessed a significant surge. While the fact that primary driver behind this surge is labor costs is widely acknowledged, there is a little attention on how cost-related shocks influence the decision to integrate robots within a firm. This paper examines how manufacturing firms in Turkey respond to a sudden 33.5% increase in the minimum wage in 2016 concerning their decisions to import robots. Using administrative employer-employee data, along with firm-level trade and balance sheet data, and employing a difference-in-differences approach with continuous treatment, the study finds that the minimum wage shock does not significantly impact robot adoption. However, this finding is contingent on firm size. Medium-sized firms exhibit a positive and significant propensity to adopt robots, with this effect being more pronounced for large firms compared to their smaller counterparts. Quantitatively, a one-point increase in the share of minimum wage employment in total employment corresponds to a 0.4% and 2.4% increase in the probability of importing robots for medium and large firms, respectively. These results hold robustly across different definitions of robot adoption. Notably, these firms display a tendency to augment their existing robotic equipment when confronted with a minimum wage shock.

Keywords: robots, minimum wage, Turkey, difference-in-differences
JEL Classification: O14, J30, O39

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1 Introduction

In recent years, the utilization of industrial robots in the manufacturing industry has experienced a notable surge. According to the International Federation of Robotics (IFR), the operational stock of robots has tripled since 2010. While nearly half of these robots are deployed in Europe, the US, and South Korea, China accounts for two-thirds of the remainder. Concurrently, firms in other developing countries are increasingly adopting robotics to revolutionize their production processes.

This transformative shift in manufacturing has prompted scholars to investigate the impact of robotics on employment and wages. While many studies suggest that the adoption of robots significantly reduces employment and earnings, especially in developed countries (Dauth et al., 2021; Acemoglu et al., 2020; Bessen et al., 2022; Acemoglu and Restrepo, 2020; Artuc et al., 2019), there are also studies demonstrating no negative employment effects and, in some cases, positive effects of robotization in developing (Calì et al., 2022; Graetz and Michaels, 2018) and certain developed countries (Dottori, 2021; Klenert et al., 2022; Tuhkuri, 2022). Various mechanisms, such as productivity effects, diminishing returns, and product innovation, have been proposed to explain this puzzle.

However, in the literature, determinants of robot adoption, particularly cost-related variables, are not extensively studied due to two main challenges. The first challenge is the measurement issue of robots. Some studies use survey data to identify when and which firms adopt robots (Tuhkuri, 2022; Bessen et al., 2022; Acemoglu et al., 2020; Deng et al., 2021), while others develop exposure indices using country-industry level data obtained from the IFR (Klenert et al., 2022; Dauth et al., 2021; Acemoglu and Restrepo, 2020; Calì et al., 2022). The former approach faces representation issues, while the latter is influenced by variation from employment weights. The latest studies utilize trade data to measure robot adoption (Acemoglu et al., 2023). Another issue in robot studies is the endogeneity of possible determinants with robot adoption (Fan et al., 2021). For example, Koch et al. (2021) finds self-selection among Spanish firms. However, Acemoglu and Restrepo (2018) emphasizes the role of factor prices in the adoption of robots in production. Acemoglu et al. (2023) estimate a robot adoption model and find a negative association between labor share and the likelihood of importing a robot. In summary, empirical evidence regarding the effect of labor market shocks on robot adoption is limited. As for causal evidence, Deng et al. (2021) and Fan et al. (2021) use minimum wage variation as a quasi-natural experiment for Germany and China, respectively, and observe that the minimum wage is more likely to drive firms toward robot adoption.

This study aims to investigate how a minimum wage shock alters the robot adoption decisions of Turkish enterprises. In 2016, Turkey implemented a sudden 33.5% increase in the minimum wage. This shock provides an opportunity to isolate exogenous shocks to labor costs and test the price mechanism. Moreover, we can observe how labor market shocks affect the robotization process in a developing country at the early stages of automation. Our empirical strategy relies on differences-in-differences to examine how firms are affected by the 2016 minimum wage increase when considering the purchase of robots. The ratio of minimum wage employment to total employment of a firm in 2015 will be used as the treatment intensity. Our outcome variable, the robot adoption of a firm, is defined in terms of the extensive and intensive margins.

Our baseline findings show that the minimum wage shock insignificantly affects the decision of firms to import and adopt robots. However, we find that this null effect is attributed to the dominance of small firms in the sample. After interacting firm size with the variable of interest, we observe that firm size matters in responding to the minimum wage shock in terms of adopting robotization. Medium and, particularly, large firms have a more significant probability of importing and adapting robots. Moreover, it is not a one-time purchase; these firms are more likely to continue purchasing robots over time, according to intensive margin results.

2 Data

2.1 Robot adaption

We utilize the administrative data from Turkish firms, sourced from the Enterprise Information System (EIS) of the Ministry of Science, Industry, and Technology. This comprehensive dataset merges trade, balance sheet, and firm-to-firm domestic trade, allowing for merging using the firm identifier for the period spanning 2010 to 2021[1].

The identification of firms adapting robotic technologies into their production processes is accomplished through the trade dataset. Industrial robots are classified under code 847950 in the Harmonized System (HS). Descriptive analysis reveals that 716 manufacturing firms in Turkey have imported these robots at least once. While

[1]For our analysis, we exclude the last two years due to the disruptive effects of the COVID-19 shock.

this may seem a modest fraction relative to the total number of manufacturing enterprises (465,587), it constitutes a substantial share among large firms. Out of 2,006 firms employing 250 or more individuals, 258 firms have engaged in robot imports.

Figure 1 depicts the annual import of robots categorized by firm size. Until 2014, large firms exhibited considerable volumes of robot imports. Although they continue to lead in subsequent years, the total imports across all firm sizes exhibit a stabilized pattern. Figure 2 portrays the total deployment of robots for each year, utilizing the International Federation of Robotics (IFR) dataset, which aggregates robot sales from producer companies. A noteworthy proportion of these installations is attributed to the automotive industry, aligning with global trends.

The geographic distribution of the number of robot importers during our analysis period is illustrated in Figure 3. The graph highlights a concentration of robot importers in specific regions, notably central Anatolia, northwest, and west. This spatial pattern is unsurprising, given that these regions boast a higher share of the manufacturing industry, particularly in the automotive sector as IFR dataset showed in Figure 2.

2.2 Employment data

We integrate the previously mentioned trade data with the employer-employee administrative dataset provided by the Social Security Institute of Turkey. This dataset offers detailed information about employees, including firm details (enterprise and plant), occupation, gender, age, workdays, and daily wage. Consequently, we calculate the minimum wage share of each firm by aggregating the earnings of workers around the daily minimum wage and dividing it by the total employment[2]. We focus on the firm shares in 2015, the last year preceding the minimum wage shock.

Our analysis reveals that 391,861 workers were employed by firms that imported robots between 2010 and 2019. Of these, 92% were engaged in the manufacturing sector, with large firms employing 90% of these workers, while the remaining workforce is distributed among small and medium-sized firms, with only 0.1% in micro firms. According to the International Standard Classification of Occupations (ISCO), 22% are classified as high-skilled, exceeding the corresponding rate for the manufacturing industry (13.5%). Demographically, 56% fall into the young-aged category (18-34),

[2] An employee is identified as a minimum wage worker if their daily wage falls within the lower (95%) and upper (105%) bounds of the announced minimum wage level during the specified period.

surpassing the overall manufacturing industry average of 50%. Additionally, over 85% of employees are male, mirroring the distribution in the manufacturing industry.

Importantly, firms importing robots tend to have fewer minimum wage employees, primarily due to a significant proportion of robot importers being large-scale enterprises. Only 4.8% of total workers in this group are minimum wage earners, contrasting with the overall employee population where this figure exceeds 40%.

3 Identification

We employ a difference-in-differences estimation with a continuous treatment framework, enabling a comparison of pre-treatment outcomes considering different minimum wage/total employment intensities. Specifically, we estimate the following equation:

$$y_{it} = \alpha + X_{it}'\Phi + \beta \text{minimum wage share}_{it} + D_i + D_t + D_{kt} + D_{pt} + \varepsilon_{it} \qquad (1)$$

where the outcome variable y_{it} takes two forms. Firstly, the extensive margin is a dummy variable equal to 1 if firm i adopts robotization in its production at time t. We use two definitions to identify a firm as a robot adapter: the first considers any robot import irrespective of its value, and the second, following Acemoglu et al. (2023), designates firms as adapters if the cumulative monetary value of their robot imports exceeds the median robot import value ($47,000) of all firms. As the second form of the outcome variable, the intensive margin is calculated as the log of cumulative monetary value and quantity (weight) of robot imports adopted by firm i. X_{it} are minimum wage share quantile fixed effects multiplied by time trend to capture the domination of small firms that had never imported robot. D_i and D_t are time-invariant firm and year fixed effects, respectively. Industry-level shocks for each period are captured using industry-year fixed effects D_{kt}. D_{pt} represents province-year fixed effects to control for regional shocks over time. Finally, β denotes the effect of the ratio of the minimum wage employment share of a firm in 2015 on the likelihood of being a robot adapter. We track minimum wage employees using their daily wages. As a robustness check, we also adopt a gap measure frequently used in the minimum wage literature, representing the proportion of potential change in the total minimum wage payments of the firm to the total wage bill. Additionally, we interact the variable of interest with firm size to test the hypothesis that large firms are more likely to implement robotization than their smaller counterparts[3].

4 Results

Table 1 presents the results of the extensive margin estimation based on Equation (1). Due to the presence of high-dimensional fixed effects, we employ the linear probability model (LPM) estimator. In the first column, we report the effect of the minimum wage share of the firm without incorporating any firm size interaction. While a positive coefficient is observed, indicating a potential effect, there is no significant impact on the decision to import robots. However, when firm sizes are considered, it becomes evident that medium and large firms are more inclined to import robots. Quantitatively, a one-point increase in the ratio of minimum wage workers in total employment corresponds to a 0.4% and 2% increase in the likelihood of robot import for medium and large firms, respectively. We corroborate these findings when employing a binary outcome variable indicating whether the firm imported robots above the median import value in columns 3 and 4. Nevertheless, the magnitudes of the coefficients are lower than those in columns 1 and 2, and the significance levels are weaker.

The results for the intensive margin can be found in Table 2. In column 1, as observed in the corresponding column of Table 1, the minimum wage share insignificantly affects the robot import value of firms. However, column 2 demonstrates that firm size plays a role in the decision to adopt robots in response to a minimum wage shock. Medium firms with a higher minimum wage share import 4.1% more robots compared to small firms with the same share. Furthermore, the propensity to import is 30% higher for large firms. These numbers slightly decrease when considering robot quantity, as seen in column 4.

As a robustness check, we alter the variable of interest using the gap measure of the minimum wage share. Extensive margin results in Table 3 reveal that while baseline specifications (columns 1 and 3) remain insignificant, firm size-interacted models report higher magnitudes and stronger significance compared to Table 1. Intensive margin results in Table 4 also present similar findings when compared to Table 2.

As an additional robustness check, we implement an event study design in Figures 4 to 7. These figures correspond to columns 2 and 4 in Tables 1 and 2. The plots reveal that large firms gradually increase their probability of robot importation and

[3] We use OECD employment definition to identify the firm size. 10-50, 50-249 and 249+ are small, medium and large firms, respectively.

adoption. Moreover, after integrating robots into their production stages, they escalate the number of equipment over time. Medium firms exhibit a similar tendency but to a lesser extent.

5 Conclusion

It is widely recognized that competition forces firms to manage costs effectively and embrace new technologies to enhance productivity. The rapid penetration of robotic technologies into firms in recent years has prompted scholars to scrutinize how labor costs influence the adaptive behavior of firms towards automation, despite limited empirical evidence linking the two.

This study aims to elucidate how firms adjust their adoption behavior of automation when confronted with a cost shock that can be partially mitigated through the use of robots. Leveraging a quasi-experiment involving a sudden and substantial minimum wage increase, our findings reveal that, on average, manufacturing firms in Turkey did not significantly alter their robot purchasing behavior. However, medium and large-scale firms with a high intensity of minimum wage employment are notably more inclined to adopt robots compared to smaller firms. As evidenced by the results on the intensive margin, these larger firms also amplify their existing robot imports in response to the minimum wage shock.

Our future endeavors in this study involve exploring whether the occupation and gender composition of firms play a role in their response to the minimum wage shock, thereby enhancing the robustness of results across various estimators.

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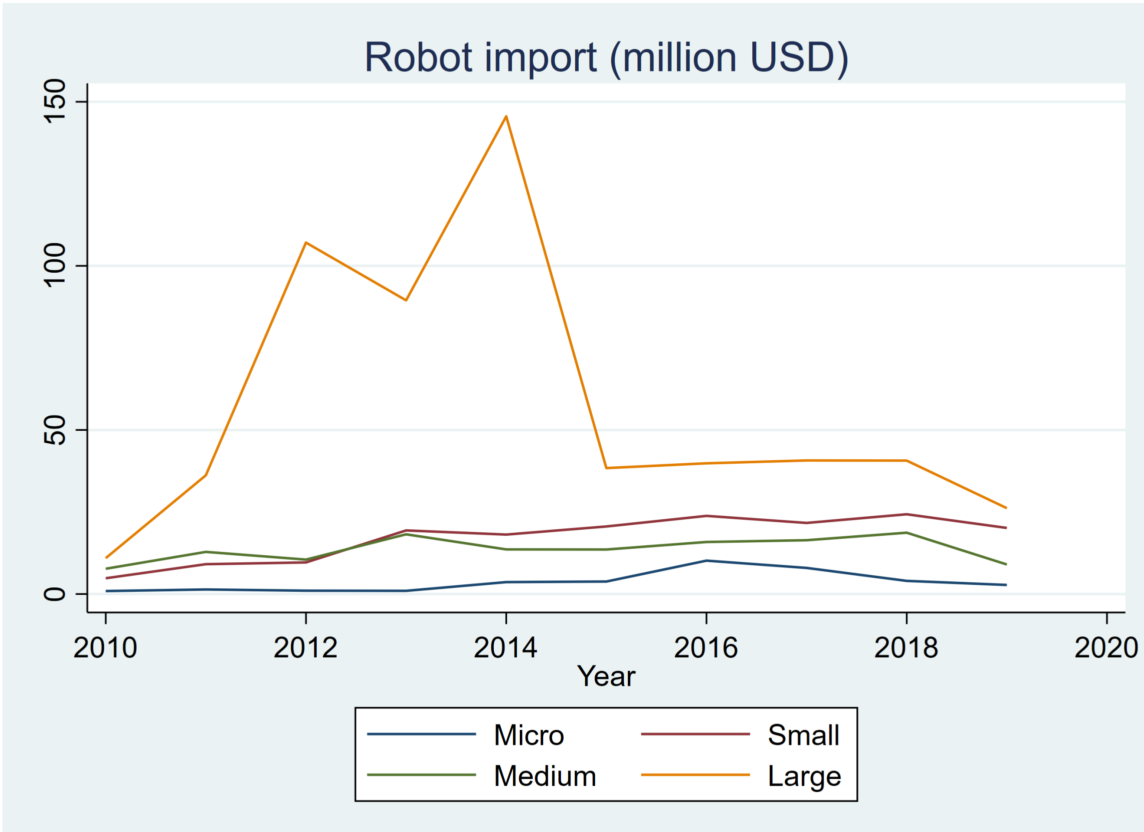
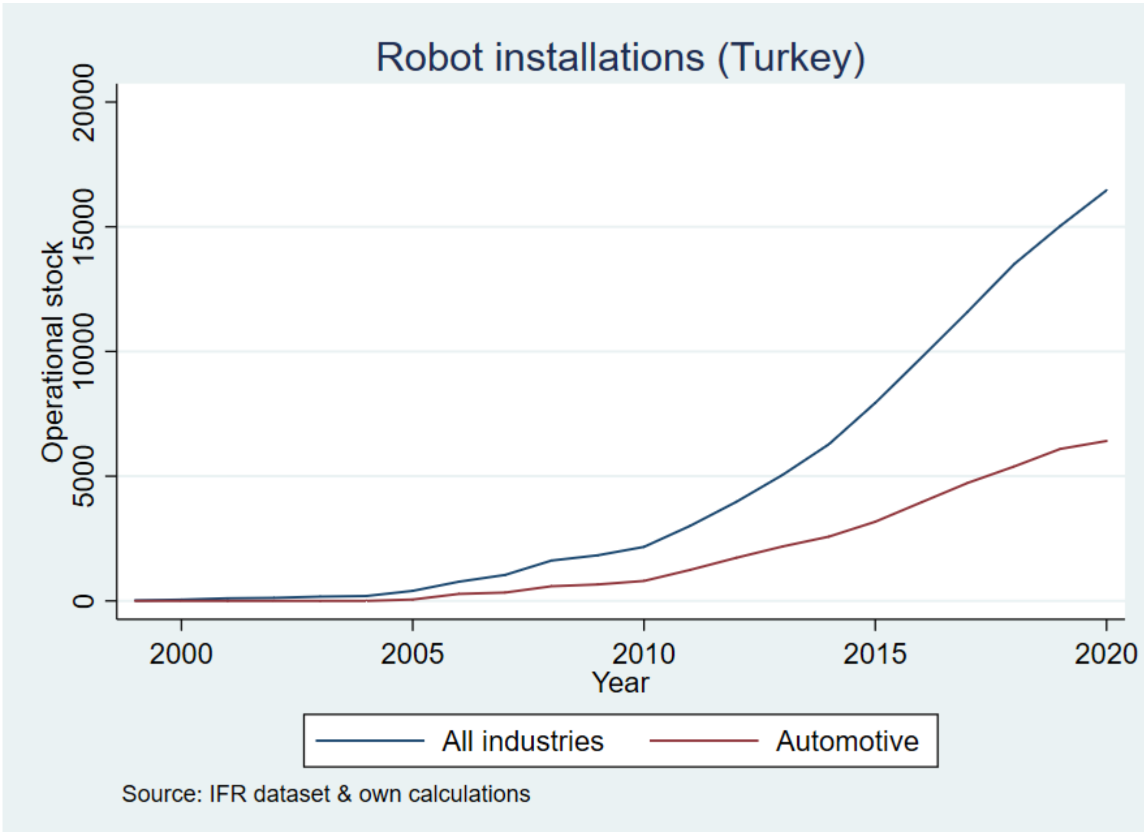
Figure 1. Total robot import by firm size



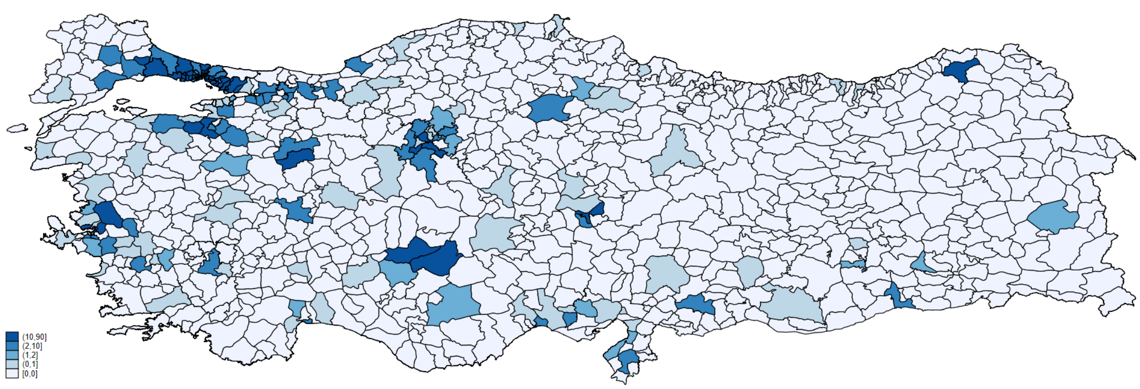
Source: Authors' own calculations using EIS dataset.

Figure 2. Total robot installations, all and automotive industry



Source: Authors' own calculations using IFR dataset.

Figure 3. Regional distribution of number of robot importers



Source: Authors' own calculations using EIS dataset.

Table 1. Effect of minimum wage shock on robot adaption, extensive margin

Dependent Variables:	Robot importer		Robot adapter	
	No interaction	Medium and large	No interaction	Medium and large
Model:	(1)	(2)	(3)	(4)
Variables				
minimum wage share$_{it}$	0.0003	0.0002	0.0002	0.0001
	(0.0013)	(0.0013)	(0.0010)	(0.0010)
minimum wage share$_{it}$		0.0040^{**}		0.0016^{*}
$\times$ medium		(0.0015)		(0.0008)
minimum wage share$_{it}$		0.0247^{**}		0.0190^{*}
$\times$ large		(0.0099)		(0.0085)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes
Min. wage share quantile FE $\times$ t.trend	Yes	Yes	Yes	Yes
Fit statistics				
Observations	411,531	411,531	411,531	411,531
R^2	0.82486	0.82491	0.82829	0.82832
Within R^2	0.00537	0.00562	0.00576	0.00594

Notes: Each coefficient shows the effect of total minimum wage employment employment/total employment ratio on likelihood of robot importer (columns 1 and 2) and robot adapter (columns 3 and 4) for 2010-19 period. Robot adapter is defined as binary outcome if firm has above the median robot import value. In columns 2 and 4 we interacted variable of interest with firm size. We use firm size definition of OECD based on employment. Base category is small firms. Firm, year, NACE $\times$ year, province $\times$ year, and minimum wage quantile FE $\times$ time trend are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at Firm & year.

Table 2. Effect of minimum wage shock on robot adaption, intensive margin

Dependent Variables:	Log(Cumulative robot value+1)		Log(Cumulative robot quantity+1)	
	No interaction	Medium and large	No interaction	Medium and large
Model:	(1)	(2)	(3)	(4)
Variables				
minimum wage share$_{it}$	0.0022	0.0013	0.0023	0.0017
	(0.0148)	(0.0148)	(0.0102)	(0.0102)
minimum wage share$_{it}$		0.0410**		0.0280**
$\times$ medium		(0.0154)		(0.0104)
minimum wage share$_{it}$		0.3017**		0.2176**
$\times$ large		(0.1159)		(0.0829)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes
Min. wage share	Yes	Yes	Yes	Yes
quantile FE $\times$ t.trend				
Fit statistics				
Observations	411,531	411,531	411,531	411,531
R^2	0.85095	0.85099	0.85850	0.85854
Within R^2	0.00714	0.00741	0.00748	0.00775

Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the log of cumulative robot import value (columns 1 and 2) and quantity (columns 3 and 4) for 2010-19 period. In columns 2 and 4 we interacted variable of interest with firm size. We use firm size definition of OECD based on employment. Base category is small firms. Firm, year, NACE $\times$ year, province $\times$ year, and minimum wage quantile FE $\times$ time trend are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at Firm & year.

Table 3. Effect of minimum wage shock on robot adaption, extensive margin, gap measure

Dependent Variables:	Robot importer		Robot adapter	
	No interaction	Medium and large	No interaction	Medium and large
Model:	(1)	(2)	(3)	(4)
Variables				
minimum wage share$_{it}$	0.0018	0.0019	0.0004	0.0006
	(0.0051)	(0.0051)	(0.0036)	(0.0037)
minimum wage share$_{it}$		0.0142^{**}		0.0057^{*}
$\times$ medium		(0.0049)		(0.0027)
minimum wage share$_{it}$		0.0925^{**}		0.0634^{**}
$\times$ large		(0.0353)		(0.0270)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes
Min. wage gap share quantile FE $\times$ t.trend	Yes	Yes	Yes	Yes
Fit statistics				
Observations	411,531	411,531	411,531	411,531
R^2	0.82510	0.82510	0.82850	0.82850
Within R^2	0.00670	0.00700	0.00730	0.00750

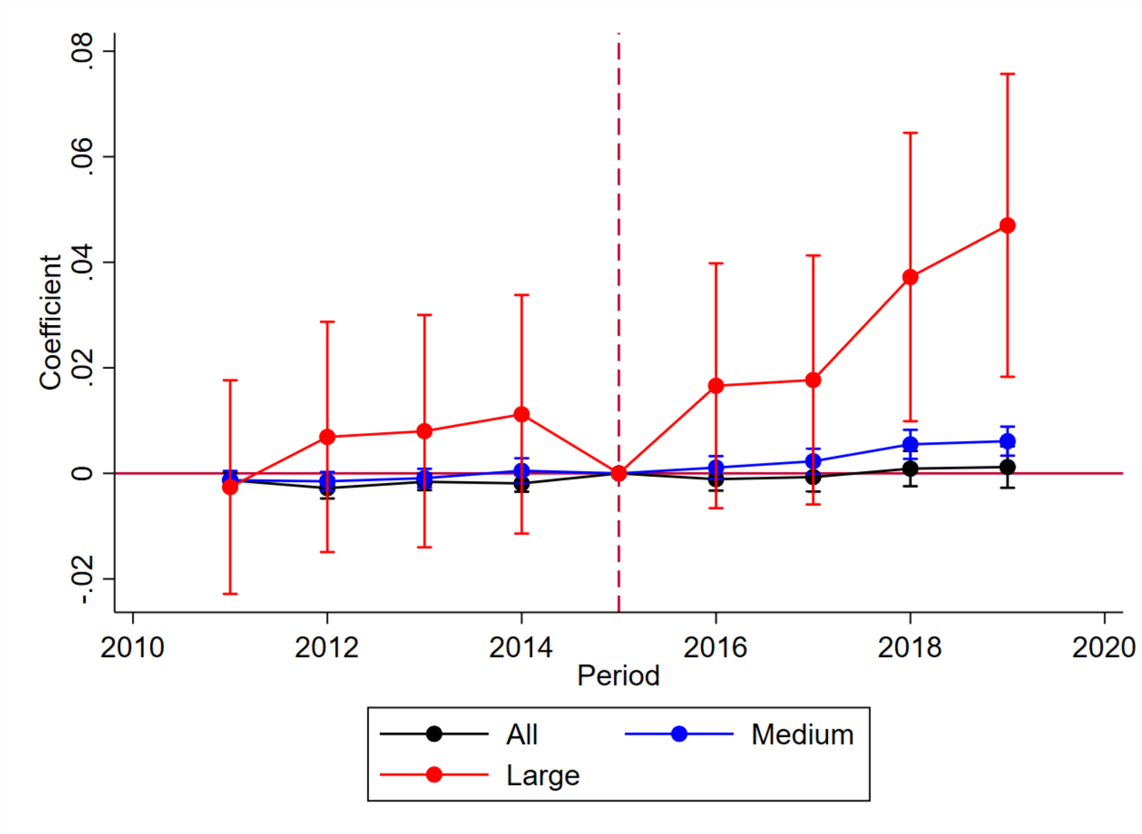
Notes: Each coefficient shows the effect of total minimum wage payment bill employment/total wage bill ratio on likelihood of robot importer (columns 1 and 2) and robot adapter (columns 3 and 4) for 2010-19 period. Robot adapter is defined as binary outcome if firm has above the median robot import value. In columns 2 and 4 we interacted variable of interest with firm size. We use firm size definition of OECD based on employment. Base category is small firms. Firm, year, NACE $\times$ year, province $\times$ year, and minimum wage quantile FE $\times$ time trend are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at Firm & year.

Table 4. Effect of minimum wage shock on robot adaption, intensive margin, gap measure

Dependent Variables:	log(Cumulative robot value+1)		log(Cumulative robot quantity+1)	
	No interaction	Medium and large	No interaction	Medium and large
Model:	(1)	(2)	(3)	(4)
Variables				
minimum wage share$_{it}$	0.0118	0.0141	0.0082	0.0100
	(0.0597)	(0.0602)	(0.0423)	(0.0427)
minimum wage share$_{it}$		0.1423**		0.0937**
$\times$ medium		(0.0498)		(0.0332)
minimum wage share$_{it}$		1.102**		0.7815**
$\times$ large		(0.4008)		(0.2845)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes
Min. wage gap share quantile FE $\times$ t.trend	Yes	Yes	Yes	Yes
Fit statistics				
Observations	411,531	411,531	411,531	411,531
R^2	0.85120	0.85120	0.85870	0.85880
Within R^2	0.00900	0.00940	0.00940	0.00980

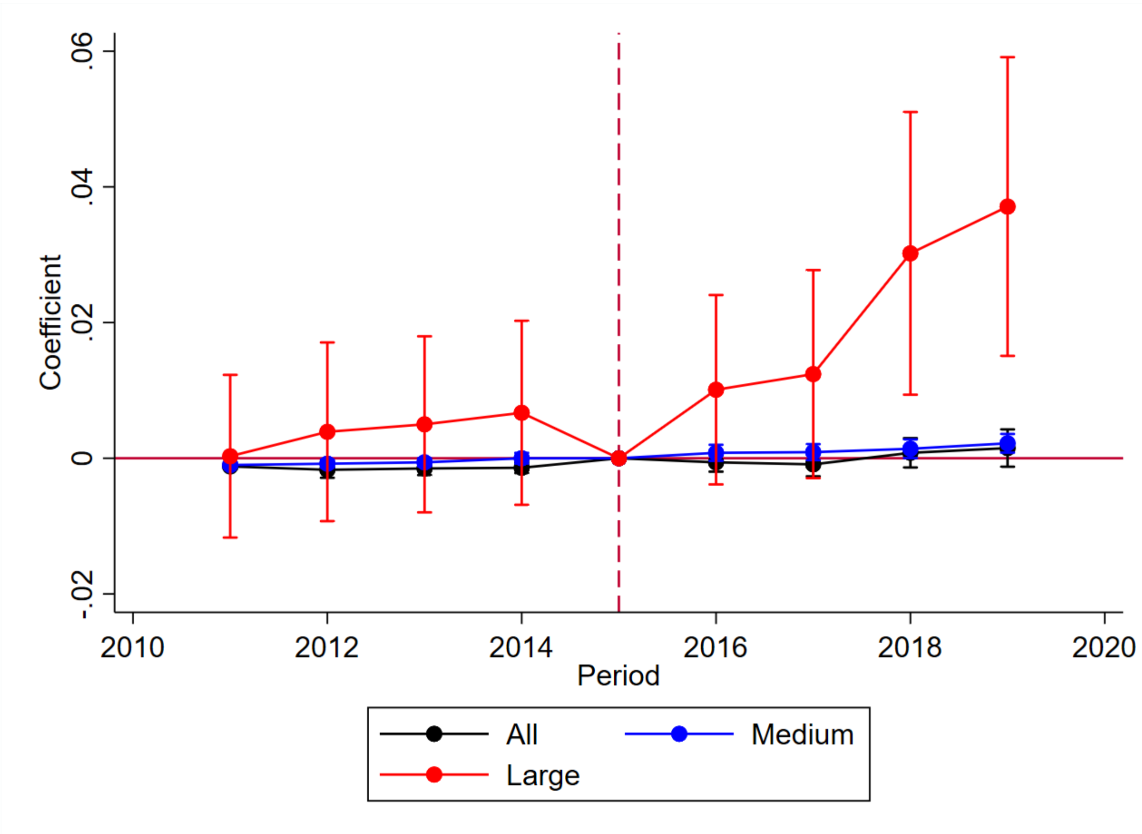
Notes: Each coefficient shows the effect of minimum wage payment bill/total wage bill ratio on the log of cumulative robot import value (columns 1 and 2) and quantity (columns 3 and 4) for 2010-19 period. In columns 2 and 4 we interacted variable of interest with firm size. We use firm size definition of OECD based on employment. Base category is small firms. Firm, year, NACE × year, province × year, and minimum wage gap quantile FE × time trend are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at Firm & year.

Figure 4. Minimum wage shock and robot importer probability: Coefficient estimates for each year, extensive margin



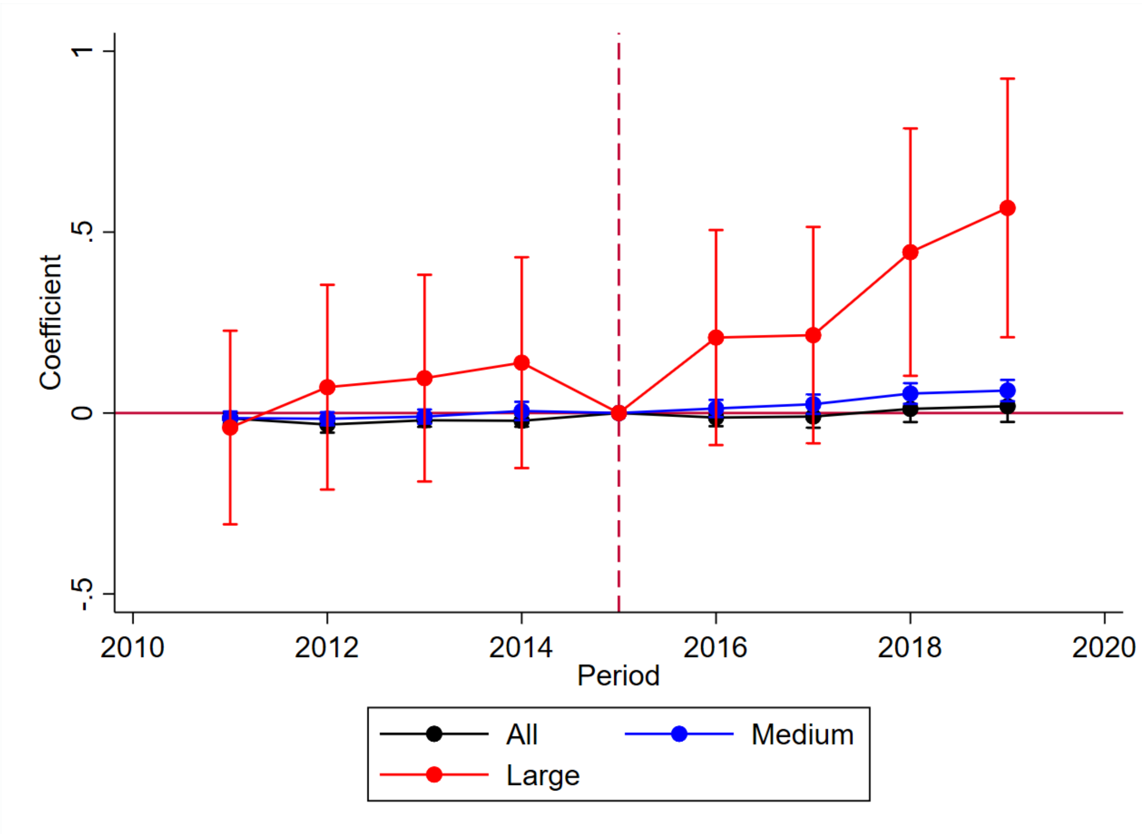
Notes: This figure plots the coefficients of the regression examining the yearly effects of minimum wage shock on being robot importer from 2011 to 2019. Estimated model is identical to Equation (1). Variable of interest (minimum wage share$_{it}$) is interacted with firm size. While medium defines the firms having employees between 50 and 250, large is above 250 as discussed in Section 3. Base catogory is small firms. The confidence intervals are at 95% level.

Figure 5. Minimum wage shock and robot adapter probability: Coefficient estimates for each year, extensive margin, extensive margin



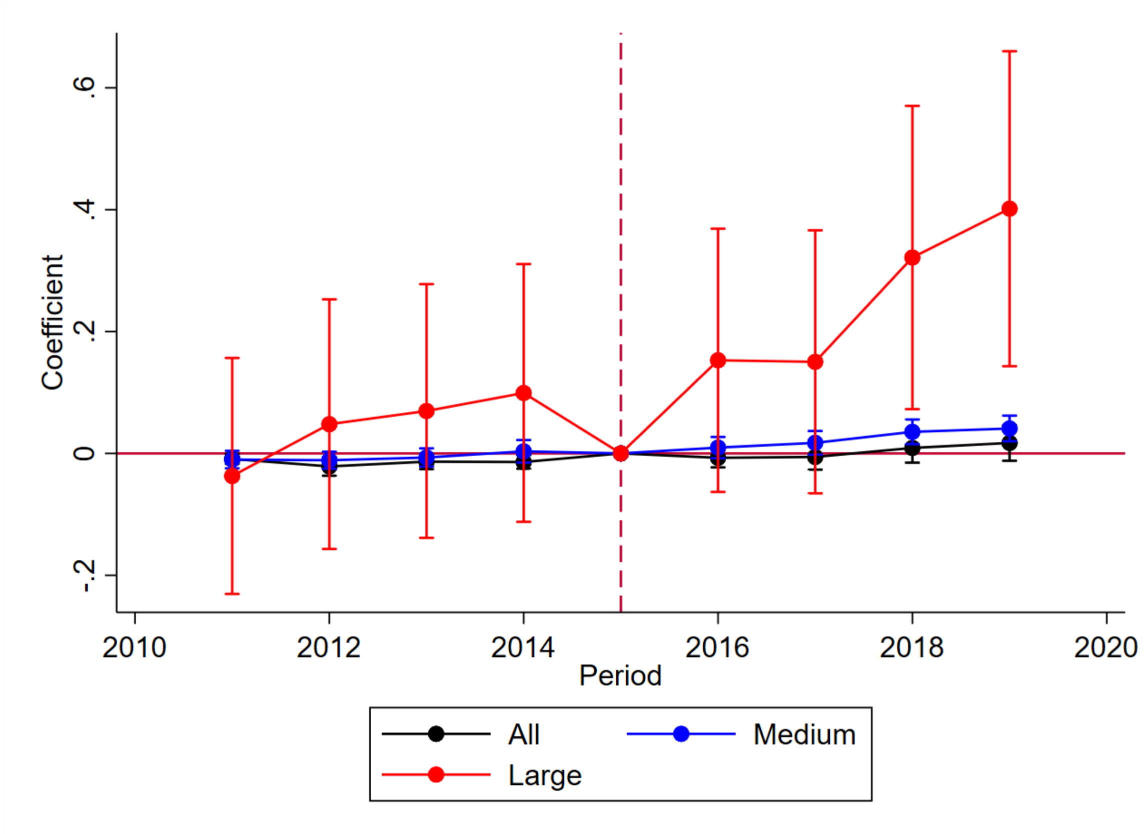
Notes: This figure plots the coefficients of the regression examining the yearly effects of minimum wage shock on being robot adapter from 2011 to 2019. Being robot adapter is defined if cumulative robot import value of firm is above the median value of robot import value among all robot importers in whole period. Estimated model is identical to Equation (1). Variable of interest (minimum wage share$_{it}$) is interacted with firm size. While medium defines the firms having employees between 50 and 250, large is above 250 as discussed in Section 3. Base catogory is small firms. The confidence intervals are at 95% level.

Figure 6. Minimum wage shock and cumulative robot import value: Coefficient estimates for each year, extensive margin, intensive margin



Notes: This figure plots the coefficients of the regression examining the yearly effects of minimum wage shock on the log of cumulative robot import value from 2011 to 2019. Estimated model is identical to Equation (1). Variable of interest (minimum wage share$_{it}$) is interacted with firm size. While medium defines the firms having employees between 50 and 250, large is above 250 as discussed in Section 3. Base catogory is small firms. The dependent variable is in logs. The confidence intervals are at 95% level.

Figure 7. Minimum wage shock and cumulative robot import quantity: Coefficient estimates for each year, extensive margin, intensive margin



Notes: This figure plots the coefficients of the regression examining the yearly effects of minimum wage shock on the log of cumulative robot import quantity (weight) from 2011 to 2019. Estimated model is identical to Equation (1). Variable of interest (minimum wage share$_{it}$) is interacted with firm size. While medium defines the firms having employees between 50 and 250, large is above 250 as discussed in Section 3. Base catogory is small firms. The dependent variable is in logs. The confidence intervals are at 95% level.