ERF Working Papers Series

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ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

Working Paper No. 1768
December 2024

THE IMPACT OF MINIMUM WAGE SHOCK ON ROBOT ADAPTION IN TURKEY

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December 2024

This paper was originally presented during the ERF 30th Annual Conference on "Tragedies of Regional Conflicts and Promises of Peacebuilding: Responding to Disruptors and Enablers of MENA Development Pathway", April 21-23, 2024.

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First published in 2024 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Abstract

In recent years, the surge in industrial robot usage has been prominently driven by labor costs. However, the impact of cost-related shocks on firms' decisions to integrate robots has received limited attention. This study investigates how manufacturing firms in Turkey reacted to a sudden 33.5% increase in the minimum wage in 2016 regarding their robot importation decisions. Utilizing administrative employer-employee data, firm-level trade, and balance sheet data, and employing a difference-in-differences approach with a continuous treatment, we find that the minimum wage shock overall does not significantly affect robot adoption. Yet, this effect varies by firm size; medium-sized firms show a positive and significant propensity to adopt robots, which is even more pronounced in large firms. Quantitatively, a one-point increase in the share of minimum wage employment in total employment leads to a 0.4% increase in the probability of importing robots for medium firms and a 2.7% increase for large firms. These findings are consistent across both extensive and intensive margins of robot adoption. Firms with a high intensity of blue-collar and routine task workers are particularly more likely to import robot in response to a minimum wage shock. Moreover, competitive pressures in the industries also spur firms towards robot adoption.

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

ملخص

في السنوات الأخيرة، كانت الزيادة في استخدام الروبوتات الصناعية مدفوعة بشكل بارز بتكاليف العمالة. ومع ذلك، فإن تأثير الصدمات المرتبطة بالتكلفة على قرارات الشركات بدمج الروبوتات قد حظي باهتمام محدود. تبحث هذه الدراسة في كيفية تفاعل شركات التصنيع في تركيا مع الزيادة المفاجئة بنسبة 33.5٪ في الحد الأدنى للأجور في عام 2016 فيما يتعلق بقرارات استيراد الروبوتات. باستخدام البيانات الإدارية بين صاحب العمل والموظف، والتجارة على مستوى الشركة، وبيانات الميزانية العمومية، واستخدام نهج الاختلاف في الاختلاف مع المعاملة المستمرة، نجد أن صدمة الحد الأدنى للأجور بشكل عام لا تؤثر بشكل كبير على اعتماد الروبوت. غير أن هذا الأثر يختلف باختلاف حجم الشركة ؛ تُظهر الشركات متوسطة الحجم ميلًا إيجابيًا وهامًا لتبني الروبوتات، وهو أمر أكثر وضوحًا في الشركات الكبيرة. من الناحية الكمية، تؤدي الزيادة بمقدار نقطة واحدة في حصة الحد الأدنى للأجور في إجمالي العمالة إلى زيادة بنسبة 0.4٪ في احتمال استيراد الروبوتات للشركات المتوسطة وزيادة بنسبة 2.7٪ للشركات الكبيرة. هذه النتائج متسقة عبر كل من الهوامش الواسعة والمكثفة لاعتماد الروبوت. من المرجح بشكل خاص أن تستورد الشركات ذات الكثافة العالية من ذوي الياقات الزرقاء وعمال المهام الروتينية الروبوت استجابة لصدمة الحد الأدنى للأجور. علاوة على ذلك، تحفز الضغوط التنافسية في الصناعات الشركات أيضًا على تبني الروبوت.

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 indicate that the minimum wage shock does not significantly impact the overall decision of firms to import and adopt robots. However, this seemingly null effect is primarily due to the prevalence of small firms in our sample. Upon analyzing the interaction between firm size and the variable of interest, it becomes evident that firm size plays a crucial role in responding to the minimum wage shock, particularly in terms of robot adoption. Specifically, medium and large firms demonstrate a significantly higher likelihood of importing and adapting robots. This trend extends beyond initial purchases, as evidenced by intensive margin results, which show that these firms are likely to continue acquiring robots over time.

Furthermore, the same firms, characterized by a high intensity of blue-collar and routine task occupations among their workers, are also more inclined to adopt robots. This suggests that the robot adoption behavior of medium and large-scale firms is largely driven by their need to automate repetitive tasks that are well-suited for robotic substitution. Additionally, irrespective of their size, firms that are heavily engaged in research and development and operate in competitive industries tend to integrate robots into their production processes.

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 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.

The geographic distribution of the number of robot importers during our analysis period is illustrated in Figure 1. The graph highlights a concentration of robot importers in specific

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

regions, notably central Anatolia, northwest, and west.

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), 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].

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:

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

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 import time to identify a firm as a robot importer, considering any robot import irrespective of its

[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.

[3] Even though this share seems little, wage bill would be equivalent to a large amount for a large firm because of their high number of employees.

value. After that year, we assume this firm as robot importer even if it did not import a robot. 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[4].

4 Results

4.1 Baseline results

Table 1 presents the estimation results based on Equation (1). In the first three column, we report the effect of the minimum wage share of the firm without incorporating any firm size interaction. Due to the presence of high-dimensional fixed effects, we employ the linear probability model (LPM) estimator in extensive margin part as seen in the columns 1. Even though a positive coefficient is observed, there is no significant impact on the decision to import robots. Similar findings are obtained for intensive margin results in column 2 and 3.

On the other hand, when firm sizes are considered, it becomes evident that medium and large firms are more inclined to import robots when they face a minimum wage shock. 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.

Intensive margin results allowing for firm size heterogeneity can be found in the last two columns of Table 1. While the minimum wage share insignificantly affects the robot import value of firms in column 5, it 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 4.6% more robots compared to small firms with the same

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

share. Furthermore, the propensity to import is 32.5% higher for large firms. These numbers slightly decrease when considering robot quantity, as seen in column 6.

4.1.1 Event study results

As an additional robustness check, we implement an event study design in Figures 2 to 4. These figures correspond to columns 4 to 6 in Table 1. The plots reveal that large firms gradually increase their probability of robot importation and adoption. Moreover, after integrating robots into their production stages, they escalate the number of equipment over time. Medium firms also exhibit a similar tendency but to a lesser extent.

4.2 Firm heterogeneity

We further investigate the impact of varying firm characteristics on automation decisions in response to the minimum wage shock. First, we consider the intensity of blue-collar job roles within firms. Given that automation primarily targets routine and repetitive tasks, firms with a high proportion of blue-collar and routine job workers might be more inclined to advance their adoption of automation technologies following such a cost-related shock. Secondly, we explore the likelihood of firms engaging in innovation and research activities to import robots after the minimum wage shock. For instance, Koch et al. (2021) suggest that firms that adopt robots are also more prone to innovate. We hypothesize that firms allocating substantial resources to R&D are more likely to adopt robots. Lastly, we consider the role of competition, hypothesizing that it may compel firms to reduce their wage bills and import robots as a strategy to mitigate the cost shock. To this end, we interact the minimum wage shock variable with market concentration.

4.2.1 Blue collar and routine job intensity

Table 2 presents the estimation results from equation (1). The variable of interest is multiplied by the share of blue-collar workers in all minimum wage employment in 2015 [5]. The initial three columns, which do not account for firm size, indicate a positive but statistically insignificant effect across both extensive and intensive margin outcomes. This suggests that the presence of blue-collar workers does not necessarily prompt firms to adopt robots in response to labor cost shocks. However, when accounting for firm size, the results show a significant effect; column 4 demonstrates that larger firms, when the variable of interest is interacted with firm size bins and blue-collar share, are more inclined

[5] We classify a worker as occupying a blue-collar job if their first digit ISCO occupation code ranges from 6 to 9, following the classification standards by Eurofound (see `https://www.eurofound.europa.eu/en/coding-and-classification-standards-0`). Our findings remain robust under broader definitions.

to adopt their first robot. Additionally, as indicated in columns 5 and 6, firms that have previously adopted robots increase their robot inventories under the intensive margin. Table 3 presents the results using a task-based approach. To examine the impact of the minimum wage share on robot adoption across varying routine task intensities, we first calculate the share of workers engaged in routine tasks among all minimum wage workers in 2015 [6]. The interaction of this intensity with the variable of interest reveals, similar to the findings related to blue-collar intensity, that firm size is a significant determinant. Notably, while firms with high routine task intensity generally do not adopt robots in response to a minimum wage shock, medium and large firms are more likely to adapt through robot adoption. Contrasting with the results for blue-collar interactions, medium-sized firms here show a significantly higher propensity to adopt robots.

4.2.2 R&D intensity

In Table 4, we present estimates that illustrate the heterogeneous effects of the minimum wage shock based on the R&D expenditures of firms. The first three columns show the interaction between the treatment variable and the logarithmic value of R&D expenditures, without adjusting for firm size. We find that firms with higher investment in research activities are more likely to adopt robots for the first time, as indicated in column 1. Furthermore, these firms continue to import robots, as demonstrated in columns 2 and 3. In the last three columns, we adjust the R&D expenditures by dividing by the number of workers. Here, we observe a positive and significant coefficient across all specifications, albeit with somewhat reduced significance. This suggests that the strong evidence found in the initial columns may be indicative of the influence of firm size. However, subsequent columns reveal that all firms engaged in research activities are also more inclined to adopt robots in response to labor cost shocks.

4.2.3 Market concentration

We incorporate the dimension of firm competition and present the corresponding estimation results in Table 5. We calculate the four-digit Herfindahl-Hirschman Index (HHI) using the total sales values of firms in 2015. This measure of market concentration is then interacted with our continuous treatment variable. We observe that the interaction term between the treatment variable and the HHI index is negative and significant. This result indicates that increased competition among firms encourages the adoption of automation technologies. Our results are also robust to the other concentration definitions such as

[6] Following Mann and Pozzoli (2023), workers are considered to be in routine-intensive occupations if their routine task score exceeds 0.7. Task scores are derived using the classification developed by Mihaylov and Tijdens (2019).

two- or four-concentration rate and Lerner index.

5 Conclusion

It is well-established that competition compels firms to manage costs effectively and adopt new technologies to boost productivity. The burgeoning integration of robotic technologies in various industries has led scholars to explore how labor costs might drive firms' adaptive responses towards automation, albeit with limited empirical evidence directly connecting the two.

This study examines how firms alter their automation adoption behaviors in response to a cost shock, which can be partially offset through robotic integration. Utilizing a quasi-experimental design prompted by a sudden and significant increase in the minimum wage, our findings indicate that manufacturing firms in Turkey, on average, did not significantly change their robot acquisition patterns. However, medium and large-scale firms, particularly those with a high proportion of minimum wage workers, were more likely to integrate robots compared to their smaller counterparts. Further, as evidenced by intensive margin results, these larger firms also increased their existing robot imports in response to the minimum wage shock.

When accounting for other firm characteristics, we observe that medium and large firms, characterized by high intensities of blue-collar and routine job roles, are more likely to adopt robotic technologies. These results underscore that while firms leverage automation to mitigate sudden cost shocks, such applicability predominantly pertains to those of a certain scale.

Conversely, some firm characteristics appear independent of firm size. Firms engaged in research and development activities consistently show a propensity towards adopting robotic technologies. Additionally, the degree of competition influences firms' decisions to adopt automation, possibly as a mechanism to enhance productivity by reducing the use of inputs whose costs have surged. Accordingly, policymakers should consider the implications of automation and employment responses when crafting minimum wage and labor policies.

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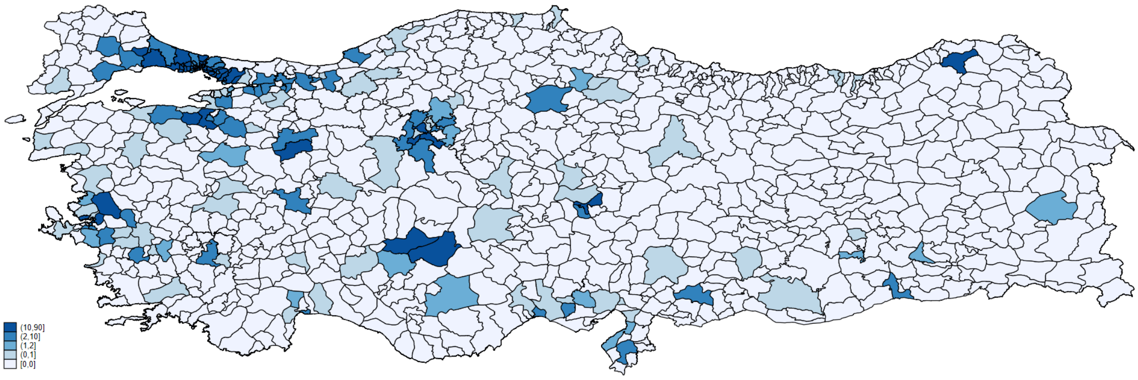
Figure 1: Regional distribution of number of robot importers



Source: Authors' own calculations using EIS dataset.

Table 1: Effect of minimum wage shock on robot adaption by firm size

Dependent Variables:	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
minimum wage share$_{it}$	0.0009	0.0081	0.0060	0.0008	0.0069	0.0052
	(0.0008)	(0.0091)	(0.0062)	(0.0008)	(0.0091)	(0.0062)
minimum wage share$_{it}$ × medium				**0.0045*****	**0.0457****	**0.0308*****
				(0.0011)	**(0.0114)**	**(0.0080)**
minimum wage share$_{it}$ × large				**0.0270*****	**0.3251*****	**0.2278*****
				(0.0066)	**(0.0740)**	**(0.0528)**
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
NACE × year	Yes	Yes	Yes	Yes	Yes	Yes
Province × year	Yes	Yes	Yes	Yes	Yes	Yes
Min. wage share quantile FE × t.trend	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	440,735	440,735	440,735	440,735	440,735	440,735
R^2	0.76755	0.76768	0.78697	0.76762	0.78301	0.78703
Within R^2	0.00620	0.00685	0.00770	0.00649	0.00780	0.00799

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the likelihood of importing a robot (column 1 and 4) or log of cumulative robot import value (columns 2 and 5) and quantity (columns 3 and 6) for 2009-19 period. In columns 4 to 6 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 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.

Table 2: Effect of minimum wage shock on robot adaption by firm size and blue collar minimum wage share

Dependent Variables:	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
minimum wage share$_{it}$	0.0001	0.0001	-0.0008	0.0003	0.0024	0.0018
	(0.0009)	(0.0006)	(0.0070)	(0.0009)	(0.0102)	(0.0069)
minimum wage share$_{it}$				**0.0029****	**0.0287****	**0.0201****
$\times$ medium				**(0.0013)**	**(0.0135)**	**(0.0094)**
minimum wage share$_{it}$				0.0123	0.1437	0.1019
$\times$ large				(0.0083)	(0.0984)	(0.0702)
minimum wage share$_{it}$	0.0004	0.0049	0.0038	-0.0005	-0.0050	-0.0027
$\times$ blue collar share of min. wage	(0.0007)	(0.0073)	(0.0052)	(0.0006)	(0.0067)	(0.0048)
minimum wage share$_{it}$				0.0038	0.0404	0.0254
$\times$ blue collar share of min. wage $\times$ medium				(0.0030)	(0.0327)	(0.0234)
minimum wage share$_{it}$				**0.0259***	**0.3208****	**0.2213***
$\times$ blue collar share of min. wage $\times$ large				(0.0140)	**(0.1612)**	**(0.1142)**
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes
Min. wage share quantile FE $\times$ t.trend	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	392,718	392,718	392,718	392,718	392,718	392,718
R^2	0.76787	0.78434	0.78956	0.76797	0.78444	0.78966
Within R^2	0.01333	0.01687	0.01733	0.01377	0.01734	0.01779

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the likelihood of importing a robot (column 1 and 4) or log of cumulative robot import value (columns 2 and 5) and quantity (columns 3 and 6) for 2009-19 period. In columns 4 to 6 we interacted variable of interest with firm size and share of blue collar workers in total minimum wage employment. We identify blue collar workers whose one-digit ISCO codes are 6, 7, 8 and 9. 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 by firm size and routine job worker minimum wage share

Dependent Variables:	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
minimum wage share$_{it}$	0.0004	0.0030	0.0027	0.0008	0.0075	0.0059
	(0.0009)	(0.0103)	(0.0070)	(0.0009)	(0.0101)	(0.0069)
minimum wage share$_{it}$				**0.0022****	**0.0204***	**0.0136***
× medium				**(0.0010)**	**(0.0106)**	**(0.0073)**
minimum wage share$_{it}$				**0.0155***	**0.1904***	**0.1260***
× large				**(0.0090)**	**(0.1025)**	**(0.0732)**
minimum wage share$_{it}$	-0.0010	-0.0097	-0.0077	**-0.0025*****	**-0.0260*****	**-0.0191*****
× Routine job share of min. wage	(0.0009)	(0.0097)	(0.0068)	**(0.0008)**	**(0.0084)**	**(0.0060)**
minimum wage share$_{it}$				**0.0096***	**0.1043***	**0.0708***
× Routine job share of min. wage × medium				**(0.0049)**	**(0.0551)**	**(0.0391)**
minimum wage share$_{it}$				0.0370	**0.4315***	**0.3256***
× Routine job share of min. wage × large				(0.0229)	**(0.2562)**	**(0.1865)**
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
NACE × year	Yes	Yes	Yes	Yes	Yes	Yes
Province × year	Yes	Yes	Yes	Yes	Yes	Yes
Min. wage share	Yes	Yes	Yes	Yes	Yes	Yes
quantile FE × t.trend						
Fit statistics						
Observations	392,718	392,718	392,718	392,718	392,718	392,718
R^2	0.76787	0.78434	0.78956	0.76798	0.78446	0.78697
Within R^2	0.01334	0.01688	0.01733	0.01383	0.01739	0.01785

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the likelihood of importing a robot (column 1 and 4) or log of cumulative robot import value (columns 2 and 5) and quantity (columns 3 and 6) for 2009-19 period. In columns 4 to 6 we interacted variable of interest with firm size and share of blue collar workers in total minimum wage employment. We identify routine job task-intensive workers whose routine task score is greater than 0.7. We use firm size definition of OECD based on employment. Base category is small firms. Firm, year, NACE × year, province × year, and minimum wage 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.

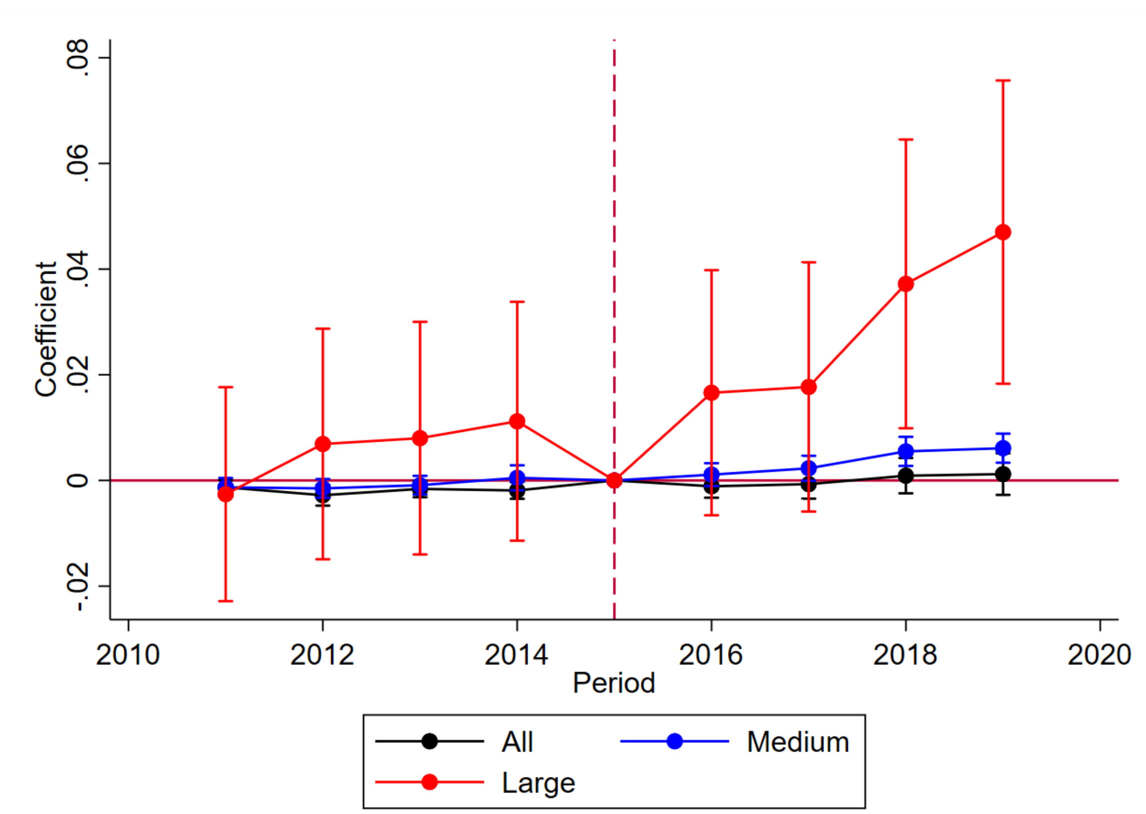
Table 4: Effect of minimum wage shock on robot adaption by interacted by R&D expenditure

Dependent Variables:	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)
R&D definition	Log(R&D+1)	Log(R&D+1)	Log(R&D+1)	Log(R&D per capita+1)	Log(R&D per capita+1)	Log(R&D per capita+1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
minimum wage share$_{it}$	0.0006	0.0046	0.0033	0.0006	0.0048	0.0035
	(0.0011)	(0.0122)	(0.0085)	(0.0011)	(0.0122)	(0.0085)
minimum wage share$_{it}$	**0.0011****	**0.0129****	**0.0091****	0.0010	**0.0121***	**0.0085***
$\times$ Log(R&D expenditure+1)	**(0.0005)**	**(0.0053)**	**(0.0037)**	(0.0006)	**(0.0062)**	**(0.0043)**
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes
Min. wage share quantile FE $\times$ t.trend	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	397,173	397,173	397,173	397,173	397,173	397,173
R^2	0.77968	0.79546	0.80150	0.77967	0.79545	0.80149
Within R^2	0.00476	0.00572	0.00578	0.00471	0.00567	0.00573

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the likelihood of importing a robot (column 1 and 4) or log of cumulative robot import value (columns 2 and 5) and quantity (columns 3 and 6) for 2009-19 period. In columns 1 to 3 we interacted the variable of interest with the log of R % D. In columns 4 to 6 we interacted the variable of interest with log of R%D per capita. 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.

Figure 2: 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

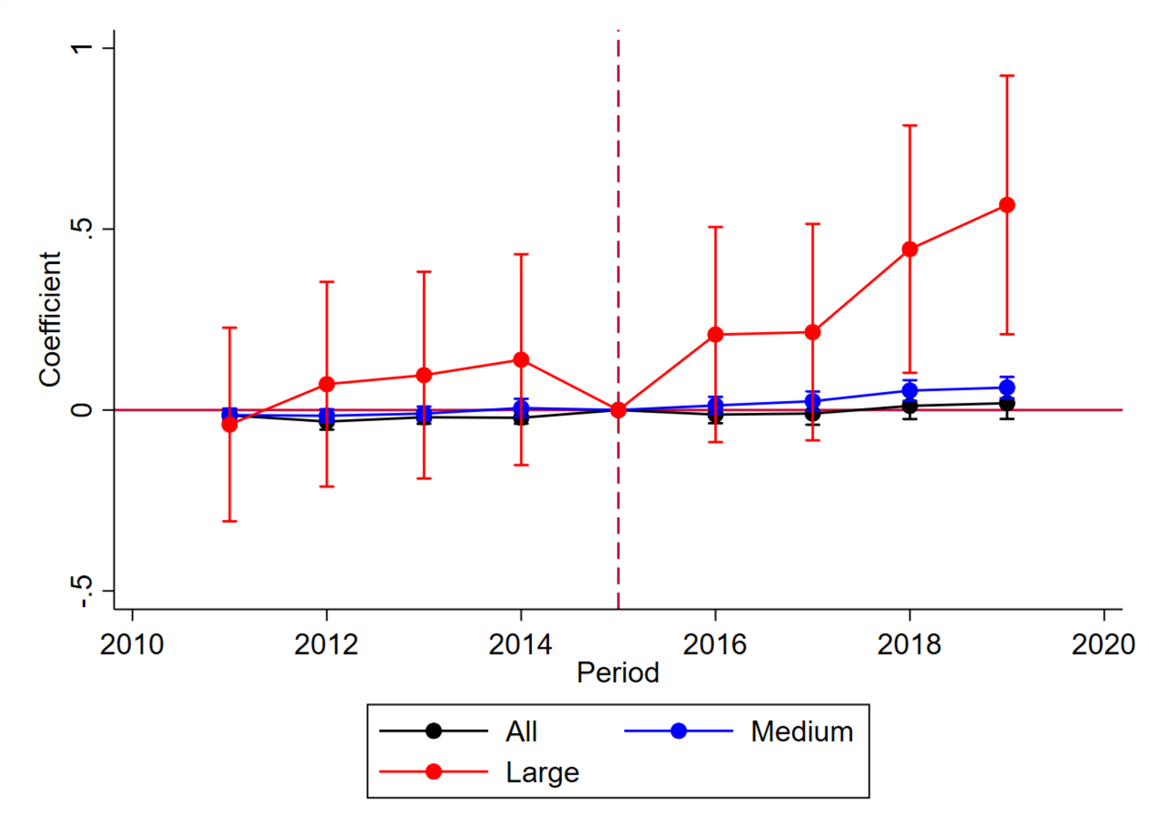
Table 5: Effect of minimum wage shock on robot adaption interacted by market concentration

Dependent Variables:	Robot importer	Log(Cum. robot value+1)	Log(Cum. robot quantity+1)
Model:	(1)	(2)	(3)
Variables			
minimum wage share$_{it}$	**0.0045*****	**0.0522*****	**0.0362*****
	(0.0010)	**(0.0118)**	**(0.0081)**
minimum wage share$_{it}$	**-0.1195*****	**-1.4700*****	**-1.0120*****
$\times$ HHI	**(0.0248)**	**(0.2909)**	**(0.2032)**
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
NACE $\times$ year	Yes	Yes	Yes
Province $\times$ year	Yes	Yes	Yes
Min. wage share quantile FE $\times$ t.trend	Yes	Yes	Yes
Fit statistics			
Observations	455,490	455,490	455,490
R^2	0.76423	0.77912	0.78291
Within R^2	0.00792	0.00847	0.00861

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

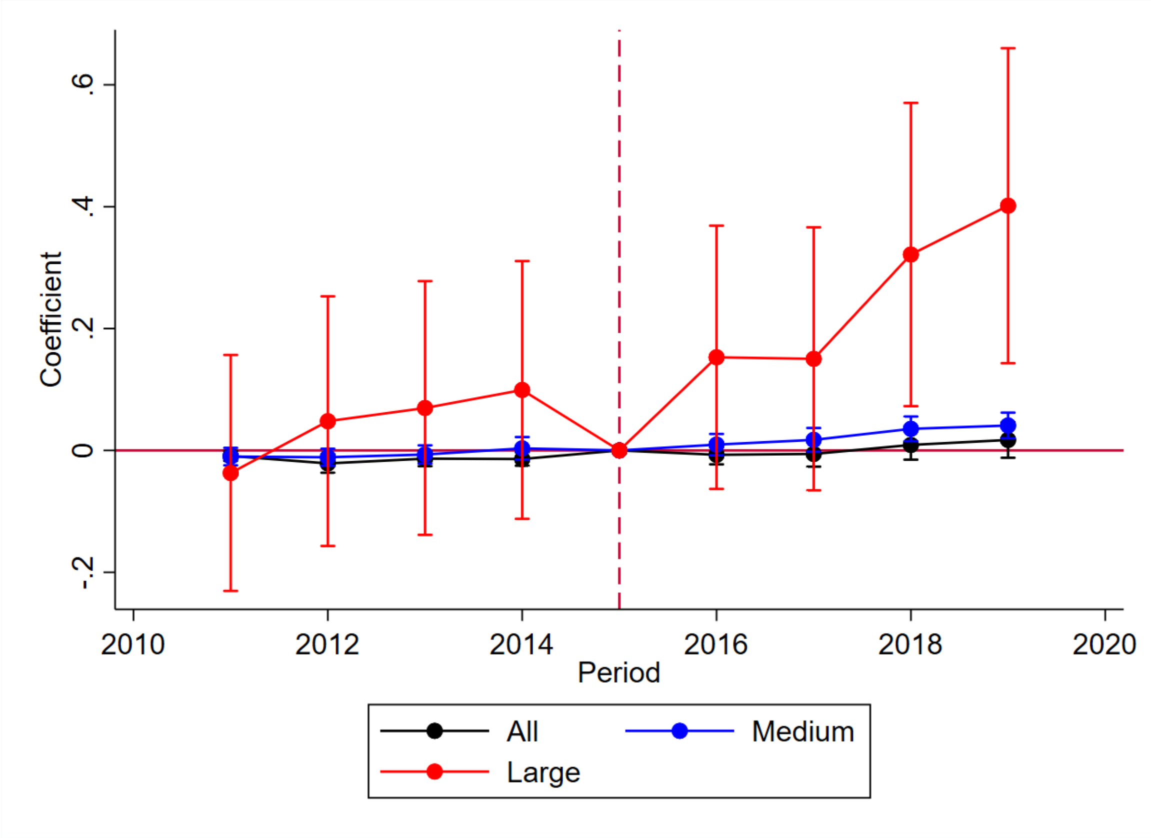
Notes: Each coefficient shows the effect of minimum wage employment/total employment ratio on the likelihood of importing a robot (column 1) or log of cumulative robot import value (columns 2) and quantity (columns 3) for 2009-19 period. In all 1 to 3 we interacted the variable of interest with the 2015 HHI index value of each four digit NACE industry. 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.

Figure 3: Minimum wage shock and cumulative robot import value: Coefficient estimates for each year, 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 4: Minimum wage shock and cumulative robot import quantity: Coefficient estimates for each year, 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.