Robots, Employment and Wages: Evidence from Turkish Labor Markets

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Abstract

In recent years, effects of automation on labor market were outpaced due to the widespread usage of robots in various industries. However, empirical studies mostly cover developed countries. Our aim in this study is to investigate how the robotization in Turkey affects local and worker level labor market outcomes in Turkey. Using novel employer-employee data and Federation of Robotics (IFR) database for 2014-2021 period, we find in our baseline specification that unlike the existing literature, robot exposure has positive effects on employment growth of districts. This effects hold for manufacturing and nonmanufacturing industrues separately, arguing that instead of crowding out of labor, reallocation between main industries -especially for younger aged workers- occurs. Moreover, we see this positive employment effect due to the robotization in automotive industry. Finally, worker level analysis reveal that incumbent workers in manufacturing industry have reduced their employment when they face robot exposure. Moreover, they were likely to separate their original workplace and occupation and unlikely to find another job in nonmanufacturing industry. However, if they manage to find a job, their earnings are found to be significantly higher than their initial job.

Keywords: Robots, employment, wages, automation, Turkish Labor Markets
JEL Classification: J23, J24

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1 Introduction

For a long time there has been a controversy among economists and policymakers on whether automation technologies cause to reduce in labor share of output and employment. It can be dated to early 1800s by David Ricardo in the Industrial Revolution age. In modern times, Keynes (1930) had explored the issue further developed ”technological unemployment” concept. Afterwards, demand for skills and inequality effect of automation has been another dimension of this controversy (Griliches, 1969). Under certain technological projections, it is emphasized job polarization and inequality due to the disappearing some occupations (Autor et al., 2003; Acemoglu and Autor, 2011; Frey and Osborne, 2017).
In recent years this debate were outpaced due to the widespread usage of robots in various industries. In line with these developments, theoretical foundations of labor market effects of automation and robots have been reconsidered. While these studies present various mechanisms such as labor-saving structure and increasing labor demand due to the lower price and higher productivity, overall effect is an empirically ambiguous issue. Among them different industry compositions and institutional structures of countries manifest these effects in a wide range. In a cross-country analysis conducted by Graetz and Michaels (2018), for example, it is shown that robot adaption did not reduce total employment but employment share of low skill workers. According to Acemoglu and Restrepo (2020), each additional robot per thousand workers in US is associated with a decrease in employment to population ratio and wages by 0.2% and 0.42%, respectively. For Germany, Dauth et al. (2018) find no total employment losses due to the mobility of employees from manufacturing to nonmanufacturing (composition effect) industries and negative wage effect of robots . Apart from these three seminal studies, many papers confirm negative employment and wage effect of robots (Acemoglu and Restrepo, 2018; Chiacchio et al., 2018; Giuntella and Wang, 2019; Bessen, 2019; Acemoglu et al., 2020; Bonfiglioli et al., 2020; Faber, 2020; Dottori, 2021; Bessen et al., 2022).
On the other hand, there are some papers reporting positive employment effect. Klenert et al. (2022) analyzed the data from EU countries and find that robot use is linked to increase in manufacturing employment. As an evidence for developing country context, the study by Calì et al. (2022) examines effects of robotization for Indonesian manufacturing industries and shows the employment gains from automation. Aghion et al. (2020) also obtain similar evidence for France. These studies refers to mechanism that increased productivity induces higher scale and higher labor demand. Tuhkuri (2022), find similar results but argue that the reason why robotization positively affects employment in Finland is that firms adopting automation are more likely to focus on producing new products rather than displacing labor.[1] In addition, evolution of manufacturing production from

[1]Tuhkuri (2022) present a theoretical model based on Dixit and Stiglitz (1977) and Melitz (2003) and empirically test the implications. Findings show that Finnish firms are interested in product type and flexible specialization. Our future task in this study is to test the validity of this mechanism for Turkish firms using survey data collected by TurkStat.

mass to flexible specialization puts different set of technology and labor relations. Thus, flexible specialization is not necessarily labor-reducing or skill-biased.[2] Finally, Cheng et al. (2019) present anecdotal evidence on how the number of employees of Chinese enterprises implemented ”replacement of workers with robots” incentive are unaffected by the robot exposure. [3]

This paper examines the the relationship between the robot adaption and labor market outcomes in Turkey. This study aims to contribute to this growing area of research by exploring the automation effects on labor market outcomes in a developing country context, which has lack of evidence in the literature. By using novel employer-employee data having firm information such as production, wage, trade, and worker information provided by Enterprise Information System (EIS) of Ministry of Industry and Technology of Turkey and International Federation of Robotics (IFR) database that which reports number of robots at country and industry level between 2014 and 2021, we regress the labor market outcomes on the variation in the robot exposure at district level. We also take account the endogeneity between robot exposure and error term by instrumenting robot exposure with number of robots of nine countries leading in robotic technology in EU.

There are two primary aims of this study. The first one is to identify local labor market effects of robot exposure. In this respect, we explore the net effect of robots on the change in employment and wages following Acemoglu and Restrepo (2020) methodology. Moreover we carry out this effect for different industry, skill level, and age groups of employment to see whether composition changes across these groups occur. Finally, source of the robotization effect by splitting the robot exposure as automotive and other industries is examined.

Our local labor market findings accord with the second group of papers we mention above. As far as the relationship between robot exposure and employment is concerned, our results suggest that robot exposure should not only be responsible for job losses, but also it creates more job opportunities and gives rise to the number of employed workers. Calì et al. (2022) have documented that robot exposure results in a positive impact on employment when taking into consideration the developing countries instead of developed ones. Results from earlier studies demonstrate a strong and consistent association between job losses and robot adoption. Nevertheless, their analysis bases on developed economies such as the US and Germany and they fail to recognize the fact that developing countries possess different characteristics in terms of how inefficiently they organize their production processes. The reason might be attributed to the idea that the average productivity gains from the use of robots in the production process for the developing countries might only create demands for additional workers for the automated tasks and consequently automation might not be adopted to replace the tasks that were previously performed by workers, rather it might

[2]Piore and Sabel (1984) also emphasize the this evolution, arguing that SMEs focus on product varieties with low output level.

[3]They argue also that even if small number of workers left their job, they were employed by other firms.

be used in order to expand the production capacity of the plant or the plant might be established with the necessary amount of automated processes in the first place. We argue lack of a precise and one-sided trade-off between robot and employment due to the high marginal productivity of automation. Moreover, flexible production techniques that began to become widespread in recent times and is not necessarily only displace labor may explain our findings. In addition, our findings do not only verify the employment-enhancing effect of automation in manufacturing sector, but also give insight into the existence of a certain amount of displacement effect. We find positive and statistically significant coefficients in service sector, which suggests that there is a reallocation effect in this sector. We know that automation mainly affects manufacturing sector and its impact on employment in service sector is indirectly determined so as unemployed workers in manufacturing sector find new jobs in service sector. The positive coefficients in service sector prove that there exist a displacement effect in manufacturing sector. As a result, this study advocates that there are both positive and negative effects of automation on employment at the same time where positive effect is considerably higher than the negative one.

Secondly, we deal with how workers in manufacturing industry adjust their employment and wages when they are exposed to robots. By doing so, it also allows us to comment on labor market outcomes resulted from workers' decision on staying at their original workplace or switching to another workplace. We cumulate employment days and earnings of the workforce who employed manufacturing sector in 2014. Our results reveal that robotization negatively effect the total employment of incumbent workers. In addition, this effect mainly from those that stays at their original workplace. In other words, likelihood of keeping same employment effort in a nonmanufacturing industry reduces when incumbents face a robot exposure. Staying at original firm and manufacturing industry is also negatively affected by robotization. But earnings of the former group is improved in higher robot exposure industries. This finding confirms that automation has complementary relation with those keeping their employment in original firm. This evidence is more apparent when these workers are employed in different occupation within the same firm.

The remainder of the paper proceeds as follows. First part of the section 2 discusses estimation method and identification strategy to overcome the endogeneity problem arising from labor demand shocks and automation. Second part of the section presents data and some descriptive overview. We then present our empirical results for local labor market and worker level in Section 3. Finally, section 4 concludes.

2 Identification and data

We carry out this study at both local labor market and worker level. Unit of analysis in the former is district (ilçeler) in Turkey. However, these units are defined with political boundaries and does not exactly consider the commuting patterns, which is important dimension to isolate the shocks to labor markets. In order to control this movements of workers further, we merged central districts as one local labor market because they are very close. [4] Hence, this operation reduced our resulting sample from 951 to 861. Let subscript i represent district, the model to be estimated is as follows:

$$\Delta y_i = \alpha + X_i^{'}\theta + \beta \Delta robots_i + \varepsilon_i \tag{1}$$

where dependent variable Δy_i is change in employment to population ratio, change in log employment or average wage in district i. To calculate average wage, we construct demographic cells summing real wages by age group, gender, and skill level (defined by ISCO) and dividing by number of workers in this group. [5] X_i is district-specific controls such as imports from China, occupation and age group share of employment, five region dummies and employment share in manufacturing industry. β is coefficient of interest and shows the effect of change in the number of robots over the number of workers or average wage in district i. Our challenge in equation 1 is to measure the robot exposure at regional level because we have not available data at reporting the robot adaption for each district. To measure district level robot intensity, we will adopt Bartik style approach as other studies applied, which uses employment shares of industries in each province as weight:

$$\Delta robots_i^{TR} = \sum_{i=1}^{861} \ell_{ij,2014} \frac{(robot_{j,2021}^{TR} - robot_{j,2014}^{TR})}{emp_{j,2014}^{TR}} \times 1000 \tag{2}$$

where ℓ_{ij} is employment share of industry j in district i. $robot_{j,2021}^{TR}$ and $emp_{j,2014}^{TR}$ number of robot stock and total employment in industry j, respectively.

Estimating the equation 1 using OLS may be problematic because of two issues: Firstly some industries might have decided to adopt robots because of the trends that not related with labor market conditions directly. However, these trends may impact labor demand subsequently. Secondly external shock to labor demand in a province directly affects the robot adaption. We overcome this problem by instrumenting Turkish exposure to robots with number of robots in leading nine countries in terms of robot stock in EU. [6] Similar approaches have been utilized by other studies (see Dauth et al. (2021); Giuntella and Wang (2019); Acemoglu and Restrepo (2020); Klenert et al. (2022)). Our shift-share

[4]We also carry out this analysis at district level without merging and obtain similar results with those we present here. We gladly share them upon request.

[5]ISCO defined managers, professionals, and technicians and associate professionals as high skill level while rest of them are medium skill except elementary occupations (low skill). By simplicity, we divided two by assuming first group is high and rest is low.

[6]These countries are Germany, Spain, Finland, France, Denmark, Italy, United Kingdom, and Sweden

instrument formula is as follows:

$$\Delta robots_i^{EU8} = \sum_{i=1}^{861} \ell_{ij,2010} \frac{(robot_{j,2021}^{EU8} - robot_{j,2014}^{EU8})}{emp_{j,2014}^{EU8}} \times 1000 \tag{3}$$

Here we use shares of province in 2010 period to eliminate the endogeneity concerns further as Dottori (2021) applied.

We then will proceed to worker-level analysis to see how workers adjust their outcomes against robot exposure following Dottori (2021) and Dauth et al. (2021). Our equation can be written:

$$y_{wj} = \alpha + X_{wj}^{'}\theta + \beta \Delta robots_j + \varepsilon_{wj} \tag{4}$$

where dependent variable y_{wj} is log of either total workdays or wages of worker w in industry j. X_{wj} is individual, firm and industry level characteristics such as gender, age dummies, firm size, tenure, and industry and region dummies. Industry, plant, and occupation mobility will be taken account when cumulating the outcomes to see how they are affected by robots. Note that variable $\Delta robots_j$ is industry-level here and the formula is following equation:

$$\Delta robots_j^{TR} = \frac{(robot_{j,2021}^{TR} - robot_{j,2014}^{TR})}{emp_{j,2014}^{TR}} \times 1000 \tag{5}$$

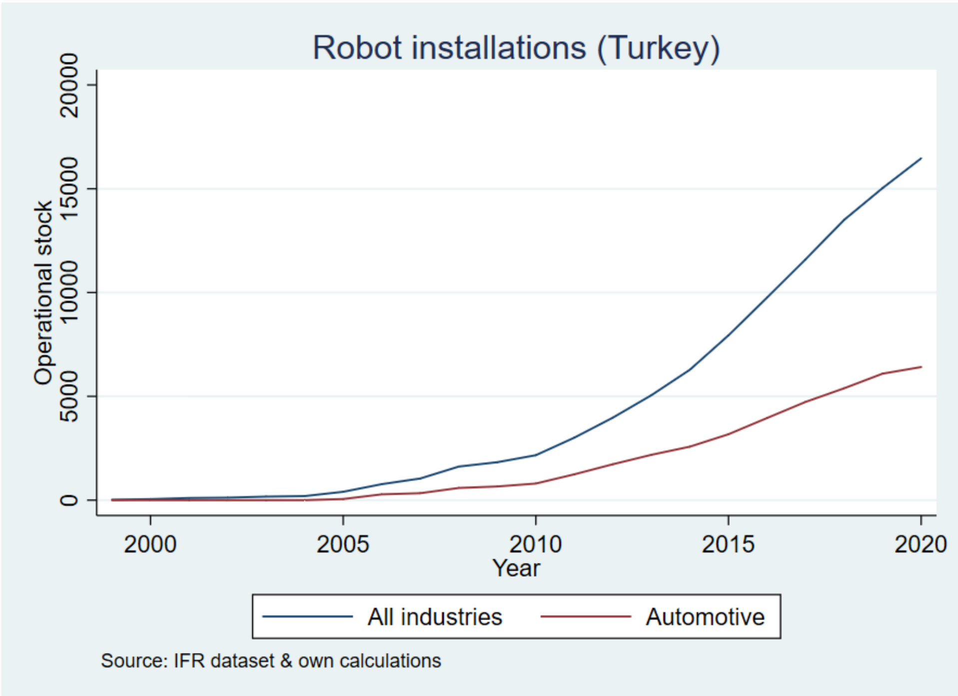
Since data coverage of EIS span 2014 to 2021 and IFR is from 2005 and 2021, we will use EIS range to estimate the regressions above. We also instrument $\Delta robots_j$ with nine EU countries.

We use three data source to effect of robots on the employment and wage in Turkey. First of all, EIS provide administrative data for firms collecting from different institutions and for workers from Social Security Information of Turkey. Merging two via firm identifier allows us to construct employer-employee dataset from 2006 to 2021. The fact that six digit ISCO occupation and worker ID variable is recorded from 2014 starts all identify initial period as that year. Secondly, robot counts are obtained from IFR for a number of countries at industry level. It is collected from robot sales of firms. Finally, EU KLEMS provide us country-industry level employment dataset to construct instruments (Jäger, 2017). In all analysis, we use IFR industry classification since KLEM and EIS datasets have more disaggregated level classifications. Therefore, we aggregate all industry definitions to 17 IFR industries.

Figure 1 shows the total robot stocks in Turkey over time. We observe that after 2010s robot counts have been accelerated. What stands out in this figure is high share of automotive industry in all robot stock. Actually it is similar with the composition of other countries. Below we split the total robot exposure as automotive and others to see whether exposure differs among sectors.

Figure 2 compares total robots per thousand workers with selected leading countries and EU. It reveals a general increasing trend for all of them. However, there has been a sharp rise in South Korea after 2010, reaching the robot highest penetration per 1000 workers. Turkey is lowest penetration and has slight increase in the same period. This figure also may help to explain our positive employment effect of robot exposure we present below. As Calì et al. (2022) and Aghion et al. (2020) argue that low levels of robotization in a developing country provides high productivity and it generates labor demand.

Figure 1: Robot penetration in Turkey, 1999-2021



In Figure 3, we mapped the variable $\Delta robots_i$ in equation 1 to see how robot exposure is dispersed. The graph shows that robot exposure is substantially similar to industrialization levels of provinces in Turkey. Western regions are more likely to have manufacturing industry employment while eastern ones are concentrated on agriculture and services. Since robot industry is specifically concentrated on automotive and electronic sector, it directly reflects to the our exposure index. Marmara regions (northwest), Aksaray, and Kirikkale (boldest regions in central) provinces are such examples of this situation. Among central regions Karabuk, Cankiri, and Kayseri have highest exposure. In figure 4 that shows the exposure outside the automotive industry, we see similar pattern but there are some notable differences. Firstly, highest value is 18.20 in Figure 3 and 3.56 in Figure 4. This evidence shows that robot exposure of regions are substantially different when take account automotive industry. On the other hand, variance across districts is significantly reduced, pointing out that exposure is relatively equal than Figure 3.

Figure 2: Robot per thousand worker, 1999-2021

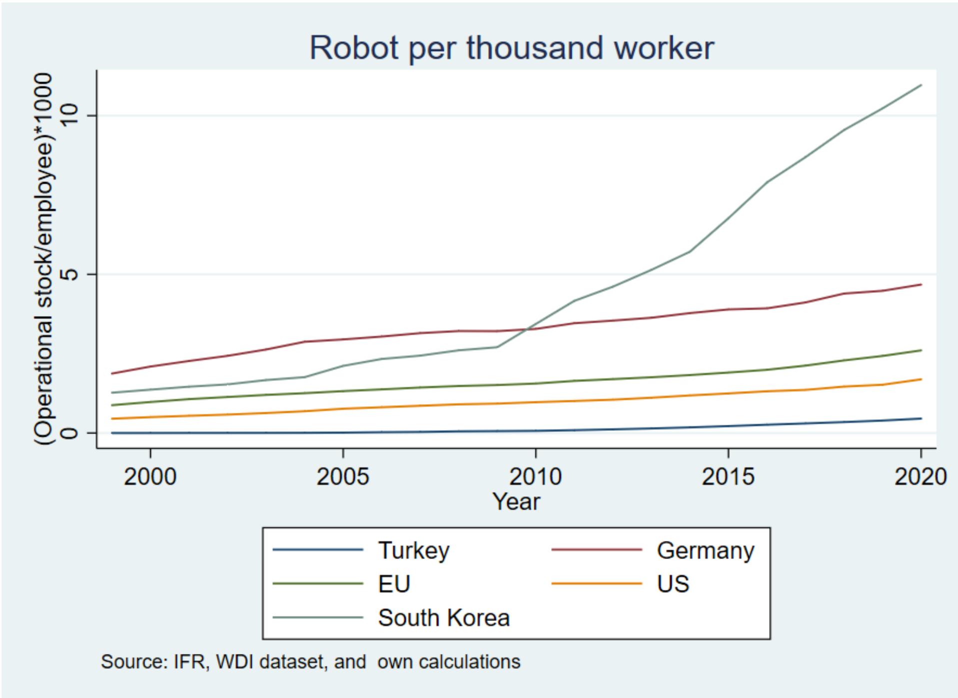
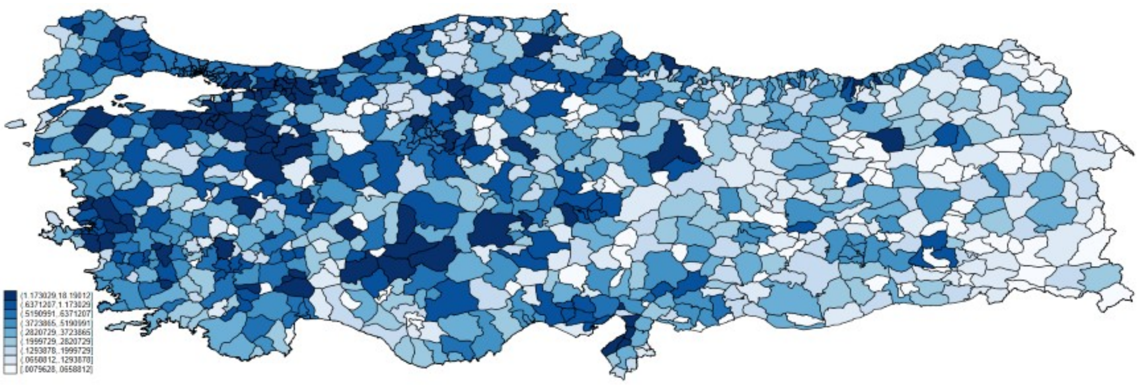
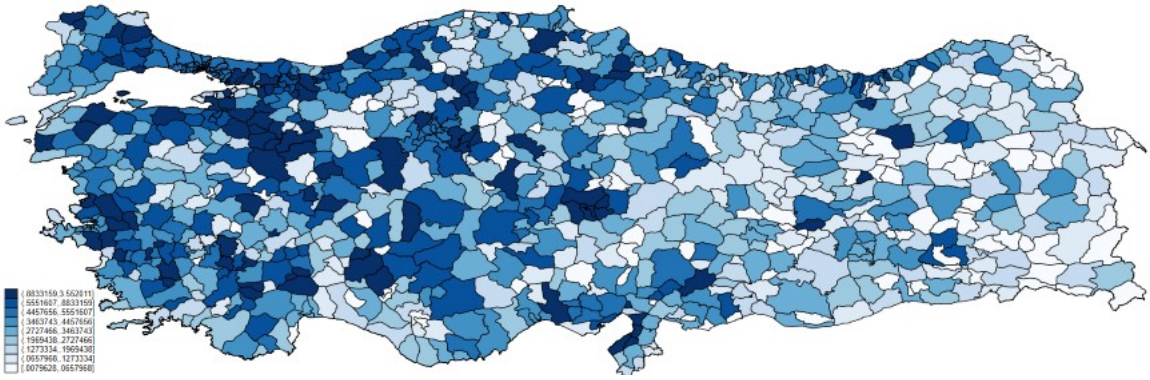


Figure 3: Robot exposure of Turkey, all industries



Source: Authors' own calculations using IFR and EIS data.

Figure 4: Robot exposure of Turkey, outside the automotive industry



Source: Authors' own calculations using IFR and EIS data.

3 Results

3.1 District level analysis

Panel (A) in Table 1 presents how change in log employment can be caused from the exposure to robots. In Column (1), by using OLS estimation, we only regress robot exposure on log change in employment. The estimated effect is positive and statistically significant at 1 percent confidence level. Our results demonstrate that our estimates yield significant results even without adding all control variables. Nevertheless, our main challenge is to explain why robot exposure should result in a positive effect on employment. Even though vast majority of the literature find a negative relationship between automation and employment, we need to explain how it might be mistaken to accept it as a common pattern, especially considering how developing economies behave divergent from developed ones. As we add more variables to enrich the specifications, our results do not change in terms of the significance and the sign of the coefficient of robot exposure, rather we see differences in the volume of it. From now on, we will explain how different specifications lead to different values for the effect of robot exposure. In Column (2), we added manufacturing share and find a larger effect for robot exposure. In Column (3), we also include net export change per worker and find almost the same effects. Our results in Column (2) and Column (3) indicate the fact that the positive effect of robot exposure will be persistent in numerous specifications, which states that even controlling more variables only increases the positive impact of robot exposure on employment.

Considering IV results of our analysis, from Column (4) to (6), they are less than OLS estimates but no significant differences were found between them. Therefore, from now on, we will continue with 2SLS specifications since our IV tests justify the high validity of our instrument variables. First stage F-statistics in the last row of the table also ensure that instruments as a whole are strong predictor of the variable of interest.

In Panel (B), we re-regressed new independent variable, namely the change in E/POP, on the same model specifications before. The reason for why we add E/POP is to make out results comparable to Acemoglu and Restrepo (2020). We find positive and highly significant estimates for the predicted robot exposure in almost entire models. Our results suggest that using E/POP as dependent variable does not affect our main results, but only results in different values for the effect of predicted robot exposure. In OLS specifications , from Columns (1) to (3), are arguably higher than 2SLS ones, from Columns (4) to (6). It should be noted that the coefficients of the latter models yield lower significance at 10 percent confidence level.

In Panel (C), we regressed the same model specifications with the change in log average wage. We find insignificant estimates for both OLS and 2SLS. The coefficients are still almost the same along with both estimators. Our results suggest that predicted robot exposure does not increase log average wages. In other words, workers could not enjoy higher wages as automation takes place. These findings show that even though robotization leads to increase labor demand in Turkey, this does not channel into the higher income.

Panel A in Table 2 indicates how the effect of predicted robot exposure on percentage change in employment differs in manufacturing and nonmanufacturing industries. As we discussed above, it is mainly found in the literature that robot adoption mostly hurts the employment in manufacturing sector since robots are mainly used in plants to enhance the productivity of industrial production. Henceforth, it is suggested in the related studies that employment should be more adversely affected in manufacturing sector. Moreover, it is also suggested that other sectors should increase their demand for labor due to the fact that all industries are dependent on each other when producing final goods. As for our study, we expect that the effect of both sectors should have an positive impact on employment. Our estimations are positive and highly significant in our specifications except column (4). There are notable differences between estimates having manufacturing share and net export and those not having them. The models in columns (1)-(3) show the estimates based on percentage change in manufacturing employment. The estimates are positive and highly significant; however the coefficients with only demographics and five region fixed effects are almost half of those of full specification models. Columns (4)-(6) demonstrates the effect on non-manufacturing sector. It can be stated that predicted robot exposure results in an increase in employment in both sectors and the effect is approximately three times higher in manufacturing sector than in non-manufacturing sector. It is understandable to have positive coefficient due to the fact that we have found positive effect for predicted robot exposure, but still our predictions are in contradiction with the literature because employment increases in manufacturing more than non-manufacturing sector.

We re-run the models in panel A, but we put the change in E/POP as dependent variable in panel B. We find similar results for manufacturing sector. All specifications in columns (1)-(3) yield positive and highly significant estimates. It should be noted that coefficients of weighted models in columns (1)-(3) are almost similar in all specifications. Unlike panel A, our estimates for service sector are not statistically significant and are close to zero. This pattern persists in columns (4)-(6). Our results suggest that even though automation results in an increase in E/POP for manufacturing sector, it does not necessarily mean that E/POP should be affected in service sector as well. Following Acemoglu and Restrepo (2020), using E/POP as dependent variable might provide comparisons between Turkey and US. In developing economies such as Turkey, we suggest that automation does not have to deteriorate employment by displacing workers in favor of getting more robots. As a result, it can be claimed that the displacement effect of automation is ambiguous. On the other hand there, might not be any re-allocation effects in service sector. It might explain why our estimates are significant in manufacturing sector but insignificant (or weakly significant) in non-manufacturing sector. Using different sub-samples such as age and skill level below shed light on this puzzle.

As for panel C, our estimations in all of our model specifications do not indicate any significance evidence for the effect of predicted robot exposure on percentage change in average wages. These results are consistent with our previous estimations in Table 1. It further suggests that wages are not related to automation even using different estimations for manufacturing and non-manufacturing sectors.

The Appendix consists some robustness checks to our main specification. Table A1 presents pre-trend test results. This allows whether dependent variables in Table 1 and 2 have existing trend before 2014 or affected by other shocks. Presence of such trends threats to validity of our results. All panels shows that there are no significant pre-trends.

Table A2 shows the estimates using only firms being present in 2014 sample. Aim of this exercise is to identify how existing firms react when they faced automation shock. We see in the Panel A of the table that manufacturing employed is positively affected by robotization as seen in columns (3) and (4). This evidence may also provide the argument of productivity effect of robotization that would results with increasing labor demand. [7] However, null effect of robotization is evidenced in total and nonmanufacturing employment. This finding, when combining with the baseline and industry composition effect results, points out that newly created firms in nonmanufacturing industry might absorb the employment in this period. Panel B also highlights the similar results for manufacturing industry but significant and results for total employment. This evidence stems from the former because nonmanufacturing industry effect is null.

Apart from the composition effect between main industries, predicted robot exposure may have affected the different effects on employment by different job task levels. As we discussed above, while some studies finds skill biased effects of automation, others

[7] To test this argument speficically, we would estimate a productivity model as Calì et al. (2022) applied. However, EIS database contain only information related with labor market outcomes at plant-level.

do not. In this part we test how robotization change the composition of employment in regions. We utilize task scores developed by Mihaylov and Tijdens (2019) to measure the routine content of an occupation. This approach is relied on assigning 3,264 tasks to four digit occupations. To do so, they firstly construct the task category (non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual) scores for each job. Then they sum the scores and obtain routine task intensity (RTI), ranging from -1 (perfect non-routine) to +1 (perfect routine). In this paper, we code (non-) routine intensive job if RTI of an occupation is zero and above (below).

The results[8], as shown in Panel A of Table 3, indicate the positive effect of robots on the employment growth of both task group in only manufacturing industries (Column (2) and (5)). However, because of similar magnitudes of coefficients, we can not observe presence of skill composition effect of robotization. On the other hand, null effect of robotization on total employment and nonmanufacturing employment growth for both task level has been obtained.

Table 4 shows the composition effects across age groups. Column (1), (4), and (7) reports the effect of robotization in all industries. We see that young aged workers are more likely to enjoy greater employment opportunities than middle and older aged workers. Quantitatively, an increase in one unit robot per thousand worker leads to contribute to the employment by 4%. Main source of this effect mostly comes from the manufacturing industry as shown in column (2). Contrary to other age groups, column (3) points out that nonmanufacturing industry employment have been significantly affected by robotization. This finding also presents an mechanism for the results in panel A of Table 1, which implies that nonmanufacturing employment growth mainly stems from young aged workers. This finding, while preliminary, suggests that robotization contribute to employment of younger generations.

Turkey has a big automotive industry, which possesses a large part of total robots. Therefore, an increase in the number of robots in this sector results in notable outcomes on numerous macroeconomic indicators including employment and wages. In Table 5, we try to control the effect of automotive industry on how predicted robot exposure might affect overall results. In Panel A, it should be noted that non-automotive robot exposure yields no significant results in in total and manufacturing employment. On the other hand, this exposure significantly decrease the nonmanufacturing industry. This finding implies the reallocation effect among industries. However, predicted robot exposure in automotive industry is positive and highly significant for all specifications. Our results give insights into the fact that we might focus specifically on automotive industry since it can be considered as one of the most important element for the effect of automation. In total employment, the coefficient of predicted robot exposure is nearly equal to 3.7, which

[8]These findings must be interpreted with caution because significant share of workers in EIS data has missing ISCO code or has been coded as ”999999”. We drop these workers here and it caused to loss some regions in the analysis, especially in the manufacturing industry.

meets our expectations formed from the previous estimation results since the coefficients are close to the related estimates of baseline total employment model in Table 1. These estimations imply , as the previous findings, that automation gives rise to employment in automotive and service sector but there might be some displacement effect in automotive so that some of these workers are re-allocated to the service sector, which might be the main reason for the increase in employment stemming from automation. It is claimed that the behaviour of automotive industry is very similar to the manufacturing sector in general. Therefore, automotive sector is considered as representative for manufacturing.

3.2 Worker level analysis

Panel A in Table 6 reveals how workers' adjustments take place in the case of automation. Column (1) indicates the effect of predicted robot exposure on total employment. Since other columns represent the decomposition of all employers into different sectors, the sum of the coefficients in columns (2)-(4) is equal to total effect in column (1). Column (2) presents a negative and significant effect on employment, which suggests that the jobs in the original plants are not guaranteed and these workers are subject to losing their jobs easily when automation takes place. It might be the result of less legal barriers to fire workers so that workers can be displaced from the workplace without any serious costs. In columns (2) and (3), the coefficients are small, negative and statistically significant. These results point out that workers have no institutionalized job security in their original plant and they are partly discouraged from finding another job in the service sector.

Panel B in Table 6 adds another dimension to analysis by incorporating earnings into the analysis. It is important to get an overall idea about the impact of automation on the labor market outcomes. It seems that automation has a positive impact on earnings for all employers. The coefficient is equal to 2.632 and highly significant. When we divide these into different parts, we see in column (6) that most of the rise in earnings stem from workers staying at the original firm. While column (7) and (8) suggest a lower increase when workers are employed by another firm, other firms in manufacturing sector can be considered as advantageous comparing to those in service sector. We will look at this results closely in Table 7 to see how they are related to one's choice to change her occupation.

Panel A in Table 7 checks the ability of workers to find a new job with a different occupation. Columns (1) and (2) extend the results in column (2) of Panel A in Table 6. The main aim is to understand if workers staying in the original firm are able to achieve it with the same occupation or with a different one. Our results suggest that there is no common tendency to change the occupation in the same plant since the coefficients of same and different occupation are almost equal to each other as shown in columns (1) and (2). Another interesting result is that even though workers are mainly discouraged from finding a new job in other sectors, as in Panel A in Table 6, finding a new job with different occupation is more difficult than one's own occupation. One possible explanation of these results is that automation not only results in displacement of workers from the workplace but also destroys occupations in general. It means that if workers are lucky enough, they are offered with an opportunity to handle their original occupation or another occupation in the same plant. However, when they are unemployed and searching for a new job, their original occupation does attract only a small amount of interest and other firms do not trust enough to employ them in a different occupation. When we focus on the comparison of time spent on one's original occupation and on a different occupation, the sum of columns (1) and (3) indicates the former, while the sum of columns (2) and (4) is the latter. These values are close to each other due to the fact that the coefficient on different occupation on different firm is considerable larger. If we compare time spent on the same occupation and on a different occupation, the sum of columns (5) and (7) is equal to -1,420 and that of columns (6) and (8) is -1,706. Our calculations yield the result that there is no significant difference between time spent on one's original occupation and on a different occupation. We conclude that automation supports occupational mobility but not in considerable magnitudes.

Panel B indicates what happens to earnings in different occupations in response to automation. Our estimates yield highly significant estimates. The findings point out that automation only results in a slight reduction in earnings for workers staying at the same plant and doing the same occupation. However, other specifications imply a positive impact on earnings. This effect is considerable higher for workers switched to a different occupation both in the same plant or another one. These results suggest that certain occupations are seriously damaged in the case of automation and workers are forced to adopt to a different occupation. If workers manage to handle a different occupation, then they will be better of both at the same or different plant in terms of their earnings.

4 Conclusion

The effects of automation on labor market outcomes such as employment and earnings have been widely discussed in literature. However, because of the low manufacturing share in their economy and high marginal productivity or robotization, developing country context may provide different perspectives to the this debate even though previous studies are mostly limited to developed countries. The present study was designed to determine the effect of robotization on the local and individual labor market outcomes in Turkey. The results of this investigation using regression analysis taking account of the covariates and and the endogeneity show that robot exposure positively affect the local labor markets even though most studies find opposite. Moreover, we strongly confirm this finding for young aged workers of manufacturing and nonmanufacturing industries or when robotization in automotive industries take account separately. This findings point out that rather than any crowding out effects, reallocation mechanism between main industries occurs. This helps to explain the positive employment effect in both side. In addition, we see that this positive effect mostly comes from the robotization in the automotive industry, which consists half of the total number of robots in Turkey. Policymakers should take account these dimensions to direct technology and labor policies at regional level. Our future research is to analyze the motivations of firms to decide to obtain a robot. This would put forward how labor-cost related issues exists. In this sense, survey data involving information technology usage of firms can be used.

Our worker level analysis show that robotization separate incumbent workers in manufacturing industry from their original workplaces and occupations. In addition, it is difficult for them to find job in nonmanufacturing industry. On the other hand, their wage premium is higher when they are employed. Training programs for employment to complement with robotization can help workers to improve their outcomes and living standards.

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Table 1: Main specification

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
	A. Change in log employment, 2014-2021					
Predicted robot exposure	2.690***	4.108***	3.978***	2.017**	3.421***	3.328***
	(0.771)	(1.117)	(1.113)	(0.816)	(1.224)	(1.222)
R-squared	0.303	0.314	0.322	0.170	0.184	0.192
	B. Change in employment to population ratio, 2014-2021					
Predicted robot exposure	0.778***	0.813**	0.812**	0.706**	0.679*	0.677*
	(0.251)	(0.344)	(0.343)	(0.276)	(0.373)	(0.373)
R-squared	0.066	0.067	0.067	0.086	0.086	0.086
Observations	861	861	861	861	861	861
	C. Change in log average wage, 2014-2021					
Predicted robot exposure	1.250	0.583	0.528	1.283	0.693	0.607
	(0.881)	(0.945)	(0.935)	(0.978)	(1.049)	(1.024)
R-squared	0.016	0.020	0.020	0.020	0.025	0.026
Observations	16,950	16,950	16,950	16,950	16,950	16,950
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	-	+	+		+	+
Net export visavis China and East import	-	-	+	-	-	+
First stage F-statistic				256	214.6	213

Notes: Each column shows the effect of robot exposure on local labor market outcome. Each specification is weighted by population of district in 2014. Columns (1)-(3) and (4)-(6) report OLS and 2SLS results, respectively. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Employment share in manufacturing industry and net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table 2: Composition effects: manuf. vs nonmanuf. industries

	(1) Manuf.	(2) Manuf.	(3) Manuf.	(4) Nonmanuf.	(5) Nonmanuf.	(6) Nonmanuf.
	A. Change in log employment, 2014-2021					
Predicted robot exposure	3.700*	7.681***	7.484***	0.901	1.679*	1.622*
	(1.930)	(2.397)	(2.376)	(0.591)	(0.938)	(0.936)
R-squared	0.043	0.075	0.086	0.170	0.175	0.178
	B. Change in employment to population ratio, 2014-2021					
Predicted robot exposure	0.666***	0.583*	0.580*	0.037	0.097	0.097
	(0.242)	(0.311)	(0.311)	(0.074)	(0.087)	(0.086)
R-squared	0.156	0.158	0.159	0.012	0.014	0.014
Observations	835	835	835	861	861	861
	C. Change in log average wage, 2014-2021					
Predicted robot exposure	1.340	0.480	0.389	0.020	-0.267	-0.268
	(0.964)	(1.015)	(1.003)	(0.868)	(0.936)	(0.930)
R-squared	0.004	0.012	0.013	0.024	0.024	0.024
Observations	9,874	9,874	9,874	16,950	16,950	16,950
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	-	+	+	-	+	+
Net export visavis China and East import	-	-	+	-	-	+
First stage F-statistic	252.6	210.8	209.3	256	214.6	213

Notes: Each column shows the effect of robot exposure on local labor market outcome using IV estimator. Each specification is weighted by population of district in 2014. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Employment share in manufacturing industry and net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table 3: Composition effects: non-routine vs routine occupations

	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Manuf.	Nonmanuf.	Total	Manuf.	Nonmanuf.
		Non-routine			Routine	
	A. Change in log employment, 2014-2021					
Predicted robot exposure	6.563	16.909**	-0.186	6.459	14.613*	-1.595
	(8.173)	(6.930)	(10.181)	(8.401)	(7.767)	(10.572)
R-squared	0.177	0.134	0.179	0.082	0.097	0.106
Observations	861	734	861	859	778	857
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	+	+	+	+	+	+
Net export visavis China and East import	+	+	+	+	+	+
First stage F-statistic	213	206.6	213	212.8	209	212.8

Notes: Each column shows the effect of robot exposure on local labor market outcome using IV estimator. To identify the routine content of workers, the classification developed by Mihaylov and Tijdens (2019) is used. Each specification is weighted by population of district in 2014. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Employment share in manufacturing industry and net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table 4: Robots and employment by age groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Manuf.	Nonmanuf.	Total	Manuf.	Nonmanuf.	Total	Manuf.	Nonmanuf.
		18-34			35-54			55-64	
	A. Change in log employment, 2014-2021								
Predicted robot exposure	4.100***	8.523***	2.452**	2.312*	6.232***	0.473	1.589	1.851	1.368
	(1.309)	(2.839)	(1.218)	(1.265)	(2.154)	(0.801)	(1.198)	(3.266)	(0.831)
R-squared	0.291	0.097	0.285	0.069	0.061	0.048	0.062	0.024	0.109
Observations	861	814	861	861	817	861	844	619	839
Demographics	+	+	+	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+	+	+	+
Manufacturing share	+	+	+	+	+	+	+	+	+
Net export visavis China and East import	+	+	+	+	+	+	+	+	+
First stage F-statistic	213	207.1	213	212.8	208.3	213	212.7	190.6	213.3

Notes: Each column shows the effect of robot exposure on local labor market outcome. Each specification is weighted by population of district in 2014. Columns (1)-(3) and (4)-(6) report OLS and 2SLS results, respectively. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Employment share in manufacturing industry and net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table 5: Role of automotive industry

	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Total	Manuf.	Manuf.	Nonmanuf.	Nonmanuf.
	A. Change in log employment, 2014-2021					
Predicted robot exposure in other ind.	-0.501	-0.848	13.524*	12.805	-5.901**	-5.916*
	(4.329)	(4.474)	(7.853)	(8.083)	(2.695)	(3.486)
Predicted robot exposure automotive ind.	3.716***	3.640***	7.238***	7.083***	2.244***	2.249**
	(1.152)	(1.164)	(1.984)	(1.980)	(0.765)	(1.022)
R-squared	0.181	0.189	0.079	0.089	0.172	0.172
Observations	861	861	835	835	861	861
	B. Change in log average wage, 2014-2021					
Predicted robot exposure in other ind.	5.978**	5.784**	0.769	0.512	2.234	2.249
	(2.729)	(2.644)	(2.904)	(2.975)	(1.941)	(1.947)
Predicted robot exposure automotive ind.	0.594	0.524	0.476	0.388	-0.315	-0.309
	(0.916)	(0.899)	(1.020)	(1.010)	(0.958)	(0.950)
R-squared	0.032	0.033	0.013	0.013	0.026	0.026
Observations	16,950	16,950	9,874	9,874	16,436	16,436
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	+	+	+	+	+	+
Net export visavis China and East import	-	+	-	+	-	+
First stage F-statistic	308	307.5	312	311.5	308	307.5

Notes: Each column shows the effect of robot exposure for each automotive and non-automotive sector on local labor market outcome. Each specification is weighted by population of district in 2014. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Employment share in manufacturing industry and net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table 6: Industry mobility

	(1) All employers	(2) Original firm	(3) Other firm in manuf.	(4) Other firm in nonmanuf.	(5) All employers	(6) Original firm	(7) Other firm in manu.	(8) Other firm in nonmanuf.
	OLS				IV			
	Panel A. Industry mobility-employment							
Predicted robot exposure	-3.379***	-2.782***	-0.270***	-0.327***	-3.126***	-2.416***	-0.307***	-0.404***
	(0.060)	(0.076)	(0.045)	(0.024)	(0.059)	(0.076)	(0.045)	(0.024)
R-squared	0.177	0.146	0.054	0.050	0.071	0.066	0.000	0.009
	Panel B. Industry mobility-earning							
Predicted robot exposure	2.936***	1.542***	0.881***	0.512***	2.632***	1.472***	0.771***	0.389***
	(0.150)	(0.110)	(0.049)	(0.044)	(0.145)	(0.107)	(0.048)	(0.042)
R-squared	0.108	0.053	0.075	0.061	0.102	0.047	0.064	0.054
Observations	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130

Notes: Each column shows the effect of robot exposure on cumulated employment days (Panel A) and earnings (Panel B) of workers who were employed in manufacturing industry in 2014. Predicted robot exposure of nine EU countries are used as instrument in Column (5) to (8). Column (1) and (5) presents estimates all workdays and earnings of workers. Column (2) and (6) presents estimates of cumulated workdays and earnings in original firms of workers. Column (3) and (7) presents estimates of cumulated workdays and earnings in manufacturing industry of workers. Column (4) and (8) presents estimates of cumulated workdays and earnings in non-manufacturing industry of workers. Log initial wage and gender, age, skill, firm size, province, five region and KLEM industry fixed effects are included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses.

Table 7: Occupation mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Same occup. and same firm	Different occup. and same firm	Same occup. and different firm	Different occup. and different firm	Same occup. and same firm	Different occup. and same firm	Same occup. and different firm	Different occup. and different firm
	OLS				IV			
	Occupation mobility-employment							
Predicted robot exposure	-1.298***	-1.484***	-0.243***	0.353***	-1.195***	-1.221***	-0.225***	-0.485***
	(0.035)	(0.067)	(0.016)	(0.045)	(0.035)	(0.067)	(0.016)	(0.045)
R-squared	0.108	0.187	0.071	0.071	0.026	0.037	0.001	0.008
	Occupation mobility-earning							
Predicted robot exposure	-0.091***	1.633***	0.102***	1.291***	-0.091***	1.563***	0.094***	1.066***
	(0.025)	(0.102)	(0.016)	(0.065)	(0.024)	(0.099)	(0.016)	(0.063)
R-squared	0.033	0.057	0.034	0.105	0.005	0.044	0.014	0.095
Observations	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130	2,631,130

Notes: Each column shows the effect of robot exposure on cumulated employment days (Panel A) and earnings (Panel B) of workers who were employed in manufacturing industry in 2014. Predicted robot exposure of nine EU countries are used as instrument in Column (5) to (8). Column (1) and (5) presents estimates all workdays and earnings of workers who stayed in original occupation and workplace. Column (2) and (6) presents estimates of cumulated workdays and earnings of workers stayed in original firms but different occupations. Column (3) and (7) presents estimates of cumulated workdays and earnings of workers who are employed in different firms but same occupations. Column (4) and (8) presents estimates of cumulated workdays and earnings of workers who are employed in different firm and occupation. Log initial wage and gender, age, skill, firm size, province, five region and KLEM industry fixed effects are included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses.

A Appendix

Table A1: Pre-trends

	(1) Total	(2) Total	(3) Manuf.	(4) Manuf.	(5) Nonmanuf.	(6) Nonmanuf.
	A. Change in log employment, 2010-2014					
Predicted robot exposure	-1.993	-2.026	4.027	3.957	-4.741	-4.787
	(2.287)	(2.291)	(2.522)	(2.529)	(2.928)	(2.917)
R-squared	0.096	0.097	0.155	0.156	0.062	0.063
	B. Change in employment to population ratio, 2010-2014					
Predicted robot exposure	0.646	0.644	0.482	0.482	0.173	0.171
	(0.648)	(0.647)	(0.356)	(0.354)	(0.364)	(0.363)
R-squared	0.114	0.114	0.109	0.109	0.149	0.149
	C. Change in log total wage, 2010-2014					
Predicted robot exposure	-2.988	-3.014	2.509	2.434	-4.334	-4.374
	(2.329)	(2.334)	(2.712)	(2.724)	(2.712)	(2.704)
R-squared	0.071	0.071	0.071	0.071	0.049	0.050
Observations	849	849	849	849	849	849
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	+	+	+	+	+	+
Net export visavis China and East import	-	+	-	+	-	+
First stage F-statistic	176	175.9	172.4	172.4	176	175.8

Notes: Each column shows the effect of robot exposure on local labor market outcome for the period 2010-14. Each specification is weighted by population of district in 2014. Columns (1)-(2), (3)-(4), and (5)-(6) report total, manufacturing, and nonmanufacturing industry results, respectively. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Table A2: Main specification: firms in 2014

	(1) Total	(2) Total	(3) Manuf.	(4) Manuf.	(5) Nonmanuf.	(6) Nonmanuf.
	A. Change in log employment, 2014-2021					
Predicted robot exposure	1.348	1.274	7.030**	7.006**	-1.774	-1.811
	(2.083)	(2.046)	(3.258)	(3.232)	(1.607)	(1.601)
R-squared	0.404	0.416	0.212	0.215	0.238	0.242
	B. Change in employment to population ratio, 2014-2021					
Predicted robot exposure	0.720**	0.717**	0.523**	0.522**	0.207	0.206
	(0.318)	(0.316)	(0.221)	(0.220)	(0.158)	(0.157)
R-squared	0.779	0.779	0.386	0.388	0.840	0.841
Observations	858	858	798	798	858	858
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Manufacturing share	+	+	+	+	+	+
Net export visavis China and East import	-	+	-	+	-	+
First stage F-statistic	215.4	216	215	217.2	215.4	216

Notes: Each column shows the effect of robot exposure on local labor market outcome for the period 2014-21. Each specification is weighted by population of district in 2014. Columns (1)-(2), (3)-(4), and (5)-(6) report total, manufacturing, and nonmanufacturing industry results, respectively. Robot exposure of eight countries leading robotics in EU is instrumented with variable of interest. Demographics are female population share, secondary and tertiary education population share, 50 years population share in 2014. Net export vis a vis China and Eastern Europe per worker are added as shown above. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.