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Research Article

Robots, Employment and Wages: Evidence from Turkish Labor Markets[a]

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This paper investigates how robotization affects local- and worker-level labor market outcomes in Turkey for 2014-2021. We estimate shift-share specifications, instrumenting Turkish industry-level robot adoption with the same indicator in eight leading European countries, utilising a combined dataset of administrative employer-employee data and industry-level robot stocks. Contrary to evidence from advanced economies, we find positive effects of robot exposure on district-level employment growth, concentrated in manufacturing and driven by the automotive industry. This pattern is consistent with the theoretical insight that the labor market effects of automation depend on an economy's position relative to the global productivity frontier. We complement the local-level analysis with an intensive-margin, worker-level exercise that tracks the 2014 manufacturing-worker cohort through 2021. The results reveal that incumbent workers in more-exposed industries experience a reduction in cumulative workdays at their original plants and are unlikely to transition outside manufacturing. The aggregate employment gains, therefore, accrue through firm expansion and new worker entry rather than through intensive-margin expansion of the incumbent workforce.

JEL codes: J23, J24

Keywords: Robots; Employment; Wages; Automation; Turkish labor markets

1 Introduction

There has been a controversy that can be dated to the early 1800s during the Industrial Revolution among economists and policymakers on whether automation technologies lead to a reduction in the labor share of output and employment. In modern times, Keynes (2010)

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had explored the issue further by developing the "technological unemployment" concept. Afterwards, the demand for skills and the inequality effects of automation have been other dimensions of this controversy (Griliches, 1969). Under certain technological projections, job polarization and inequality are emphasized due to the disappearing occupations (Autor et al., 2003; Acemoğlu & Autor, 2011; Frey & Osborne, 2017).

In recent years, this debate has been outpaced due to the widespread use of robots across various industries. In line with these developments, theoretical foundations of the 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, the 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 & Michaels (2018), for example, it is shown that robot adoption did not reduce total employment but the employment share of low-skill workers. According to Acemoğlu & Restrepo (2020), each additional robot per thousand workers in the US is associated with decreases in the employment-to-population ratio and wages of 0.2% and 0.42%, respectively. For Germany, Dauth et al. (2018) finds no total employment losses due to the mobility of employees from manufacturing to non-manufacturing industries (i.e., composition effect) and the negative wage effect of robots. Apart from these three seminal studies, many papers confirm the negative employment and wage effect of robots (Acemoğlu & Restrepo, 2018; Chiacchio et al., 2018; Giuntella & Wang, 2019; Bessen, 2019; Acemoğlu et al., 2020; Bonfiglioli et al., 2020; Faber, 2020; Dottori, 2021; Bessen et al., 2025).

There are also studies reporting positive employment effects. Klenert et al. (2022) analyzes the data from the European Union (EU) countries and finds that robot use is linked to an increase in manufacturing employment. In a developing country context, Calì & Presidente (2022) examines the effects of robotization in Indonesian manufacturing industries and shows the employment gains from automation. Aghion et al. (2020) also obtains similar evidence for France. These studies refer to the mechanism that increased productivity induces higher scale and higher labor demand. Tuhkuri (2022) finds similar results but argues 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, the evolution of manufacturing production from mass to flexible specialization puts different sets of technology and labor relations. Thus, flexible specialization is not necessarily labor-reducing or skill-biased.[2] Finally, Cheng et al. (2019) presents anecdotal evidence on how the number of employees of Chinese enterprises implementing the "replacement of workers with robots" incentive is unaffected by the robot exposure.[3]

This paper examines the relationship between robot adoption 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

[1] Tuhkuri (2022) presents a theoretical model based on Dixit & Stiglitz (1977) and Melitz (2003) and empirically tests the implications. Findings show that Finnish firms are interested in product-focused 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 the Turkish Statistical Institution (TurkStat).

[2] Piore & Sabel (1984) also emphasizes this evolution, arguing that SMEs focus on product varieties with low output levels.

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

limited evidence in the literature. By using novel employer-employee data having firm information such as production, wage, trade, and worker information provided by the Enterprise Information System (EIS) of the Ministry of Industry and Technology of Turkey and the International Federation of Robotics (IFR) database that reports the number of robots deployed 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 account for endogeneity between robot exposure and the error term by instrumenting robot exposure with the number of robots in eight EU countries leading in robotic technology.

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

Our findings of local labor market analysis accord with the second group of papers we mention above. Robot exposure is associated with positive employment effects in Turkish districts, in contrast to the negative effects documented for advanced economies. This pattern is consistent with a broader theoretical insight that the labor market effects of automation depend on a country's position relative to the global productivity frontier (Acemoğlu et al., 2006; Acemoğlu & Restrepo, 2018; Acemoğlu et al., 2020). In economies operating closer to the frontier, the displacement effect of automation may dominate, as documented in the US (Acemoğlu & Restrepo, 2020) and Germany (Dauth et al., 2021). In economies further from the frontier, automation may complement existing factors of production and enable firms to expand output and labor demand, as documented for Indonesia (Calì & Presidente, 2022) and France (Aghion et al., 2020). Turkey's intermediate position in the global productivity distribution may help explain why we observe positive aggregate employment effects in our setting. We emphasize that we do not directly test the distance-to-frontier mechanism, as this would require comparable industry-level productivity data across Turkey and a frontier economy that is not available in our dataset; we therefore present this framing as a candidate explanation consistent with our findings rather than as a tested hypothesis.

Secondly, we deal with how workers in the 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 resulting from workers' decisions on staying at their original workplace or switching to another workplace. We cumulate employment days and earnings of the workforce employed in the manufacturing sector in 2014. Our results reveal that robotization negatively affects the total employment of incumbent workers, which is mainly stemming from those staying at their original workplace. In other words, the likelihood of maintaining the same level of employment in a non-manufacturing industry decreases when incumbents face robot exposure. Staying at the original firm and manufacturing industry is also negatively affected by robotization, but earnings of the former group are likely to increase in higher robot exposure industries. This finding confirms that automation has a complementary relationship with those who retain their employment at the original firm. This evidence is more apparent when these workers are employed in different occupations within the same firm.

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

2 Identification and data

We carry out this study at both the local- and worker-level labor markets. The unit of analysis in the former is the district (ilçe), the smallest administrative unit in Turkey. However, these units are defined with political boundaries and do not exactly consider the commuting patterns, which is an important dimension to isolate the labor market shocks. In order to control the mobility 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. The model given in eq. (1) is estimated.

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

where the dependent variable Δy_i is the change in employment-to-population ratio, change in log employment, and the average wage in district i. To calculate the average wage, we construct demographic cells by summing real wages across age groups, genders, and skill levels (defined by ISCO[5]), and divided by the number of workers in each group.[6] X_i is district-specific controls such as net exports vis-à-vis China and Eastern Europe, occupation and age group share of employment, five region dummies, and employment share in the manufacturing industry. We also use the population of each district in the initial year as weights. β is the coefficient of interest and shows the effect of changes in the number of robots on the number of workers or the average wage in district i. Our challenge in eq. (1) is to measure the robot exposure at the regional level because we have no available data on robot adoption at the district level. To measure district-level robot intensity, we will construct an exposure variable as other studies have applied, which uses employment shares of industries in each province as weights:

$$\Delta robots_i^{TR} = \sum_j \ell_{ij,2014} \frac{\left(robot_{j,2021}^{TR} - robot_{j,2014}^{TR}\right)}{emp_{j,2014}^{TR}} \times 1000 \tag{2}$$

where ℓ_{ij} is employment share of industry j in district i, $robot_{j,2021}^{TR}$ and $emp_{j,2014}^{TR}$ are numbers of robot stock and total employment in industry j, respectively. Since the exposure measure interacts pre-period industry shares with common (industry-level) shifts, two

[4] We also carry out this analysis at the district level without merging and obtain similar results with those we present here. These results are available upon request.

[5] International Standard Classification of Occupations (ISCO) classifies managers, professionals, technicians, and associate professionals as high-skill. Elementary occupations are classified as low-skill, and the remaining occupations are considered medium-skill. By simplicity, we merged the last two groups as low-skill.

[6] All region-level specifications are estimated in long differences between 2014 and 2021. Panels A and B of Table 1 use the district as the unit of observation (N = 861). Panel C estimates the wage regression at the district × demographic cell level (N = 16,950), where cells are defined by age group, gender, and skill level, to control for compositional changes in the employed workforce.

regions with identical pre-period industry composition receive the identical exposure values. Our identification strategy, therefore, rests on the assumption that regional variation in actual robot adoption is captured by pre-period industrial composition, up to factors orthogonal to the outcomes of interest.[7]

Ordinary least square (OLS) estimation of eq. (1) may be problematic for two reasons. First, some industries might have decided to adopt robots because of trends that are not directly related to labor market conditions. However, these trends may impact labor demand subsequently. Second, an external shock to labor demand in a district directly affects the robot adoption. We overcome this problem by instrumenting Turkish exposure to robots using the number of robots in the leading eight EU countries by robot stock.[8] Similar approaches have been utilized by other studies (e.g., Dauth et al., 2021; Giuntella & Wang, 2019; Acemoğlu & Restrepo, 2020; Klenert et al., 2022). Our Bartik-style shift-share instrument formula is as follows:

$$\Delta robots_i^{EU8} = \sum_j \ell_{ij,2010} \frac{\left(robot_{j,2021}^{EU8} - robot_{j,2014}^{EU8}\right)}{emp_{j,2014}^{EU8}} \times 1000 \tag{3}$$

where the province's shares in 2010 are used to further address endogeneity concerns, following Dottori (2021).

We then proceed to worker-level analysis to examine how workers adjust their outcomes in response to 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 the dependent variable y_{wj} is the log of either total workdays or wages of worker w in industry j, X_{wj} includes individual, firm, and industry-level characteristics such as gender, age dummies, firm size, tenure, and industry and region dummies. Industry, plant, and occupation mobility are taken into account when cumulating the outcomes to see how they are affected by robots. Note that variable $\Delta robots_j$ is industry-level in eq. (4) and calculated as

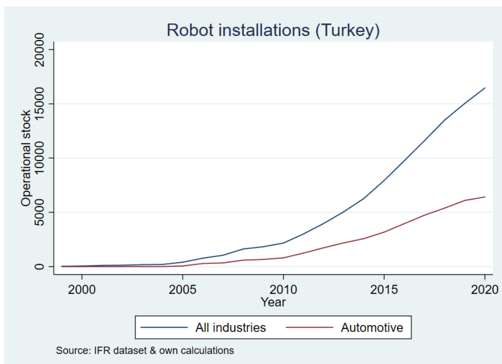
$$\Delta robots_j^{TR} = \frac{\left(robot_{j,2021}^{TR} - robot_{j,2014}^{TR}\right)}{emp_{j,2014}^{TR}} \times 1000 \tag{5}$$

We draw on three data sources to study the effect of robots on employment and average wages in Turkey. The first is the Entrepreneur Information System (EIS, spanning from 2014 to 2021), which compiles administrative data on firms from multiple institutions and on workers from the Turkish Social Security Administration. Merging these records through a common firm identifier yields a linked employer-employee dataset covering 2006 to 2021. Because six-digit ISCO occupation codes and worker identifiers are recorded only from 2014 onward, we take 2014 as our baseline period. Second, we obtain industry-level robot

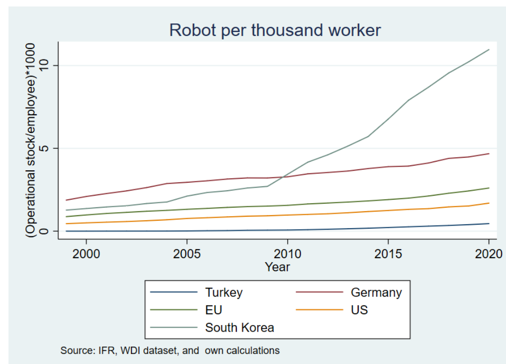
[7] Nonetheless, we address this concern in two ways, as detailed in the following sections. First, we instrument Turkish robot adoption with industry-level robot adoption of a foreign country distributed via Turkish pre-period industry shares, eq. 2, isolating variation driven by the global technological frontier rather than by endogenous Turkish firm responses. Second, we verify that regions with higher predicted exposure did not exhibit differential pre-trends in labor market outcomes.

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

counts, collected from firms' robot sales, from the International Federation of Robotics (IFR, spanning from 2005 to 2021) for a number of countries.[9] Finally, EU KLEMS[10] provides country-industry-level employment data that we use to construct our instruments (Jäger, 2016). Because both KLEMS and EIS report industry classifications at finer levels of disaggregation than IFR, we aggregate all industry definitions to the 17 IFR industries used in our analysis.



(a) Total robots in Turkey, 1999-2021



(b) Robot per thousand worker, 1999-2021

Figure 1: Robot penetration

Figure 1a indicates that after the 2010s, robot counts accelerated, with a significant contribution from the automotive industry. Figure 1b compares the total number of robots per thousand workers in selected leading countries and the EU. Although there is a general upward trend across all countries, there has been a sharp rise in South Korea after 2010, reaching the highest robot penetration per 1000 workers. Turkey has the lowest penetration and has a slight increase in the same period. This figure may also help to explain the positive employment effect of robot exposure that we present below. As Calì & Presidente (2022) and Aghion et al. (2020) argue, low levels of robotization in a developing country provide high productivity and generate labor demand.

Figure 2 maps the variable $\Delta robots_i$ in eq. (1) to see how robot exposure is dispersed. It is evident that robot exposure is substantially similar to the industrialization levels of provinces in Turkey. Western regions are more likely to have manufacturing employment, while eastern provinces are concentrated on agriculture and services. Since the robotics industry is concentrated in the automotive and electronics sectors, it directly reflects our exposure index, with the Marmara region (northwest), Aksaray, and Kırıkkale (the boldest regions in central) provinces as examples. Among the central regions, Karabük, Çankırı, and Kayseri have the highest exposure.

When the exposure, excluding the automotive industry, is considered, as depicted in Figure 3, we see a similar pattern with some notable differences. First, the highest value of our index is 18.2 in Figure 2 and 3.6 in Figure 3. While the overall level of predicted

[9] Due to the inconsistent coverage between EIS and IFR, the EIS range is used to estimate the models.

[10] It is an industry-level, growth and productivity research project in the EU, where KLEMS stands for capital, labor, energy, materials and service inputs, respectively.

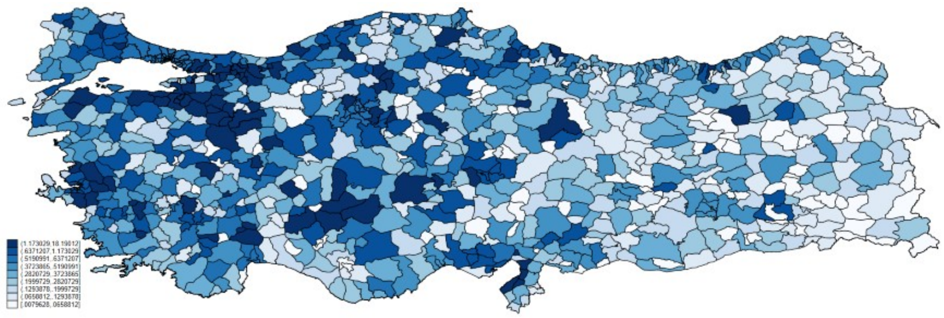


Figure 2: Robot exposure of Turkey

robot exposure is lower when the automotive industry is excluded - reflecting the high robot intensity of that sector - the cross-regional distribution of exposure remains very similar. Since identification in our specification comes from variation across regions rather than from absolute levels, this pattern indicates that the automotive industry shifts the mean of exposure but does not drive the cross-regional variation that underlies our estimates. On the other hand, variance across districts is significantly reduced, indicating that exposure is relatively uniform when the automotive industry is excluded.

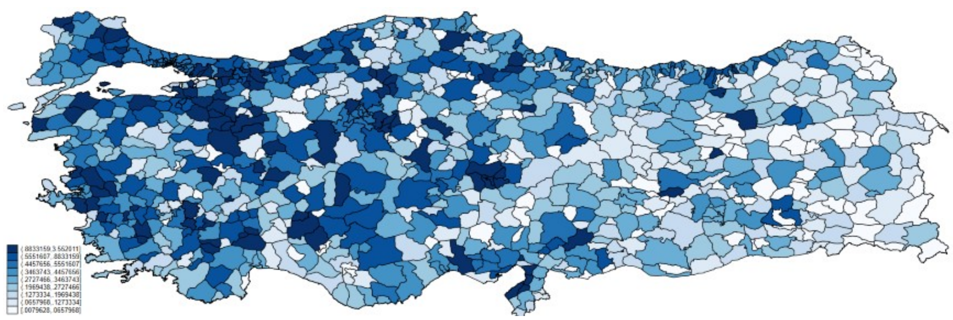


Figure 3: Robot exposure of Turkey, outside the automotive industry

3 Results

3.1 District level analysis

Panel A of Table 1 reports the effect of predicted robot exposure on the change in log employment between 2014 and 2021. Following standard practice in the regional and urban economics literature, our preferred specifications, provided in Columns (4) to (6), weight districts by their 2014 population. The estimated effect of predicted robot exposure is positive and statistically significant at the 1% level across all three weighted specifications, ranging from 0.035 to 0.046. The coefficient is stable across increasingly demanding sets of controls, including demographics and five-region fixed effects (Column 4), the addition of the manufacturing employment share (Column 5), and the further inclusion of net exports vis-à-vis China and Eastern Europe (Column 6), suggesting that the estimated effect is not driven by confounding regional trends.

Table 1: Main specification

	Unweighted			Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Change in log employment, 2014-2021					
Predicted robot exposure	0.016	0.018	0.017	0.035***	0.046***	0.046***
	(0.010)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
R-squared	0.027	0.027	0.037	0.107	0.119	0.123
	Panel B: Change in employment-to-population ratio, 2014-2021					
Predicted robot exposure	0.014***	0.014***	0.014***	0.008***	0.008***	0.008***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
R-squared	0.085	0.086	0.086	0.077	0.077	0.077
K-P Wald test	259.4	233.5	212.6	242.4	249.2	221.3
	Panel C: Change in log average wage, 2014-2021					
Predicted robot exposure	0.013**	0.013*	0.013*	0.013	0.006	0.006
	(0.006)	(0.007)	(0.007)	(0.010)	(0.011)	(0.011)
R-squared	0.001	0.001	0.002	0.022	0.025	0.026
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	-	+	+		+	+
Net exports	-	-	+	-	-	+
K-P Wald test	259.6	242.5	223.8	373.2	245.2	245.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes. Panels A and B are estimated at the district level (N=861), and Panel C is estimated at the district × demographic cell level, where cells are defined by age group, gender, and skill level (N=16,950). All specifications show long differences between 2014 and 2021, and report 2SLS results, in which robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Columns (4) to (6) are weighted by the district population in 2014. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share of the manufacturing (M); the net export (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.

For completeness, Columns (1) to (3) report unweighted instrumental variable (IV) estimates, where the point estimates remain positive but are smaller in magnitude and statistically insignificant. Given that Turkish districts are highly dispersed in population size - with a small number of large urban centers coexisting with many sparsely populated rural districts - unweighted estimates place disproportionate weight on small districts whose labor market dynamics are less representative of aggregate Turkish employment trends. We, therefore, interpret the population-weighted estimates as the more informative of the two, consistent with standard practice in this literature. The Kleibergen-Paap Wald F statistics reported at the bottom of each panel are well above conventional thresholds for instrument strength in all specifications, confirming that weak identification is not a concern.

Nevertheless, our main challenge is to explain why exposure to robots should have a positive effect on employment. Even though the vast majority of the literature finds a negative relationship between automation and employment, we need to explain why it might be mistaken to accept this as a common pattern, especially given how developing economies diverge 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; we see differences in its magnitude. From now on, we will explain how different specifications yield different estimates of the effect of robot exposure. In Column (5), we added the manufacturing share and found a larger effect for robot exposure. In Column (6), we also include the net export change per worker and find similar effects. Our results in those columns indicate that the positive effect of robot exposure will be persistent across numerous specifications, meaning that even controlling for additional variables does not alter its positive impact on employment. First-stage F-statistics in the last row of the table also ensure that instruments as a whole are a strong predictor of the variable of interest.

Panel B of Table 1 replicates the specification using the change in the employment-to-population ratio as the dependent variable. This outcome facilitates direct comparison with Acemoğlu & Restrepo (2020) and further accounts for district population size. We again find positive and statistically significant effects of predicted robot exposure in our preferred population-weighted specifications (Columns 4 to 6), with coefficients of 0.008 and significant at the 1% level across all three models. The unweighted estimates (Columns 1 to 3) are larger in magnitude (0.014) and also significant. The consistency of the positive sign across weighted and unweighted specifications reinforces the main finding from Panel A: greater robot exposure is associated with increased local labor demand in Turkey.

Panel C of Table 1 reports estimates for the change in log average wages. In our preferred population-weighted specifications (Columns 4 to 6), the coefficient on predicted robot exposure is positive but statistically insignificant. The unweighted estimates (Columns 1 to 3) are positive and marginally significant at the 10% level, though the point estimates are similar in magnitude across the two estimators. Taken together, these results suggest that predicted robot exposure does not translate into higher average wages in the Turkish local labor markets. In contrast with the positive employment effects documented in Panels A and B, workers in more exposed districts do not appear to capture productivity gains in the form of higher wages. This asymmetry– positive employment effects without corresponding wage gains– is consistent with a setting in which the labor supply curve is relatively elastic at the local level, so that the increased labor demand is absorbed primarily through quantity rather than price adjustments.

Panel A of Table 2 indicates how the effect of predicted robot exposure on percentage change in employment differs in manufacturing and non-manufacturing industries. As we discussed above, the literature indicates that robot adoption generally lowers employment in the manufacturing sector, since robots are primarily used to enhance industrial productivity. Hence, related studies suggest that employment should be more adversely affected in the manufacturing sector, whereas other sectors should increase their labor demand due to the fact that all industries are dependent on each other when producing final goods. Our estimates are positive and highly significant in the manufacturing industry (Columns 1 to 3), regardless of whether district size and control variables are included. Adding these dimensions to the model increases the effect of robotization. As demonstrated by Columns (4)-(6), predicted robot exposure results in an insignificant employment effect in these sectors, implying that robotization only increases the labor demand in manufacturing industries.

We rerun the models in Panel A, using the change in the employment-to-population ratio as the dependent variable, and find similar results for the manufacturing sector, Panel B of Table 2, where all specifications in Columns (1) to (3) yield positive and highly significant estimates. It should be noted that the coefficients of weighted models in columns (1) to (3) are almost similar in all specifications. Our estimates for the services sector are not statistically significant and close to zero, suggesting that although automation increases the employment-to-population ratio in the manufacturing sector, this does not necessarily imply that the employment rate should be affected in the services sector as well. Following Acemoğlu & Restrepo (2020), using the employment-to-population ratio as a dependent variable might provide comparisons between Turkey and the 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 reallocation effects in the services sector, which might explain why our estimates are significant in the manufacturing sector but insignificant (or weakly significant) in the non-manufacturing sector. Using different sub-samples, such as age and skill level, might shed light on this puzzle. As shown in Panel C of Table 2, all model specifications, consistent with the previous results in Table 1, provide no significant evidence that predicted robot exposure affects the percentage change in average wages. It further suggests that wages are not related to automation, even when different estimates are used for the manufacturing and non-manufacturing sectors.[11]

Table 2: Composition effects: Manufacturing vs non-manufacturing industries

	Manufacturing			Non-manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
	Unweighted	Weighted	Weighted	Unweighted	Weighted	Weighted
	Panel A: Change in log employment, 2014-2021					
Predicted robot exposure	0.089***	0.128***	0.126***	-0.013	0.007	0.007
	(0.022)	(0.027)	(0.027)	(0.010)	(0.008)	(0.008)
R-squared	0.079	0.099	0.109	0.037	0.098	0.099
	Panel B: Change in employment-to-population ratio, 2014-2021					
Predicted robot exposure	0.012***	0.008***	0.008***	0.001	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
R-squared	0.255	0.176	0.176	0.006	0.012	0.012
Observations	830	830	830	861	861	861
K-P Wald test	249.3	238.7	251.8	316.2	221.2	242.3
	Panel C: Change in log average wage, 2014-2021					
Predicted robot exposure	0.018*	0.005	0.004	-0.001	-0.003	-0.002
	(0.009)	(0.010)	(0.010)	(0.002)	(0.010)	(0.010)
R-squared	0.009	0.013	0.013	0.001	0.024	0.024
Observations	9,874	9,874	9,874	16,436	16,436	16,436
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	-	+	+	-	+	+
Net exports	-	-	+	-	-	+
K-P Wald test	229.3	233.5	254.8	332.2	222.2	212.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes using the IV estimator. Columns (1) and (4) are weighted by the district population in 2014. Robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share of the manufacturing (M.); the net exports (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.

A central question raised by our estimates is why robot exposure increases local employment in Turkey, in contrast to the negative employment effects documented for the US (Acemoğlu & Restrepo, 2020) and other advanced economies. We hypothesize that this divergence reflects Turkey's position as a developing economy: Turkish manufacturing firms operate substantially below the global productivity frontier, and robot adoption may enable existing firms to expand production and labor demand rather than displace workers. Under this mechanism, the productivity gains from automation surpass the displacement effect,

[11] The Appendix presents robustness checks for our main specification. Table A.1 presents pre-trend test results. This allows us to determine whether the dependent variables in Tables 1 and 2 exhibit a trend before 2014 or are affected by other shocks. The presence of such trends threatens the validity of our results. All panels show no significant pre-trends.

generating a net positive employment response –the opposite of the pattern observed in advanced economies where firms are closer to the frontier and displacement effects prevail.

To examine the source of the aggregate employment response, Table A.2 restricts the sample to firms active in 2014 and re-estimates our baseline specification. This exercise distinguishes between two channels: employment expansion among existing firms versus employment generated by new firm entry. We find that manufacturing employment in incumbent firms responds positively to predicted robot exposure (Columns 3 and 4 of Panel A), while effects on total and non-manufacturing employment among incumbents are statistically insignificant. This pattern indicates that the positive aggregate employment effect in manufacturing operates at least in part through expansion at existing firms rather than solely through new firm entry. We caution, however, that this result does not directly test the distance-to-frontier mechanism. Incumbent firms may benefit disproportionately from robot adoption for several reasons unrelated to productivity catch-up: greater absorptive capacity for new technologies, larger initial scale that supports robotization investments, or selection effects in which more productive firms are more likely to adopt robots in the first place. We view the incumbent-firm result as one piece of evidence consistent with a productivity-expansion channel, but acknowledge that disentangling these alternative mechanisms requires firm-level productivity data, which are not available in our setting. The stability of the baseline coefficient across specifications –with and without employment share of manufacturing (Column 5) and net exports vis-à-vis China and Eastern Europe (Column 6)– further supports the interpretation that the positive employment effect reflects a genuine productivity channel rather than confounding industry or trade trends. The Kleibergen-Paap Wald test results in the bottom row confirm that the instruments are strong predictors of predicted robot exposure in all specifications.

Apart from the composition effect across main industries, predicted robot exposure may have affected employment differently across job-task levels. As we discussed above, while some studies find skill-biased effects of automation, others do not. In this section, we examine how robotization affects the task composition of regional employment, utilizing task scores developed by Mihaylov & Tijdens (2019) to measure the routine content of occupations. Their approach assigns 3,264 tasks to four-digit occupations and constructs task-category scores - non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual - for each occupation. 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 jobs if the RTI of an occupation is zero or above (below).

The results in Table 3 indicate the positive effect of robots on the employment growth of both task groups in only manufacturing industries (Columns 2 and 5).[12] However, the null effect has been observed in services for routine and non-routine jobs. On the other hand, a significant effect of robotization on total employment growth at both task levels has been obtained, suggesting that a positive manufacturing employment effect of robotization also drives the total employment.

[12] These findings must be interpreted with caution because a significant share of workers in the EIS data have missing ISCO codes or have been coded as "999999". Excluding these workers caused a loss of some regions from the analysis, especially in the manufacturing industry.

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

	Non-routine			Routine		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	M	NM	Total	M	NM
Predicted robot exposure	0.039***	0.113**	0.012	0.048***	0.122***	-0.001
	(0.012)	(0.035)	(0.012)	(0.017)	(0.036)	(0.010)
R-squared	0.086	0.096	0.046	0.207	0.109	0.227
Observations	861	767	861	859	808	857
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	+	+	+	+	+	+
Net exports	+	+	+	+	+	+
K-P Wald test	249.3	238.7	251.8	316.2	221.2	242.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes using the IV estimator, and is weighted by the district population in 2014 for Total, manufacturing (M), and non-manufacturing (NM). The classification developed in Mihaylov & Tijdens (2019) is used to identify workers' routine content. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share in the manufacturing (M.); the net exports (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.

Table 4 shows the composition effects across age groups. Columns (1), (4), and (7) report the effect of robotization in all industries. We see that younger workers are more likely to enjoy greater employment opportunities than middle-aged and older workers. Quantitatively, a one-unit increase in robots per thousand workers contributes to employment by 4%, primarily driven by the manufacturing industry, as shown in Column (2). Columns (3), (6) and (9) point out that non-manufacturing employment has been insignificantly affected by robotization. This finding also provides a mechanism for the results in Panel A of Table 1, implying that manufacturing employment growth mainly stems from young workers. This finding suggests that robotization contributes to the employment of younger generations.

Table 4: Robots and employment by age groups

	18-34			35-54			55-64		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	T	M	NM	T	M	NM	T	M	NM
Predicted robot exposure	0.049***	0.137***	0.010	0.072***	0.173***	-0.011	0.001	0.001	-0.001
	(0.011)	(0.028)	(0.012)	(0.027)	(0.041)	(0.009)	(0.001)	(0.001)	(0.001)
R-squared	0.192	0.115	0.181	0.067	0.106	0.019	0.155	0.161	0.144
Observations	861	805	861	861	811	861	845	606	840
Demographics	+	+	+	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+	+	+	+
Employment share of M.	+	+	+	+	+	+	+	+	+
Net exports	+	+	+	+	+	+	+	+	+
First stage F-statistic	249.3	321.8	249.3	249.3	321.2	249.3	231.4	217.5	249.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes, and is weighted by the district population in 2014. T, M, and NM stand for total, manufacturing, and non-manufacturing, respectively. Columns (1)-(3) and (4)-(6) report OLS and 2SLS results, respectively. Robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share in the manufacturing (M.); the net exports (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces.

Since Turkey has a large automotive industry, which accounts for a large share of total robots, an increase in the number of robots in this sector has notable effects on numerous macroeconomic indicators, including employment and wages. In Table 5, we control the effect of the automotive industry on how predicted robot exposure might affect overall results. In Panel A, note that non-automotive robot exposure yields no significant results for total and manufacturing employment. On the other hand, this exposure decreases significantly in the non-manufacturing industry, implying an interindustry reallocation effect. However,

Table 5: Role of automotive industry

	Total		Manufacturing		Non-manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Change in log employment, 2014-2021					
Predicted robot exposure in other industry	-0.001	-0.003	0.204**	0.198**	-0.067*	-0.067*
	(0.046)	(0.046)	(0.080)	(0.082)	(0.036)	(0.036)
Predicted robot exposure in the automotive industry	0.051***	0.050***	0.120***	0.119***	0.014*	0.014*
	(0.012)	(0.012)	(0.029)	(0.029)	(0.008)	(0.008)
R-squared	0.118	0.122	0.104	0.113	0.098	0.099
K-P Wald test	259.4	233.5	212.6	242.4	249.2	221.3
Observations	861	861	830	830	861	861
	Panel B: Change in log average wage, 2014-2021					
Predicted robot exposure in other industry	0.059**	0.058**	0.007	0.005	0.024	0.024
	(0.027)	(0.027)	(0.029)	(0.029)	(0.020)	(0.020)
Predicted robot exposure in the automotive industry	0.006	0.005	0.005	0.004	-0.004	-0.004
	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)
R-squared	0.033	0.033	0.013	0.013	0.027	0.027
Observations	16,950	16,950	9,874	9,874	16,436	16,436
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	+	+	+	+	+	+
Net exports	-	+	-	+	-	+
K-P Wald test	259.6	242.5	223.8	373.2	245.2	245.3

Notes: Each column shows the effect of robot exposure in the automotive and non-automotive sectors on local labor market outcomes, and is weighted by the district population in 2014. Robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share of the manufacturing (M.); the net exports (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.

predicted robot exposure in the automotive industry is positive and highly significant for all specifications. Our results provide insights that we might focus specifically on the automotive industry, as it is considered one of the sectors most affected by automation. In total employment, the coefficient on predicted robot exposure is nearly 0.05, which aligns with our expectations based on the previous estimation results, as the coefficients are close to the corresponding estimates in the baseline total employment model in Table 1. These estimates, like the previous findings, imply that automation creates employment in the automotive and services sectors, but there may be some displacement from the automotive sector to the services sector, which may be the main reason for the increase in employment stemming from automation. It is claimed that the behaviour of the automotive industry is very similar to that of the manufacturing sector in general. Therefore, the automotive sector is considered representative of manufacturing.

3.2 Worker level analysis

The region-level analysis in Section 3.1 documents that predicted robot exposure raises net local employment in Turkish districts. However, this aggregate estimate cannot identify how individual workers adjust to exposure to robots. We complement the region-level analysis with a worker-level exercise that examines intensive-margin adjustment: we track the cumulative labor market trajectory of workers employed in manufacturing in 2014 through 2021, conditioning on the 2014 cohort. The estimates, therefore, capture how continued labor market attachment, mobility across plants and industries, and cumulative earnings vary with workers' initial industry exposure to robot adoption. They do not capture extensive-margin displacement in the sense of redundancy, since our outcomes are cumulative measures for workers who were employed at the start of the period.

The worker-level intensive-margin analysis follows Dottori (2021) and Dauth et al. (2021), who conduct similar exercises for Germany and Italy, respectively. Both papers document reductions in cumulative days worked and earnings for incumbent workers exposed to robot adoption. To our knowledge, ours is the first paper to conduct an intensive-margin worker-level analysis of robot exposure in a developing-economy setting. This allows us to examine whether the patterns of incumbent worker adjustment documented in advanced economies extend to a setting where the aggregate employment effect of robot exposure is positive.

The worker-level specification answers three questions that the district-level estimates cannot. First, by decomposing cumulative outcomes across employment categories, it identifies which adjustment margins account for the aggregate employment response - plant retention, within-industry mobility, cross-industry transitions within manufacturing, or sectoral exit. Second, estimating parallel specifications for workdays and earnings reveals whether workers who move to new employers face a wage cost or capture a wage premium. Third, conditioning on the 2014 worker cohort isolates the individual-level adjustment trajectory of incumbent workers from the district-level aggregate, which mixes incumbent adjustment with new worker entry.

Table 6 reports the effect of industry-level robot exposure on cumulative workdays (Panel A) and earnings (Panel B), estimating eq (4), decomposed across four employment categories. Column (1) reports the total effect across all employers; Columns (2) to (5) decompose this total into workdays (or earnings) at the original plant, at a different plant in the same four-digit industry, at a plant in a different manufacturing industry, and at a non-manufacturing plant, respectively. Columns (6) to (10) report the corresponding IV estimates. The Kleibergen-Paap Wald F-statistics reported at the bottom of the table indicate strong first-stage relationships in all specifications.

The IV estimates reveal a pattern of within-industry reallocation; an increase of one robot per thousand workers in predicted exposure reduces cumulative workdays at the original plant by 1.63 log points (Column 7) and reduces workdays at other plants in the same four-digit industry by 0.90 log points (Column 8). Workdays at plants in other manufacturing industries rise modestly by 0.15 log points (Column 9), while workdays in non-manufacturing fall by 0.16 log points (Column 10). The total effect across all employers is negative (Column 6: -1.64 log points), indicating that greater exposure reduces the cumulative labor market attachment of the 2014 cohort.

Table 6: Industry mobility

	OLS					IV				
	(1) All employers	(2) Org. firm	(3) Other M. firm	(4) Other firm in M.	(5) NM. firm	(6) All employers	(7) Org. firm	(8) Other M. firm	(9) Other firm in M.	(10) NM. firm
Panel A: Industry mobility-employment										
Predicted robot exposure	-1.802***	-1.982***	-0.888***	0.186***	-0.006	-1.641***	-1.634***	-0.903***	0.148***	-0.155***
	(0.049)	(0.073)	(0.041)	(0.050)	(0.036)	(0.049)	(0.073)	(0.042)	(0.051)	(0.036)
Panel B: Industry mobility-earning										
Predicted robot exposure	4.009***	1.166***	0.625***	1.691***	1.243***	3.787***	1.196***	0.513***	1.536***	1.055***
	(0.135)	(0.054)	(0.091)	(0.102)	(0.073)	(0.130)	(0.054)	(0.084)	(0.096)	(0.071)
K-P Wald test						332.6	322.8	317.0	319.2	330.1

Notes: Each column shows the effect of robot exposure on cumulative employment days (Panel A) and earnings (Panel B) of workers employed in the manufacturing (M) industry in 2014. Predicted robot exposure of eight EU countries leading in robotics is used as an instrument in Columns (6) to (10). Columns (1) and (6) present estimates for all workdays and earnings of workers. Columns (2) and (7) present estimates of cumulated workdays and earnings of workers in their original firms. Columns (3) and (8) present estimates of cumulated workdays and earnings of workers in the manufacturing (M) industry outside their original four-digit industry. Columns (4) and (9) present estimates of cumulated workdays and earnings of workers in other firms in the manufacturing (M) industry. Columns (5) and (10) present estimates of cumulated workdays and earnings in the non-manufacturing (NM) industry. Log initial wage and gender, age, skill, firm size, province, five regions and KLEM industry fixed effects are included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. The number of observations in each column is 2,774,131. K-P stands for Kleibergen-Paap.

Table 7: Occupation mobility

	OLS				IV			
	(1) Same occup. and same firm	(2) Different occup. and same firm	(3) Same occup. and different firm	(4) Different occup. and different firm	(5) Same occup. and same firm	(6) Different occup. and same firm	(7) Same occup. and different firm	(8) Different occup. and different firm
Panel A: Occupation mobility-employment								
Predicted robot exposure	-0.930***	-1.503***	0.277***	-0.097*	-0.889***	-0.745***	0.274***	-0.281***
	(0.033)	(0.069)	(0.014)	(0.057)	(0.032)	(0.069)	(0.013)	(0.057)
Panel B: Occupation mobility-earning								
Predicted robot exposure	0.030*	1.135***	0.327***	2.606***	0.015	1.182***	0.311***	2.290***
	(0.016)	(0.051)	(0.022)	(0.121)	(0.016)	(0.051)	(0.021)	(0.116)
K-P Wald test					332.6	322.8	317.0	319.2

Notes: Each column shows the effect of robot exposure on cumulative employment days (Panel A) and earnings (Panel B) of workers employed in the manufacturing industry in 2014. Predicted robot exposure of eight EU countries leading in robotics is used as an instrument in Columns (5) to (8). Columns (1) and (5) present estimates of all workdays and earnings of workers who stayed in the original occupation and workplace. Columns (2) and (6) present estimates of cumulated workdays and earnings of workers who stayed in original firms but in different occupations. Columns (3) and (7) present estimates of cumulated workdays and earnings of workers who are employed in different firms but in the same occupations. Columns (4) and (8) present estimates of cumulated workdays and earnings of workers who are employed in a different firm and occupation. Log initial wage and gender, age, skill, firm size, province, five regions and KLEM industry fixed effects are included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. The number of observations in each column is 2,774,131. K-P stands for Kleibergen-Paap.

This pattern indicates that incumbent workers in robot-exposed industries experience reductions in cumulative workdays at their original plants and, to a lesser extent, at other plants within their original four-digit industry. The limited gains in other manufacturing industries suggest that within-manufacturing reallocation partially offsets the decline at the original plant but does not fully compensate for it. Workers in exposed industries do not transition into non-manufacturing in net terms. Taken together, the worker-level evidence indicates that the positive aggregate employment effect documented at the district level is not driven by intensive-margin expansion among incumbent workers - rather, it reflects labor market entry or reallocation by workers outside the 2014 cohort.

Despite the decline in workdays, cumulative earnings rise substantially among workers in more-exposed industries. The IV estimate for total earnings is 3.79 log points per additional robot per thousand workers (Column 6). Decomposing by employment category, earnings rise at the original plant by 1.20 log points (Column 7), at other plants in the same industry by 0.51 log points (Column 8), at other manufacturing industries by 1.54 log points (Column 9), and in non-manufacturing by 1.06 log points (Column 10). All coefficients are highly significant. The combination of Panel A and Panel B of Table 6 reveals an important pattern: workers accumulate fewer workdays in robot-exposed industries but earn more per unit of time worked. This is consistent with two non-exclusive mechanisms. First, workers who remain attached to labor market may be positively selected - those with higher productivity or better outside options are more likely to retain jobs. Second, robot adoption may raise wages among retained workers through productivity complementarities, even as it reduces employment at the extensive margin. The earnings gains are largest for workers who transition to other manufacturing industries (Column 9), suggesting that the returns to industry mobility exceed those to plant mobility within the original industry.

Table 7 decomposes the employment and earnings response along a second dimension - occupational mobility. Columns (1) to (4) report OLS estimates, and Columns (5) to (8) report IV estimates for four categories: same occupation and same firm (Columns 1 and 5), different occupation and same firm (Columns 2 and 6), same occupation and different firm (Columns 3 and 7), and different occupation and different firm (Columns 4 and 8). The IV estimates show that an increase of one robot per thousand workers in exposure substantially reduces cumulative workdays in the original occupation at the original firm (Column 5: -0.89 log points) and in a different occupation at the original firm (Column 6: -0.75 log points). Workdays accumulated in the same occupation at a different firm rise modestly (Column 7: +0.27 log points), while workdays in a different occupation at a different firm decline (Column 8: -0.28 log points).

This pattern indicates that robot-exposed workers experience reduced attachment to their original firm regardless of whether they remained in their original occupation, suggesting that intensive-margin adjustment is driven primarily by separation from the original firm-occupation match rather than by occupation-specific obsolescence. Workers who transition to new employers are more likely to retain their original occupation than to switch: positive workdays accrue only in the "same occupation, different firm" category. Occupational switching, whether within or across firms, is associated with reduced cumulative attachment for the 2014 cohort.

This pattern indicates that robot-exposed workers are displaced from their original firm, regardless of whether they remain in their original occupation, suggesting that displacement is driven primarily by the elimination of the firm-occupation match rather than by occupation-specific obsolescence. Workers who transition to new employers are significantly more likely to retain their original occupation than to switch: positive workdays accrue only in the "same occupation, different firm" category. Occupational switching, whether within or across firms, is associated with reduced cumulative attachment.

The IV earnings estimates reveal that while cumulative workdays decline sharply for workers who switch occupations, those who remain employed in a new occupation capture substantial earnings premiums. Earnings rise by 1.18 log points for workers in a different occupation at the same firm (Column 6) and by 2.29 log points for workers in a different occupation at a different firm (Column 8). Workers staying in the same occupation at the same firm experience no significant earnings change (Column 5), and those who move to a new firm in the same occupation see a more modest gain (Column 7: +0.31 log points).

The contrast between Panels A and B points to a strong selection margin in occupational mobility. Occupation switching is rare (negative coefficients in Panel A Columns 6 and 8), but those workers who do switch - particularly those who move to new firms - accumulate substantially higher earnings. This is consistent with occupational transitions being feasible only for workers with the skills or outside options to secure higher-paying roles, and it suggests that the aggregate earnings gains documented in Panel B of Table 6 reflect not just within-industry productivity effects but also a reallocation of a subset of workers toward higher-paying occupational matches.

The worker-level analysis complements the district-level findings by characterizing intensive-margin adjustment among incumbent workers. Three patterns emerge. First, greater robot exposure reduces cumulative workdays for the 2014 cohort, with the decline concentrated at original plants and only partially offset by reallocation to other plants in the same industry. Second, despite the decline in workdays, workers who remain attached to labor market capture substantial earnings gains, concentrated among those who transition across industries or occupations. Third, the positive district-level employment effect documented in Section 3.1 is therefore not driven by intensive-margin expansion among incumbent workers but by labor market entry and reallocation beyond the 2014 cohort. Taken together, the worker- and district-level results suggest that robot adoption in Turkey generates aggregate employment growth through firm expansion and new worker entry, even as it reduces the cumulative attachment of incumbent manufacturing workers - a pattern distinct from the negative aggregate effects observed in advanced economies.

4 Conclusion

The effects of automation on labor market outcomes such as employment and earnings have been widely discussed in the literature. However, because of the low manufacturing share in their economy and high marginal productivity or robotization, a developing country context may provide different perspectives on 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 the endogeneity, show that robot exposure positively affects the local labor markets, even though most studies find the opposite. Moreover, we strongly confirm this finding for younger workers of manufacturing industries or when robotization in automotive industries is taken into account separately. These findings point out that rather than any crowding-out effects, the productivity mechanism in this sector occurs because incumbent firms absorb the labor force. In addition, we see that this positive effect mostly comes from the robotization in the automotive industry, which accounts for half of the total number of robots in Turkey. Policymakers should take into account these dimensions to direct technology and labor policies at the 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 exist. In this sense, survey data on firms' information technology usage can be used.

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

Our findings also engage a long-standing debate between Schumpeterian and Marxian perspectives on technological change. The Schumpeterian view emphasizes creative destruction: innovation destroys old activities but generates net employment gains through the creation of new industries and firms. The Marxian perspective instead emphasizes capital-for-labor substitution and the displacement of workers, with gains concentrated among owners of capital. Our results span both traditions. Positive aggregate employment effects at the district level are consistent with Schumpeterian scale expansion, while worker-level evidence of incumbent displacement reflects the Marxian concern. The resolution lies in the distribution of gains: aggregate employment growth in Turkey accrues through firm expansion and new worker entry rather than through incumbent retention, suggesting that robot adoption in a developing-economy context generates employment gains for some groups while displacing others.

Our study has limitations that suggest directions for future research. Our worker-level specification uses cumulative outcomes over 2014-2021, which precludes worker fixed effects; a panel extension would enable them. The sample period is also constrained by the availability of six-digit ISCO codes and worker identifiers in the EIS data from 2014 onward. Future work employing panel specifications would extend the analysis in these directions.

References

Acemoğlu, D., Aghion, P., & Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, *4*(1), 37–74. doi:10.1162/jeea.2006.4.1.37

Acemoğlu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (Vol. 4, pp. 1043–1171). Elsevier. doi:10.1016/S0169-7218(11)02410-5

Acemoğlu, D., Lelarge, C., & Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings*, *110*, 383–88. doi:10.1257/PANDP.20201003

Acemoğlu, D., & Restrepo, P. (2018). *Demographics and robots* (Working Paper, No. W24421). National Bureau of Economic Research (NBER). http://www.nber.org/papers/w24421.

Acemoğlu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *128*(6), 2188–2244. doi:10.1086/705716

Aghion, P., Antonin, C., Bunel, S., & Jaravel, X. (2020). *What Are the Labor and Product Market Effects of Automation? New Evidence from France* (No. 225). https://www.jstor.org/stable/resrep51923.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. doi:10.1162/003355303322552801

Bessen, J. (2019). Automation and jobs: when technology boosts employment*. *Economic Policy*, *34*(100), 589–626. doi:10.1093/epolic/eiaa001

Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2025). What Happens to Workers at Firms that Automate? *The Review of Economics and Statistics*, *107*(1), 125-141. doi:10.1162/rest_a_01284

Bonfiglioli, A., Crinò, R., Fadinger, H., & Gancia, G. (2020). Robot Imports and Firm-Level Outcomes. *The Economic Journal*, *134*(664), 3428–3444. doi:10.1093/ej/ueae055

Calì, M., & Presidente, G. (2022). *Robots For Economic Development* (Working Paper). ZBW - Leibniz Information Centre for Economics. https://hdl.handle.net/10419/249581.

Cheng, H., Jia, R., Li, D., & Li, H. (2019). The rise of robots in China. *Journal of Economic Perspectives*, *33*(2), 71–88. doi:10.1257/jep.33.2.71

Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). *The impact of industrial robots on EU employment and wages: A local labour market approach* (Working Paper, No. 02). Bruegel. https://www.econstor.eu/bitstream/10419/207001/1/1028792522.pdf.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2018). *Adjusting to Robots: Worker-Level Evidence* (Working Papers, No. 13). Opportunity and Inclusive Growth Institute, Federal Reserve Bank of Minneapolis. doi:10.21034/IWP.13

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, *19*(6), 3104–3153. doi:10.1093/JEEA/JVAB012

Dixit, A. K., & Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *The American Economic Review*, *67*(3), 297–308.

Dottori, D. (2021). Robots and employment: evidence from Italy. *Economia Politica*, *38*(2), 739–795. doi:10.1007/S40888-021-00223-X/TABLES/14

Faber, M. (2020). Robots and reshoring: Evidence from Mexican labor markets. *Journal of International Economics*, *127*, 103384. doi:10.1016/j.jinteco.2020.103384

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. doi:10.1016/j.techfore.2016.08.019

Giuntella, O., & Wang, T. (2019). *Is an Army of Robots Marching on Chinese Jobs?* (Discussion Paper, No. 12281). IZA. https://docs.iza.org/dp12281.pdf.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768. doi:10.1162/rest_a_00754

Griliches, Z. (1969). Capital-skill complementarity. *The Review of Economics and Statistics*, *51*(4), 465–468. doi:10.2307/1926439

Jäger, K. (2016). *EU KLEMS growth and productivity accounts 2016 release - Description of Methodology and General Notes.* https://dataverse.nl/api/access/datafile/357095.

Keynes, J. M. (2010). Economic Possibilities for Our Grandchildren. In *Essays in Persuasion* (pp. 321–332). Palgrave Macmillan, London. doi:10.1007/978-1-349-59072-8_25

Klenert, D., Fernández-Macías, E., & Antón, J.-I. (2022). Do robots really destroy jobs? Evidence from Europe. *Economic and Industrial Democracy*, 0143831X2110688. doi:10.1177/0143831X211068891

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, *71*(6), 1695–1725. doi:10.1111/1468-0262.00467

Mihaylov, E., & Tijdens, K. G. (2019). *Measuring the routine and non-routine task content of 427 four-digit isco-08 occupations* (Discussion Paper, No. 2019-035/V). Tinbergen Institute. https://papers.tinbergen.nl/19035.pdf.

Piore, M. J., & Sabel, C. F. (1984). *The Second Industrial Divide: Possibilities for Prosperity* (No. 171). Columbia Law School, Faculty Books. https://scholarship.law.columbia.edu/books/171.

Tuhkuri, J. (2022). *Essays on Technology and Work* (Doctoral dissertation, Massachusetts Institute of Technology). https://hdl.handle.net/1721.1/144769.

Appendix Additional tables

Table A.1: Pre-trends

	Total		Manufacturing		Non-manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Change in log employment, 2010-2014					
Predicted robot exposure	-0.002	-0.020	0.041	0.040	-0.048	-0.048
	(0.023)	(0.023)	(0.026)	(0.026)	(0.029)	(0.029)
R-squared	0.096	0.097	0.155	0.156	0.065	0.066
	Panel B: Change in employment-to-population ratio, 2010-2014					
Predicted robot exposure	0.654	0.651	0.488	0.486	0.176	0.173
	(0.663)	(0.663)	(0.364)	(0.365)	(0.372)	(0.371)
R-squared	0.114	0.114	0.109	0.109	0.149	0.149
	Panel C: Change in log total wage, 2010-2014					
Predicted robot exposure	-0.030	-0.030	0.026	0.025	-0.043	-0.044
	(0.023)	(0.023)	(0.028)	(0.028)	(0.027)	(0.027)
R-squared	0.071	0.071	0.121	0.123	0.051	0.052
Observations	849	849	796	796	849	849
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	+	+	+	+	+	+
Net exports	-	+	-	+	-	+
K-P Wald test	229.1	232.6	213.5	254.2	202.2	235.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes for the period 2010-14, and is weighted by the district population in 2014. Columns (1)-(2), (3)-(4), and (5)-(6) report total, manufacturing, and non-manufacturing industry results, respectively. Robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share of the manufacturing (M); the net export (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.

Table A.2: Main specification: firms in 2014

	Total		Manufacturing		Non-manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Change in log employment, 2010-2014					
Predicted robot exposure	0.042***	0.042***	0.085**	0.084**	0.024**	0.024**
	(0.013)	(0.013)	(0.025)	(0.025)	(0.011)	(0.011)
R-squared	0.270	0.273	0.094	0.102	0.262	0.263
Observations	861	861	836	836	861	861
Demographics	+	+	+	+	+	+
Five region FE	+	+	+	+	+	+
Employment share of M.	+	+	+	+	+	+
Net exports	-	+	-	+	-	+
K-P Wald test	229.1	232.6	213.5	254.2	202.2	235.3

Notes: Each column shows the effect of robot exposure on local labor market outcomes for the period 2014-21, and is weighted by the district population in 2014. Columns (1)-(2), (3)-(4), and (5)-(6) report total, manufacturing, and non-manufacturing industry results, respectively. Robot exposure for eight EU countries leading in robotics is instrumented using the variable of interest. Demographics, which include the female population share, the secondary and tertiary education population share, and the 50-year-old population share in 2014; the employment share of the manufacturing (M); the net export (vis-à-vis China and Eastern Europe per worker); and five region fixed effects, are included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by provinces. K-P stands for Kleibergen-Paap.