Robots, Employment and Wages: Evidence from Turkish Labor Markets at District and Worker Level

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Introduction

- It is widely recognized that automation displaces labor.
- 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. On the other hand, this labor market effect of robotization is an empirical issue.
- Graetz and Michael (2018) found no significant effect for total employment.
- For example, Acemoglu and Restrepo (2020) found that automation displaces employment and reduces wage in US. They also estimated similar results for France.
- On the other hand, Dauth et al. (2021) found composition effects for Germany.

This paper

- Our aim in this study is to investigate how the robot exposure in Turkey affects local labor markets (districts, -ilceler-) in Turkey.
- Using novel employer-employee data having firm information such as production, wage, trade, and worker information between 2014-2021 provided by Enterprise Information System (EIS) of Ministry of Industry and Technology of Turkey.
- We will merge this data with International Federation of Robotics (IFR) database, which reports number of robots at country and industry level.

Identification

Local labor market analysis

- Our unit analysis is districts. Let subscript i represent this region, the model to be estimated is as follows:

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

where dependent variable Δy_i is change in employment or average wage in demographic cell (skill, age, and gender) in region i. X_i is region specific controls such as imports from China, occupation and age group share of employment, region dummies, and ICT import. We also use population of each district in initial year as weight. β is coefficient of interest and shows the effect of change in the number of robots over the number of workers in district i. To measure district level robot intensity, we will adopt Bartik style, which uses employment shares of industries in each district as weight.

Bartik style robot exposure index & endogeneity

- $$\Delta robots_i^{TR} = \sum_j \ell_{ij} \frac{(robot_{j,2021}^{TR} - robot_{j,2014}^{TR})}{emp_j^{TR}}$$
- Where ℓ_{ij} is employment share of industry j in region i
  $\ell_{ij} = emp_{ij}/emp_i$
- In order to overcome endogeneity problem in eq. 1, we instrumented the predicted robot exposure of Turkey with robot exposure of nine EU countries . As a result we estimated a over-identified model in first stage.
- $$\Delta robots_i^{EU8} = \sum_j \ell_{ij,2010} \frac{(robot_{j,2021}^{EU8} - robot_{j,2014}^{EU9})}{emp_j^{EU8}}$$

Worker level analysis

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

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

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:

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

Figure: Robot penetration in Turkey, 1999-2021

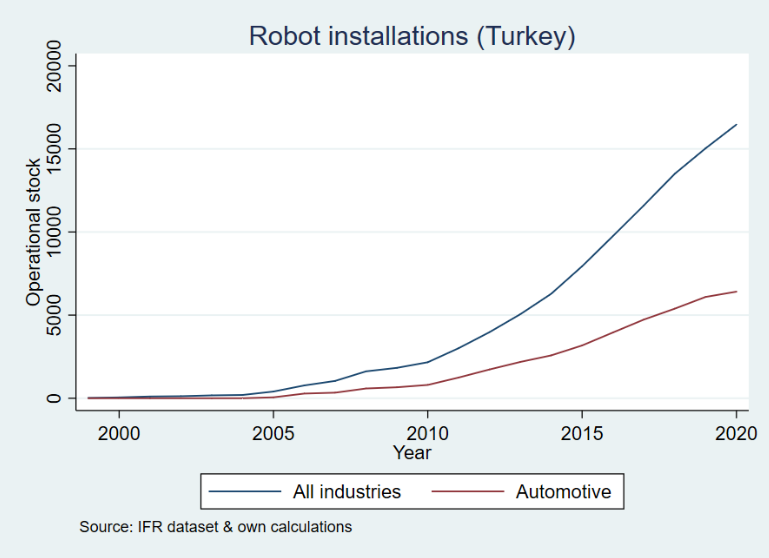
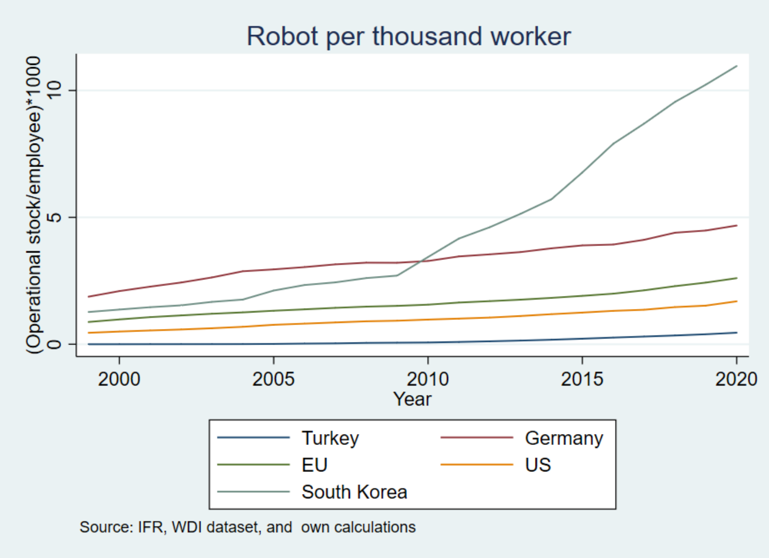
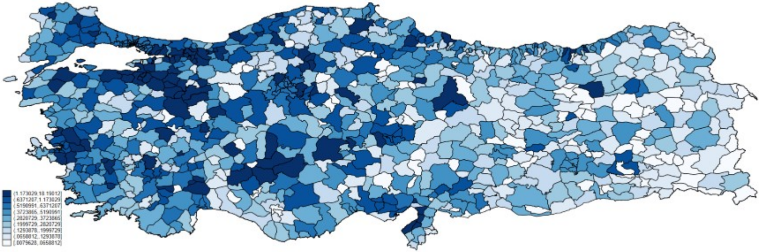


Figure: Robot per thousand worker, 1999-2021



How dispersed is the robot exposure in Turkey?

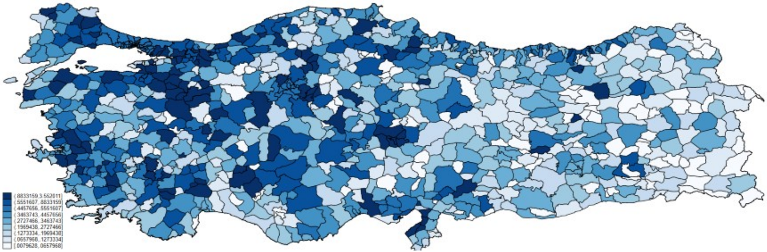
Figure: Robot exposure of Turkey, all industries



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

How dispersed is the robot exposure in Turkey?

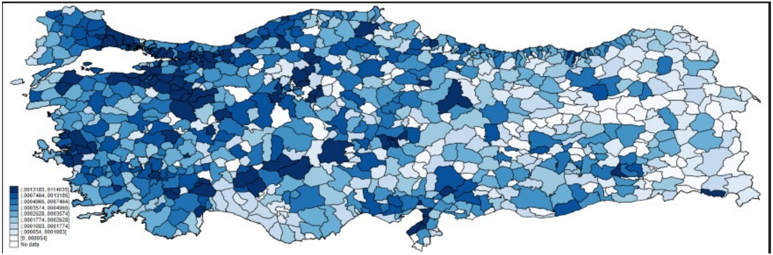
Figure: Robot exposure of Turkey, outside the automotive industry



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

How dispersed is the robot exposure in Turkey?

Figure: Germany robot exposure, all industries



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

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
Observations	861	861	861	861	861	861
	B. 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

Composition effects: manu. vs nonmanu

	(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
Observations	835	835	835	861	861	861
	B. 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

Composition effects: non-routine vs routine

	(1) Total	(2) Manuf.	(3) Nonmanuf.	(4) Total	(5) Manuf.	(6) Nonmanuf.
		Non-routine			Routine	
	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

Composition effects by age group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Manuf.	Nonmanuf.	Total	Manuf.	Nonmanuf.	Total	Manuf.	Nonmanuf.
		18-34			35-54			55-64	
	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

Automotive vs nonautomotive industries

	(1) Total	(2) Total	(3) Manuf.	(4) Manuf.	(5) Nonmanuf.	(6) 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

Composition effects: manu. vs nonmanu

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

Industry mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	All employers	Original firm	Original industry	Other manuf. firm	Other firm in in manuf.	Other nonmanuf. firm
	IV estimator					
	Panel A. Industry mobility-employment					
Predicted robot exposure	-3.128***	-3.043***	1.189***	-0.676***	0.513***	-0.598***
	(0.060)	(0.080)	(0.034)	(0.044)	(0.054)	(0.037)
	Panel B. Industry mobility-earning					
Predicted robot exposure	2.584***	0.489***	1.062***	0.409***	1.470***	0.625***
	(0.145)	(0.056)	(0.058)	(0.096)	(0.112)	(0.077)
Observations	2,621,583	2,621,583	2,621,583	2,621,583	2,621,583	2,621,583

Occupation mobility

	(1) Same occup. and same firm	(2) Different occup. and same firm	(3) Same occup. and different firm	(4) Different occup. and different firm
		IV		
		Occupation mobility-employment		
Predicted robot exposure	-1.524***	-1.519***	0.105***	-0.190***
	(0.034)	(0.074)	(0.014)	(0.060)
		Occupation mobility-earning		
Predicted robot exposure	-0.250***	0.738***	0.249***	1.846***
	(0.017)	(0.053)	(0.030)	(0.129)
Observations	2,621,583	2,621,583	2,621,583	2,621,583

Conclusion

- In this project we estimate the effect of robot exposure on local and individual labor market outcomes.
- Our results reveals that robotization increases employment significantly. Manuf. industries are affected positively, contrary to Dauth et. al (2022) for Germany and Dottori (2022) for Italy.
- This evidence is consistent with other studies (Cali and Presidente, 2022; Klenert, Fernandes-Macias, & Anton 2020; Tuhkuri, 2022; Aghion et al. 2020) This finding present different implications: short time span in our sample or lack of diminishing productivity of returns to robots as explained by (Cali and Presidente (2022))

Conclusion

- On the other hand, Tuhkuri (2022) argue that firms focus on new product when deciding to deploy a robot, rather than replacing employment with robot.
- Piore and Sabel (1984) point out that in flexible manufacturing environment there are different labor-technology relationships.
- Finally, this employment generation comes from automotive industry and there is no skill composition effect.
- Wage effects are strong and positive for manuf. employment.
- Worker level analysis shows that robot exposure reduce only employment of those separating from manufacturing industry.
- In addition, changing occupation but firm make gainful earnings to employees.

Thank you for listening.

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