Robots, Employment and Wages: Evidence from Turkish Labor Market

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Summary of the paper

- **Objective:** To investigate how robotization in Turkey affects local and worker-level labor market outcomes in Turkey.
- Empirical framework:
 - Employs a cross-sectional regression using the difference between the 2021 and 2014
 - Uses a district level robot exposure variable. Total sectoral robot installment is distributed to the districts using district level sectoral employment shares
 - Endogeneity: Uses a shift-share instrument (sectoral robot installments of 8 EU countries)
- **Contribution:** May be the first study for Turkey?

Summary of the paper

• Main findings:

• District level analyses

- ✓ Robot exposure has positive effects on the employment growth of districts
- \checkmark Positive effects for both the manufacturing and service sector
- \checkmark This effect mainly arises from robotization in the automotive industry.

Worker level analyses

- ✓ Incumbent workers in the manufacturing industry have reduced their employment
- ✓ likely to separate their original workplace and occupation and unlikely to find another job in the nonmanufacturing industry
- ✓ if they manage to find a job, their earnings are found to be significantly higher than their initial job

Emprical Strategy

- Assuming robots are distributed by the sectoral employment shares of districts may be problematic because, capital structure of the firms in the same sector but located one in south east and one in west could be different.
 - Instead of employment shares may be used the share of machinery and equipment shares
- Regressions are at the district level. Loosing heterogeneity and low sample size
 - Regressions could be run at the firm-level using the same district level exposure variable.
 - Even the exposure could be defined at the firm-level using employment share or (M&E shares)
 - Then move to district level estimations. Close the gap between district level and worker level estimations.

Empirical Strategy

- Why are we looking at the 2021 and 2014 difference and running a cross-sectional regression? A lot of effects are in charge.
 - We have data for all years, panel regressions could be run.
- 5 region dummies may not be enough,
 - Can be tried with nuts1 or nuts2 dummies.
- Why we are using the 2010 weights in the shift-share instrument?
 - 2013 could be better.
- Why do we expect imports from China to affect wages and employment?
 - It could be dropped
- What is the time period for individual regression? 2014 to 2021 is a very long time span.
- Moreover, occupation data was not well reported before 2018. So it is very likely that workers' occupations change because of correct reporting after 2018.
- Instead of "Predicted robot exposure" use robot exposure.

Findings

- The paper finds a positive effect in manufacturing employment and a positive effect in service employment but mentions the displacement effect. How can we know, there is unemployment in manufacturing and they moved to the service sector based on these results?
- "These estimations imply, as the previous findings, that automation gives rise to employment in manufacturing and service sector but there might be some displacement effect in automotive so that some of these workers are reallocated to the service sector, which might be the main reason for the increase in employment stemming from automation." We can directly run a regression for the automobile industry.

Findings

- The paper pays particular attention to the automobile industry as the largest robot installer sector. But how big in terms of employment?
- The coefficients are very large. Interpretations are missing.
- Robot exposure in non-automobile industries leads to a decline in nonmanufacturing. How? Reallocation effect?
- It is a cross section estimation so need to change the writing in some parts of the study, such as abstract and introduction.