Intersecting Shocks: Automation, Immigration, and Their Combined Impact on Non-College Educated Workers

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Labor market shocks disadvantage non-college educated workers

Non-college educated workers are increasingly disadvantaged in the labor market
(Acemoglu and Autor, 2011; Autor, 2019)

This widening disparity can (in part) be attributed to a confluence of labor market shocks

- Automation of tasks
- Immigration
- Globalization of product and labor markets

Labor Market Shocks: Level of Impact and Spillovers

- Labor market shocks can occur at different levels
  - Local labour market (LLM), industry, firm, occupation, task
- Spillovers: Shocks to one specific group of workers can affect other groups of workers depending on substitutability / complementarity of workers (e.g. Dauth et al., 2021)
- Importantly: (seemingly unrelated) shocks can have important intersecting effects!

This paper: Intersecting Shocks of Automation and Immigration

- Two key trends shaping the labor market (for the non-college educated).
  - Extensive literature on the labour-market consequences of immigration (e.g. Bratsberg & Raaum, 2012)
  - Rapidly growing literature on the labour-market consequences of automation (e.g. Acemoglu & Restrepo, 2020, Barth et al., 2020)
- We merge these literatures and highlight the importance of considering the interplay between various labor market shocks.
  - Automation: Direct effect mainly in manufacturing
  - Immigration: Direct effect mainly in construction (in our setting)
- Highlight the need for an integrated approach to understanding labor market dynamics.

What We Do

We investigate the effects of **automation** at the local labour market level and identify separate effects for native workers by exposure to **immigration** at the industry level

- Focus on non-college educated workers

Exogenous variation:

- **Automation**: Shift-share instrument using LLM industry composition (Acemoglu and Restrepo, 2020)
  - Exogenous *area-level* shock exploits differential exposure to automation
- **Immigration**: 2004 European Union expansion and occupation licensing (Bratsberg & Raaum, 2012)
  - Exogenous *industry-level* shock exploits differential exposure to immigration within construction industry

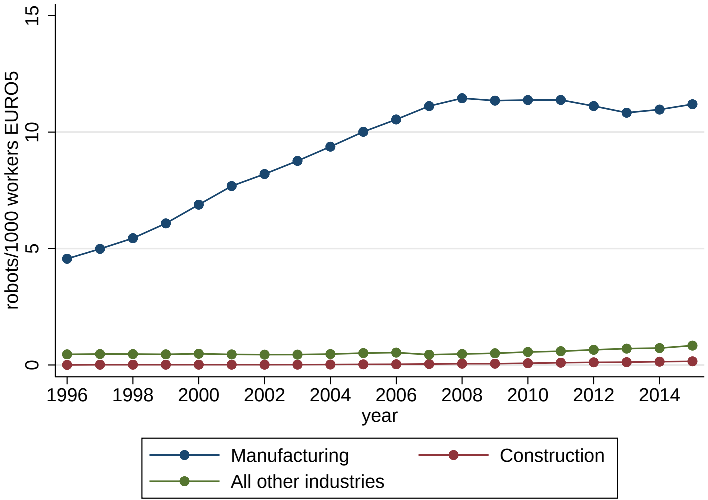
What We Find

1. Automation negatively affects non-college educated workers & those in manufacturing and construction industries
   - **Spillover**: Decline in construction despite the fact that automation is concentrated among manufacturing jobs
2. Immigration shock **amplifies** the impacts of automation
   - Declines among construction workers concentrated among those exposed to immigration
   - Automation has no impacts on earnings of those insulated from immigration shock
3. Mechanisms: automation pushes workers treated by immigration expansion down the pay scale in multiple ways
   - Flows between construction and manufacturing are important, and decline considerably over the period
   - Plants matter: work in worse plants
   - Occupations matter: shift to (lower paid) service occupations

Contribution

- New evidence on how the labor market impacts of one shock depend on the presence of other shocks
  - Automation: Autor & Dorn, 2013, Graetz & Michaels (2018), Acemoglu & Restrepo (2020), Barth et al. (2020), Dauth et al. (2021), Humlum (2021), Koch et al. (2021), Acemoglu & Restrepo (2022).
  - Immigration: e.g. Bratsberg & Raaum (2012)
- Tandem of shocks: Autor, Dorn, Hanson (2015), Mandelman and Zlate (2022)
- Immigration and technology adoption: Lewis (2011), Peri (2012), Hornbeck & Naidu (2014), Akgündüz & Torun (2020), Olney & Pozzoli (2021), Hegna & Ulltveit-Moe (2021), Mann & Pozzoli (2022)

Automation Shock



Notes: automation defined as in Acemoglu and Restrepo (2020)

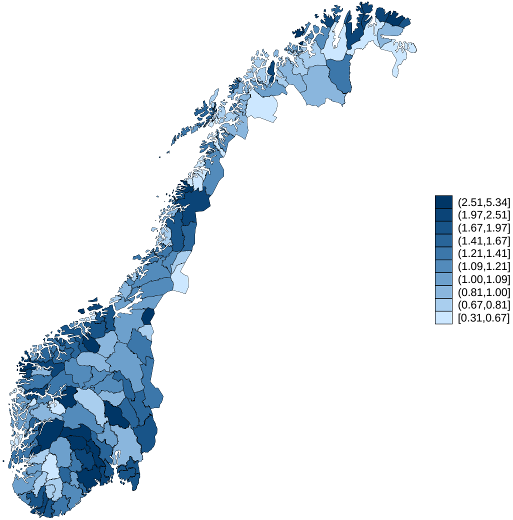
Automation shock

- Robot exposure is measured at the area-level, using IFR data from 1993-2015.
- We abstract from endogenous domestic robot exposure and use EURO5 (Denmark, Finland, France, Italy, and Sweden) adoption as in Acemoglu & Restrepo (2020).
- Area level exposure is a Bartik type measure which pairs variation in a given industry in robot adoption and initial area-level specialization.

$$\overline{\textit{adjusted penetration robots}_j} = \frac{1}{5}\sum_c \frac{M^c_{j,e} - M^c_{j,s}}{L^c_{j,s}} \qquad (1)$$

where $M_{j,e}$ is the number of robots in industry j at the end of the period, $M_{j,s}$ is the number of robots in industry j at the start of the period $L_{j,s}$ is baseline employment in industry j

Automation Shock

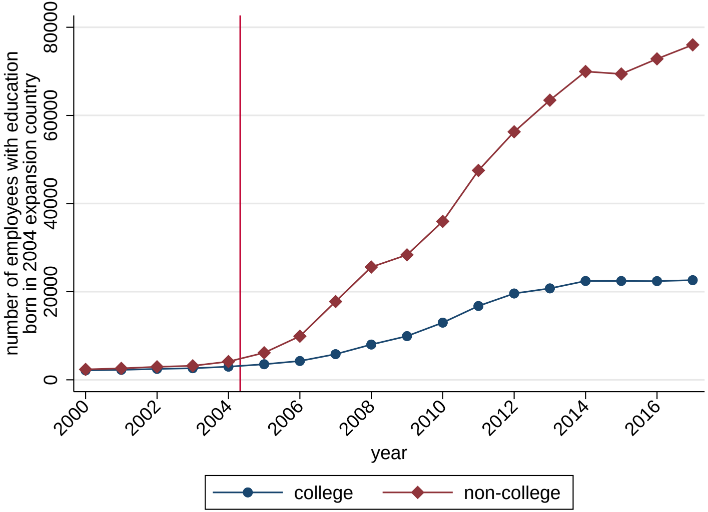


Immigration Shock—2004 EU Expansion

- EU expands in 2004
  - Focus on immigration eight countries: the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia
  - Although Norway is not an EU member, makes immigration considerably easier
    - Establishment of common European labor market meant from 1994 EU countries could access Norwegian labor market (Bratsberg & Raaum, 2012)
    - After expansion in 2004, the new member countries could immigrate to Norway in similar fashion
- Licensing requirements in certain industries forced workers immigrating into specific industries (Bratsberg & Raaum, 2012)

Immigration Shock

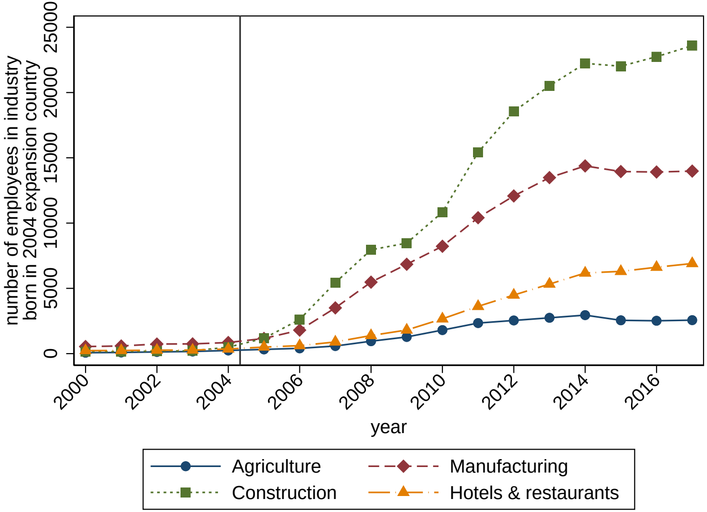
Number of Immigrants Employed by Education



Notes: Sample of workers 18–59.

Immigration Shock

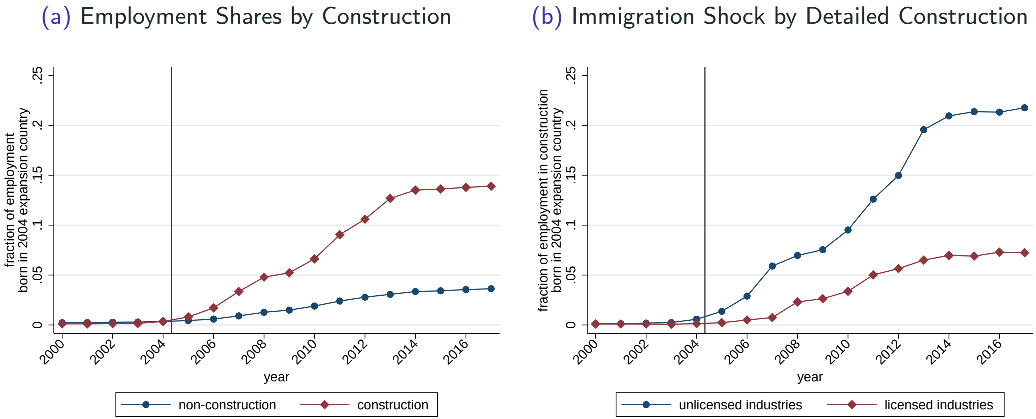
Number of Immigrants by Industry



Notes: Shows top 4 industries according to group level. Sample of workers 18–59.

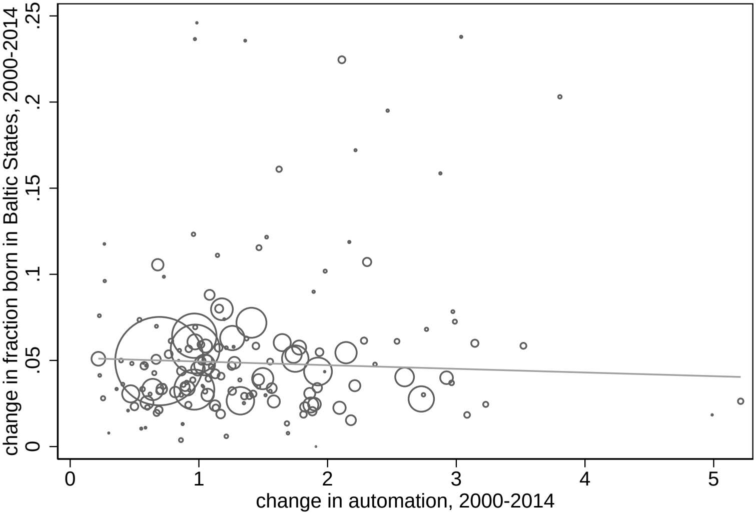
Immigration Shock

Focusing on Construction Industry



Notes: Sample of workers 18–59.

Overlap Between the Two Shocks at the Area-Level



fit line beta -.002; se .003

Data and Estimation sample

Focus on non-college educated workers aged 18–46 in 2000

- Employees in manufacturing and construction:
  - Low educated, predominantly male relative to all other private sector employees
- Of first order importance for understanding impacts of automation & immigration
- Classify Norway into 160 local labor markets (LLM) as in Gundersen & Juvkam (2013)
- Define workers treated by immigration shock as those working in unlicensed construction industries in 2000 (before immigration shock)
  - Counterfactual: licensed construction industries
  - Licensing requirements limited the ability of immigrants to work in specific types of construction (Bratsberg and Raaum, 2012)
- Sample period: 2000–2015, annual occupation data from 2003

Empirical Specification

$$\Delta y_i = \beta_0 + \beta_1 \Delta Auto_{m(i)} + cohort_{c(i)} + educ_{e(i)} + \varepsilon_i \tag{2}$$

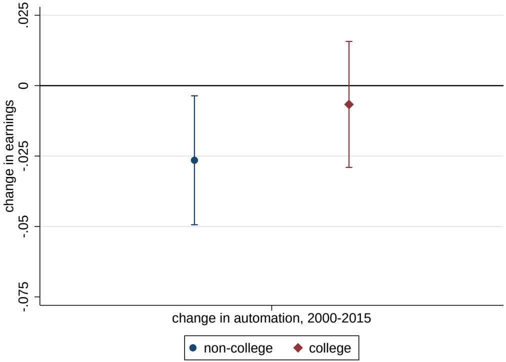
- for individual i living in area m, born in cohort c, with level of education e, working in industry j

$$\begin{aligned} \Delta y_i = \delta_0 + \delta_1 \Delta Auto_{m(i)} + \delta_2 ImmExp_{j(i)} \\ + \delta_3 \Delta Auto_{m(i)} \times ImmExp_{j(i)} + \varepsilon_i \end{aligned} \tag{3}$$

- Triple difference specification estimates the additional impact of automation among construction workers treated by the immigration shock *within* the same area

The Impacts of Automation on Earnings, by Education

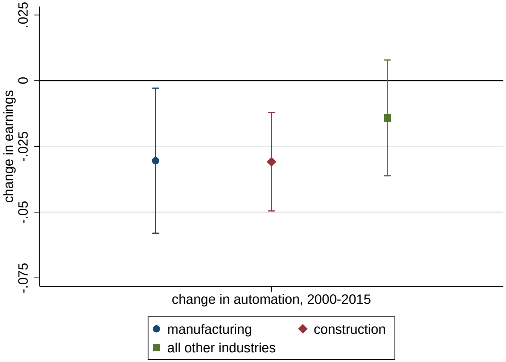
Figure: Earnings



Notes: Earnings measured as the log of annual earnings from labor. Separate regressions estimated by education.

The Impacts of Automation on Earnings, by Industry

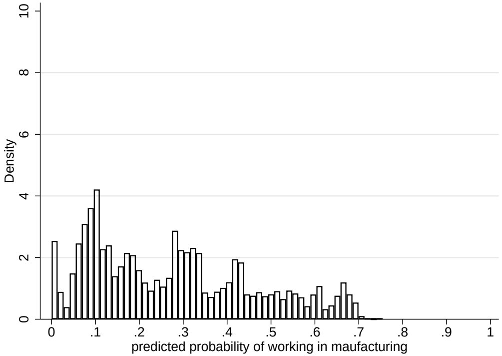
Figure: Earnings



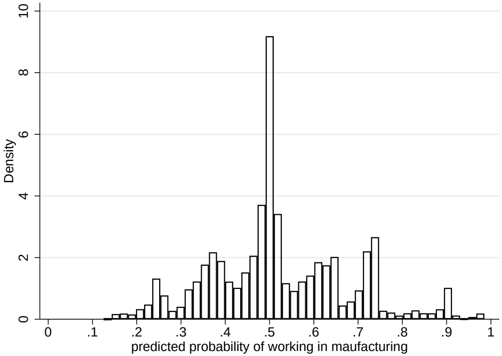
Notes: Earnings measured as the log of annual earnings from labor. Separate regressions estimated by industry.

Why spillover effects to construction? - Predicted likelihood of shifting to manufacturing

(a) All workers

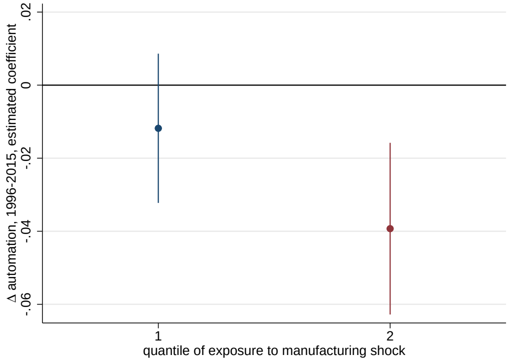


(b) Construction workers



Spillover effects within construction

Figure: Effects by likelihood of shifting to construction



Interaction effects of automation and immigration

Change in earnings from 2000–2015 for **construction workers**

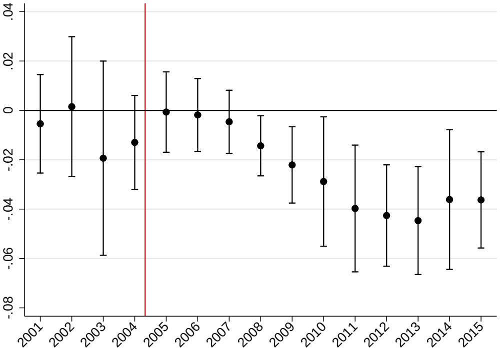
Table: The Interaction Between Automation & Immigration

	Δ Log Earnings		
	(1) Full Sample	(2) Licensed	(3) Unlicensed
Δ automation, 1996-2015	-0.014	-0.014	-0.036***
	(0.015)	(0.015)	(0.010)
Unlicensed 2000	-0.024		
	(0.021)		
Δ automation $\times$ unlicensed 2000	-0.024**		
	(0.011)		
Education FE (1 digit)	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Individuals	82459	41533	40926
Average x	1.328		

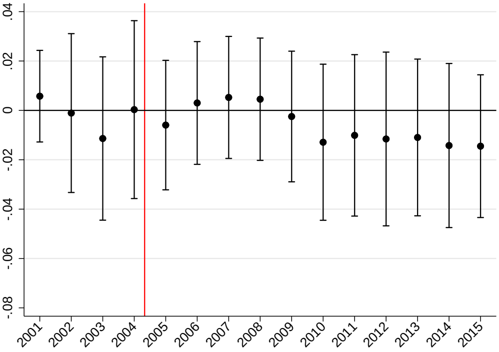
The Effects of Automation on Log Earnings Over Time

One additional robot per 1000 workers lowers earnings among treated construction workers by 4%

(a) Treated (Unlicensed)

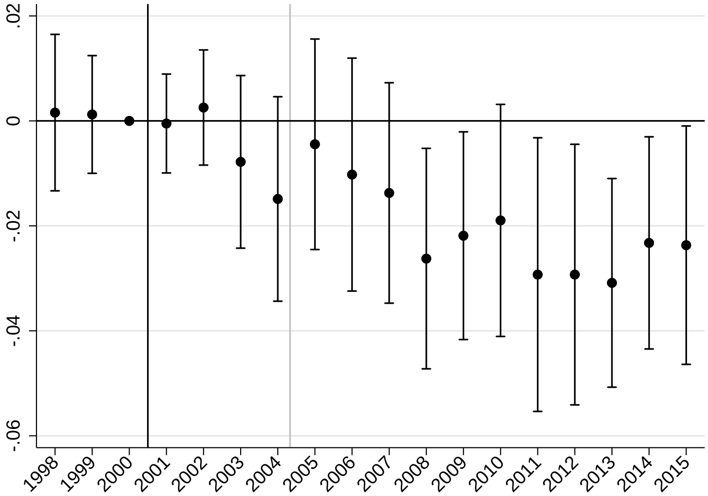


(b) Counterfactual (Licensed)



Notes: vertical line at 2004 represents when EU expansion occurs.

Additional Impacts of Automation Among Workers Treated by Immigration



Notes: vertical line at 2004 represents when EU expansion occurs.

Validation

	Excluding High Exposure	Additional Controls					
	(1) Δ Log Earnings	(2) Δ Log Earnings	(3) Δ Log Earnings	(4) Δ Log Earnings	(5) Δ Log Earnings	(6) Δ Log Earnings	(7) Δ Log Earnings
Δ automation $\times$ unlicensed 2000	-0.0277**	-0.0233**	-0.0238**	-0.0226**	-0.0227**	-0.0233**	-0.0223**
	(0.0129)	(0.0114)	(0.0115)	(0.0113)	(0.0111)	(0.0114)	(0.0113)
Manufacturing share	No	Yes	No	No	No	No	Yes
Exposure to Chinese Imports	No	No	Yes	No	No	No	Yes
Demographic Controls	No	No	No	Yes	No	No	Yes
Union Density	No	No	No	No	No	Yes	Yes
Population Controls	No	No	No	No	Yes	No	Yes
Observations	81736	82459	82459	82459	82459	82459	82459

Worker level response: Occupation Shifts

Table: The Interaction Between Automation & Immigration, Occupational Shifts

	(1) Δ Service	(2) Δ Professional	(3) Δ Blue Collar	(4) Δ Elementary
Δ automation × unlicensed 2000	0.010***	-0.006	-0.014	0.003
	(0.004)	(0.005)	(0.009)	(0.003)
Education FE (1 digit)	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Individuals	70047	70047	70047	70047
Average x	1.326	1.326	1.326	1.326

Worker level response: Shifting Employers

Table: The Interaction Between Automation and Immigration, plant-level outcomes

	(1) Δ Plant Rank All Workers	(2) Δ Plant Rank Native Workers	(3) Δ Frac. Native	(4) Δ Frac. College Educ.	(5) Δ Frac. Comp. Educ.
Δ automation × treated	-1.293**	-1.401**	0.003	-0.003	-0.006
	(0.528)	(0.585)	(0.003)	(0.004)	(0.005)
Education FE (1 digit)	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
Individuals	78322	78322	78323	78323	78323
Average x	1.327	1.327	1.327	1.327	1.327

Concluding remarks

- Labor market shocks can have important intersecting effects
  - Spillover effect of automation to construction workers
  - The labor market impacts of automation are significantly worse among workers simultaneously affected by expansion of immigration
- Important policy implications
  - Extensive literature on place-based policies and targeted policies for non-college educated
  - Why places decline and the disparity between college and non-college educated are multidimensional and complex

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, Volume 4, pp. 1043–1171. Elsevier.

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Autor, D. H. (2019, May). Work of the past, work of the future. *AEA Papers and Proceedings 109*, 1–32.

Bratsberg, B. and O. Raaum (2012). Immigration and wages: Evidence from construction. *The Economic Journal 122*(565), 1177–1205.