Infection Risk at Work, Automatability, and Employment

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Introduction

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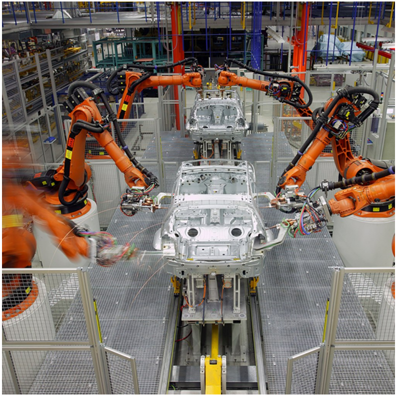
Introduction



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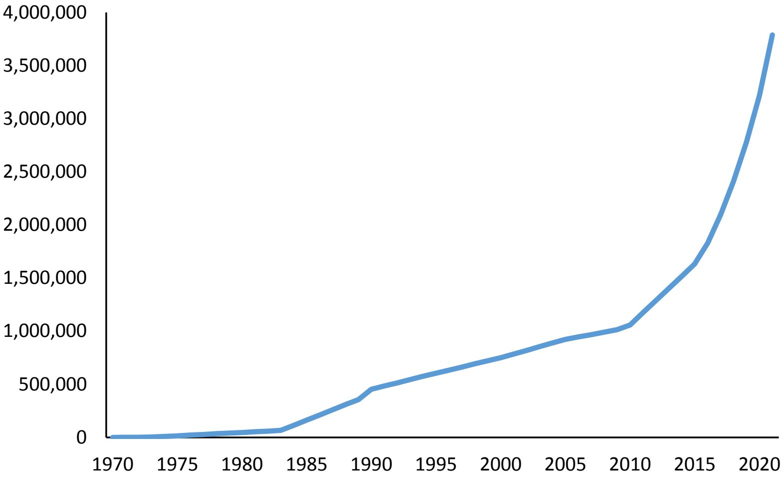
Industrial robots worldwide



Worldwide Stock of Operational Industrial Robots (source: IFR, 2018)

Different forms of automation

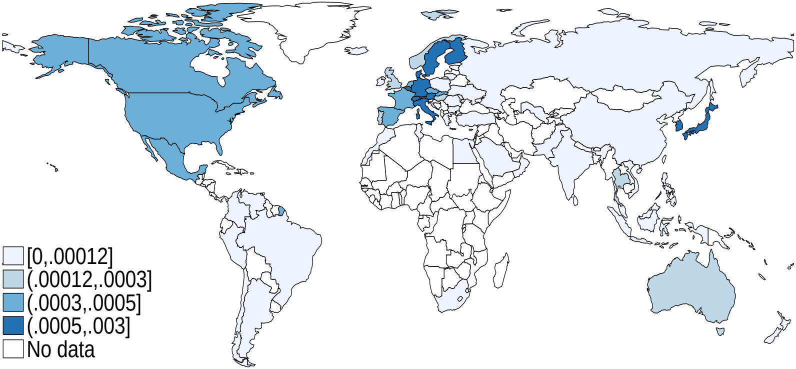
1. Industrial robots (mass production).
2. 3D printers (customized production).
3. Autonomous driving (taxis and trucks).
4. Machine learning and AI:
    - ChatGPT,
    - writing reports, newsflashes, ads, etc.,
    - diagnosing diseases (IBM Watson),
    - doing science.

Literature so far

What are the causes of automation?

1. Technological change (Frey and Osborne, 2017; Arntz et al., 2017).
2. High wages (Acemoglu and Restrepo, 2018; Krenz et al., 2021).
3. Labor market tightness (Cords and Prettner, 2022).
4. Demographic change (Acemoglu and Restrepo, 2022; Abeliansky and Prettner, 2023).

Global robot density and demography



Global Robot Density. Source: Abeliansky and Prettner (2023)

This paper

Is there a role for transmissible diseases?

- Robots cannot be infected by (biological) pathogens.
- Robots do not transmit diseases.
- Robots are typically not on sick leave.
- Robots do not suffer from reduced productivity when sick and from long-term consequences of infection.

$\Rightarrow$ All of this should imply that a pandemic raises the incentives to automate.

This paper

Is there indication that the pandemic matters?

1. We provide a theory of the decision to employ workers versus robots in the face of a pandemic.
2. We test the theory on Austrian employment data before and after COVID-19.

Theory: Final goods production and tasks

- Goods producers have access to a production function of the form

$$Y_t = {K_t}^{1-\alpha} \sum_{\omega=1}^{J} x_{t,\omega}^{\alpha},$$

  where

  - K_t is traditional capital (the assembly line);
  - $x_{t,\omega}$ are tasks performed along the assembly line.

- The inverse demand function for specific tasks follows as

$$pr_{t,\omega} = \alpha K_t^{1-\alpha} x_{t,\omega}^{\alpha-1}.$$

Theory: Task production

- Tasks can be supplied according to a production function of the form

$$x_{t,\omega} = \left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\beta},$$

  where

  - $a_{t,l,\omega}(i_{t,l,\omega})$ is the productivity of humans;
  - $a_{t,p,\omega}$ is the productivity of robots;
  - technically, humans and robots are perfect substitutes.

- Task suppliers (could be in-house) maximize profits given by

$$\begin{aligned}\pi_{t,\omega} &= pr_{t,\omega}x_{t,\omega} - w_{t,l}l_{t,\omega} - \gamma r p_{t,\omega} \\ &= \alpha h_t^{1-\alpha}\left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\alpha\beta} - w_{t,l}l_{t,\omega} - \gamma r p_{t,\omega}.\end{aligned}$$

Theory: Employment and robot use

- Profit maximization implies

$$\frac{\partial \pi_{t,\omega}}{\partial l_{t,\omega}} = 0,$$
$$\frac{\partial \pi_{t,\omega}}{\partial p_{t,\omega}} = 0.$$

This allows determining optimal human employment and robot use:

$$l_{t,\omega} = \left[\frac{w_{t,l}}{a_{t,l,\omega}(i_{t,l,\omega})\alpha^2\beta K_t^{1-\alpha}}\right]^{\frac{1}{\alpha\beta-1}} \cdot \frac{1}{a_{t,l,\omega}(i_{t,l,\omega})},$$
$$p_{t,\omega} = \left[\frac{\gamma r}{a_{t,p,\omega}\alpha^2\beta K_t^{1-\alpha}}\right]^{\frac{1}{\alpha\beta-1}} \cdot \frac{1}{a_{t,p,\omega}}.$$

Theory: Production choice I (profits)

- Profits of firms that produce with workers ($\pi_{t,\omega,l}$):

$$\pi_{t,\omega,l} = (1-\alpha\beta)\alpha K_t^{1-\alpha} \left[\frac{w_{t,l}}{a_{t,l,\omega}(i_{t,l,\omega})\alpha^2\beta K_t^{1-\alpha}} \right]^{\frac{\alpha\beta}{\alpha\beta-1}} .$$

- Profits of firms that produce with robots ($\pi_{t,\omega,p}$):

$$\pi_{t,\omega,p} = (1-\alpha\beta)\alpha K_t^{1-\alpha} \left[\frac{\gamma r}{a_{t,p,\omega}\alpha^2\beta K_t^{1-\alpha}} \right]^{\frac{\alpha\beta}{\alpha\beta-1}} .$$

- Sort tasks according to the **effective cost of production** and search for a solution where $\pi_{t,\omega,l} = \pi_{t,\omega,p}$.

Theory: Production choice II (cut-off productivity)

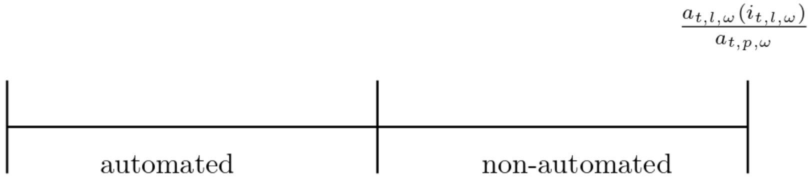
- After some reformulations, we arrive at the cut-off condition:

$$\frac{a_{t,l,\omega}(i_{t,l,\omega})}{a_{t,p,\omega}} = \frac{w_{t,l}}{\gamma r}.$$

- Interpretation:
  - LHS: productivity ratio between workers and robots.
  - RHS: Cost ratio between workers and robots.
  - In case of a higher productivity ratio, task is performed by workers.
  - In case of a lower productivity ratio, task is performed by robots.

Theory: Sorting of tasks according to automatibility

- If $\frac{a_{t,l,\omega}(i_{t,l,\omega})}{a_{t,p,\omega}} > \frac{w_{t,l}}{\gamma r}$, task is produced by workers.
- If $\frac{a_{t,l,\omega}(i_{t,l,\omega})}{a_{t,p,\omega}} < \frac{w_{t,l}}{\gamma r}$, task is produced by robots.
- If a pandemic occurs, $i_{t,l,\omega}$ shifts upwards.
- This changes the ratio of productivity between workers and robots.
- **However:** This only affects workers who are susceptible to automation.



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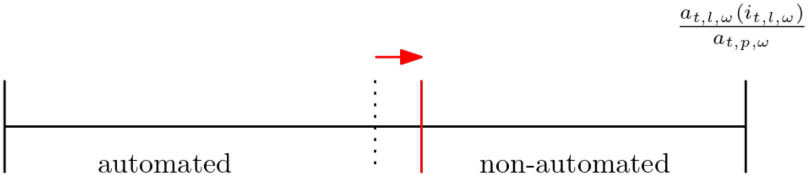


Testable hypotheses

Testable hypotheses

1. Automation risk **reduces employment**.
2. The COVID-19 pandemic has **negative effects** on employment for workers that exhibit a **high automation risk**.
3. The COVID-19 pandemic has **no effect on employment** for workers that that exhibit a **low automation risk**.

Empirical strategy

Regression equation:

$$L_{g,s,a,\omega,j,r,t} = \beta_0 + \beta_1 \cdot VTR_\omega + \beta_2 \cdot C19 + \beta_3 \cdot RTI_\omega + \beta_4 \cdot (VTR_\omega \cdot C19) + \\ + g + s + a + j + r + \omega + \epsilon_{g,s,a,\omega,j,r,t},$$

where

- VTR is the viral transmission risk and RTI the automatibility of occupation ω;
- We control for gender (g), skills (s), age (a), industry (j), and region (r);
- Our hypotheses imply:
  - Hypotheses 1: $\beta_3 < 0$;
  - Hypothesis 2: $\beta_4 < 0$ for automatable jobs;
  - Hypothesis 3: $\beta_4 = 0$ for non-automatable jobs.

Data sources

- Time period: 2015-2021.
- Austrian microcensus ("Mikrozensus Arbeitskräfteerhebung"):
    - employment,
    - hours worked (work volume),
    - age, gender, education, industry, region, occupation.
- VTR: constructed for Austria based on Chernoff and Warman (2023).
- RTI: constructed for Austria based on Autor et al. (2003).

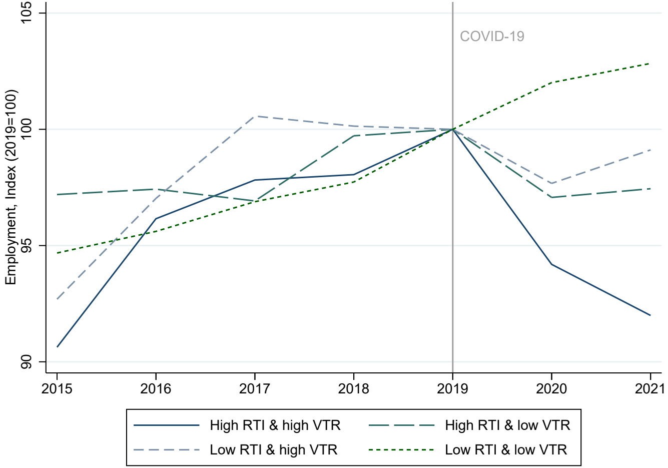
Results

Table: COVID-related labor market outcomes

	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
RTI	-0.3856**	-0.1330	-0.1431	-0.5919***	-0.1219	-0.1829
	(0.1313)	(0.1282)	(0.0944)	(0.0935)	(0.2098)	(0.1394)
VTR	0.5726*	0.3205***	0.4102**	0.4733*	0.3840**	0.4031*
	(0.2756)	(0.0793)	(0.1305)	(0.2154)	(0.1300)	(0.1879)
VTR x C19	-0.0772**	0.0596	0.0296	-0.1513***	0.0447	-0.0032
	(0.0214)	(0.0661)	(0.0357)	(0.0390)	(0.1062)	(0.0573)
C19	0.0207***	-0.0188	-0.0155	-0.0138	-0.0811*	-0.0676**
	(0.0051)	(0.0292)	(0.0157)	(0.0145)	(0.0359)	(0.0208)
Controls	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	96,671	75,141	171,812	92,693	72,185	164,878
R-sq.	0.3515	0.3472	0.3326	0.3279	0.3049	0.3017

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Two-way standard errors clustered at the level of ISCO-1-digit occupations and years. Standard errors in parenthesis.

Employment over time across different risk groups



Employment in different occupations before and after COVID-19

Conclusions

- Automatibility affects employment in the Austrian labor market.
- Viral transmission risk at work affects employment in a pandemic.
- The employment effect, however, is only visible for automatable jobs.
- Effects are stronger for work volume as compared with number of workers.
- This implies that the "Kurzarbeit" schemes have had the intended effects.

Thank you very much!