

Importing Automation and Wage Inequality through Foreign Acquisitions

Malin Gardberg Fredrik Heyman Joacim Tåg

IFN Stockholm and Hanken School of Economics

June 20th 2023

Motivation

Important structural changes in recent decades driven by:

- technological change
- globalization

Puts pressure on firms and workers to adapt to changing circumstances:

- can potentially affect many different firm and worker outcomes
- large literature on how new technologies and globalization can affect wage inequality
- less work on the interaction between technological change and globalization and the role of **firms** in **spreading wage inequality across borders** through the **market for corporate control**

This paper

Do cross-border M&As in spread wage inequality through automation?

Study workers in Swedish firms acquired by foreign firms using LEED data:

- Foreign acquirer heterogeneity: software and database **intensity** / robot intensity
- Worker task heterogeneity: **exposure** to software or robotics

Identification

- Stacked/"clean" difference-in-differences and triple DiD regressions
- "Triangulation": results only in subsamples where the mechanism is in play

Matters for trade, technology and labor market policy:

- many countries have ambitious goals on digitization, robots and AI
- an active trade policy could help countries advance technologically...
- ... but may also contribute to increased domestic wage inequality

Related research

M&As and Human Capital: Tate and Yang (16), Agrawal and Tambe (16 RFS), Olsson and Tåg (16 JOLE+18 EL), Antoni, Maug and Obernberger (19 JFE), Ma, Ouimet and Simintzi (22), Lagaras (23 JF), Bach, Bos, Baghai and Silva (23) + Bena, Lu and Wang (23)

- new dimension of firm heterogeneity from the cross-border M&A lit. (Bena, Ferreira, Matos and Pires 12 JFE, Erel, Jang, and Weisbach 22)

FDI and multinational wage premium: Heyman, Sjöholm and Tingvall (11 JIE), Setzler and Tintelnot (21 QJE)

- new dimensions of worker and firm source heterogeneity

Firm-level literature on foreign ownership, productivity, IT and innovation: Guadalupe, Kuzmina, Thomas (12 AER) and Bloom, Sadun and Van Reenen (12 AER)

- impacts on workers from technology transfer across borders

Data and empirical design

Data

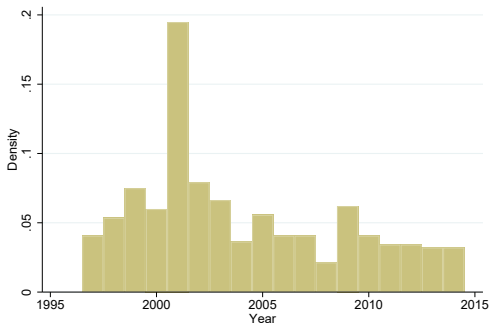
Firms:

- **Acquirer nationality:** Swedish Agency for Economic & Regional Growth
- **Financial statements and tech use:** Statistics Sweden
- **Software intensity:** Software & database capital to total capital from EU Klems
- **Robot intensity:** Robot stock to employment from IFR Robot Database
- **High intensity:** If higher than in target industry that year

Workers:

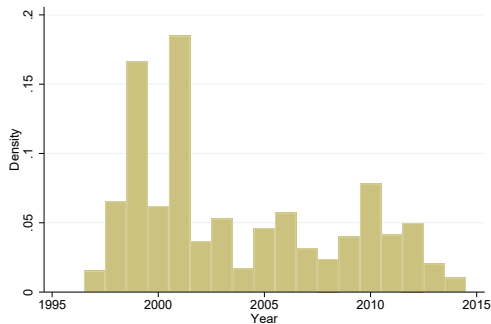
- **Wages and occupation:** Salary Structure Statistics at Statistics Sweden
- **Demographics and background info:** LISA at Statistics Sweden
- **Exposure to software, robotics and AI:** Webb (2022)
- **High exposure:** top decile of occupations

Acquisitions 1996-2015



Total acquired firms: 467

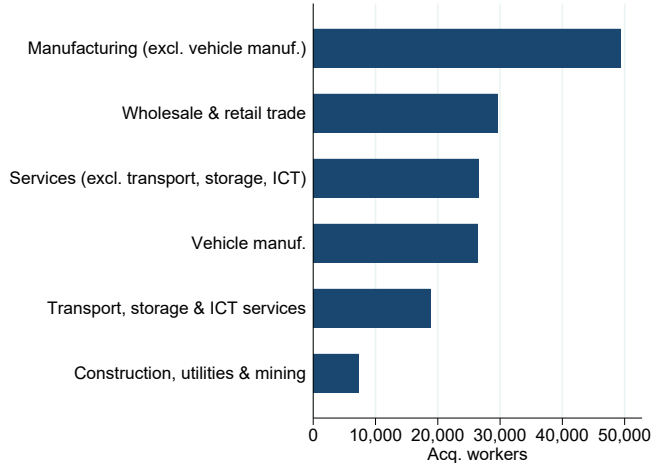
467 Acquired firms



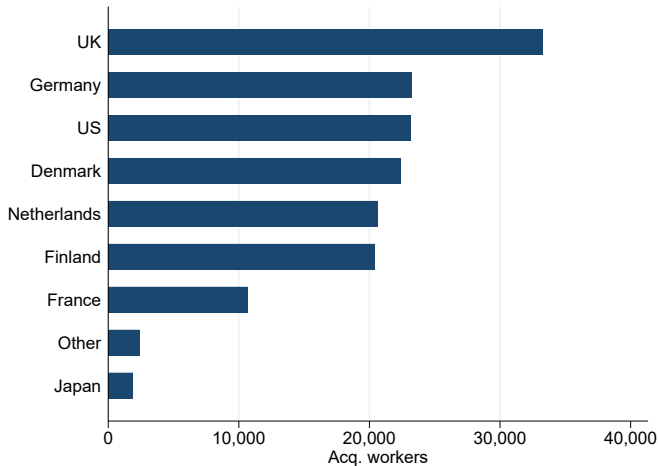
Total acquired workers: 158,109

~ 160,000 Acquired workers

Acquired workers per industry



Acquired workers per country



Empirical strategy

Stacked/"clean" difference-in-differences regressions

- For each year with foreign acquisitions, create benchmark workers not part of a foreign acquisition through random selection within bins on **occupation, location, firm type**
- Create panel, normalize time, stack, and run standard DiD and DiDiD with controls from $t = -1$
- Avoids problems with staggered TWFE models (Baker et al 2022 JFE)

Observations:

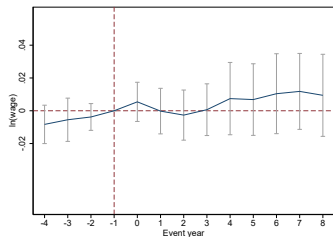
- Benchmark workers forced to be identical on **few** characteristics, but balance on **many**
- Conditions on employment at $t = -1$ (careful with e.g. Callaway and Sant'Anna 21, JE)
- "Triangulation": results only in subsamples where the mechanism is in play \rightarrow selection stories has to hit in exact same subsamples & only DiDiD trends matter (Olden and Møen 22, EcJ)

Treated and control worker comparison

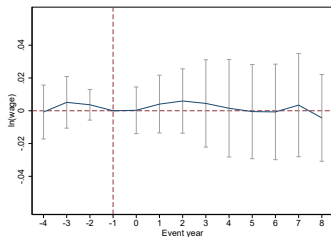
| | Treated | Control | Difference | Norm. T-value |
|---------------------------|---------|---------|------------|---------------|
| Worker observables | | | | |
| In wage | 9.988 | 9.980 | 0.008 | 0.018 |
| Software exposure | 0.541 | 0.541 | 0 | 0.000 |
| Robot exposure | 0.512 | 0.512 | 0 | 0.000 |
| AI exposure | 0.528 | 0.528 | 0 | 0.000 |
| Age | 39.39 | 40.97 | -1.58 | -0.128 |
| Education (1-7) | 3.712 | 3.657 | 0.055 | 0.028 |
| Experience | 20.67 | 22.33 | -1.65 | -0.125 |
| Female (%) | 0.348 | 0.341 | 0.007 | 0.011 |
| Major city resident (%) | 0.693 | 0.693 | 0 | 0.000 |
| Prev. unemp (%) | 0.117 | 0.104 | 0.013 | 0.030 |
| ≥ 3 year tenure (%) | 0.556 | 0.666 | -0.110 | -0.161 |
| Firm observables | | | | |
| In Firm size | 7.158 | 7.223 | -0.065 | -0.027 |
| Share high skilled (%) | 0.289 | 0.300 | -0.011 | -0.034 |
| Swedish MNE (%) | 0.524 | 0.524 | 0 | 0.000 |
| VA/L | 0.556 | 0.669 | -0.112 | -0.135 |
| Observations | 158,109 | 158,109 | 316,218 | |

Results

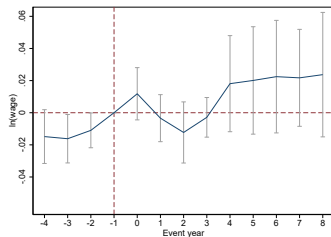
Foreign M&A wage effects (DiD)



Full sample
N=2.3M, 0.006 (0.008)

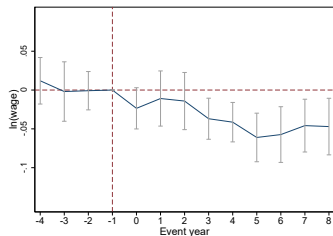


High Software Intensity
N=1.2M, -0.001 (0.011)

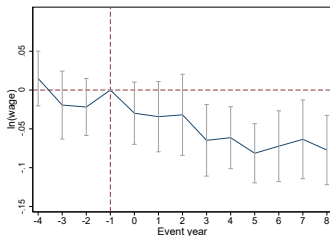


Low Software Intensity
N=1.1M, 0.014 (0.010)

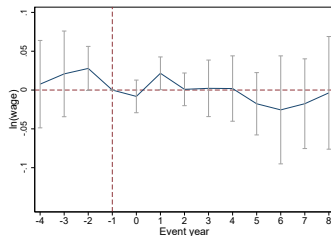
High Software Exposed (DiDiD)



Full sample
N=2.3M, -0.032*** (0.011)

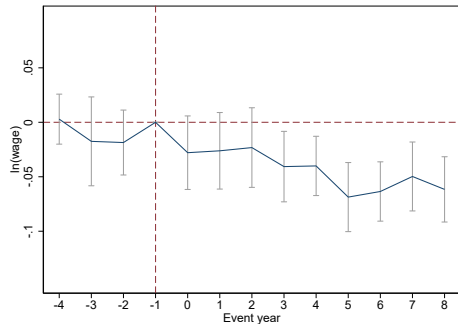


High Software Intensity
N=1.2M, -0.042*** (0.015)

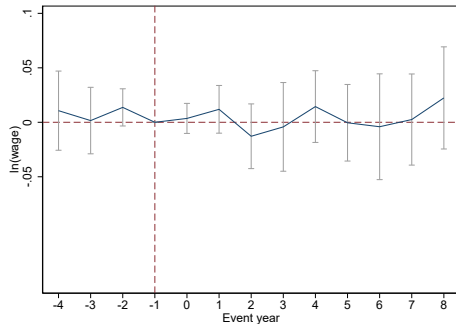


Low Software Intensity
N=1.1M, -0.013 (0.024)

High Software Exposed Subsample (DiD)

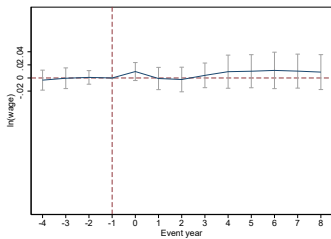


High Software Intensity
N=0.1M, -0.033*** (0.009)

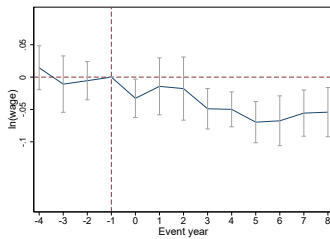


Low Software Intensity
N=0.1M, -0.003 (0.016)

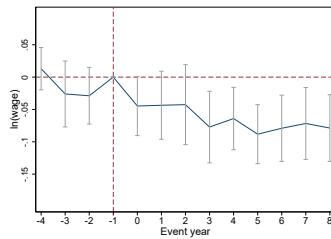
High Robot Exposed



Full sample (DiD)
N=1.7M, 0.005 (0.009)

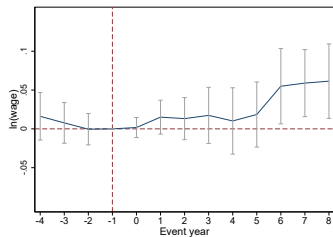


Full sample (DiDiD)
N=1.2M, -0.037*** (0.012)

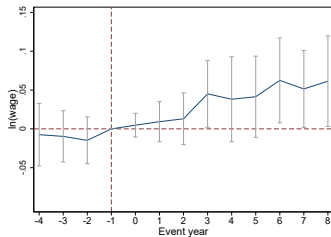


High Robot Intensity (DiDiD)
N=1.0M, -0.035** (0.015)

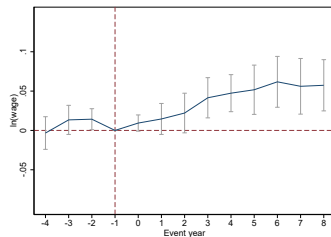
High AI Exposed



Full sample (DiDiD)
N=2.3M, 0.014 (0.015)

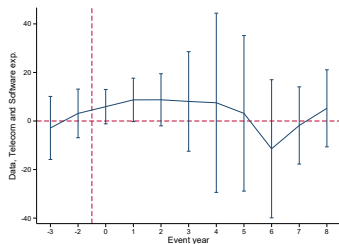


High Software Intensity (DiDiD)
N=1.2M, 0.035** (0.017)

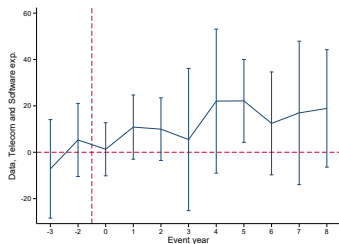


High Softw. & High AI (DiD)
N=0.1M, 0.023** (0.011)

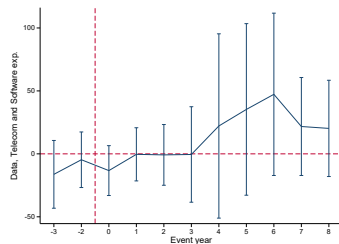
Firm expenditures on IT



Full sample (DiD)
N=1037, 6.5M (7.457)



High Software Intensity (DiD)
N=601, 14.8M** (6.816)



Full sample (DiDiD)
N=1037, 20.5M (14.323)

Additional analyses

Additional analyses:

- Results only present where we expect them
- Results not driven by offshoring
- Results remain for 90th/10th percentile DiDiD
- Stayers experience larger wage drops
- Tenure protects against wage drops
- Wage gains for managers and professionals

Takeaway

Takeaway

Foreign software intense acquisitions lead to:

- relative wage losses of 3.2% for software-exposed workers
- relative wage gains for AI-exposed workers, managers and professionals
- increases investments in software and telecommunications (14.8M SEK)

Foreign robotics intense acquisitions lead to:

- relative wage losses of 2.1% for robotics-exposed workers
- not driven by software exposed workers

Implications:

- Policy: technology, trade, and labor market policies are interlinked
- Theory: labor market implications of cross-border tech transfer

Thank you!