New Evidence on the Effect of Tecnology on Employment and Skill Demand

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Economists are revising their views on robots and jobs

There is little evidence of a pandemic-induced surge in automation

Figure: The Economist on this study on Jan 22, 2022.

The Research Question

- **The research question:**
  - What are the effects of advanced technologies on employment and skill demand?
- **The dominant view:**
  1. Employment: Substitute for labor and ultimately make some workers redundant.
     - The Luddites; Keynes (1931); Brynjolfsson and McAfee (2014).
  2. Skill demand: Complement skilled labor and could increase inequality.
     - The skill-biased technological change hypothesis; Griliches (1969); Tinbergen (1975).
- **But an open question:**
  - Hard question because measuring and identifying the effects of technologies are difficult.

This Paper

- **Novel research design:**
  - Technology-subsidy program in Finland (Northern Europe) that induced sharp increases in technology supply to specific manufacturing firms.
  - Compare close winners and losers of technology subsidies.

- **Large-scale data:**
  - Register-based data track all firms and workers over time (1994–2018).
  - Text data: perform matching and measure technologies using subsidy application texts.

Context: New Technologies in Manufacturing

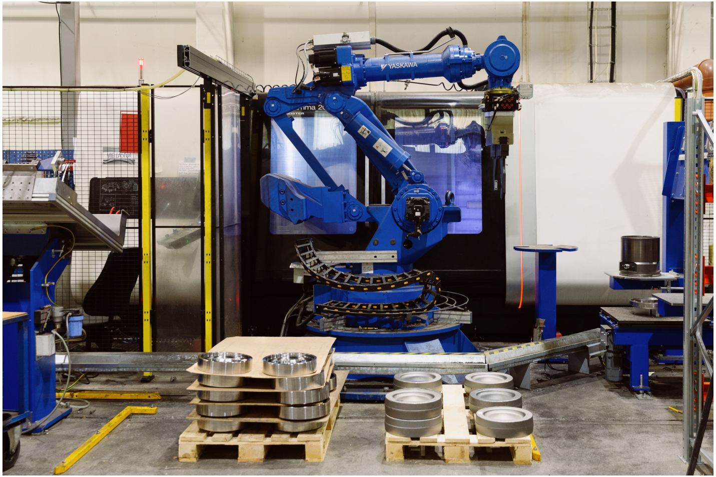

Figure: A robot and a CNC machine (2021).

Main Results

- **Clear main result:**
  - Sharply more technologies.
  - Increase in employment.
  - No change in skill composition.
- **A puzzle:**
  - No labor replacement or skill-bias from technologies in the manufacturing firms.
  - Contrast with the two common ideas.
- **A new interpretation:**
  - Idea: *process* vs. *product*
  - Novel evidence: firms used technologies to <u>expand</u> with new products, <u>not lower costs</u>.

Moore's Law for Pistons

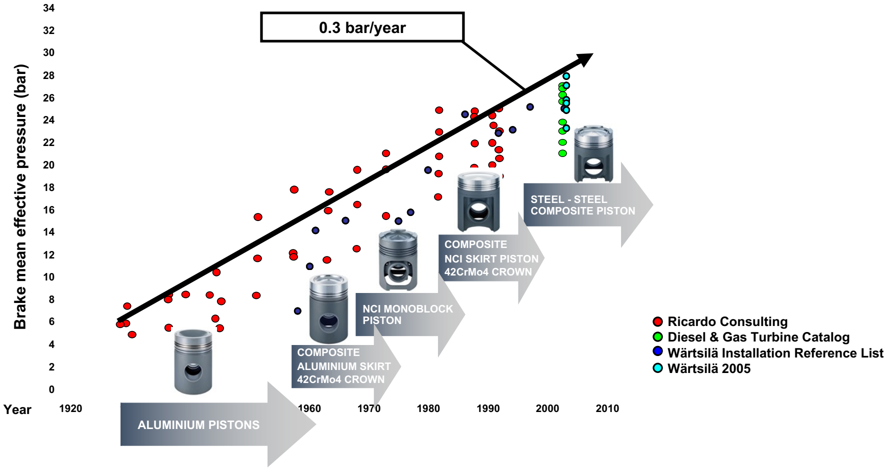

Figure: The trend of piston materials' development over the past 100 years.

Related Literature: Technologies' Effects on Work

- **This paper:**
  1. Directly measure of technologies, skills, and work.
  2. First paper to evaluate manufacturing technologies' effects using policy variations.

  $\longrightarrow$ Based on the new evidence: **Novel result and interpretation.**

- **Related research:**
  - Physical technologies (similar): Doms, Dunne & Troske (1997), Koch, Manuylov & Smolka (2021), Dixon, Hong & Wu (2021), Aghion et al. (2020), Curtis et al. (2021).
  - Digital technologies (different): Akerman, Gaarder & Mogstad (2015), Gaggl & Wright (2017), Autor, Levy & Murnane (2003), Michaels, Natraj & Van Reenen (2014).
  - Worker level: Bessen et al. (2020), Feigenbaum & Gross (2021).
  - Macro level: Katz & Murphy (1992), Lewis (2011), Acemoglu & Restrepo (2020).

Outline

- **Part 1: Causal Effects ◀**
  - Context
  - Data
  - Design
  - Estimates
- **Part 2: Mechanism**
  - Theory
  - Evidence
  - Context

Context

- **Timeline:** 1994–2018.
- **Technologies**: New production technologies in manufacturing: robots, CNC machines, laser cutters, surface-treatment technologies, CAD/CAM, ERP.
- **Workers**: Production workers (70%); machinists, welders, machine operators, etc.; typically with vocational training.
- **Industries**: Manufacturing; fabricated metal products, machinery, wood products.
- **Firms**: Primarily SMEs, but also large firms; specialized intermediate goods, e.g., pistons for engines, typically contract manufacturers, tradable output.

Data: Direct Measurement Using Novel Large-Scale Data

- **Technologies**
  - Financial data: directly measure technology investment.
  - Text data: *type* and *use* of technology (e.g., a welding robot *to* weld longer seams).
  - Customs data: type of technology (manually classify 621 technologies).
  - Survey data: use of technology (CIS).
- **Work and Skills**
  - Employment and wages: full coverage over time.
  - Education: level & type, school grades
  - Occupations and tasks: 3-digit level & EWCS survey on task content.
  - Cognitive performance and personality: military test data for men born 1962–79.
- **Firm Performance**
  - Large set of data: revenue, productivity, profits, exports, products, prices.

Design: The EU Subsidy Program

- **Program:** Local centers provide direct funding for firms' technology investment.
- **Aim:** Advance the adoption of new technologies in firms.
- **Typical case:** €100K cash grant (paid against verifiable technology costs).
- **Expected effect:** Lowers the price of technology for the subsidy grantees.
  - Technologies required to be new (e.g., not old or used machines).
  - Follows technology neutrality—firms can choose the type of technology.

Design and Data: Constructing Data from Texts

- **Novel text-analysis methods:**
  - Construct data from subsidy texts (applications and evaluations)
  - These novel methods could be used widely in policy evaluation.

- **Use 1:** Measure Technology Categories
  - Uses of Technologies: Process vs. Product

- **Use 2:** Match Similar Applications
  - Use evaluation report *texts* to control for differences between treatment and control.
  - The idea: Map evaluation texts into propensity scores to compare similar applicants.

Winners-Losers Design

- Empirical strategy:
  - Event-study design that contrasts similar firms with nearly identical applications, one of which was approved while the other was not. *All plan to adopt*.
  - Builds on Angrist (1998), Greenstone et al. (2010), and Kline et al. (2019).
- Event-study specification (stacked by event-time τ; D_j = treatment):

$$Y_{jt} = \alpha_j + \kappa_t + \sum_{\tau \in \mathscr{T}} \left[I_{jt}^{\tau} \cdot (\gamma_\tau + \beta_\tau \cdot D_j) \right] + X_{jt}^{\tau} + \varepsilon_{jt}$$

- First-difference estimates (simplified version, base-year $\tau = -3$):

$$\Delta Y_j = \beta \cdot D_j + X_j + \varepsilon_j$$

Summary Statistics

	Treatment Group		Control Group		Both		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p
Machinery Inv. (EUR K)	109.93	369.14	82.60	233.11	0.00	27.24	233.80
Revenue (EUR M)	3.20	25.39	1.64	5.29	0.16	0.96	5.67
Employment	17.81	47.16	9.67	21.29	1.40	7.90	37.00
Wages (EUR K)	22.23	9.08	18.40	10.22	11.26	22.30	31.61
Subsidy Applied (EUR K)	112.05	129.25	47.01	81.30	8.89	58.13	290.06
Subsidy Granted (EUR K)	81.77	103.02	0.00	0.00	3.24	35.64	200.23
Educ. Years	11.71	0.99	11.45	1.12	10.50	11.73	12.67
College Share (%)	15.51	16.80	11.63	18.42	0.00	12.50	33.33
Production Worker Share (%)	70.53	21.53	70.37	28.61	42.86	72.73	100.00
Observations	1885		146		2031		

Table: Summary Statistics for the Baseline Winner-Losers Design.

The First Stage

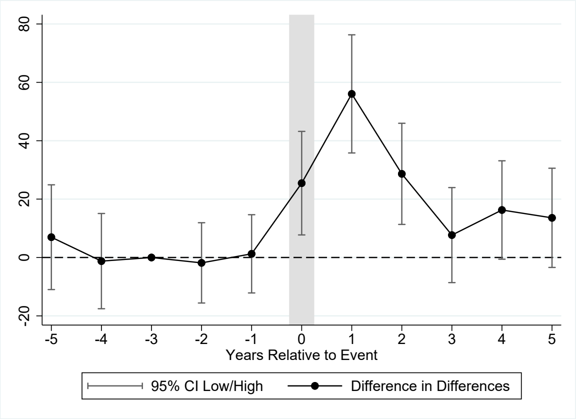

Figure: The Effect of Technology Subsidies on Machinery Investment (€K).

Notes: The estimates indicate a cumulative €130K effect on machinery inv. Application year in grey. No added controls. Baseline machinery investment €108K per year.

Employment Effects

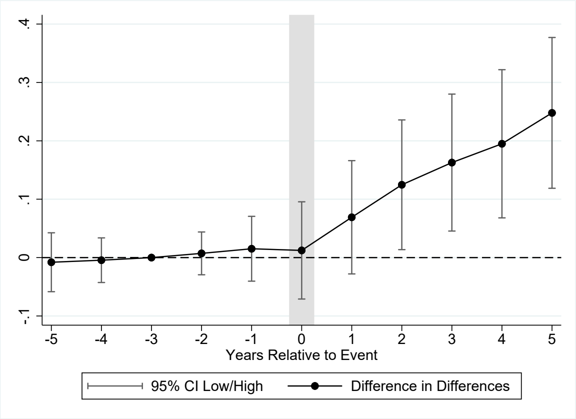

Figure: The Effect of Technology Subsidies on Employment (in %).

Notes: The estimates indicate approx. 20% increase in employment. No added controls.

Skill Effects: Main Measures

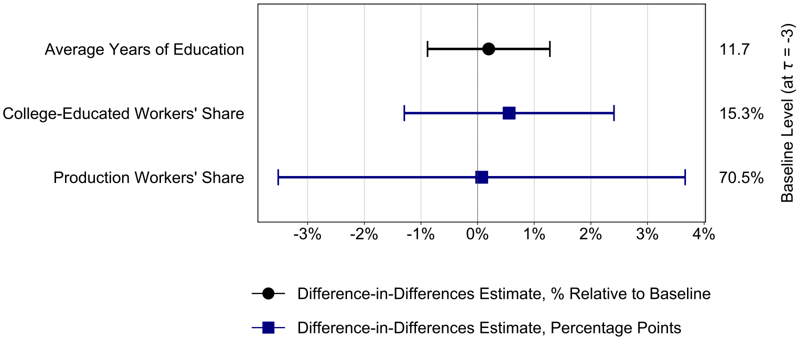

Figure: The Effect of Technology Subsidies on Skill Composition.

Notes: The estimates indicate no detectable effects on skill composition. Skill effects broadly zero for more detailed measures: type of education and occupation, cognitive performance, grades, personality.

Firm-Level Effects

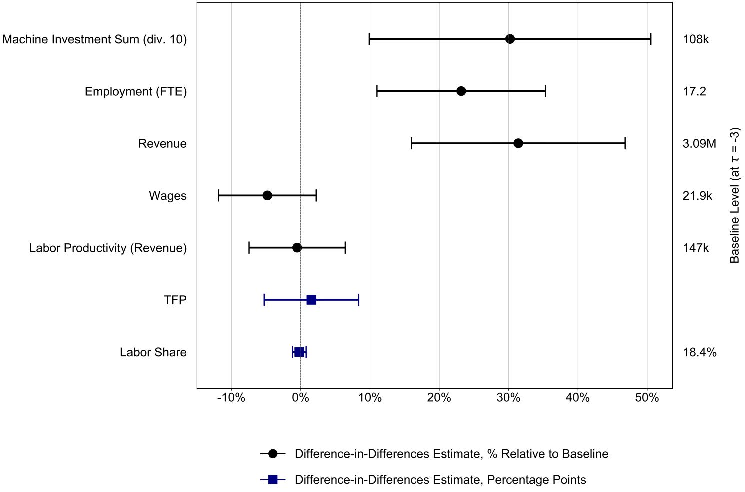

Figure: Difference-in-Differences Estimates on Selected Firm-Level Outcomes.

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Process vs. Product

- Core idea of the model simplified as a composite function:

$$F\left(T_E; f\left(T_I; L\right)\right)$$

- Two types of technologies:
  - **Process** (The Intensive Margin) T_I
    - This affects the production "recipe" of how labor is used in production.
      Example: a welding robot replaces a welder's tasks.
      Labor replacement and skill bias are generally about this.
  - **Product** (The Extensive Margin) T_E
    - This affects the "lens" through which the production is projected into markets.
      Example: a welding robot makes longer seams than a human welder.
      Standard expansion investments are part of this class.

Evidence: Testing Process vs. Product

- **Next: Test process vs. product using novel data.**
  - Use the model to speak back to data.

- **Step 1: Treatments** (D)
  - Directly measure the type of technological change.
  - Text and survey data, fieldwork.
- **Step 2: Outcomes** (Y)
  - Test the mechanism with new outcomes.
  - Data on exports, products, marketing, and prices.

Treatments: Measuring Technologies Using Text Data

Process	Product
Lower the costs of production	Manufacture new types of pistons
Increase automation	Faster response time to orders
"Solve bottlenecks"	Transition to more environmentally sustainable production
Automate welders' tasks	Manufacture larger items
	Increase the degree of processing (new features)
	Respond to changing demand conditions

Table: Measuring process vs. product type technological changes from text data.

Notes: Examples of technology investment type based on the description of the use of technology. Manually coded all technology applications in the main sample.

Treatments: Measuring Technologies Using Text Data

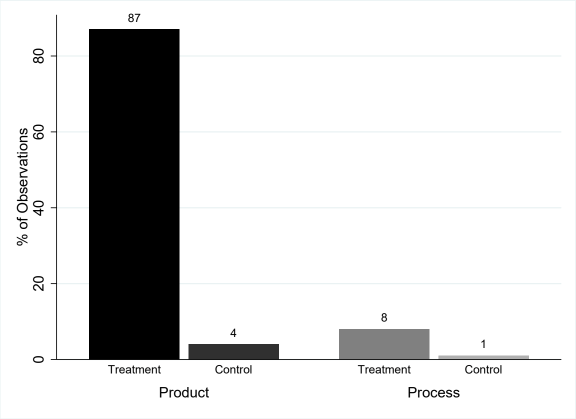


Figure: Text Data: Technology Categories. **Product:** use technologies to produce a new type of output. **Process:** use technologies to produce the same type of output more efficiently. *Survey results similar.*

Outcomes: Export Effects

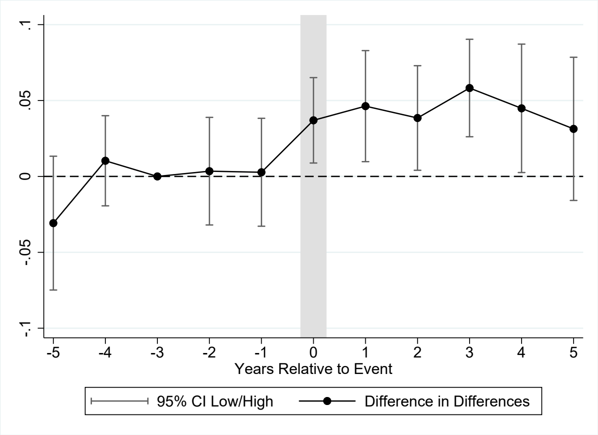


Figure: Export Effects: The Export Status. Notes: The estimates indicate approx. a 4%-point increase on the indicator of being a exporter from the baseline of 28%. Application year in grey.

Outcomes: Export and Product Effects

	(1) Export Status	(2) Export Share	(3) Export Regions	(4) Products	(5) Prod. Introduce	(6) Prod. Discontinue
Treatment	0.0404^{**}	0.00935^{*}	0.219^{***}	0.155^{**}	0.0880^{**}	0.0664^{**}
	(0.0134)	(0.00451)	(0.0568)	(0.0599)	(0.0282)	(0.0223)
Baseline	0.284	0.0523	1.498	1.546	0.498	0.539
N	2031	2031	2031	2031	2031	2031

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table: Products and Exports. Notes: Difference-in-differences estimates. Products measured from the customs data at the 6-digit HS/CN level. N refers to firms.

Context: Flexible Manufacturing

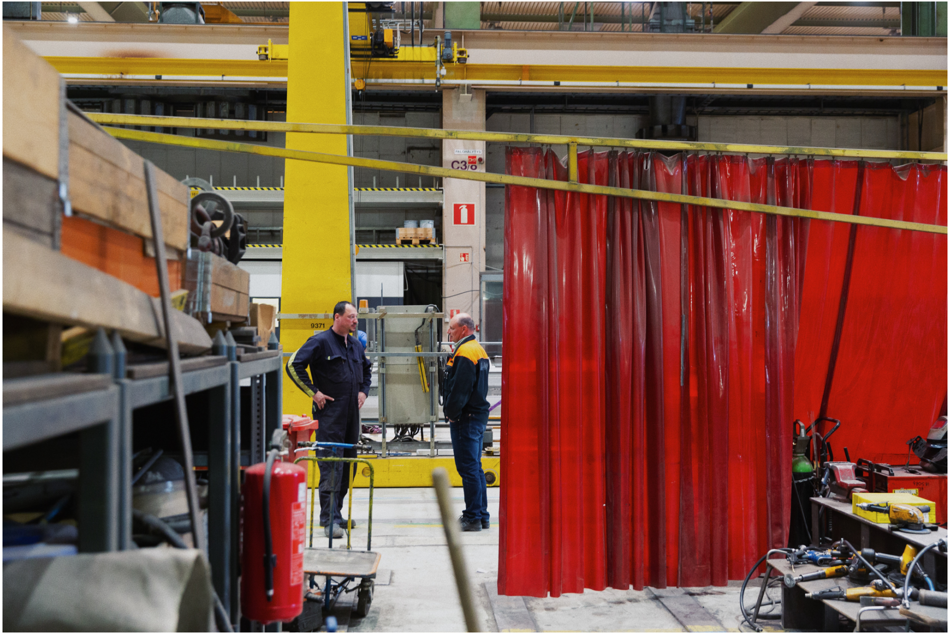
- **Recap:** A tale of two forms of technology adoption.
  - Different effects that can be empirically distinguished.
- **A central question:** When and why is one more likely to occur than another?
  - **Mass Production** (Taylor 1911, Ford 1922)
    - ★ Standardized products, large volumes, stable market (the task model)

    $\longrightarrow$ Process improvements
  - **Flexible specialization** (Piore and Sabel 1984, Milgrom and Roberts 1990)
    - ★ Specialized products, small volumes, unstable market

    $\longrightarrow$ Product improvements
- **Main point**: The effects of new technologies depend on whether we are in a world of flexible or Taylorist firms. Our context is flexible.

Conclusion

- **New finding**
  - Technology adoption led to increases in employment and no change in skill composition, contrary to common ideas about technology and labor markets.
- **Methodological advances**
  - Data: Directly measure of technologies, skills, and work.
  - Research design: First paper to evaluate manufacturing technologies' effects using policy variations.
  - Text analysis: Demonstrate novel methods to use text data in program evaluation.
- **New interpretation based on theory and evidence**
  - Firms used new technologies to increase competitiveness by changing output, not by replacing work.
- **Relation to earlier research**
  - The result does not mean that technology in general would not change work.
  - But it does clarify a specific mechanism.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