What Do Technology Grants Do?

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The Economist

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Free exchange

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.

Research Question

- **Research question:**
  - How do subsidies for technology adoption impact labor and skill demand?
- **Two views:**
  1. **Automation:** Displace workers and increase the demand for skilled labor.
     - Labor replacement: Keynes (1931), Acemoglu and Restrepo (2018).
     - Skill-biased technological change: Griliches (1969), Tinbergen (1975)
  2. **Expansion:** Allow firms to expand. Worker effects uncertain.
     - Factory-floor observations: Solow et al. (1989), Berger (2013).
- **Hard question:**
  - This paper: Direct evidence on the labor demand effects at the firm level, and we explore mechanisms that help explain what happens, what does not happen, and why.
  - Current key evidence from Criscuolo et al. (2019) and Curtis et al. (2022).

Concrete Context: New Technologies in Manufacturing

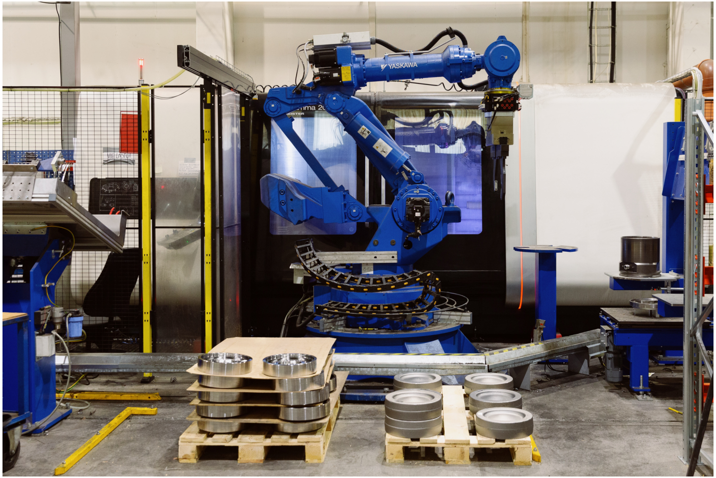


Figure: A robot and a CNC machine. Our sample firms are primarily manufacturing SMEs (18 employees, on average), in metal and wood product industries, adopting new machinery.

Winners–Losers Design

- **Program:** EU gives direct funding for firms' technology investment in Finland.
- **Aim:** Advance the adoption of new technologies.
- **Bottom up**: Firms can choose the type.
- **Typical case:** €80K cash grant, paid against verifiable technology costs.
- **Expected effect:** Lowers the price of new technology for the subsidy grantees. *All plan to adopt*.

Text Matching

- A novel method for program evaluation based on text data.
    - Use *evaluation* report texts to control for differences between treatment and control.
    - Evaluation reports written by subsidy officers that aim for a clear referee report.
    - Given a similar report (W), treatment assignment (D) more likely to reflect idiosyncratic variations than systematic differences (as-if random).
- Propensity score (predicted probability of receiving the subsidy):

$$p(W_j) \equiv P\left[D_j = 1 | W_j\right]$$

- Three steps:
    1. Represent text as data (vector representation, FastText; Bojanowski et al. 2016).
    2. Estimate propensity scores using the data (support vector machines).
    3. Control for confounders using propensity scores.

The First Stage

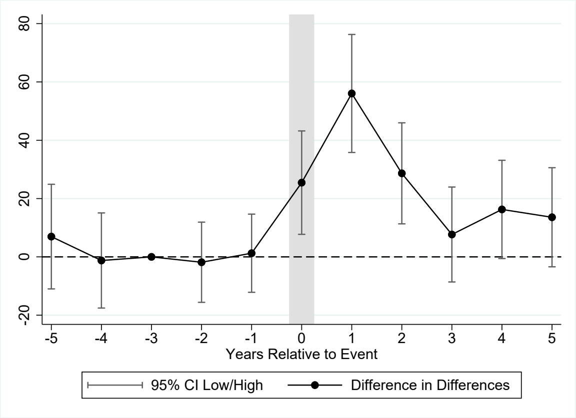


Figure: The Effect of Technology Subsidies on Machinery Investment (€K).

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

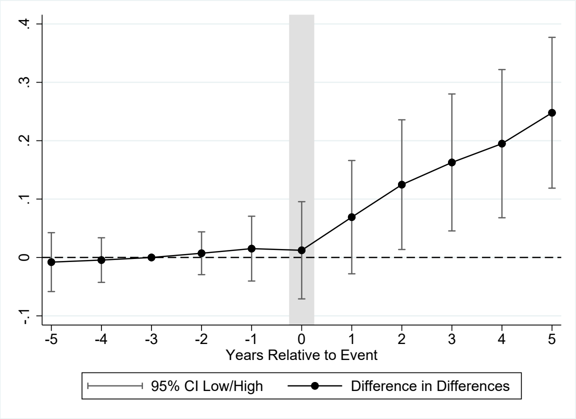


Figure: The Effect of Technology Subsidies on Employment (in %).

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

No Skill Effects

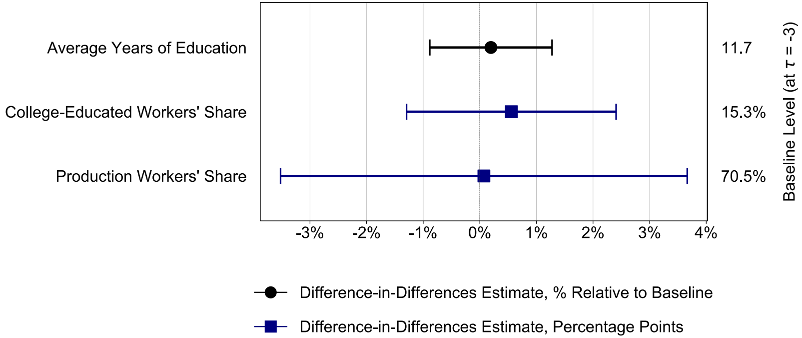


Figure: The Effect of Technology Subsidies on Skill Composition.

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.

Employment and Skill Effects with Matching

	Machine Investment (EUR K)			Employment			Education Years		
	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match
	107.9***	100.3***	127.9***	0.232***	0.234**	0.217***	0.0246	-0.00385	0.0303
	(17.53)	(21.90)	(6.556)	(0.0614)	(0.0746)	(0.0183)	(0.0611)	(0.0752)	(0.0207)
N	2031	1812	3200	2031	1812	3200	1884	1676	2999

Table: Difference-in-Differences Estimates on the Main Firm-Level Outcomes.
Notes: The coefficient 107.9 refers to €107.9K increase in machinery investment, 0.232 to 23.2% increase in employment, and 0.0246 years to no change in the average level of education.

Baseline: controls for the industry and firm size.
Prop. Score: controls for the text propensity score.
Match: compares the treatment group to a matched non-applicant group.

Moore's Law for Pistons

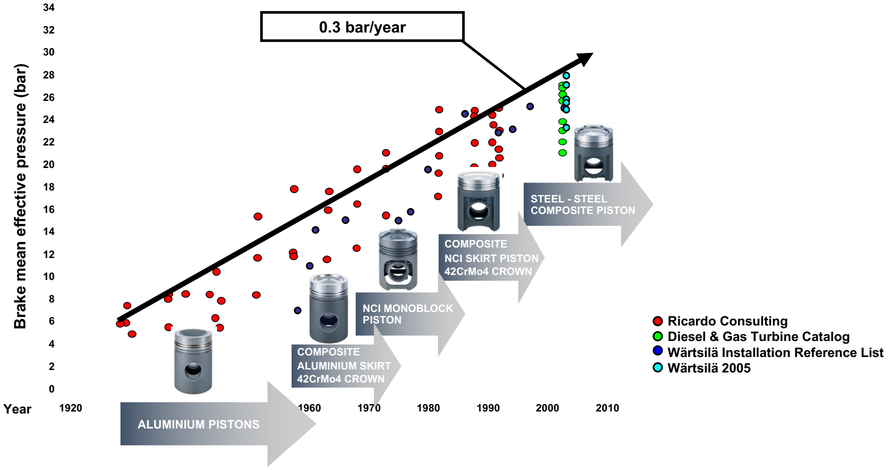
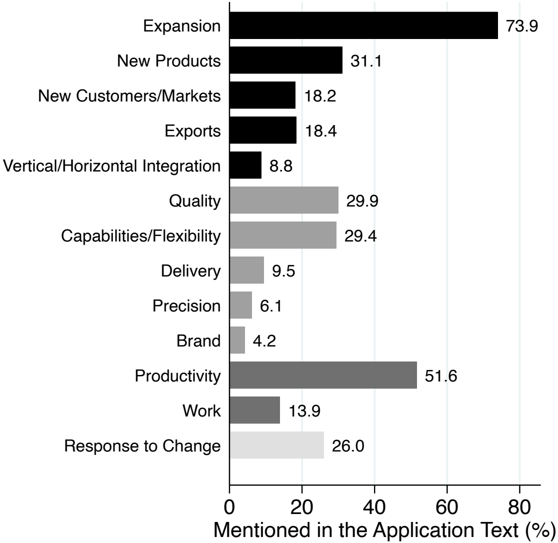
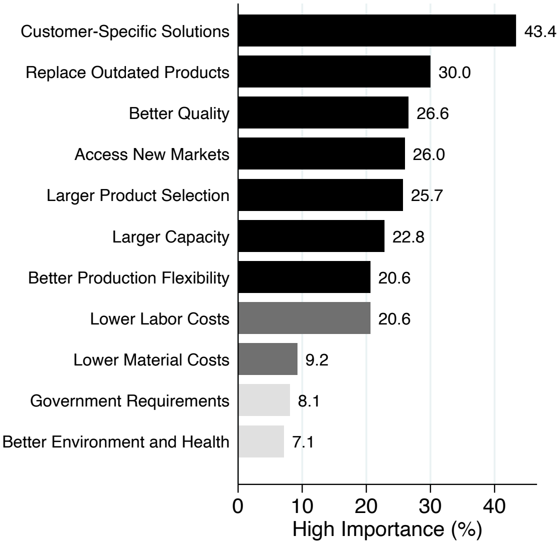


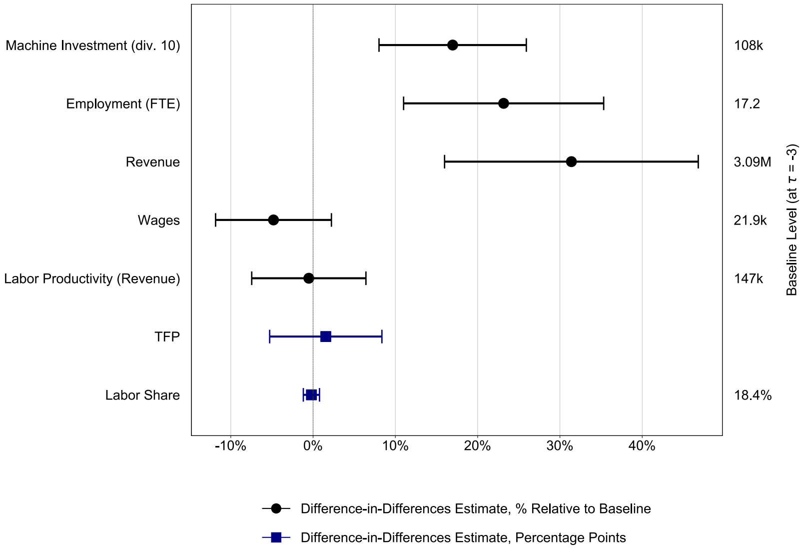
Figure: The trend of piston materials' development over the past 100 years.

Text and Survey Data Reveal Firms' Intentions





Firm-Level Effects: Scaling Up



Exports Rise

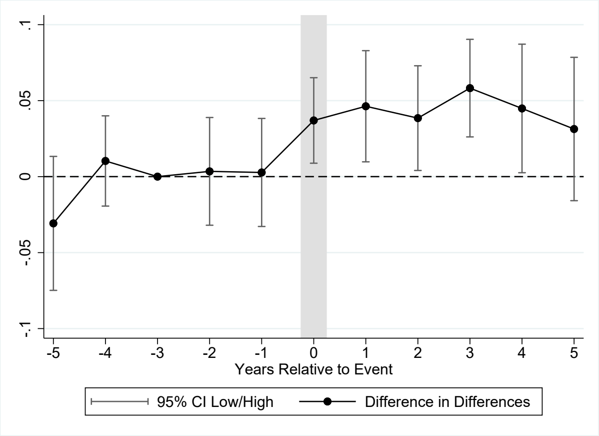


Figure: Export Effects: The Export Status. Notes: The estimates indicate approx. a 4%-point increase on the indicator of being a exporter from the baseline of 28%. Application year in grey.

Prices Rise

	(1) Price (Exports)	(2) Price (Manufacturing)
Treatment	0.291	0.308**
	(0.328)	(0.102)
N	400	217

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table: Price Effects. Notes: Difference-in-differences estimates, in %. Product-level prices computed from the customs data and the manufacturing survey. N refers to firms.

Profits: No Change in Margins, Levels Rise

	(1) Profit Margin	(2) Gross Profits	(3) Net Profits
Treatment	0.00121	143.5***	123.6**
	(0.00772)	(51.15)	(51.61)
Mean	0.052	274.8	-16.07
Median	0.050	52.85	37.56
N	2031	2031	2031

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

Table: Profit Effects. Notes: Difference-in-differences estimates, in EUR. Discounting at a 5% rate yields net profits of EUR 95.8K, and at a 10% rate, EUR 73.7K. The average effect on received subsidies (EUR 70.22K) falls within the 95% confidence intervals of both, suggesting a 1:1 increase.

Our LATE Reflects Incremental Investments

- What local average treatment effect (LATE) do our estimates approximate?
  - *Whose* causal effects do we estimate?

1. **Constraints $\longrightarrow$ Big effects**
   - Financial constraints limit firms' ability to adopt new technologies, and EU subsidies lower these barriers, enabling large investments.
2. **About efficient market $\longrightarrow$ Marginal effects**
   - Firms already have sufficient resources, and subsidies fund standard, incremental investments with limited productivity impact.
   - Our findings support the latter view: Modest average subsidies (EUR 80K), no productivity effects, not moving from no technology to full automation—already had some technologies, no larger effects for more credit constrained firms.

Our Context is Flexible Manufacturing

- **Recap:** Motivation outlines two forms of technology adoption (automation & expansion).
  - 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)
    - $\longrightarrow$ Automation; efficiency improvements
  - **Flexible specialization** (Piore and Sabel 1984, Milgrom and Roberts 1990)
    - ⋆ Specialized products, small volumes, unstable market
    - $\longrightarrow$ Expansion; product improvements
- **Main point**: The effects of new technologies may depend on whether we are in a world of flexible firms or mass production.

Our Results Are About Machinery. IT Is Different.

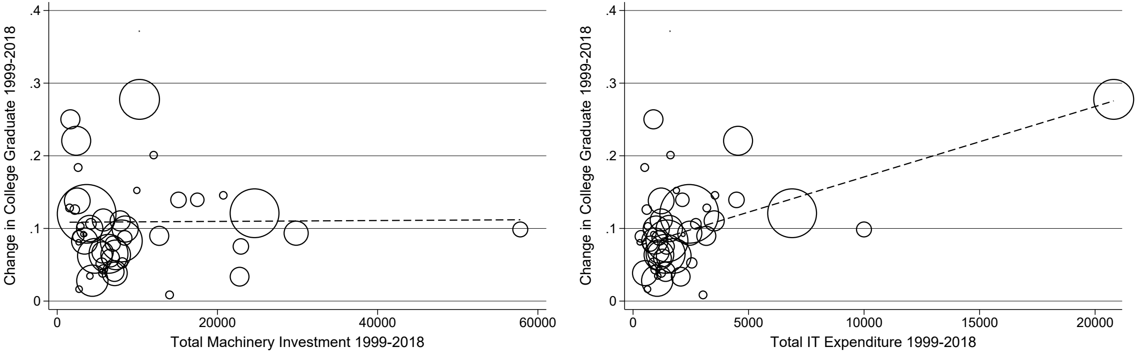
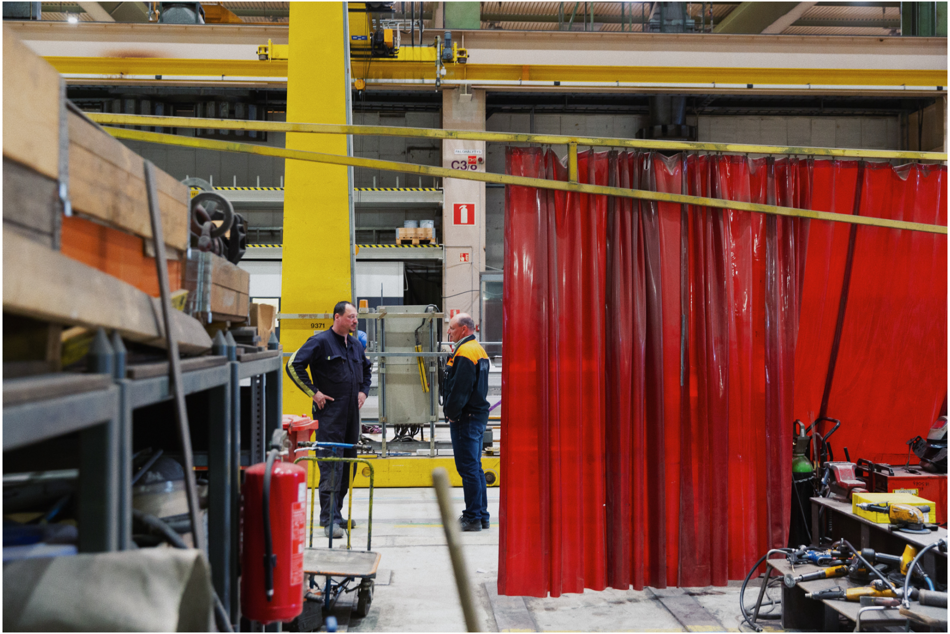


Figure: Industry-level graphs on predicting long changes in skill mix with total machinery investment (left) and IT expenditure (right) between 1999–2018. The technology variables are measured in EUR per worker-years (FTE) and skill outcomes in percentage points.

Conclusion

- **Novel causal evidence on technology subsidies and labor demand:**
  - Technology grants increased employment by 23% with no change in skill composition.
  - No detectable effects on workers' education levels, occupation mix, or labor share.
- **Likely firm-level mechanism:**
  - The subsidies primarily supported expansion rather than automation.
  - Systematically document how firms actually use these grants. 74% of firms cited expansion motives in applications. Only 14% mentioned workforce-related objectives.
- **Text-as-data for program evaluation**
  - Use ML on evaluation report texts to create propensity scores. Demonstrate how to extract comparable treatment/control groups from administrative text data.
  - Method applicable to other policy contexts (e.g. judge decisions).
- **Understanding: Why do some technologies bias toward skills while others don't?**
  - Answer: IT $\neq$ Machinery, and expansion $\neq$ automation.
  - Policy perspective: Technology grants expanded opportunities for non-college workers.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