Winners and Losers of Technology Grants

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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

- How do subsidies for technology adoption shape workers' opportunities?
- **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:** Enable firms to expand. Worker effects uncertain.
     - Factory-floor observations: Solow et al. (1989), Berger (2013).
- **Hard question:**
  - Limited evidence because *measuring* and *identifying* the effects of firm subsidies are hard.

This Paper

- **Novel 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 (LATE effects).
  - Develop novel **text matching**: contrast firms with similar evaluation report texts.

- **Large-scale data:**
  - Register data track all firms and workers over time (1994–2018).
  - Text data: measure technology plans and evaluations using grant application texts.
  - Surveys and scraped media articles covering our firms.

Our Context: New Technologies in Manufacturing

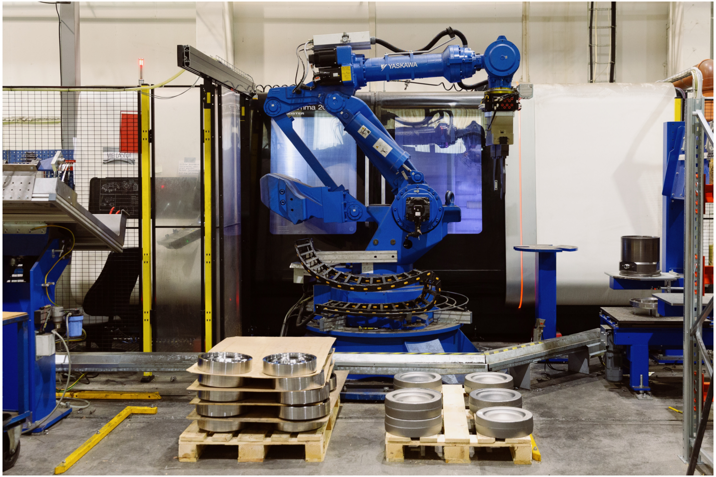


Figure: A robot and a CNC machine (2021).

Main Result

- **Clear main result:**
  - Sharply more technologies.
  - Increase in employment.
  - No change in skill composition.

- **A puzzle:**
  - No labor replacement or skill-bias from technology subsidies in the manufacturing firms.
  - Contrast with the concern about automation.

- **An interpretation:**
  - Idea: Expansion vs. automation
  - Evidence: Firms used technologies to <u>expand</u>, <u>not cut costs</u>.
  - Lesson: How firms *choose* to use technology matters (not all is automation).

Moore's Law for Pistons

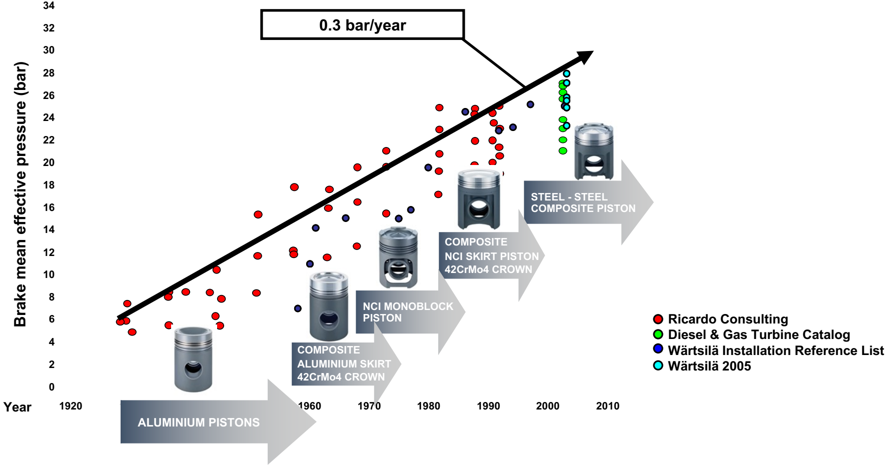


Figure: The trend of piston materials' development over the past 100 years.

Contribution to the Literature

- **This paper:**
  1. Firm-level effects of subsidies to manufacturing technologies.
  2. Directly measure of technologies, skills, and work.

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

- **Related research:**
  - Industrial policy: Criscuolo et al. (2019), Curtis et al. (2021), Becker et al. (2010)
  - Machinery (this paper): Doms et al. (1997), Bartel et al. (2007), Aghion et al. (2022).
  - IT (*not* this paper): Akerman et al. (2015), Gaggl & Wright (2017), Autor et al. (1998).
  - Automation (*not* this paper): Feigenbaum & Gross (2024), Bessen et al. (2023).

Outline

- **Part 1: LATE Effects**
  - Context
  - Data
  - Design
  - Estimates
- **Part 2: Mechanism**
  - Framework
  - Evidence
- **Part 3: Zooming Out**

Context: Outside

Figure: Typical sample manufacturing plant outside (2021).

Context: Inside

Figure: Typical sample manufacturing plant inside (2021).

Context: Machine Operators and a Milling Machine

Figure: Machine operators workign together with a milling machine (2021).

Context: Welders at Work

Figure: Welders (2021). From a CEO: “A company does not just pay a welder to weld.”

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: type and use of technology (CIS + own survey).
- **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.

Research Designs

1. **Main Design: Winners-Losers Design ◀ <u>This Talk</u>**
    - A. Winners vs. Losers (baseline)
    - B. Winners vs. Losers with Text Matching
    - C. Winners vs. Matched Non-Applicant Control Group

2. **Internal Validity: Regression Discontinuity Design**
    - Change in the threshold for a small firm—applied retrospectively.

3. **External Validity: Spikes Design**
    - Evaluate technology adoption events *without* the program with the novel data.

Design: The EU Subsidy Program

- **Program:** Local ELY centers provide direct funding for firms' technology investment.
- **Aim:** Advance the adoption of new technologies in firms.
- **Typical case:** €80K cash grant (paid against verifiable technology costs).
- **Expected effect:** Lowers the price of technology for the subsidy grantees.
    - Follows technology neutrality—firms can choose the type of technology.
    - Technologies required to be new (e.g., not old or second-hand machinery).

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

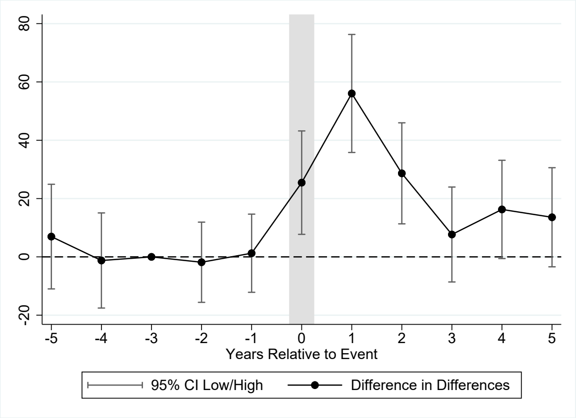


Figure: The Effect of Technology Subsidies on Machinery Investment (€K).

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

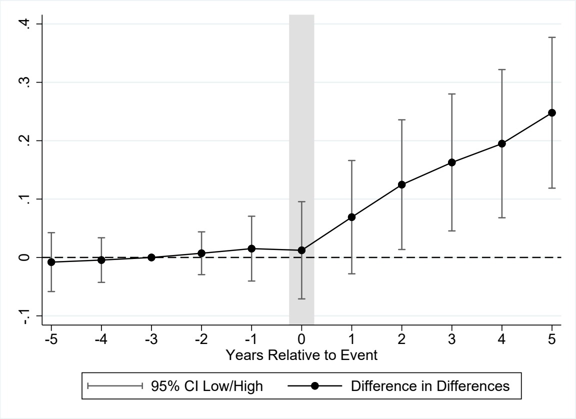


Figure: The Effect of Technology Subsidies on Employment (in %).

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

Skill Effects: Main Measures

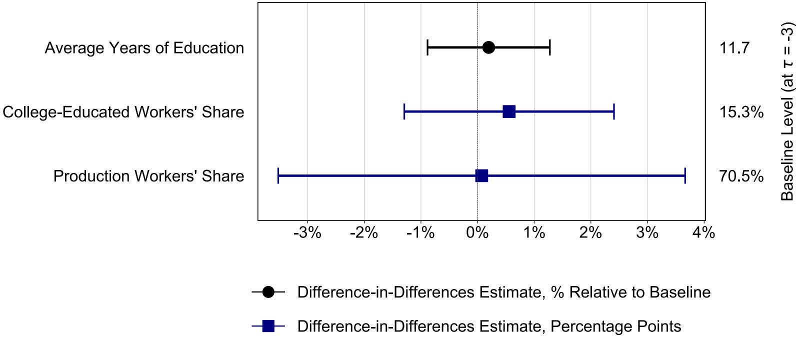


Figure: The Effect of Technology Subsidies on Skill Composition.

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.

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.

Text Propensity Score Calibration

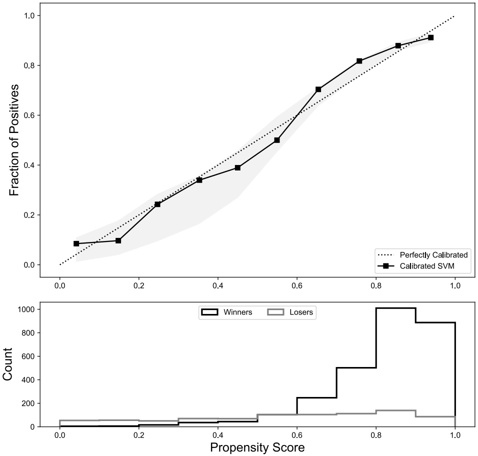


Figure: The Text Propensity Score Calibration Plot.
Notes: Predicted probabilities on the x-axis, realized probabilities on the y-axis.

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.

Conceptual Framework

- Consider a simple composite function:

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

- Two views on how firms could respond to technology subsidies:
  - **Intensive margin** T_I: Automation
    - ★ This affects the production "recipe" of how labor is used in production.
      Example: a welding robot replaces a welder's tasks.
      The ideas of automation and skill bias are generally about this.
  - **Extensive margin** T_E: Expansion
    - ★ This affects the "lens" through which the production is projected into markets.
      Example: a welding robot makes longer seams than a human welder.

Detailed Evidence

- **Next: Investigate the mechanism with deeper evidence.**
  - Use the conceptual ideas to speak back to data.
  - Main point: the effects of technology subsidies is an open empirical question.
- **Step 1: Outcomes** (Y)
  - Explore the mechanism with new outcomes.
  - Use data on revenues, productivity, profits, exports, products, marketing, and prices.
- **Step 2: Treatments** (D)
  - Directly measure firms' intentions with text and survey data.

Outcomes: Firm-Level Effects

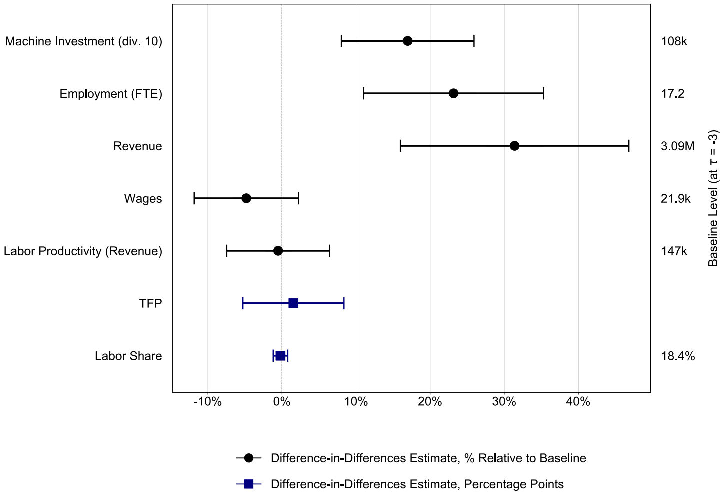


Figure: Difference-in-Differences Estimates on Selected Firm-Level Outcomes.

Outcomes: Exports

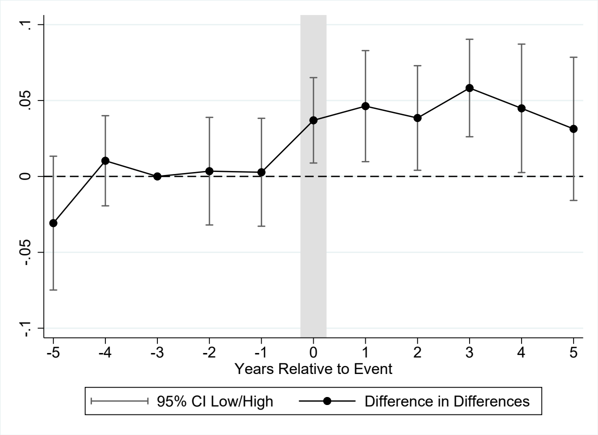


Figure: Export Effects: The Export Status. Notes: The estimates indicate approx. a 4%-point increase on the indicator of being a exporter from the baseline of 28%. Application year in grey.

Outcomes: Exports and Products

	(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.

Outcomes: Marketing

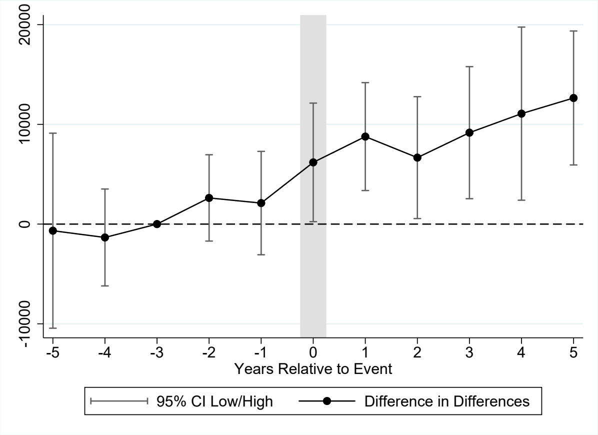


Figure: Marketing Effects: Marketing Expenditure. Notes: The estimates indicate approx. a €10K increase in marketing expenditure. Marketing signals that the firm intends to change how the customers perceive their output, not only the production costs. Application year in grey.

Outcomes: Prices

	(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 %. Prices incease, inconsistent with expansion via task automation. Product-level prices computed from the customs data and the manufacturing survey. N refers to firms.

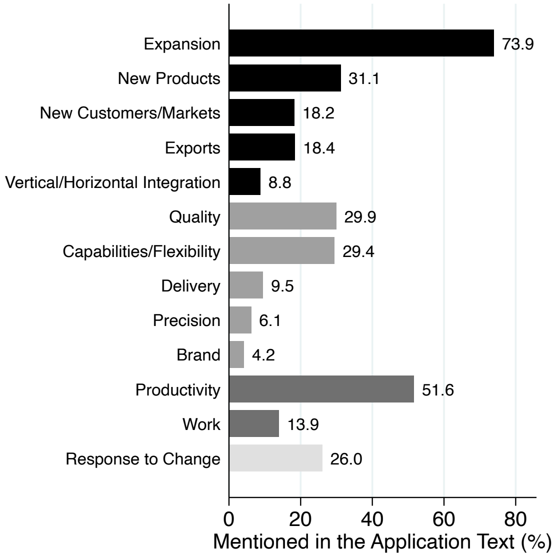
Outcomes: Profits

	(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

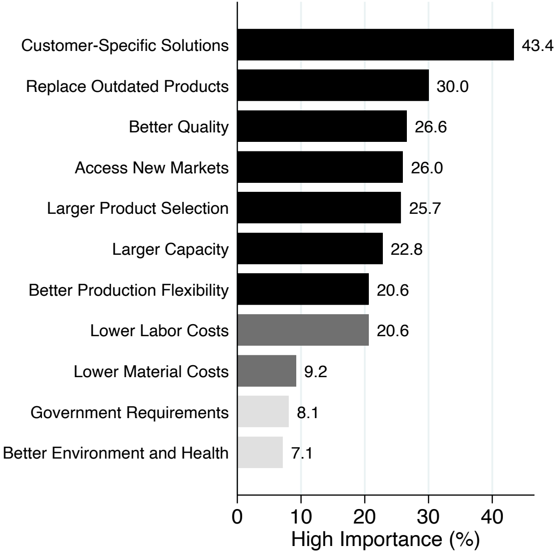
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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.

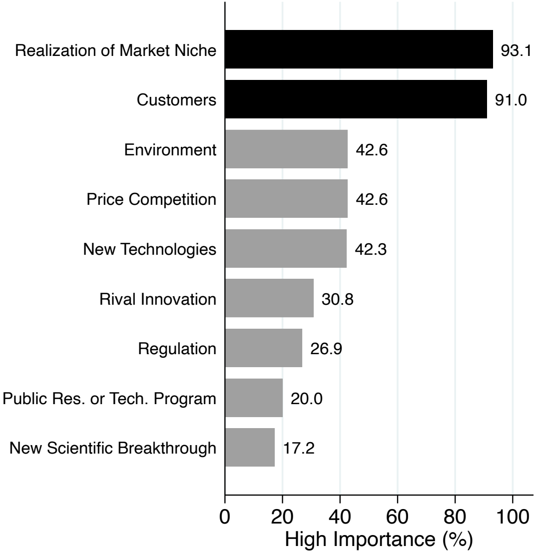
Treatments: Text Data Reveals Firms' Intentions



Treatments: Survey Data Document the Same Idea



Treatments: Journal Articles Back Up the Story



Our LATE Reflects Incremental Investments

- What local average treatment effect (LATE) do our estimates approximate?
  - *Whose* causal effects do we estimate?
- One argument: **Constraints** $\longrightarrow$ **Big effects**
  - Firms face financial constraints to adopting new technologies, and EU subsidies help alleviate these constraints, leading to large investments.
- Another argument: **About efficient market** $\longrightarrow$ **Marginal effects**
  - Firms could already have sufficient resources for investments, and subsidies simply lead to standard, incremental investments with limited impact on productivity.
  - Evidence more consistent with this: small average subsidies (EUR 80K), no productivity effects, not moving from no technology to full automation—already had some technologies, no larger effects for ex-ante more credit constrained firms.

Our Context is Flexible Manufacturing

- **Recap:** A tale of 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)
    - ⟶ Process improvements
  - **Flexible specialization** (Piore and Sabel 1984, Milgrom and Roberts 1990)
    - ⋆ Specialized products, small volumes, unstable market
    - ⟶ Product improvements

- **Main point**: The effects of new technologies depend on whether we are in a world of flexible or Taylorist firms.

Zooming Out

- **Question:** So where is the skill bias then?
- **Literature:**
  - Machinery: Not that skill-biased (Doms et al. 1997, Bartel et al. 2007, Curtis et al. 2022).
  - IT: Mostly skill-biased (Autor et al. 1998, Akerman et al. 2015, Gaggl and Wright).
- **Next:**
  - Zoom out to manufacturing firms outside the program.
  - Find that IT more strongly correlated with skill upgrading than machinery.
  - The program supported machinery, not IT.
  - This contrast could reconcile the findings with the literature.

Machinery vs. IT

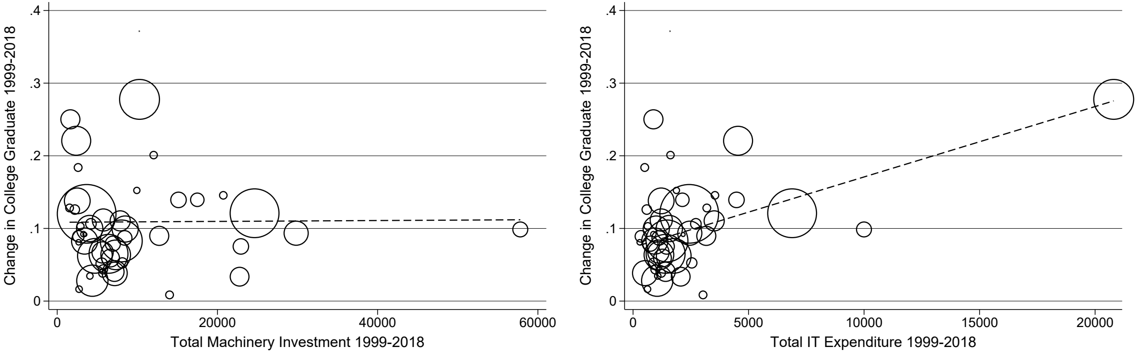


Figure: Industry-level graphs on predicting long changes in skill mix with total machinery investment (left) and IT expenditure (right) between 1999–2018. The technology variables are measured in K EUR per worker-years (FTE) and skill outcomes in percentage points.

Survey Differences

A: Robots	CIS *Robots' Importance* High	CIS *Robots' Importance* Low	ICT *Robot-User* Yes	ICT *Robot-User* No	Etla *Robot-User* Yes	Etla *Robot-User* No	Customs *Robot-Importer* Yes	Customs *Robot-Importer* No	Customs *Robot-Importer* No*
College Share	0.325	0.294	0.312	0.355	0.294	0.340	0.316	0.145	0.208
	(0.022)		(0.003)		(0.015)			(< 0.001)	
Production Worker's Share	0.600	0.555	0.633	0.549	0.600	0.529	0.565	0.694	0.634
	(0.0129)		(< 0.001)		(0.002)			(< 0.001)	
N	271	1,195	357	521	298	306	760	260,434	91,880

B: IT	*Digitalization's Importance* High	*Digitalization's Importance* Low	*Computer Users' Share vs. Median* Above	*Computer Users' Share vs. Median* Below	*Big Data and Analytics* Yes	*Big Data and Analytics* No
College Share	0.397	0.273	0.428	0.248	0.383	0.291
	(< 0.001)		(< 0.001)		(< 0.001)	
Production Worker Share	0.473	0.623	0.481	0.685	0.506	0.599
	(0.046)		(< 0.001)		(< 0.001)	
N	192	1263	436	443	137	493

Table: Worker shares by technology survey responses.

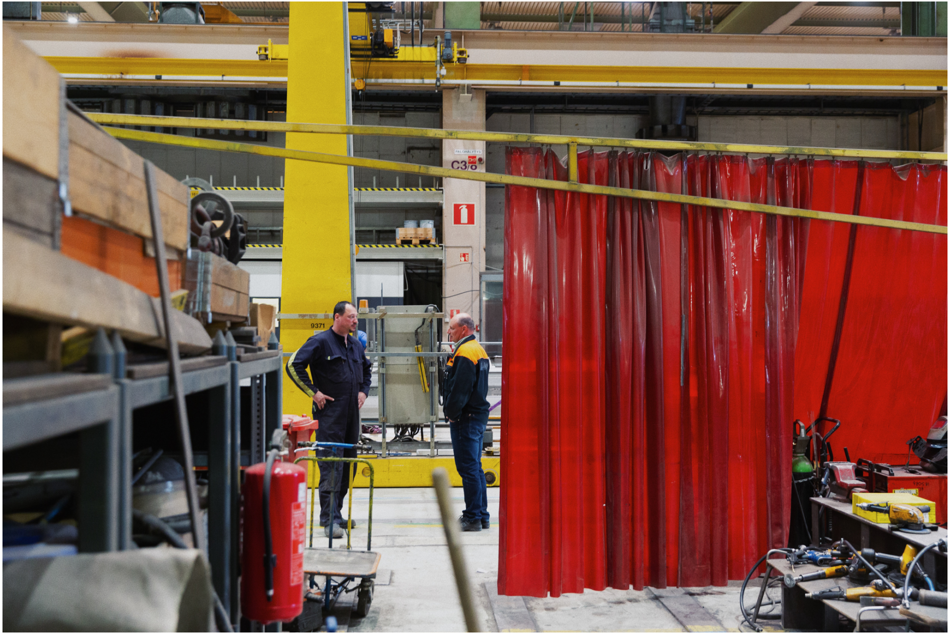
Cross-Sectional Correlations in Large-Scale Firm Data

	(1)	(2)	(3)	(4)
A: Machinery Investment				Mean
College Share	3651.1***	1646.3**	916.7	0.217
	(727.8)	(523.8)	(574.9)	
Production	1481.9*	99.26	888.9	0.612
Workers' Share	(611.1)	(476.8)	(512.6)	
B: IT Expenditure				
College Share	7779.8***	6607.8***	5569.2***	0.217
	(426.2)	(283.1)	(286.6)	
Production	-5646.4***	-4577.6***	-3579.1***	0.612
Workers' Share	(394.6)	(237.7)	(208.5)	
Controls	Year	+ Industry	+ Firm Size	

Table: Cross-sectional firm estimates: worker shares predicting machinery investment and IT expenditure per worker. 1 pp in college share predicts 55.69 higher IT expenditure.

Conclusion

- **New finding**
  - Technology subsidies led to increases in employment and no change in skill composition, contrary to common ideas about technology and labor markets.
- **Methodological advances**
  - Research design: First paper to evaluate technology subsidies' effects on skill demand.
  - Text analysis: Develop novel methods to use text data in program evaluation.
  - Data: Directly measure of technologies, skills, and work.
- **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 policy-relevant mechanism.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