Online Appendix

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

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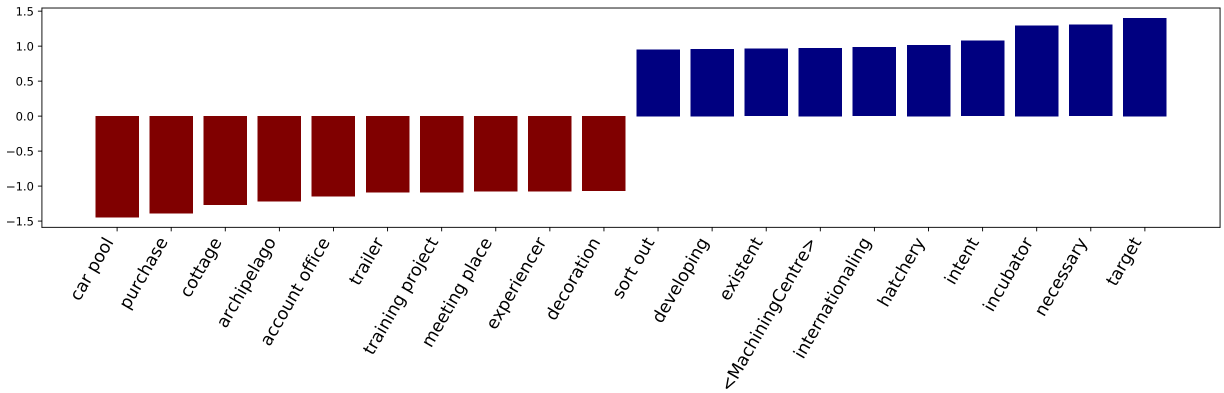
May 6, 2022

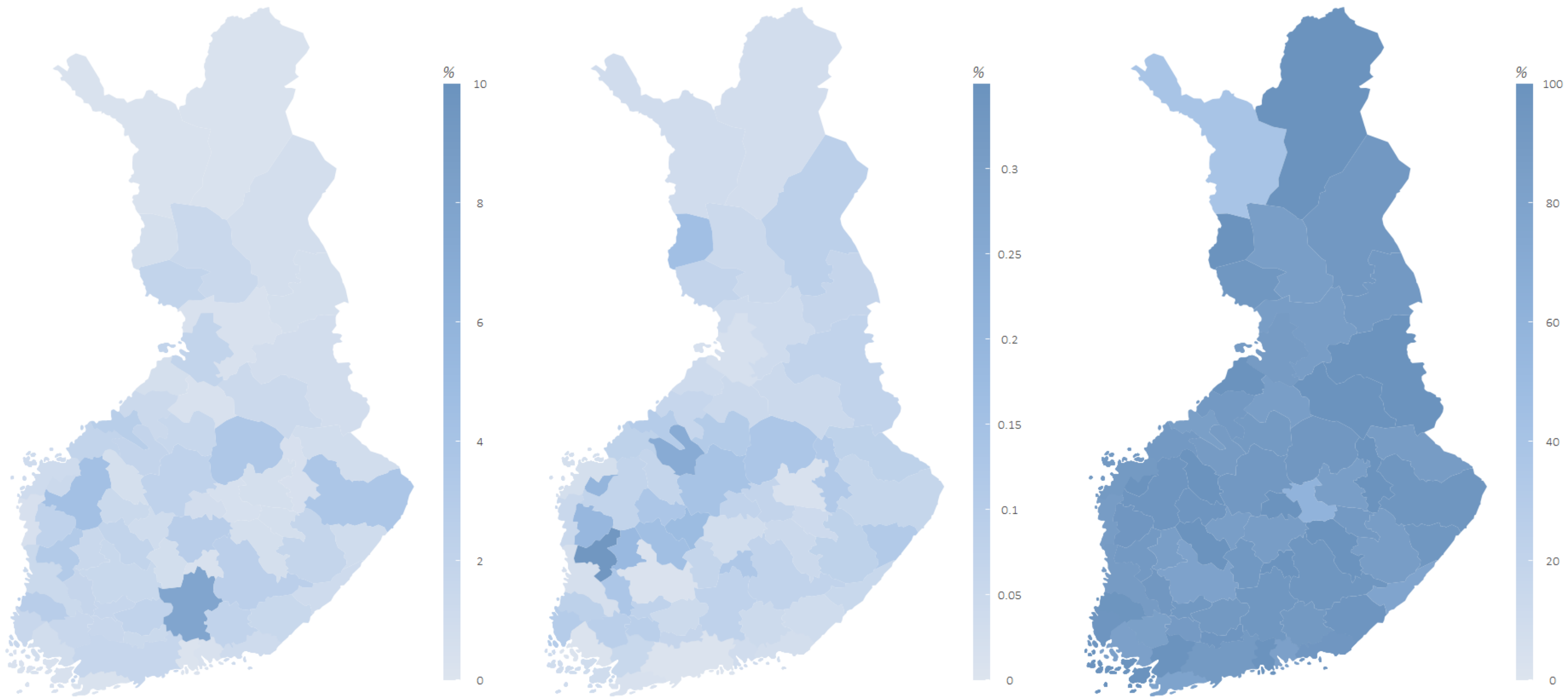
Contents

1 The Winners-Losers Design: Research Design

Figure 1: Predictive Features for Winning a Technology Subsidy.



Notes: The features (words) are plotted from top and bottom SVM coefficients predicting treatment status. The y-axis refers to the coefficient size and indicates the relative importance of each feature. Positive (negative) values indicate that the word is typically (not) associated with applications winning a subsidy. The sample is the main analysis sample (subsidies design).



(a) Share of Applications.

(b) Applications per Capita.

(c) Acceptance Rate.

Figure 2: Maps of Application Statistics.

Notes: The maps visualize descriptive statistics of sample applications (firms) at the subregion level: (a) distribution of the sample over subregions, (b) sample firm count per capita over subregions, i.e., adjusting for the population in each subregion, (c) the win rate by subregion. The sample is the main analysis sample (subsidies design). Applications are more represented in areas with a large manufacturing industry (e.g., the Lahti region). The acceptance rates do not vary significantly by region, barring some outliers with only few applications.

Table 1: Predicting Treatment.

	(1) Treatment	(2) Treatment	(3) Treatment
Employment (Log)	0.0287***	0.0340***	0.0248***
	(0.00613)	(0.00738)	(0.00706)
Revenue per Worker (EUR 100K)	-0.00850	-0.00924	-0.00462
	(0.00496)	(0.00517)	(0.00456)
Average Wage (EUR 100K)	-0.0251	-0.120	-0.0958
	(0.111)	(0.124)	(0.118)
Profit per Worker (EUR 100K)	-0.108*	-0.127*	-0.0524
	(0.0508)	(0.0546)	(0.0491)
Value Added per Worker (EUR 100K)	0.129*	0.145*	0.0570
	(0.0636)	(0.0686)	(0.0625)
Propensity Score			0.494***
			(0.0645)
Observations	2031	2031	1812

Standard errors in parentheses.

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

Notes: Coefficients for different variables measured at $\tau = -3$ from OLS estimation, where treatment status is the dependent variable. The sample is the main analysis sample (subsidies design). The propensity score is based on the application texts. The first column reports the coefficients without any controls, the second with a basic set of controls (year indicators and 2-digit industry), and the third when adding text-based propensity score to the controls. Log employment is most predictive of receiving a subsidy: the coefficient is between 0.025-0.034 and is significant in all specifications. Still, the effect is very small, as holding all else equal, doubling the employment of a firm would result in only a 2.0-2.4 percentage points increase in its probability of receiving a subsidy. Interestingly, the first two columns imply that increasing the profit per worker by 10K euros would reduce the probability of a successful application by about 1.1-1.3 percentage points, but a similar increase in value added per worker would increase the probability by about 1.3-1.5 percentage points. Based on these numbers, it seems that high profits themselves would not increase the chances of a successful subsidy application, but a high conversion rate of money spent on materials to value-added increases the probability. Adding the propensity score in Column 3 as a control eradicates the significance of both of these coefficients, leaving only log employment as statistically significant at any of the conventional levels. This implies that the propensity score captures firm characteristics correlated with both profits and value added. Since the coefficient of log employment is so small, and we control for baseline employment in all of our estimates, together with the propensity score, year indicators, and industry controls, the remaining selection bias in our specification and context is potentially minor. The propensity score itself has a highly significant and large coefficient, about 0.49. Thus the score is not perfect in predicting treatment (as it would be if the coefficient were to be unity) but performs reasonably well.

Table 2: Controlling for the Propensity Score from the Register Data.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Profit	(6) Productivity	(7) Labor Share	(8) Educ. Years	(9) College Share	(10) Prod. Worker Share
Treatment	54.72**	0.310***	0.386***	-0.000362	-0.00297	-0.00571	0.000597	0.0288	0.00657	0.000871
	(17.44)	(0.0594)	(0.0777)	(0.0347)	(0.00788)	(0.0353)	(0.00498)	(0.0616)	(0.00936)	(0.0182)
Propensity Score	2224.7***	-3.276***	-3.017***	-2.127***	0.175**	0.0229	-0.109***	-0.267	-0.0643	-0.00860
	(181.1)	(0.469)	(0.533)	(0.282)	(0.0575)	(0.200)	(0.0320)	(0.524)	(0.0745)	(0.151)
Observations	2031	2031	2031	1952	2031	2031	2031	1884	1884	1891

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

Notes: First-difference estimation results on selected outcomes with balance sheet-based propensity score controls. The sample is the main analysis sample (subsidies design). The propensity scores are constructed by first estimating a logit model based on average wages, employment, revenue at $\tau = -3$, and employment and revenue trends from $\tau = -3$ to $\tau = 1$. The predicted treatment probability is then used as the propensity score. Machine investment is summed over $\tau = 0$ to $\tau = 2$ in EUR K. We find qualitatively similar effects as in our baseline estimation: the first stage on machinery investment is clear, employment and revenue grow significantly, but there is no evidence of skill-bias, with fairly precise zeros in most of the other outcomes. Interestingly, the first stage effect is around half in size of that in our preferred estimates (55K vs. 103K EUR). On the other hand, the employment and revenue effects are somewhat larger (about 6 and 14 percentage points respectively) than without the control.

Table 3: Controlling for Selection Bias Using Qualitative Evaluations.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Productivity		(5) Labor Share		(6) College Share	
No good	103.2***	95.38***	0.234***	0.238**	0.298***	0.315**	-0.0104	-0.0122	-0.000850	0.000771	0.00382	0.00329
	(18.43)	(23.23)	(0.0645)	(0.0790)	(0.0823)	(0.102)	(0.0357)	(0.0429)	(0.00509)	(0.00617)	(0.00988)	(0.0123)
No jobs	106.8***	99.24***	0.225***	0.224**	0.306***	0.321**	-0.00710	-0.0109	-0.00240	-0.00110	0.00592	0.00638
	(17.94)	(22.54)	(0.0628)	(0.0768)	(0.0799)	(0.0990)	(0.0353)	(0.0432)	(0.00507)	(0.00620)	(0.00966)	(0.0121)
Propensity Score		✓		✓		✓		✓		✓		✓
N, No-good	2021	1803	2021	1803	2021	1803	2021	1803	2021	1803	1875	1668
N, No jobs	2026	1807	2026	1807	2026	1807	2026	1807	2026	1807	1879	1671

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

Notes: The effects on selected outcomes when dropping losing (control) firms deemed to not satisfy basic financial requirements ("no-good," n = 10) and not produce enough jobs ("no jobs," n = 5) by the administrative evaluator. The sample is a subset of the main analysis sample (subsidies design). The table addresses the concern of bad counterfactuals explaining our results. As the set of control firms (i.e. those not receiving a subsidy despite applying for one) in our baseline sample is relatively small (n = 146), we are able to read through the evaluation texts written by the program officers for each firm and determine potentially bad counterfactuals. "No-good" refers to the applications where the rejection is due to the firm's poor financial health or other factors indicating that the firm is likely to sustain its business in the long term. "No-jobs" refers to the cases where the officer rejected the application due to it not creating new jobs, a condition not required for acceptance, but in some cases detrimental to the decision. Dropping these potentially problematic control firms does not change the results in any meaningful way.

Table 4: Propensity-Score Trimmed Samples.

Panel A: Investment, Employment, Wages, and Firm Performance.

	(1)		(2)		(3)		(4)		(5)	
	Machine Inv. (EUR K)		Employment		Revenue		Wages		Profit Margin	
5%	112.3***	107.5***	0.245**	0.248**	0.301**	0.327**	-0.0124	-0.00497	-0.00420	-0.00628
	(24.97)	(25.36)	(0.0815)	(0.0828)	(0.116)	(0.118)	(0.0439)	(0.0441)	(0.0118)	(0.0119)
10%	127.4***	123.7***	0.251**	0.254**	0.313*	0.324*	-0.00737	-0.00578	-0.00304	-0.00472
	(28.57)	(28.65)	(0.0953)	(0.0956)	(0.132)	(0.133)	(0.0472)	(0.0473)	(0.0134)	(0.0134)
20%	91.05*	91.01*	0.188	0.188	0.242	0.242	0.00738	0.00652	0.000227	0.000249
	(37.71)	(37.74)	(0.124)	(0.125)	(0.174)	(0.174)	(0.0561)	(0.0559)	(0.0151)	(0.0152)
Propensity Score		✓		✓		✓		✓		✓
N, 5%	1631	1631	1631	1631	1631	1631	1570	1570	1631	1631
N, 10%	1449	1449	1449	1449	1449	1449	1395	1395	1449	1449
N, 20%	1088	1088	1088	1088	1088	1088	1049	1049	1088	1088

Standard errors in parentheses.

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

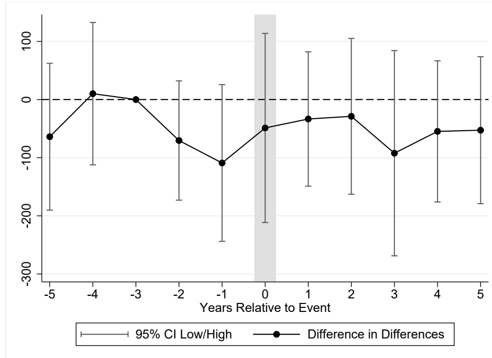
Panel B: Skill Composition, Productivity, and The Labor Share.

	(1)		(2)		(3)		(4)		(5)	
	Productivity		Labor Share		Educ. Years		College Share		Production Worker Share	
5%	-0.0311	-0.0203	0.00105	0.000261	-0.0636	-0.0499	0.00144	0.00226	-0.0316	-0.0309
	(0.0489)	(0.0494)	(0.00677)	(0.00686)	(0.0900)	(0.0911)	(0.0136)	(0.0138)	(0.0227)	(0.0229)
10%	-0.0314	-0.0294	0.000653	0.000813	-0.0273	-0.0251	0.00519	0.00449	-0.0496*	-0.0489
	(0.0553)	(0.0554)	(0.00759)	(0.00765)	(0.102)	(0.103)	(0.0154)	(0.0154)	(0.0252)	(0.0253)
20%	-0.0193	-0.0193	0.00113	0.00106	-0.0281	-0.0286	0.00570	0.00562	-0.0128	-0.0125
	(0.0681)	(0.0682)	(0.00924)	(0.00927)	(0.128)	(0.128)	(0.0180)	(0.0181)	(0.0296)	(0.0296)
Propensity Score		✓		✓		✓		✓		✓
N, 5%	1631	1631	1631	1631	1519	1519	1519	1519	1533	1533
N, 10%	1449	1449	1449	1449	1352	1352	1352	1352	1366	1366
N, 20%	1088	1088	1088	1088	1018	1018	1018	1018	1030	1030

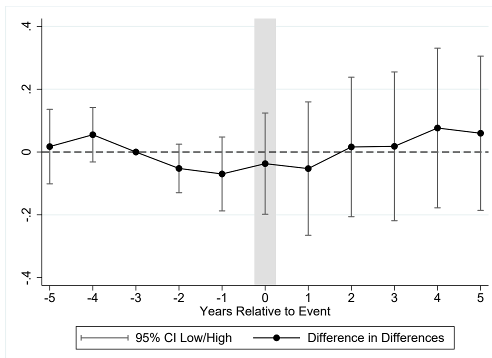
Standard errors in parentheses.

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

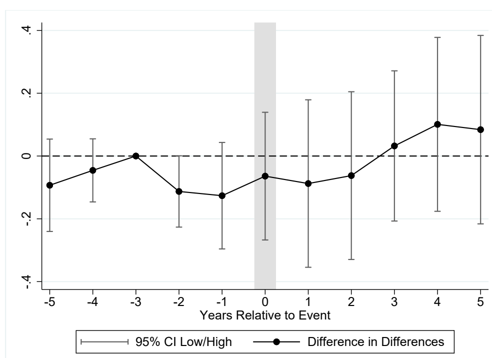
Notes: The estimated effects for the main sample with top and bottom 5%, 10%, and 20% of propensity score values dropped. The results are robust to excluding firms with small and large values of the propensity score. The sample is a subset of the main analysis sample (subsidies design).



(a) Machinery Investment.



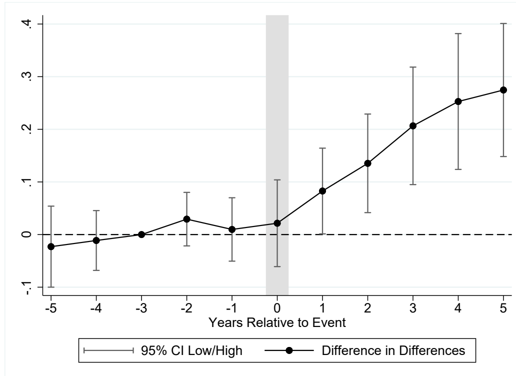
(b) Employment.



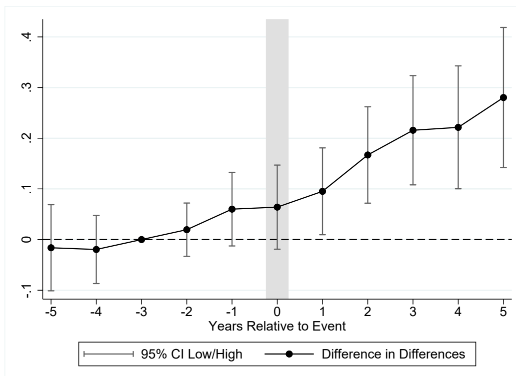
(c) Revenue.

Figure 3: Placebo Test: The Effects of Insignificant Subsidies.

Notes: Event-study estimates for the effects of insignificant (to the firm) subsidies. The sample includes firms that applied for a subsidy that was less than 10% of their capital stock three years before application. This "placebo test" investigates whether these small subsidies also create treatment effects on machinery investment, employment, and revenue. One concern would that the observed effects in the main sample are coming from the facts winning firms are positively selected: e.g., they are likely to perform better in the future and thus would grow even without the subsidy. If this were true, we would be likely to find positive effects on employment and revenue also in firms where the subsidy itself plays a small role. Reassuringly, we find zero effects on both for all post-application years.



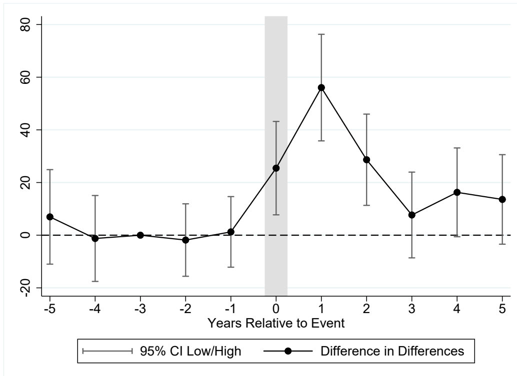
(a) Log Employment.



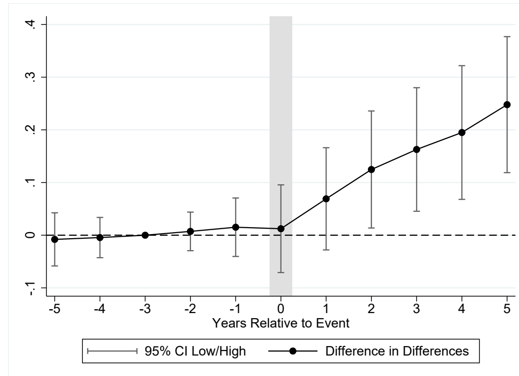
(b) Log Revenue.

Figure 4: Log Effects.

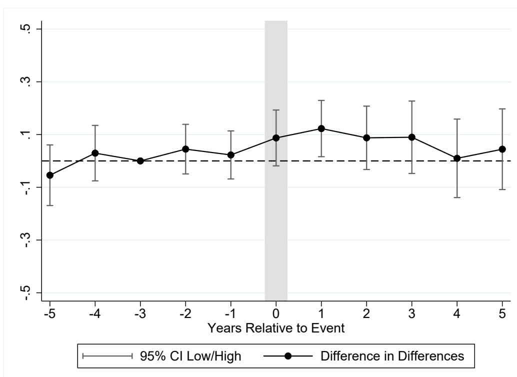
Notes: The sample is the main analysis sample (subsidies design). Event study graphs of log employment and revenue. The results are very similar to the baseline versions in relative units.



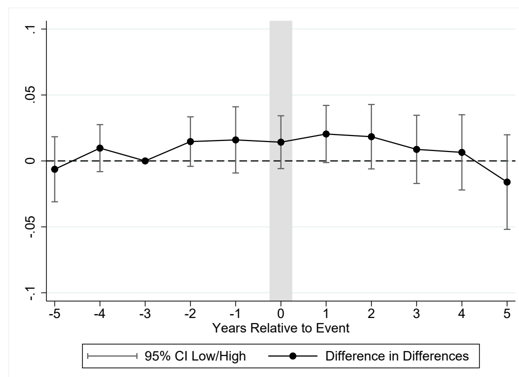
(a) Machinery Investment.



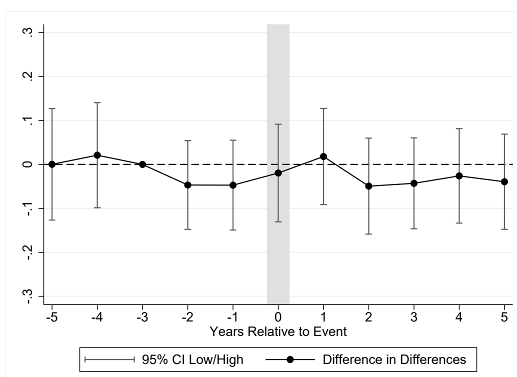
(b) Employment.



(c) Education Years.



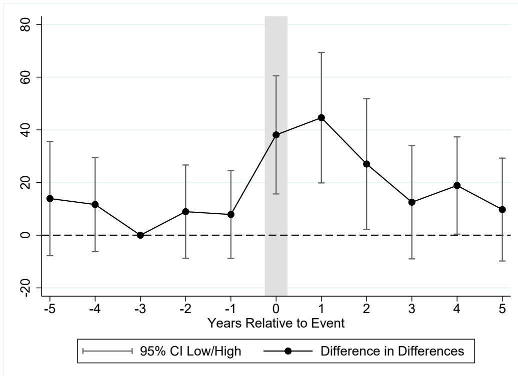
(d) College-Educated Workers' Share.



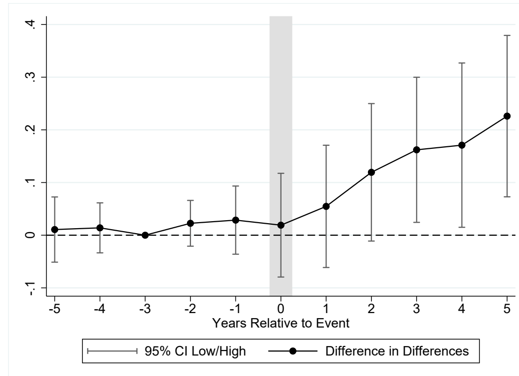
(e) Production Workers' Share.

Figure 5: Without Controls: Event-Study Estimates of Winners vs. Losers.

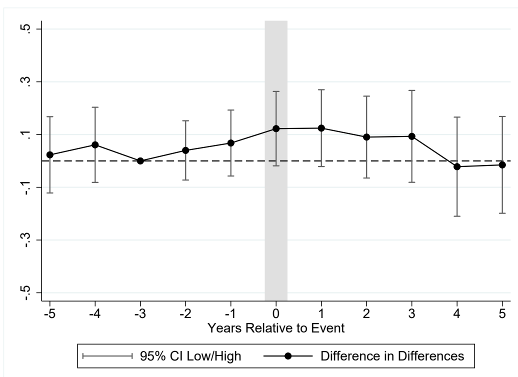
Notes: The sample is the main analysis sample (subsidies design). Event study estimates for machinery investment, employment (% relative to $\tau = -3$), average years of education, the employment share of college-educated workers, and the employment share of production workers. No additional controls.



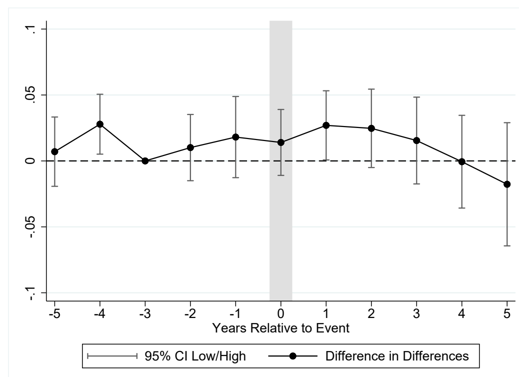
(a) Machinery Investment.



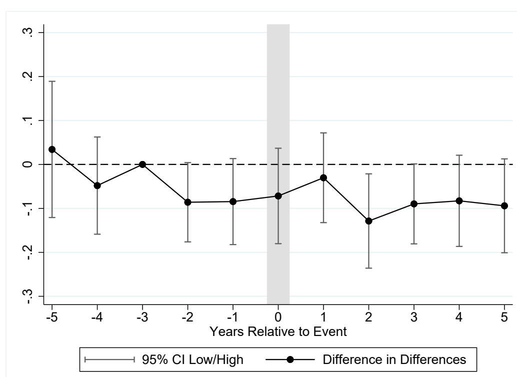
(b) Employment.



(c) Education Years.



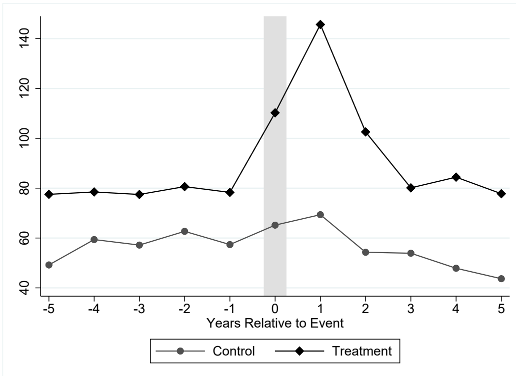
(d) College-Educated Workers' Share.



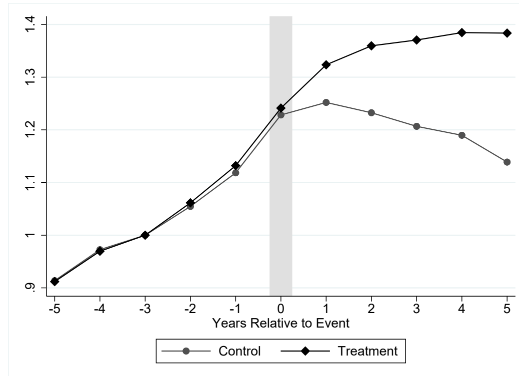
(e) Production Workers' Share.

Figure 6: With Controls: Event-Study Estimates of Winners vs. Losers.

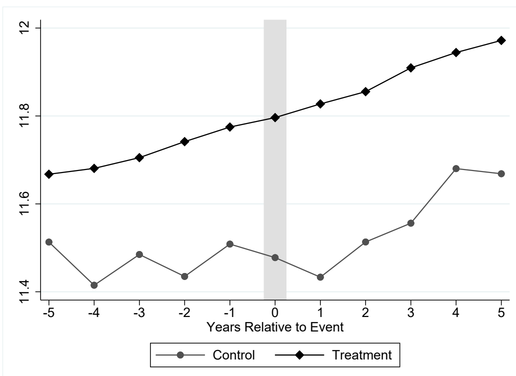
Notes: The sample is the main analysis sample (subsidies design). Event study estimates for machinery investment, employment (% relative to $\tau = -3$), average years of education, the employment share of college-educated workers, and the employment share of production workers. The specification controls for the firm's employment at $\tau = -3$ interacted with the event-time indicators, 2-digit industry interacted with the calendar-time indicators, and for the text-based propensity score interacted with event-time indicators.



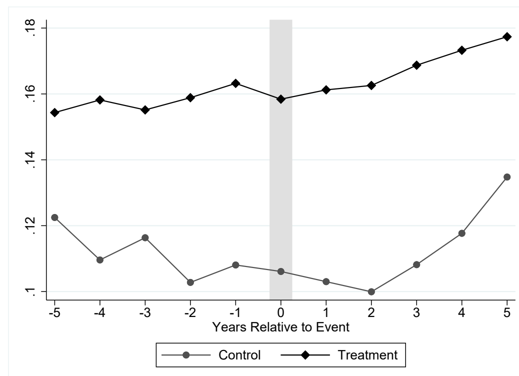
(a) Machinery Investment.



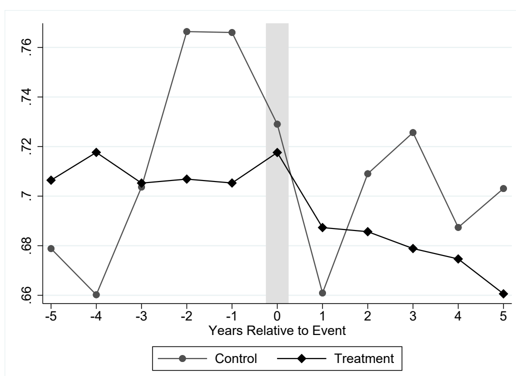
(b) Employment.



(c) Education Years.



(d) College-Educated Workers' Share.



(e) Production Workers' Share

Figure 7: Raw Means: Winners vs. Losers

Notes: The sample is the main analysis sample (subsidies design). Mean graphs of machinery investment, employment (relative to $t = -3$ level), years in education, the employment share of college-educated workers, and employment share of production workers. Production workers' share is calculated only for firms with more than two full-time employees in a given year.

Table 5: The Subsidy Program's Maximum Allowed Rates by Area.

Panel A: Years 2000-2006.

Region	Small firm	Medium-sized firm	Large firm
I	40	40	30
II	34	34	25
III	25	25	20
IV	15	0	0

Panel B: Years 2007-2003.

Region	Small firms	Medium-sized firms	Large firms
I	35	25	15
II	25	15	10
III	15	7.5	0
IV	0	0	0

Panel C: Years 2014-2020.

Region	Small firms	Medium-sized firms	Large firms
I	35	25	15
II	30	20	10
III	20	10	0
IV	0	0	0

Notes: The numbers refer to the maximum subsidy rate (%) by area and year. The maximum subsidy rate means the recommended maximum share of the project that the ELY center can subsidize. Source: Finnish Law, sections 1200/200, 1/2007, 675/2007. Accessible at finlex.fi.

Table 6: Firm Size Definitions.

Size	Workers (M EUR)		Turnover (M EUR)		Balance sheet total (M EUR)
Micro-firm	< 10	and either	≤ 2	or	≤ 2
Small firm (-2007)	< 50	and either	≤ 7	or	≤ 5
Small firm (2007-)	< 50	and either	≤ 10	or	≤ 10
Medium-sized firm	< 250	and either	≤ 50	or	≤ 43
Large firm	≥ 250	or both	≥ 50	and	≥ 43

Notes: The firm size definitions by the EU, used in the subsidy program rules.

Table 7: Investment and Subsidy Statistics.

Sample Firm Subsidies Share of Manufacturing Investment (All Years)	0.5%
Sample Firm Investment Share of Manufacturing Investment (All Years)	6.9%
Sample Firm Subsidies Share of Manufacturing Investment (Panel Years)	0.4%
Sample Firm Investment Share of Manufacturing Investment (Panel Years)	3.2%
Sample Firm Subsidies Share of Manufacturing Investment (t = 0-2)	0.3%
Sample Firm Investment Share of Manufacturing Investment (t = 0-2)	1.6%
Sample Investment in Total	2,872 M EUR
Manufacturing Investment in Total	93,171 M EUR
Sample Subsidies in Total	320 M EUR
Program Technology Subsidies in Total	758 M EUR
Program Subsidies in Total	2,015 M EUR

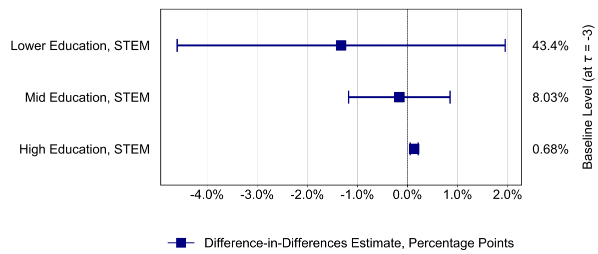
Notes: The sample is the main analysis sample (subsidies design). Sample firms are measured at $\tau = -3$, all manufacturing firms cover all possible firm-year combinations that satisfy similar restrictions as the sample firms. The first two numbers represent shares of sample firms appearing in any year, the next two over panel years only ($\tau = -5$ to $\tau = 5$) and the next three over the application year and the two following years ($\tau = 0$ to $\tau = 2$).

Table 8: Application Count Distribution.

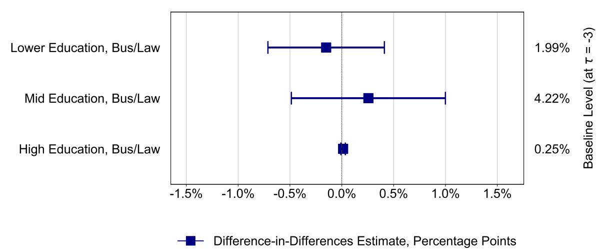
Number of Applications	Treatment Firms	Control Firms
1	505	122
2	386	21
3	289	3
4	227	0
5	161	0
6	123	0
7	84	0
8	52	0
9	34	0
10	9	0
11	6	0
12	6	0
13	3	0
Total	1885	146

Notes: Sample is main analysis sample (subsidies design). The table shows number of treatment and control firms in our sample with a given number of applications over the years 1999 to 2017. These include applications from years outside the eleven-year horizon around the chosen application event year. Median number of applications are 3 (treatment) and 1 (control), and the mean 3.3 (treatment) and 1.2 (control). The table implies that 1380 treatment firms have applied in some other year as well. For 1243 of them this year is in the eleven-year analysis panel horizon. The same numbers for control group firms are 24 and 15.

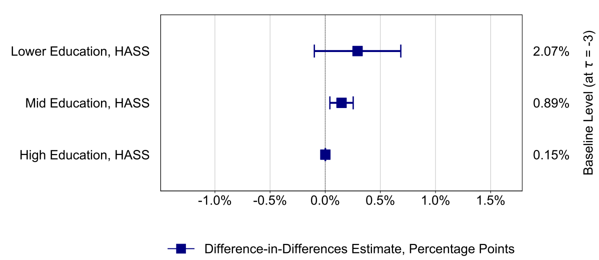
2 The Winners-Losers Design: Work and Skills



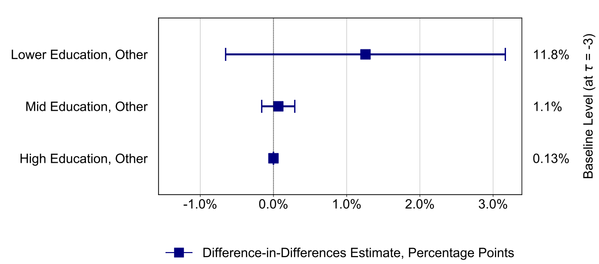
(a) STEM.



(b) Business and Law.



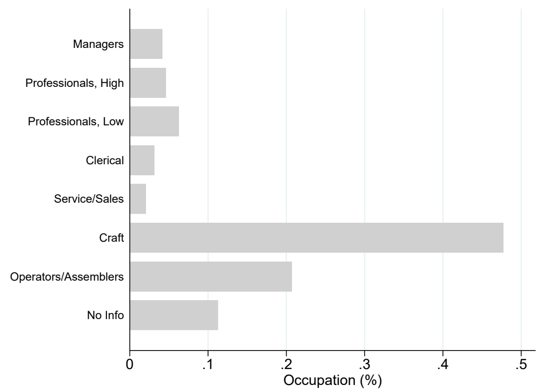
(c) HASS.



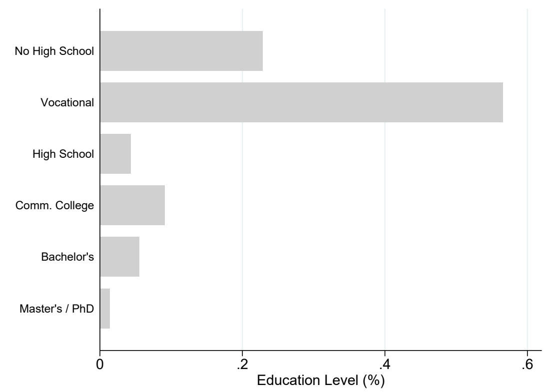
(d) Other.

Figure 8: Skill Effects: Education by Level and Type.

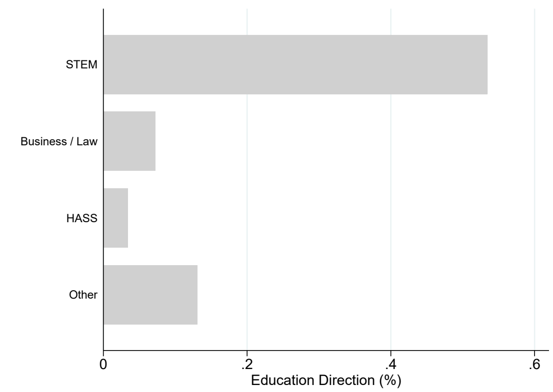
Notes: The sample is the main analysis sample (subsidies design). The types of education are grouped into science, technology, engineering, mathematics (STEM); business and law; humanities, arts, social sciences (HASS); and others. The levels of education are grouped into lower (high-school or equivalent), mid (BA or equivalent), and high (MA or PhD). We find no economically significant skill composition effects in any of the subgroups of workers. The winning firms increase the share of STEM-educated workers with a Master's or PhD by about 0.15 percentage points. While the effect is very small in the absolute sense, it is significant and translates to around a 20% increase in the group's employment share. There is also a similar effect, about 0.17 percentage points, in the share of HASS-educated workers with a mid-level degree.



(a) Occupations.



(b) Education Levels.



(c) Education Types.

Figure 9: Sample Worker's Occupations and Education.

Notes: The figures show the distribution of sample workers' 1-digit occupations, and education levels and types. The sample is the main analysis sample (subsidies design). The shares are unweighted means of the sample firms at $\tau = -3$. We study production work: a vast majority of the workers in the sample firms are craftworkers, operators, and assemblers. The mean share of production workers in the sample firms is approximately 70% of all workers. Notably, the share of clerks and other operation support workers and workers in sales is low. Most workers in the sample hold a vocational school degree or only a primary school degree. The share of workers with a bachelor's degree or higher is low, accounting for less than 20%. A majority, over 50%, of the degrees the workers in the sample firms hold are in STEM fields. Note that the shares in each subfigure do not add up to hundred percent because not all workers have data on occupation or education.

Table 9: Wage Effects by Occupation and Education.

	Occupation			Education			
	Prod. Workers	Non-Prod. Low	Non-Prod. High	No Education	Low Education	Mid Education	High Education
Treatment	-0.0342	-0.0746	-0.00812	-0.00776	-0.00774	-0.0428	0.259*
	(0.0237)	(0.0812)	(0.0491)	(0.0470)	(0.0263)	(0.0677)	(0.130)
Baseline	27423.7	25030.4	39791.4	23829.5	24868.1	32054.7	47541.5
N	1833	883	1233	1455	1797	1217	236

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

Notes: The estimated effects on average wages for different occupation and education groups. The group definitions are given in the main text. The sample is the main analysis sample (subsidies design). The second to last row shows the average levels of wages three years prior to the application for sample firms. The effects are zero for all subgroups of workers other than highly-educated workers (those with MA or PhD degrees). As only 236 firms employ at least one highly-educated worker, the 25.9% positive effect is not necessarily representative of the whole sample. Nonetheless, it could hint toward skill-bias in a subset of the sample firms or rent sharing—part of the increased profits being directed to the owners and executives of the firm, who often are highly educated. In many of the smaller firms, the owners are also employees of the firm.

Table 10: Wage Effects: Different Wage Outcomes.

Panel A: Level (EUR K).

	(1) Wages (SF; EUR K)		(2) Wages (EUR K)		(3) Wages (Excl. Highest; EUR K)		(4) Highest Wage (EUR K)	
Treatment	0.110	0.340	-0.358	0.217	-0.117	0.386	3.015^{**}	4.250^{***}
	(0.495)	(0.590)	(0.451)	(0.527)	(0.461)	(0.555)	(0.931)	(1.091)
Propensity Score		✓		✓		✓		✓
Baseline	21.95	22.55	25.36	25.61	23.59	23.84	44.92	45.73
N	2031	1812	1884	1676	1766	1577	1884	1676

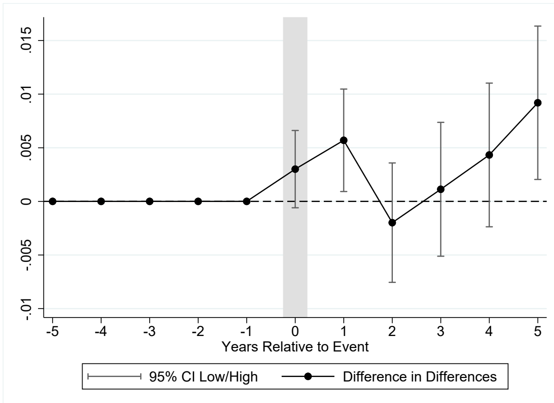
Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B: Relative (%).

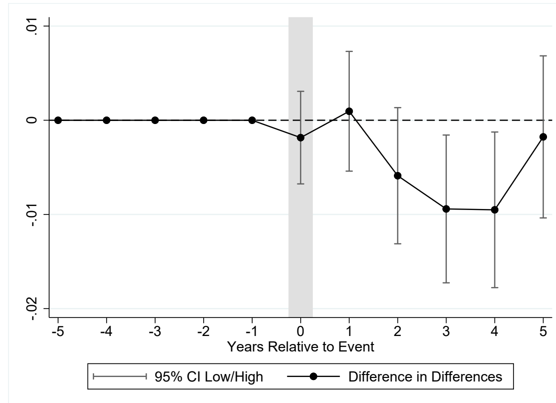
	(1) Wages (SF; %)		(2) Wages (%)		(3) Wages (Excl. Highest; %)		(4) Highest Wage (%)	
Treatment	-0.0481	-0.0285	-0.0293	-0.0000285	-0.0238	0.00106	0.0578^{*}	0.0927^{**}
	(0.0355)	(0.0407)	(0.0239)	(0.0278)	(0.0280)	(0.0341)	(0.0288)	(0.0332)
Propensity Score		✓		✓		✓		✓
Baseline	21.95	22.55	25.36	25.61	23.59	23.84	44.92	45.73
N	1952	1738	1884	1676	1766	1577	1884	1676

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

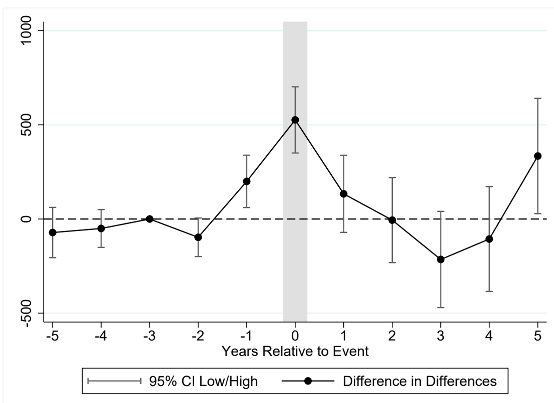
Notes: The estimated effects on wage outcomes, both in levels (Panel A) and relative % compared to $\tau = -3$ (Panel B). The baseline means are measured at $\tau = -3$. Treatment is the win-lose indicator. The sample is the main analysis sample (subsidies design). Column 1 wage measure is computed from the firm-level records of Statistics Finland (SF), and the other wage measures are from the worker-level records. The discrepancy between the two wage measures in Columns 1 and 2 are due to the first being the average wage per full-time employee, and the latter per employee headcount. The wage effect is zero in general, but top earner wages appear to grow by about 3 to 4.3 K EUR (or 5.8 to 9.3 percent). Similar to the positive wage effects of highly-educated workers (see Table 9), one potential reason is that the monetary benefits of the subsidy are directed partly to the wages of the owners and top executives of the firm.



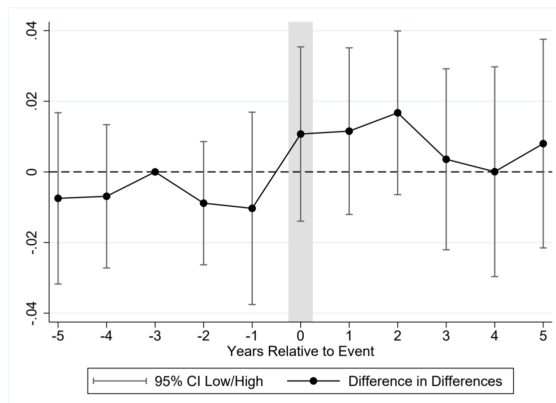
(a) Employed.



(b) Employed at the Baseline Firm.



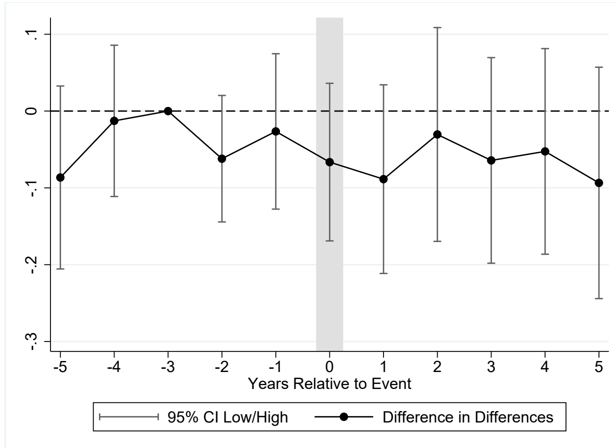
(c) Income.



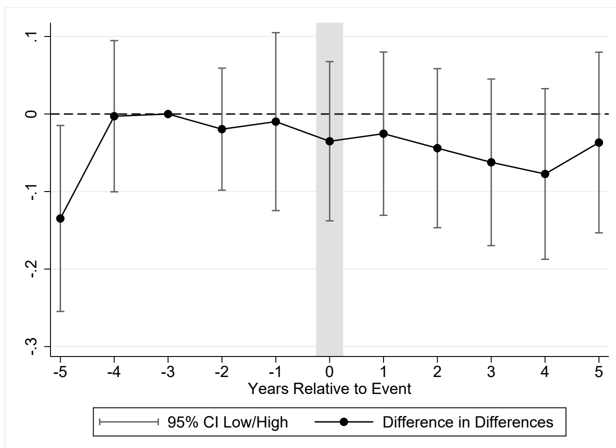
(d) Income Relative to Baseline.

Figure 10: The Effects on Baseline Workers: Event Studies.

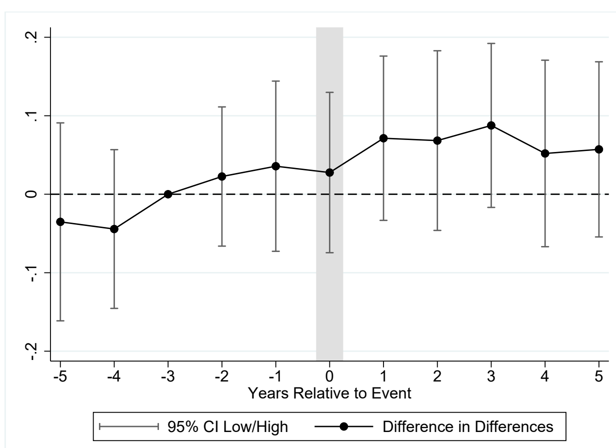
Notes: The sample is the baseline workers (employed at the firm from $\tau = -5$ to $\tau = -1$) in the main analysis sample (subsidies design). The first two and the last outcomes are in percentage points, the third in euros. The baseline workers in treatment group firms are slightly more likely to be employed in general, but less likely to be employed in the baseline firm after the event. The same workers also receive extra income of about 1,000 euros in total in the three years around the application. This corresponds to a salary of about two weeks. One potential reason for this is that the employees could work more hours during the new technology adoption.



(a) Visuospatial.



(b) Mathematics.



(c) Verbal.

Figure 11: Skill Effects: Cognitive Performance Event Studies.

Notes: Event study estimates for the average cognitive performance in the firm in standard deviations. The sample is the main analysis sample (subsidies design).

3 The Winners-Losers Design: Firm Performance

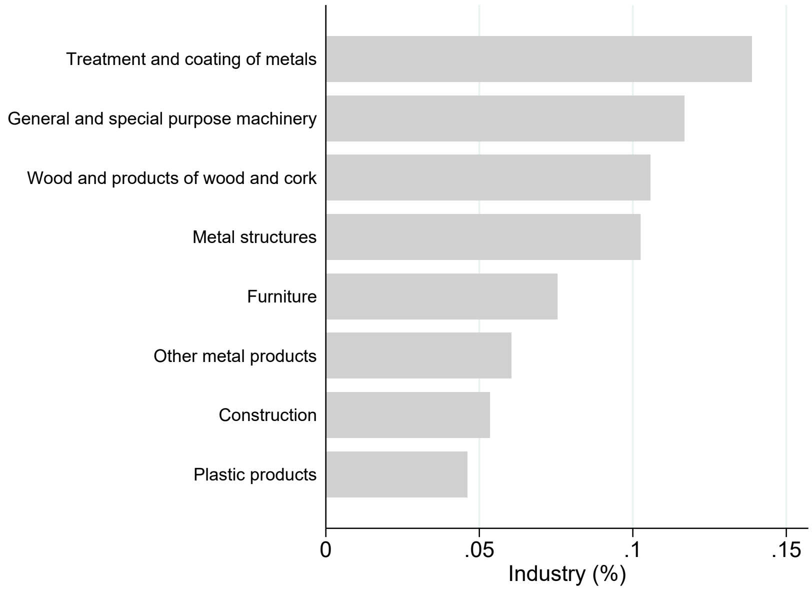
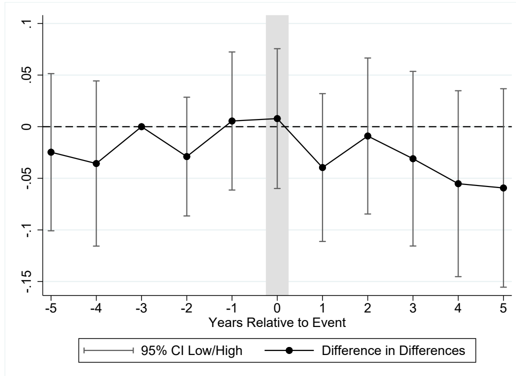
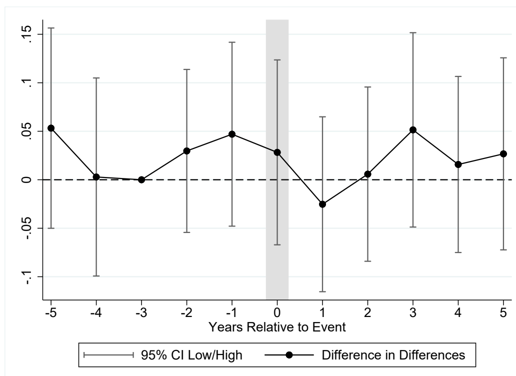


Figure 12: Sample Firm's Industries.

Notes: The sample firms' top eight industries. The sample is the main analysis sample (subsidies design). The shares are unweighted means of the sample firms at $\tau = -3$. Most firms in the sample operate in metal-related industries, machinery, and construction. Note that the shares do not add up to hundred percent because the industries figure shows only the top eight industries.



(a) Olley-Pakes.



(b) Levinsohn-Petrin.

Figure 13: Total Factor Productivity: Alternative Versions.

Notes: The sample is the main analysis sample (subsidies design). Event study graphs of log total factor productivity, estimated as in Olley and Pakes (1992) (a) and Levinsohn and Petrin (2003) (b). The results are in line with the Cobb-Douglas version, showing no effect.

Table 11: The Effects on Capital per Worker.

	(1) Capital per Worker (Win/Lose)	(2) Capital per Worker (Continuous)
Treatment	-84.81	0.00216
	(86.83)	(0.0883)
Baseline	23.85	23845.9
N	1550	1550

Standard errors in parentheses.

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

Notes: The estimates on capital per worker. Treatment is win/lose status in Column 1 and the amount of subsidies the firm was granted in Column 2. The sample is the main analysis sample (subsidies design). We find no effects.

Table 12: The Estimated Returns to Capital.

2SLS, Capital Stock Instrumented with Subsidies.

	(1) Gross Profits	(2) Net Profits	(3) Financial Costs
Capital Stock	0.637*	0.256	0.380***
	(0.297)	(0.285)	(0.0539)
Baseline	274006.2	-16074.0	290080.1
N	1560	1560	1560

Standard errors in parentheses.

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

Notes: The sample is the main analysis sample (subsidies design). 2SLS estimated effects on profits and financial costs. The instrument, dependent value, and outcomes are in EUR. Each column specifies the outcome. Gross and net profits refer to profit before and after financial costs are deducted. The capital stock in euros is instrumented with the amount of subsidies in euros. In principle, the coefficients are interpreted as the response in profits or financial costs.

4 The Winners-Losers Design: Mechanism

Table 13: The Effects of Specific Uses of Technologies on Specific Occupations.

	(1) Worker Share	(2) Wages	(3) Educ. Years	(4) Labor Share
Machining- Machinists	0.0454*** (0.0106)	0.0753 (0.0816)	-0.00340 (0.0179)	0.0360* (0.0158)
Baseline	0.0227	25751.0	11.78	0.107
N	554	51	51	51
Welding- Welders	0.0135 (0.00995)	0.0598 (0.0938)	0.0295 (0.0214)	0.00971 (0.00839)
Baseline	0.0683	25831.3	11.48	0.0594
N	300	88	88	88
Painting- Painters	0.00518 (0.00358)	0.0114 (0.0750)	0.0258 (0.0279)	0.00825 (0.00590)
Baseline	0.0250	21076.8	10.58	0.0411
N	307	65	65	65
Logistics- Logistics (Non-Office)	-0.000775 (0.000488)	-0.0936 (0.144)	0.0413 (0.0524)	-0.00759 (0.00699)
Baseline	0.0120	25330.9	10.76	0.0191
N	799	58	58	58
Logistics- Logistics (Office)	0.0000555 (0.000246)	0.298 (0.301)	-0.0884 (0.112)	-0.000707 (0.00189)
Baseline	0.00399	29623.5	11.70	0.00696
N	799	40	40	40

Standard errors in parentheses.

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

Notes: The effects of specific technologies on specific workers. The technologies refer to the description of the technology in the subsidy application text. The idea is to see whether a specific technology affects a specific set of workers associated with the technology. The occupations are from the worker's occupational records. The technology-to-worker pairs are: (1) machining-machinists, (2) welding-welders, (3) painting-painters, and (4-5) logistics words (e.g. "driving," "hoisting") to logistics occupations (non-office and office). N refers to the sample size (number of firms) where the given outcome is defined. Note that employment shares are defined for all firms with the given technology, but the other three outcomes require at least one worker with the given occupation, hence the smaller sample size. We find positive effects on the employment share and the wage-bill (labor) share of machinists when the firm has applied for a subsidy specifying the intended use to be an investment in technologies associated with machining. These effects are sizable, considering the relatively small baseline share of workers with the occupational title "machinist" employed. The sample is winners matched to non-applicants (the matching procedure described in the paper).

Table 14: The Effects of Specific Types and Uses of Technologies Measured from the Text Data.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Sh.	(7) Educ. Years	(8) College Sh.	(9) Prod. Sh.	(10) Obs.
Types of Technology										
CNC	158.0***	0.168***	0.180***	0.0367	-0.0100	0.00299	-0.0331	0.00304	-0.0211	628
	(11.76)	(0.0398)	(0.0492)	(0.0212)	(0.0266)	(0.00498)	(0.0513)	(0.00771)	(0.0144)	
Robot	294.4***	0.233*	0.416**	-0.0380	0.0124	-0.0133	0.0311	0.00256	0.0198	232
	(53.60)	(0.0921)	(0.136)	(0.0291)	(0.0593)	(0.00787)	(0.0581)	(0.00961)	(0.0192)	
Laser	164.1***	0.322**	0.313*	-0.0272	-0.0831	0.000777	0.0578	0.0180	0.0139	224
	(38.69)	(0.0979)	(0.132)	(0.0415)	(0.0501)	(0.0101)	(0.0919)	(0.0157)	(0.0286)	
Uses of Technology										
Machining	227.7***	0.246***	0.276***	-0.00449	-0.0187	-0.00126	0.0136	0.00862	-0.0121	584
	(22.60)	(0.0471)	(0.0663)	(0.0227)	(0.0302)	(0.00514)	(0.0505)	(0.00899)	(0.0137)	
Welding	109.1***	0.352***	0.385***	-0.00611	-0.0146	-0.0100	0.0185	-0.00120	0.00966	312
	(18.61)	(0.0835)	(0.0821)	(0.0352)	(0.0431)	(0.00760)	(0.0700)	(0.0122)	(0.0218)	
Painting	161.9***	0.267***	0.318***	-0.0223	0.00608	-0.00591	-0.0112	-0.00147	-0.00148	312
	(28.80)	(0.0634)	(0.0836)	(0.0302)	(0.0396)	(0.00636)	(0.0627)	(0.00946)	(0.0193)	
Logistics	162.2***	0.304***	0.404***	0.00781	0.0348	-0.00659	0.0207	0.0148*	-0.0106	822
	(16.02)	(0.0404)	(0.0544)	(0.0171)	(0.0255)	(0.00388)	(0.0370)	(0.00611)	(0.0108)	
Automation	177.2***	0.178***	0.217***	0.00216	0.0249	-0.00237	0.0546	0.00942	0.000592	678
	(22.54)	(0.0350)	(0.0446)	(0.0189)	(0.0259)	(0.00422)	(0.0391)	(0.00650)	(0.0113)	

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

Notes: The effects of specific types and uses of technology on selected outcomes for the relevant subsets of treatment firms matched to non-applicant control firms. The first three rows show the effects for treatment firms that intend to buy the given technology, and the latter four are the firms that specify the listed uses for the technologies. The "Obs." column refers to the sample size: the number of firms with subsidy application texts containing keywords associated with the given technology or its use. Machine investment is in EUR K. The broad interpretation of the results is that the firm-level effects do not vary significantly across the specified technologies or their uses. The sample is the winners matched to non-applicants (the matching procedure described in the paper).

Table 15: Hardware vs. Software Events.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Productivity		(5) Labor Share		(6) College Share		(7) Obs.
Hardware (Register)	81.52***	80.72***	0.216***	0.212**	0.299***	0.308**	-0.000775	-0.00660	-0.00138	-0.0000368	0.00390	0.00548	1,726
	(15.60)	(20.05)	(0.0625)	(0.0754)	(0.0791)	(0.0970)	(0.0354)	(0.0433)	(0.00502)	(0.00607)	(0.00946)	(0.0118)	
Software (Register)	281.8***	260.1***	0.296***	0.330**	0.361***	0.388**	-0.0584	-0.0553	-0.00298	-0.00132	0.0189	0.0109	451
	(30.10)	(38.55)	(0.0826)	(0.105)	(0.102)	(0.134)	(0.0431)	(0.0534)	(0.00585)	(0.00741)	(0.0115)	(0.0148)	
Hardware (Text)	105.7***	99.68***	0.234***	0.238**	0.312***	0.337***	-0.0137	-0.0101	-0.00151	-0.000185	0.00527	0.00599	1,971
	(18.13)	(22.49)	(0.0634)	(0.0761)	(0.0804)	(0.0979)	(0.0360)	(0.0435)	(0.00506)	(0.00610)	(0.00959)	(0.0116)	
Software (Text)	-19.96	-9.464	0.329	0.450	0.573	0.873	-0.113	0.00135	0.00929	-0.0168	-0.0286	-0.0212	107
	(178.3)	(207.5)	(0.253)	(0.371)	(0.392)	(0.584)	(0.237)	(0.277)	(0.0264)	(0.0308)	(0.0457)	(0.0580)	
Propensity Score		✓		✓		✓		✓		✓		✓	

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

Notes: The effects of hardware and software events. The sample is a subset of the main analysis sample (subsidies design). The first two rows include the treatment firms that have software purchases in the three-year period after the application (software row) and those that did not (hardware row). These groups are mutually exclusive. The latter two rows include firms stating the intention to purchase hardware or software technologies in the application texts. They both include all losing (control group) firms. The text-based categories are not mutually exclusive, so that an application can include both intended hardware and software investments and thus appear in both categories. The results for text-based software events are highly imprecise, largely due to the small sample size (n = 107). The register-based classification implies that subsidies associated with software purchases induce larger investment and lead to larger employment and revenue effects.

Table 16: The Effects by Industry Type: Automation, Skill-Level, and Tradability.

Panel A: High vs. Low Automation.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
High Automation	115.8***	0.189	0.212	-0.0369	-0.0900	0.00405	0.0675	0.000842	-0.00197
	(25.96)	(0.104)	(0.122)	(0.0481)	(0.0516)	(0.00702)	(0.0866)	(0.0149)	(0.0246)
Low Automation	143.0***	0.277*	0.295	-0.0000105	-0.0568	0.00835	0.0687	0.0211	-0.00410
	(31.95)	(0.109)	(0.156)	(0.0695)	(0.0805)	(0.00907)	(0.121)	(0.0166)	(0.0451)
N, High Automation	1223	1223	1223	1179	1223	1223	1136	1136	1142
N, Low Automation	474	474	474	457	474	474	448	448	443

Panel B: High vs. Low Skill.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
High Skill	114.4***	0.255	0.445***	-0.121	-0.0881	-0.00237	0.225	0.0526*	0.0438
	(31.79)	(0.130)	(0.100)	(0.0901)	(0.0790)	(0.0103)	(0.127)	(0.0224)	(0.0472)
Low Skill	103.1***	0.225**	0.282**	-0.0263	0.0148	-0.00143	-0.0289	-0.00680	-0.00962
	(20.32)	(0.0699)	(0.0946)	(0.0380)	(0.0393)	(0.00571)	(0.0690)	(0.00985)	(0.0195)
N, High Skill	532	532	532	511	532	532	499	499	497
N, Low Skill	1499	1499	1499	1441	1499	1499	1385	1385	1394

Panel C: Tradable vs. Non-Tradable Industries.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
Tradable	130.0***	0.230**	0.298**	-0.0430	-0.0451	0.00132	0.0852	0.00939	0.0146
	(22.86)	(0.0837)	(0.101)	(0.0474)	(0.0436)	(0.00637)	(0.0747)	(0.0128)	(0.0239)
Non-Tradable	70.58**	0.234**	0.334**	-0.0537	0.0525	-0.00632	-0.0480	0.00113	-0.0186
	(26.59)	(0.0902)	(0.123)	(0.0533)	(0.0573)	(0.00791)	(0.103)	(0.0136)	(0.0280)
N, Tradable	1509	1509	1509	1450	1509	1509	1402	1402	1404
N, Non-Tradable	522	522	522	502	522	522	482	482	487

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

Notes: The sample is a subset of the main analysis sample (subsidies design). Estimated effects on selected outcomes for firms in high vs. low automation (Panel A), high vs. low skill industry (Panel B), and tradable vs. non-tradable output industry (Panel C). The division with respect to automation level is defined by using classifications in Acemoglu and Restrepo (2020) harmonized to the Finnish industries. An industry is classified into high skill if it is above the median industry in average years of education of its workers, and low skill if below. Tradability is defined by using classifications in Mian and Sufi (2014) harmonized to the Finnish industries. Machine investment is in EUR K.

Table 17: The Effects by Industry Type With Propensity Score Controls: Automation, Skill-Level, and Tradability.

Panel A: High vs. Low Automation.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
High Automation	101.1^{**}	0.114	0.213	-0.0217	-0.0337	0.000346	0.0656	0.00420	-0.0292
	(32.45)	(0.124)	(0.146)	(0.0509)	(0.0574)	(0.00827)	(0.110)	(0.0190)	(0.0291)
Low Automation	135.3^{**}	0.385^{**}	0.370^{*}	-0.00960	-0.136	0.0155	-0.0423	0.0146	-0.0253
	(43.81)	(0.129)	(0.186)	(0.0892)	(0.111)	(0.0115)	(0.148)	(0.0186)	(0.0561)
N, High Automation	1098	1098	1098	1055	1098	1098	1016	1016	1026
N, Low Automation	414	414	414	399	414	414	391	391	390

Panel B: High vs. Low Skill.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
High Skill	102.5^{*}	0.415^{*}	0.624^{***}	-0.0660	-0.129	0.00306	0.379	0.0802^{*}	0.0252
	(45.34)	(0.180)	(0.177)	(0.113)	(0.106)	(0.0136)	(0.198)	(0.0331)	(0.0657)
Low Skill	95.39^{***}	0.197^{*}	0.278^{*}	-0.0163	0.0175	-0.000739	-0.0796	-0.00951	-0.0277
	(24.74)	(0.0830)	(0.111)	(0.0434)	(0.0464)	(0.00671)	(0.0796)	(0.0116)	(0.0220)
N, High Skill	461	461	461	442	461	461	431	431	433
N, Low Skill	1351	1351	1351	1296	1351	1351	1245	1245	1259

Panel C: Tradable vs. Non-Tradable Industries.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
Tradable	121.4^{***}	0.190	0.283^{*}	-0.0409	-0.0476	-0.000244	0.0813	0.00877	-0.0220
	(29.74)	(0.107)	(0.132)	(0.0538)	(0.0559)	(0.00784)	(0.0987)	(0.0168)	(0.0285)
Non-Tradable	62.85	0.293^{**}	0.387^{**}	-0.00810	0.0505	0.000338	-0.102	0.00436	-0.0201
	(32.72)	(0.100)	(0.135)	(0.0653)	(0.0663)	(0.00942)	(0.117)	(0.0160)	(0.0323)
N, Tradable	1344	1344	1344	1289	1344	1344	1243	1243	1254
N, Non-Tradable	468	468	468	449	468	468	433	433	438

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

Notes: The sample is a subset of the main analysis sample (subsidies design). Estimated effects on selected outcomes for firms in high vs. low automation (Panel A), high vs. low skill industry (Panel B), and tradable vs. non-tradable output industry (Panel C). The division with respect to automation level is defined by using classifications in Acemoglu and Restrepo (2020) harmonized to the Finnish industries. An industry is classified into high skill if it is above the median industry in average years of education of its workers, and low skill if below. Tradability is defined by using classifications in Mian and Sufi (2014) harmonized to the Finnish industries. Machine investment is in EUR K. Propensity score is included as control.

Table 18: The Effects by Management Scores.

Panel A: Investment, Employment, Wages, and Firm Performance.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity
High Score	465.5***	0.476***	0.644***	-0.0316	0.0700
	(97.44)	(0.0953)	(0.128)	(0.0231)	(0.0454)
Low Score	298.6	0.518**	0.425*	0.0112	-0.00715
	(188.7)	(0.180)	(0.174)	(0.0363)	(0.0819)
N, High Score	184	184	184	184	184
N, Low Score	80	80	80	80	80

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

Panel B: Skill Composition and The Labor Share.

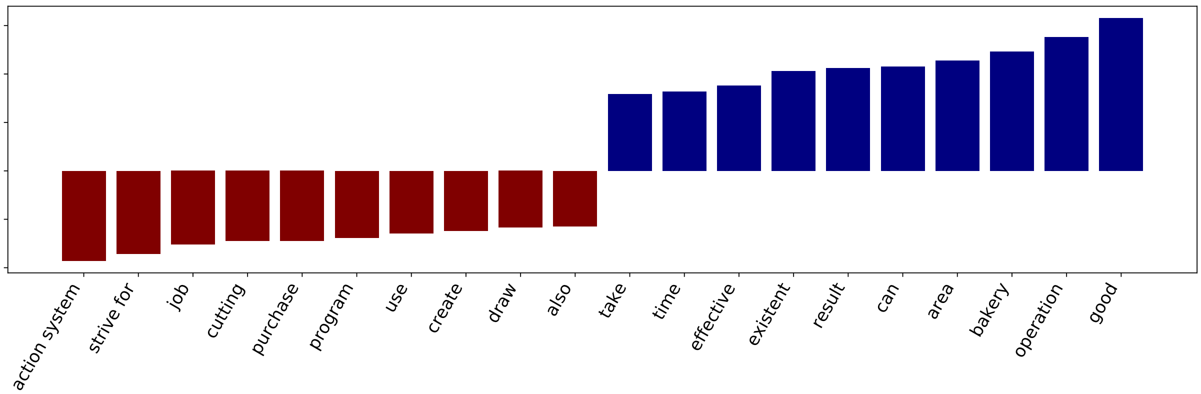
	(1) Labor Share	(2) Educ. Years	(3) College Share	(4) Production Worker Share
High Score	-0.0113	-0.0215	-0.00426	0.0140
	(0.00723)	(0.0478)	(0.00870)	(0.0157)
Low Score	0.000285	-0.132	-0.00919	-0.0117
	(0.0106)	(0.109)	(0.0168)	(0.0248)
N, High Score	184	184	184	184
N, Low Score	80	80	80	80

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

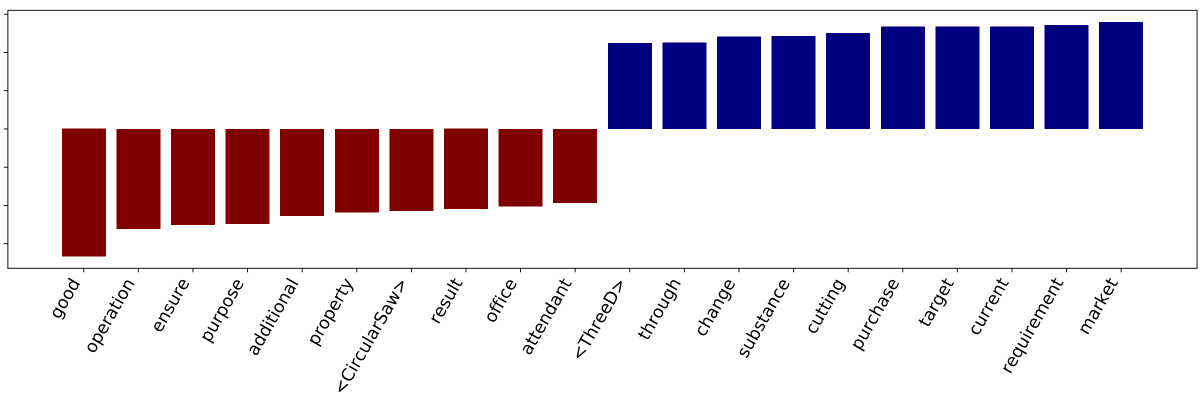
Notes: The sample is a subset of the main analysis sample (subsidies design). Estimated effects on selected outcomes for firms with high vs. low management score, measured using the FMOP as surveyed and defined in Ohlsbom and Maliranta (2021).

Figure 14: Predictive Features for Text Categories: Process and Product

Panel A: Process.



Panel B: Product.



Notes: The features (words) are plotted from top and bottom SVM coefficients predicting the two uses of technologies. The y-axis refers to the coefficient size, and it measures the relative importance of each feature. Positive (negative) values indicate that the word is typically (not) associated with applications in the category.

Table 19: Continuous Treatment Estimates by Text Categories.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Production Share
Product	1.323^{***}	0.194^{***}	4.585^{***}	-1.663	150.7	-0.000345^{*}	0.000338	0.000296	-0.0000846
	(0.0865)	(0.0239)	(0.613)	(9.767)	(124.2)	(0.000130)	(0.00113)	(0.000192)	(0.000323)
Process	1.243^{***}	0.194	1.115	26.97	-359.8	0.000615	-0.00567	-0.00138	0.00123
	(0.216)	(0.109)	(2.399)	(40.53)	(603.8)	(0.000534)	(0.00739)	(0.00144)	(0.00135)
N, Product	2046	2046	2046	2046	2046	2046	1905	1905	1921
N, Process	198	198	198	198	198	198	186	186	186

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

Notes: The sample is a subset of the main analysis sample (subsidies design). Product type changes refers to technology projects that aim to produce a new type of output. Process type change refers to technology projects that aim to produce the same type of output with the new technologies. Columns 1 and 3 are in EUR. Treatment is scaled to EUR 10,000 for rest of the columns. Columns 6, 8, and 9 (shares) are in percentage points. Column 7 (education years) is in years. Machine investment is the sum over $\tau \in [0, 2]$. Other outcomes are averages over $\tau \in [2, 5]$. N refers to matched observations (matching procedure is described in the paper).

Table 20: Export Products' and Regions' Skill Intensity.

	(1) Product Skill Intensity	(2) Region Skill Intensity
Treatment	-0.0267	-0.00139
	(0.0599)	(0.0316)
Baseline	12.64	12.87
N	401	401

Standard errors in parentheses.

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

Notes: The effects on export product and region skill intensity for the sample firms that export. The sample is a subset of the main analysis sample (subsidies design). To construct the outcomes, we first take the average worker education years for each export product and region by taking the average over all years from firms that export the given product and export to the given region. Then for each exporting firm in our sample, we calculate the skill intensity each year by taking the unweighted average of the skill intensities of the products the firm exports that year or the regions it exports to. Export regions and products are measured from the Finnish Customs' Foreign Trade Statistics. A concern about the lack of skill-bias effects in our sample is that it exists, but is subtle and hard to find empirically. One way to explore this possibility is to estimate whether, after adopting new technologies, the firms export products which require more skills or export to regions that do. If this is true, the firms are likely also to exhibit an increased need for skills, even if we do not detect these effects in the short term. This table explores these effects on export products' and regions' skill intensity. The coefficients on both outcomes are fairly precise zeros, implying that the hypothesis of undetected skill bias through this channel does not receive support.

Table 21: Exporter and Non-Exporter Firms' Skill Intensity.

	Sample; Non-Exporters	Sample; Exporters	Manufacturing; Non-Exporters	Manufacturing; Exporters
Educ. Years	11.66	12.03	11.54	12.30
Firm-Year Observations	1,390	641	218,945	41,275
Firm Observations	1,390	641	16,437	2,102

Notes: Descriptive statistics on the exporter and non-exporter firms' skill intensity. The sample is the main analysis sample (subsidies design) and Finnish manufacturing. The table reports mean worker education years for (1) sample firms that do not export, (2) sample firms that export, (3) all manufacturing firms that do not export, and (4) all manufacturing firms that export. Sample firms are measured at $\tau = -3$, all manufacturing firms cover all possible firm-year combinations that satisfy similar restrictions as the sample firms. Export status is measured using the definition by Statistics Finland. A firm is defined as an exporter in a given year if its total export value is over 12K EUR during the calendar year spread over at least two different months, or a single export event is over 120K EUR in value. Exporting firms in both groups employ more educated workers, confirming a common proposition that exporting firms are more skill intensive. Notably, this difference is smaller in the analysis sample than in manufacturing.

Table 22: Import and Input Outcomes.

	(1) Import Value (EUR K)	(2) Import Share	(3) Machine Import Value (EUR K)	(4) Machine Import Share	(5) Input Value (EUR K)	(6) Input Share
Treatment	20.60***	0.00287*	3.437***	0.000452	-115.6	-0.0521
	(5.989)	(0.00136)	(1.031)	(0.000249)	(663.6)	(0.0438)
Baseline	152.9	0.0203	27.80	0.00373	3457.9	0.292
N	2031	2031	2031	2031	321	321

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

Notes: The sample is the main analysis sample (subsidies design). Effects on total value and shares (total value share of revenue) for imports and inputs. Machinery imports include only imports we classified as machinery based on customs codes. The baseline means are measured at $\tau = -3$. The results show that the effects on both machinery imports and all imports (including machinery imports) are positive and significant: machinery imports increase by about 3.4K euros and all imports by about 20.6K euros. While these effects are small, it is important to note that only a small fraction of the sample firms import at all during the panel years. Thus it is less surprising that the average effect is smaller. Similarly, we detect small effects on import share of revenue: about 0.3 percentage points for all imports and zero on machinery import share. The estimated effects on input outcomes (including non-imports) are imprecise, but close to zero. This is partly due to a small sample size (n = 321), as we only observe input outcomes for a subset of firms that have answered the manufacturing survey issued by Statistics Finland.

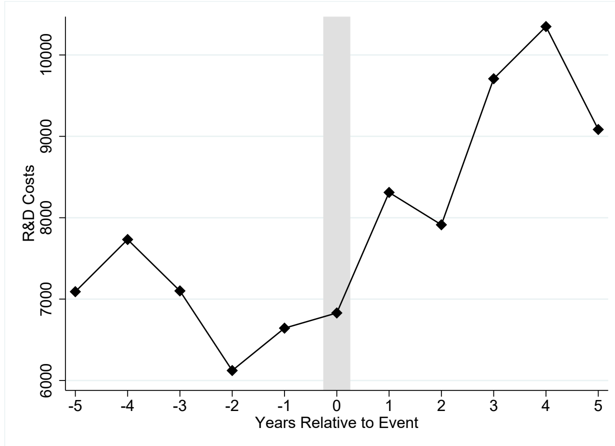
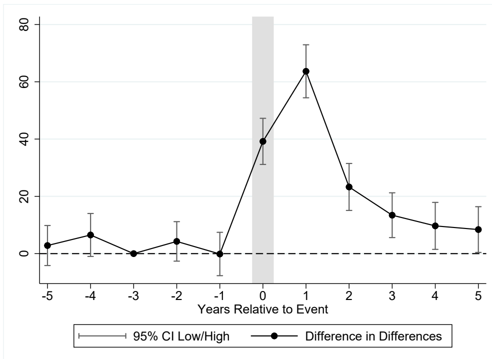


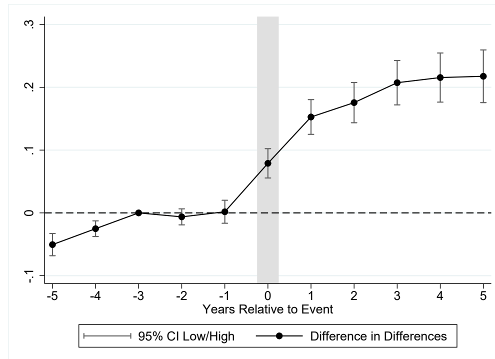
Figure 15: R&D Expenditure.

Notes: The raw means of R&D expenditure for the subsidy applicant firms, both treatment and control. The sample is the main analysis sample (subsidies design).

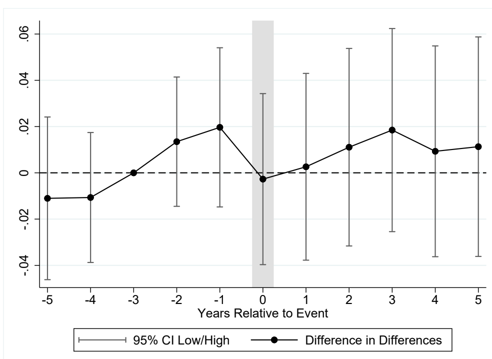
5 The Matched Control Group



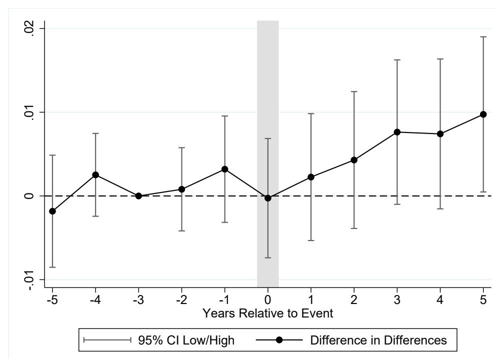
(a) Machinery Investment.



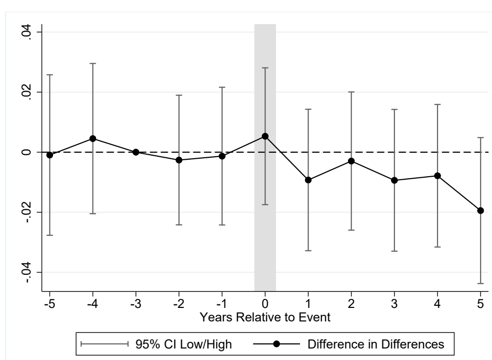
(b) Employment.



(c) Education Years.



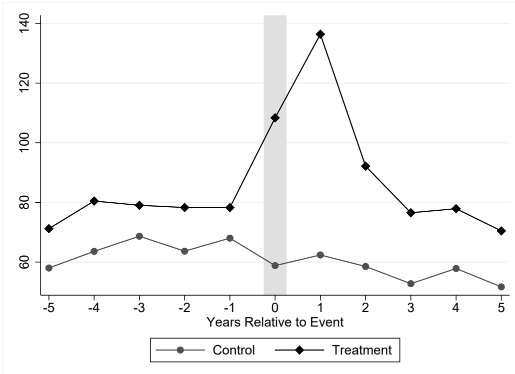
(d) College-Educated Workers' Share.



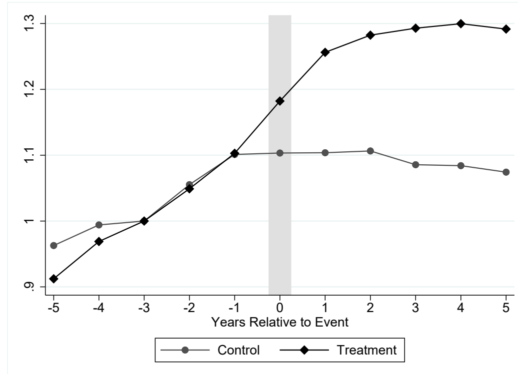
(e) Production Workers' Share.

Figure 16: The Match Control: Event-Study Estimates.

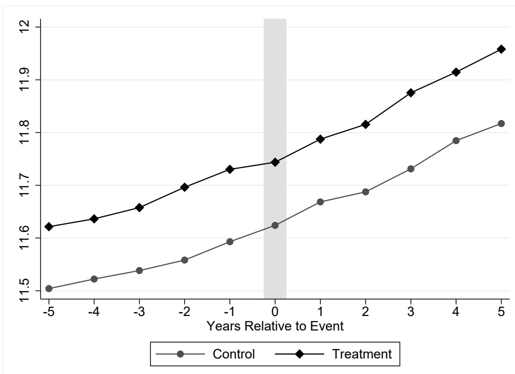
Notes: The sample is winners matched to non-applicants (matching procedure is described in detail in the paper). The figures show event study graphs of machinery investment, employment (relative to $\tau = -3$ level), years in education, the employment share of college-educated workers, and the employment share of production workers. The treatment group is the subsidy winners (the main treatment group), and the control group is constructed via matching. We use coarsened exact matching (CEM). We match by revenue, employment, wages at $\tau = -3$ plus revenue and employment changes in percentages from $\tau = -3$ to $\tau = -1$ and industries' main sectors (letter classes). The CEM percentiles are 10, 25, 50, 75, 90, and 99. The match is 1:1 with replacement. Event time $\tau = 0$ refers to the application year. Calendar year indicators are included as controls.



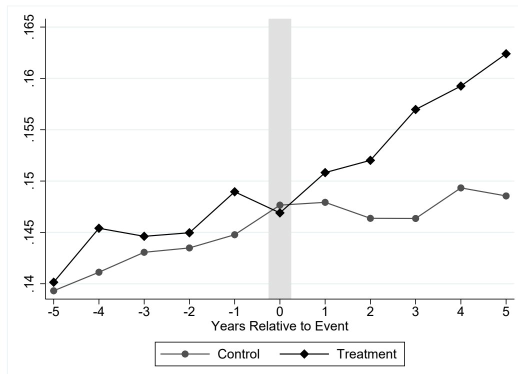
(a) Machinery Investment.



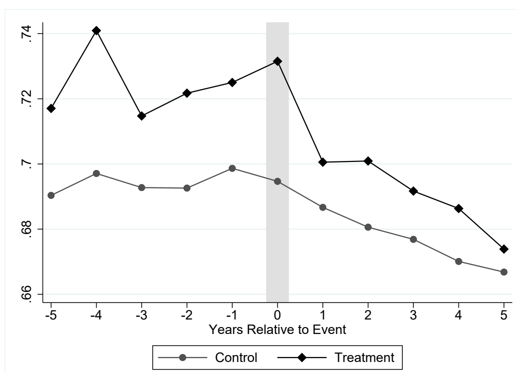
(b) Employment.



(c) Education Years.



(d) College-Educated Workers' Share.



(e) Production Workers' Share.

Figure 17: Raw Means: Winners vs. Matched Control.

Notes: The sample is winners matched to non-applicants (the matching procedure described in the paper). The figures show mean graphs of machinery investment, employment (relative to $t = -3$ level), years in education, the employment share of college-educated workers, and the employment share of production workers.

Table 23: The Effects on Export Outcomes for the Matched Sample.

	(1) Export Status	(2) Export Share	(3) Export Regions	(4) Products	(5) Products Introduced	(6) Products Discontinued
Treatment	0.0351***	0.00707***	0.206***	0.172***	0.0686***	0.0698***
	(0.00849)	(0.00175)	(0.0245)	(0.0247)	(0.0112)	(0.0109)
Baseline	0.261	0.0466	1.353	1.622	0.527	0.578
N	3200	3200	3200	3200	3200	3200

Standard errors in parentheses.

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

Notes: The estimated effects on export outcomes. The sample is the matched control sample to explore robustness of the export results on the particular sample.

Table 24: The Effects by Firm Size for Spikes Design.

Panel A: Large Firms.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Sh.	(7) Educ. Years	(8) College Sh.	(9) Prod. Work. Sh.
Treatment	7235.1**	0.325*	0.240**	0.00368	-0.00122	-0.000446	-0.0372	-0.00826	0.0284
	(2430.8)	(0.153)	(0.0893)	(0.0174)	(0.0343)	(0.00504)	(0.0412)	(0.00847)	(0.0146)
Obs.	368	368	368	368	368	368	368	368	345

Panel B: Medium-Sized Firms.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Sh.	(7) Educ. Years	(8) College Sh.	(9) Prod. Work. Sh.
Treatment	1015.6***	0.0681*	0.0981*	0.0400	0.0141	0.000103	0.0136	0.00387	0.00949
	(149.4)	(0.0319)	(0.0411)	(0.0340)	(0.0261)	(0.00393)	(0.0274)	(0.00466)	(0.00707)
Obs.	788	788	788	788	788	788	788	788	727

Panel C: Small Firms.

	(1) Machine Inv.	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Sh.	(7) Educ. Years	(8) College Sh.	(9) Prod. Work. Sh.
Treatment	391.3***	0.156*	0.160	-0.0256	0.00889	-0.00359	-0.00782	0.00970	-0.00517
	(46.69)	(0.0667)	(0.0895)	(0.0157)	(0.0297)	(0.00492)	(0.0415)	(0.00680)	(0.00852)
Obs.	887	887	887	887	887	887	887	887	830

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

Notes: The sample is the spikes design sample. Estimated effects on selected outcomes for different firm sizes. Large firms (FTE $>$ 75), Medium Firms (FTE $>=$ 25 & FTE $<=$ 75), Small Firms (FTE $<$ 25). Machine investment is in EUR K. The effects are qualitatively similar in firms of all sizes.

7 The Regression Discontinuity Design

Table 25: RD: The IV Estimates.

	(1) Total Investment	(2) Employment Change
Granted Subsidy (2007)	4.952*	3.224
	(2.446)	(2.643)
N	1273	6005

Notes: The estimates are from IV version of estimating equation as described in text. The instrument is the cut-off indicator (balance sheet under 10M in 2004) and the dependent variable is the investment in machinery and equipment. The outcomes are defined first differences. Standard errors are in parentheses, clustered by three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8 Text Data

This section presents details on the text analysis performed in the paper.[1]

Preprocessing We apply similar preprocessing steps both to the description texts (used in classifying the type and use of the technology) and the evaluation texts (used in constructing the propensity scores and cosine similarity matching). These steps are:

1. All text is converted to lowercase.
2. Non-letter symbols are removed.
3. Common "stop words" are removed using the Finnish corpus in the Natural Language Toolkit (Bird et al., 2009).
4. Words are returned to their base form (also known as lemmatization) using Voikko.[2]
5. Single-character words are removed, as there are none in Finnish.
6. Words indicating firm type are removed (such as "Oy", which translates to "LLC").
7. Countries, cities, municipalities, known firm names, and technology-related words are changed to generalized versions.[3]
8. Different versions of words associated with technology are replaced with generalized versions of those words. This is mainly to generalize compound words, which are common in Finnish.[4]

Classification After the pre-processing, we turn to scikit-learn (Pedregosa et al., 2011) to perform the classification. We first transform the texts into a Bag of Words (BoW) representation, where each application text corresponds to a vector of the length of the corpus (containing all the words appearing in any texts). Then, the corresponding indices of the vector mark the number of occurrences of each word appearing in the application's text. The vectors are then transformed using term frequency-inverse document frequency (TF-IDF) weights (Salton and Buckley, 1988). The general idea of TF-IDF is to give higher weights to informative words appearing often within an application text. These weighted vectors are finally used in training a support vector machine

[1] All text-related data work is done using Python 3.7.

[2] Voikko performs a variety of NLP preprocessing tasks for Finnish text (`https://voikko.puimula.org/`).

[3] The generalized versions of the words are inside the symbols "<" and ">". For example, the word "Helsinki" (the capital of Finland) is changed to "<City>".

[4] For example, after each prior preprocessing step, the word "hitsausrobotti" (welding robot in English) is a distinct word from both "welding" and "robot". After the last preprocessing step, the word is replaced with "<Weld><Robot>" to capture its similarity to the words "<Robot>" and "<Weld>".

(SVM) classifier.[5] We also performed the classification using other classifiers than SVMs, such as boosting algorithms and neural network variants, but the SVMs performed the best for our purposes. To cross-validate the classifier's performance, we use K-fold cross-validation with five splits. We search the grid for optimal hyperparameters in the learning rate (or alpha), the penalty function, and several other parameters used in vectorization.[6] The score to be optimized is the F_1-score, which gives equal importance to minimizing both false negatives and false positives, as neither one is more crucial in our classification problem. The optimized parameters are (for both technology and automation classification):[7]

1. Learning rate set to .00001
2. Penalty function set to elastic net.
3. Words appearing in more than 50% of application texts are removed.
4. In addition to single words, combinations of two and three words are also used as elements in the training vectors.

This training procedure attains around 90% F-score and 95% accuracy for both technology and automation classification in our out-of-sample tests. We classify manually the applications in our sample into the remaining categories to maximize precision.

Word Vectors Word Vectors are an increasingly popular method of transforming text into numerical form to use in natural language processing tasks, as they have been shown to outperform other text presentation models in multiple different applications (Pennington et al., 2014). Word Vectors are also capable of capturing word semantics, something that simpler transformation methods are not able to do. Put simply, word vectors represent individual words as vectors, often in high dimensions. The similarity of different words can therefore be measured as the distance of their respective vectors: the closer they are in the metric space, the more similar they are.

We construct word vectors using FastText by Facebook (Bojanowski et al., 2016). FastText builds on a model by Mikolov et al. (2013) which creates vector representations of words by predicting "context words" (e.g. words appearing before or after a given word). A key feature that makes FastText attractive for our purposes is its skip-gram approach to building the word vectors: the

[5]SVMs divide the n-dimensional space of vectors (where n is equal to the length of the corpus) with a $(n-1)$-dimensional hyperplane. In the case of a binary classification problem, points on one side of the hyperplane are classified as belonging to one category, and points on the other side to the other category.

[6]These include the n-gram range and the threshold for corpus specific stop words.

[7]All other parameters are set to default ones in the SGDClassifier estimator in the scikit-learn library. We tested optimizing other parameters as well using randomized search, but find virtually no improvements in accuracy.

model creates word vectors of combinations of characters also appearing inside words. That allows the model to capture better the semantic meaning of two forms of the same word. For example, the words “technology” and “technologies” both have essentially the same meaning in many contexts, but simpler models would require enough training data containing both words to construct their word vectors accurately. That is because these models treat them as entirely separate words (at least before constructing the word vectors). FastText overcomes this limitation by constructing a word vector for the common sequences of characters in both words, such as “technolog,” that contribute to the word vector values of all words containing the same sequence. Hence, words containing a common sequence that captures most of the semantic meaning all have similar vector representations. This aspect is especially important in morphologically rich languages such as Finnish, where various case suffixes are common.

In our application, the words appearing in the description text of each application (i.e., in our corpus) are first transformed into 100-dimensional vectors. We highlight the fact that we use the corpus of subsidy application texts to train the model, rather than using pre-trained models of the Finnish dictionary, for example. The reason for this is that words appearing in the subsidy application texts are likely to hold different semantic meanings than the same words in more general contexts. After constructing the initial word vectors, each of them is weighted by the term frequency-inverse document frequency (TF-IDF). Finally, another 100-dimensional vector is built for each application text by taking the average over each of the TF-IDF weighted word vectors in the text. Hence, we end up with each firm in our main analysis sample having one “sentence vector” giving its application texts contents in 100 dimensions. We then use these sentence vectors to build propensity score measures and match recipients to non-recipients with replacement.

Propensity Score The procedure is explained in more detail in Section 4.3 of the main text. We use the CalibratedClassifierCV estimator in the scikit-learn library to calibrate the linear SVM model, as it is not by default a probabilistic classifier. The sentence vectors are used as features and the model outputs the estimated probability of the application being successful (i.e. probability of treatment assignment).

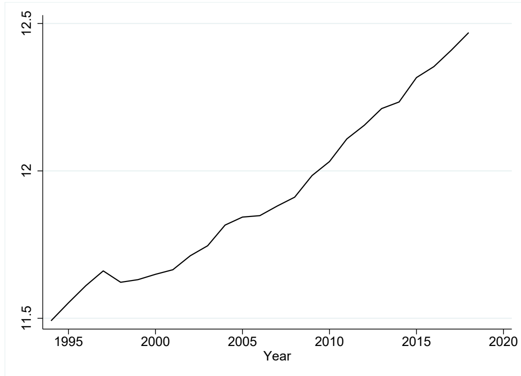
Cosine Similarity Matching The procedure is explained in more detail in Section 4.3 of the main text. Cosine similarity gives a similarity metric between two vectors. We calculate this metric for each winner-loser pair in our main analysis sample using the sentence vectors. The match is 1:1 with replacement, so we keep only the matched loser firm with the highest similarity with a given winning firm. After manual inspection of the match quality, we also discard all matched pairs where the similarity metric between the texts is less than .85, where unity reflects identical documents.

9 Context

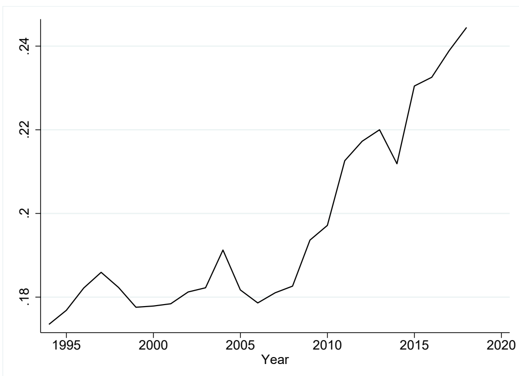
The Economy Finland is an industrialized, small open economy and part of the EU. The GDP per capita is similar to other northern European economies such as Germany and the UK. The industry's employment share was 21% in 2019 (OECD: 23.0%, US: 20%; ILO 2021). Finnish labor costs are close to the Euro area average and the US (Eurostat 2020; BLS 2020). Labor-market flexibility is higher than OECD average: short-term contracts are typical and authorized, but regulations constrain dismissals of regular contracts (OECD 2020). Union membership is common: 70% of workers reported being union members in 2018 (Statistics Finland 2019). Sectoral bargaining agreements set wage floors, but unions do not directly negotiate about technology adoption.

Skills Education attainment in Finland is above the OECD average: 46% of adults had obtained tertiary education in 2019 (OECD 2020). Skill measures, such as PISA for school-age students and PIAAC for adult skills, rank Finland among the world's highest (PISA 2018, PIAAC 2018). Secondary vocational education is common in Finland: it enrolls 46.5% of 17-year-olds, near the European average (OECD 2017; Silliman and Virtanen 2021). Continuous training in manufacturing firms is also common: 46.3% of manufacturing workers participated in continuing vocational training courses in 2015 (Eurostat 2021).

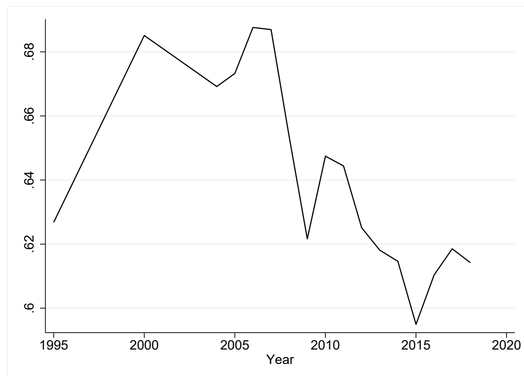
Trends The recent economic trends in Finland, such as manufacturing employment decline (Statistics Finland 2020), job polarization (Kerr, Maczulskij, and Maliranta 2020), and regional divergence (Böckerman and Maliranta 2001) have been similar to the US. We document the relevant trends in manufacturing firms over 1994–2018 in this Section's figures. The average education level (measured in years of education) increased from 11.5 to 12.5 years. The college-educated workers' employment share increased from 18% to 24%. The production-worker employment share declined from 68% to 62%. Similar trends apply to the wage-bill shares. The average wages increased from 22,500 EUR to 35,000 EUR per year (all monetary values are in 2017 euros). The college to non-college wage ratio increased from 1.3 to 1.37, and the production vs. non-production workers' wage ratio declined from 1.08 to .90. Productivity has increased from 120K to 180K per worker.



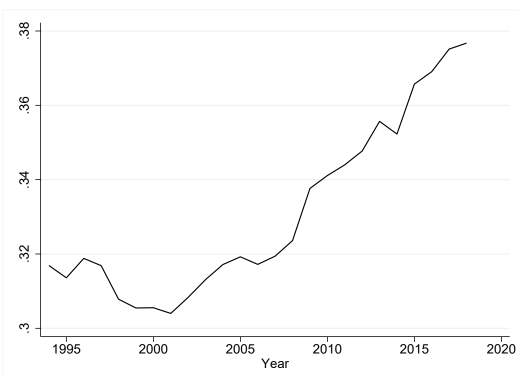
(a) Average Years of Education.



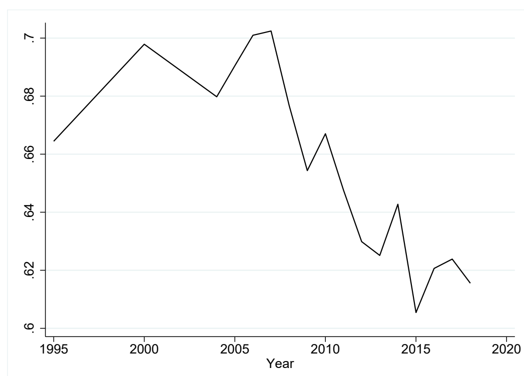
(b) College Educated Employment Share.



(c) Production Worker Employment Share.



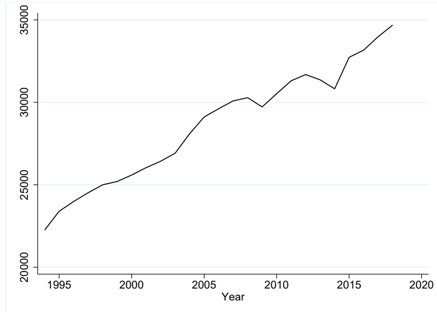
(d) College Educated Wage Bill Share.



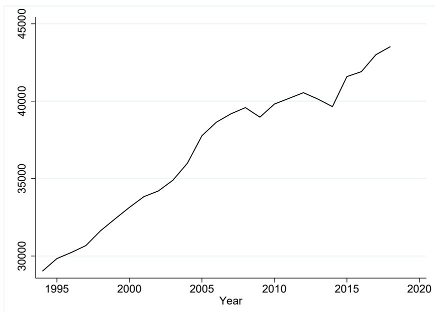
(e) Production Worker Wage Bill Share.

Figure 18: Manufacturing Skill Composition Trends.

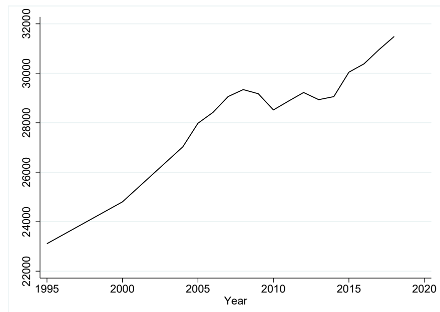
Notes: Trends in Finnish manufacturing over 1994–2018. We restrict to firms with at least 3 workers. We compute year-level averages from firm-level observations. The numbers are unweighted to match our research design. The employment-weighted numbers are similar.



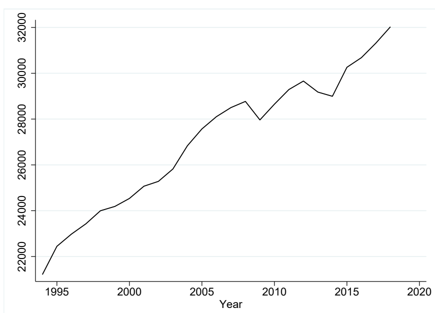
(a) Average Wages.



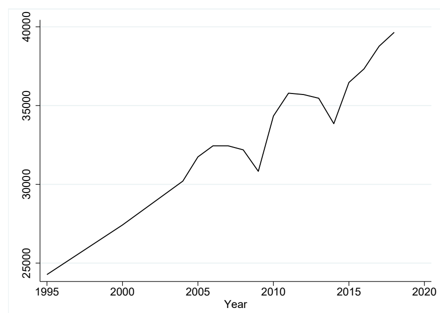
(b) College Educated Wages.



(c) Production Worker Wages.

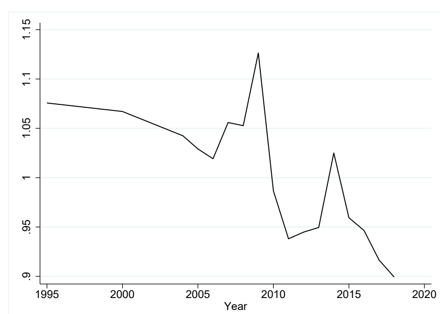


(d) Non-College Educated Wages.



(e) Non-Production Worker Wages.

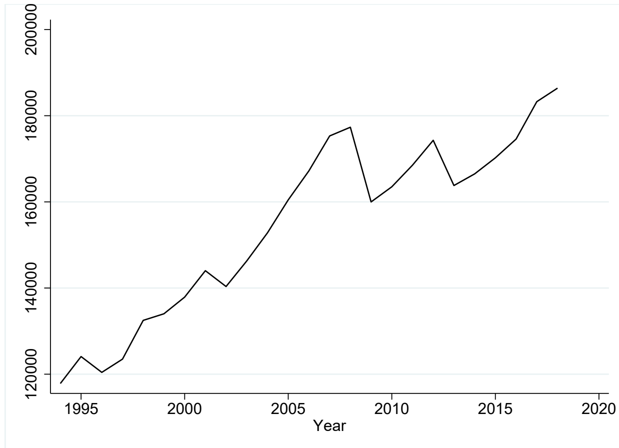
(f) College vs. Non-College Wage Ratio.



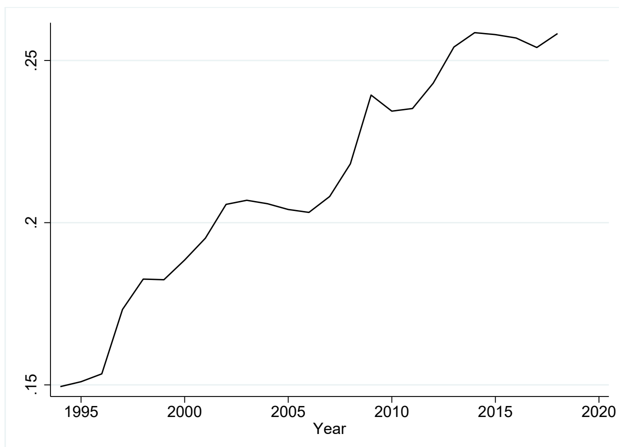
(g) Prod. vs. Non-Prod. Wage Ratio.

Figure 19: Manufacturing Wage Trends.

Notes: Trends in Finnish manufacturing over 1994–2018. We restrict to firms with at least 3 workers. We compute year-level averages from firm-level observations. The numbers are unweighted to match our research design. The employment-weighted numbers are similar.



(a) Productivity (Revenue Divided by Employment).



(b) Labor Share (Wage Bill Divided by Revenue).

Figure 20: Manufacturing Productivity and Labor Share Trends.

Notes: Trends in Finnish manufacturing over 1994–2018. We restrict to firms with at least 3 workers. We compute year-level averages from firm-level observations. The numbers are unweighted to match our research design. The employment-weighted numbers are similar.

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