WINNERS AND LOSERS OF TECHNOLOGY GRANTS*

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Abstract

We present new evidence on the impact of EU technology subsidies on employment and skill mix in Finnish small- and medium-sized manufacturing firms from 1994 to 2018. The subsidies funded new machinery, including robots. Comparing closely matched grant winners and losers, we find that subsidized investments increased employment without changing the skill composition. We use machine learning on application texts to match firms based on their evaluation reports. We then analyze firms' stated plans and show that the subsidies primarily supported expansion—such as launching new products—rather than automating work. In contrast, in a broader sample of manufacturing firms outside the program, we find that IT investments are more strongly associated with skill upgrading than machinery investments, consistent with different technologies shaping skill demand in different ways. Our findings suggest that these grants created opportunities for non-college-educated workers.

Keywords: Subsidies, Industrial Policy, Technological Change, Labor Demand, Skills.
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I Introduction

Industrial policies that support technology investments are widespread but controversial. One view is that technology subsidies encourage automation, which could displace less-skilled workers and increase inequality. A contrasting view is that these subsidies help firms expand—scaling up, entering new markets, launching new products—and that worker outcomes depend on how those expansions unfold. Despite substantial public spending on technology adoption, evidence on how subsidized investments affect workers remains remarkably limited, with a few notable exceptions (Becker et al., 2010; Criscuolo et al., 2019; Curtis et al., 2022). The key open question is how technology subsidies affect different types of workers and how they operate at the firm level.[1]

This paper examines how technology grants shape workers' opportunities. We exploit variation in EU subsidies for technology investments in Finnish small- and medium-sized manufacturing firms from 1994 to 2018. The program funded new machinery—for example, robots and computer numerically controlled (CNC) machines. Comparing matched grant winners and losers, we find that subsidies increased employment by 23% without changing the skill mix. Our micro-level evidence and text analysis suggest that, even when used to acquire advanced manufacturing technologies, these grants primarily supported expansion rather than the automation of work.

ELY Center technology subsidies, the policy we study, are part of the European Structural and Investment Funds—one of the world's largest industrial policies (budgeted at EUR 535 billion in 2014–2020). These grants lower the cost of new technology investments but let firms decide which to adopt. We track matched winners and losers over ten years using a novel design. A distinctive feature is the use of text data from evaluation reports to identify close winners and losers. These firms had similar assessments, but only some received the subsidy. We use machine learning to turn these texts into firm-level propensity scores for winning the grant, measuring how close each firm came to approval. We also contrast winners to matched non-applicant control firms.

We merge administrative records, surveys, and field observations, creating a high-quality dataset on technologies and workers. These data track firms' technology choices and workforce composition before, during, and after applying for subsidies. For example, we document firms' adoption of robots, CNC machines, and IT, as well as employees' education, cognitive skills, and personality. Text data from the subsidy program let us see up close why firms applied and how they planned to use the investments. Field visits and interviews with CEOs, managers, shop-floor workers, and grant officials clarify the context. This combination of administrative data and text analysis provides a rare, direct view of how technology subsidies work and whom they benefit.

The first part of the paper reports our core findings on employment and skill mix. Receiving a technology grant led to a 23% increase in employment, but we find no detectable effects on the

[1] The first view reflects the ideas of labor replacement (Keynes, 1931; Brynjolfsson and McAfee, 2014) and skill-biased technological change (Griliches, 1969; Welch, 1970; Tinbergen, 1975; Katz and Murphy, 1992). Existing research suggests that new technologies, such as computers and IT, have replaced workers' tasks and favored skilled labor (Berman et al., 1994; Autor et al., 1998, 2002; Akerman et al., 2015; Gaggl and Wright, 2017; Acemoglu and Restrepo, 2020; Feigenbaum and Gross, 2024). The second view relates to factory-floor observations (Dertouzos et al., 1989; Berger, 2013) and evaluations of investment subsidies (Criscuolo et al., 2019; Curtis et al., 2022) finding that subsidies raise employment but, so far, offer limited systematic evidence on how such programs shift the skill mix.

skill mix—measured by the share of highly educated workers, years of education, or the share of production workers. We also find no effect on the labor share. These results contrast sharply with the concern that technology subsidies would reduce employment or lead to skill-biased changes. In practice, trained machinists and skilled welders were needed before and after the subsidy. The firms did not employ relatively more educated workers after the subsidy-induced investments. Looking more closely at detailed skill measures—education and occupation groups, cognitive performance, and personality—we generally find no effects.

Several observations support the validity of our findings in this context. The subsidy program induced a sharp first stage: firms experienced a sharp rise in technology investments after receiving subsidies. Treated and control firms followed similar pre-trends in investment, employment, and skill mix before applying. Our results are robust to controls for the evaluation texts of the subsidy applications, as well as industry, firm size, and regional trends. The results also hold across three alternative designs: (1) a comparison to matched non-applicant firms, (2) a regression discontinuity (RD) design based on changes in the criteria for small firms, and (3) an event-study design without the subsidy program. Our fieldwork on factory floors further supports these findings.

The second part investigates potential firm-level mechanisms. Our fieldwork suggests two stylized views of how firms could respond to subsidies. One is that subsidies push firms to automate, replacing human tasks, lowering costs, and raising productivity. Previous work argues that this could displace workers, reduce labor shares, and shift the skill mix if low-skill or routine tasks are automated (Acemoglu and Restrepo, 2018a,b; Autor et al., 2003). The other is that subsidies help firms expand—scaling up or shifting into new activities—without necessarily increasing productivity or fundamentally changing the production process. If firms use the subsidies to expand, the effects on workers are also uncertain, but this could result in increased revenues, new products, or even new work (Braguinsky et al., 2021; Autor et al., 2024). In short, the micro-level effects of technology subsidies are ex-ante uncertain. Firms may choose to use subsidies to automate, expand, both, or neither.

Next, we present evidence on firm performance. We find strong positive effects on revenue but no detectable changes in productivity, profit margin, or capital intensity from the subsidy program. Together with employment increases and no effects on the labor share, this evidence is consistent with the idea that firms expanded rather than automated tasks. Zooming in, our detailed evidence shows that subsidies led firms to export, introduce new products, discontinue old ones, and raise prices and marketing expenditures. These new products and markets were equally skill-intensive to the existing ones. Firms' profits increased roughly one-to-one with the average subsidy received.

Text data from subsidy applications provide a novel way to understand firm responses. We hand-code firms' application texts into distinct, concrete categories that reflect firms' motivations. We find that 74% of firms cited expansion, while only 14% mentioned workforce-related motives. Major reasons for buying a new technology included introducing new products (31%), improving quality (30%), and enhancing capabilities or flexibility (29%). When we analyze the limited set of firms that particularly aimed to automate, we find some increased demand for skills. Survey data from three distinct surveys corroborate these findings, with "customer-specific solutions" and "realization of a market niche" being the most frequently cited reasons for technology investments in these firms. Reducing labor or material costs was relevant but less common. Trade journal articles that we link to our firm data describe the investments as low-to-medium complexity product innovations. Fieldwork supports these observations. For example, one piston manufacturer invested in a robot and CNC machine to produce a new variant of a piston, not to replace workers. When examining the technologies, we find that our sample firms mainly used the subsidies to invest in machinery rather than IT, computers, or software.

Our findings are grounded in a specific policy and context, raising the question: What local average treatment effect (LATE) do our estimates capture? One view is that financial constraints limit firms' ability to adopt new technologies, and EU subsidies lower these barriers, enabling large investments. Another view is that firms already have sufficient resources, and subsidies fund incremental investments with limited productivity impact. Our findings support the latter view. The average grant size (EUR 80K) suggests that the program financed marginal upgrades rather than transformative changes. These firms did not move from no technology to full automation—they already had some in place. Our estimates capture local effects for firms on the margin of investment—those induced by the subsidy—but not all firms (Zwick and Mahon, 2017; Lileeva and Trefler, 2010). We find limited evidence that credit constraints, employment biases, signaling, or spillovers drive our results.

We focus on flexible manufacturing, where small- and medium-sized enterprises (SMEs) produce specialized, low-volume products to meet shifting demand. This setting stands apart from mass production (Taylor, 1911; Ford, 1922). Although automation and skill bias are central to the literature, not all technology investments displace labor tasks or favor more skilled workers (Goldin and Katz, 1998; Autor et al., 2024; Restrepo, 2024). Piore and Sabel (1984) argue that flexible manufacturing changes the relationship between technology and labor. In these differentiated goods producers, new technologies often support expansion and product variety alongside skilled labor, rather than automation (Milgrom and Roberts, 1990; Berger, 2020). Focusing on this context is both a strength and a limitation: the results may not generalize to all settings, but flexible manufacturing represents a substantial share of industrial activity (Berger, 2020).

The third part steps outside our quasi-experimental setting to place the findings in a broader context. Why didn't subsidized machinery investments generate the skill-biased effects documented in earlier work? (Akerman et al., 2015; Gaggl and Wright, 2017; Autor et al., 1998; Berman et al., 1994) We explore three possibilities: (1) the effects operate between rather than within firms, (2) the subsidies funded machinery rather than IT, and (3) skill demand in Finland differs from contexts studied before. Testing these hypotheses is not straightforward—it requires unusually detailed, linked data on firms, technologies, and workers over time. Our Finnish administrative and survey data allow us to track both the workforce composition and technology choices of manufacturing firms before and after adoption. The results point to a sharp distinction: IT investments—such as spending on computers and software—are consistently associated with skill upgrading, while machinery investments are not.

At the macro level, technology grants can raise skill demand through two channels. First, within firms: Companies adopting new technologies may increase their demand for skilled workers. Second, through compositional changes: Firms that were already more skilled before adoption grow faster when they adopt new technologies, shifting the overall workforce toward higher skill levels.

Comparing subsidy applicants to non-applicants, we find that applicants had lower labor shares and somewhat more educated workers before adoption. Following the program, applicant firms grew faster than comparable non-applicants. This evidence is consistent with compositional effects, which increase aggregate skill levels and reduce labor shares. However, the skill differences are modest—less than 0.1 years—creating a natural upper bound on these effects.

Expanding the analysis beyond our subsidy sample to all Finnish manufacturing firms, we find that machinery investments are moderately—but not strongly—more common in firms whose workforces are more highly educated. Aggregating data at the industry level, we find that industries investing more in machinery have not changed their skill composition more than other industries.

But IT investments tell a different story. In firms outside our subsidy sample, IT investments—such as software and computers—are concentrated in more educated firms. At the industry level, industries that adopted more IT have significantly increased their share of skilled workers. These findings align with Autor et al. (1998, 2008), and Berman et al. (1994).

Taken together, these observations are consistent with the interpretation that the skill-neutral effects of technology subsidies could reflect the types of investments they supported. In our setting, the program supported primarily machinery acquisitions, with limited IT investment. Our quasi-experimental and correlational analyses reveal only a limited association between machinery investments and changes in the skill mix. In contrast, correlational evidence shows that IT investments are positively linked to skill upgrading. This contrast could reconcile our findings with earlier studies documenting skill-biased effects from IT (Autor et al., 2002; Akerman et al., 2015; Gaggl and Wright, 2017). However, because the program focuses on machinery rather than IT, there is limited scope for comparing these two within our design.

Finally, the study's backdrop is that the overall manufacturing sector in Finland is shifting toward greater skill demand, reflected in the rising share of educated workers. This trend matches global patterns, such as in the US (Acemoglu and Autor, 2011).

Our research contributes to the literature on firm subsidies, including Criscuolo et al. (2019), Curtis et al. (2022), Becker et al. (2010), Cerqua and Pellegrini (2014), Cingano et al. (2025), and Muraközy and Telegdy (2023).[2] This literature offers limited evidence on which types of workers benefit from subsidized technology adoption and which ones do not. The answer to this question is critical for understanding the consequences for inequality. Our distinct contribution is novel, direct causal evidence on how industrial technology subsidies affect firm-level employment and skill

[2]Beyond these papers, our research builds on the literature on firm subsidies in the EU (Becker et al., 2012, 2013, 2018; Bernini and Pellegrini, 2011; Bronzini and de Blasio, 2006; Decramer and Vanormelingen, 2016; Devereux et al., 2007; Einiö and Buri, 2020; Pellegrini and Muccigrosso, 2017; Siegloch et al., 2024) and elsewhere (Brown and Earle, 2017; Kalouptsidi, 2018), business and capital taxes (Garrett et al., 2020; House and Shapiro, 2008; Yagan, 2015), R&D subsidies (Bronzini and Iachini, 2014; Dechezlepretre et al., 2023; Einiö, 2014; Howell, 2017; Takalo et al., 2013), historical cases of industrial policy (Lane, 2025; Giorcelli, 2019; Mitrunen, 2024), and place-based policies (Busso et al., 2013; Incoronato and Lattanzio, 2023; Kline and Moretti, 2014), reviewed by Akcigit and Stantcheva (2021); Ehrlich and Overman (2020); Lane (2020); Neumark and Simpson (2015), and Slattery and Zidar (2020).

mix, and on the mechanisms through which they operate. To this end, we develop a new approach to use machine learning (ML) in program evaluation that matches grant winners and losers based on their evaluation reports. We assemble an unusually rich dataset on firms, technologies, and workers, and strengthen our analysis with an RD based on firm-size thresholds and by analyzing investment spikes outside the program. This micro-level evidence and text analysis enable us to document how firms actually use these grants. We find that subsidy-induced machinery investments led to employment gains without shifting the skill mix. The overall evidence is consistent with the idea that these firms used the grants more often to expand rather than to automate. Since these firms primarily employ production workers without higher education, our findings suggest that the subsidies expanded opportunities for workers without a college degree.

Our study connects to research on technology and work.[3] A central idea in this literature is that technology shapes skill demand (Autor et al., 2024).[4] Our findings—that technology grants increased employment *without* shifting the skill mix—are consistent with recent evidence on subsidized capital investments in the UK and US (Criscuolo et al., 2019; Curtis et al., 2022), earlier results on factory-floor machinery (Doms et al., 1997), and recent work on manufacturing capital (Aghion et al., 2024). They differ, however, from studies showing skill-biased effects from IT adoption (Akerman et al., 2015; Gaggl and Wright, 2017; Autor et al., 1998, 2002; Berman et al., 1994). While several factors may reconcile this difference, our evidence points to one: the program funded machinery rather than IT.[5] Our results also contrast with studies where automation directly replaced workers' tasks (Feigenbaum and Gross, 2024; Bessen et al., 2025). The evidence shows that automation of this kind was uncommon under this subsidy program. We caution against overinterpreting the results. Still, our research provides critical evidence on a prominent industrial policy and informs the design of future policies that tax or support technology adoption, such as robot taxes (Acemoglu et al., 2020a; Guerreiro et al., 2022; Costinot and Werning, 2023).

The paper proceeds in three parts. The first presents our design and main results on employment and skill composition. The second explores firm-level mechanisms, presents evidence on firm outcomes and intentions, and discusses our LATE and context. The third places our findings in broader context, drawing on descriptive evidence from the wider manufacturing sector.

[3]Relevant work includes Autor et al. (2003, 2008); Bartel et al. (2007); Battisti et al. (2023); Beaudry et al. (2010); Bloom et al. (2014); Bresnahan et al. (2002); Bockerman et al. (2019); Boustan et al. (2024); Caroli and Van Reenen (2001); Genz et al. (2021); Goos and Manning (2007); Hémous et al. (2025); Kogan et al. (2023); Krusell et al. (2000); Lashkari et al. (2024); Lewis (2011); Lindner et al. (2022); Machin and Van Reenen (1998); Michaels et al. (2014); Spitz-Oener (2006). Evidence on robot adoption comes from Acemoglu and Restrepo (2020); Acemoglu et al. (2020b); Adachi et al. (2024); Benmelech and Zator (2022); Bonfiglioli et al. (2024); Chung and Lee (2023); Dauth et al. (2021); Dixon et al. (2021); Eggleston et al. (2021); Graetz and Michaels (2018); Humlum (2021); Koch et al. (2021). For surveys, see Acemoglu and Autor (2011) and Restrepo (2024).

[4]Recent research on AI provides a related point: AI tools supported *less-skilled* workers more than highly skilled ones in two case studies (Noy and Zhang, 2023; Brynjolfsson et al., 2025). Our findings also resonate with Babina et al. (2024), who found that AI-investing firms experienced growth primarily from product innovation.

[5]Other relevant factors include: (1) firms choosing to use technology subsidies for expansion rather than automation; (2) our estimates capturing local average treatment effects (LATE) specific to subsidized firms; (3) the flexible manufacturing context of our study; and (4) differences between micro and macro-level effects on skill demand.

II Moore's Law for Pistons

Consider the piston. To understand how technology adoption plays out among small- and medium-sized manufacturing firms, we conducted fieldwork that led us to an industrial piston manufacturer. Pistons are cylinders that move up and down inside combustion engines, converting fuel into motion. This firm's experience sheds light on our broader context.

The company invested in a new CNC machine, a robotic arm, a measurement device, and computer-aided design (CAD) software. When we asked the CEO why they adopted these technologies, he emphasized a central theme in piston manufacturing: constant quality improvement. "With the old technologies, we couldn't make these pistons," he explained. Figure 1 illustrates the development of piston quality over the last 100 years—a trend the firm referred to as the "Moore's Law for pistons."

The new technology enabled the production of larger, lighter, and more efficient pistons, allowing the firm to stay competitive and expand its revenue and employment. As a small-scale, specialized manufacturer, quality is important; pistons represent only a fraction of an industrial engine's cost, but their failure can be extremely costly for clients. This resembles the O-ring theory of production (Kremer, 1993; Autor, 2015), where the reliability of each component is critical.

Interestingly, the firm's primary motivation for adopting technology wasn't cost-cutting or automating work, although the robotic arm did automate certain tasks. Instead, the focus was on possible expansion. The technology investment led to "small but important changes" in production processes and the work experience. For example, the new production design incorporated a proprietary method of attaching the piston to the machining platform.

The adoption required workers to acquire new skills: Production workers learned to operate the CNC machine and robotic arm, while the R&D team has updated their proficiency with the latest CAD software. Despite these changes, there was no significant shift in the formal educational composition of the workforce, although there has been a gradual increase over time.

The company operates in niche markets where demand for each specific product is limited, effectively making them monopolists or oligopolists in these specialized segments. Because they cannot significantly expand by increasing production of existing products, they attempt to grow by introducing new ones—often incremental variations of their current offerings.

Other firms we studied shared similar experiences, suggesting that these mechanisms might be common among manufacturing firms focused on flexible, specialized production. However, they also noted that in contexts like mass production and digitalization, technology might be adopted differently, potentially with a greater emphasis on automation.

III Winners-Losers Design

We estimate how EU technology subsidies affect firm employment and skill mix. The subsidies temporarily lower the cost of investment for recipient firms. Our event-study tracks close winners and losers before and after award. Its identification logic parallels that in Angrist (1998), Greenstone et al. (2010), and Kline et al. (2019).

A novel aspect is the use of text data to create comparisons of close winners and losers. To do so, we use evaluation reports written by the program officers. We map these report texts into propensity scores that reflect the likelihood of receiving a subsidy and control for the scores to compare similar winners and losers (see also Roberts et al., 2020, for text matching). We also compare subsidy winners with matched non-applicant firms.

The Appendix presents two complementary designs: (1) an RD design based on a change in the threshold that determines a priority for small firms in the program (to address internal validity), and (2) a spikes design based on the precise timing of technology adoption events without the program (to explore external validity).

III.A ELY Center Subsidy Program

We analyze the effects of technology subsidies in manufacturing firms in Finland, 1994–2018.

The technology subsidy program is administrated in Finland by the Centers for Economic Development, Transport and the Environment (the ELY Centers).[6] These centers promote regional business policy through various activities, including advisory, financing, and development services. Technology subsidies are part of a service called Business Development Aid. The service provides funding for technology adoption, export promotion, R&D, and several smaller categories, such as starting a new company. Based on the subsidy records, the service granted EUR 2 billion over our sample period 1994–2018 and directed EUR 758 million toward technology subsidies. Technology subsidies were, on average, 0.7% of machinery and equipment investment in Finland. This paper is the first quantitative evaluation of the program.

The program is part of the European Structural and Investment Funds (ESIF), one of the world's largest industrial policy programs. ESIF aims to promote economic development across all EU countries, especially in remote regions. The 2014–2020 program granted EUR 535 billion from the EU budget (European Commission, 2023). In the Finnish context, the national government and the EU fund technology subsidies together, typically 50/50. Decisions are made locally by the ELY Centers. The EU regulates the budget and rules for giving subsidies. This study speaks to the firm-level effects of the broader EU program.

The technology subsidies aim to promote the adoption of new technologies. The broader agenda behind this objective is to improve firms' competitiveness. Technology subsidies in Finland have a long tradition based on the idea that the government can foster growth and structural change through industrial and regional policy (Rodrik, 2007; Kekkonen, 1952; Mitrunen, 2024). The program follows the EU's technology neutrality principle from the bottom up—firms can choose their technology as long as it is new—and is not primarily about the direction of technology, for example, automation vs. non-automation (Acemoglu, 2002).[7]

[6]There are 15 ELY Centers in our data. Until 2009, these centers were called TE Centers. Since 2014, four RR-ELY Centers have administrated all technology subsidies (RR denotes European Structural and Investment Funds). ELY Centers are separate from Business Finland (previously TEKES), which provides funding specifically for R&D.

[7]The standard economic rationales for the subsidies could be external economies of scale, coordination problems,

A typical technology subsidy is an EUR 80K cash grant, reimbursing 15–35% of technology costs. Subsidy-induced investments are primarily new production technologies for manufacturing: new CNC machines, robots, laser cutters, surface-treatment equipment, measurement devices, and enterprise-resource-planning (ERP) and computer-aided-design (CAD) software. The most common industries are fabricated metal products and machinery. The firms are mostly small- and medium-sized enterprises (SMEs), often contract manufacturers producing specialized intermediate goods in small batches, such as pistons for engines, sold to large exporters. Workers are primarily production employees (median share: 70%), for example, machinists, welders, and machine operators, who are typically vocationally trained. Grants are paid by ELY Centers as reimbursements for verified costs, and approximately 30% of recipients are audited. Figure A1 illustrates typical technologies, firms, and workers in our sample.

The selection process works in typical cases in three stages, outlined in Figure 2.

1. Application. Starting from all firms, some firms apply for technology subsidies. For our research design, it means that we compare firms that all plan a technology investment. Firms do not apply because (a) they do not plan to invest, (b) they do not know about the program, (c) anticipate they are not eligible, or (d) consider the opportunity cost higher than benefits.

2. Pre-screening. In the pre-screening stage, firms contact ELY Centers that pre-screen them before submitting formal applications. This stage is helpful for our design: after pre-screening, the centers' goal is that all firms have a realistic chance of winning the subsidy. The coarse evaluation criteria are size, industry, and general economic position. The program requires the firms to be primarily in manufacturing and SMEs, not owned by large firms, not in financial difficulties and able carry out their technology plan. Firms may decide to skip this stage, but that does not improve their chances of winning the subsidy (but may create rejected applications from otherwise high-performing firms that are, for example, not SMEs).

3. Decision. In the decision stage, firms submit a formal application explaining the investment and timeline. Funding is discretionary. Subsidy winners are selected based on the program rules and local and temporal budget priorities and constraints, and an identical firm could receive a subsidy in a given year but not the other. ELY Centers do not score the applications on a formal scale, but we use the evaluation reports to match applicants. In the decision stage, ELY Centers re-evaluate the coarse criteria: size, ownership structure, industry, and financial position. The centers make an impact assessment to evaluate the effectiveness of the subsidy. Cases where the subsidy is more likely to have any impact are more likely to receive it. In addition, firms satisfying the criteria for small firms and firms in remote regions are prioritized.[8] ELY centers evaluate potential market distortions and sometimes reject applications if they suspect the subsidy negatively interferes with local competition. About 15% of applications

credit and information frictions, and pure transfers to lower-income regions. However, typically in political discourse the program is not assessed in contrast to the free-market benchmark but seen in the context of economic planning.

[8]Our regression discontinuity (RD) design is based on changes in the criteria defining a small firm.

are rejected.[9]

What separates winners from losers? Text data allow us to read evaluations of winning and losing applications. Winning applications' evaluations state why the project satisfies the criteria, and the officer recommends a subsidy. Losing applications' evaluations specify why the officer does not recommend granting a subsidy. Typical reasons for rejection are (1) effectiveness: the subsidy is not expected to affect the project, the project is small and unlikely to have a meaningful effect, the firm had already started the project or received a subsidy for a similar project, (2) industry, size, and investment-type restrictions: the firm is not an SME, e.g., owned by a large firm, a particular industry or investment is not supported at that time or region, the firm proposes to buy second-hand machinery, which is generally not allowed, (3) budget constraints: subsidy funds are limited at that region and time, (4) technical issues: the firm did not provide the required information by the deadline, (5) firm's financial position and the owners' history: ongoing corporate restructuring, foreclosure, or tax liability, and (6) interference with local competition. Employment-related reasons do not appear as typical primary reasons for rejection; we discuss this aspect in Section VII.

Table A1 compares the main sample to all Finnish manufacturing firms. Technology subsidy applicants are different from non-applicants. The median subsidy sample firm is larger (despite being an SME), more profitable, slightly more educated, and has a lower labor share compared to the median manufacturer. These observations highlight that non-winning applicants could provide a better control group than average manufacturers because all applicants have indicated a strong interest in technology adoption. Our estimates approximate the local average treatment effect (LATE) for firms close to investing in technologies. We return to the LATE interpretation in Section VII and discuss what these differences could mean for more aggregate effects in Section IX.

We conceptualize the technology subsidy as a temporary price reduction for technology. If a firm is close to the margin on whether or not to invest, a temporary price reduction might push it to invest. Firms and subsidy officers reported in our interviews that subsidies affect investment because they lower the price of technology, including the associated costs, future risk of debt, mental investment and courage. At the same time, they said that the moderately-sized subsidies unlikely affect firms that are far from investing; that the grants more likely affect marginal investments. We return to this interpretation in Section VII.

We clarify the source of variation using a dynamic model adapted from Cooper et al. (1999) in Appendix H. The model maps the price changes induced by the program into the firm's technology adoption decision and factor demand. Under the model, the firm's technology adoption reflects four forces: (1) the replacement cycle, (2) shocks to technologies' prices, (3) shocks to technological progress, and (4) shocks to productivity. Our design based on technology subsidies aims to isolate the LATE effects of the shocks to technologies's prices. We discuss dynamics in Section VI.

[9] Corruption is unlikely to play a significant role in the process. The Corruption Perceptions Index (CPI) ranked Finland as having one of the lowest levels of corruption in 2012–2020.

III.B Baseline Design

Our main empirical strategy is an event-study design that contrasts similar firms, one of which was approved for technology subsidies while the other was not. The identification strategy is based on the idea that subsidy decisions are quasi-randomly assigned with respect to the counterfactual changes in firm outcomes after conditioning on the information used in the screening process. We assess the comparability of winners and losers and provide several alternative estimation strategies, including a matched non-applicant control group and matching with text data in the next section.

We estimate two types of equations. Our main specification is a stacked event study:

$$Y_{jt} = \alpha_j + \kappa_t + \sum_{\tau \in \mathcal{T}} \left[I^{\tau}_{jt} \cdot (\gamma_\tau + \beta_\tau \cdot D_j) \right] + X^{\tau}_{jt} + \varepsilon_{jt} \tag{1}$$

where Y_{jt} is an outcome for firm j in year t, D_j is the treatment indicator, I^{τ}_{jt} is the event-time indicator for firm j's decision having occurred τ years ago, and the set $\mathcal{T} = \{-5, -4, \dots, 4, 5\}$ defines the five-year horizon over which we study dynamics. Our parameters of interest are the coefficients β_τ. They summarize the differential trajectory of mean outcomes for winning and losing firms by the time relative to their application. Note that event-time is explicitly defined also for the control group by application year, and firms are only in the treatment or control group for the entire panel.[10] Estimates before the event serve as a test of differential pre-trends between the treatment and the control group. The coefficients γ_τ capture the common event-time τ effects. The term α_j denotes the set of firm indicators, κ_t is the set of calendar-time t indicators, and X^{τ}_{jt} contains potential pre-period controls interacted with both time indicators (the main figures are reported without). We designate $\tau = -3$ as our base event period and omit it. We set the base clearly before the event to avoid contrasting the post-period to any anticipation effects (e.g., Ashenfelter's dip) but our results are robust to the choice of base year, as indicated by the event-study graphs. For clarity, we present all main estimates in reduced form (i.e., intention to treat, ITT).[11]

To summarize the dynamic estimates into a single number, we estimate the stacked first-differences specifications:

$$\Delta Y_j = \beta \cdot D_j + X_j + \varepsilon_j \tag{2}$$

where ΔY_j is the change in the outcome from the base year $\tau = -3$ to the post period that we define in each context. The main regressor is D_j, an indicator for whether the firm won the subsidy. We also estimate continuous versions where D_j refers to the amount of subsidies. The control term X_j controls for potential differential trends across firm and application characteristics. We report standard errors that are robust to heteroskedasticity and cluster by firm.

We report the event studies without additional controls. In the first-differences specifications, we control for the baseline firm characteristics at $\tau = -3$ potentially correlated with subsequent changes in our variables of interest: the 2-digit industry, firm size, and calendar-time t fixed effects.

[10] We focus on a never-treated control group to avoid biases from staggered adoption. Robustness to alternative DiD estimators is shown at the end of Section V (de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021).

[11] With ± 5 years of follow-up, event years span 1999–2013 in data from 1994–2018.

We show the results are robust to different controls (Tables 3, A9).

We construct the analysis sample in the following way. We first restrict to technology applications based on the text data (explained in Section IV). We then restrict to manufacturing and construction industries for three reasons: the program targets these industries, they produce physical outputs, and we have a concrete understanding of what their new technologies are based on our fieldwork.[12] We exclude the largest 5% of applications because they tend to have poor control units. Event-time indicator $\tau = 0$ refers to the year the subsidy application was submitted. The treatment group is defined by selecting the largest approved subsidy application for each firm,[13] and the control group is defined by the largest rejected application. Repeated applications for the same project are generally not allowed and untypical. Finally, we restrict to a balanced sample over the five-year horizon.[14]

The ideal experiment that could capture the causal effects of technology subsidies on employment, skill mix, and firm performance would randomly assign the subsidies to firms. While a perfect technology-subsidy experiment is hard to engineer, our identification strategy is based on the quasi-random assignment of technology subsidies, D_j. The identifying assumption is that treatment assignment is conditionally independent of the outcomes (here in changes):

Assumption 1 (Rosenbaum and Rubin, 1983, CIA): $(Y_{1j}, Y_{0j}) \perp\!\!\!\perp D_j \mid X_j$,

where Y_{1j} and Y_{0j} are potential outcomes for the firm if it wins or loses a subsidy.

Our identification strategy exploits the fact that the subsidy program induces quasi-exogenous variation in selection into technology adoption. We compare subsidy-receiving firms to firms that applied for subsidies but did not receive them. Because the sample includes only pre-screened applicants to the subsidy program, these comparisons control for differences between technology adopters and nonadopters that originate in the decision to apply for technology subsidies. Again, pre-screened non-winning applicants probably provide a better control group for technology adopters than conventional samples because they have indicated a strong interest in technology adoption. But such comparisons do not control for all criteria used by the program to decide which applicants to accept. The data analyzed here contain information on most characteristics used by the program to accept applicants, including the evaluation report itself. Therefore, the remaining selection bias induced by the decision stage can be eliminated using regression techniques or matching by the information used in the decision process.

Table 1 reports summary statistics for the treatment and control groups. The groups are reasonably similar in terms of revenue, employment, and worker composition. The main differences are that the losing firms are smaller and applied for smaller subsidies. While our design is based on comparing short-term trends between the treatment and control, the pre-period level differences motivate our matching strategy in the next section.

[12] This leaves out some potential technology subsidies, for example, for hotels' online reservation systems.

[13] Some applications are low-value, and we focus on ex-ante higher-value subsidies similar to the approach in Kline et al. (2019). In Section V, we show the results are robust to alternative treatment-group definitions.

[14] The main reason for this restriction is to ensure that employment and skill estimates come from the same sample; skill shares are only defined for existing firms. We show the results are robust to a non-balanced sample (Table A13) and separately analyze firm survival (Figure A15).

An alternative and important counterfactual is similar firms that did not apply for subsidies. We use coarsened exact matching (CEM; Iacus et al., 2012) to define these similar firms. This matching strategy addresses the concern that the losing firms are not a reasonable counterfactual for what would have happened if the approved firms had not received the subsidy. We match by revenue, employment, and wages at $\tau = -3$; 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. We define matched control samples for both winning and losing firms; the latter is a placebo test. Tables B1 and B2 show the covariate balance for the matched samples. The matched control groups also serve to assess whether the patterns in the losing firms are typical or specific to the losing applicants.

III.C Text Matching

We demonstrate a novel method of crafting a research design by controlling for program participants' underlying differences using text data. The subsidy records contain a report written by the officer evaluating the application. Given similar reports, treatment assignment is more likely to reflect quasi-random variation than systematic differences. The reports record qualitative characteristics related, for example, to the firm's future trajectory. Text matching methods allow us to control for these characteristics (see, Romer and Romer, 2004; Roberts et al., 2020; Mozer et al., 2020).

Our main text-matching method controls for propensity scores computed from evaluation reports of applications. The propensity score is a predicted probability that conditional on a text (W_j), the firm will win a subsidy:

$$p(W_j) \equiv P\left[D_j = 1 | W_j\right]. \tag{3}$$

The propensity score theorem (Rosenbaum and Rubin, 1983) states that, in principle, controlling for the probability of treatment allows for satisfying Assumption 1. Propensity scores are valuable in this context as a dimension-reduction tool as directly controlling for texts is not feasible.[15]

The subsidy records contain three types of texts that track the decision process: (1) description, (2) evaluation, and (3) decision texts. The description and evaluation texts are written by a middle-rank officer responsible for administrating the subsidy and presenting it to a manager for a decision. We use the evaluation texts to compute the propensity scores as they are most likely to capture potential differences between the firms. Based on our interviews, the subsidy officers' goal is to present an unbiased evaluation.[16]

The text propensity score method works in three steps.

1. We represent the text as data. We use a vector representation based on word embedding. In particular, we employ the FastText (Bojanowski et al., 2016) library for the Finnish language. The advantage of the vector representation is that it captures the semantic meanings of the text instead of a word collection. This is helpful in our context because our goal is to extract

[15] There is only one report for applicant firm j, and hence the propensity score $p(W_j)$ contains only subscript j.

[16] The evaluation text is available for 89% of the main analysis sample.

information from the evaluations beyond clear markers of success or failure. The pre-processing of the texts is detailed further in Appendix F.C.3.

2. We estimate the propensity scores using the data. We use a machine learning method, support-vector machines (SVMs), to calibrate the word vectors into probabilities. We train the model on all possible subsidy applications. The probabilities are calibrated using Platt scaling: a logistic regression on the SVM's scores, fit by five-fold cross-validation on the training data (Zhang, Damerau and Johnson, 2002).[17] Figure 3 provides the calibration plot for our analysis sample: The predicted probabilities based on text data are on the x-axis and the probability of subsidy receipt on the y-axis. The predicted probabilities closely match the empirical probabilities.[18]

3. We control for confounders using the propensity score. Regression adjustment is our preferred approach. We compare the estimates to coarsened exact matching (CEM) and inverse probability weighting (IPW; Hirano et al., 2003).[19]

As an alternative text-matching method, we use cosine similarity. It measures similarity between two non-zero vectors of an inner product space:

$$\text{cosine similarity } = \frac{\bar{A} \cdot \bar{B}}{\|\bar{A}\| \|\bar{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}, \tag{4}$$

where A_i and B_i are components of vector $\bar{A}$ and $\bar{B}$. Cosine similarity allows us to directly compute a similarity score between the texts' vector representations without projecting them first to a single-dimensional propensity score. A conceptual difference is that the propensity score measures the text's predictive power on treatment assignment, while cosine similarity detects overall similarity between evaluation texts. We construct a matched sample for the winners by selecting the nearest-neighbor from the losing firms with replacement. We choose a lower bound for the similarity as 0.85 to ensure a close match but the results are robust to this choice. Table A2 reports the summary statistics for the cosine-similarity matched sample.

Opening the Black Box The propensity score summarizes the evaluation text into a single number between 0 and 1, reflecting the likelihood of winning a grant. Because we construct the propensity scores from evaluation reports, they capture critical information managers use when deciding whether to award the subsidy. Recall that all applications in our sample have gone through pre-screening and thus have a realistic opportunity to win a grant. Adjusting for the scores then

[17] Hastie et al. (2001) suggest selecting five or ten folds for cross-validation to balance bias and variance, following findings from Breiman and Spector (1992) and Kohavi (1995).

[18] We calibrate the propensity scores with all possible applications, including exports and R&D. The propensity scores are robust to fully out-of-sample calibration but less precise. We estimate standard errors by bootstrap.

[19] There are multiple ways to implement each of these steps: represent the text as data, model and estimate $p(W_j)$, and use $p(W_j)$ to control for the underlying differences (Angrist and Pischke, 2009; Gentzkow et al., 2019). The results are broadly robust to each method we have implemented.

aims to control for factors that are not directly observable (as numbers) or known ex-ante but predict the acceptance decision and potentially the outcomes of interest.

Researchers often face a trade-off between prediction accuracy and model interpretability when using machine learning (James et al., 2021). Here text matching aims to create accurately predicted probabilities. When using word vectors, there are limited methods to pinpoint the text features driving specific propensity scores—an issue that ongoing research (e.g., Ludwig and Mullainathan, 2024) is beginning to address. However, we can build intuition by returning to the text data: investigating specific cases, and systematically analyzing features that predict winning the grant. Delving deeper into the text data also complements our interviews, allowing us to construct a more comprehensive understanding of the program.

Table A3 shows examples of successful and unsuccessful applications with identical propensity scores. The text data are confidential: These cases are translated, anonymized, and chosen to be representative, but we caution against overinterpreting specific cases.

Examining application descriptions (not used for matching), we find that applications with the same propensity scores are relatively similar. The descriptions typically list technologies and some contextual details. For example, the winning and losing cases include "investments [in] a flatbed laser, welding robot, deep-drawing equipment, etc." and replacing "old machinery with a new computer-controlled engraver." Descriptions are also relatively similar across different propensity scores.

Analyzing evaluation texts (used for matching), we find that evaluations with similar propensity scores are similar, but those with different propensity scores are different. At the higher end, evaluation texts are consistently positive. For example, the 0.94 winning case details: "the flatbed laser enhances the competitiveness [...]" The 0.94 losing case similarly states: "The acquisition of a new engraving machine will speed up delivery times and increase quality, delivery reliability, and capacity." At the lower end, winning and losing applications often discuss the project's pros and cons. For example, a 0.50 winning case describes that while the project is modest, it could still be eligible because it could be a prerequisite for further investments.

More systematically analyzing these patterns, Figure A2 documents that words reflecting the project's significance ('significant' and 'high-quality') and technical terms ('statement' and 'report') predict subsidy approval. Conversely, words linked to rejection cover the same themes in negative terms (for example, 'minor,' 'conventional,' and (likely missing) 'information'). Reassuringly, the word 'approve' strongly predicts grant approval, and 'negative' predicts rejection. Longer descriptions weakly correlate with higher approval rates, but text length does not predict propensity scores, as shown in Table A7.

Our main observation is that despite some differences, the evaluation texts between different propensity score levels above 0.60 appear relatively similar. For example, the 0.94 and 0.78 evaluations are both positive compared to the 0.5 cases. One interpretation would be that the propensity scores fail to capture the key elements predicting acceptance. The evidence from the texts and our interviews with the program officials offers a more likely interpretation: Many applications are relatively similar to one another, and the decisions are thus more heavily based on idiosyncratic factors rather than differences in evaluations. While this makes text matching less powerful in our context, it lends credibility to our research design more generally. Table A11 confirms that even when removing applications with top and bottom 5%, 10%, and 20% of the propensity score values in our sample, the main results remain qualitatively similar.[20]

Finally, we manually analyze the alternative cosine similarity approach. Unlike the propensity score, this method mechanically creates matches with similar description texts. The matched texts share a substantial amount of semantic content. For example, 'Purchase of CAD-Cam software' and 'Financial management software, computer, fax' have a similarity of 0.94. Using vector representation rather than matching word-by-word, we focus on pairs of semantically close evaluations according to the vector representation's embedded understanding of the Finnish language.[21]

IV Data on Workers, Firms, and Subsidies

We construct a novel linkage of several administrative datasets that provide panel data on subsidies, firms' technology and performance, and workers' employment and skills.[22]

IV.A Workers

Our data track all individuals in Finland over time, independent of their labor market status. We measure employment and wages from Statistics Finland's registers. We link these data to various skill measures: education (level and type), 9th-grade GPA, high-school exit exams, and cognitive and personality assessments from universal male conscription. Occupations are classified at the 3-digit ISCO level based on employment records. To analyze occupational tasks, we use the European Working Conditions Survey (EWCS), which provides task data collected through face-to-face interviews.[23]

[20] Table A4 displays decision texts that, while not factored into propensity score calculations, provide information about grant applications. Positive decisions often echo their evaluation reports. For instance, a decision for an application with a 0.94 score explicitly endorses it: "The project raises the technological level of the company's production and improves its long-term competitiveness." In contrast, rejections often articulate specific deficiencies. For example, a decision rejects a 0.94 score application by stating the second-hand machine has minor value and lacks sufficient importance. For a 0.78 score, the rejection specifies the ineligibility of the industry and the preemptive start of the project as disqualifying factors exacerbated by depleted funds at that point. A decision with a 0.50 score cites industry restrictions, competition effects, grant effectiveness, and procedural flaws as reasons for application failure.

[21] Examples of matched text pairs:

1. 'Acquiring a CNC machine.' and 'Acquiring a CNC milling machine.' Similarity: 0.992.
2. 'Purchase of CAD-Cam software.' and 'Financial management software, computer, fax.' Similarity: 0.940.
3. 'Expanding operation. Constructing new facilities and acquiring machinery and equipment.' and 'Production hall construction and machinery and equipment investment.' Similarity: 0.854.

When using cosine similarity, we match the applications on the short version of the description texts available in the text data instead of the longer evaluation reports (the first sentence in the description columns on Table A3).

[22] Appendix F provides comprehensive details of the data. To ensure consistent measurement, we developed new crosswalks to harmonize Finnish occupation, industry, and geography classifications, accessible at joonastuhkuri.com.

[23] We develop measures for routine, manual, abstract, social, and cognitive tasks at the occupation level building on Kauhanen and Riukula (2024). EWCS has two advantages in our context: the survey responses come from European countries (we use data for Finland, Sweden, Denmark, Norway, and Germany to trade off relevance and statistical precision) and the data link directly to our ISCO occupational classification.

IV.B Firms

Our primary source for technology investments is the Finnish Financial Statement Register, which provides data on firms' machinery investments and IT expenditure. Machinery includes hardware such as CNC machines and robots. IT expenditure covers software and consulting services, excluding internal staffing costs. Statistics Finland compiles these figures from tax registers and through direct data collection. The dataset covers all major Finnish industries from 1994 to 2018.

We use four additional types of data on technologies. (1) Text data from the subsidy program enable us to investigate firms' motivations for receiving grants. We code each application into categories that describe firms' technologies (e.g., robots, CNC machines) and intentions (e.g., expansion, new products, quality). (2) Survey data from the EU Community Innovation (CIS), ICT, and Etla surveys give us a view of firms' technology plans and their environment. (3) Literature-based data from the SFINNO project, drawing on articles from 15 trade journals and linked to our sample firms, provide unique qualitative information on technology investments. (4) Customs data record 621 types of imported machinery, enabling a comparison between automated vs. non-automated technologies, building on Acemoglu and Restrepo (2022). We provide information on each dataset and how we code the variables when we present our results.

We measure firm performance—revenue, productivity, and profits—from the Financial Statement Register. We gauge productivity by revenue per worker and total factor productivity (TFP), calculated via the Cobb-Douglas production function, and for robustness, using methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003). We winsorize firms' monetary values at the 5% level and deflate all economic values to 2017 euros using the Statistics Finland CPI. Export data, including destinations and the number of products, come from the Finnish Customs Register; we classify products at the 6-digit CN level and track new and discontinued items. We derive product prices from the revenue per unit sold, using information from the Customs Register and Industrial Production Statistics. R&D and marketing expenditure data come from the Financial Statement Register. Patent data come from the Finnish Patent Database.

IV.C Subsidies

The ELY Center subsidy dataset tracks the application process from submission to decision for both successful and unsuccessful applications. Industrial subsidies are often difficult to measure (Kalouptsidi, 2018). This confidential dataset offers direct firm-level measurement that has not been systematically assembled by researchers before.[24] The dataset includes unstructured text data, generated as part of the application process. We use these text data for three purposes: text matching, identifying technology subsidies, and measuring firms' intentions.[25]

[24] We track other potential received firm subsidies using Statistics on Business Subsidies.

[25] Many policy programs and firms' decisions leave a trail of text records. Researchers can use these texts as data to measure aspects that would be otherwise hard to measure. A novel part of our research is to measure technologies directly within firms. Recent research uses text data, especially patents, to measure other technological changes (Alexopoulos, 2011; Atalay et al., 2020; Autor et al., 2024; Howell et al., 2021; Hémous et al., 2025; Kalyani et al., 2025; Kogan et al., 2023; Mann and Puttmann, 2023; Webb, 2020).

This section details our method for identifying technology-related subsidies within the dataset, which includes 42,909 applications across categories such as technology, export, R&D, and startup grants. While these categories are routinely recognized by ELY centers, they are not explicitly coded in the dataset and instead appear in the application texts. Our method follows a two-step process: We first manually code half of the applications to establish a benchmark, then use support vector machines (SVM) to automate and extend the coding to the remaining applications. Appendix F provides details on the classification.

We code 21,210 randomly selected texts as technology-related or not. This step is manual. To identify technology subsidies, we focus on the description texts written by program officers. These texts provide information on firms' plans because the plan is binding: firms only receive subsidies against verifiable costs mentioned in the application. We aim for an understandable classification that is not a very specific or broad view of technological change.

Our decision rule is simple: the text must explicitly mention a technology or technological advancement. We interpret technology in its everyday sense. Robots, CNC machines, laser cutters, and CAD software, and upgrading production methods or modernizing production are counted as technologies. In most cases, technology applications involve acquiring new machinery and equipment. On the other hand, non-technologies include export promotion subsidies ("starting to export in the Nordics"), R&D projects that don't involve adopting new technology ("a new rifle support device"), and starting new businesses ("starting to mine nickel ore"). While this could be a nuanced issue, in our context, the decision rule is fairly straightforward, often clear from the application title. Table A5 provides anonymized examples of texts we classify as technology and non-technology.

Our design captures technological changes mainly involving new machinery and equipment, reflecting the focus of the subsidy program. But not all technological advances fit this category. Our coding and the program itself exclude cases like productivity gains not linked to technology adoption, R&D, organizational changes, and technologies in new firms (since our event study needs a pre-period). We use a conservative approach, classifying a case as technology only when it clearly meets the decision rule. Ambiguous cases, though uncommon, were cross-checked by multiple coders.

We then use machine learning (ML) to code the remaining 21,699 texts. ML is used only to scale the manual classification. We pre-process texts into a clean format, use the bag-of-words representation with TF-IDF weights, and employ support vector machines (SVMs) for prediction. The pre-processing, weighting, and prediction are described in Appendix F.

Our method achieves 95% accuracy in predicting technology applications in the pool of all applications (Table A6). To explore what the ML algorithm picks up, Figure A3 presents features that best predict being in the technology category. The predictors for technologies are intuitive. The top positive predictors include machine, line, device, cutter, CNC, and robot. These features also illustrate what our manual coding determined as technologies. The top negative predictors include markers for the other categories, R&D, internationalization, and 'launch.' To cross-validate the classification, we manually re-checked the applications in our main design.

As an alternative coding approach, we employed K-means clustering to see whether an unsupervised learning method provides a similar classification (Steinley, 2006; Bonhomme et al., 2019).

The unsupervised learning method uncovers four clusters of texts related to technology, R&D, exports, and starting a new business. This observation, combined with interviews with subsidy officers, increases confidence that our supervised classification captures meaningful categories.

V Main Estimates on Employment and Skills

Core estimates show how technology subsidies affect employment, wages, and skill mix. The main result is clear: We find no evidence that technology subsidies reduce employment or bias the skill mix across a comprehensive set of skills. The estimates show that after winning a technology grant, firms invested sharply more in machinery and hired more workers, but did not alter their skill composition. Before receiving a technology subsidy, winners and losers had similar trends in investment, employment, and skill mix. Results are robust to conditioning on text-propensity scores and additional covariates. The RD and spikes designs in Appendices C and D show similar results.

The First Stage Figure 4 shows the first-stage event-study estimates β_τ from Equation 1, with technology investment as the outcome, measured by machinery and equipment investment. Winning a subsidy is associated with a sharp increase in technology investment. Before the subsidy application, the groups follow parallel trends. Figure A4 shows alternative first-stage estimates for all possible subsidies granted and received. The results indicate that winners and losers are granted a different amount of subsidies exactly in the event year, not before or after. The pattern for received subsidies matches technology investment. Table 2 reports first-stage estimates for the main winners-losers design, both with and without text matching. Outcomes include technology subsidies, technology investment, and capital. The first stage remains robust when controlling for the text propensity score. We return to analyzing the specific types of investments in Section VI.

Employment and Wages Figure 5 displays the event-study estimates β_τ from Equation 1. The outcome is employment relative to the base period $\tau = -3$. The estimates indicate that technology subsidies led to approximately 20% higher employment in the five years after receiving it. As the figure shows, the employment pre-trends were similar between the treatment and control groups. Figure 8 visualizes and Table 3 reports the first-difference estimates from Equation 2, with and without the text propensity control, and with the matched non-applicant control group. These estimates combine the multiple event-study estimates into a single number. The specification with the propensity control indicates a statistically precise 23% increase in employment.

Another way to assess the potential replacement effects of advanced technologies is through the labor cost share. It measures the share of revenue a firm pays workers—a telltale sign of task automation (Acemoglu and Restrepo, 2018b; see also Kehrig and Vincent, 2021; Grossman and Oberfield, 2022). We find a precise zero estimate, reported in Table 3. We also generally find zero effects on wages; in some specifications, there is a small, statistically insignificant negative effect. This absence of wage effects at the firm level could reflect sector-wide collective bargaining, where these SMEs exert limited influence on wages. The zero effects could also mask different mechanisms.

On the one hand, technological advances may exert downward pressure on wages, but this effect might be counterbalanced by the increased wages necessary to recruit additional workers if firms face upward-sloping labor supply. On the other hand, technological advances may exert upward pressure on wages, but unobserved reductions in the skills of the new hires may offset this effect. We describe the local labor markets these firms operate in at the end of Section VIII.

Figure A6 presents the effects on incumbent workers, those employed at the firm before the subsidy event but not restricted to it afterward. We generally find small effects: a 0.5% positive effect on employment but approximately the same-sized negative effect on the likelihood of staying in the treated firm. We find an income bump at the time of application of EUR 500, potentially reflecting additional hours during technology adoption or rent-sharing from the grant.

The employment estimates are similar when using the matched non-applicant control group (Table 3 and Figures B1, B3), regression discontinuity design (Figure D4 and Table D4), and spikes design without subsidies (Figures C3, C5). The employment results are also robust to different text matching versions (Table A8), different controls (Tables A9, A10), and are clearly present in the mean graphs that compare the treatment and control group means over time (Figure A5).

Skill Composition Figure 6 displays the event-study estimates for the main firm-level skill measures: the average years of education, college-educated workers' share, and production workers' share. We find no change in these measures, either before or after the technology subsidy. Figure 7 summarizes the estimates and Table 3 reports the numerical values. Our 95% confidence interval excludes over 0.15 year changes in the average years of education. The results stand in contrast with the view that technology subsidies would necessarily increase the share of more educated workers and decrease the share of production workers in manufacturing firms. We observe that trained machinists and skilled welders were needed before and after the subsidy receipt. The main skill-composition estimates hold in all our research designs and are robust to a variety of controls referenced in the employment results, including text matching.

We zoom into more detailed skill outcomes: education groups (Figure A7), occupation groups (Figure A8), cognitive performance (Figure A9), school performance (Figure A10), personality (Figure A11), demographics (Figure A12), and task composition (Figure A13). The big picture is that the effects are primarily skill neutral in the sense that the skill composition does not change. Another central observation is that the baseline skill levels of workers in the sample firms are well below the median. For example, the average cognitive performance is 0.3 standard deviation lower than the average population, and the average 9th grade GPA is 0.56 standard deviation below the population average. The sample workers also score lower in tests designed to measure personality traits valued by the Finnish Defence Forces, such as achievement aim and dutifulness. The only personality trait the workers score higher than average is masculinity (+0.15 standard deviation). We return to the role of baseline skills in Section VIII. Finally, there are some patterns of changes in the skill composition that are consistent with the observations from our fieldwork, while not statistically significant and subject to multiple testing concerns. The treatment effect on average school GPA is 0.1 standard deviation (Figure A10), and the treatment effects on activity-energy, achievement aim, and sociability are 0.05 standard deviation (Figure A11). The managers and workers we interviewed pointed to these traits as complementary to advanced technologies, in contrast to higher education or non-production occupations.[26]

Selection Bias A natural concern when estimating the impact of industrial subsidies is bias due to a potential correlation between subsidy receipt and recipients' unobserved characteristics. These concerns are less likely to be important in our setting (as described in Section III) because comparisons by recipient status are restricted to a sample of applicants to the program. Non-winning applicants probably provide a better control group for winners than conventional cross-section samples because, like winners, all applicants have indicated a strong interest in technology adoption. Moreover, the data analyzed here contain information on most characteristics used by the subsidy program to screen applications. The selection bias induced by subsidy program screening can therefore be eliminated using regression techniques or by matching on the covariates used in the screening process. Our results are robust to controlling for the pre-application characteristics and the evaluation report texts (Tables 3, 5, A8, A9, and A10).

Our text data allow us to qualitatively explore the robustness of our results. To investigate whether the rejected applications are reasonable counterfactual for the approved applications, we examined the approved and rejected applications in the analysis sample. We found ten rejected applications that did not seem likely to receive subsidies in any situation: either the entrepreneur had a concerning history or the firm's financial position was unstable. Our results are robust to excluding these applications.

Text propensity scores enable us to narrow the sample to specific types of applications. A potential concern is that particularly good or bad applications, or undesirable comparisons between them, might drive our results. Table A11 addresses this concern by excluding applications with the highest and lowest 5%, 10%, and 20% propensity scores. The results continue to be robust and consistently point in the same direction.

We also find similar effects when using a matched non-applicant control group (Table 3). As a placebo test, we contrast losing firms to matched non-applicants (Figure B1). We find no first stage on investment and a small positive transitory effect on employment, indicating that the subsidy losers grew somewhat faster than similar non-applicant firms.

We use three different research designs: (1) the winner-losers design, (2) a regression discontinuity design using unanticipated changes in the subsidy program rules (Appendix D), and (3) an event-study design focusing on technology adoption events (Appendix C). These designs generate similar results. This suggests that selection bias in any single design is unlikely to drive our results.

The remaining concern is selection bias common to all our research designs. The concern would be that none of the control groups we analyze here represents a reasonable counterfactual for subsidy recipients. To address this concern, we can analyze trends in treatment firms without any control group. Figure A5 shows the evolution of treatment group means for machinery investment,

[26] Managers and workers emphasized the non-cognitive skills required: initiative, cooperation, and adaptability, and that workers perform multiple tasks. One CEO explained: "A company does not just pay a welder to weld."

employment, and years of education. Machinery investment increased sharply after the technology subsidy application; winners increased their employment but did not change their skill composition disproportionately.

Statistical Power A concern particularly relevant to presenting a null result is statistical power. Are our results precise and technology-adoption events large enough to justify our conclusion about no significant changes in skill composition measured by education and occupation? The estimates with the text propensity score indicate a -0.004 change in the average years of education at the firm level, with a standard error of 0.075 years, meaning that we can exclude over 0.15 year increases in the average education. In comparison, the treatment and control firms increase their education on average over the 11-year event window by 0.4 years.

Statistically, the null effects are unlikely to be driven by small events: (1) The average effect on machinery investment is EUR 100K, which doubles the firm's annual investment. This is a lower bound, as the purchase price covers only part of the total cost. In US manufacturing, Berger (2020) documents that machinery costs account for just 25% of the total investment, with the remainder covering installation, the machine bed, and integration work. (2) The subsidy program requires technology investments to represent significant advances for the firm. (3) We also examine large technology investment events in the spikes design (Appendix C) and find no effect on skill mix, measured by education and occupations. We address how the relatively small grants affect our interpretation in Section VII.

Estimation Methods We probe our results' robustness to different estimation methods. Recent research proposes new estimators that address issues that arise when estimating dynamic treatment effects (Borusyak et al., 2024; de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Figure A14 shows consistent results across these novel estimators. This robustness likely stems from our design choices: focusing on a control group never treated and a treatment group experiencing a single treatment shift.

When we defined our treatment group, we selected the largest subsidy event from firms with multiple applications to ensure we focus on meaningful events. The first stage (Figures 4, A4) shows that this choice effectively isolates distinct technology-subsidy events. This approach is loosely related to Kline et al. (2019), who focus on ex-ante high-value patenting events. We examine the robustness of our results to this choice in Table A12.

Panel A narrows our analysis to firms with only one subsidy application, successful or not.[27] Consistent with our main results, we observe a robust first stage, rising employment, and no educational shift. Here, the effects are subdued: halved for the first stage and reduced by 30% for employment. This aligns with these firms applying for grants 50% smaller on average, at EUR 64K for recipients and EUR 45K for non-recipients.

[27]This trims the sample to 1,011 firms. 51% had a single application from 1994 to 2018, while 36% had two to three, and 10% had four to five. These predominantly represent multiple successful applications; only 0.5% (ten firms) had two, and one had three rejections. Figure A4 suggests that the potential multiple applications tend to be small compared to the largest application in the 11-year window.

Panel B selects the first subsidy application in the data to serve as the treatment or control. Focusing on the first application maintains the sample size nearly unchanged, with minor adjustments from applying sample restrictions. The findings here mirror our primary results. Note that defining a first application is somewhat arbitrary in our context: first refers to the earliest recorded since 1994 in our dataset, not necessarily the company's actual initial application; the subsidy program's history spans several decades.

Finally, we focus on a balanced panel of firms because our primary interest, skill composition, can only be measured in existing firms. For comparison, results from an unbalanced panel are reported in Table A13. Compared to the balanced panel, we observe larger but consistent effects. Figure A15 directly examines firm survival, indicating incremental impacts: the effects are 10% or less within the first five periods.

VI Understanding Firm Responses

To recap our main results, we have found that the EU technology subsidies were associated with increases in employment and no changes in skill composition. The second part of the paper explores possible mechanisms for what may have happened at the firm level.

Based on our fieldwork, we first outline two potential mechanisms for how firms could react to technology subsidies. On the one hand, technology subsidies may cause firms to use technologies to automate human tasks. On the other hand, the subsidies may enable firms to expand or allow them to do a different set of things with potentially limited effects on productivity. The main point is that technology subsidies could lead to several different outcomes, and their firm-level effects are an open empirical question.

We then use several datasets and approaches to shed light on the mechanisms at play. We find that technology subsidies led to higher revenues without changing firms' productivity. Firms entered new markets, changed product mix, and increased marketing. In the subsidy application texts, firms wrote about their plans to expand rather than automate. Survey responses show that developing customer-specific solutions and realizing market niches were typical motivations. While our data have limitations, and firms often implemented a combination of changes, our observations are consistent with the view that the subsidies primarily encouraged expansion (or scaling up).

VI.A Conceptual Motivation

The idea is simple: Subsidies lower the effective price of technology, but firms choose which technology to adopt and how to use it. We outline two stylized mechanisms of how firms might respond to subsidies aimed at supporting technology investment.[28]

[28] Appendix G present these ideas in a simple model, building on Melitz and Redding (2014). The key ingredient is imperfect substitutability between products, which allows technology to generate new horizontal product varieties—following the logic of standard growth models (Romer, 1990)—not only increase productivity.

Consider the composite function:

$$F\left(T_E; f\left(T_I; X\right)\right). \tag{5}$$

The inner function $f(\cdot)$ captures how firms combine inputs X with technology T_I. The outer function $F(\cdot)$ maps this into market outcomes, using a different set of technology T_E. This setup helps illustrate two broad channels through which subsidies might operate.

In one view, subsidies accelerate automation. Firms adopt technologies that replace human tasks, cut costs, and raise productivity. The intensive margin, $f(T_I; X)$, captures this idea: technology changes how existing inputs are used. A welding robot that substitutes for a skilled welder is a textbook case. Models by Acemoglu and Restrepo (2018a,b) and Acemoglu et al. (2020b) formalize this channel, where task automation lowers labor shares, raises productivity, and may increase skill demand if low-skill tasks are displaced.

Another view is that subsidies support expansion—helping firms enter new markets, develop new products, or simply scale up operations—without fundamentally altering how production is done. This is the extensive margin, $F(T_E; \cdot)$. In the *Moore's Law for Pistons* example, the firm used new machines to make new kinds of pistons, not to automate away labor. The effects on employment and skill demand are ambiguous (as they are also in the case of automation) and depend on how—and where—the expansion takes place.[29]

The point is that technology subsidies have uncertain effects. Subsidies may support automation, but not all machinery investments automate tasks (Restrepo, 2024). Some could instead help firms scale up or improve quality, with limited impact on workforce composition or productivity. In the end, empirical evidence is needed to understand how subsidies shape firm behavior and employment. Next, we track a broad set of outcomes—exports, product mix, patents, R&D, marketing, and prices—to capture how treated firms evolved. We then use application texts and survey responses to learn how firms said they would use the new technology.

VI.B Evidence on Firm Performance

We now turn to firm outcomes. Tables 3 and 4 summarize the results. We find increases in revenue, exports, product turnover, marketing, and prices. In contrast, we observe no changes in productivity, profit margins, or capital intensity. We conclude by discussing magnitudes and dynamics.

[29] Related concepts include automation vs. augmentation (Autor et al., 2024), automation vs. horizontal innovation (Hémous and Olsen, 2022), cost vs. differentiation (Porter, 1985), and process vs. product (Utterback and Abernathy, 1975). We could also consider these as the textbook case of substitution and scale effects. If higher productivity leads a firm to expand its product line, as in Bernard et al. (2011), the line between expansion and automation becomes blurred. While we abstract from different factors in X, we can explicitly write it, for example, as $F(T_E; f(T_I; K, L_H, L_L))$, to clarify the relationship between technology T_I, capital K, and high- and low-skilled labor L_H and L_L. T_E can be viewed as Hicks-neutral productivity term (not affecting the balance of labor and capital), while T_I embeds both capital and labor-augmenting changes with two different types of skills (see also Acemoglu, 2003; Acemoglu and Autor, 2011; Lewis, 2011).

Revenue, Productivity, and Profits Figure 8 and Table 3 report the first-difference estimates from Equation 2 for revenue, productivity, and profit margin. We find that technology subsidies led to approximately 30% higher revenues in the five years after. In contrast, we find no evidence of changes in productivity or the profit margin. The results are robust to controlling for the text propensity scores and comparing to the matched non-applicant control group.

We measure productivity as revenue per worker and TFP using the Cobb-Douglas production function. Revenue per worker is robust to different production functions and our preferred measure. TFP is not ideally suited to measure firm performance in our context because some firms change their product mix (as we will show later). We also estimate TFP using the Olley and Pakes (1996) and Levinsohn and Petrin (2003) methods and find null effects (Figure A18).

Firm survival, often cited as a measure of firm performance in our interviews, improves with subsidies, as shown earlier in Figure A15. This is relevant for interpreting our productivity results: We see no productivity effects, but productivity is only observed for the surviving firms.

The zero productivity effects are consistent with the existing evidence: Criscuolo et al. (2019), Curtis et al. (2022), and Cerqua and Pellegrini (2014) who observe no productivity effects from capital-investment incentives in the UK, US, and Italy.

Table 4, Panel E, reports more detailed estimates on profits. The average profit margin is 5.2% and the subsidies do not appear to increase the profit margin, as noted before. But as the firms expand, winning a subsidy leads to an increase in gross profits by EUR 143.5K and net profits by EUR 123.6K over the post-period without discounting. Discounting the future profits at a 5% rate yields present-value net profits of EUR 95.8K, and at a 10% rate, EUR 73.7K. The average received subsidy (EUR 81.77K) falls within the 95% confidence intervals of both, suggesting that the data are consistent with a hypothesis that profits increase approximately one-to-one with the subsidies.[30]

Exports and Products Figure 9 visualizes the event-study estimates for firms' export status. Subsidy winners are more likely to become exporters. Table 4, Panel A, reports an effect of four percentage points from the baseline of 28%.[31] The effect on the exports' revenue share is 0.9 percentage points from the baseline of 5.2%. The winners exported to an additional 0.2 regions from the baseline of 1.5.

Export data allow us to examine changes in exported products and product mix. Table 4, Panel A, reports an effect of 0.15 products from the baseline of 1.55 products per firm. We also observe an increase in product turnover: treatment firms both introduce and discontinue products at higher rates. However, subsidy-winning firms switch between products and regions that have the same skill intensity (Table A14). Overall, exporters had more educated workforces than non-exporters, both in Finnish manufacturing and our sample.

The increased exporting as a response to technology subsidies is consistent with the idea that access to capital and foreign markets are complements, echoing Lileeva and Trefler (2010) and Koch

[30]Our sample includes only seven publicly traded firms, preventing analysis of subsidy decisions on stock values.

[31]The definition from Statistics Finland identifies a firm as an exporter in a given year if its annual exports exceed EUR 12K across at least two months, or if it has a single export transaction exceeding EUR 120K.

et al. (2021). Some research observes that exports and new products tend to be skill-biased (Bernard and Jensen, 1997; Xiang, 2005; Matsuyama, 2007). A potential reason why we do not find skill bias here is that these changes are a normal part of how these firms operate. We observe in our fieldwork that these manufacturers have short production runs, identify shifts in demand, and redeploy their productive resources to new uses using new technologies.[32]

Inputs and Imports Table 4, Panel B, examines firms' input use. While subsidies increased machinery investment, this did not lead to higher capital per worker. We also find no change in input intensity, measured by the share of input costs to revenue. These null results align with our finding of no effect on labor productivity: Firms did not make production more capital- or input-intensive but scaled operations proportionally. We observe a slight increase in imports relative to revenue but overall, firms' (relative) input use remained unchanged.

Patents, R&D, and Marketing We next analyze three outcomes tied to different stages of innovation: patents, R&D, and marketing, reported in Table 4, Panel C. A relatively clear picture emerges: We observe no effect on patenting, a small EUR 564 increase in R&D expenses, and a larger EUR 1,389 increase in marketing costs.

These results are consistent with the expansion view: Technology subsidies appear to have led to increased marketing and less so in technological development reflected in patents or R&D. Figure A19 plots the dynamics of marketing effects. Marketing is a relevant signal for the interpretation. If the firms were purely interested in automation and production costs, there would have been limited incentives to market that. If the firms, however, aimed to expand, potentially with new offerings, marketing could be valuable. These estimates also reflect how the subsidy program appears work: it supports firms scaling from idea to production (consistent with the ideas in Berger, 2013, and Gruber and Johnson, 2019).[33]

Prices Table 4, Panel D, reports price effects, measured from the Customs Register and Industrial Production Statistics (a survey of manufacturing firms). We compute prices as product-level revenue divided by quantity and focus on the firm-level unweighted average. We find a 29.1% increase in the customs prices and 30.8% in the manufacturing survey. The price data are noisy and cover only a subset of the sample, making these estimates more sensitive than our main findings. At a minimum, we do not observe price declines. Prices provide relevant information for contrasting automation versus expansion. Acemoglu et al. (2020b) clarify that automating firms expand by lowering prices.

[32] Earlier fieldwork in manufacturing SMEs in the US and Europe by Dertouzos et al. (1989) and Berger (2013, 2020) is consistent with these observations. Relevant research on exports, products, intermediate inputs, and technologies include Verhoogen (2008); Goldberg et al. (2010); Bernard et al. (2010, 2011); Bustos (2011); and Kugler and Verhoogen (2012). See also Hottman et al. (2016); Flach and Irlacher (2018); Argente et al. (2024); and Braguinsky et al. (2021) on product innovation, appeal, and differentiation.

[33] These results are less stable than our core estimates on employment, revenue, and skills. One reason may be that the underlying measures include many zeros and some large values. Future research may be able to study patenting responses more precisely in other settings.

In contrast, subsidies may have ambiguous effects on prices; for instance, quality improvements could raise prices (Khandelwal, 2010).

Magnitudes Table 5 reports the first-difference estimates from Equation 2 with a continuous treatment variable, the subsidy granted in EUR. The estimates indicate that EUR 1 in subsidies is associated with a EUR 1 increase in machinery investment. Firms' revenue increased by EUR 5.3 per EUR 1 of subsidies. We interpret these results cautiously because the continuous treatment is subject to additional selection concerns.

What is the implied cost per job from this industrial policy, based on our estimates? The employment increase is 0.25 jobs per EUR 10K subsidies, indicating a back-of-the-envelope estimate of EUR 40K (USD 45K) per job. This number matches what managers reported for machinery per worker in our interviews, often about EUR 35K. Our estimate is also close to the average among the cost-per-job estimates reviewed by Criscuolo et al. (2019). It is relatively close to the cost per job estimates of USD 43K by Pellegrini and Muccigrosso (2017) and USD 68K by Cerqua and Pellegrini (2014) in the context of capital subsidies to businesses in the least developed regions in Italy, and the estimate of USD 63K by Glaeser and Gottlieb (2008) for the US Empowerment Zones. Criscuolo et al. (2019) report an estimated USD 27K at the firm level, Siegloch et al. (2024) estimate USD 19K for regional subsidies, and Garrett et al. (2020) suggest that the bonus capital depreciation policy in the US had a cost per job between USD 20–50K.

Dynamics The employment effects increase gradually over five years after the subsidy (Figure 5). In our design, the quality of the comparison may decline over time. This makes it hard to tell whether longer-run effects are genuine or artifacts of the design. We extend the analysis to eight years after the application to assess longer-term dynamics (Figure A16). Most increases occur within the first four years post-intervention. The matched control version shows this more clearly (Figures B1, A16). Some increases occur after four years, though the 95% confidence interval does not rule out a flat trend. In contrast, the spikes design shows employment effects that initially increase but later become smaller (Figure C3). This may result from restricting the sample to firms without post-period spikes.

Other dynamic patterns also emerge within the five-year window after the event. Some outcomes react rapidly. The first-stage estimates show a sharp rise in investment rates between years 0 and 2, followed by a moderate increase (Figure 4). Exporting and marketing react quickly; effects appear in the application year and largely materialize by $\tau = 1$ (Figures 9, A19). In contrast, employment responds gradually (Figure 5). Firm survival also shows gradual effects, but estimates using the standard measure stabilize by $\tau = 3$ (Figure A15, Panel C). Skill mix remains flat throughout (Figure 6). Note that investment is a flow, whereas employment, survival, and skill mix are stocks, which naturally have smoother patterns. Our precision is limited in resolving patterns beyond increases, flat trends, or declines.

Retrospectively, these dynamics offer several insights. The positive contemporaneous effect on machinery investment suggests the subsidies were additive. We find no evidence of substitution from later periods for the treatment group. The control group does not catch up later. In short, subsidies raised overall investment rather than simply shifting the timing of machinery replacement (Cooper et al., 1999; our dynamic model in Appendix H).

A key question is whether the grants produced temporary or lasting improvements. The gradually rising effects on employment and firm survival favor lasting gains. Firms explained in our interviews that, when applying for subsidies, they already had an idea for how to expand with the funds. For example, in application texts, several firms cite responding to foreign demand as a reason to acquire new technology. This would likely show up in the data as an immediate increase in export status measured as an indicator, and later expansion in employment if the exporting was successful (consistent with the scaling up from a blueprint discussed by Berger, 2013, and Gruber and Johnson, 2019). By contrast, if automation were the main goal, we would expect to see higher productivity and lower output prices simultaneously with potential expansion (Acemoglu et al., 2020b). Our results do not show these dynamics (or these effects more broadly).

There are alternative explanations for the lasting effects. (1) The subsidy can make a decisive difference in whether firms continue to expand or face closure in the years following their application. (2) Firms may learn by doing, which induces extended growth (Lucas, 1984). (3) Receiving a subsidy might enable further upgrades, contributing to the gradual rise in employment and survival rates.

The literature on dynamic effects is mixed. Becker et al. (2018) find that EU grants led to temporary improvements that reversed when funding ended. In contrast, Curtis et al. (2022) document lasting employment gains driven by capital accumulation. Garrett et al. (2020) report enduring employment effects but only short-term earnings gains. Criscuolo et al. (2019) find persistent employment effects with no impact on wages, but note that losing subsidies led to negative employment effects. Some of these differences may reflect the level of analysis. We examine firm-level dynamics, whereas Becker et al. (2018) and Garrett et al. (2020) focus on local labor markets.

VI.C Text and Survey Evidence

We use three complementary sources to uncover firms' intentions: (1) subsidy application texts describing how firms planned to use the grants, (2) survey responses on technological goals, and (3) trade journal articles detailing firms' projects. Each source has limitations, but together they paint a consistent picture.

Text Evidence from Subsidy Applications The application texts offer a novel window into firms' motivations. Consider a firm buying a robot—a multipurpose technology. Some firms may use it to automate tasks previously done by workers; others may use it to expand capacity, introduce new products, improve quality, or shorten delivery times. Firms in our sample describe these intentions in their applications, which we analyze systematically.

Our approach is straightforward. We use the application records to answer the question: What did the firm plan to do with the subsidy? Previously, we examined how firms changed their operations after receiving the grant. Here, we focus on firms' plans prior to treatment. The analysis is descriptive rather than causal.

We hand-code each application into detailed categories that reflect firms' stated intentions. Table 6 defines these categories—such as expansion, new products, quality, productivity, and work—and gives representative examples. The categories are grounded in our fieldwork and reflect goals that firms described in interviews and the texts themselves. In practice, we read each application and assigned one or more categories based on concrete statements. The texts provide sufficient information for coding in 88.9% of cases (1,805 firms).

We use narrow, concrete categories to ensure that they capture clear and interpretable objectives. This approach allows us to document firms' goals as they describe them, without collapsing distinct intentions into broader groupings. We are conservative: A category is assigned if the text is concrete about it. For example, "new products" requires a direct mention of a new product, service, or business area. "Productivity" applies only if the firm refers to efficiency, cost savings, or a similar goal. A firm that writes, "The project contributes to improving the company's competitiveness as it expands the product range," is coded as "new products." Another that states, "The new production line increases the company's capacity by approximately 30–40%," is classified as "expansion." Appendix F contains full descriptions, additional examples, and details on the coding process.[34]

Figure 10, Panel A, presents the main findings from the text coding analysis. About 74% of firms reported expansion motives, such as growth, scaling up, or increased capacity. When we combine objectives directly tied to expansion—expansion, new customers/markets, and exports—80.1% of firms referenced at least one. Another 8.8% aimed to expand through vertical or horizontal integration, such as mergers and acquisitions.

New products (31.1%), quality (29.9%), and new capabilities or flexibility (29.4%) were common objectives. Firms often described new capabilities in terms of being able to offer customized solutions. Other goals included improved delivery (9.5%), precision (6.1%), and brand (4.2%). Overall, 64.5% of firms reported plans to modify their output—via new products, quality, delivery, branding, precision, or capabilities and flexibility.[35]

Fewer firms mentioned automation of work: only 13.9% referenced work-related motives. We group all mentions of technology aimed at reducing labor costs or improving labor productivity into a single category. This choice helps avoid understating work-related motives—especially important given the focus of the paper. The firms do not always distinguish between automation and other work-related objectives, so we cannot separate these categories reliably. To isolate narrowly defined labor-saving uses, we focus on firms that report work-related motives but do not mention changing

[34]Appendix F.C presents anonymized and translated examples that illustrate the text features leading to each classification. The original application texts are confidential and cannot be shared publicly. To ensure transparency, we recorded the specific passages that motivated each classification. Our coding approach is conservative: when a category assignment is uncertain, we leave it blank. The reported frequencies likely represent lower bounds. Some categories—such as exports, new products, and quality—tend to be clearly signaled by specific words or phrases, while others—such as capabilities/flexibility and adaptation—require broader interpretation and contextual reading and are potentially more uncertain.

[35]The "New Products" category requires an explicit reference to new products. In contrast, "Capabilities/Flexibility" refers to increased production potential without specifying a product. A related goal, "New Customers/Markets" involves targeting new customers or markets. "Quality" and "Precision" are coded separately, based on specific language. These categories help clarify firms' stated goals. Precisely distinguishing between them—especially in edge cases—is not central to the paper's core findings.

output—excluding new products, quality, precision, or capabilities/flexibility. Under this criterion, 4.7% of our sample could be classified as "work only." In either case, the findings suggest that automation was not the primary objective for many firms—at a minimum, these firms pursued additional objectives. The contrast with prior automation-focused studies may help explain differences in findings (Bessen et al., 2025; Feigenbaum and Gross, 2024).[36]

At the same time, productivity was a common stated goal: 51.6% of firms mentioned it. This stands in contrast to our earlier null results on measured productivity. Several explanations are possible. TFP might take time to materialize (though we do not observe trends within 5 years). Firms may have aimed to improve productivity but failed. In interviews, firms often used "productivity" to mean overall success—e.g., higher revenue or firm survival. They may have referred to productivity improvements in parts of their operations—"solving bottlenecks" as they sometimes described it—which eventually led them to hire more workers, and hence, there was no firm-level improvement in labor productivity (echoing standard scale effects). Finally, our productivity results condition on firm survival. For instance, 26% of firms cited adaptation to market conditions and often implied that, without the investment, their trajectory would have been worse. Understanding the lack of measured productivity effects—both in our setting and in similar programs studied by Criscuolo et al. (2019) and Curtis et al. (2022)—is an important direction for future work.

Table 7 examines heterogeneity in impacts by stated intentions. We define four groups based on application texts: (1) work only, (2) productivity only, (3) work or productivity only (the union), and (4) the complement group, excluding all three. The first three groups exclude firms that also mentioned new products, quality, precision, or new capabilities, in order to better isolate labor-saving or productivity-enhancing objectives that do not involve output change. For precision, we compare each group to matched non-applicants, since the "loser" subgroups are small. The results are as follows. (1) The work-only group shows some skill bias and the largest estimates on years of education, alongside a smaller employment effect. (2) The productivity-only group shows a 4.5% positive productivity estimate, though it is not statistically significant at the 5% level. (3) The complement group—firms not focused on labor-saving or productivity goals—shows larger employment effects than the other groups or the full sample.

One interpretation is that there is limited heterogeneity in treatment effects across stated objectives. Most firms in this context appear to have pursued expansion, though their strategies varied.

This text analysis has several limitations. (1) Classification is qualitative and requires judgment. There is inherent uncertainty around coding any specific goal. We address this by using concrete categories and avoiding overreliance on any single one. (2) Coding is based on what firms stated; lack of mention does not imply lack of intent. (3) Intentions are self-reported and firms may have framed their intentions strategically, for example by emphasizing expansion. Our main check is whether the patterns in the texts are consistent with patterns in the survey and trade journal data.

[36] The term *automation* in the application texts does not necessarily refer to the automation of work. It also describes automation in a narrow part of the production process—for example, automatic defect sensing in piston quality—or refers to the technology itself operating autonomously. However, the data include some cases of task automation, for example: "The machine requires fewer personnel resources than before. The sanding machine is a new acquisition; previously, sanding was done manually."

Survey Evidence on Firms' Intentions Survey data provide a complementary perspective. The EU's Community Innovation Survey (CIS) asks firms about their objectives for product and process innovation, such as expanding product lines, enhancing quality, and reducing labor costs. This information helps us understand firm' overall technology strategies. We matched these survey responses to 708 firms in our sample. The Appendix F documents the surveys.

Survey data serve as a critical check to triangulate whether different data sources provide similar answers. Firms are likely to respond truthfully to the survey because it is confidential and unrelated to the subsidy program. The survey also captures objectives firms might consider less important or overlapping with others that they might not mention in their applications. The survey categories align with our text analysis.

Figure 10, Panel B, shows that firms rated customer-specific solutions (43.4%), replacing outdated products (30.0%), better quality (26.6%), accessing new markets (26.0%), and larger product selection (25.7%) as highly important. Lower labor costs, while relevant, were not a top priority; only 20.6% of firms reported them as highly important. Lower material costs were a high priority for 9.2% of firms.

The Etla survey of Finnish SMEs provides similar observations. Figure A20 shows that 88.3% of our sample firms (N = 202) reported producing at least somewhat differentiated products, though only 2.1% considered their products strongly differentiated. Looking ahead three years, 45.3% planned to introduce new products or services and 55.8% aimed to develop production methods that would moderately or strongly differentiate them from competitors. The lowest panel shows that, over the past year, 40.2% had introduced new or substantially improved products. Additionally, over half had solicited customer feedback and made changes in response.

Evidence from Trade Journals Technical and trade journals report industry news and cover firms' technology investments. The SFINNO database, which tracks innovations in Finland, is based on a systematic review of 15 such journals from 1985 to 2020. We match 213 articles from this database to firms in our sample.[37]

These data have two advantages: the articles were written by independent journalists rather than the firms themselves, and the coding was conducted by independent researchers, not by us. SFINNO surveyed the firms to supplement the text-based information. Figure A22 shows an example from a metal industry journal included in the database.

Figure 10, Panel C, shows that common motivations included filling a market niche (93.1%) and meeting customer needs (91.0%). Figure A21 breaks down innovation types: 89.7% were product innovations, 8.9% process innovations, and 1.4% services. Most innovations were low- to medium-complexity—such as redesigned pistons. Key technical aspects included developing and integrating components and modules (38.4%) and commercializing the firm's core technology (27.4%). Overall, the evidence from trade journals, combined with targeted surveys, aligns with our earlier findings.

[37] Appendix F describes the SFINNO data. See Palmberg et al. (1999) for details on SFINNO and Coombs et al. (1996) on the literature-based innovation output (LBIO) method. The current version of SFINNO identifies 5,481 innovations from approximately 1,700 firms.

VI.D Which Technologies Did Firms Adopt?

Our data enable us to measure specific technologies, categorize them into meaningful groups, and contextualize our findings. We define these technologies ex-ante, rather than based on observed ex-post effects. The evidence shows that firms primarily adopted machinery, with far less investment in IT. This distinction sets our study apart from research focused on IT and digitalization (Akerman et al., 2015; Gaggl and Wright, 2017).

The Financial Statement Register separates machinery investment from IT expenditure. Machinery investment includes physical equipment, such as CNC machines, laser cutters, and robots. IT expenditure covers software, programming, computer design, and IT consulting. While both categories can have significant effects, they represent distinct types of technology. Tables 2 and A15 show the first-stage results for each. Baseline rates are EUR 108.0K for machinery and EUR 46.2K for IT. The data indicate that subsidies increase machinery investment by EUR 103.8K but raise IT expenditure by only EUR 4.1K.

Text data reveal a similar pattern. We manually code each application into machinery and IT categories. As before, machinery refers to physical investments like CNC machines, robots, and laser cutters, while IT includes software and digital tools such as enterprise resource planning (ERP) and computer-aided design (CAD) software. This division is informed by our fieldwork and uses terms familiar to most manufacturers. The coding shows that only 5% (107 firms) of our sample mentioned IT, software, or digital technologies.[38]

Text data enable us to examine specific types of machinery in more detail. Table A18 reports results for firms mentioning CNC, robots, or lasers in their applications. We define these technologies based on keywords common in this context (CNC, robot, laser, and plasma). Our main findings hold qualitatively across each type, showing that results are robust across different machinery categories. We find no significant differences in effects between machinery types.

We look into specific technology-occupation pairs: machining and machinists, welding and welders, painting and painters, and logistics and logistics workers in Table A19, identified by keywords and occupational registers. Our results suggest these technologies generally complement, rather than substitute, related workers. For example, the share of machinists rises by 4.5 percentage points in firms adopting machining technologies. For other technologies, we observe no changes in the share, wages, or education levels of these employees, aligning with our overall findings.

Finally, we group technologies into two categories—automated and non-automated—drawing on Acemoglu and Restrepo (2022). This classification uses application texts and customs data, where we manually code all sample application texts and 621 technologies from customs records. While not always clear-cut, the main criterion is whether the technology requires active human operation. Automated technologies include robots, CNC machining centers, conveyor belts, and other automatic non-hand-operated machinery that can run independently for at least a period. Non-automated

[38] Appendix F provides a detailed description with examples. Do the IT cases show different effects? Firms with above-median IT expenditure or those mentioning software potentially saw smaller employment effects (Table A17). However, given the limited number of IT cases, our precision is limited, and we do not find major differences in their within-firm effects. However, IT investing firms are ex-ante more educated and have lower production-worker shares.

technologies, such as manual welding tools, vehicles, and hydraulic presses, require human operators. This coding reflects the type of machinery, not whether firms used it for automation. Appendix F documents the classification with examples. Figures A23 and A24 show that, as with other technology groupings, the effects are consistent across both categories, with increases in employment and no shifts in skill composition. The firms and technologies in our sample are relatively similar, so these comparisons may not capture variation across technologies in other settings.

Next, we contextualize our findings in three sections. Section 7 discusses our source of variation, Section 8 overall manufacturing context, and Section 9 zooms outside our subsidy sample to position our findings in the broader trends and analyze different technologies.

VII What Is Our LATE?

Our conceptual motivation proposes that technology subsidies may produce a range of effects, depending on how firms respond. What causal impacts does the quasi-experiment identify, and whose effects do we estimate—in other words, what is our LATE?

The EU subsidy program functions as an intent-to-treat policy. Not all firms take up the policy; only a subset chooses to make qualifying technology investments. The treatment effects approximate the LATE impacts for the firms induced to invest by the program, capturing a non-random, non-representative subset of firms that respond to the subsidy.

This brief section notes that the observed effects likely reflect incremental investments induced by the subsidies. We consider alternative explanations, such as credit constraints, employment biases, signaling effects, and spillovers. While these factors may matter, we find limited evidence that they drive the results.

Incremental Investments One hypothesis is that financial constraints limit technology adoption, and EU subsidies lift these constraints, enabling firms to make large investments. Alternatively, firms may already be capable of investing, and the subsidies lead to incremental investments with limited productivity effects. Our results support the latter view.

We focus on firms close to the investment margin. Both winners and losers intended to invest, as shown by their applications. Winners received a modest grant (EUR 80K), reimbursed after the investment, which reduced their effective investment cost. These firms were plausibly near the margin of indifference, where the subsidy pushed them to invest slightly more.

Five observations support this interpretation: (1) Firms already owned some technology and did not shift from no technology to full automation. (2) The average subsidy (EUR 80K) was relatively small, close to firms' average annual investment, suggesting incremental changes unless it caused substantial additional investment. (3) Machinery investment rose close to one-to-one with subsidies, indicating firms typically invested the grant amount but not substantially more. (4) Profits also rose approximately one-to-one with the average subsidy, consistent with break-even investments at the margin. (5) Losing firms also invested (Figure A5), suggesting we estimate a relative effect among firms that all invested.

This may help explain why subsidies did not lead to substantial productivity gains. If large productivity gains from automation were feasible and profitable, firms would potentially have pursued them without the subsidy. Firms that responded to the program appear to have expanded incrementally.

Fieldwork and interviews reinforce this interpretation. On the one hand, program officers would like to see larger-than-marginal changes and sometimes reject applications deemed too small. On the other hand, several CEOs explained that the program most likely affects firms on the verge of making incremental investments, and is less effective for firms already planning significant investments or those too constrained to benefit.[39]

Credit Constraints A related alternative explanation is that the effects are primarily due to access to credit rather than technologies—an exclusion restriction concern for the interpretation. While credit constraints may play a role in allowing the subsidies to induce firms to invest more, several arguments counter this explanation as the primary cause for the employment and skill results: (1) We observe a strong first stage on technology investment; at minimum, the firms acquired new machinery. (2) We do not observe consistently larger effects for firms that are ex-ante more likely to be credit-constrained, such as small firms (Table A20) or those with higher financial costs or relative debt (Table A21). Controlling for these measures, we observe similar effects. (3) To measure credit constraints more directly, we link our sample firms to CIS data on self-reported credit constraints. When asked about obstacles to innovation, only 6.3% cited lack of credit as highly relevant. (4) We observe the same effects without the program in Appendix C.

Signaling Value A reasonable concern is that winning the subsidy might not only reduce the cost of technology adoption but also serve as a positive signal about the firm's prospects. If these signaling effects were significant, we would expect to see positive employment effects even when the subsidy is small relative to the firm's size. To test this, Figure A17 narrows the sample to cases where the subsidy is a small share of the firm's total costs in the base year ($\tau = -3$), progressively reducing the sample from the bottom 50% to the bottom 10%. Reassuringly, the relative employment effects of a subsidy shrink to zero when the subsidy constitutes a negligible share of firms' total costs. Small grants do not appear to create large effects.

Employment Bias Another possible explanation is that the program itself is biased toward low-skill employment. This concern is based on accurate observations: One objective of the ELY Center subsidy program is to stimulate employment by supporting the adoption of advanced technologies in manufacturing firms. However, several factors suggest that program biases are not the main driver of our findings: (1) We find similar results when we analyze technology adoption events outside of the subsidy program in Appendix C. (2) To some extent, the text propensity scores systematically address concerns about employment bias: If employment-related phrases predicted

[39]Some firms noted that automation and significant productivity improvements are costlier than expansion. Combined with medium-sized grants, this may lead firms to prioritize expansion over automation. See also Lashkari et al. (2024) on scale dependence.

subsidy acceptance, the propensity score would control for them. Under employment bias, controlling for the scores would lower the employment effects (which we do not find). (3) Interviews with firm managers suggest that technology adoption events supported by subsidies tend to be similar to typical technology adoption events in this context. (4) Interviews with administrators show that major technology projects are rarely rejected for low employment effects, though minor projects may be if they lack technological advances. The program does not enforce employment outcomes; firms make their own hiring decisions after receiving subsidies. Additionally, the program does not specifically target low-skill jobs; ELY Centers also support high-skill hires in manufacturing firms. (5) We reviewed rejected applications and found that none appeared to be denied primarily for employment-related reasons. Five reports mentioned employment concerns, but these were secondary to low projected technological advancement. Our findings remain robust when these applications are excluded.

Spillover Effects These firm-level results are consistent with potential spillover effects. A firm's technology adoption can affect others, so total employment and skill impacts may differ from our estimates. Estimating these effects is challenging because (1) these firms are small, and (2) they trade globally (our sample is primarily tradable per Mian and Sufi, 2014), making local spillovers likely dispersed. Empirically, we find similar results using the matched non-applicant control group, suggesting that spillovers from winning to losing firms are unlikely to drive our findings. Furthermore, new hires at winning firms rarely come from losing firms (Table A22).

Conceptually, whether technology adoption replaces employment elsewhere depends on the types of technology and resulting externalities. For example, we found that these firms sometimes expanded by introducing new products, typically intermediate goods or machinery used by final goods producers. In Romer (1990), this type of variety expansion promotes growth, raising the possibility that some externalities may be positive. However, new intermediate goods could also replace older versions, creating negative business stealing effects and aligning with Schumpeterian models of quality improvements and creative destruction (Grossman and Helpman, 1991; Aghion and Howitt, 1992). Investigating these externalities further, as in Acemoglu et al. (2020b), Koch et al. (2021), and Oberfield and Raval (2021), is a promising direction for future research.

VIII Our Context is Flexible Manufacturing

We study small- and medium-sized firms that produce non-standard products in short, flexible runs and adapt to client demand. Our estimates may not extend to high-volume, standardized production, where technology adoption and constraints could differ.

VIII.A Flexible Manufacturing $\neq$ Mass Production

Our conceptual motivation highlights two potential responses to technology subsidies: automation versus expansion. A central question raised by our empirical analysis is: When and why is one more likely to occur than the other? We mostly observe the latter in our context. But both responses occur in practice, and studies document capital substituting for workers' tasks elsewhere (Feigenbaum and Gross, 2024; Restrepo and Hubmer, 2021; Acemoglu and Restrepo, 2020). We explain next why our findings are distinctive but logical, and potentially applicable to other settings with similar incentives for technology adoption.

Consider two contrasting views of manufacturing: mass production (Taylor, 1911; Ford, 1922) and flexible manufacturing (Piore and Sabel, 1984; Milgrom and Roberts, 1990). Mass production is characterized by standardized products, high volume output, and stable environments. The production process is divided into tasks that can be automated, as in high-volume assembly lines. Flexible manufacturing is characterized by specialized products, low volumes, and dynamic environments. Firms in this setting rely on multi-skilled workers to adapt—for example, producers of advanced machinery, defense equipment, or high-end textiles. These distinctions suggest that the effects of technology subsidies could vary by manufacturing context. Evidence from one setting might not generalize to another (see also Goldin and Katz, 1998; Klette and Kortum, 2004; Akcigit and Kerr, 2018; and Flach and Irlacher, 2018).

We hypothesize that the prevalence of expansion over automation in our context could be, in part, due to the characteristics of the setting. This hypothesis is not new: While automation is a widely accepted concept in the literature, not all investments in modern manufacturing technologies aim to automate worker tasks (Acemoglu and Restrepo, 2018b). Most importantly, Piore and Sabel (1984) argue that different technology-labor relations emerge in flexible manufacturing, particularly in technologically advanced SMEs producing specialized products in small volumes for a changing market. These firms are more likely to use new technologies to expand, replace outdated products, and provide customer-specific solutions, rather than automate work.

Automation entails significant fixed costs, justifiable only in long, uninterrupted production runs typical of mass production. Flexible manufacturers, whose competitive advantage lies in creating specialized products and differentiating their offerings, do not find this model attractive. For example, one manufacturer we interviewed could automate their assembly but would need to commit to specific models and parts. This commitment was unattractive due to the frequent need to update their products to stay competitive. "I could see the business case for automation," the company CEO said, "in a standardized environment, with many workers performing routine work, and with unions and strikes." But that was not their context.

A large body of literature documents the shift from mass production to more flexible, specialized production since the 1980s (Dertouzos et al., 1989; Berger, 2013). These new forms emphasize quality and responsiveness to market conditions while using advanced technologies and a multi-skilled workforce. Piore and Sabel (1984) call this the second industrial divide, Kenney and Florida (1993) describe it as moving beyond mass production, and Milgrom and Roberts (1990) call it modern manufacturing. Despite different approaches, the common observation is that "the business environment is no longer conducive to producing standardized products for a stable market" (Piore, 1994). A manager in Berger (2020) explained: "American manufacturing has been transformed. It's become highly engineered, highly specialized, and highly customized. I see this across all manufacturing. This is a different country. It's no longer the mass production of the past."

Research suggests several reasons for this shift: Consumers moved away from standardized goods (Bils and Klenow, 2001), globalization lowered the cost of specialization (Berger, 2005), and new technologies reduced setup times and made switching between products easier (Bartel et al., 2007).

VIII.B Documenting the Context

The firms in our sample produce specialized products in low volumes, operate in shifting market environments, and rely on skilled labor. While we lack data from contrasting contexts—even the spikes design in Appendix C covers similar firms—documenting our context provides a basis for future work to compare these findings across settings.[40]

Specialized Products The firms we interviewed produce specialized products for markets with limited demand for each product. For example, the industrial piston manufacturer featured in our fieldwork explained that they could not significantly expand within a product by lowering prices but they might be able to expand by introducing new products.

Our surveys document this specialized context. CIS data show that a common motivation for innovation was creating customer-specific solutions. Similarly, 93% of SFINNO respondents identified realizing a market niche as important. Etla data indicate that 88% of firms produced at least somewhat differentiated products (Figures 10, A20).

Industry evidence corroborates this view. The Rauch (1999) index, a measure of a good's commodity status, indicates that 91% of the sample firms operate within specialized industries. Our most common industries—fabricated metal products, machinery, equipment, and wood products—are categorized as specialized according to this index. Our sample includes few, if any, firms producing non-differentiated goods like cement or sugar, or engaged in high-volume assembly.

Low Volumes In our interviews, most managers explained that they are specialized low-volume producers who invest in advanced technologies to meet the unique demands of a few industrial customers. There is typically no production line; instead, firms produce in small batches or even one unit at a time. Several firms explained that the possibilities for automation are limited because they would need higher production volumes to cover the upfront investment needed to automate workers' tasks. The evidence supports this: Firms in our sample are mainly SMEs, as shown in Table 1—not mass producers. Subsidy application texts frequently mention small batch production. The fact that we study short-term subsidies for SMEs connects our results to Zwick and Mahon (2017) and Criscuolo et al. (2019), who find larger effects from investment incentives for small firms.

Adaptation Needs The firms in our context described operating in a changing environment that required continual adaptation. One firm described using robots to handle demand volatility: They could not hire skilled workers for short periods during demand peaks, so they used robots as

[40] Other relevant factors include the technical feasibility of automation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), employment protection (Saint-Paul, 2002; Manera and Uccioli, 2021), and complementary resources such as venture capital, trade associations, and suppliers (Berger, 2013; Gruber and Johnson, 2019).

temporary support. Other firms in our fieldwork described that the need for adaptation arises from changes in clients' needs and technological obsolescence.[41]

The need for adaptation could be reflected in (1) higher product turnover in addition to new products, and (2) a negative trajectory for firms that did not adopt the technology, contrasting with higher survival rates for adopters. Our evidence confirms both predictions (Table 4, Figures A5, A15). More directly, our text data record that 26% of firms invested in technologies to respond to changing demand, and 29% described improved flexibility and capabilities (often mentioned together, hence coded together). The CIS survey data show that 30% of firms regarded replacing outdated products as highly important. The Etla survey documents that 85% had made changes due to customer feedback over the past year (Figures 10, A20).

Skilled Workers and the Labor Market The conceptual frameworks of flexible manufacturing (Piore and Sabel, 1984) emphasize the role of a multi-skilled and adaptable workforce. One interpretation of our evidence is that because these workers are already skilled and continue to learn new skills, we do not observe changes in skill composition even if the technologies are skill-biased. To some degree, this is likely true.

The workers are already skilled: The typical manufacturing workers in our context are skilled welders and trained machinists with vocational degrees, rather than unskilled workers. These workers possess foundational skills that they apply to non-standard manufacturing tasks—closer to modern artisanal work than to routinized mass production. The CIS survey shows that only 7.5% of our sample firms reported that a lack of skilled employees constrained innovation. However, these workers are not highly educated: only 15% have a college degree, and their primary school GPA is 0.56 SD below the population average. Figure A25 presents descriptive statistics on the workers.[42]

The workers also learn new skills: Managers we interviewed reported that technology adoption was combined with worker training. New technologies required new skills, but current workers were typically best suited to learn and apply them. This adjustment was sometimes challenging, involving trial and error, but ultimately led to successful upskilling. Importantly, the skills managers discussed were not about formal education or replacing the production workers with college graduates, but upskilling production workers. These observations echo Bartel et al. (2007), who found that CNC machinery investments shifted skill requirements for largely high-school-educated workers, rather than requiring higher educational levels.

Several other aspects of the Finnish labor market are relevant. Firms generally have autonomy in hiring, firing, and technology decisions. Unions do not directly negotiate technology adoption or new

[41] Firms that cannot compete on cost may respond to low-cost rivals by introducing new product varieties (Porter, 1985; Aghion et al., 2005). This mechanism is consistent with evidence that import competition induces innovation and product differentiation (Bloom et al., 2016; Fieler and Harrison, 2023). See also Bernard et al. (2010) on product switching as a form of within-firm reallocation and Argente et al. (2024) n product life cycles.

[42] The labor supply to these firms is skilled. For example, the PIAAC survey ranks Finland among the world's highest in adult skills (OECD, 2019). In 2016, 46.5% of 17-year-olds were enrolled in vocational education (Silliman and Virtanen, 2022), most male workers in our sample are military trained, and nearly half of manufacturing workers participated in continuing vocational training in 2015 (CVTS, 2015). At the same time, Weaver and Osterman (2017) emphasize that most manufacturing work does not require high levels of formal education. See Katz (2014) for a commentary on the emerging artisan economy.

hires. Short-term contracts are common. Terminating permanent staff is somewhat restricted, but Finland's employment protection aligns with OECD standards (OECD, 2020). Firms can terminate contracts for "production-related grounds," including changes in production technology.

Wage setting in Finland is moderately inflexible: Collective bargaining coverage is high, and unions and employer associations negotiate contracts for industries and occupations. Union coverage ranged from 78.5% in 1994 to 59.4% in 2017 (Ahtiainen, 2023). However, firms retain some flexibility within these contracts, and Harju et al. (2025) find that the impacts of firm wage policies on wage variation align with global estimates. The relative rigidity in the Finnish wage setting may contribute to the absence of observed wage effects. Our wage estimates could have been different in a context with a more flexible wage setting.

We focus on small- and medium-sized firms (the average size is 18 employees), which are unlikely to impact local wages significantly or have considerable labor market power. These SMEs are also more inclined to follow industry wage agreements than to engage in firm-level negotiations. Moreover, half of the new hires come from outside employment rather than other firms (Table A22). Still, the observed negligible effects on wages may also stem from various mechanisms. For example, technologies may exert downward pressure on wages, but this effect could be counterbalanced by the increased wages required to attract more workers if the firms have some labor market power. Conversely, technologies may also exert upward pressure on wages, but this effect might be offset by lower unobserved skills of the marginal new workers (e.g., lower experience, as seen in Figure A12). Further evidence is required to unpack these mechanisms.

IX Zooming Out

In this final section we step outside the subsidy program to place our results in the wider context of technology adoption in manufacturing. Using subsidy records and a broader sample of Finnish manufacturers, we examine firm- and industry-level patterns in technology adoption and workforce composition. This descriptive evidence shows that IT expenditure is more strongly linked to skill upgrading than machinery investment. Because the subsidy program primarily supported machinery rather than IT, this contrast may reconcile our findings with earlier studies reporting skill-biased effects of IT adoption (Berman et al., 1994; Doms et al., 1997; Autor et al., 1998).

IX.A Big Trends

Before we begin the analysis, we ask: Are Finland's broad skill trends comparable to those in other countries? Our study's backdrop is the general shift in Finnish manufacturing toward higher skill demands. This trend is visible in the rising share of educated labor, a declining share of production workers, and an increasing college wage premium, as shown in Figure 11 from 1994–2018. These trends align with global patterns (Acemoglu and Autor, 2011) and are also reflected within our treatment and control firms, where skill levels increase steadily over time (Figure A5).

IX.B Compositional Effects

We next examine compositional effects. Our firm-level estimates may differ from macro-level impacts. At the macro level, technology subsidies can increase skill demand in two ways: (1) within-firm effects, where subsidized firms raise their demand for skilled workers, and (2) compositional changes, where grants go to firms with higher pre-adoption skill levels, allowing these firms to grow their market shares. We examine whether subsidies primarily target high-skill, low-labor-share firms and, if so, whether these grants raise aggregate skill demand and reduce labor shares by favoring such firms.[43]

Table A1 compares subsidy applicants to non-applicants in Finnish manufacturing. Applicants have lower labor shares (18.45% vs. 25.86%) and are slightly more educated (11.69 vs. 11.61 years), with modestly higher college shares (15.28% vs. 14.76%). These differences suggest that firms with lower labor shares and more educated workers were more likely to participate in the program and expand, consistent with compositional effects that lower aggregate labor shares and raise skill levels. These compositional effects may help reconcile our findings with earlier research linking technology adoption to aggregate declines in the labor share (Grossman and Oberfield, 2022).[44]

The movement of workers may shape compositional effects. Table A22 shows that new hires joining winning firms generally come from larger, more productive firms (451 workers, EUR 184K per worker), with higher labor shares (26.45%) and more skilled workforces (12.04 years). This movement aligns with labor-share-reducing compositional effects, as new hires are drawn from firms with relatively high labor shares. However, the flow of workers from more educated firms to less educated ones contrasts with the potential skill-biased compositional effects. Nearly all new hires come from outside the program: only 0.7% are from other winners and 0.02% from losers.[45]

In sum, the evidence provides mixed support for skill-biased compositional effects. Pre-adoption skill differences point in this direction but are modest—less than 0.1 years—and even if the program were scaled up, this creates an upper bound on compositional effects. Worker flows also point in the opposite direction. Evidence on labor shares is more clear-cut, both with respect to pre-adoption differences and worker movement.

[43] These two channels are not the only ways subsidies may affect skill demand. Other mechanisms include: (1) product or factor market externalities, such as firms competing for the same clients; (2) technological spillovers influencing how other firms adopt new technologies; (3) macro-level shifts, where technologies reshape industries or practices—e.g., self-booking platforms displacing travel agents or the internet transforming job search; and (4) new economic sectors created by technologies, as with the Apollo program's impact.

[44] We assess compositional effects by comparing applicants and non-applicants. Comparing winners and losers (Table 1), winners have higher labor shares (18.68% vs. 15.47%), are moderately more educated (11.71 vs. 11.45 years), and have higher college shares (15.51% vs. 11.63%). Production-worker shares and labor productivity remain similar across both groups.

[45] We focus on new workers in winning firms to assess whether this expansion contributes to compositional effects. We found no important differential effects between winners and losers. A fuller understanding of compositional effects would require knowing where the workers would have gone had they not joined these firms—information our design does not identify. Additional data show that 46% of new hires come from non-employment, including education (21%), retraining (3.54%), military service (3.20%), and unemployment (13.53%). Of those previously employed, most retain their occupation (69%) and half stay in the same industry (51%). On average, new workers gain a 2.39 km shorter commute.

IX.C Cross-Sectional Correlations

Outside the subsidy program, how does skill mix predict technology adoption? Our data allow us to investigate skill differences in technology adoption beyond subsidies. We find that the relationship between skill mix and technology adoption varies by type: Firms adopting machinery have skill levels similar to non-adopters, while IT adopters are distinctly more skilled. Both technologies are associated with lower labor shares.

Our registers measure two types of technologies: machinery investment and IT expenditure. Machinery investment refers to investments in physical machinery and equipment, such as CNC machines, laser cutters, and robots. IT refers to software, programming, and computer-design expenditure. The data cover all Finnish manufacturing firms. We focus on manufacturing because the data are consistently defined and well-understood based on our fieldwork. We include firms from 1999 to 2018 with a minimum of two workers (IT data are available from 1999). Section IV and Appendix F provide detailed descriptions of the data.

Table 8 shows the results of predicting firms' machinery investment and IT expenditure per worker with college share, production workers' share, labor share, and productivity. These cross-sectional estimates are weighted by employment and include controls for year fixed effects.

We observe that the skill mix has some but limited predictive power on machinery investment. Initially, without controls, a one percentage point higher college share predicts 36.5 euros more machinery investment per worker, with a low R^2 of 0.01. After controlling for the 2-digit industry and firm size, the coefficient becomes an insignificant 9.2, which is close to zero compared to the baseline of 5321.7 euros per worker. The estimates also show that the production workers' share is not a strong predictor of machinery investment.

The results for IT are strikingly different: Skill mix strongly predicts IT expenditure. A one percentage point higher college share predicts 77.8 euros more IT expenditure per worker, with an R^2 of 0.26. After controlling for industry and firm size, the estimate remains significant at 55.7 euros. Compared to the mean of 1016.1 euros IT expenditure per worker, this corresponds to a 5.5% increase. A commonality between machinery and IT adoption is that both are robustly predicted by lower labor shares and higher productivity.

Five robustness checks are relevant. First, the results are robust to controlling for firms' revenue and age. Second, expanding the sample to include all firms (not just manufacturing) keeps the results consistent. Third, examining small versus large firms (those with under or over 50 workers) reveals similar relationships, with a starker difference between machinery and IT for large firms. Fourth, the unweighted estimates are similar but smaller in absolute terms. Finally, adjusting the definitions of machinery and IT by revenue rather than employment shows similar relationships between skills and technologies as reported here.

Survey data in Table 9 provide a complementary method to measure technologies in firms, with a smaller sample size but greater specificity. We use three separate surveys: CIS, ICT, and Etla survey, which include measures of robots—a type of machinery—and IT. We link these surveys to register data on manufacturing firms' college shares, production workers' shares, labor shares, and productivity. All these data are documented in Appendix F.

What do these survey data reveal about skill differences between technology adopters and non-adopters? First, Panel A examines robot use. Similar to the register data, robot users are about as educated as non-robot users who responded to the survey. The CIS survey shows that robot users are slightly more educated than non-users, while the ICT and Etla surveys suggest that robot users are slightly less educated. Surveyed firms are generally more educated than all manufacturing firms (Table A1). All three surveys indicate that robot users have higher shares of production workers compared to non-using manufacturing firms. Additionally, the survey data consistently show that robot adopters have lower labor shares and higher productivity.

Next, Panel B examines IT use. IT users are more educated than non-users and also compared to robot users. Firms with above-median computer use had a 43% college share, while those below the median had a 25% college share. Firms that highly value digitalization had college shares over ten percentage points higher than those that did not. Additionally, firms with higher IT use had a lower proportion of production workers. While the patterns for labor share and productivity are less clear, the evidence suggests that computer users may have higher productivity.

Customs data provide an alternative view on robot adoption. Some firms import their robots, leaving a trace in customs records (recorded in the 6-digit CN code for robots, as explained in Sections IV and VI). Table 9 shows that robot importers are more educated than average manufacturers, with a college share of 31.8% compared to 14.5%. However, these firms have similar education levels to those that participated in robot surveys but did not use robots. Firms that imported other goods, but not robots, also have higher college shares at 20.8%. These observations suggest caution when comparing robot-importers to non-importers.

We briefly return to our winners–losers design to examine IT. Table A16 shows a familiar pattern: Firms with higher IT investment have higher college shares, more educated workforces, and fewer production workers. Similar patterns appear among firms that mention software in their application texts. Even within our subsidy sample, IT investment is associated with a more skilled workforce prior to adoption. In summary, the evidence indicates that machinery and IT adoption follow distinct skill patterns, suggesting that different technologies relate to skill mix in different ways.[46]

IX.D Industry Trends

At the industry level, how do technology investments relate to shifts in skill composition? We find that industries investing more heavily in machinery have not experienced faster skill upgrading, whereas industries adopting more IT have significantly increased their skill shares.

We started this section by thinking about the more aggregate effects of firms' technology adoption. For many different mechanisms, these aggregate effects could be visible in industry-level regressions. If a technology is skill-biased, the industries that invested more heavily in it would

[46] The spikes design, which focuses on significant machinery investment events at the firm level (Appendix C), provides a somewhat mixed message. Firms that made substantial one-off technology investments are clearly ex-ante more educated and productive compared to the average manufacturers. However, compared to matched non-spiking firms, they are equally educated and productive—even though we match by employment, revenue, and wages in the cross-section before the spike (not by education, productivity, or labor share).

possibly see starker changes in their skill composition. In our closing step, we aggregate our register data up to the industry level and look at how technology adoption across industries relate to relative skill mix.

Figure 12 illustrates the overall patterns. It shows the relationship between our technology measures—machinery and IT—and changes in the employment shares of college graduates from 1999 to 2018. We find no consistent relationship between industries' machinery investment and skill shares. However, there is a strong positive relationship between IT expenditure and skill shares. That is, machinery and IT predict different patterns at the industry level. In Panel A, the highest machinery investors were the oil product and basic chemicals industries, while among the lowest were the shipbuilding and footwear industries. Despite this, all these industries saw about average increases in their college shares. In Panel B, the highest IT expenditure was in the electronics industry, which also saw the highest increase in college shares. Industries with lower IT expenditures, like treatment and coating of metals (the most common industry in our design), experienced lower educational upgrading.

Table 10 collects the estimates for three educational outcomes: college, high school (HS), and below high-school educated workers' shares. Machinery investment per worker does not predict changes in educational composition, as shown in Panel A. In contrast, IT expenditure predicts an increase in the college-graduate share and a decline in the high-school graduate share (Panel B). Specifically, 1000 euros in total IT expenditure per worker-year from 1999 to 2018 predicts a one percentage point higher college share. For reference, the average industry IT expenditure is 2,306 euros per worker-year, and machinery investment is 9,236 euros. Notably, when predicting college shares, the R^2 is below 0.001 for machinery but 0.59 for IT.

The past skill mix of an industry could predict both future skill mix and technology adoption. Controlling for pre-period college share in 1999, as shown in Column (2), makes some changes to the coefficients but keeps the basic pattern unchanged. In itself, this control predicts polarized future changes: higher shares of college-educated workers and those without high school degrees but lower shares of those with exactly a high school degree.

Looking at other outcomes, Table E1 shows the estimates for labor share, productivity, and production workers' share. Both machinery and IT predict lower labor shares. IT predicts higher productivity, while machinery's coefficient is not significant. The main difference is that machinery investments predict higher production workers' shares, whereas IT expenditures predict lower shares. This observation is consistent with the cross-sectional firm-level estimates.

We performed several robustness checks on these industry-level results. We find similar relationships when we include all industries, not just manufacturing, except the machinery estimates in Table 10, Column (2), become zero. Figure 12 shows that one industry, electronics, had particularly high IT expenditure and a significant increase in college shares (also documented by Houseman, 2018). Excluding the electronics industry keeps the machinery results consistent but slightly alters the IT results: the college share increase remains similar, but the high-school graduate share now increases and the below high-school share declines. The non-weighted estimates are less precise but generally similar. Comparing large vs. small firms (above vs. below 50 workers), we find qualitatively similar estimates, with large-firm industry estimates being more precise. We also produce similar estimates when defining machinery and IT as changes over 1999–2018 rather than as cumulative totals. In that specification, the magnitudes change moderately; for example, the IT-college estimate is about double, 0.029 (SE 0.0089). We also observe similar relationships when we adjust machinery and IT by industry revenue rather than employment: IT expenditure predicts then a higher college share, and machinery investment predicts a marginally lower college share.

The finding that IT correlates more strongly with skill mix than machinery may help reconcile our results with prior research. Our estimates for machinery investments align with studies focused on machinery, including Doms et al. (1997), Curtis et al. (2022), and Aghion et al. (2024), while our distinct estimates for IT are consistent with IT-focused studies by Berman et al. (1994), Autor et al. (1998, 2002), Akerman et al. (2015), Gaggl and Wright (2017), and Lashkari et al. (2024). One interpretation is that our finding of no relation between subsidized machinery investments and skill mix could reflect the nature of machinery investments funded by subsidies.

X Conclusion

We examine the micro-level effects of EU technology subsidies on the quantity and quality of jobs. The main finding is that firms receiving subsidies increased their employment without changing their skill mix. These employment gains primarily benefited non-college-educated workers.

We develop novel methods for using text data in program evaluation. Many policy programs generate text records that capture details otherwise difficult to measure. We demonstrate how to use this text data for both matching and constructing outcome measures. In the spirit of Roberts et al. (2020) and Mozer et al. (2020), we craft a research design that controls for underlying differences among program participants using text as data. This approach could prove helpful in other settings, such as estimating the effects of judge decisions.

We are explicit about what our estimates do and do not capture. This paper contributes novel firm-level evidence to the literature on how firm subsidies shape workers' job opportunities (Criscuolo et al., 2019; Curtis et al., 2022). We provide unique evidence on skill mix and show how technology subsidies were used at the firm level—we find that the subsidies stimulated incremental investments in new machinery and increased revenue, exports, and product variety.

But our estimates do not capture all potential effects of technological change. Our findings shed light on the types of advances firms implemented under the subsidy program, but they largely exclude other technologies aimed at task automation or productivity enhancement. For example, prior research shows that certain technological advances can replace workers' tasks, as shown in large-scale studies (Acemoglu and Restrepo, 2020; Bessen et al., 2025) and more specific cases (Autor et al., 2002; Feigenbaum and Gross, 2024). Our evidence suggests that this context did not include many such cases. Other innovation activities—such as R&D and organizational changes—and technological advances in other countries may also yield distinct effects (Machin and Van Reenen, 1998; Caroli and Van Reenen, 2001; Lindner et al., 2022; Battisti et al., 2023).

Our LATE estimates complement previous work on factory-floor investments (Doms et al., 1997).

By contrast, studies of IT adoption typically find skill-biased effects (Gaggl and Wright, 2017; Akerman et al., 2015; Autor et al., 2002). Consistent with this contrast, our descriptive evidence shows different patterns for machinery and IT. In our context, subsidies induced investments in machinery rather than IT.

A relevant question is whether similar effects would emerge in other contexts. Our study focuses on a setting where firms have adopted quality-centered, flexible production approaches, as described by Piore and Sabel (1984) and Milgrom and Roberts (1990). Observations from our fieldwork—including interviews with managers, workers, and subsidy officials—suggest that these approaches were central to how firms used subsidies and adapted their operations. Importantly, our findings may not apply to mass production settings described by Taylor (1911) and Ford (1922).

The findings of this paper inform the design of policies that tax or support technology adoption. Our results suggest that well-designed subsidy programs can simultaneously promote technology investment and expand opportunities for non-college-educated workers.

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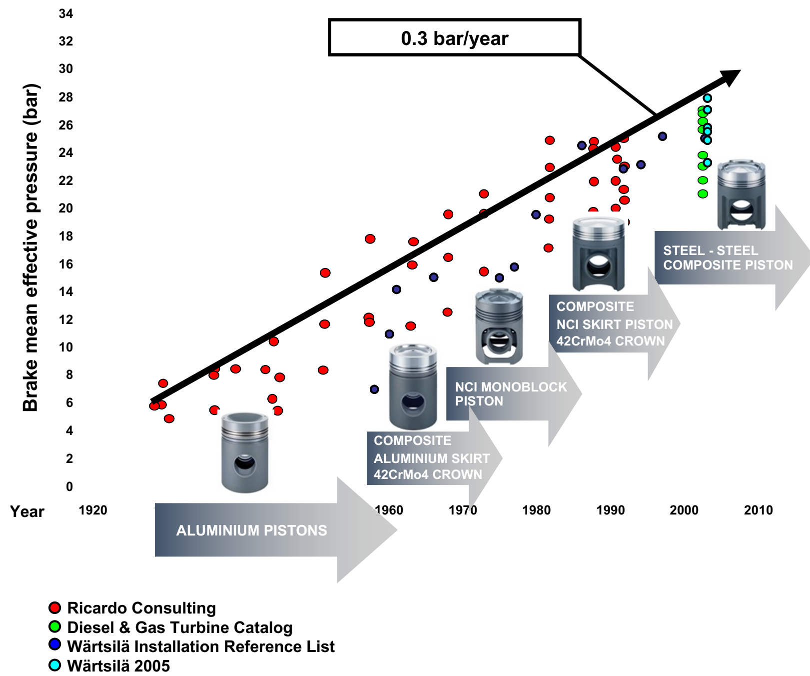


Figure 1: Moore's Law for Pistons.

Notes: The development trend of piston materials over the last 100 years. Data received from Wärtsilä Corporation. Back to Section II.

Figure 2: ELY Center Subsidy Application Process.

Notes: Details in the main text. Back to Section III.

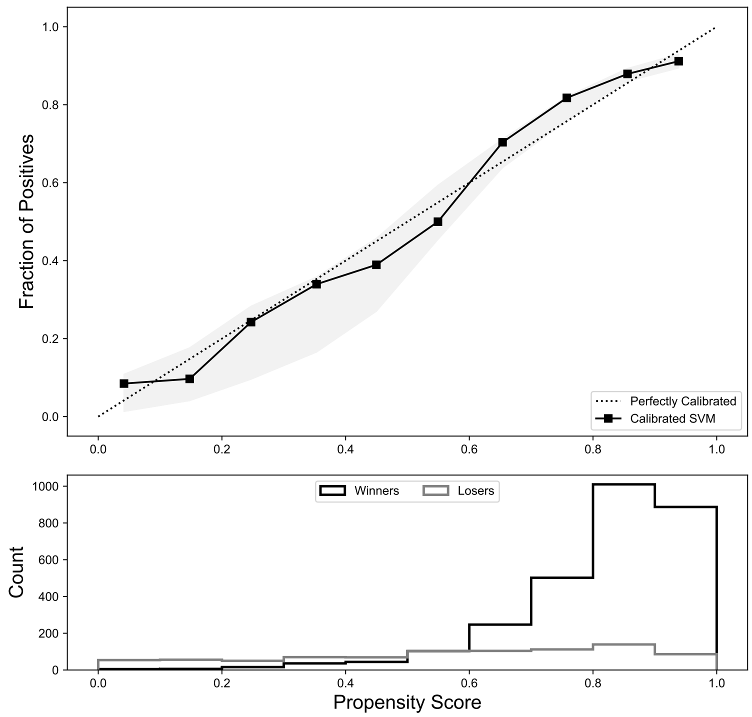


Figure 3: Text Propensity Score Calibration Plot.

Notes: **Upper panel:** The predicted probabilities of winning the subsidy based on text data are on the x-axis, and the observed probabilities on the y-axis. The text data are evaluation reports of the applications written by the subsidy program officers. The predicted probabilities are calibrated using a vector representation of the texts and SVM. Standard errors are estimated by non-parametric bootstrap. The calibration is performed using all possible subsidy applications. The predicted probabilities across the bins closely match the empirical probabilities. **Lower panel:** Distribution of the predicted values. Most of the applications have high predicted values reflecting the overall high acceptance rate. Back to Section III.

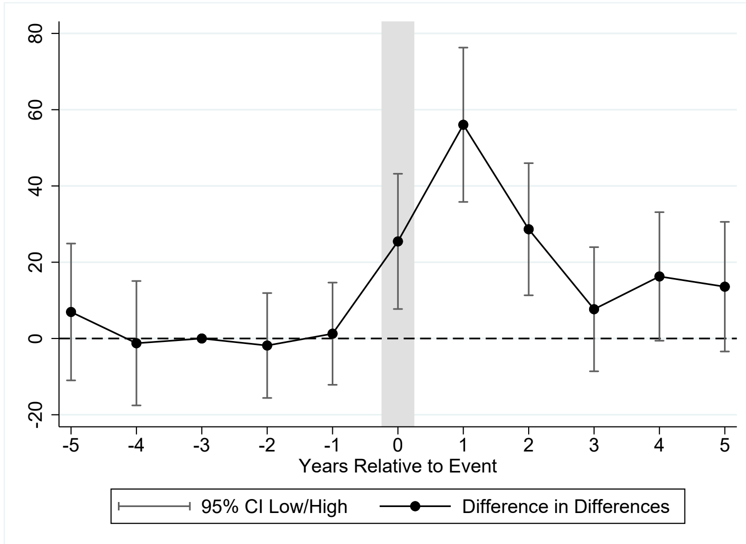


Figure 4: The First Stage: Effect of Technology Subsidies on Machinery Investment.

Notes: Event-study estimates from Equation 1. The outcome is investment in machinery and equipment (in EUR K) measured from the Financial Statement Register. Event time $\tau = 0$ refers to the application year. The estimate for $\tau = 1$ indicates that the treatment group invested EUR 60K more than the control group in the year after subsidy application. The estimates indicate a cumulative EUR 100K effect on machinery investment over $\tau \in [0, 2]$. This event-study specification contains no controls in the term X^{τ}_{jt} of Equation 1. Back to Sections V and VI.

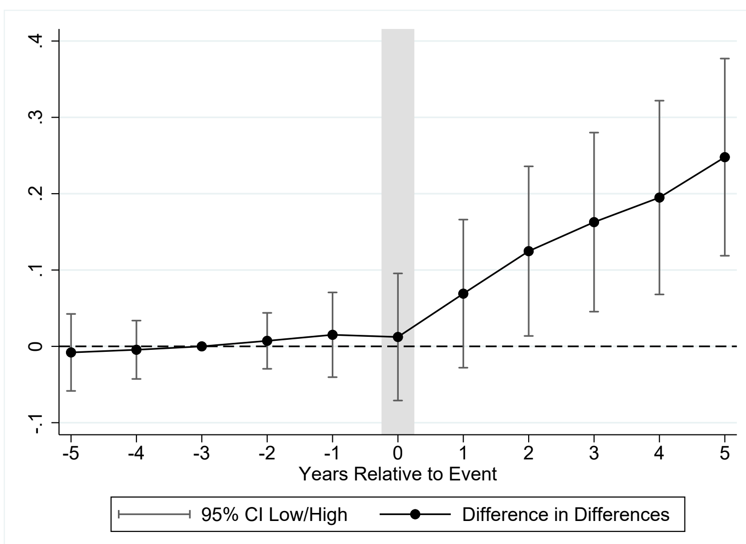
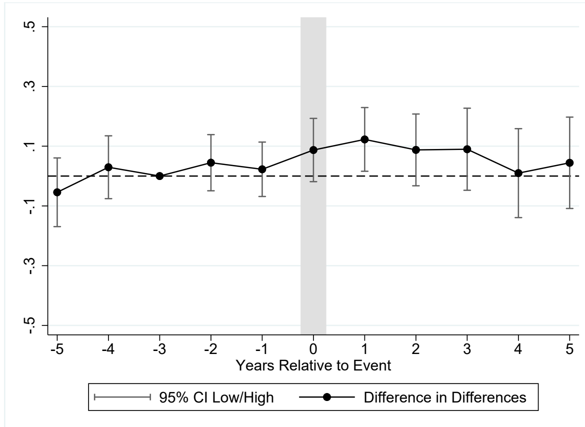
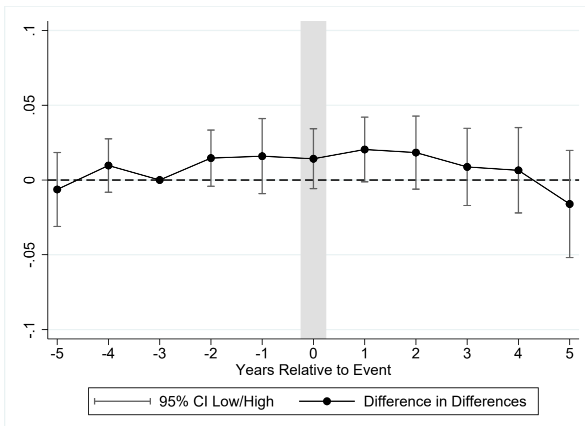


Figure 5: Employment Effects: Effect of Technology Subsidies on Employment (%).

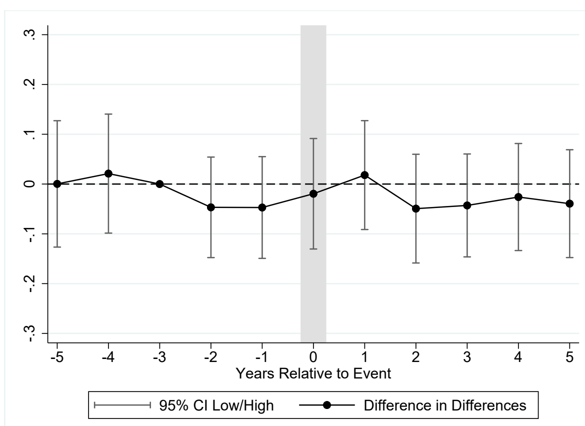
Notes: Event-study estimates from Equation 1. The outcome is employment relative to the base year $\tau = -3$. Event time $\tau = 0$ refers to the application year. The estimates indicate approximately 20% increase in employment after five years. This event-study specification contains no controls in the term X^{τ}_{jt} of Equation 1. Back to Sections V and VI.



(A) Education Years.



(B) College-Educated Workers' Share.



(C) Production Workers' Share.

Figure 6: Skill Effects: Effect of Technology Subsidies on Main Skill Outcomes.

Notes: Event-study estimates from Equation 1. The outcomes are relative to the base year $\tau = -3$. Event time $\tau = 0$ refers to the application year. The estimates indicate approximately zero changes in the main skill measures. Education years are defined as the average years of education among the workers in the firm (measured in years); college-educated workers' and production workers' shares are the shares of employment of that group (measured in percentage points). These event-study specifications contain no controls in the term X_{jt}^{τ} of Equation 1. Back to Sections V and VI.

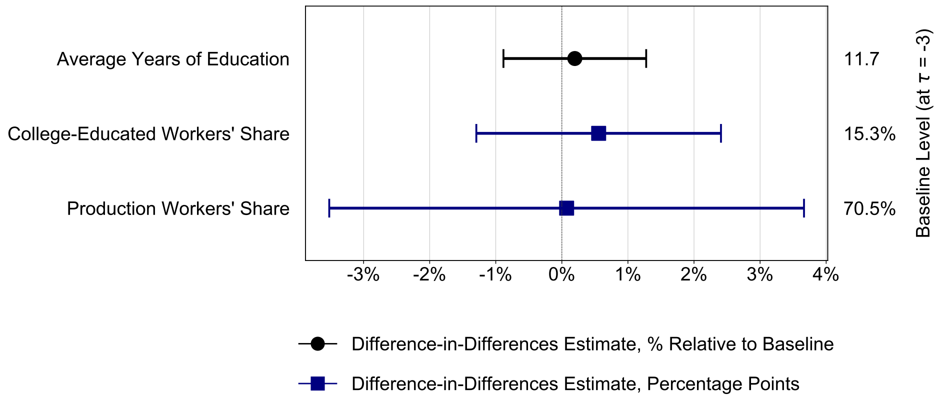


Figure 7: Skill Effects: First-Difference Estimates on Main Skill Outcomes.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. Education is measured as a relative change (%) in the average years of education in the firm between $\tau = -3$ and the average over $\tau \in [2, 5]$. The shares are measured in percentage-point changes. The estimates indicate no detectable changes in the skill composition. The specifications include two-digit industry and firm size as controls. Back to Section V.

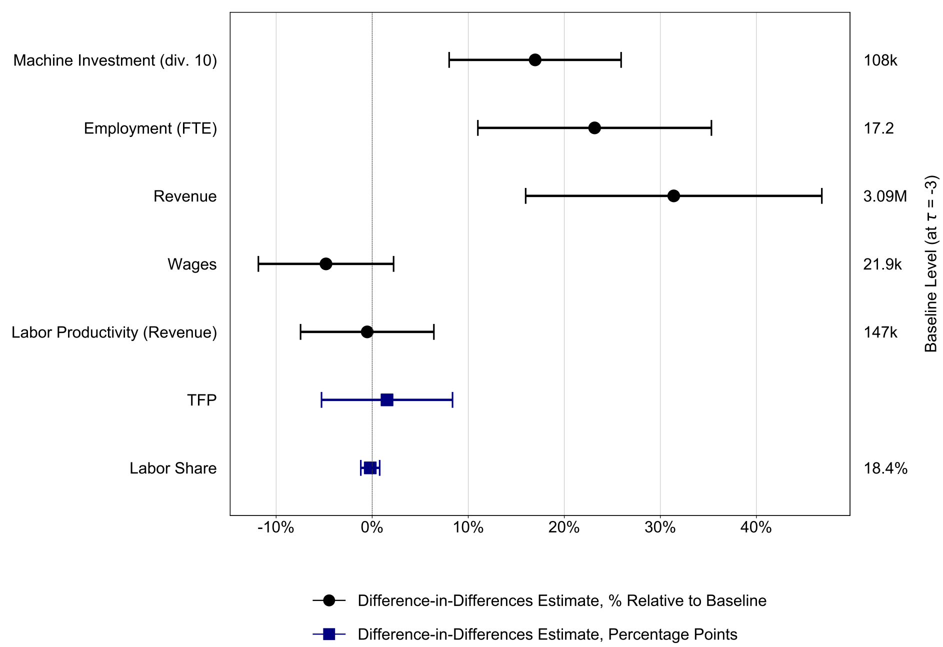


Figure 8: Firm-Level Effects: First-Difference Estimates on Main Firm-Level Outcomes.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$ (omitted for TFP). Machine Investment, Employment, Revenue, Wages, and Productivity are measured by relative changes to baseline at $\tau = -3$. For Machine Investment, the post-period outcome is the average of investment over $\tau \in [0, 2]$ and for other outcomes, the average over $\tau \in [2, 5]$. The specifications include two-digit industry and firm size as controls. Back to Sections V and VI.

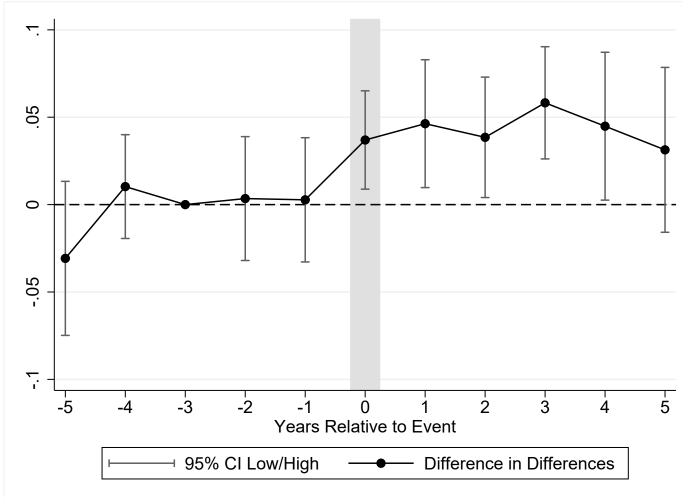
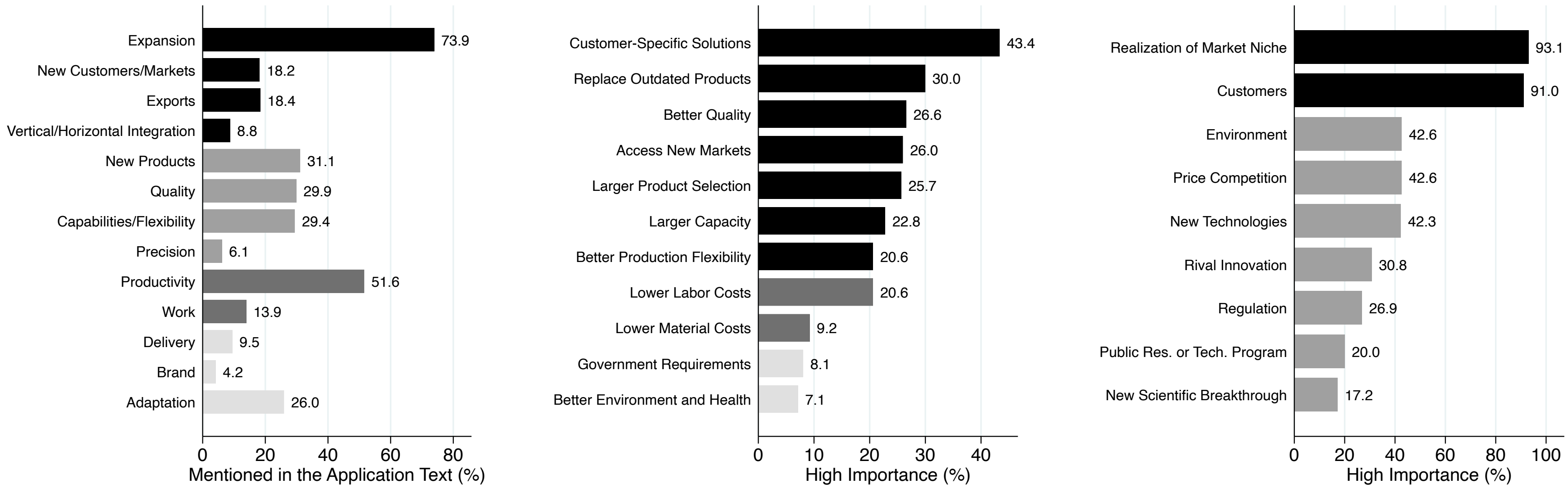


Figure 9: Export Effects: Effect of Technology Subsidies on Export Status.

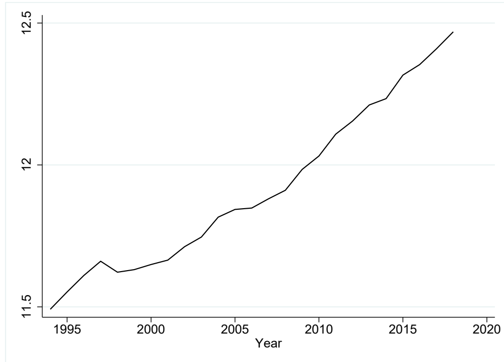
Notes: Event-study estimates from Equation 1. Event time $\tau = 0$ refers to the application year. The outcome is the firm's export status indicator (exporter vs. non-exporter). The estimates indicate an approximately 4 percentage point increase. The baseline value is 0.28 (28%). Exports are measured from the Finnish Customs' Foreign Trade Statistics. The definition from Statistics Finland identifies a firm as an exporter in a given year if its annual exports exceed EUR 12K across at least two months, or if it has a single export transaction exceeding EUR 120K. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section VI.



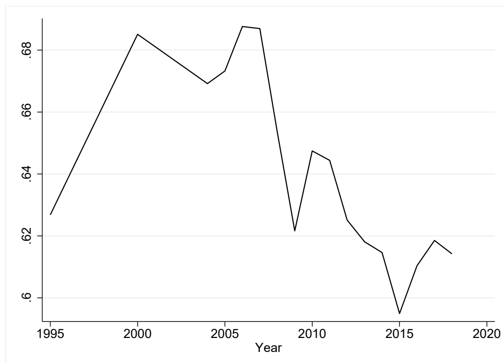
(A) Text Evidence. (B) Survey Evidence. (C) Literature-Based Evidence.

Figure 10: Evidence on Firms' Intentions From Application Texts, Surveys, and Trade Journals.

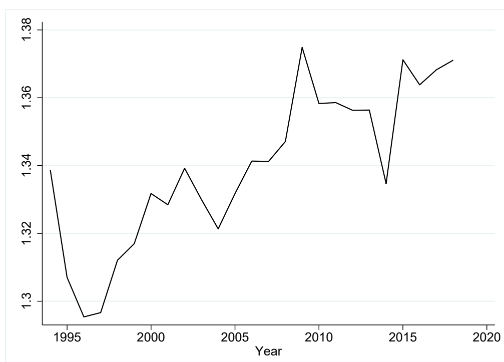
Notes: **Panel A:** The application texts contain information on the firms' intentions for the grant. This graph shows the prevalence of each objective. Colors reflect thematic grouping the intentions: expansion, product changes, productivity and work, and other intentions. **Panel B:** The Community Innovation Survey (CIS) asks firms about the importance of different objectives for process and product innovations, including technology adoption. This figure shows the share of firms in our main sample that said a certain objective was highly important to them. The data come from survey rounds 1996, 2000, -04, -06, -08, -10, -12, -14, -16, -18. If the firm has responded to multiple rounds of CIS, we consider the closest survey to its subsidy application. N = 708 (the number of main-sample firms covered in these CIS rounds). **Panel C:** Evidence from the SFINNO database that collected information from 15 technical and trade journals. The figure reports answers to a targeted survey question: "How significant have the following factors been for the commencement of innovations's development?" The numbers refer to the share of firms in our main sample that said the factor was important to them. The options are not mutually exclusive. N = 73 (the firms in our main sample matched to the survey). Details in the main text and Appendix F. Back to Sections VI and VIII.



(A) Average Years of Education.



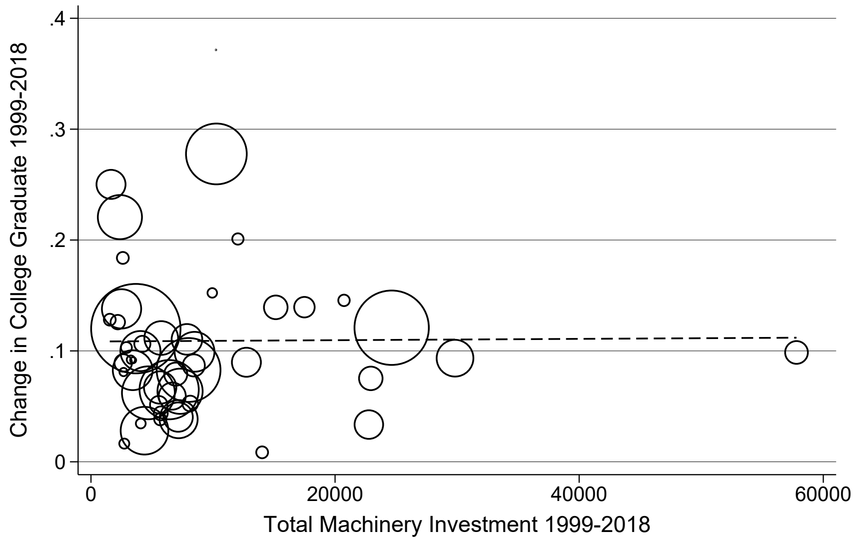
(B) Production Worker Employment Share.



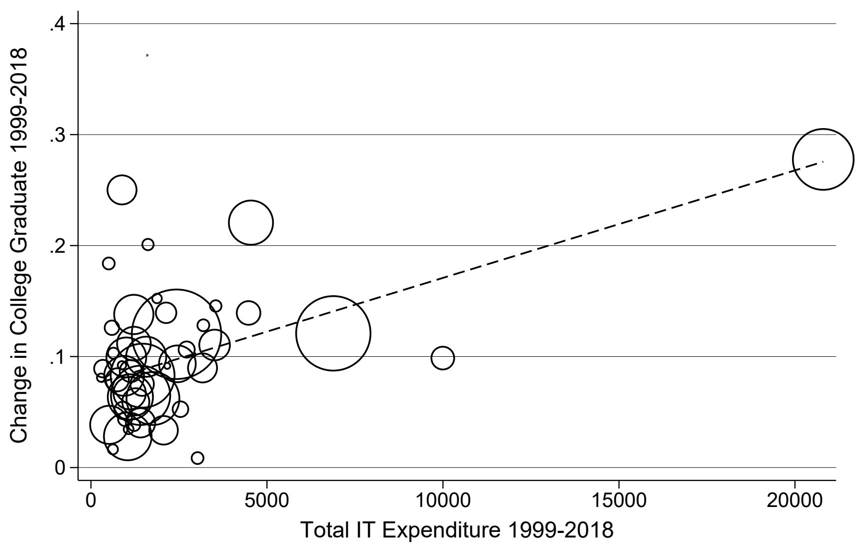
(C) College vs. Non-College Wage Ratio.

Figure 11: Skill Trends in Finnish Manufacturing.

Notes: These figures document trends in Finnish manufacturing over 1994–2018. We restrict to firms with at least three workers. Note that occupation data, and thus also production worker employment share, is missing for years 1996–1999 and 2001–2003. We compute the year-level averages from firm-level observations. The numbers are unweighted to match our research design. The employment-weighted numbers are similar. Back to Section IX.



(A) Machinery Investment.



(B) IT Expenditure.

Figure 12: Industry-Level Evidence on Machinery and IT.

Notes: Industry-level graphs on predicting skill mix changes with total machinery investment (Panel A) and IT expenditure (Panel B) between 1999–2018. The technology variables are measured in EUR per worker-years (FTE). The outcome measure is the change in share of college-educated workforce in the industry in percentage points (i.e., .1 refers to 10 p.p.). Each bubble indicates an industry. The observations are weighted by industry employment, reflected in the size of the bubble. The related estimates are in Table 10. Back to Section IX.

Table 1: Summary Statistics: Winner-Losers Design.

	Treatment Group		**Control Group**		**Both**			**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	p10	Median	p90	p-value
Machine Investment (EUR K)	109.93	369.14	82.60	233.11	0.00	27.24	233.80	0.378
Revenue (EUR M)	3.20	25.39	1.64	5.29	0.16	0.96	5.67	0.458
Employment	17.81	47.16	9.67	21.29	1.40	7.90	37.00	0.039
Wages (EUR K)	22.23	9.08	18.40	10.22	11.26	22.30	31.61	0.000
Labor Share (%)	18.68	9.31	15.47	10.28	6.49	18.03	30.70	0.000
Labor Productivity (EUR K)	146.82	163.84	145.61	87.86	72.35	118.60	228.49	0.930
Subsidy Applied (EUR K)	112.05	129.25	47.01	81.30	8.89	58.13	290.06	0.000
Subsidy Granted (EUR K)	81.77	103.02	0.00	0.00	3.24	35.64	200.23	0.000
Educ. Years	11.71	0.99	11.45	1.12	10.50	11.73	12.67	0.004
College Share (%)	15.51	16.80	11.63	18.42	0.00	12.50	33.33	0.012
Production Worker Share (%)	70.53	21.53	70.37	28.61	42.86	72.73	100.00	0.966
F-test								0.000
N	1885		146		2031			2031

Notes: All variables measured at $\tau = -3$ except for subsidies applied and received which are sums over $\tau \in [0, 2]$. Machinery investment and revenue are measured from the Financial Statement Register. Data on employment, and wages come from the firm- and worker-level registers. Subsidies applied and granted are from the subsidy application data. Education years, college share, and production worker share are measured based on the worker composition within the firm. The variables are not winsorized prior for these summary statistics. Back to Sections III and VIII.

Table 2: The First Stage: First-Difference Estimates.

	(1) Subsidies Granted		(2) Machine Inv.		(3) Capital Stock	
Treatment	66.06***	70.22***	103.8***	100.3***	49.78**	41.60
	(3.119)	(4.907)	(22.56)	(29.29)	(18.26)	(23.60)
Propensity Score		✓		✓		✓
Observations	2031	1812	2031	1812	1560	1540

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2 with and without the text propensity score control. The outcomes are in EUR K. To measure capital stock, we use the official records on firms' balance sheets. The post-period outcomes are means over $\tau \in [0, 2]$ multiplied by three (the number of periods). The specifications include two-digit industry and firm size as controls. Back to Section V.

Table 3: Main Firm-Level Estimates: Different Specifications.

Panel A: Investment, Employment, and Revenue.

	Machine Investment (EUR K)			Employment			Revenue		
	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match
Treatment	103.8***	100.3***	124.5***	0.232***	0.234**	0.217***	0.314***	0.333***	0.261***
	(22.56)	(29.29)	(9.358)	(0.0614)	(0.0746)	(0.0183)	(0.0779)	(0.0958)	(0.0232)
Observations	2031	1812	3200	2031	1812	3200	2031	1812	3200

Panel B: Wages, Profit Margin, and Productivity.

	Wages			Profit Margin			Productivity		
	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match
Treatment	-0.0481	-0.0285	0.00306	0.00121	-0.00791	-0.00685*	-0.00516	-0.00622	0.0117
	(0.0355)	(0.0407)	(0.00290)	(0.00772)	(0.00978)	(0.00290)	(0.0350)	(0.0427)	(0.0120)
Observations	1952	1738	3080	2031	1812	3200	2031	1812	3200

Panel C: Labor Share and Skill Composition.

	Labor Share			Education Years			College Share			Production Worker Share		
	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match	Baseline	Prop. Score	Match
Treatment	-0.00202	-0.000700	-0.00293	0.0246	-0.00385	0.0303	0.00557	0.00592	0.00542	0.000723	-0.0213	-0.00464
	(0.00496)	(0.00601)	(0.00203)	(0.0611)	(0.0752)	(0.0207)	(0.00935)	(0.0116)	(0.00330)	(0.0181)	(0.0212)	(0.00605)
Observations	2031	1812	3200	1884	1676	2999	1884	1676	2999	1891	1692	3011

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

Notes: Difference-in-differences estimates from Equation 2. The table reports the treatment effects on selected outcomes for the main sample with and without the text propensity-score control and the matched control sample. "Baseline" refers to a baseline specification with calendar-year indicators, two-digit industry, and firm size as controls. "Prop. Score" refers to estimation with the text propensity score included as an additional control. "Match" refers to estimation in the matched sample, where the control group is formed from matched non-applicant firms. **Panel A:** Machinery investment is in EUR K. Employment and revenue are in relative changes, e.g., 0.20 would refer to a 20% increase. **Panel B:** Wages and productivity are relative changes; the profit margin is in percentage points. **Panel C:** Education years is in years. The labor, college, and production worker shares are in percentage points. For machinery investment, the post-period outcome is the average of investment between $\tau \in [0, 2]$ multiplied by three (the number of periods) and for other outcomes, the average of $\tau \in [2, 5]$. The pre-period for the estimations is $\tau = -3$. Back to Sections V and VI.

Table 4: Detailed Firm-Level Estimates.

Panel A: Exports and Products.

	(1) Exporter Status	(2) Export Share	(3) Export Regions	(4) Products Number	(5) Products Introduced	(6) Products Discontinued
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)
Mean	0.284	0.0523	1.498	1.546	0.498	0.539
N	2031	2031	2031	2031	2031	2031

Panel B: Inputs and Imports.

	(1) Capital per Worker	(1) Input Value	(2) Input Share	(3) Import Value	(4) Import Share	(5) Machine Imp. Value	(6) Machine Imp. Share
Treatment	-0.085	-115.6	-0.0521	20.60^{***}	0.0029^{*}	3.437^{***}	0.0005
	(0.087)	(663.6)	(0.0438)	(5.989)	(0.0014)	(1.031)	(0.0002)
Mean	23.85	3457.9	0.292	152.9	0.0203	27.80	0.0037
N	1550	321	321	2031	2031	2031	2031

Panel C: Patents, R&D, and Marketing.

	(1) Patents	(2) R&D Costs	(3) Marketing Costs
Treatment	0.002	0.564^{*}	13.89^{***}
	(0.008)	(0.239)	(4.162)
Mean	0.056	7.101	31.42
N	1535	1842	2028

Panel D: Prices.

	(1) Prices, Exports	(2) Prices, Manuf. Survey
Treatment	0.291	0.308^{**}
	(0.328)	(0.102)
N	400	217

Panel E: 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Difference-in-differences estimates from Equation 2. The specifications include two-digit industry and firm size as controls. The baseline means are measured at $\tau = -3$. All level estimates are in EUR K and shares in percentage points. The export, input, and import shares are defined over revenue. Patents are measured as the average annual patenting rates. Prices are computed as product-level revenue divided by quantity from the Customs Register and the Industrial Production Statistics (a survey of manufacturing firms). Post-period values calculated as the average over $\tau \in [2, 5]$, except for the profit levels that are over $\tau \in [0, 5]$ multiplied by the number of periods, 6, to scale them to the overall effect without discounting. The pre-period for the estimations is $\tau = -3$. More details are in the main text and Appendix F. Back to Sections VI and VIII.

Table 5: Continuous Treatment Estimates.

	(1) Machine Inv.		(2) Employment		(3) Revenue	
Granted Amount	1.011***	0.973***	0.249***	0.230***	5.292***	4.973***
	(0.115)	(0.118)	(0.0213)	(0.0220)	(0.468)	(0.478)
Propensity Score		✓		✓		✓
Observations	2031	1812	2031	1812	2031	1812

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

Notes: Difference-in-differences estimates from Equation 2. Treatment is the subsidy amount in EUR, scaled to EUR 10K for employment. For machinery investment, the post-period outcome is the sum of investment between $\tau \in [0, 2]$ and for other outcomes, the average over $\tau \in [2, 5]$. The pre-period for the estimations is $\tau = -3$. The specifications include two-digit industry and firm size as controls. Back to Section VI.

Table 6: Text Categories of Firms' Intentions.

Category	Description	Examples
Expansion	Expand production, operations, or firm scale.	*Increase output, build production capacity, pursue growth.*
New Customers/Markets	Target new customers or markets.	*Win new customers, enter a new market.*
Exports	Expand or improve exporting.	*Start exporting, appeal to foreign markets.*
Vertical/Horizontal Integration	Shift firm's position in the value chain.	*Bring tasks in-house, mergers and acquisitions.*
New Products	Introduce or develop new products or services.	*New product, expand product range.*
Quality	Raise product or production quality.	*Improve product quality, meet stringent quality requirements.*
Capabilities/Flexibility	Enhance production capabilities or flexibility.	*Offer customized and diverse solutions.*
Precision	Improve precision or accuracy.	*Increase precision, enable more accurate measurement.*
Productivity	Raise productivity or reduce costs.	*Cut costs, increase productivity, enhance efficiency.*
Work	Affect labor costs, tasks, or productivity.	*Automate tasks, reduce labor costs, increase labor productivity.*
Delivery	Improve delivery speed, reliability, or logistics.	*Accelerate deliveries, enhance delivery reliability.*
Brand	Improve branding or public image.	*Enhance image, improve reputation*
Adaptation	Respond to new challenges or demands.	*Adapt to changing customer needs.*

Notes: This table lists categories of firms' intentions that we first defined and then hand-coded from the subsidy application texts. Each application may belong to one or more of these categories (not mutually exclusive). Bold text indicates the category name, regular text provides a description, and italicized text gives examples of common phrases appearing in the applications. Full details and more detailed examples are available in Appendix F. Back to Section VI.

Table 7: Heterogeneous Effects by Firms' Intentions.

Subgroup	Employment	Educ. Years	Labor Share	Productivity	N
All	0.217***	0.030	-0.003	0.012	3,200
	(0.018)	(0.021)	(0.002)	(0.012)	
	17.7	11.6	0.185	144,204	
Work Only	0.165*	0.220*	-0.012	0.027	138
	(0.068)	(0.094)	(0.010)	(0.057)	
	21.0	11.5	0.188	132,724	
Productivity Only	0.143***	0.064	-0.004	0.045	542
	(0.043)	(0.050)	(0.005)	(0.029)	
	22.9	11.6	0.188	141,218	
Work or Productivity Only	0.143***	0.068	-0.005	0.047	562
	(0.042)	(0.048)	(0.005)	(0.029)	
	22.5	11.6	0.187	142,013	
Excluding Work or Productivity Only	0.234***	0.021	-0.003	0.008	2,638
	(0.020)	(0.023)	(0.002)	(0.013)	
	16.7	11.6	0.184	144,671	

Standard errors in parentheses and baseline means on every third row.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table presents estimates by subgroup using the matched control group. Each estimate is from a separate firm-level regression. The **All** category contains all applications as a reference. The **Work Only** category contains applications that mention a work-related motive but no product changes (new products, quality improvements, capabilities/flexibility, or precision). The **Productivity Only** category similarly contains applications that mention a productivity-related motive but no product changes. The **Work or Productivity Only** category is the union of these two. **Excluding Work or Productivity Only** is the complement: It excludes the Work or Productivity Only category from all applications. Descriptions of the underlying narrow text categories are provided in Table 6 and Appendix F. Outcomes: Employment and productivity are in relative changes, e.g., 0.20 would refer to a 20% increase. Education years is in years. Labor share is in percentage points. Post-period values are calculated as the average over $\tau \in [2, 5]$. The pre-period for the estimations is $\tau = -3$. Back to Section VI.

Table 8: Predicting Machinery Investment and IT Expenditure in Firm Register 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 Workers' Share	1481.9*	99.26	888.9	0.612
	(611.1)	(476.8)	(512.6)	
Labor Share	-38251.2***	-16093.1***	-15733.8***	0.236
	(1966.0)	(937.5)	(972.2)	
Productivity	19460.9***	9069.6***	8958.6***	0.173
	(1217.1)	(821.8)	(858.5)	
B: IT Expenditure				
College Share	7779.8***	6607.8***	5569.2***	0.217
	(426.2)	(283.1)	(286.6)	
Production Workers' Share	-5646.4***	-4577.6***	-3579.1***	0.612
	(394.6)	(237.7)	(208.5)	
Labor Share	-10719.0***	-7339.8***	-6200.8***	0.236
	(581.2)	(314.4)	(325.8)	
Productivity	5850.5***	4418.4***	3961.3***	0.173
	(288.5)	(250.0)	(266.6)	
Year Controls	Yes	Yes	Yes	
Industry Controls	No	Yes	Yes	
Firm Size Control	No	No	Yes	
Machinery	R^2	R^2	R^2	N
College Share	0.013	0.298	0.299	159,583
PW Share	0.009	0.311	0.313	125,817
Labor Share	0.103	0.310	0.310	161,336
Productivity	0.179	0.318	0.318	161,338
IT				
College Share	0.256	0.475	0.508	159,583
PW Share	0.177	0.453	0.510	125,817
Labor Share	0.182	0.428	0.478	161,336
Productivity	0.332	0.472	0.517	161,338
	Mean	10p	90p	Obs. $\neq 0$
Machinery	5321.7	0	14054.0	116,032
IT	1016.1	106.0	2343.0	149,988

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

Notes: Pooled cross-sectional estimates predicting machinery investment (Panel A) and IT expenditure (Panel B) with college share, production workers' share, labor share, and productivity. Each estimate is from a separate firm-level regression. Shares are on a scale of 0 to 1 (estimates reflect a change from 0 to 100%), productivity in EUR M (revenue per worker), and machinery and IT in euros per worker. N refers to firm × year observations. The data contain all Finnish manufacturing firms with > 2 full-time equivalent employees (FTE) from 1999–2018. Estimates are weighted by firm employment. Back to Section IX.

Table 9: Contrasting Robot and IT Use in Survey and Customs Data.

	(1)		(2)		(3)		(4)		
	CIS *Robots' Importance*		**ICT** *Robot-User*		**Etla** *Robot-User*		**Customs** *Robot-Importer*		
A: Robots	High	Low	Yes	No	Yes	No	Yes	No	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)	
Labor Share	0.199	0.246	0.200	0.230	0.235	0.258	0.172	0.232	0.205
	(< 0.001)		(< 0.001)		(0.037)			(< 0.001)	
Productivity (€K)	311	246	324	275	231	212	209	140	173
	(< 0.001)		(0.009)		(0.258)			(< 0.001)	
N	271	1,195	357	521	298	306	760	260,434	91,880
Share	0.185	0.815	0.407	0.593	0.493	0.507	0.003	0.994	0.351
Years	2014–2018		2018		2015			2000–2018	

	CIS *Digitalization's Importance*		**ICT** *Computer Users' Share vs. Median*		**Etla** *Big Data and Analytics*	
B: IT	High	Low	Above	Below	Yes	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)	
Labor Share	0.240	0.234	0.210	0.225	0.254	0.245
	(0.527)		(0.097)		(0.500)	
Productivity (€K)	263	257	342	249	232	213
	(0.734)		(< 0.001)		(0.324)	
N	192	1263	436	443	137	493
Share (%)	0.132	0.868	0.496	0.504	0.217	0.783
Years	2014–2018		2018		2015	

Notes: Group means by technology use in the CIS, ICT, and Etla surveys and the Finnish Customs data. The text in italics refers to the question from each survey. The p-values in parentheses are based on a t-test for the difference between the groups. The data contain Finnish manufacturing firms with more than two full-time equivalent employees (FTE) overlapping with the surveys and customs records. In Column 4, No* refers to firms that did not import robots but imported something. Productivity is measured as revenue per worker. More details in the main text and Appendix F. Back to Section IX.

Table 10: Industry-Level Evidence on Machinery and IT.

	(1)			(2)		
	College	HS grad	Less than HS	College	HS grad	Less than HS
A: Machinery Investment	0.0001 (0.0007)	0.0017 (0.0009)	-0.0018 (0.0009)	-0.0006 (0.0008)	0.0027*** (0.0005)	-0.0022** (0.0007)
Pre-Period College Share				0.396* (0.165)	-0.657*** (0.167)	0.261*** (0.0586)
B: IT Expenditure	0.0097*** (0.0006)	-0.0114*** (0.0018)	0.0017 (0.0015)	0.0082*** (0.0010)	-0.0065* (0.0025)	-0.0017 (0.0020)
Pre-Period College Share				0.123 (0.0862)	-0.411*** (0.104)	0.288** (0.0833)
N	49	49	49	49	49	49
Mean Pre-Period	0.245	0.471	0.284	0.245	0.471	0.284
Mean Change	0.104	0.0494	-0.153	0.104	0.0494	-0.153
R^2, Machinery	0.000	0.035	0.118	0.356	0.646	0.421
R^2, IT	0.592	0.509	0.036	0.614	0.660	0.268
	Mean Total	10p	90p			
Machinery	9.236	2.560	21.75			
IT	2.306	0.610	4.011			

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

Notes: Industry-level long-difference estimates on predicting skill mix changes with total machinery investment (Panel A) and IT expenditure (Panel B) between 1999–2018 in Finnish manufacturing industries. The technology variables are measured in EUR K per worker-year (FTE). The educational variables are in long-changes over the timeline. The educational groups are mutually exclusive. "College" refers to the employment share of college-educated employees in the industry, "HS grad" to the share of exactly high-school educated workers including vocational degrees, and "Less than HS" to the share of those without a high-school or vocational degree. The estimates and means are weighted by pre-period industry employment sum between 1999–2002. The pre-period is elsewhere defined as the year 1999. N denotes the number of 2-digit manufacturing industries. Figure 12 illustrates the estimates for the college share. Back to Section IX.

Winners and Losers of Technology Grants

Online Appendix

Johannes Hirvonen
Aapo Stenhammar
Joonas Tuhkuri

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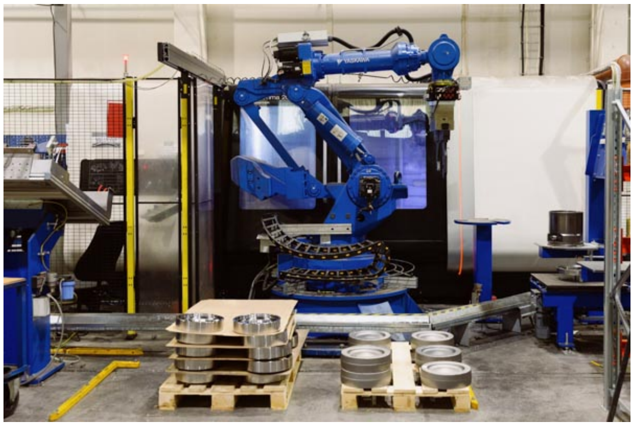
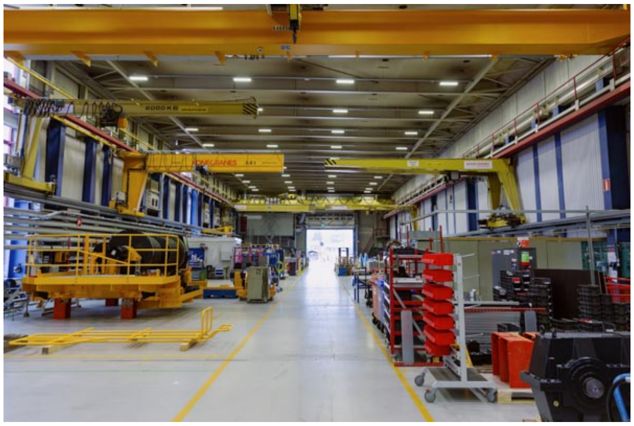
A Winners-Losers Design



(A) A CNC Machine and a Robot.



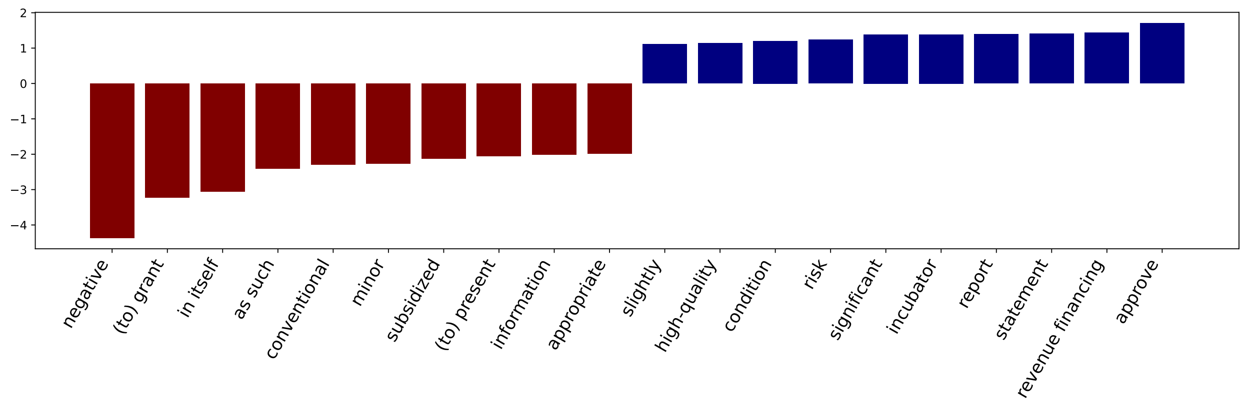
(B) Inside an Industrial Manufacturing Plant.

(C) Machine Operators and a Milling Machine.

Figure A1: Fieldwork: Documenting the Context.

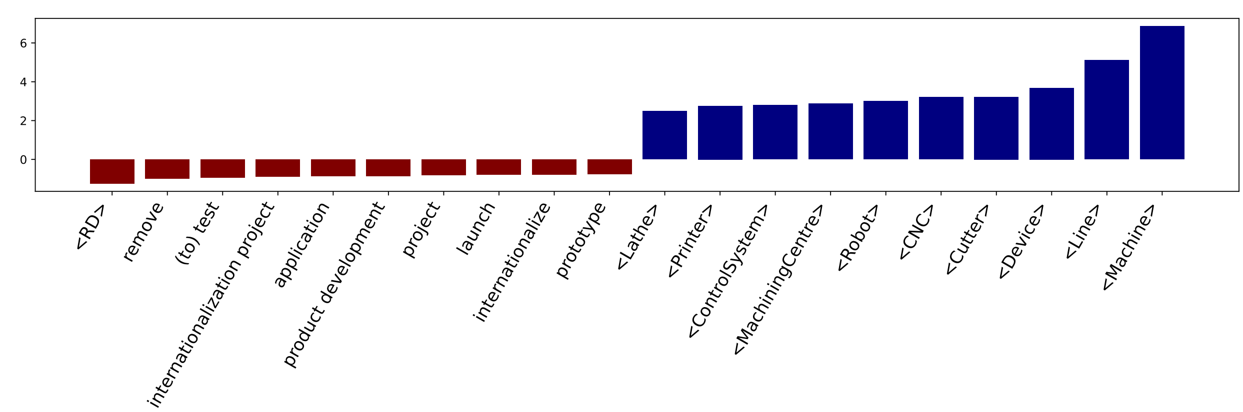
Notes: Photographs from fieldwork. Back to Section III.

Figure A2: Predictive Words for Winning a Subsidy in the Application Texts.

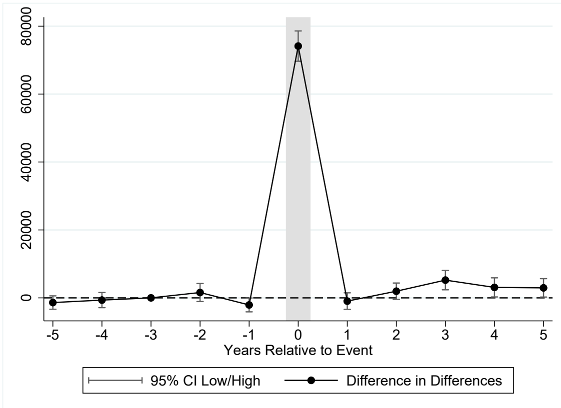


Notes: The features (words) are plotted from top and bottom linear SVM coefficients predicting treatment status in the evaluation texts of the applications. The texts are represented as TF-IDF-weighted bag-of-words vectors so that the coefficients for individual words are interpretable. The y-axis refers 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 features are translated from Finnish into English. Back to Section III.

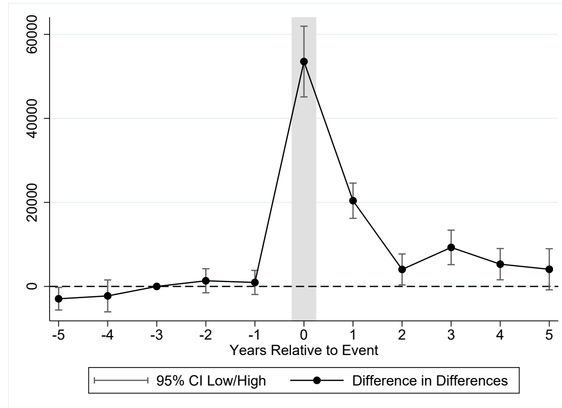
Figure A3: Predictive Words for Technology in the Application Texts.



Notes: The features (words) are plotted from top and bottom linear SVM coefficients predicting technology in the short description texts of the applications. The texts are represented as TF-IDF-weighted bag-of-words vectors so that the coefficients for individual words are interpretable. 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 contains all applications which we have hand-classified as technology vs. not technology. N = 21,699. The features are translated from Finnish into English. Features in $<>$ refer to compound terms combining similar spelling versions of the same term. Back to Section IV.



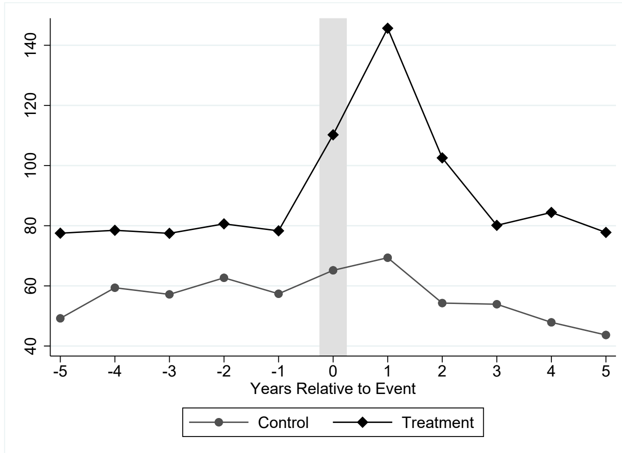
(A) Granted.



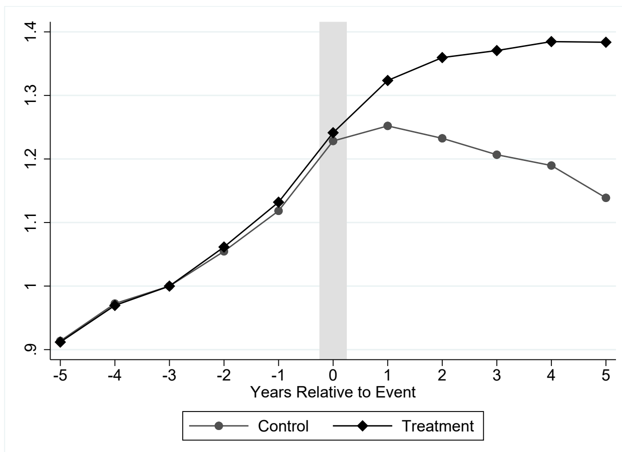
(B) Received.

Figure A4: The First Stage: Effect of Winning a Subsidy on Granted and Received Subsidies.

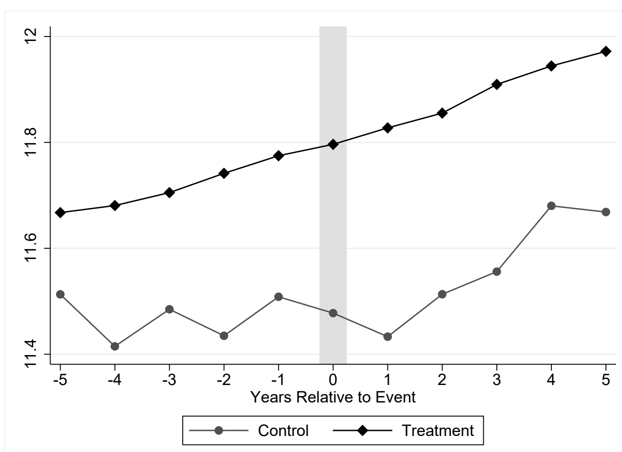
Notes: Event-study estimates from Equation 1. The outcomes are (A) any subsidy granted and (B) received, measured from the Finnish Statistics on Business Subsidies. Event time $\tau = 0$ refers to the application year. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section V.



(A) Machinery Investment.



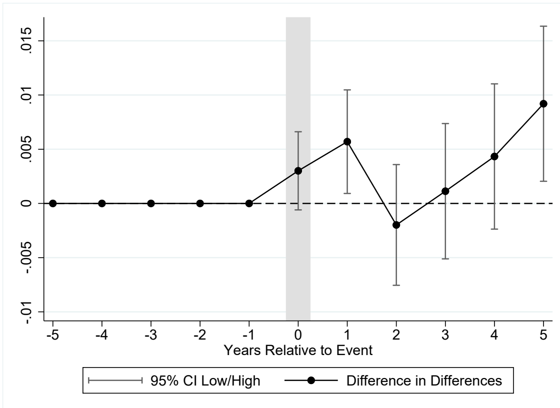
(B) Employment.



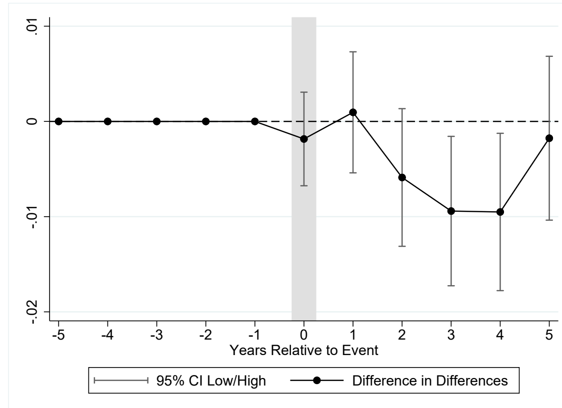
(C) Education Years.

Figure A5: Raw Means of Machinery Investment, Employment, and Education.

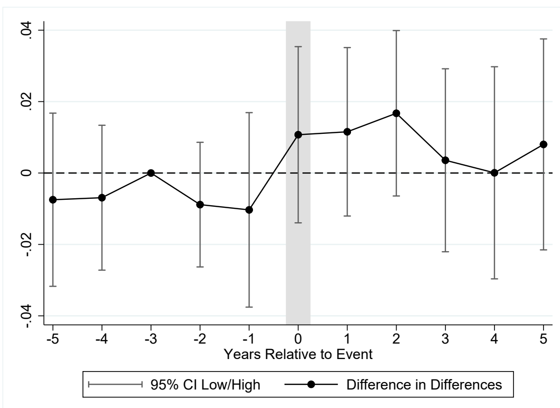
Notes: Means over time for the main treatment and control groups (winners vs. losers). Machinery investment in EUR K, employment in % relative to $\tau = -3$, and education in years. Back to Sections V, VII, and IX.



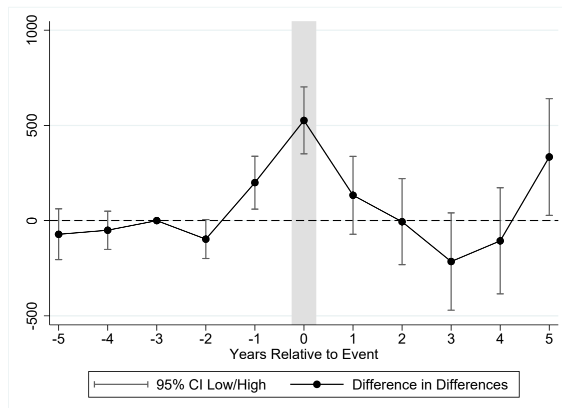
(A) Employed.



(B) Employed at the Baseline Firm.



(C) Income in % Relative to Baseline.



(D) Income in Euros.

Figure A6: Effects of Technology Subsidies on Incumbent Workers.

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 outcomes are in percentage points, the third in percentages, and the fourth 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 500 euros in the year of the application. This corresponds to a salary of about one week. We present here results for the high-tenure workers. The modest effects are robust to relaxing that assumption. Back to Section V.

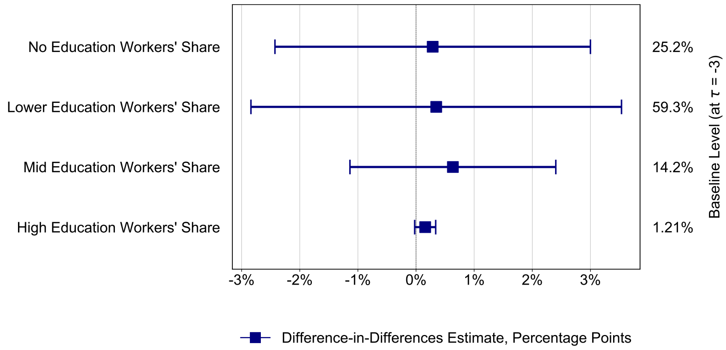


Figure A7: Skill Effects: Effect of Technology Subsidies on Education Group Shares.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The data are from Finnish educational registers. Education groups are defined in Appendix F. Back to Section V.

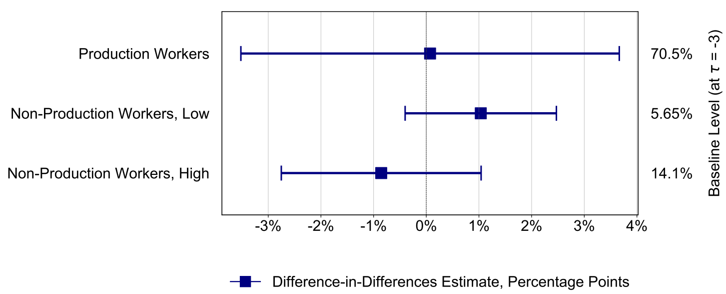


Figure A8: Skill Effects: Effect of Technology Subsidies on Occupation Group Shares.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The data are from the Finnish occupation registers. Occupation groups are defined in Appendix F. The shares do not sum to 100% because some workers do not have occupational info. Back to Section V.

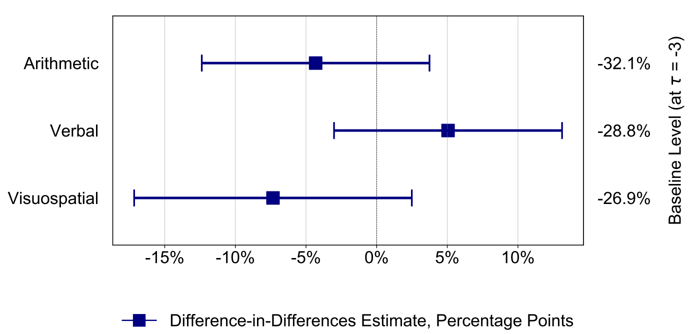


Figure A9: Skill Effects: Effect of Technology Subsidies on Average Worker Cognitive Performance Measures.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The estimates are in percentages of standard deviations. The data are from the Finnish Defence Forces. Appendix F provides more information. Back to Section V.

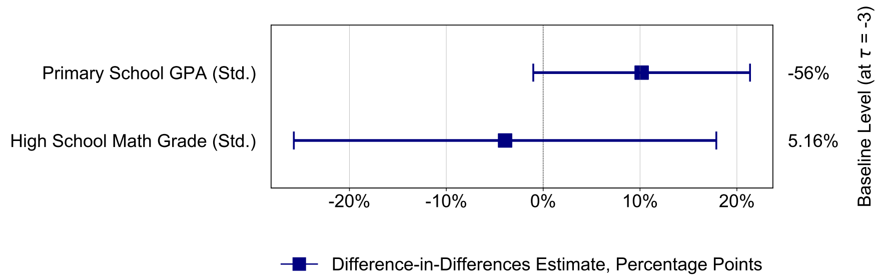


Figure A10: Skill Effects: Effect of Technology Subsidies on Average Worker School Performance.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The estimates are in percentages of standard deviations. The data are from the Secondary Education Application Register and the Finnish Matriculation Examination Board Register. School variables are defined in Appendix F. Back to Section V.

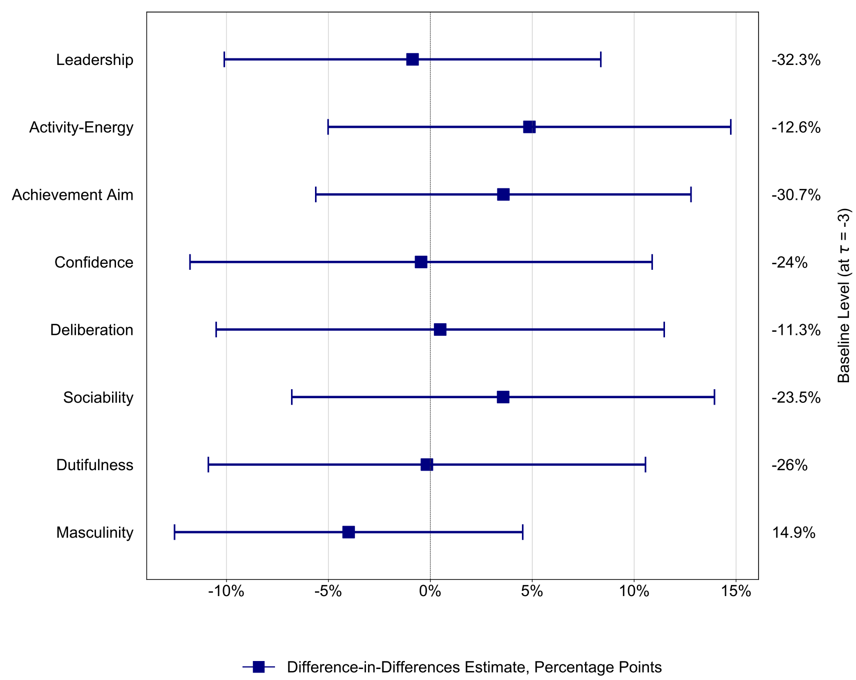


Figure A11: Skill Effects: Effect of Technology Subsidies on Average Worker Personality Measures.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The estimates are in percentages of standard deviations. The data are from the Finnish Defence Forces. Personality variables are defined in Izadi and Tuhkuri (2024). Back to Section V.

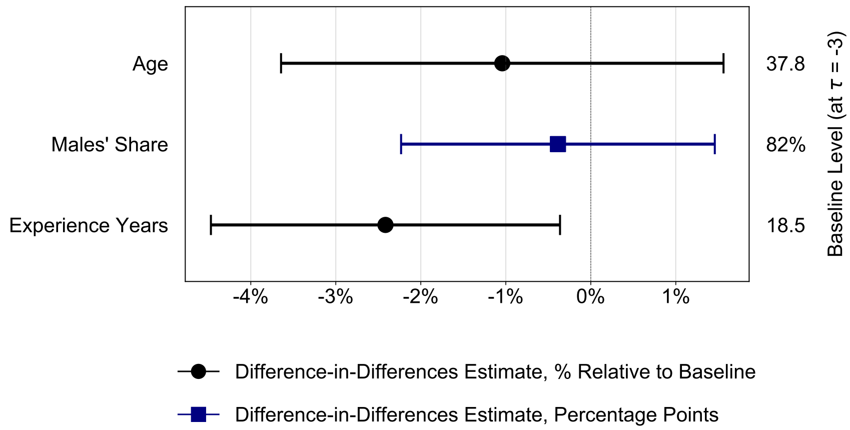


Figure A12: Skill Effects: Effect of Technology Subsidies on Average Worker Demographics.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. The data are from the Finnish worker and population registers. Back to Sections V and VIII.

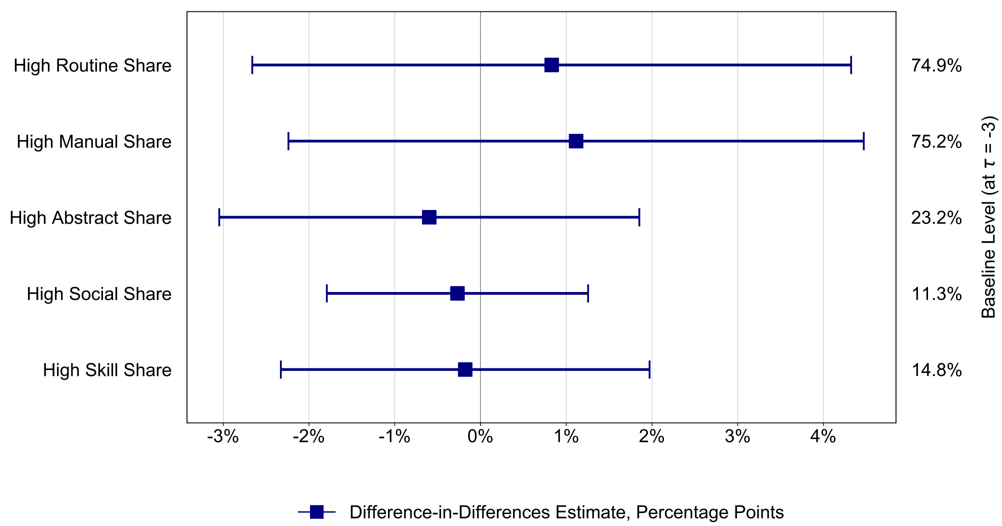
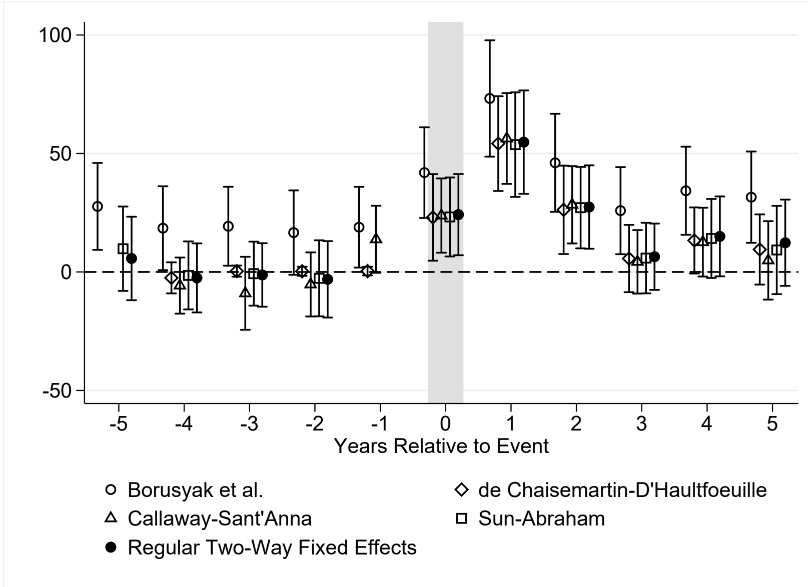
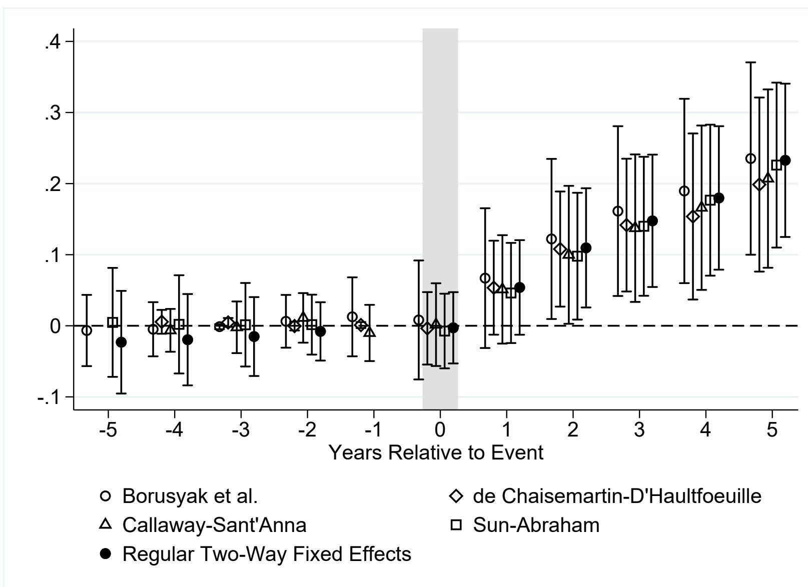


Figure A13: Skill Effects: Effect of Technology Subsidies on Task Content.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. We discretize the data for each worker into above vs. below median (high/low) because it has no natural scale. Median refers to the median task intensity in the Finnish labor force. For example, the first row indicates that 74.9% of workers in our sample firms are in an occupation times industry cell that is above the median in routine task content. The treatment group increases the share of these workers by a statistically insignificant 1% compared to the control group. The data are from the Finnish occupation registers and the European Working Conditions Survey (EWCS). More details in F. Back to Section V.



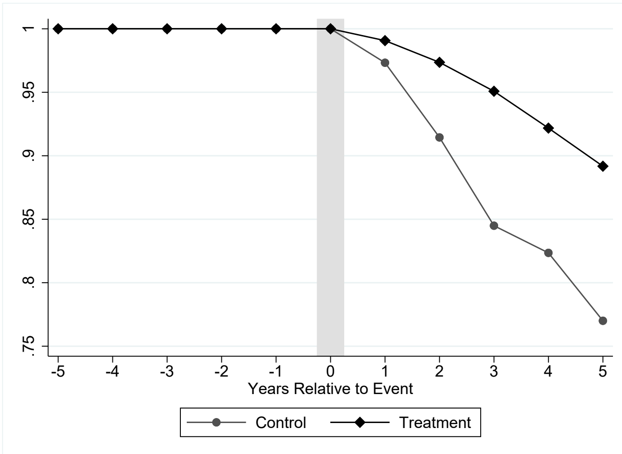
(A) Effect of Technology Subsidies on Machinery Investment.



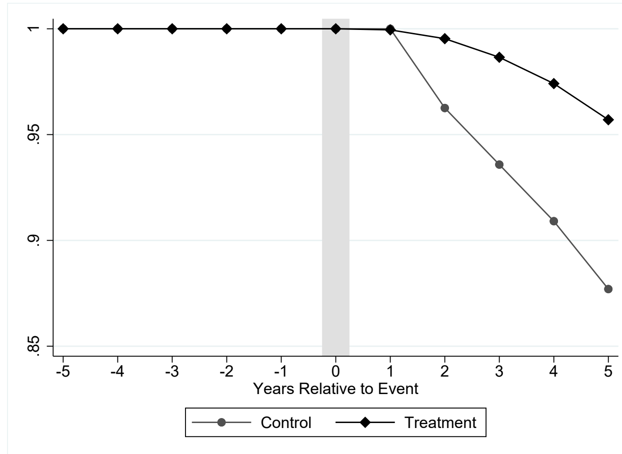
(B) Effect of Technology Subsidies on Employment (%).

Figure A14: Robustness to Different Event-Study Estimators.

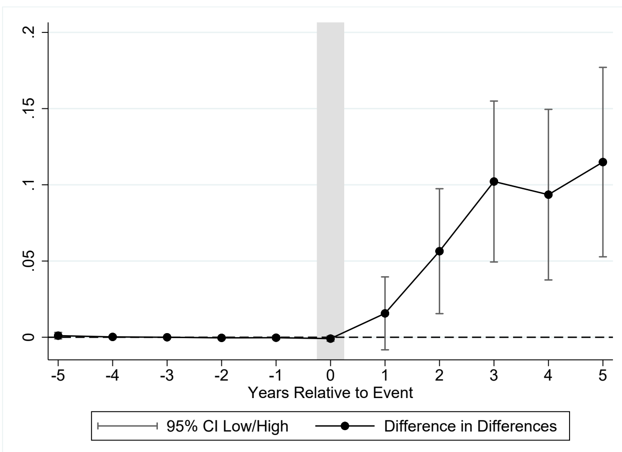
Notes: Results from different recent event-study estimators: Borusyak et al. 2024; de Chaisemartin and D'Haultfoeuille 2020; Callaway and Sant'Anna 2021; Sun and Abraham 2021. The regular two-way fixed effects refer to event-study estimates from Equation 1. Event time $\tau = 0$ refers to the application year. **Panel A:** The outcome is investment in machinery and equipment (in EUR K) measured from the Financial Statement Register. **Panel B:** The outcome is employment relative to the base year $\tau = -1$. These event-study specifications contain no controls in the term X_{jt}^{τ} of Equation 1. Back to Section V.



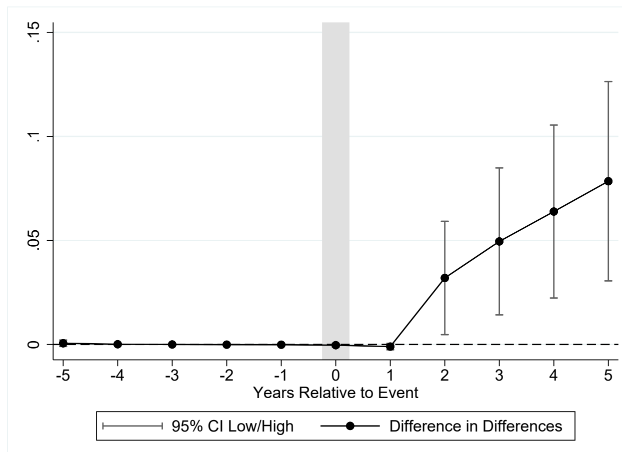
(A) Firm Survival Based on the Firm Register.



(B) Firm Survival Based on Worker Flows.



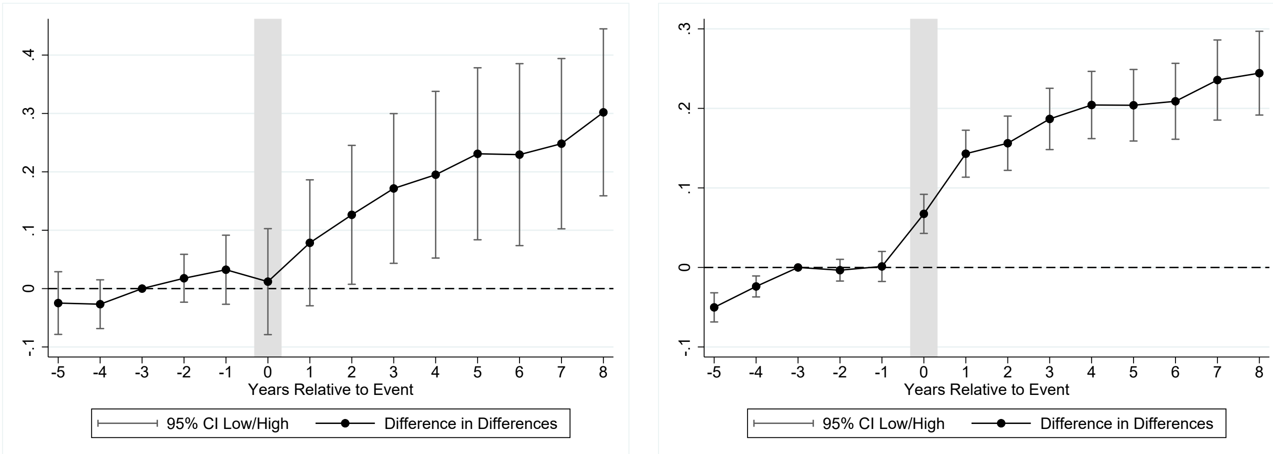
(C) Firm Survival Based on the Firm Register.



(D) Firm Survival Based on Worker Flows.

Figure A15: Effect of Technology Subsidies on Firm Survival.

Notes: Group means and event-study estimates from Equation 1. **Panels (A, C):** Survival is measured from whether the firm ID exists in the firm register. **Panels (B, D):** Survival is extended to include mergers and acquisitions (and other cases the firm ID changes), where at least 50% of workers continue under the same new firm ID. The main estimates are reported for a balanced sample over the 5-year window. The estimates are robust to a non-balanced sample, shown in Table A13. Back to Sections V, VI, and VIII.



(A) Winners vs. Losers.

(B) Matched Control Group.

Figure A16: Longer-Term Effects: Effect of Technology Subsidies on Employment until $\tau = 8$.

Notes: Event-study estimates from Equation 1 with an extended post-event horizon. The outcome is employment relative to the base year $\tau = -3$. Event time $\tau = 0$ refers to the application year. The balanced sample requirement is extended to $\tau = 8$. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section VI.

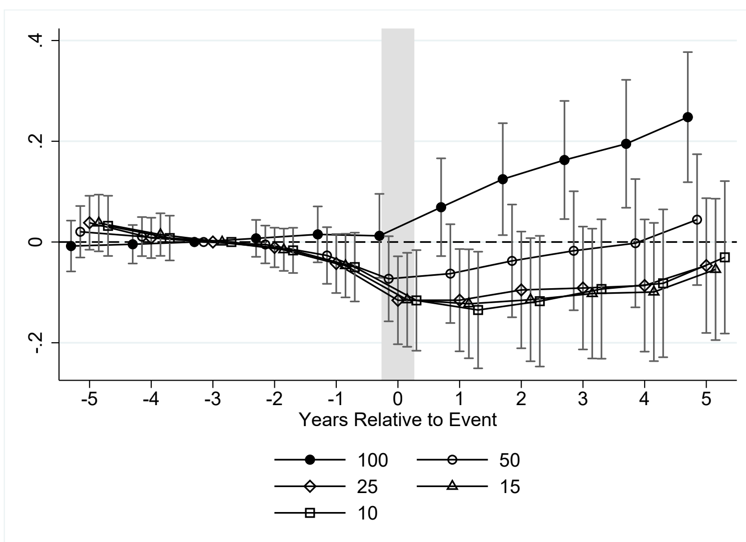
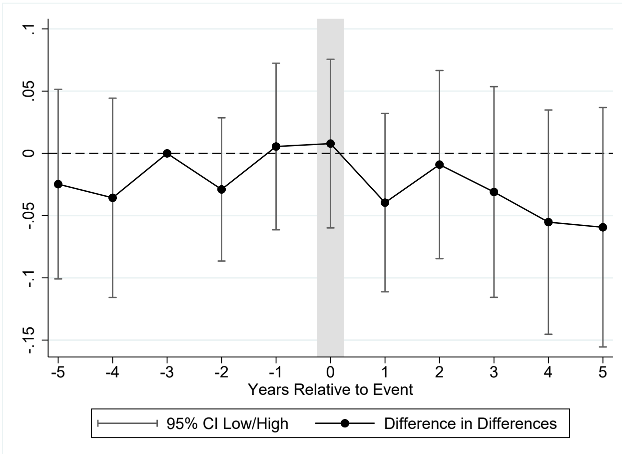
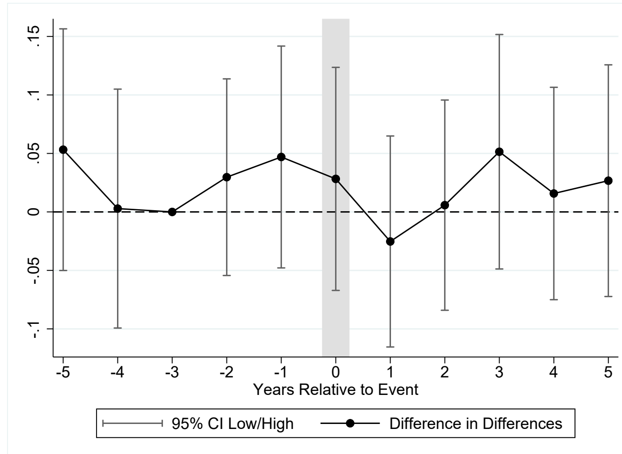


Figure A17: Placebo Test: The Employment Effects of Insignificant Subsidies (%).

Notes: Event-study estimates from Equation 1. The graphs restrict the sample to cases where the subsidy is a progressively smaller share of the firm's total costs in the base year $\tau = -3$. 100% contains full sample, 50% the subsidies that are below median share of total costs, 25% below the first quartile of total costs, etc. The control group here contains all losing firms, as the control sample is small. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section VII.



(A) Olley-Pakes.



(B) Levinsohn-Petrin.

Figure A18: TFP: Alternative Versions.

Notes: The sample is the main analysis sample (subsidies design). Event study graphs of log total factor productivity, estimated as in (a) Olley and Pakes (1996) and (b) Levinsohn and Petrin (2003). The results are in line with the Cobb-Douglas version, showing no effect. Back to Section VI.

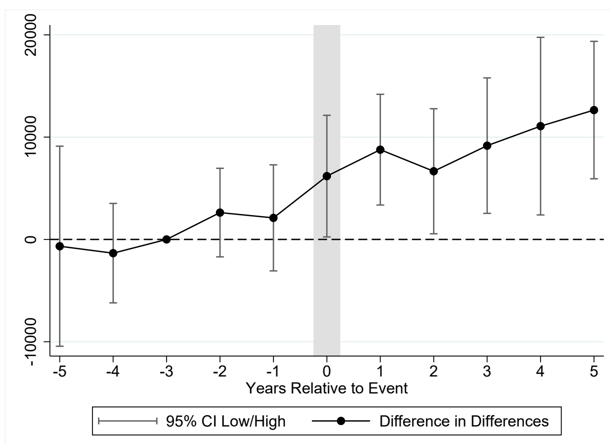


Figure A19: Effect of Technology Subsidies on Marketing Expenditure.

Notes: Event-study estimates from Equation 1. The outcome is the firm's marketing expenditure in euros, measured from the Finnish Financial Statement Register. Event time $\tau = 0$ refers to the application year. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section VI.

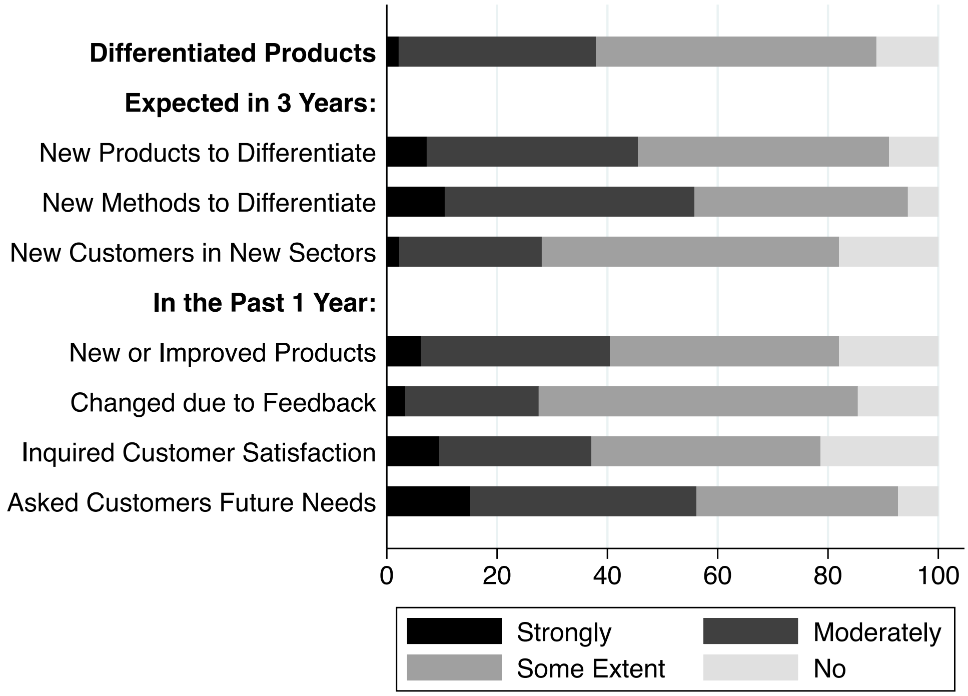
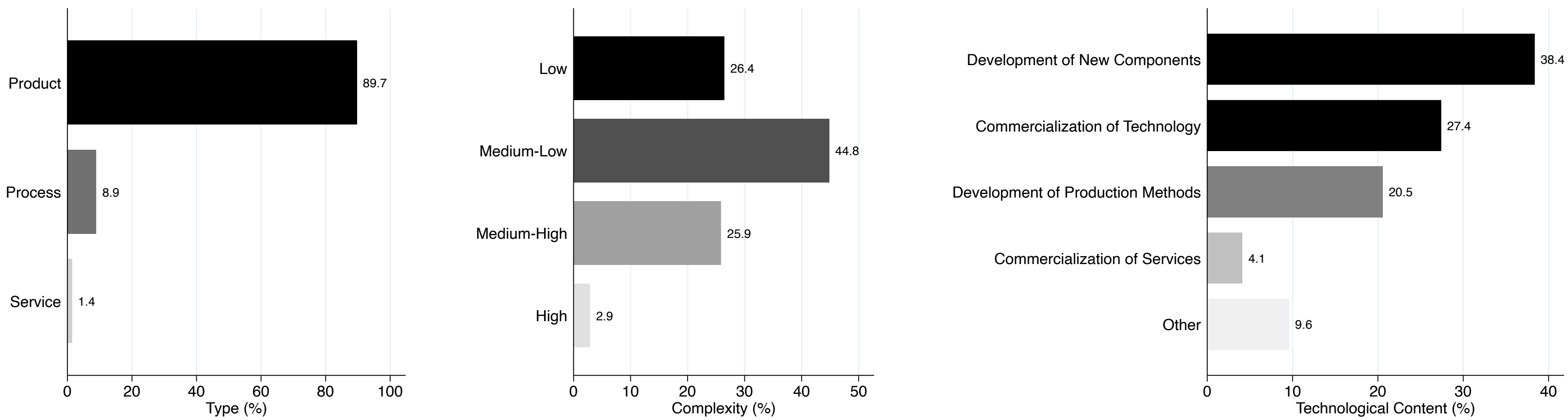


Figure A20: Etla Survey: Intentions.

Notes: The Etla survey provides information on firms' objectives and strategy. The full questions are "To what extent do your own products/services differ from other options on the market?", "To what extent do you think your company will change in the next 3 years?", where the subtopics are "We will bring products/services to the market that differentiate us from our competitors.", "We will develop production methods for our products/services that will differentiate us from our competitors.", and "We will acquire customers from new sectors.", and whether "During the last 12 months, we have..." "introduced new or substantially improved products to the market;" "changed our operations based on feedback received from customers"; "surveyed customer satisfaction;" and "asked customers about their future needs." N = 202 (firms matched to our winner-losers design). Back to Sections VI and VIII.

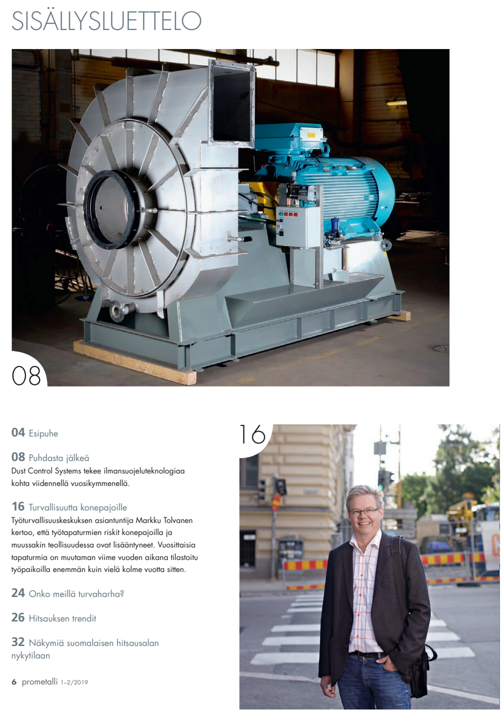


(A) Type. (B) Complexity. (C) Technological Content.

Figure A21: Literature-Based Evidence on Technologies from Trade Journals.

Notes: Evidence from 15 technical and trade journals that featured our sample firms, supplemented with targeted surveys and collected by the SFINNO project. **Panel A:** Shares of cases coded as product, process, or service using the definitions of the Oslo Manual (OECD, 2018) based on the journal article. N = 213 (the number of firms in our main sample matched to the journal data). **Panel B:** Shares of cases coded by their complexity based on the journal article. N = 174. Low complexity: *Innovation is a single coherent unit. Examples: glue-laminated timber, mobile phone cover.* Medium artefactual complexity / low developmental complexity: *Innovation is a unit, development is based on knowledge base from one discipline. Examples: electronic wheel chair, drill.* Medium artefactual complexity / high developmental complexity: *Innovation is a unit, development is based on knowledge bases from several disciplines. Examples: pharmaceuticals, software, generator.* High complexity: *Innovation is a system consisting of several functional parts, development is based on several disciplines. Examples: paper machine, mobile phone network, cruise ship.* **Panel C:** The survey question asked to choose the primary technological content of the innovation. The options are mutually exclusive. N = 73. Details in Appendix F. Back to Section VI.

(A) Cover.



SISÄLLYSLUETTELO

08

16

04 Esipuhe

08 Puhdasta jälkeä
Dust Control Systems tekee ilmansuojeluteknologiaa kohta viidennellä vuosikymmenellä.

16 Turvallisuutta konepajoille
Työturvallisuuskeskuksen asiantuntija Markku Tolvanen kertoo, että työtapaturmien riskit konepajoilla ja muussakin teollisuudessa ovat lisääntyneet. Vuosittaisia tapaturmia on muutaman viime vuoden aikana tilastoitu työpaikoilla enemmän kuin vielä kolme vuotta sitten.

24 Onko meillä turvaharha?

26 Hitsauksen trendit

32 Näkymiä suomalaisen hitsausalan nykytilaan

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(B) Contents.

KUVA: DUST CONTROL SYSTEMS OY

Kokonaan toinen luku on sitten se, että muutamassa vuodessa keltanokasta ammattilaiseksi kapuava metalliosaaja saattaa korkeasuhdanteessa mittauttaa markkina-arvonsa ja hypätä toisen työnantajan kelkkaan. Tällöin ”kasvattajaseura” jää ilman siirtosummaa. Korhosen työnkuvaan kuuluu siis miettiä myös sitä, miten kovat tekijät saadaan viihtymään ja jäämään Kymenlaakson maisemiin.

”Meillä on paljon nuoria ja sitten on konkariosasto. Välistä puuttuu melkein kokonaan nelikymppisten ikäluokka”, hän kuvailee.

Edellinen rekrytointi tehtiin tammikuussa ja taas on haku päällä: ”Meillä on tarvetta kasvaa ja laajentaa toimintoja, joten ammattitaitoista väkeä tarvitaan lisää.”

Keräilyeristä jatkoon

Korhonen on saanut rekrymurheisiinsa ilahduttavasti tulitukea paikkakunnan TE-keskuksesta, jonka kautta useampikin taitava tekijä on päätynyt DCS:n riveihin.

”Meillä on ollut hyvä yhteyshenkilö, joka ymmärtää sen, mitä me tarvitaan täällä.” Näin pajalle on tullut koviksi työmiehiksi paljastuvia liki kuusikymppisiä, joilla on vielä paljon löpöä tankissa; ja vastaavasti koulun jälkeen työttöminä olleita kavereita, jotka ovat joutuneet odottamaan näytön paikkaa kauan – eivätkä hassaa hyvää saumaa, kun se kohdalle viimein tulee.

”Minulla ei ole muuta kuin hyvää sanottavaa yhteistyöstä TE-keskuksen kanssa”, Korhonen kiittelee.

Kasva tai kuihdu

2020-luvun ollessa jo kulman takana Korhonen tietää, että yrityksen nykyinen, passeli koko on huomenna jo liian pieni. ”Niin se oli myös vuonna 2007, ja asialle tehtiin jotain. Nyt meillä on samanlainen prosessi edessä.”

Korhosen ajattelussa yrityksen pitää jatkuvasti kasvaa ja puskea uusille urille tai sitä ei kohta enää ole. Pienet jäävät armotta jalkoihin – samoin myös ne, jotka tyytyvät varmistelemaan saavutettuja asemia.

”Markkina on kasvava, ja myös yritykselle kasvu on välttämätöntä. Välttämätöntä, mutta myös mahdollista”, summaa Korhonen. ■

Dust Control Systems

– toimipaikka Voikkaa Kouvolassa
– 30 työntekijää
– perustettu 1983
– tarjoaa hitsaus-, koneistus- ja kokoonpanopalveluja
– erikoistunut keskiraskaiden yksittäiskappaleiden ja piensarjojen nopeisiin toimituksiin sekä vientiteollisuuden sopimusvalmistukseen
– kilpailukyky perustuu henkilöstön kokemukseen ja tietotaitoon, hyvään konekantaan sekä erityisesti pieniin omakustannuksiin
– konekanta ja oma maalaamo mahdollistavat tehokkaan palvelun vaativissa hitsaus- ja levytöissä, koneistuksessa, pintakäsittelyssä ja kokoonpanossa
– toimitusjohtaja Ilkka Korhonen

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(C) Part of an article.

Figure A22: Literature-Based Data: Examples from Pro Metalli Magazine.

Notes: Example of the types of articles included in the data. This particular case is outside our sample timeline to ensure anonymity. Back to Section VI.

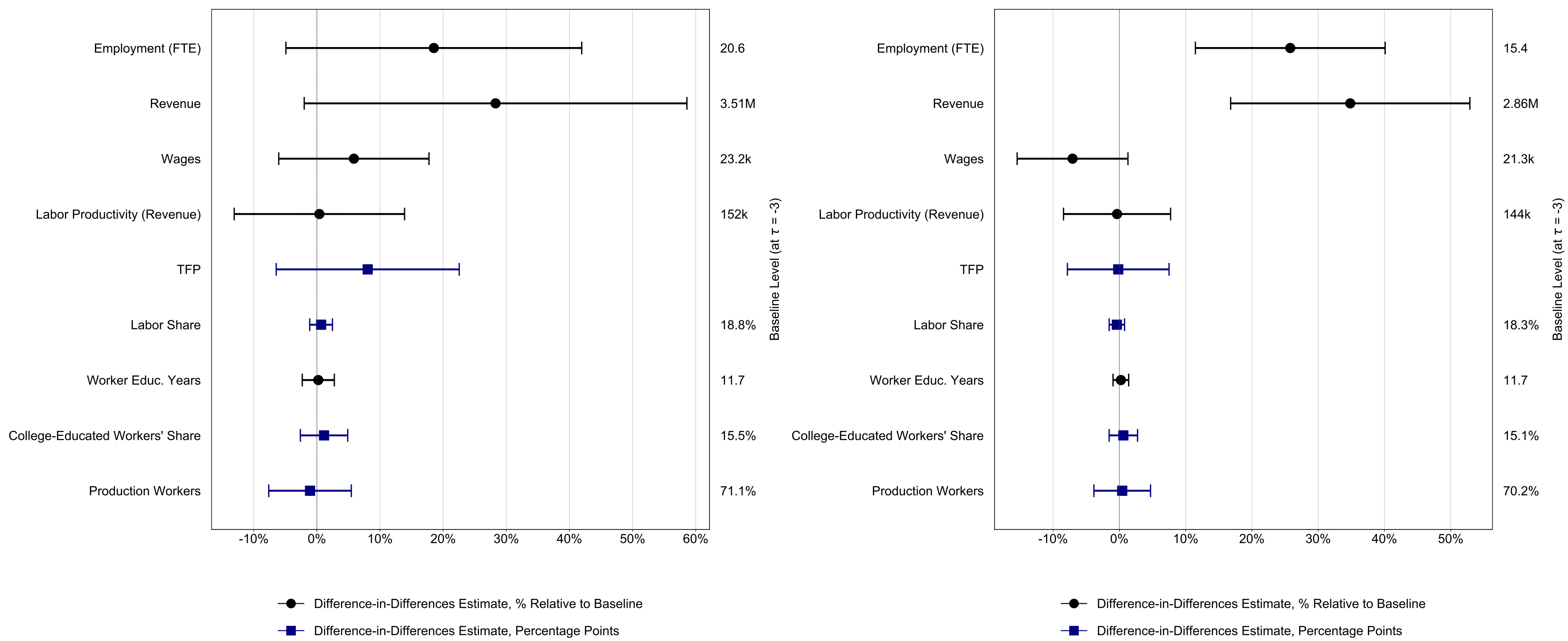


Figure A23: Firm-Level Effects: Automated (left) vs. Non-Automated (right) Technologies from Text Data.

Notes: Difference-in-differences estimates from Equation 2. Automated vs. non-automated technologies are measured from text data as described in Section IV and Appendix F. Automated (N): Treatment 678, Control 30. Non-Automated (N): Treatment 1207, Control 116. Back to Section VI.

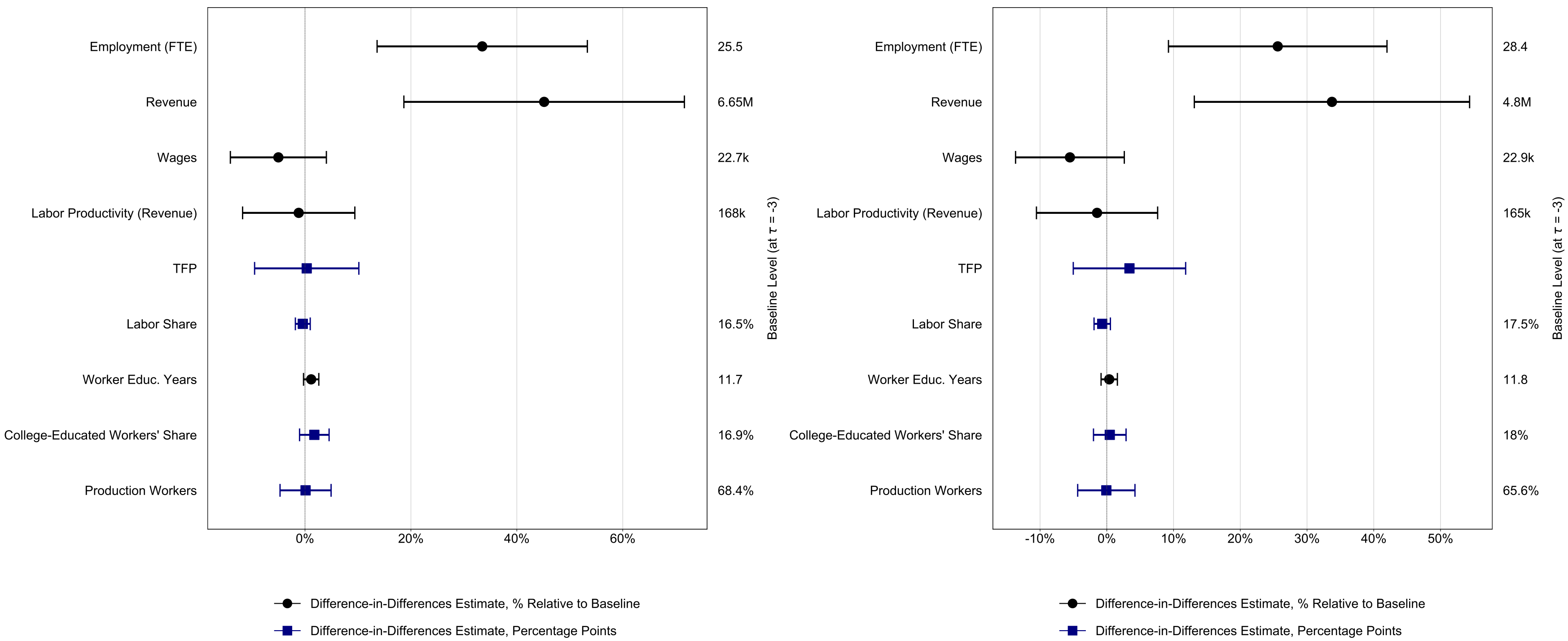
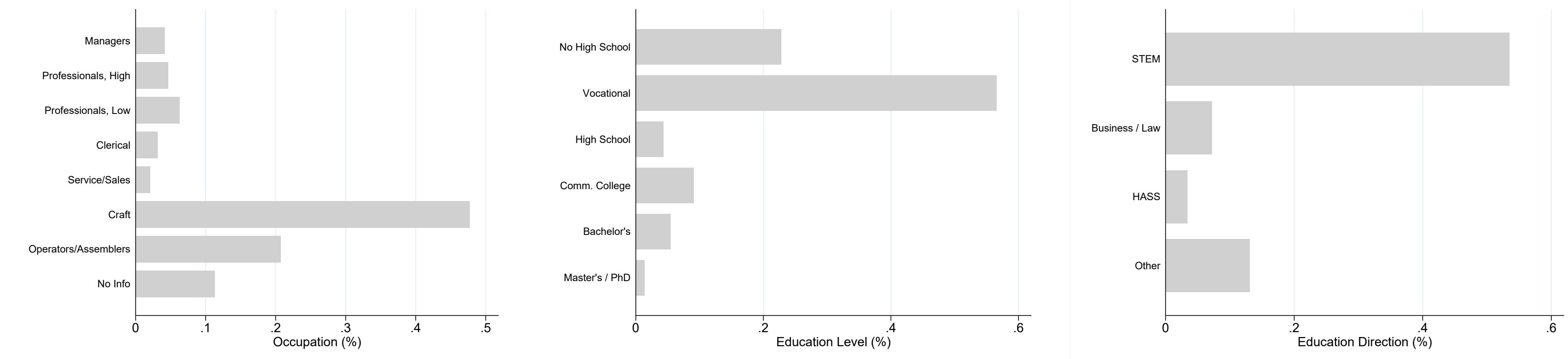


Figure A24: Firm-Level Effects: Automated (left) vs. Non-Automated (right) Technologies from Customs Data.

Notes: Difference-in-differences estimates from Equation 2. Automated vs. non-automated technologies are measured from customs data as described in Section IV and Appendix F. A project is classified as automated if over 50% of the imported machinery are automated technologies. A project is classified as non-automated if over 50% of the imported machinery are non-automated technologies. Automated (N): Treatment 220, Control 146. Non-Automated (N): Treatment 319, Control 146. Back to Section VI.



(A) Occupations.

(B) Education Levels.

(C) Education Types.

Figure A25: 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 (winners-losers 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. Back to Section VIII.

Table A1: Summary Statistics: Benchmarking Subsidy Sample to All Manufacturing.

	Subsidy Sample				**Finnish Manufacturing**			
Variable	Mean	p10	Median	p90	Mean	p10	Median	p90
Revenue (EUR M)	3.09	0.17	0.96	5.67	7.26	0.20	0.63	5.46
Employment	17.22	2.20	7.90	37.00	25.69	2.50	5.50	32.80
Wages (EUR K)	21.95	13.72	22.30	31.40	24.84	14.98	24.17	34.59
Labor Productivity (EUR K)	146.73	72.35	118.60	228.49	150.63	62.51	114.95	246.23
Labor Share (%)	18.45	6.53	18.03	30.70	25.86	7.98	20.09	36.74
Profit Margin (%)	5.22	-3.44	4.97	18.51	-15.10	-6.75	4.12	18.03
Employment Change (%, Five Year)	88.74	-26.61	20.67	165.83	165.83	-31.67	16.67	180.95
Revenue Change (%, Five Year)	100.69	-20.08	37.75	218.08	211.46	-33.51	27.08	220.78
Subsidy Applied (EUR K)	107.38	8.89	58.13	290.06	4.74	0.00	0.00	0.00
Subsidy Granted (EUR K)	75.89	3.24	35.64	200.23	2.61	0.00	0.00	0.00
Educ. Years	11.69	10.50	11.74	12.67	11.61	10.29	11.67	12.81
College Share (%)	15.28	0.00	12.50	33.33	14.76	0.00	9.09	38.63
Production Worker Share (%)	70.74	44.08	72.73	100.00	69.98	33.33	74.19	100.00
Number of Observations	2031				254,008			
Number of Unique Firms	2031				19,661			
Number of Years	16				16			

Notes: Manufacturing means are measured for each firm-year and pooled together over 1994–2018. Manufacturing firms include all firms that satisfy the subsidy sample's balance-sheet-based restrictions and have over two full-time employees. The subsidy sample is measured at event-time $\tau = -3$, expect for subsidies applied and received which are sums over $\tau \in [0, 2]$. The subsidy variables for the manufacturing sample are sums for the firm for its overall life span. The summary statistics are not winsorized. Back to Sections III and IX.

Table A2: Summary Statistics: Text Matching Using Cosine Similarity.

	Treatment Group		**Control Group**		**Both**			**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	p10	Median	p90	p-value
Machine Investment (EUR K)	96.86	240.06	91.43	229.23	0.00	20.03	201.79	0.525
Revenue (EUR M)	2.26	4.44	1.68	3.85	0.13	0.72	4.68	0.000
Employment	15.77	26.04	11.15	24.65	1.10	5.90	27.40	0.000
Wages (EUR K)	21.24	8.15	19.28	10.29	6.73	21.27	29.23	0.000
Labor Share (%)	18.49	9.31	15.76	10.59	3.54	16.62	30.65	0.000
Labor Productivity (EUR K)	138.81	100.83	151.79	93.55	73.51	121.83	231.61	0.000
Subsidy Applied (EUR K)	110.02	128.33	64.64	105.44	4.60	38.35	241.32	0.000
Subsidy Granted (EUR K)	78.31	99.14	0.00	0.00	0.00	0.34	124.65	0.000
Educ. Years	11.67	0.98	11.42	1.04	10.50	11.63	12.50	0.000
College Share (%)	15.18	16.75	11.05	16.30	0.00	10.30	33.33	0.000
Production Worker Share (%)	70.62	22.17	72.65	27.18	40.00	75.00	100.00	0.215
F-test								0.000
Observations	1508		1508		3016			3016

Notes: All variables measured at $\tau = -3$, expect for subsidies applied and received which are sums over $\tau \in [0, 2]$. The summary statistics are not winsorized. Details in the main text. Back to Section III.

Table A3: Propensity Score Text Examples: Descriptions and Evaluations.

	Description		**Evaluation**	
P-Score	**Winner**	**Loser**	**Winner**	**Loser**
0.94	Machine and equipment investments include a flatbed laser, welding robot, deep-drawing equipment, etc. The applicant is investing in new production equipment, with the flatbed laser (*sum*) being the most significant. Additionally, the company will purchase a robot, deep-drawing equipment, and other production tools. Modifications worth [*sum*] will be made to the facilities.	Purchase of an engraving machine. [*Firm name*] specializes in engraving products, often featuring logos and individual text sections on various materials. With a steady customer base and typically small, quick orders, the company emphasizes flexible service. They are replacing old machinery with a new computer-controlled engraver, bought used, for more efficient, higher-quality, and less error-prone production. It costs [*sum*] euros and is financed by a [*bank name*] loan, with a 15% subsidy requested. No prior national or EU subsidies were claimed on the used [*technology name*] engraving machine, as certified by the seller [*firm name*]. A new machine of similar type currently costs about [*sum*] euros.	The project signifies a shift in the company's production toward utilizing technologically more advanced production machinery. In particular, the flatbed laser enhances the competitiveness of the company's production. Additionally, the implementation of robotics can significantly improve productivity.	The acquisition of a new engraving machine will speed up delivery times and increase quality, delivery reliability, and capacity. The purchase, which includes new technology, is essential for the uninterrupted and high-quality continuation of the company's business operations. It is expected to raise the technological level of production/products.
0.78	Hall and machine investments: Hall expansion and machinery. The project includes expanding a hall by 100 square meters at a cost of [*sum*], purchasing a washing machine for [*sum*], a teflon machine for [*sum*], a vehicle for [*sum*], and a grinding machine for [*sum*]. Other acquisitions are expansion purchases, except for the grinding machine, which replaces an old machine. The application seeks support only for the price difference between the old and the new machine. The new machine's technology is significantly more advanced than before. The project is scheduled for completion in the winter of [*year*]-[*year*].	Purchase of a pipe bursting machine. The company is acquiring a pipe bursting machine along with tools and equipment for use in sewer renovations.	The company has the financial capabilities and expertise to implement the project. The project will have a positive impact on profitability and the company's finances, and the timing for its execution is well chosen. The project will improve the company's competitive position and will not disruptively affect the industry.	The project involves a machinery investment by a successful company with solid financing. The project further enhances the company's competitiveness in its sewer renovation contracting work.
0.50	Operational development: Construction of a timber warehouse, acquisition of a cutting line. The company's operational framework has remained unchanged, leading to cramped production and storage spaces due to expansion. This has complicated production, with the immediate issue being length-specific cutting needing additional capacity. Investment and development needs have been identified with the help of external experts and training programs focused on generational change. The project is divided into two phases: the first for a lumber warehouse and cutting line, and the second for a new machining hall and efficient log joinery line. The company seeks financing for the first phase, with construction by an external supplier. The project had not started when the company visit took place. No conflicts of interest are known. [Discusses the use of training programs, ongoing generational change, budget, and timeline for the two phases]	ERP system for building services engineering. The company is seeking to establish a manufacturing partnership with house factories, which requires investment in the development of their enterprise resource planning system. The application includes an offer from [*firm name*] that covers the estimation of new construction and renovation projects, the preparation of bids and contracts, integration with inventory management, and user interfaces for potential contract partners' systems.	The project improves competitiveness through the enhancement of production facilities and, to a lesser extent, product quality. The project can be considered justified because storing goods in production spaces and unsuitable temporary spaces currently hinders labor productivity, causing unnecessary movement of goods multiple times. The investment in the first phase is modest, but it is a prerequisite for implementing the second phase. In this sense, the project can be considered eligible for financing, even though facilities investments in the [*region*] region have been considered secondary investment targets. Financing combines grants, bank loans, and revenue. The plan can be considered realistic. The growth of the project comes mainly from an increase in value added. The subsidy can be considered to have an impact on the project.	From the perspective of business development, the project is favorable and could provide the company with the competitive edge needed to initiate collaboration with house factories. However, due to the competitive situation in the industry, granting support for the project is not justified.

Notes: The table shows examples of description and evaluation texts of winning and losing applications with the same propensity scores. The propensity scores are estimated based on the evaluation texts. The texts have been translated to English and longer texts have been slightly shortened without removing important details. We cannot share any identifying information on individual cases, so certain parts of the texts have been replaced with generic terms in brackets. The application pairs are the same as in Table A4. Back to Sections III and IV.

Table A4: Propensity Score Text Examples: Decisions.

P-Score	**Decision** Winner	Loser
0.94	I propose granting the applicant an investment subsidy of [*sum*]. The project raises the technological level of the company's production and improves its long-term competitiveness.	A used machine of relatively small total value, acquired to replace an older device, cannot be considered to have sufficient importance for the overall operation or growth of the company. The amount of [*sum*] euros cannot also be regarded as significant for the company's operations. The presenter of the case does not support granting the aid.
0.78	This project report replaces the previous one dated [*date*], ref. no. [*number*]. It corrects the breakdown of expenses and the granted aid according to the payment decisions (dated [*date*]).	The application is recommended to be rejected. The company in question primarily contracts sewer renovations for municipalities and cities. According to the financing guidelines of the ELY Center, development assistance for companies has not generally been granted for contracting activities due to the distorting effects on competition. The project has already started, and according to the evaluator's assessment, the subsidy would not have a significant impact on the project's implementation. Furthermore, supporting the project would not be possible as the budget is all but exhausted. [Discusses reasons for why the project is not suitable for rural funding either.]
0.50	The project improves competitiveness through the enhancement of production conditions. At this stage, the project is relatively small in size. Growth in the first phase of the investment comes from an increase in value added. Conditions for profitable operations exist. The support has an impact on the project. The level of support follows the department's guidelines.	Referring to the reasons presented in sections 5.1 and 5.2, the application is recommended for rejection. The business in question operates in contracting, and support for such projects has generally been approached with caution due to the distorting effects of grants on competition. The project is relatively small in terms of the company's operational scale and its financial resources. The company can easily implement the project without assistance. This assessment is reinforced by the fact that the company has not submitted additional information requested on [*date*] and [*date*], nor has it otherwise been in contact with the application manager, whose contact details were provided to the applicant. No response has been received to the requests, so the application has been processed with the information available (Administrative Law 434/2003, Section 33).

Notes: The table shows examples of decision texts of winning and losing applications with the same propensity scores. The propensity scores are estimated based on the evaluation texts, not the decisions. The texts have been translated to English and longer texts have been slightly shortened without removing important details. We cannot share any identifying information on individual cases, so certain parts of the texts have been replaced with generic terms in brackets. The application pairs are the same as in Table A3. Back to Section III.

Table A5: Examples of Application Texts Classified as Technology.

Technology:

- Machinery and equipment.
- Vertical machining center.
- Laser welding technology investment.
- Acquisition of Mazak Multiplex 6200 machine tool.
- Acquisition of laser cutter, measuring equipment, and edger steel sets, obtaining the CE SFS-EN 1090-2 certificate for the manufacturing of steel structures, and improving the utilization rate of production facilities.
- Streamlining the production of demonstration samples. The goal of the project is to invest in and improve the manufacturing of demonstration samples to meet the demand from the market. The objective is to have the enhanced equipment for the production of demonstration samples operational by the end of August.

Not Technology:

- Internationalization project in Germany.
- Market research in the USA. The goal of the project is to assess market opportunities in the USA, including market size, pricing and distribution structures, product adaptation needs, consumer preferences, and requirements for market entry.
- Product development project.
- Development of a fuel-efficient snow blower.
- Start-up support.
- Launch of a short-term care and rehabilitation facility.

Notes: Examples of what is classified as a technology and what is not from the application data. The first four of technology examples are one-sentence versions of the description while the latter two are the full description texts available in the data. The second example of not technology is also the full description text. The Appendix F presents additional examples. Back to Section IV.

Table A6: Predictive Accuracy: Coarse Text Category Predictions Using SVM.

Class	Precision	Recall	F1-score	Test Support	Number of Cases
Technology (1)	0.88	0.92	0.90	571	11887
Not Technology (0)	0.97	0.96	0.96	1550	31022
Accuracy			0.95	2121	42909
Balanced Accuracy			0.94	2121	42909
Macro Avg.	0.93	0.94	0.93	2121	42909
Weighted Avg.	0.95	0.95	0.95	2121	42909

Notes: Test Support refers to the 10% random out-of-sample of the applications classified by hand, from which accuracy measures are computed. The number of cases refers to the total number of subsidy applications with labels (both classified by hand and predicted). Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Recall (Sensitivity) is the ratio of correctly predicted positive observations to all observations in the category. F1 Score is the harmonic mean of Precision and Recall. Accuracy is the ratio of correctly predicted observations to the total observations. Back to Section IV and Appendix F.

Table A7: Predicting Treatment Status and Propensity Scores Using Text Lengths.

	(1)		(2)
A. Evaluation Text	Accepted		Propensity Score
Characters (K)	0.0478***	0.0386***	-0.0004
	(0.009)	(0.008)	(0.005)
B. Description Text			
Characters (K)	0.0413***	0.0309***	0.0061
	(0.008)	(0.007)	(0.004)
Propensity Score		✓	
Observations	1831	1812	1812

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

Notes: The table shows the results from regressing the acceptance indicator (Column 1) and the propensity score (Column 2) on character counts in the evaluation (Panel A) and the description (Panel B) texts. The character counts are measured in thousands. There is a small positive correlation: Applications with longer description texts and evaluation reports are more likely to win a subsidy, even when controlling for propensity score. In contrast, no statistically significant correlation exists when regressing the propensity score on the lengths. Back to Section III.

Table A8: Firm-Level Effects: Different Text Matching Versions.

Panel A: Coarsened Exact Matching (CEM).

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Educ. Years	(5) College Share	(6) Production Worker Share
Treatment	95.82***	0.260***	0.332***	-0.0501	-0.000688	-0.0105
	(27.41)	(0.0684)	(0.0944)	(0.0664)	(0.0106)	(0.0206)
Observations	1254	1254	1254	1161	1161	1162

Panel B: Inverse Probability Weighting (IPW).

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Educ. Years	(5) College Share	(6) Production Worker Share
Treatment	146.0***	0.358***	0.455***	-0.0430	0.00569	-0.0274
	(31.50)	(0.0904)	(0.116)	(0.0846)	(0.0161)	(0.0301)
Observations	1812	1812	1812	1676	1676	1692

Panel C: Cosine Similarity.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Educ. Years	(5) College Share	(6) Production Worker Share
Treatment	112.7***	0.169***	0.195***	0.0133	-0.00224	0.00278
	(10.50)	(0.0249)	(0.0335)	(0.0219)	(0.00542)	(0.0103)
Observations	3016	3016	3016	2678	2678	2715

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2 with different text matching versions. Details in the main text. Back to Section V.

Table A9: Firm-Level Effects: Robustness to Different Controls.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity	(6) Labor Share	(7) Educ. Years	(8) College Share	(9) Prod. Work. Share
No Controls	114.3***	0.185**	0.261***	-0.0553	-0.00559	-0.00242	0.0225	0.00480	-0.0235
	(22.25)	(0.0606)	(0.0770)	(0.0353)	(0.0341)	(0.00492)	(0.0599)	(0.00927)	(0.0359)
Controls 1	110.7***	0.219***	0.302***	-0.0499	-0.00379	-0.00247	0.0252	0.00587	-0.0263
	(22.53)	(0.0615)	(0.0779)	(0.0356)	(0.0351)	(0.00496)	(0.0611)	(0.00936)	(0.0357)
Controls 2	103.8***	0.232***	0.314***	-0.0481	-0.00516	-0.00202	0.0246	0.00557	-0.0256
	(22.56)	(0.0614)	(0.0779)	(0.0355)	(0.0350)	(0.00496)	(0.0611)	(0.00935)	(0.0357)
Controls 3	100.4***	0.249***	0.327***	-0.0385	-0.00670	-0.000862	0.0252	0.00572	-0.0255
	(22.43)	(0.0609)	(0.0773)	(0.0350)	(0.0349)	(0.00490)	(0.0612)	(0.00942)	(0.0363)
Controls 4	67.69**	0.210***	0.284***	-0.0344	-0.00658	-0.000101	0.0247	0.00509	-0.0268
	(23.64)	(0.0607)	(0.0770)	(0.0351)	(0.0350)	(0.00493)	(0.0614)	(0.00946)	(0.0363)
Controls 5	56.89*	0.191**	0.259**	-0.0360	-0.0141	0.00186	0.0181	0.00374	-0.00103
	(24.05)	(0.0623)	(0.0796)	(0.0354)	(0.0356)	(0.00505)	(0.0629)	(0.00976)	(0.0185)
Observations	2031	2031	2031	1952	2031	2031	1884	1884	1891

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2 with different controls.

Controls 1: industry (2-digit).

Controls 2: industry (2-digit), employment (at the base year).

Controls 3: industry (2-digit), employment (at the base year), ELY Center indicators.

Controls 4: industry (2-digit), employment (at the base year), ELY Center indicators, applied subsidy amount.

Controls 5: industry (2-digit), employment (at the base year), ELY Center indicators, applied subsidy amount, text category indicators.

Back to Section V.

Table A10: Continuous Treatment Estimates: Controlling for the Subsidies Applied.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue	
Granted Subsidy	0.915***	0.960***	0.129**	0.140**	1.546	2.074*
	(0.228)	(0.239)	(0.0464)	(0.0500)	(0.960)	(1.038)
Applied Subsidy	✓	✓	✓	✓	✓	✓
Propensity Score		✓		✓		✓
Observations	2031	1812	2031	1812	2031	1812

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2. Treatment is the received subsidy amount in EUR. Treatment is scaled to EUR 10K for employment. Applied subsidy is the applied subsidy amount in EUR. Machinery investment is the sum between $\tau \in [0, 2]$. Other outcomes are averages over $\tau \in [2, 5]$. Back to Section V.

Table A11: Firm-Level Effects: Propensity-Score Trimmed Samples.

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

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Wages		(5) Profit Margin	
5%	108.0**	105.5**	0.245**	0.248**	0.301**	0.327**	-0.0124	-0.00497	-0.00420	-0.00628
	(34.22)	(34.76)	(0.0815)	(0.0828)	(0.116)	(0.118)	(0.0439)	(0.0441)	(0.0118)	(0.0119)
10%	115.8**	113.2**	0.251**	0.254**	0.313*	0.324*	-0.00737	-0.00578	-0.00304	-0.00472
	(40.07)	(40.16)	(0.0953)	(0.0956)	(0.132)	(0.133)	(0.0472)	(0.0473)	(0.0134)	(0.0134)
20%	76.47	76.89	0.188	0.188	0.242	0.242	0.00738	0.00652	0.000227	0.000249
	(51.98)	(51.88)	(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

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

	(1) Productivity		(2) Labor Share		(3) Educ. Years		(4) College Share		(5) 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 where firms with top and bottom 5%, 10%, and 20% of propensity score values are dropped. Our main results are robust to excluding firms with small and large values of the propensity score. The samples are subsets of the main analysis sample (winners-losers design). Back to Sections III and V.

Table A12: Robustness to Different Sample Specifications: Single and First Events.

A. Single Event	(1) Machine Inv. (EUR K)		(2) Employment		(3) Educ. Years	
Treatment	51.79**	56.67*	0.165*	0.188*	0.0178	-0.0319
	(18.24)	(24.15)	(0.0665)	(0.0805)	(0.0624)	(0.0782)
B. First Event						
Treatment	81.67***	87.79**	0.286***	0.312***	0.00550	-0.0350
	(20.03)	(26.96)	(0.0635)	(0.0776)	(0.0539)	(0.0659)
Propensity Score		✓		✓		✓
N, Single	1011	888	1011	888	937	819
N, First	1980	1668	1980	1668	1895	1589

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2. **Panel A**: We restrict the sample to firms with only one (either successful or unsuccessful) subsidy application. **Panel B**: We select the first subsidy application in the data to serve as the treatment or control. The specifications include two-digit industry and firm size as controls, and are presented with and without the text propensity-score control. For machinery investment, the post-period outcome is the average of investment over $\tau \in [0, 2]$ multiplied by three (the number of periods) and for other outcomes, the average over $\tau \in [2, 5]$. Back to Section V.

Table A13: Robustness to an Unbalanced Sample: Firm-Level Effects Allowing for Firm Exit.

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

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Wages		(5) Profit Margin	
Treatment	73.04**	93.17***	0.310***	0.268***	0.400***	0.364***	-0.0371	-0.0442	0.000834	-0.0125
	(22.40)	(26.43)	(0.0547)	(0.0694)	(0.0667)	(0.0849)	(0.0372)	(0.0445)	(0.00782)	(0.00996)
Propensity Score		✓		✓		✓		✓		✓
Observations	2118	1880	2118	1880	2118	1880	1977	1754	2060	1831

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

	(1) Productivity		(2) Labor Share		(3) Educ. Years		(4) College Share		(5) Production Worker Share	
Treatment	-0.00742	-0.0148	0.000989	0.00210	-0.0338	-0.0610	-0.00531	-0.00562	0.00735	-0.00679
	(0.0345)	(0.0417)	(0.00500)	(0.00620)	(0.0513)	(0.0649)	(0.00836)	(0.0106)	(0.0181)	(0.0213)
Propensity Score		✓		✓		✓		✓		✓
Observations	2056	1828	2060	1831	1953	1733	1912	1697	1896	1708

Standard errors in parentheses.

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

Notes: The sample is the main analysis sample (winners-losers design) without the balanced panel requirement. For the firms that exited, the first three outcomes in Panel A are defined as zero, all others are defined as missing. Back to Sections III and V.

Table A14: Effects on 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 the skill intensity of exported products and export regions. We use data on all Finnish exporting firms to construct the outcomes. We first compute 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 or 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. Back to Section VI.

Table A15: The First Stage: IT Expenditure.

	(1)	(2)	(3)	(4)
	IT Expenditure			
Treatment	4.101**	2.395		
(Indicator)	(1.355)	(1.831)		
Granted Subsidy			0.0516***	0.0489***
(Continuous)			(0.0073)	(0.0073)
Propensity Score		✓		✓
Observations	2031	1812	2031	1812

Standard errors in parentheses.

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

The baseline IT expenditure is 46.2K EUR at $\tau = -3$.

Notes: Difference-in-differences estimates from Equation 2 with and without the text propensity control. To measure IT, we use the official records on the Financial Statement Register. The post-period outcomes are means over $\tau \in [0, 2]$ multiplied by three (the number of periods). The units are EUR K (Columns 1 and 2) and EUR (Columns 3 and 4). The specifications include two-digit industry and firm size as controls. Back to Section VI.

Table A16: Summary Statistics by IT Status.

A. Register Data

	IT above median		**IT below median**		**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	p-value
Machine Investment (EUR K)	105.15	447.60	110.78	246.22	0.725
Revenue (EUR M)	4.10	34.39	2.08	4.23	0.063
Employment	20.63	61.70	13.82	19.40	0.001
Wages (EUR K)	23.05	10.23	20.85	7.94	0.000
Labor Share (%)	18.77	9.71	18.13	9.11	0.127
Labor Productivity (EUR K)	150.43	189.93	143.03	121.92	0.296
Subsidy Applied (EUR K)	96.53	121.23	118.22	132.67	0.000
Subsidy Granted (EUR K)	66.63	95.67	85.14	106.20	0.000
Educ. Years	11.78	0.99	11.60	1.00	0.000
College Share (%)	16.67	17.31	13.86	16.45	0.000
Production Worker Share (%)	69.17	22.40	72.58	20.86	0.028
Observations	1015		1016		2031

B. Text Data

	Software mentioned		**Machinery mentioned**		**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	p-value
Machinery Inv. (EUR K)	134.89	308.26	108.10	362.15	0.440
Revenue (EUR M)	4.15	6.27	3.06	24.86	0.653
Employment	27.71	32.99	17.03	46.18	0.016
Wages (EUR K)	25.50	8.93	21.81	9.19	0.000
Labor Share (%)	21.11	9.34	18.45	9.46	0.003
Labor Productivity (EUR K)	185.39	496.94	146.17	161.47	0.010
Subsidy Applied (EUR K)	95.88	105.48	108.67	128.66	0.316
Subsidy Granted (EUR K)	66.96	87.50	76.99	102.47	0.323
Educ. Years	11.85	1.03	11.69	0.99	0.092
College Share (%)	18.87	16.75	15.19	16.94	0.026
Production Worker Share (%)	64.30	22.14	70.49	21.93	0.027
Observations	107		1971		2007

Notes: Summary statistics by IT expenditure and mentions of machinery vs. software in the application texts. The sample is the main analysis sample (winners vs. losers design). **Panel A:** The groups are defined by IT expenditure over $\tau \in [0, 2]$ in the register data. **Panel B:** The groups are defined by whether the application text data mentions software or machinery. The summary statistics are not winsorized. Back to Section IX.

Table A17: Firm-Level Effects by IT Status.

	(1)		(2)		(3)		(4)		(5)	
A. Register Data	Machinery Inv. (EUR K)		Employment		Educ. Years		Labor Share		Productivity	
IT below median	93.99*	85.38	0.288**	0.298**	-0.0498	-0.0183	0.00273	0.00503	0.0169	0.0475
	(41.16)	(55.57)	(0.0895)	(0.111)	(0.0919)	(0.118)	(0.00735)	(0.00942)	(0.0557)	(0.0659)
IT above median	60.57*	59.07	0.164	0.151	0.0892	0.0236	-0.00477	-0.00432	-0.0137	-0.0396
	(23.84)	(30.69)	(0.0849)	(0.102)	(0.0817)	(0.0957)	(0.00683)	(0.00800)	(0.0472)	(0.0576)
B. Text Data										
Machinery mentioned	95.66***	92.40**	0.234***	0.238**	0.00755	0.00240	-0.00151	-0.000185	-0.0137	-0.0101
	(23.07)	(29.62)	(0.0634)	(0.0761)	(0.0611)	(0.0754)	(0.00506)	(0.00610)	(0.0360)	(0.0435)
Software mentioned	115.1	108.6	0.329	0.450	-0.0938	-0.0685	0.00929	-0.0168	-0.113	0.00135
	(229.2)	(269.9)	(0.253)	(0.371)	(0.343)	(0.441)	(0.0264)	(0.0308)	(0.237)	(0.277)
Propensity Score		✓		✓		✓		✓		✓
N, Below Median IT	1016	886	1016	886	947	822	1016	886	1016	886
N, Above Median IT	1015	926	1015	926	937	854	1015	926	1015	926
N, Software Not Mentioned	1971	1758	1971	1758	1827	1625	1971	1758	1971	1758
N, Software Mentioned	107	98	107	98	105	96	107	98	107	98

Standard errors in parentheses.

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

Notes: The effects by IT expenditure and mentions of machinery vs. software in the application texts. The sample is a subset of the main analysis sample (winners vs. losers design). **Panel A**: The groups are below and above median IT expenditure over $\tau \in [0, 2]$. The results are robust to defining the groups by IT expenditure at $\tau = 3$. **Panel B**: We divide the sample by the firms' stated the intention to purchase hardware or software technologies in the application texts. 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 the text-based software events are imprecise, likely due to the small sample size (n = 107). Back to Section VII.

Table A18: Firm-Level Effects: 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) N
Types of Technology										
CNC	134.0***	0.168***	0.180***	0.0367	-0.0100	0.00299	-0.0331	0.00304	-0.0211	628
	(16.87)	(0.0398)	(0.0492)	(0.0212)	(0.0266)	(0.00498)	(0.0513)	(0.00771)	(0.0144)	
Robot	207.3*	0.233*	0.416**	-0.0380	0.0124	-0.0133	0.0311	0.00256	0.0198	232
	(79.94)	(0.0921)	(0.136)	(0.0291)	(0.0593)	(0.00787)	(0.0581)	(0.00961)	(0.0192)	
Laser	110.2*	0.322**	0.313*	-0.0272	-0.0831	0.000777	0.0578	0.0180	0.0139	224
	(46.13)	(0.0979)	(0.132)	(0.0415)	(0.0501)	(0.0101)	(0.0919)	(0.0157)	(0.0286)	
Uses of Technology										
Machining	165.7***	0.246***	0.276***	-0.00449	-0.0187	-0.00126	0.0136	0.00862	-0.0121	584
	(30.65)	(0.0471)	(0.0663)	(0.0227)	(0.0302)	(0.00514)	(0.0505)	(0.00899)	(0.0137)	
Welding	103.8***	0.352***	0.385***	-0.00611	-0.0146	-0.0100	0.0185	-0.00120	0.00966	312
	(28.05)	(0.0835)	(0.0821)	(0.0352)	(0.0431)	(0.00760)	(0.0700)	(0.0122)	(0.0218)	
Painting	173.6***	0.267***	0.318***	-0.0223	0.00608	-0.00591	-0.0112	-0.00147	-0.00148	312
	(38.18)	(0.0634)	(0.0836)	(0.0302)	(0.0396)	(0.00636)	(0.0627)	(0.00946)	(0.0193)	
Logistics	163.5***	0.304***	0.404***	0.00781	0.0348	-0.00659	0.0207	0.0148*	-0.0106	822
	(22.48)	(0.0404)	(0.0544)	(0.0171)	(0.0255)	(0.00388)	(0.0370)	(0.00611)	(0.0108)	
Automation	136.3***	0.178***	0.217***	0.00216	0.0249	-0.00237	0.0546	0.00942	0.000592	678
	(29.12)	(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 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 five for the firms that specify the listed uses for the technologies. We define the technologies using keywords: "cnc" for CNC, "robo" for robots, and "laser" and "plasma" for laser. The remaining keywords (in Finnish) are provided in Appendix F. N (Column 10) refers to the treatment group sample size: the number of firms with subsidy application texts containing keywords associated with the given technology or its use. We find broadly similar effects for all the subgroups. Machinery investment is in EUR K. The sample is the winners matched to non-applicants as the sample would otherwise be small (the matching procedure is described in Section III). Back to Section VI.

Table A19: Technology × Occupation Pairs: Effects of Specific Technologies on Specific Workers.

	(1) Worker Share	(2) Wages	(3) Educ. Years	(4) Labor Share
Machining-	0.0454***	0.0753	-0.00340	0.0360*
Machinists	(0.0106)	(0.0816)	(0.0179)	(0.0158)
Mean	0.0227	25751.0	11.78	0.107
N	554	51	51	51
Welding-	0.0135	0.0598	0.0295	0.00971
Welders	(0.00995)	(0.0938)	(0.0214)	(0.00839)
Mean	0.0683	25831.3	11.48	0.0594
N	300	88	88	88
Painting-	0.00518	0.0114	0.0258	0.00825
Painters	(0.00358)	(0.0750)	(0.0279)	(0.00590)
Mean	0.0250	21076.8	10.58	0.0411
N	307	65	65	65
Logistics-	-0.000775	-0.0936	0.0413	-0.00759
Logistics (Non-Office)	(0.000488)	(0.144)	(0.0524)	(0.00699)
Mean	0.0120	25330.9	10.76	0.0191
N	799	58	58	58
Logistics-	0.0000555	0.298	-0.0884	-0.000707
Logistics (Office)	(0.000246)	(0.301)	(0.112)	(0.00189)
Mean	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 firm-level effects of specific technologies on specific workers. The sample is winners matched to non-applicants (the matching procedure is described in Section III). The technologies refer to the description of the technology in the subsidy application text (the technology keywords are listed in Appendix F). The occupations come from the workers' occupational records (exact occupational codes available in the replication package). 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 number of treatment firms where the given outcome is defined. Note that worker count (employment) shares are defined for all firms with the given technology, but the other three outcomes require at least one worker with the specific occupation and wages observed both before and after, and the smaller sample size comes from combining these restrictions. We find positive effects on the employment share and the wage-bill (labor) share of machinists when the firm has applied for a subsidy and specified the intended use to be an investment in technologies associated with machining. Back to Section VI.

Table A20: Firm-Level Effects: Firm Size.

Panel A: Large Firms.

	(1)		(2)		(3)		(4)		(5)		(6)	
	Machine Inv. (EUR K)		Employment		Revenue		Productivity		Labor Share		College Share	
Treatment	221.8*	158.9	0.305***	0.309**	0.264	0.494**	-0.136	0.0236	0.0133	-0.00853	-0.00893	-0.0159
	(94.69)	(129.0)	(0.0722)	(0.104)	(0.137)	(0.160)	(0.0834)	(0.0967)	(0.00981)	(0.0111)	(0.0167)	(0.0201)
Propensity Score		✓		✓		✓		✓		✓		✓
N	676	609	676	609	676	609	676	609	676	609	675	608

Panel B: Medium-Sized Firms.

	(1)		(2)		(3)		(4)		(5)		(6)	
	Machine Inv. (EUR K)		Employment		Revenue		Productivity		Labor Share		College Share	
Treatment	99.31	132.8*	0.296***	0.280*	0.467***	0.399**	0.0707	0.0193	-0.0104	-0.0124	0.0185	0.0200
	(52.09)	(64.17)	(0.0858)	(0.113)	(0.114)	(0.150)	(0.0551)	(0.0718)	(0.00856)	(0.00969)	(0.0162)	(0.0213)
Propensity Score		✓		✓		✓		✓		✓		✓
N	685	603	685	603	685	603	685	603	685	603	683	601

Panel C: Small Firms.

	(1)		(2)		(3)		(4)		(5)		(6)	
	Machine Inv. (EUR K)		Employment		Revenue		Productivity		Labor Share		College Share	
Treatment	22.73	25.83	0.330**	0.373**	0.355**	0.370*	-0.0410	-0.0956	0.00216	0.0162	0.00334	0.00373
	(14.06)	(19.78)	(0.103)	(0.121)	(0.125)	(0.148)	(0.0526)	(0.0615)	(0.00781)	(0.00927)	(0.0158)	(0.0192)
Propensity Score		✓		✓		✓		✓		✓		✓
N	670	600	670	600	670	600	670	600	670	600	526	467

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

Notes: Difference-in-differences estimates from Equation 2. The firm size groups are defined by FTE at $\tau = 3$, with thresholds at the 33.3 and 66.6 percentiles. Large Firms (FTE $>$ 13.3; Median 25.8, Mean 41.7), Medium-Sized Firms (FTE $>=$ 4.6 & FTE $<=$ 13.3; Median 7.9, Mean 8.2), Small Firms (FTE $<$ 4.6; Median 2.3, Mean 2.3). Back to Section VII.

Table A21: Credit Constraints: Estimates by the Cost of Capital and Debt Level.

Panel A: Effects by Average Financial Costs.

	(1)		(2)		(3)	
	Machine Inv. (EUR K)		Employment		Revenue	
	High Costs	Low Costs	High Costs	Low Costs	High Costs	Low Costs
Treatment	128.0***	75.07***	0.276***	0.194*	0.313**	0.326**
	(33.55)	(29.60)	(0.0793)	(0.0959)	(0.105)	(0.114)
N	1016	1015	1016	1015	1016	1015

Panel B: Effects by Relative Debt.

	(1)		(2)		(3)	
	Machine Inv. (EUR K)		Employment		Revenue	
	High Debt	Low Debt	High Debt	Low Debt	High Debt	Low Debt
Treatment	140.3***	63.38*	0.0676	0.384***	0.151	0.486***
	(32.24)	(30.52)	(0.0965)	(0.0687)	(0.125)	(0.0820)
N	1016	1015	1016	1015	1016	1015

Panel C: Controlling for Credit Constraint Measures.

		(1)			(2)			(3)	
		Machine Inv. (EUR K)			Employment			Revenue	
Treatment	103.8***	103.4***	104.7***	0.232***	0.242***	0.232***	0.314***	0.342***	0.314***
	(22.56)	(22.62)	(22.70)	(0.0614)	(0.0597)	(0.0614)	(0.0779)	(0.0721)	(0.0778)
Relative Debt		✓			✓			✓	
Average Financial Costs			✓			✓			✓
N	2031	2031	2031	2031	2031	2031	2031	2031	2031

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

Notes: Difference-in-differences estimates from Equation 2. Estimated effects on selected outcomes by the cost of capital (Panel A), debt level (Panel B), and with these proxies for credit-constraints as controls (Panel C). We measure baseline levels at $\tau = -3$. Average financial costs are financial expenses divided by non-current liabilities. Relative debt is the sum of current liabilities, non-current liabilities, and obligatory reserves divided by revenue. We divide the sample into two groups by whether the firms' average financial costs (Panel A) or relative debt (Panel B) are below or above the median in the sample. Panel C controls directly for the baseline value. Back to Section VII.

Table A22: Describing the Treatment Firms' New Workers.

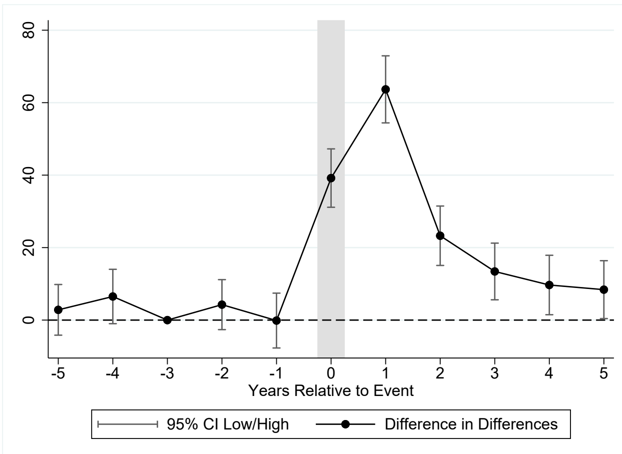
Variable	Mean
A. Origin Firm Characteristics:	
Employment	451.48
Labor Productivity (EUR K)	184.24
Average Education Years	12.04
Labor Share (%)	26.45
Average Wage (EUR K)	28.37
Survival (%)	93.00
B. Origin Firm Treatment Status:	
Other Winners (%)	0.65
Losers (%)	0.02
C. Prior Activity and Demographics:	
Employed (%)	53.63
Student (%)	21.28
Retraining (%)	3.54
Military service (%)	3.20
Retired (%)	1.64
Unemployed (%)	13.53
Other Non-Employed (%)	5.49
Male (%)	80.21
Age	33.77
Foreign-born (%)	4.13
D. Occupation, Industry, and Location:	
Same Occupation (%)	69.33
Same Industry (%)	50.97
Same County of Prior Firm (%)	41.14
Same County of Residence (%)	59.70
Change in Commute (km)	-2.39

N, Firms = 1,800.

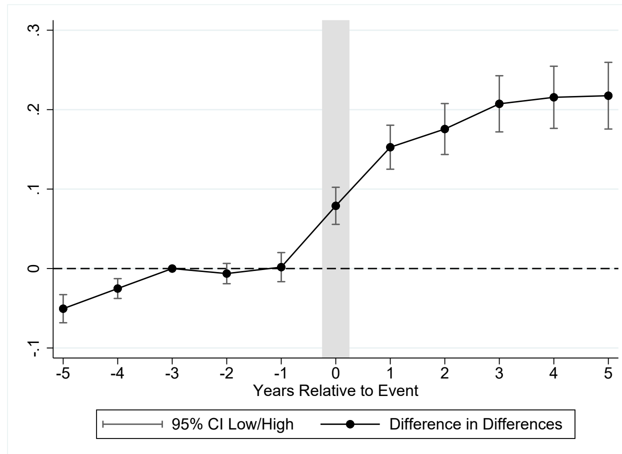
N, Workers = 40,768.

Notes: Characteristics of the new workers entering the winning firms at $\tau \in [0, 5]$. In alignment with our research design, we compute these statistics in two steps. First, we calculate the firm-level average for all treatment firms that hired new workers after winning the subsidy. Then, we average these figures across all such firms. Origin firm survival is a binary variable. It is assigned a value of one if the worker's previous firm remains operational five years following the event year of the new firm. Occupations are categorized at the 1-digit level, while industries are classified at the letter level, which represents the broadest categorization. For all variables derived from employment-related data, values are designated as missing for workers who were not employed prior to joining the new firm. Back to Sections VII, VIII, and IX.

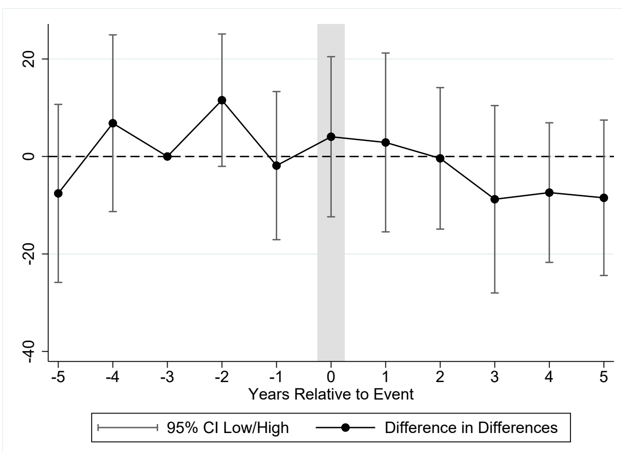
B Matched Control Group



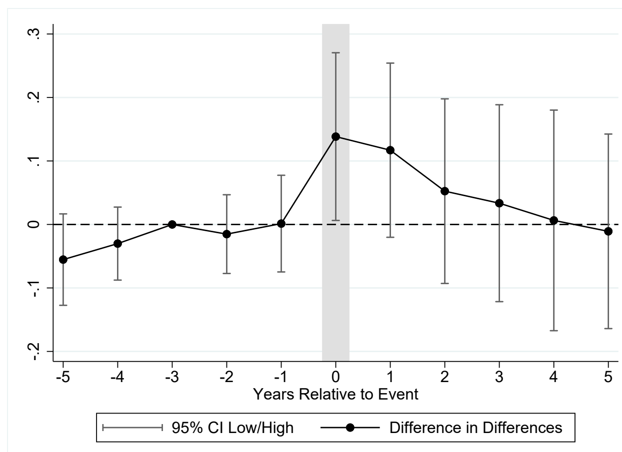
(A) Winners vs. Matched Control:
Machinery Investment.



(B) Winners vs. Matched Control:
Employment.



(C) Losers vs. Matched Control:
Machinery Investment.



(D) Losers vs. Matched Control:
Employment.

Figure B1: Matched Control Groups: The First Stage and Employment Effects.

Notes: Event-study estimates from Equation 1. **Panels (A, B):** Treatment group is the subsidy winners (the main treatment group), and control group is constructed via matching. **Panels (C, D):** Treatment group is the subsidy losers (the main control group), and the control group is constructed via matching, i.e., comparing two different control groups. 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. Back to Sections V and VI.

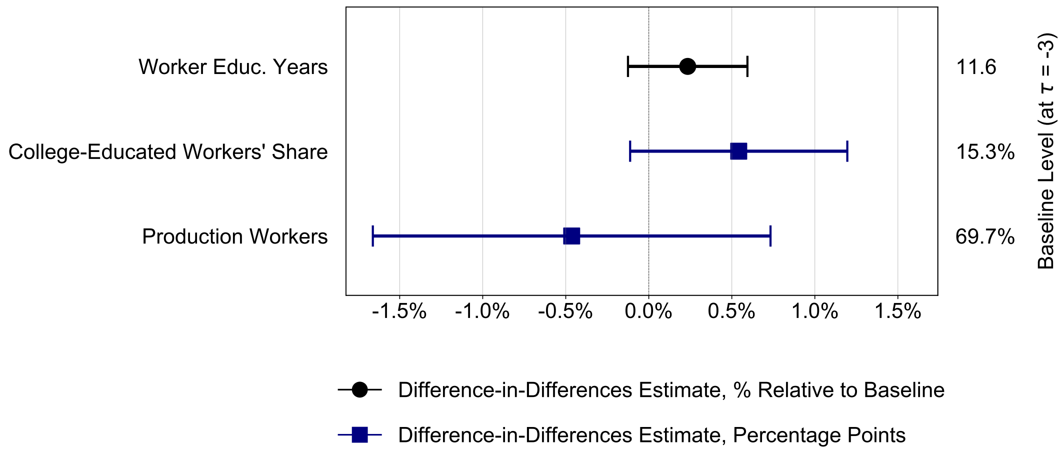


Figure B2: Matched Control Group: Skill Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the main treatment group ("winners") to a matched control group (the matching procedure is described in Section III). The right-hand side reports outcome means at $\tau = -3$. Back to Section V.

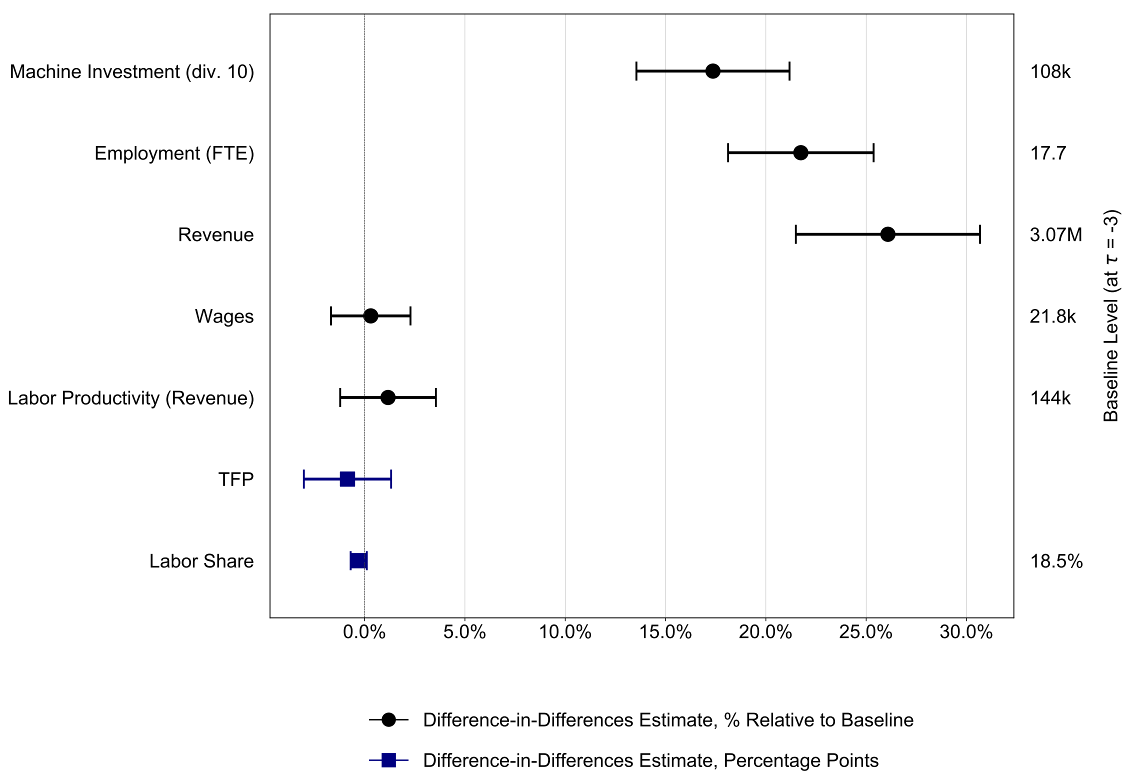


Figure B3: Matched Control Group: Firm-Level Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the main treatment group ("winners") to a matched control group (the matching procedure is described in Section III). The right-hand side reports outcome means at $\tau = -3$. Back to Section V.

Table B1: Matched Control Group: Balance Table A (Winners vs. Matched Control).

	Treatment Group		**Control Group**		**Both**			**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p	p-value
Revenue (EUR M)	3.06	26.57	3.09	9.15	0.17	0.96	6.26	0.963
Employment	17.46	46.27	18.03	38.79	1.60	8.20	37.70	0.704
Wages (EUR K)	21.60	8.08	22.06	8.36	12.15	22.43	30.56	0.109
Subsidy Applied (EUR K)	108.52	126.79	0.00	0.00	0.00	0.86	172.15	0.000
Subsidy Granted (EUR K)	78.62	100.55	0.00	0.00	0.00	0.49	122.38	0.000
Educ. Years	11.68	0.98	11.56	1.04	10.50	11.67	12.63	0.001
College Share (%)	15.24	16.84	15.39	18.45	0.00	12.50	34.62	0.820
Production Worker Share (%)	70.96	21.53	68.43	25.11	37.50	72.73	100.00	0.060
F-test								0.000
Observations	1600		1600			3200		3200

Notes: All variables measured at $\tau = -3$ expect for subsidies applied and received which are sums over τ= 0–2. The variables are not winsorized prior to calculating the summary statistics. Back to Sections III and IX.

Table B2: Matched Control Group: Balance Table B (Losers vs. Matched Control).

	Treatment Group		**Control Group**		**Both**			**Tests**
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p	p-score
Revenue (EUR M)	1.62	5.52	1.27	2.71	0.10	0.43	2.71	0.527
Employment	9.02	18.56	8.81	15.12	1.00	3.90	20.00	0.921
Wages (EUR K)	17.81	7.95	18.01	8.79	5.50	18.80	27.82	0.853
Subsidy Applied (EUR K)	47.47	76.19	0.00	0.00	0.00	0.00	65.59	0.00
Subsidy Granted (EUR K)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
Educ. Years	11.34	1.12	11.42	1.23	10.00	11.50	12.56	0.641
College Share (%)	10.50	15.47	15.41	21.76	0.00	6.90	33.33	0.050
Production Worker Share (%)	74.25	25.39	70.77	27.93	30.95	79.63	100.00	0.647
F-test								0.062
Observations	123		123			246		246

Notes: All variables measured at $\tau = -3$ expect for subsidies applied and received which are sums over τ= 0–2. The variables are not winsorized prior to calculating the summary statistics. Back to Section III.

C Spikes Design

To explore external validity, we consider technology adoption without the subsidy program. This design exploits the precise timing of technology investment events, which we call spikes, to analyze technologies' short-term effects at the firm level. The second design is valuable because the subsidy-based design is subject to two external validity concerns: (1) subsidy program as variation source, (2) program participants' representativeness. The spikes design complements the subsidy design by using a different variation source and a different sample. It is similar to a mass-layoff design (Jacobson et al., 1993) as it uses the precise event timing for identification and builds on the work of Nilsen et al. (2009), Hawkins et al. (2015) and Bessen et al. (2025). The design detects distinct events because technology investments tend to be temporally concentrated (e.g., Doms and Dunne, 1998; Caballero and Engel, 1999; Cooper et al., 1999; Nilsen and Schiantarelli, 2003).

Treatment Group We define the technology investment event, the spike, as an indicator that equals one when a firm's technology expenditures are significantly above average for the firm:

$$D_{jt} = \mathbf{1}\left\{\text{Technology Expenditure}_{jt} > \text{Threshold} \cdot \overline{\text{Technology Expenditure}}_{jT\notin t}\right\}$$

The average expenditure is computed over timeline T leaving out the current year t. For our main specification, we use the threshold of four (robust to different thresholds). We measure technology expenditure as investment in machinery and equipment from the Financial Statement Register.

The sample design is the following. We consider years 1994–2018 and restrict the sample to manufacturing, warehouse and retail, transportation industries, and firms with full-time equivalent employees (FTE) between 10 and 750 at time $\tau = -1$ relative to the event. We focus on a balanced sample and require that the firms operate at least starting from time $\tau = -9$. With these restrictions, we can exclude new rapidly growing firms that are not relevant to our research questions and event definition and ensure comparability with the subsidies design. Very large firms tend to have several units or plants, which obscures the evaluation of the spike.

The treatment group is the firms that experience a technology investment event and satisfy the sample-design criteria. In the case of multiple spikes, we choose the largest spike and require no other spikes in window $\tau \in [-5, 8]$. While this is needed for defining unique events, this requirement selects firms that do not have overly positive post-event outcomes. Figure C2 shows the treatment group's average technology expenditure by year. The event time is normalized around the event ($\tau = 0$). There is a clear investment spike: A significant fraction of technology investment at the firm level is associated with significant variations (Figure C1).

Matched Control Group To construct the control group, we match the spiking firms to non-spiking firms. The matched control group serves as a counterfactual for what would have happened in the short term had the spiking firms not invested. We provide a theoretical basis for this comparison in Appendix H. We use coarsened exact matching (CEM). We match by revenue, employment, and wages at $\tau = -3$ and industries' main sectors (letter classes). The CEM percentiles are 10, 25, 50, 75, and 90. The final caliper match is the propensity score based on the same CEM variables. The match is up to 1:5 with replacement. Table C1 shows the covariate balance for the matched samples. We match only in the pre-period cross-section to ensure that the pre-trend comparison between the treatment and control is informative.

Estimation The empirical strategy contrasts the treatment group with a spike to the matched control group that did not have a spike within the same 5-year window using a dynamic difference-in-differences design. To do so, we estimate Equations 1 and 2 from Section III.B.

The First Stage Figure C2 shows the first stage. The outcome is technology investment. Treatment group firms invested EUR 2 million more in technologies than the control firms in the event year. Before and after it, the groups invested similar amounts and were on parallel trends.

Variation We outline a dynamic model that clarifies the source of variation in Appendix H, adapted from Cooper et al. (1999). The same model provides the basis also for the subsidies design, and we refer to it in Section III.A. The main result of the model is that with adjustment costs, firms may experience low technology-investment activity periods followed by bursts of investment activity.

This result clarifies that the treatment and the matched control group could be comparable in the short run because minor initial differences may lead to significant variations in technology investment. For example, in the model, one reason a firm invests and the other similar firm does not is that they have a different replacement cycle. Our estimates from the spikes design exploit the precise timing of technology investment events.

Robustness The estimates are robust to excluding firms that simultaneously start exporting, change their management, make significant investments in buildings and property, or open a new plant before the event, and to different controls (not reported).

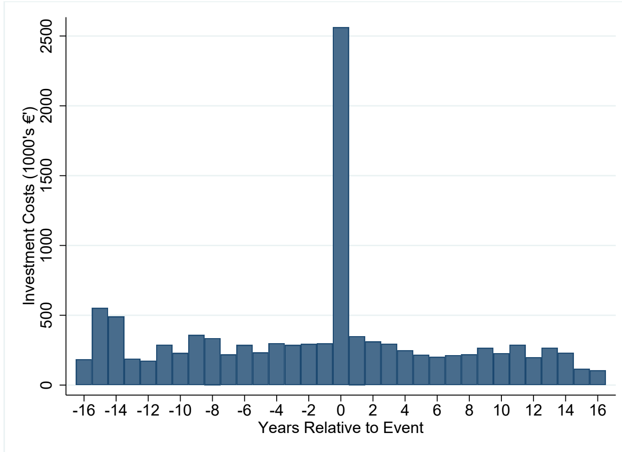


Figure C1: Spikes Design: Machinery Investment.

Notes: Machinery investment in EUR K. Event time is normalized to zero in the year of the largest machinery investment. The sample is restricted to manufacturing, retail, transportation industries and firms with employment 10–750 for comparability with the subsidies design. Consistent with the theoretical framework in Appendix H, technology investment is typically a spiky activity. Back to Section C.

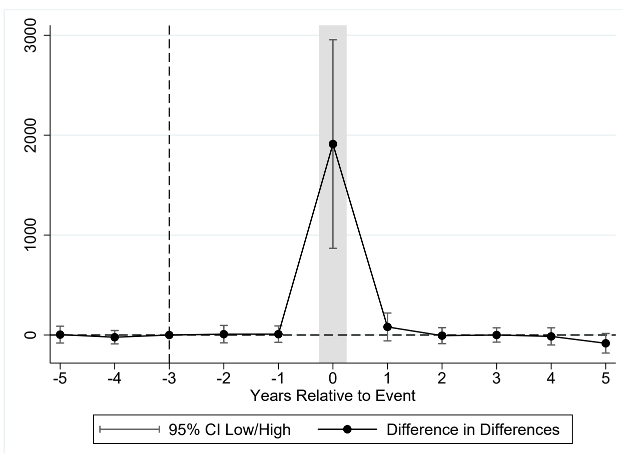
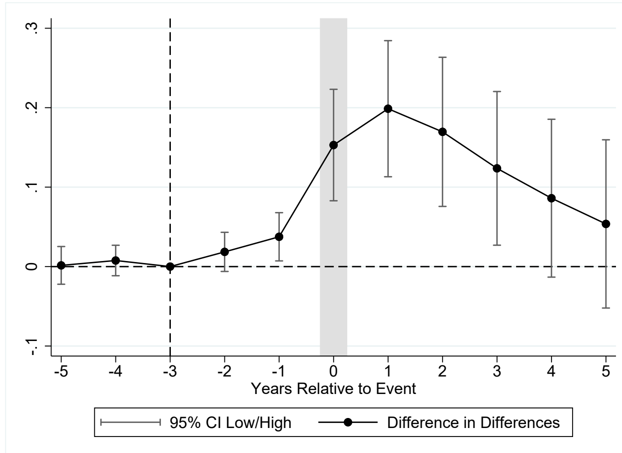
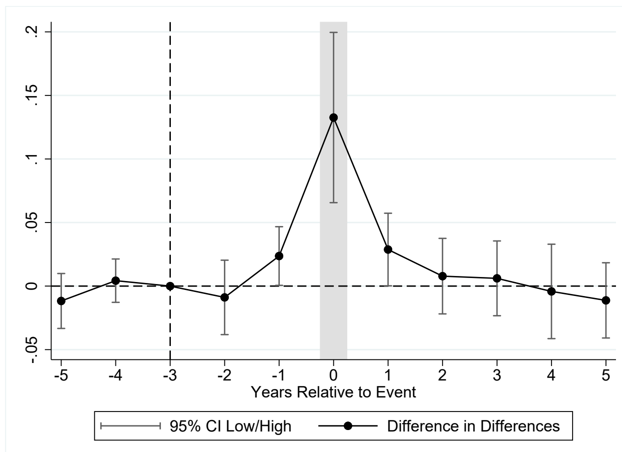


Figure C2: Spikes Design: First Stage on Machinery Investment.

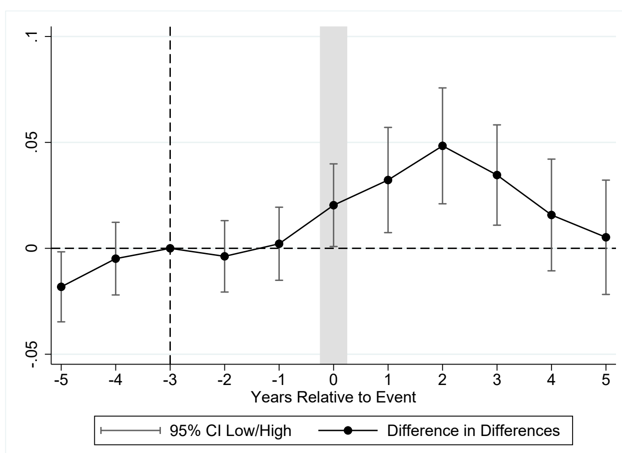
Notes: Event-study estimates from Equation 1. The estimates compare the spikes treatment group to a matched control group. The outcome is machinery investment in EUR K. Event time is normalized to zero in the year of the largest machinery investment. Back to Section C.



(A) Employment (%).



(B) Worker Entry Rate.



(C) Worker Exit Rate.

Figure C3: Spikes Design: Employment Effects.

Notes: Event-study estimates from Equation 1. The estimates compare the spikes treatment group to a matched control group. Event time is normalized to zero in the year of the largest machinery investment. Employment is in % relative to the base year $\tau = -3$. Entry (exit) rate is defined as the number of entering (exiting) workers divided by employment in the base year $\tau = -3$. Back to Sections V and VI.

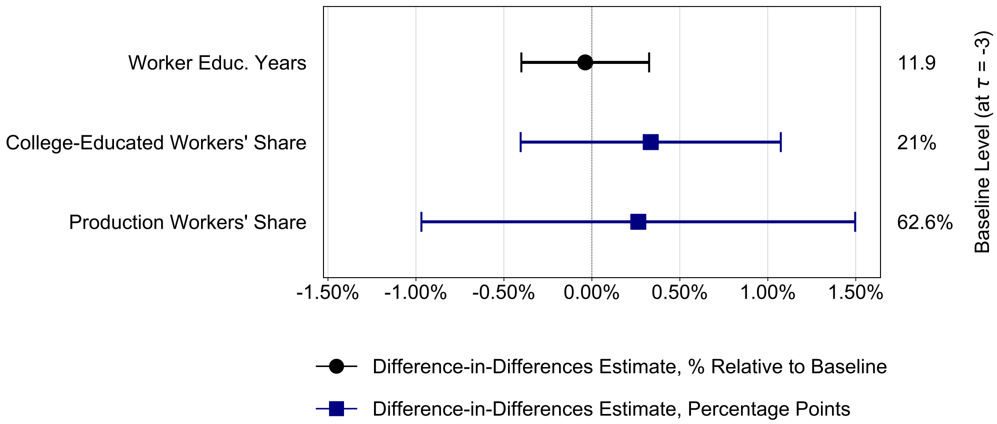


Figure C4: Spikes Design: Skill Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the spikes treatment group to a matched control group. The right-hand side reports outcome means at $\tau = -3$. Back to Section C.

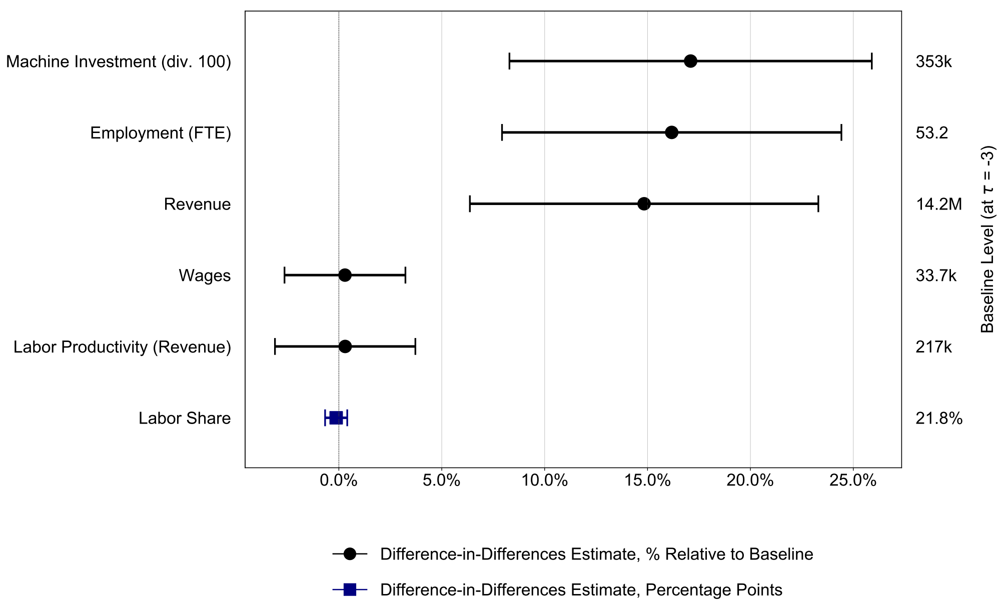


Figure C5: Spikes Design: Firm-Level Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the spikes treatment group to a matched control group. The right-hand side reports outcome means at $\tau = -3$. The machinery investment estimate is divided by 100 to avoid scale issues in the figure. Back to Section V.

Table C1: Spikes Design: Summary Statistics.

	Treatment Group		Control Group		Both			Tests
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p	p-value
Machine Investment (EUR K)	271.21	858.93	376.70	999.26	6.96	109.55	770.54	0.042
Revenue (EUR M)	14.48	30.10	14.12	69.98	1.29	4.85	26.97	0.915
Employment	51.66	68.29	53.67	71.11	11.10	28.30	119.20	0.593
Wages (EUR K)	33.68	9.26	33.75	8.21	25.12	32.56	43.20	0.882
Labor Share (%)	21.37	11.49	21.92	9.89	8.69	21.45	34.90	0.317
Labor Productivity (EUR K)	231.95	197.06	213.41	273.42	84.92	150.98	421.43	0.179
Subsidy Applied (EUR K)	265.14	757.13	200.85	543.70	0.00	0.00	565.49	0.044
Subsidy Granted (EUR K)	169.49	454.79	123.68	334.04	0.00	0.00	388.35	0.019
Educ. Years	11.89	0.91	11.86	0.87	10.88	11.78	12.94	0.476
College Share (%)	21.24	16.70	20.90	14.95	5.56	17.65	40.91	0.674
Production Worker Share (%)	58.90	30.95	63.68	25.79	14.29	71.43	88.89	0.014
F-test								0.013
Observations	450		1593		2043			2043

Notes: All variables measured at $\tau = -3$ (three years before the investment spike). We use 1:5 coarsened exact matching (CEM) with replacement (details in Section C). Back to Section C.

D RD Design

Design We use a regression discontinuity (RD) design generated by a change in the rules used to evaluate the applications as one tool to address internal validity. Einiö and Buri (2020) discuss the policy change and the RD strategy, and present related results. The advantage of the RD design is that the estimates are likely to reflect a causal relationship and satisfy Assumption 1. The disadvantages of the RD design in this context are statistical power, that the treatment is less precisely defined, and that it does not allow a natural way to use the text data to measure different types and uses of technology.

The EU expanded the definition of a small firm in 2005. Our RD design uses the fact that firms just below the new threshold were prioritized for subsidies but were otherwise similar to those just above it. Before the policy change, upper thresholds for small firms were 50 for employment, EUR 5M for the balance sheet, and 7M for turnover. The EU raised the thresholds for balance sheet and turnover to 10M. We use the balance sheet's total value as our running variable because it measured most precisely and had the most significant change; this gives us the statistical power to conduct the analysis.

The critical part is that the new rule was applied using retrospective data for firms. Thus firms could not immediately manipulate their size. However, as shown in Figure D1, firms adjusted their size later. This evidence leads us to focus only on the first year of the policy change when manipulation at the threshold was unlikely. Finland implemented the change in 2007 but considered retrospective data from 2004–2006. Our estimates use 2004 data as the running variable to avoid selection bias.

The policy change potentially affected firms' self-selection into the program, the likelihood of winning the subsidy, and the levels of subsidies. While being a small firm is not a strict criterion for receiving subsidies, the ELY Centers prioritize small firms (e.g., Takalo et al., 2013). The firms know this and are potentially more likely to apply for subsidies when the expected benefits are more significant. These facts and statistical precision lead us to focus on the reduced-form effects. There were no simultaneous policy changes at the same margin.

To produce the RD estimates, we use the following specification:

$$Y_i = \alpha + \beta E_i + f(z_{i,2004}) + \varepsilon_i \tag{6}$$

where Y_i is outcome for firm i, $f(z_{i,2004})$ is a function of the running variable (balance sheet in 2004) and E_i is the cut-off indicator (balance sheet under 10M in 2004). We use the bandwidth of five million, triangular kernel, and first-order polynomial (Gelman and Imbens, 2019) in our main specification. We cluster the standard errors at the 3-digit industry.

Results Table D1 shows the summary statistics for the RD sample firms.[47] As expected, the RD sample firms are larger than in the main design because, by definition, their revenue is around

[47] We exclude agriculture and forestry, the public sector, transportation, and finance since these sectors are generally not eligible for these ELY Center subsidies.

EUR 10M. Figure D1 documents firms starting to bunch around the new threshold after the change comes into effect. Figure D2 formally shows by a McCrary test (McCrary, 2008; implemented as in Cattaneo et al., 2018) that this is not yet the case in the pre-change year of 2004, which is the relevant year for our identification. Table D2 tests whether firms are different on different sides of the cutoff before the treatment and finds no statistically significant differences.

Next, we describe the first stage. Figure D3 shows a jump in the received subsidies at the new cutoff of EUR 10M. The running variable (x-axis) is the balance sheet in 2004 and the outcome variable (y-axis) is the total received subsidies in EUR 10K. The received subsidies are larger on the left side of the cutoff, likely because those firms became small under the new classification. Figure D3 also shows that these subsidies stimulated new investments: The linear graphs show a clear jump at the cutoff. Table D3 quantifies the same jumps using Equation 6 for subsidies received and investments made in 2007. Becoming a small firm increased the subsidies by EUR 38K and investments by EUR 188K. Both estimates are significant at the 5% level.

Table D4 presents the primary outcomes of the RD design. These results broadly confirm our main results of firm growth in employment and revenue but no skill bias. Being re-classified as a small firm increased employment by 9% and revenue by 25%. We see no changes in average wages, years of education, or the share of college-educated workers or production workers. The estimation is done by setting the average of 2003–2006 as a baseline value and comparing each observation from 2010 to 2015 separately to the baseline to increase statistical power. These differences are the outcomes in the estimation. Figure D4 visualizes a similar estimation for each year separately. We observe an increase of 8–10 employees from 2010 onwards.

We run multiple robustness and placebo tests for our estimates. Figure D5 explores robustness to the choice of bandwidth: Our results are not sensitive to it. Figure D6 runs our main specification with different thresholds: We cannot replicate our results with the placebo thresholds. Figure D7 run the estimation with placebo years' balance sheets: We observe no effect.

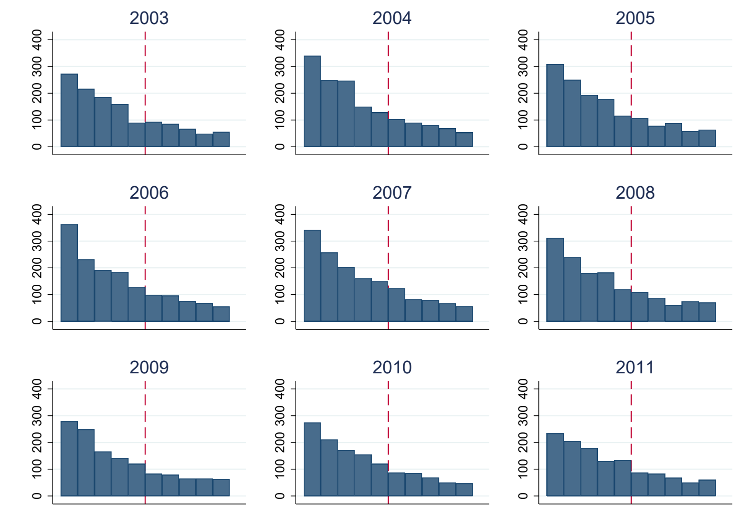


Figure D1: RD Design: Number of Firms at the Balance-Sheet Threshold.

Notes: The number of firms around the balance-sheet threshold for small firms announced in 2003, which came into effect in 2007. The distributions are plotted separately for each year 2003–2011. Back to Section D.

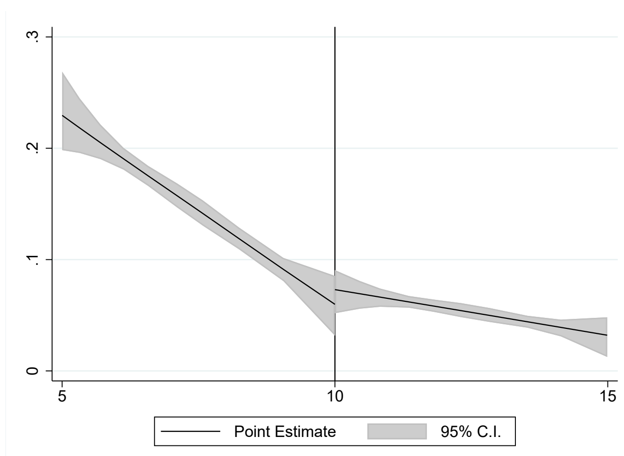


Figure D2: RD Design: Density of Firms at the Balance-Sheet Threshold.

Notes: McCrary test for the RD design (implemented as in Cattaneo et al., 2018). The horizontal axis is the firms' balance sheet in 2004 in EUR M. The vertical axis denotes the density of observations. Back to Section D.

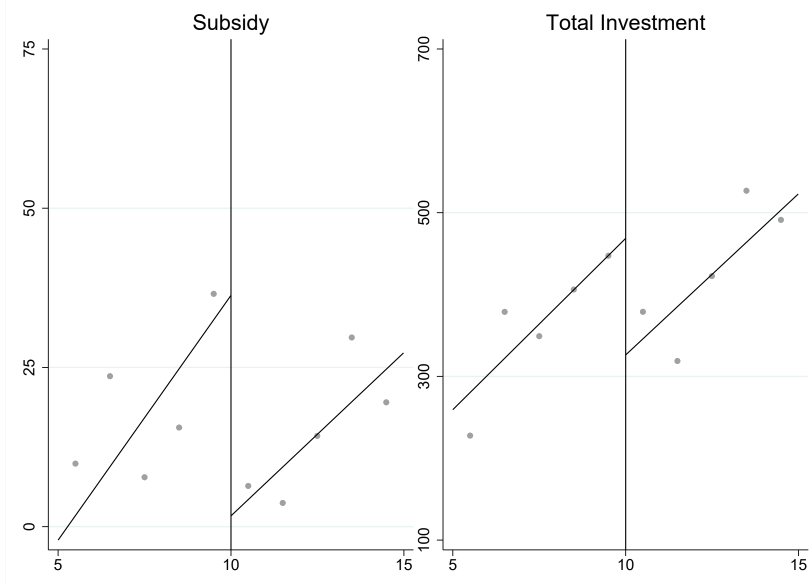


Figure D3: RD Design: The First Stage.

Notes: Discontinuity at the balance-sheet threshold for 2007 investment subsidies (left) and total investment (right). The vertical axis is in EUR K, and the horizontal axis is in EUR M. Back to Section D.

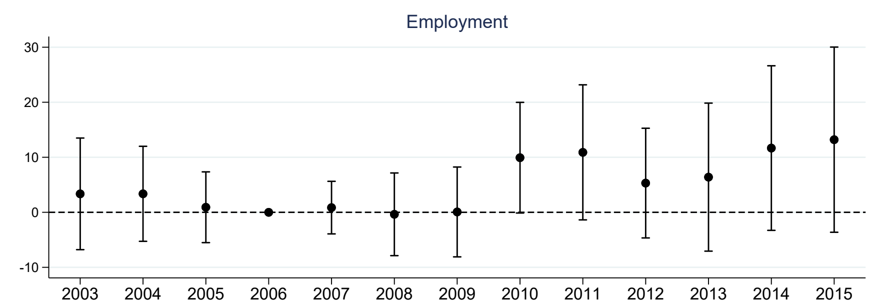


Figure D4: RD Design: Employment.

Notes: RD estimates from Equation 6. The outcome is the employment difference to base year 2006. The explanatory variable is the balance-sheet RD threshold indicator. We cluster the standard errors by three-digit industry, the kernel function is triangular, and the polynomial order is one. Back to Sections V and D.

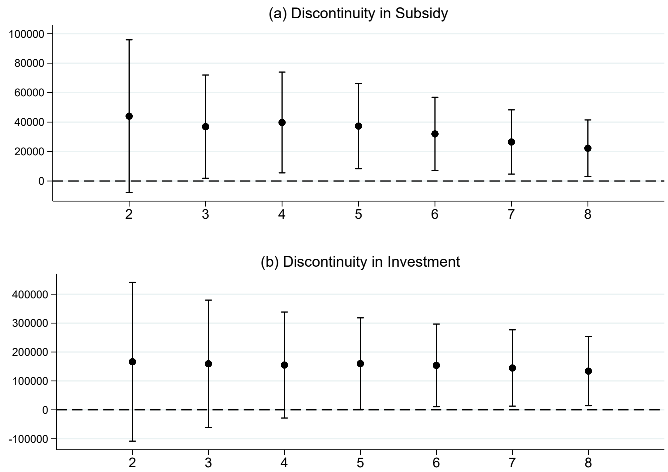


Figure D5: RD Design: Different Bandwidths.

Notes: RD estimates from Equation 6. The outcome is investment subsidies in the upper panel and total investment in the lower panel. The horizontal axis indicates the bandwidth of the estimation window. In all regressions, we cluster the standard errors by three-digit industry, the kernel function is triangular, and the polynomial order is one. Back to Section D.

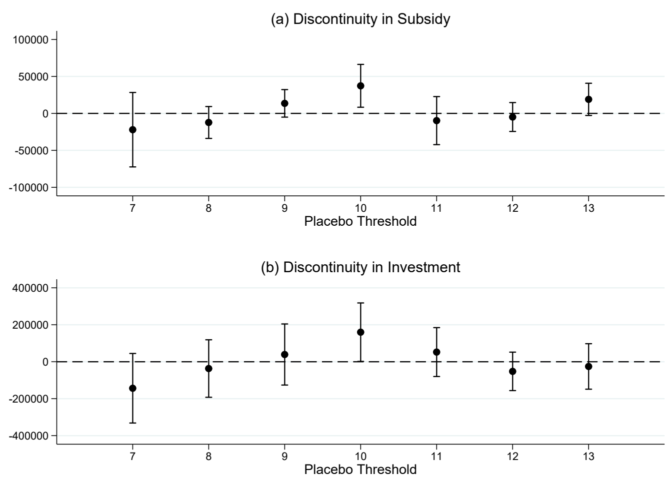
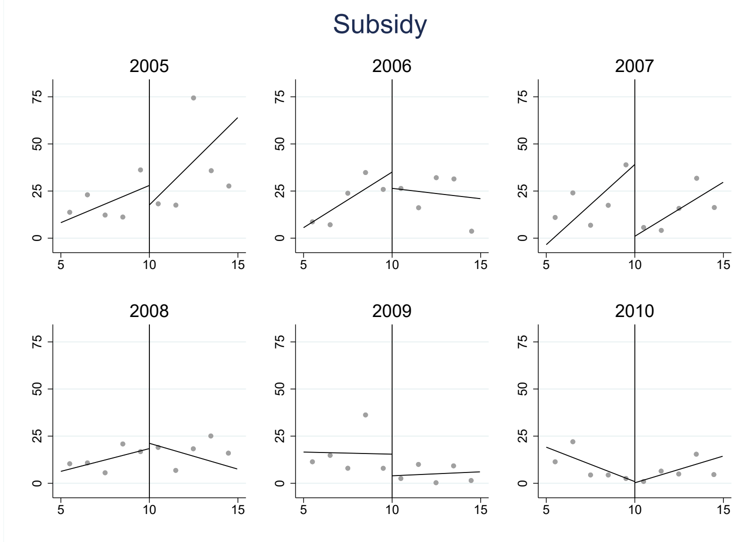
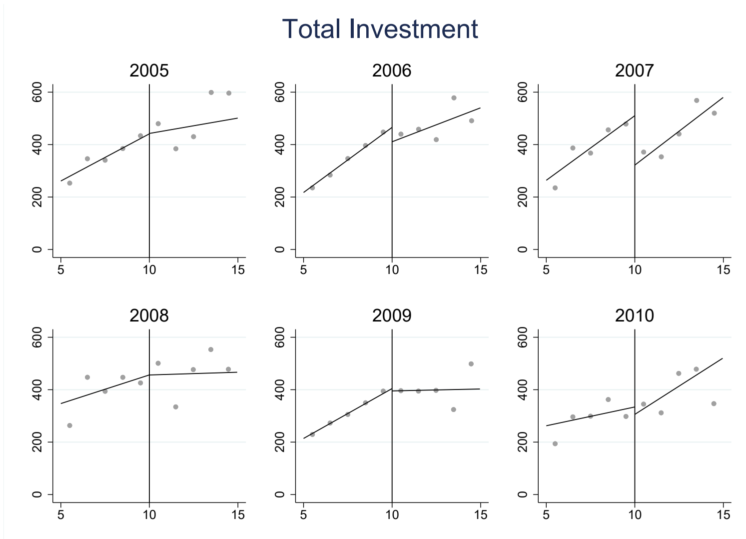


Figure D6: RD Design: Placebo Cutoffs.

Notes: RD estimates from Equation 6. The outcome is investment subsidies in the upper panel and total investment in the lower panel. The explanatory variable is the balance-sheet threshold indicator. The indicator equals one if the balance sheet is lower than the number indicated on the horizontal axis. The real cutoff of 10. In all regressions, we cluster the standard errors by three-digit industry, the kernel function is triangular, and the polynomial order is one. Back to Section D.



(A) Subsidies.



(B) Investment.

Figure D7: RD Design: Placebo Years.

Notes: Discontinuity at the balance-sheet threshold for investment subsidies (A) and total investment (B). The vertical axis is in EUR K, and the horizontal axis is in EUR M. In all versions, we consider the 2004 balance sheet. The discontinuity should be exactly in 2007. Before 2007, there should not be a discontinuity since the new balance-sheet criterion was not yet in place. After 2007, there should not be a discontinuity since the balance sheet 2004 value was no longer relevant. Back to Section D.

Table D1: RD Design: Summary Statistics.

	Mean	Std. Dev	N
Employment	65.75	76.93	1269
Revenue (EUR M)	16.7	16.5	1273
Wages (EUR K)	34.7	16.9	1269
Production Worker Share	0.40	0.32	1271
College Share	0.37	0.26	1273
Total Investment (EUR K)	377.6	579.0	1273
Investment Subsidies (EUR K)	16.2	127.6	1273
Total Subsidies (EUR K)	23.9	124.6	1273
Subsidized Loans (EUR K)	168.5	1,055.5	1273

Notes: Summary statistics for the RD sample, with balance sheet between 5 to 15 million euros. Back to Section D.

Table D2: RD Design: Pre-Treatment Covariate Balance.

	Investment	Subsidy	Revenue	Employment
Small 2004	5.771	16.17	-4.296	-7.745
	(88.22)	(19.03)	(2.849)	(10.37)
N	1273	1273	1273	1270

Standard errors in parentheses, clustered by 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: RD estimates from Equation 6. The outcomes are pre-period averages over years 2000–2004. Back to Section D.

Table D3: RD Design: First Stage Estimates.

	(1)	(2)
	Subsidy	Investment
Small 2004	38.07*	188.5*
	(16.44)	(86.53)
N	1273	1273

Standard errors in parentheses, clustered by 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: RD estimates from Equation 6. The outcomes are 2007 investment subsidies (Column 1) and 2007 total investment (Column 2). The values are in EUR K. Back to Section D.

Table D4: RD Design: Reduced-Form Estimates.

	(1) Employment	(2) Revenue	(3) Wages	(4) College Share	(5) Educ. Years	(6) Production Worker Share
Small 2004	0.0899*	0.251***	0.0214	-0.00108	-0.00902	0.00613
	(0.0417)	(0.0435)	(0.0208)	(0.0106)	(0.0625)	(0.0119)
N	6005	6006	6003	6012	6012	6012

Standard errors in parentheses, clustered by 3-digit industry.

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

Notes: RD estimates from Equation 6. The outcomes are defined in first differences. The pre-period level for the estimations is the average over 2003–2006. Employment, revenue, and wages are in relative changes, e.g., 0.20 would refer to a 20% increase. Education years is in years. The college and production worker shares are in percentage points. Back to Sections V and D.

E Additional Macro Evidence

Table E1: Industry-Level Evidence on Labor Share, Productivity, and Production Workers' Share.

	(1)		(2)		(3)	
	Labor Share		Productivity		Production Workers' Share	
A: Machinery Investment	-0.0012*	-0.0013*	0.0045	0.0040	0.0033***	0.0036***
	(0.0005)	(0.0005)	(0.0030)	(0.0033)	(0.0009)	(0.0008)
Pre-Period College Share		0.0528		0.341		-0.193
		(0.0599)		(0.307)		(0.159)
B: IT Expenditure	-0.0010	-0.0024*	0.0160***	0.0183***	-0.0043*	-0.0041
	(0.0006)	(0.0011)	(0.0019)	(0.0030)	(0.00196)	(0.0029)
Pre-Period College Share		0.113		-0.195		-0.0121
		(0.0765)		(0.184)		(0.170)
N	49	49	49	49	49	49
Mean Pre-Period	0.166	0.166	0.259	0.259	0.615	0.615
Mean Change	0.0435	0.0435	0.0802	0.0802	-0.073	-0.073
R^2, Machinery	0.150	0.185	0.130	0.216	0.168	0.236
R^2, IT	0.038	0.138	0.526	0.544	0.093	0.093
	Mean Total	10p	90p			
Machinery	9.236	2.560	21.75			
IT	2.306	0.610	4.011			

Standard errors in parentheses.

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

Notes: Industry-level long-difference estimates on predicting labor share, productivity, and production workers' share changes separately with total machinery investment (Panel A) and IT expenditure (Panel B) between 1999–2018 in Finnish manufacturing. The technology variables are measured in EUR K per worker-years (FTE). The outcome variables are in long-changes over the timeline. The estimates and means are weighted by pre-period industry employment sum between 1999–2002. Pre-period values otherwise measured in 1999, expect for production workers' share which is available for 2000. The shares are measured between 0 and 1, and productivity is measured in EUR M (revenue per worker). N refers to 2-digit manufacturing industries. Back to Section IX.

F Data and Fieldwork

This appendix describes our data on workers, firms, and subsidies, as well as our fieldwork.

F.A Workers

We directly measure individual workers' employment, wages, education, school grades, occupations, cognitive performance, and personality. Our data track all individuals in Finland over time independently of their labor-market status.

Employment and Wages We obtain employment and wage data from the registers maintained by Statistics Finland. The data contain the employment status, wages, other income, and a link to the firm. The data allow us to track all persons in Finland over time, independent of their labor-market status. The data are combined from multiple government sources (including the social security system and tax authorities) and direct data collection by Statistics Finland. These registers also record the individuals' age, gender, and home county. At the firm level, we define the labor share as the wage bill divided by the revenue.

Education We measure education and school grades. Education is measured from The Register of Completed Education and Degrees. It provides exact information on the educational degrees the individual has obtained. We measure the level of education in four categories: (1) very low (no recorded degree), (2) low (high school), (3) medium (BA or equivalent), and (4) high (MA or PhD). High school contains both academic and vocational tracks. We measure the type of education also in four categories: (1) STEM (science, technology, engineering, and mathematics), (2) HASS (humanities, arts, and social sciences), (3) business and law, and (4) other types. We map degrees to years of education based on their official length. School grades are measured from the Secondary Education Application Register and the Finnish Matriculation Examination Board Register. We focus on the 9th-grade GPA and the standardized scores in the national high-school exit exam (12th grade). We normalize both grade measures to have a mean of zero and a standard deviation of one within cohorts.

Occupations and Tasks We measure occupations from the employment registers at the 3-digit level in the ISCO classification system. We manually harmonize the occupation classifications, resulting in 48 consistently defined occupations. For most analyses, we focus on three broad occupational categories: production workers (craft workers, operators, assemblers, and elementary occupations), non-production workers in lower-level positions (clerical, service, and sales workers), non-production workers in higher-level positions (technicians, associate professionals, professionals, and managers). The occupational data are available for 1995, 2000, and 2004 onward yearly. Because of these gaps in the data, we define the pre-period for occupational outcomes as the mean of non-missing observations over $\tau \in [-5, -1]$.

We use the European Working Conditions Survey (EWCS) to measure the task content of the occupations. The survey provides information on the tasks workers perform in their jobs. The data are collected through face-to-face interviews every five years. The advantages of the EWCS data are that it is based on workers' descriptions of their work, is available for a specific country and time, and is consistent with the European occupational classification. Using these data, we construct occupation-level measures of task intensity for routine, manual, abstract, and social tasks, and cognitive skill intensity (see also Autor et al., 2003, and Kauhanen and Riukula, 2024). For example, an occupation is classified as highly routine if the workers describe they often perform repetitive and monotonous tasks and highly social if they often work with others.

We use combined data from the Nordic countries (Finland, Sweden, Denmark, Norway) and Germany to trade off statistical precision and relevance to our context. The results are essentially the same using only data for Finland. Our exact classification rubric is available as part of the replication package.

Cognitive Performance and Personality We obtain data for cognitive performance and personality from the Finnish Defence Forces (FDF). The data cover 79% of Finnish men born 1962–1979, and are measured because of universal conscription. The cognitive-performance measures are visuospatial, arithmetic, and verbal reasoning. The visuospatial test is similar to Raven's Progressive Matrices (Raven and Court, 1938). The personality-trait measures are sociability, activity-energy, self-confidence, leadership motivation, achievement motivation, dutifulness, deliberation, and masculinity. The personality test is based on the Minnesota Multiphasic Personality Inventory (MMPI). We normalize all measures to have a mean of zero and a standard deviation of one within cohorts. These are the all available cognitive performance and personality measures, we do not exclude any. The FDF data are described in Izadi and Tuhkuri (2024, 2021).

F.B Firms

Our extensive data on technologies and firm performance track all firms over time.

Financial Statement Register These data (FIRM_FSS) contain information on machinery and equipment investment, IT expenditure, and overall capital. Machinery and equipment investment measures the value of the additions in machinery and equipment. This includes, for example, CNC machines, laser cutters, and robots. IT expenditure captures IT costs billed on outside providers. It includes software, programming, and computer-design expenditure, and also IT consulting services. Statistics Finland collects the investment and expenditure data directly and combines direct inquiry with estimation for capital. The register also includes data on revenue, profits, and outside R&D and marketing expenditure. We deflate all monetary values in this paper to 2017 euros using the Statistics Finland CPI and winsorize them at the 5% level, except for marketing costs, which are not winsorized, as only a small fraction of the sample reports nonzero marketing costs. The data cover all Finnish firms in almost all industries and our analysis years 1994–2018.

Customs Register The Finnish Customs Register (TULLI_COMMOD and TULLI_ENTER) records firms' exports, export destinations, and imports. 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 EUR 12K during the calendar year spread over at least two different months or if a single export event is over EUR 120K in value. We measure firms' exported products at the 6-digit CN classification; we focus on the number of products and product turnover: introduced and discontinued products. We harmonize the product categories to be consistent over time. We do not apply any minimum level of imports or exports to the customs data. Price data for the exported products also come from the Customs Register. We focus on firm-level average prices computed as an unweighted average. We winsorize price data at the 10% level within product and year. The customs data also record 621 technologies that firms import in the 6-digit CN classification system. Together we refer to these as machinery imports. We manually classify these imported technologies into automated vs. non-automated technologies building on Acemoglu and Restrepo (2022). Sections VI and especially F.C describe this classification in more detail together with text data.

Patent Register The Finnish patent register (FIRM_PAT) covers the patents of all Finnish firms. We focus on the indicator whether the firms has patented in a given year. These data are available until 2013.

Industrial Production Statistics These data (FIRM_COMMOD) provide production statistics for a yearly sample of 3000–3500 plants. Based on our experience, the data appear imprecise for our primarily SME sample (the data focus on larger firms). For robustness, however, we compute prices from the product data, defining product-level prices as the revenue divided by the number of units sold. We winsorize price data at the 10% level within product and year. We also track the value of inputs from these data.

Industry Classifications We measure industries at a harmonized 2-digit level classification (based on NACE Rev. 2). We approximate the industry's scope for quality differentiation using the Rauch (1999) index (for robustness, with the Gollop and Monahan, 1991, and Sutton, 1998, indices). We gauge industries' tradability via Mian and Sufi (2014).

CIS Survey The Community Innovation Survey (FIRM_RDINNO) of the EU is implemented in Finland by Statistics Finland. It provides direct firm-level information on several relevant aspects for our study.

Motivations: CIS provides data on the importance of different objectives for product and process innovations as described in Section VI. The question that captures these aspects is worded typically: "How important were each of the following objectives for your activities to develop product or process innovations during the three years — to —? " or "During the three years – to –, how important were each of the following goals for your enterprise?" If multiple survey rounds match the firm, we choose the closest to the subsidy application year, and if two surveys are equally close, we choose the one before the application. Note that the option "Customer-Specific solutions" is only available in 2016.

Robots and digitalization: CIS also measures the importance of robots and digitalization as perceived by the firms. The question that captures these technologies is: "How important were the following digitization-related factors to your company's business in –year–?" We focus on "the utilization of robotics in production processes" and "the importance of digitization in producing goods and/or services." High importance means the answer is "large," and low importance means it is either "small" or "does not apply." Data on robots and digitalization are included in the survey rounds 2014–2016 and 2016–2018, and we pool them.

Constraints: CIS factors hampering innovation activities, including lack of credit, internal finance, or skilled employees, and the cost of innovation. The question was of the type "During — to —, how important were the following factors as obstacles to meeting your enterprise's goals?"

The survey is conducted every two years and we use data from years 1996, 2000, -04, -06, -08, -10, -12, -14, -16, and -18, covering the timeline of our study. The surveys used in the paper have the limitation that they cannot be tightly linked to the technology subsidy event, only to the firm. The (unrestricted) sample size varies between N = 2,000–4,000 firms and typical response rate is approximately 70%. The overlap with our main sample is 708 firms.

ICT Survey The ICT survey of Statistics Finland (FIRM_ICT) asked in 2018 directly whether the firm uses robots and what share of the workers use a computer. The robot question is: "Does your company use the following types of robotics?" The option we focus on is industrial robots, and there are two answer options: yes and no. The computer question is, "How much of your company's personnel use a computer in their work?" We discretize the answer into above/below the median in manufacturing. The overall sample size in 2018 for the survey is N = 3,028, and the response is 71%.

Etla Survey Our own Etla survey (also called the "Mittelstand survey" as it mainly focuses on SMEs) provides information on the firms' objectives and strategy. Etla stands for ETLA Economic Research, the research institute that implemented the survey in 2015.

Motivations and context: The questions cover firms' differentiation strategies and past and future changes. They probe differentiation of products/services and anticipated shifts over three years, including new products, methods, and customers. They questions also assess recent product improvements, operational changes in response to customer feedback, and firms' communication with their customers. The answer options are strongly, moderately, some extent, and no.

Robots and digitalization: The survey asks firms whether they use or plan to use robots or several forms of IT, including big data and analytics. We focus on the question: "Will the following issues related to digitization impact your industry in the next 3 years?" and the two subtopics: "Using robotics to produce products/services" and "Big data, i.e., vast data masses and their analytics." The answer options we focus on are "Yes and we invest" and "No."

The target population had 33,390 active or closing/discontinued companies. 6,268 (18.8%) companies started the survey and N = 4,673 (14.0%) finished it. The overlap with our main sample is 202 firms.

SFINNO Data SFINNO is an innovation database that tracks firms' innovations from Finnish technical and trade journal articles from 1985 to 2020. These professional journals chronicle industry trends and firm-level innovation and technology investments. The SFINNO project systematically reviewed 15 technical and trade journals, identified innovations (including technology investments), and hand-coded variables describing these innovations. The current data identify a total of N = 5,481 innovations from approximately 1,700 firms. Our main sample firm IDs were linked to SFINNO by VTT, Technical Research Centre of Finland, resulting in 213 matches.

The data coding follows the Literature-Based Innovation Output (LBIO) method (Coombs et al., 1996) and adheres to the OECD's Oslo Manual guidelines (OECD, 2018). Figure A22 provides examples of the types of articles included in the data. We use two variables coded from the journal text data: whether innovation was primarily a process or product innovation (following the definition of the Oslo Manual) and the complexity of the innovation. The data and variables are described in Palmberg et al. (1999) and (2000).

SFINNO complements the journal data by surveying the firms featured in the articles. The survey contains information on: how significant different factors have been for the commencement of the innovation's development (e.g., the realization of a market niche, the role of the customers, a new scientific breakthrough, new technologies) and the primary technological content of the innovation (e.g., development and integration of components and modules, development of production methods). The survey respondent in the firm was typically a person directly involved with the innovation project, identified from the article.

A key requirement for the firm to appear in the data is that the journal found the innovation newsworthy. While the editors of the journals included in SFINNO have confirmed in interviews that they aim to cover all important innovations in their industry (Torregrosa-Hetland et al., 2019), SFINNO is likely biased toward some forms of innovation—especially those that have relevance outside the firm. For example, product innovations might be more likely to be captured in the data (the early years until 1998 contain solely product innovations). However, sponsored material, advertisements, and simple new product listings were not included in the data. One advantage of SFINNO for us is that it oversamples SMEs (Palmberg et al., 1999). Lehtoranta (2005) and our own analysis document that SFINNO is consistent with CIS.

F.C Subsidies

Our main data sources for firm subsidies are two centralized systems, TUKI2000 and TUKI2014 (also referred to as Yrtti 1 and 2), which record all applications to the ELY Center subsidy program. These previously unstudied, confidential datasets track the full application process—from submission to decision—for every applicant. We also use the Statistics on Business Subsidies (FIRM_SUBSID) dataset to measure other types of firm support. This section provides details on the text analysis: the categories, the coding process, and how we processed the raw text data.

F.C.1 Text Categories

We code the application texts into a set of categories that can be grouped into three classes: intentions, technologies, and robustness. Intentions describe how firms planned to use the technology—for example, to expand, develop new products, or improve productivity. Technologies capture the specific tools firms intended to adopt, such as machinery, IT, robots, CNC machines, or laser cutters. Robustness flags rejected applications with firm-specific issues or employment-related concerns.

Below, we outline the coding criteria for each category. We also include anonymized examples from the application texts, with key passages underlined. These examples are translated and anonymized to preserve confidentiality. The coding team has reviewed the descriptions and examples to ensure they reflect the actual coding decisions.

We begin with the categories describing firms' intended use of the technology. Each category is hand-coded independently, so an application may fall into multiple categories. Table 6 summarizes these categories.

Expansion This category includes firms that aim to expand production capacity, output, revenue, or firm scale. Expansion must be a stated goal—not just a possible byproduct of other objectives like improved quality or lower costs. Firms may express this goal indirectly—for example, by adding production lines, building new facilities, or easing capacity constraints. These cases are included. The underlying motive is often to meet increased demand or respond to new customers. Examples:

- The new production line increases the company's capacity by approximately 30-40%.
- The company believes that the project will enable it to increase revenue and expand its export activities.
- The company invests in a new production facility (including office spaces) for the manufacture of sheet and metal structures, expanding the company's operations.
- A new computer-controlled large format printer is needed to improve the company's competitiveness and business growth.

New Customers/Markets This category includes cases where firms aim to reach new customers or enter new markets. The motivation must be explicit: applications must mention targeting new clients, contracts, partnerships, or market segments. These may include local or international markets. Examples:

- The company's operations are expanding with a new customer, necessitating investments and automation as capacity grows.
- Modern equipment will allow the company to meet current customer needs and establish new customer relationships.
- With the investment, the company has the opportunity to enter the surface materials market, offering new business opportunities.
- Developing internationalization and exploring new material procurement channels is crucial for the company to find new customers and enhance its operational opportunities.

Exports This category includes cases where firms aim to initiate or expand exports or adjust their international operations. To be included, the application must mention goals such as entering foreign markets, increasing export volumes, improving export readiness, or forming international partnerships. Both the extensive (whether to export) and intensive (how to export) margins are included. The category often overlaps with New Customers/Markets, but here the focus is specifically on foreign markets. Examples:

- [...] create opportunities to start exporting more suitable products for the international market, while increasing production capacity.
- A significant portion of new machine's production will be exported. The projects specifically aim to counter Asian competition, [...], especially in Central European markets.
- Entry into the market will be investigated with an external market study and participation in trade fairs in Sweden, Germany, France, and Russia. The project improves the conditions for the company's growth and internationalization.
- To reduce dependence on the domestic industry, the company is undergoing a heavy product development project with internationalization efforts, focusing on the development of products for export markets.

Vertical/Horizontal Integration This category includes firms that plan to shift their position in the value chain. Most firms in our sample produce intermediate goods, and integration often means bringing tasks in-house from suppliers (upstream), adding functions previously handled by customers (downstream), or merging with other firms or facilities (horizontal). The application must describe this shift explicitly. Generic references to "increasing value added" are not sufficient for classification. Examples:

- After the investment, it is possible to increase work done in-house and, correspondingly, reduce the use of subcontractors.
- The machine being acquired completes a piece in one clamping. Precision improves and the complexity increases. The firm has outsourced these tasks from abroad until now.
- Subcontracting machining increases production costs and extends delivery schedules. With the acquisition, the company can be self-sufficient and even start its own subcontracting offerings.
- The company's operations are expanding from manufacturing components to becoming a supplier of complete saunas.

New Products This category covers cases where the firm plans to introduce or develop new products or services. Common points of emphasis are expanding product portfolio, entering new business areas, or moving from product plans into production. Examples:

- The project contributes to improving the company's competitiveness as it expands the product range.
- The company has decided to expand its services to special electric motors. The new business area requires the acquisition of advanced equipment and expertise.
- The new machine significantly increases production capacity, speeds up production, and diversifies the product range.
- The applicant's strategy is to create a new business area alongside traditional activities.

Quality This category includes cases where firms aim to improve product, service, or production quality. Applications often cite the goal of meeting or upgrading quality standards. While we aim to capture quality improvements that are observable to customers, the texts do not always provide enough detail to make that distinction. We include all cases where the application clearly references quality as a stated objective. Examples:

- The quality of services does not meet the required standards for exported products. Therefore, the applicant company is investing in its own surface treatment facility. The goal is to elevate the quality of products, especially since the company aims for growth through exports.
- The new machining center ensures consistent quality and precise dimensions for the products.
- The company is upgrading its existing paint shop to a state-of-the-art one, ensuring that the quality of painting meets export market standards, and simultaneously improving the quality of all products.
- The main goal is to maintain and further develop the company's business and meet the market's quality requirements. The new laser cutter provides reliability, as well as increased quality and precision in cutting work.

Capabilities/Flexibility This category includes cases where firms seek to expand their production capabilities or improve flexibility, often in response to varied or customized client needs. Unlike the New Products category, which requires a product, service, or business area, Capabilities/Flexibility captures potential—firms signal the ability to offer more diverse, tailored, or technically complex outputs without naming a product. This distinction is especially relevant for job shops and contract manufacturers, many of which do not produce their own branded goods. In these cases, investments aim to improve versatility—for example, by enabling more complex, customized, or flexible production. Examples:

- The firm is investing in modern production technology to meet the growing demand from customers for individual, tailored products.
- The firm is investing in their sewing line for filter bags. This will make it easier to sell customized solutions to customers.
- The new machining center allows for the processing of larger and more diverse products. The machine can handle more challenging pieces, with a larger spark size and better positioning and accuracy.
- Investment in a new cutting machine is necessary as the company's current machinery does not allow for the production of complex components without specialized procedures.

Precision This category includes cases where firms adopt technology to achieve greater precision, accuracy, or tighter tolerances in production. While precision can be viewed as a component of quality, we classify it separately because the term is used with consistent and concrete meaning in the application texts. Examples:

- The investment is needed because the company's two main customers demand good dimensional accuracy from their products and adherence to delivery times.
- The goal is to acquire a fast, efficient, ergonomic, and precise machining center and a measurement tool to ensure high precision and quality of components.

- The purchase of the machine aims for more efficient, higher quality, and error-free production through new technology.
- Current customers in timber sorting demand more precise length and quality. This production needs to be promoted to reduce dependence on basic product manufacturing. Therefore, the plan is to change the current timber sorter to one that provides efficiency and, above all, precision in the sorting process.

Productivity This category includes cases where firms adopt technology to improve productivity, reduce costs, or enhance efficiency. The product's features remain unchanged from the customer's perspective (aside from price, potentially). The focus is on producing more with the same or fewer inputs. Productivity must be stated explicitly as a goal. We do not include cases where labor productivity is a byproduct of product innovation. As with all categories, applications may belong to multiple groups if multiple goals are stated. Examples:

- Through the project, the company seeks significantly more efficient production, especially in welding, which has been a production bottleneck for an extended period.
- The new equipment significantly speeds up packaging operations, being approximately five times faster than the old equipment. Accelerated production increases capacity and reduces production costs.
- A highly automated tube bending machine increases efficiency and productivity. The new machine allows for growth and the creation of new jobs.
- A more spacious operating environment allows for significant improvements in material management, workflow, and productivity.

Work This category includes cases where the application links to labor-related objectives—such as reducing labor costs, altering tasks, or improving labor productivity. To avoid undercounting, we apply deliberately inclusive criteria. Mentions of workforce impacts are broadly interpreted, and we include both automation and labor-augmenting technologies, since the texts do not consistently distinguish between them. The technology may also be part of a broader reorganization, as long as the intended effect on labor costs or productivity is clear. To be included, the text must refer directly to labor—for example, by mentioning the workforce, personnel use, task changes, labor productivity, or labor cost savings. Generic references to "efficiency" or "competitiveness" are insufficient. Examples:[48]

- The machine requires fewer personnel resources than before. The sanding machine is a new acquisition; previously, sanding was done manually. The benefits of the investment include improved production efficiency, increased quality, and expanded capacity.

[48]We highlight two choices we make regarding classification in this category:

1. "Automation" language is interpreted with care. In the application texts, the term does not necessarily refer to the automation of labor tasks. It often describes automation in a narrow part of the production process—such as automatic defect sensing—or refers to a machine operating autonomously. Still, where the application also refers to labor, we include it.
2. Labor outside the firm is excluded. Changes that reduce labor inputs in the value chain—for example, shifting a task from a supplier to an in-house automated process, or improving product quality to reduce downstream labor at the client firm—are not coded as "work."

- Automation in production increases significantly, transforming the company's production methods from largely manual to nearly fully automated.
- The company achieves significant cost savings with the investment compared to its previous operations, especially in personnel and energy costs.
- A new machining center will be operated and programmed by a new hire, bringing new expertise to the company and reducing dependence on labor overall. The aim of the bandsaw is to speed up lead times, reduce waste of sheet material, and lighten the workload for the saw operator.

Delivery Firms in this category aim to improve delivery. Typical cases refer to delivery speed, reliability, and logistics. The improvement must affect delivery to customers—internal logistics alone is not enough. Examples:

- The project improves the company's delivery reliability and ensures that its capacity is sufficient, as the company increasingly subcontracts to others.
- The company is acquiring a modern machining center, enabling faster throughput. The project improves the firm's technical readiness, delivery, and especially quality assurance.
- The project enhances the company's competitiveness, saves on costs, accelerates deliveries to customers, improves inventory turnover rates, and enhances product quality through a quality monitoring system.
- Delivery reliability and speed improve, strengthening the company's competitiveness.

Brand In this category firms aim to enhance their branding, corporate image, or public perception. These goals are often expressed as improving reputation and appearance as advanced, innovative, or as industry leaders. The intention must be stated explicitly in the application. Examples:

- Improving the perceived quality image among customers is a significant factor in the project. Overall, the investments in the project increase customer trust in production quality and significantly enhances the company's competitiveness.
- The focus is on streamlining business operations and improving the environmental awareness that can be demonstrated to customers.
- Updating the machinery is essential to attract young employees to join the company.
- Obtaining the demanding 4th class 1090-CE certification is expected to increase market share in subcontracting. The ability to provide customers with required certificates for quality is a significant advantage.

Adaptation This category includes cases where firms respond to changes—such as new customer demands or shifts in the factor market. The change must be external from the firm's perspective: it cannot be caused by the firm or the project itself. Applications often describe the need to adjust to maintain operations, retain clients, or respond to shifting conditions. General optimism about growth or rising demand is not included. The core idea is that the investment enables the firm to adapt to circumstances outside its control. Examples:

- The new machine's features meet growing customer demands. Customer requirements have evolved, particularly for industrial customers.

- By automating processes, the company can better respond to increased international competition in terms of quality and delivery reliability.

- The project aims to develop windows and doors to comply with new and potential future energy regulations.

- Spare parts are no longer available for the old machines.

Next, we discuss the categories of different types of the technologies. For completeness, we also include the overall technology category, which is also discussed in the main text and Table A5.

Technology Our main design includes only subsidies that are coded as technologies. The criterion for this classification is the mention of a technology or technological advancement. Technology is broadly defined in the everyday sense of the word. Typical cases are acquiring hardware or software. Also, improving or modernizing production technologies are considered technological advances. In contrast, we consider market expansion, marketing, pure organizational changes and R&D in the absence of new technology adoption as not technologies. This choice affects the focus of this study. Table A5, referred to in the main text, also summarizes cases that are coded as technology vs. not technology. Examples:

- The company is acquiring a new production line.

- A significant investment effort by a micro-enterprise in a new 5-axis linear motor machining center and the tools required for its operation, as well as CAM software.

- Acquisition and implementation of an ERP (Enterprise Resource Planning) system.

- Expansion of operations and automation with a CNC-controlled press brake.

- Modernization of production machinery and equipment.

- Improving productivity with a "technology leap" through the acquisition of NC-based machines.

Negative Examples:

- Hiring of expert services related to product development.

- Development of a more powerful, energy-efficient, and user-friendly product and related production methods, along with a market survey.

- The conditions for the company's market entry are explored with a market survey and by participating in trade fairs.

Machinery The Machinery category covers investments in physical technologies, and constitutes a majority of the technology subsidy applications. The key criterion is the technology being tangible (something we can touch). Typical cases include CNC machines, welding robots, laser cutters, bending presses, surface-treatment technologies, robot arms, conveyor belts, sensors, and measurement devices. Examples:

- A CNC-controlled drilling rig enables more accurate product quality, efficient production...

- The acquisition of welding robots and a painting line streamlines the production of the company's key products.
- The company is acquiring a fully automatic laser system with automatic loading.
- The roller molding line enables more cost-effective production.
- Acquisition of a CNC tube bending center.
- The new edge banding machine allows for the production of popular rounded edge trims.
- The new grinding line can process birch veneer and provide the finishing touch on pine veneer, meeting customer demands for pre-coated panels.

IT The IT (Information Technology) category includes investments in IT, software, and digital technologies, such as computers, computer programs, databases, and digital tools. Typical examples include software for enterprise resource planning (ERP), computer-aided design (CAD), production control, and warehouse management. The applications may simultaneously include machinery and IT components and belong to both categories. Examples:

- The company is acquiring a laser cutting machine and a press brake, along with the CAD/CAM software needed for control the machines.
- The new production control system allows for the management of an increasingly diverse customer and product base.
- In addition to machinery and equipment, the project includes software investments to integrate the company's production control and financial management systems.
- The company is investing in a new laser, an ERP system, a press brake, a machining center, and a press. With a need for increased capacity, the ERP system significantly improves the company's ability to respond by providing real-time information on business conditions.
- Development of the production control system.
- The project includes acquiring a modern edge banding machine and utilizing expert services for CAD/CAM program modeling and training, as well as complementary equipment acquisitions for the control of production machines.

Technology Keywords We use keywords to identify specific technologies. The application belongs to the category if the keyword is present. We also use these keywords to standardize different spellings of common technology-related words when preprocessing the text data to reduce dimensionality (see Section F.C.3).

- CNC: *cnc*
- Robot: *robo*
- Laser: *laser, plasma*
- Machining: *työstökeskus, työkeskus, koneistuskesk, monitoimisorvi, koneistus*

- Welding: *hitsau, hitsi*
- Painting: *maalaam, maalaaj, maalaus, värit, pintakäsit, pinnoitt, raepuhalt*
- Driving (logistics): *kulj, traktor, kuormaus, kuormaaj, nostolav, kulkuneuv, truk, kaivinkon*
- Hoisting (logistics): *nostolait, nostin, nosturi, vinssi, vintturi*
- Automation: *automaat, automat, automoi, automisa*

Automated We classify machinery into two broad groups: automated and non-automated. This classification is developed for both the text and customs data, building on the approach in Acemoglu and Restrepo (2022).

The automated category includes technologies that operate without active human intervention. The classification is made ex ante, based on the nature of the technology—not on observed workplace effects. In other words, we do not require that the technology replaces human tasks to be classified as automated.

This category includes robots, CNC machines, conveyor belts, automatic packaging and sorting systems, and other equipment designed to function autonomously. It also covers investments in automated production lines and cases where firms explicitly mention automation. Our approach is conservative: it must be clear from the application that the technology is automated or contains an automated component.

Examples from the text data:

- Purchase of a used profiling machine and an automatic packaging line.
- Key acquisitions include welding robot with accessories, radial drilling machine, hydraulic press, and band saw.
- Automatic blade control device for a road grader, enabling the machine to perform even more demanding work. This investment aims to raise the quality level of the offered service. Considering the increased demands from customers; not all of them can be served without automation.
- Construction of new facilities (1,200 m^2) and acquisition of a welding robot, saw, drilling machine, and computer-aided design software.
- Acquisition of a punching and laser machine integrated with a robotic press brake. This forms a cell that automatically produces components from a stack of sheets, stacked on pallets without manual intervention.
- Automation and streamlining of production across three different production lines.
- Acquisition of 3D design software, lumber pre-processing line, automatic wall panel manufacturing line, base element assembly line, and wall panel coating line.
- Increase production efficiency with the acquisition of a more automated machining center.
- Enhancing efficiency through production automation. The manufacture of aluminum doors and windows involves a significant amount of manual labor, but with this investment, production can shift more towards mass production, as already initiated with the machining center acquisition.

We complement the text data with firm-level import records from Finnish Customs, covering technologies at the 6-digit CN-code level. Our classification of automated technologies closely follows Acemoglu and Restrepo (2022) and is hand-coded to the Finnish data. We focus on imported products within CN codes 82 (tools), 84 (mechanical machinery), 85 (electrical equipment), 87 (tractors and work trucks), and 90 (instruments and apparatus). The main categories are listed below; the full product code list is available upon request.

- Industrial robots (CN Code 847950 in the Finnish data)
- Numerically controlled machines, such as CNC machines
- Automated industrial machinery (equipment used in dedicated, streamlined, or automated production processes, such as packaging, sorting, and grading machines)
- Automatic lifts and conveyors
- Automatic tools (non-hand-operated tools, for example, used in metal processing)
- Automatic welding machines
- Automatic textile machinery
- Automatic agricultural equipment
- Regulation and control instruments

Non-Automated This category includes technology investments that are not automated. In the text data, where many applications offer limited technical detail, this category functions as a residual: if a technology is not classified as automated, it is assigned to the non-automated group.

In the customs data, non-automated technologies are identified directly based on CN codes. Our classification follows the distinction proposed in Acemoglu and Restrepo (2022). These are machines or tools that are manually operated or require active human control—or at least more human input than their automated counterparts. The following broad categories are included:

- Non-automated industrial machinery (e.g., hydraulic presses or cutting machines without automation)
- Machines labeled as not numerically controlled (e.g., "grinding machines; non-NC")
- Manual tools
- Manual welding equipment
- Non-automatic conveyors and production vehicles, such as roller-tables and forklifts.
- Traditional textile machines, such as manually-operated sewing machines.
- Non-automated agricultural machinery
- Other heavy capital goods, such as pumps, freezers, refrigerators, heaters, and fans.
- Laundry equipment, including washers, dryers, and ironing machines
- Vending machines

To support the research design, we define two additional text-based categories that capture the reasons evaluators cited for rejecting applications. The administrative records—including documentation from on-site visits—allow us to compare accepted and rejected applications side by side. This comparison lets us manually identify features that contributed to rejection and code them accordingly.

No Good This category includes applications with notable issues or concerns, rendering them ineligible for subsidies even under different particular circumstances. To assess whether rejected applications provided valid counterfactuals, we reviewed all rejections in the analysis sample. Our investigation identified a small set of ten applications that were clearly unsuitable. These cases involved entrepreneurs with troubling histories or firms with unstable financial positions. Our findings remain robust after excluding these applications. Examples:

- The company falls into credit rating C (credit not recommended). Financial statements have not been received, even though they were requested during the company visit. The entrepreneur arrived one hour late for the meeting. Applicant's credit record is poor, the current financial position weak, and other financing for the project is pending.

- The applicant has not provided the necessary financial statements. Based on the available information, the company's financial position, and accumulated tax arrears burden the business to an extent that granting support is not justified.

- The requested information has not been provided. The operations have been unprofitable, and the financial condition is weak, with negative equity. The project does not have a significant impact on the company's growth.

No Jobs This category includes applications that were rejected at least partly due to job creation concerns. We read rejected applications, and found that none had employment-related issues as the primary reason for rejection. While five reports mentioned employment, the primary focus was on the potentially low initial stage on technology investment, with employment being a secondary consideration. Our findings are robust to excluding these applications. Note that, at the same time, winning applications do sometimes mention positive employment effects.

- The project involves the renewal of existing assets, but it does not contribute significantly to the company's technological capabilities, job creation, or value-added. Also, the impact of the support in implementing the project is not significant, as required by regulations.

- The growth potential of the firm is uncertain, and additional jobs are not expected to be created for many years. The value added does not increase sufficiently.

- The project is small and a routine acquisition for the company, and it is not anticipated to have such effects on revenue growth or company employment that supporting the project would be justified.

F.C.2 Manual Coding Process

Next we discuss the process of manual coding that was performed on the text data.

Step 1: Defining the Categories. Our text categories, developed from fieldwork and our conceptual framework, cover a range of motivations and technologies. Interpretations do not rely on a single category but reflect several approaches to the data. At the same time, the categories also reflect the limitations of the text data. Ideally, we would measure, for example, intended price reductions, whether the new product was designed to replace an old product, how much the technology was upgraded compared to the earlier technology, and whether work-related initiatives intended to automate work or make current work more productive. However, the text data lack precise information on these topics.

Step 2: Training the Panel. Two teams of research assistants (RAs) were trained for different classification tasks. The first team (three RAs) focused on technologies and rejection reasons, while the second team (four RAs) classified intentions. Training involved explaining categories and application contexts, discussing fieldwork observations, and how to find contextual information.

The first team and authors classified 500 random applications together. The second team and authors classified 50 applications as there were more categories to be coded. Decision rules were refined iteratively based on similarities and differences, updating category descriptions and examples. Disagreements arose mainly from cases with limited classification information. We advised a conservative approach: classify only when a category clearly fit, and avoid uncertain classifications. We discussed best practices to ensure accuracy and consistency, aiming for replicability by an external team.

Step 3: Coding the Categories. In the main classification step, RAs determined category fit in texts, recording specific parts of the text that supported the classification. Some classes essentially relied on keywords/phrases (e.g., new products, exports), while others were more nuanced (e.g., capabilities/flexibility).

The authors maintained close contact with RAs, addressing ambiguous cases and clarifying categories. RAs were encouraged to discuss cases together. Breaks were scheduled to maintain concentration and quality, with 30-minute classification sessions instructed.

We inspected the classification and category descriptions for alignment with survey and literature-based data from technical and trade journals. The RA team reviewed category descriptions for accuracy.

F.C.3 Text Processing

Pre-Processing[49] We apply similar preprocessing steps both to the application summary texts (used in classification) and the evaluation texts (used in text 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. Voikko performs a variety of NLP preprocessing tasks for Finnish text (`https://voikko.puimula.org/`).
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").

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

We apply the following two final steps to the application summary texts, but not to the evaluation texts.[50]

7. Countries, cities, municipalities, and publicly available firm names are changed to generalized versions. The generalized versions of the words are inside the symbols “<” and “>”. For example, the word “Helsinki” (the capital of Finland) is changed to “<City>”. This reduces dimensionality in the data, as a mention of a foreign country, for example, receives a one variable in the bag-of-words representation instead of one for each country.

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. For example, after prior preprocessing steps, 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>”.

Word Vectors We use Word Vectors (a case of word embedding) for the text matching. 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 represent individual words as high-dimensional vectors, and the similarity of different words can therefore be measured as the distance of their respective vectors using a suitable metric. They are also capable of capturing word semantics, something that simpler transformation methods are unable to do.

We construct word vectors using FastText (Bojanowski et al., 2016). FastText builds on the approach of 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 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 “technological” both have similar meaning in many contexts, but simpler models would require enough training data containing both words to construct their word vectors accurately, since they treat them as entirely separate words. 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 (the Finnish language generally does not contain prepositions, but the words themselves are altered to fit the meaning).

In our application, the words appearing in the evaluation texts (i.e., in our corpus) are first transformed into 100-dimensional word 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, leaving us with one 100-dimensional “sentence vector” for each application (and firm). We

[50] The reason for this is simple: the two additional steps are helpful in removing details from the text that are unrelated to classification, but the same details can be important in predicting the approval decision.

use these sentence vectors to build propensity score measures and match recipients to non-recipients with replacement.

Text Propensity Scores The procedure is explained in more detail in 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). We estimate the standard errors by bootstrap.

Cosine Similarity The procedure is explained in more detail in 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 0.85, where unity reflects identical documents.

ML-Classification We next explain how we detect the technology subsidies using ML classification. After the pre-processing, and equipped with our training data, we turn to scikit-learn (Pedregosa et al., 2011) to perform the classification into technology vs. non-technology subsidies.

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 (SVM) classifier.[51] We also performed the classification using other classifiers than SVMs, such as boosting algorithms and neural network variants. SVMs performed the best for our purposes., but the differences were relatively minor.

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.[52] 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:[53]

1. Learning rate set to 0.00001.
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.

[51] 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.

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

[53] 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.

This training procedure attains around 90% F-score and 95% accuracy for both technology and automation classification in our out-of-sample tests, as shown in Table A6.

F.D Fieldwork

We conducted fieldwork as background research to understand the changes we document at the level of specific firms and workers. We visited manufacturing plants and interviewed CEOs, technology managers, production workers, and subsidy administrators.

Firm Visits and Interviews We chose five manufacturing firms for in-depth case studies. The primary purpose of the case studies was to observe the technologies, production, and work firsthand. We spent on average four hours at each manufacturing plant observing the production and conducting interviews. We also conducted five separate firm interviews (a total of ten firms). With one firm we met twice.

Our qualitative research method was open-ended interviews, building on prior qualitative research on technologies in firms (e.g., Piore, 1979; Dertouzos et al., 1989; Piore, 2006; Berger, 2013). This method is helpful because it allows us to identify the prevalence of mechanisms we had postulated ex-ante and uncover new mechanisms that we had not anticipated. We asked the firm representatives about their production, technology adoption, motivations behind adopting technologies, the observed effects, and government subsidies.

We selected the firms to be representative of the sample and different from each other. We visited and interviewed firms with employment from approximately 30 to 20,000 workers; subsidy winners, subsidy losers, and non-applicants; firms in rural and urban areas; privately owned and publicly traded firms; firms with high levels of own capital and firms in the corporate restructuring. All firms were in the fabricated metal product, machinery, and wood product industries.

Worker Interviews We separately interviewed five production workers using similar in-depth interviews as in our firm visits. In all interviews, we asked the respondents broadly about their work and skills, technologies they use at work, other technologies at their workplace, and the effects of technologies they had observed. Our qualitative methods draw from a long social sciences tradition to directly ask the respondents how they perceive the cause and effect. We used a semi-structured approach to interviewing that uses open-ended questions to allow a wide range of responses to emerge (see, e.g., Piore, 1979; Boyd and DeLuca, 2017; Bergman et al., 2024). We recruited the interview respondents in collaboration with the Finnish Industrial Union, the largest Finnish union representing industrial workers.

Subsidy Program Interviews and Text Data To understand the subsidy program, we interviewed (1) officers in all four main ELY Centers, (2) program administrators at the Ministry of Economic Affairs and Employment, (3) an external program auditor at the Ministry of Finance, and (4) a consulting firm that assists firms in subsidy applications (a total of 18 interviewees in seven groups). We also used text records from the administrative system of the subsidy program to track the applications and qualitatively understand how the subsidy program works.[54]

[54] In addition, we studied the relevant legislature, ELY Centers' relevant strategy documents, and the official reports of the subsidy program (e.g., Ritsilä and Tokila 2005; Pietarinen 2012; Aaltonen 2013; Ramboll 2013; Auri et al. 2018; Heikkinen et al. 2019; Ilmakunnas et al. 2020, and TEM 2020).

G Conceptual Framework

We outline a framework that distinguishes two types of technological change operating along two margins: *intensive* and *extensive*.[55] The intensive margin improves productivity within an existing variety, while the extensive margin introduces new varieties. This approach builds on established models (Dixit and Stiglitz, 1977; Melitz, 2003; Bustos, 2011), but applies them in a novel context. A key feature is the imperfect substitutability between varieties, which aligns with our context and allows the framework to capture different types of products.

The intuitive idea is that a firm may choose to adopt a new technology to cut costs within an existing variety or to generate a new one. We show that these distinct margins of technological change imply different observable outcomes. In practice, technologies may combine these elements or reflect entirely different mechanisms.[56] The framework demonstrates that some technological changes enhance efficiency, while others may drive expansion through new products and services without affecting productivity—particularly in markets with differentiated products.

The key point is that the effects of technology subsidies are ex-ante uncertain and they do not always translate into predictable changes. At the same time, looking beyond the narrow link between technology and labor may help better understand the firm-level mechanisms of technology subsidies.

Before turning to the model, we note a few disclaimers. First, we do not model the allocation of labor inputs, so our framework does not directly address changes in employment or skill demand. Our fieldwork suggests these outcomes are often highly context-dependent and ultimately an empirical question. One contribution of this paper is to provide empirical evidence on the employment and skill effects effects in a context of flexible, specialized firms adopting advanced manufacturing technologies.

Second, for both types of technological advances, the model predicts zero effects on input prices, such as wages, because input prices are assumed to be determined in the sectoral equilibrium, and firms are small relative to the market. While firms in many industries may possess market power on the input side, incorporating this into the model would produce wage predictions that, like the employment and skill effects, depend on specific assumptions. Since input prices lie outside our main scope, we do not incorporate such features here.

G.A Setup

Our basic setup is based on Melitz (2003) and Melitz and Redding (2014).[57] The market structure is monopolistic competition with product differentiation and increasing returns to scale at the firm level. The model specifies preferences and firm heterogeneity in a differentiated product market. This structure allows technology to have a role in creating new varieties—as in many standard growth models (e.g., Romer, 1990). We show that the view of new varieties has different implications than one emphasizing technology's role in allowing productivity improvements within a variety.

[55] Researchers describe closely related ideas as product vs. process (Utterback and Abernathy, 1975), cost vs. differentiation (Porter, 1985), automation vs. augmentation (Autor et al., 2024), secondary vs. primary (Saint-Paul, 2002), and defensive vs. enterprise (Boone, 2000).

[56] For example, using AI for increased worker monitoring may not fit neatly into either margin.

[57] We aim to introduce the simplest model necessary to explain the findings, which captures the essence of a broad class of models featuring the two types of technological change. The Melitz (2003) framework allows for a simple way of introducing imperfect substitutability between varieties. We specifically build on the version by Melitz and Redding (2014). Related approaches include Hopenhayn (1992), Ericson and Pakes (1995), Klette and Kortum (2004), Acemoglu et al. (2018), Akcigit and Kerr (2018), and Hémous and Olsen (2022).

Preferences over sectors $j \in \{0, 1, ..., J\}$ take the Cobb-Douglas form:

$$U = \sum_{j=0}^{J} \beta_j \log Q_j, \quad \sum_{j=0}^{J} \beta_j = 1, \beta_j \geq 0. \tag{7}$$

There is a continuum of differentiated varieties within each $j \geq 1$ sector, and these preferences take the Constant Elasticity of Substitution (CES) Dixit and Stiglitz (1977) form:[58]

$$Q_j = \left[\int_{\omega \in \Omega_j} q_j\left(\omega\right)^{(\sigma_j - 1)/\sigma_j} d\omega \right]^{\sigma_j/(\sigma_j - 1)}, \quad \sigma_j > 1, j \geq 1. \tag{8}$$

Sector $j = 0$ is a homogeneous numeraire good with a unit-input requirement for production.

The upper-tier Cobb-Douglas preferences imply that consumers spend $C_j = \beta_j Y$ in sector j, where Y denotes aggregate income. The lower-tier CES preferences imply that the demand for each differentiated variety within sector j is:

$$q_j(\omega) = A_j p_j(\omega)^{-\sigma_j}, \quad A_j = C_j P_j^{\sigma_j - 1}, \tag{9}$$

where P_j is the price index:

$$P_j = \left[\int_{\omega \in \Omega_j} p\left(\omega\right)^{1 - \sigma_j} d\omega \right]^{1/(1 - \sigma_j)}, \tag{10}$$

and A_j is a market demand index, determined by sector spending and the price index. There is a continuum of firms; each firm is of measure zero relative to the market, and takes A_j as given.

Firms produce varieties using a composite input X_j with unit cost w_j in sector j. They choose to supply a distinct differentiated variety. Production has a fixed cost f_j and a constant marginal cost, inversely proportional to productivity φ. The composite input needed to produce q_j units is:

$$x_j = f_j + \frac{q_j}{\varphi}. \tag{11}$$

We focus on the equilibrium within a sector (and drop the sector j subscript for clarity). The firms choose their prices to maximize profits subject to a residual demand curve with constant elasticity σ. The equilibrium price for each variety is a constant mark-up over marginal cost derived from the first-order condition for profit maximization:

$$p(\varphi) = \frac{\sigma}{\sigma - 1} \frac{w}{\varphi}. \tag{12}$$

This gives the equilibrium firm revenue:

$$r(\varphi) = Ap(\varphi)^{1-\sigma} = A \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} w^{1-\sigma} \varphi^{\sigma - 1}, \tag{13}$$

and the equilibrium firm profit:

$$\pi(\varphi) = \frac{r(\varphi)}{\sigma} - wf = B\varphi^{\sigma-1} - wf, \quad B = \frac{(\sigma - 1)^{\sigma - 1}}{\sigma^{\sigma}} w^{1-\sigma} A. \tag{14}$$

[58]This representation has two interpretations: (1) consumers demand differentiated consumption goods with "love-for-variety" preferences (e.g., Grossman and Helpman, 1991), or (2) final-good firms demand differentiated intermediate inputs, and a greater variety of inputs increases the "division of labor" (e.g., Romer, 1987, 1990). In our context, the typical firm is an intermediate-good producing firm that sells their output to final-good producing firms.

G.B Intensive Margin

Intensive margin advances improve firms' productivity within a variety: This allows firms to produce the same product more efficiently. The change is on the factor-market side.[59]

We introduce intensive margin advances as in Bustos (2011). The firm has a constant marginal cost $1/\varphi$ within a variety. It can adopt a technology T_I that reduces that cost. This choice is a tradeoff between a fixed cost f_I and a productivity increase to $\iota\varphi$, where $\iota > 1$. The resulting total cost functions are:

$$x = \begin{cases} f + \frac{q}{\varphi} & \text{if } T_I = 0 \\ f + f_I + \frac{q}{\iota\varphi} & \text{if } T_I = 1. \end{cases} \tag{15}$$

This type of technology adoption is characterized by sorting according to firm productivity: There is a productivity cutoff φ_I^* above which the firm adopts the technology because the adoption choice involves a tradeoff between a fixed cost and a scaled productivity increase. We focus on predictions conditional on the firm finding it optimal to adopt an intensive margin technology.[60]

Firms with lower marginal costs produce more and earn higher revenues. The CES demand structure predicts that the relative outputs and revenues of firms depend on their relative productivities:

$$\frac{q(\varphi_1)}{q(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\sigma}, \quad \frac{r(\varphi_1)}{r(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\sigma-1}, \quad \varphi_1, \varphi_2 > 0 \tag{16}$$

Lower marginal costs imply higher revenue-based productivity because of the fixed production cost:

$$\frac{r(\varphi)}{x(\varphi)} = \frac{w\sigma}{\sigma-1}\left[1 - \frac{f}{x(\varphi)}\right], \tag{17}$$

where input use $x(\varphi)$ is increasing in φ.

Since the price of the composite input is fixed, an increase in revenue-based productivity also implies a higher profit margin. Firms with lower marginal costs also earn higher profits. As shown earlier:

$$\pi(\varphi) = \frac{r(\varphi)}{\sigma} - wf = B\varphi^{\sigma-1} - wf, \quad B = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} w^{1-\sigma} A. \tag{18}$$

Firms with lower costs charge lower prices because the equilibrium price for each variety is a constant mark-up over marginal cost:

$$p(\varphi) = \frac{\sigma}{\sigma-1}\frac{w}{\varphi}. \tag{19}$$

In summary, technological change on the intensive margin predicts increases in revenue, productivity, and profit margin. The intuitive idea is that firms with lower marginal costs produce more and earn higher revenues due to the CES demand structure. Lower marginal costs imply higher measured productivity and profits due to the increasing returns to scale. The firms sell more with lower prices.

[59] The process efficiency motive is present in the models of specialization (Smith, 1776), labor-saving technologies (Marx, 1867), routine-replacement (Autor, Levy and Murnane, 2003), tasks (Acemoglu and Autor, 2011), automation (Acemoglu and Restrepo, 2018b), product and process (Utterback and Abernathy, 1975), and in the Schumpeterian models (Grossman and Helpman, 1991; Aghion and Howitt, 1992).

[60] If the productivity terms (φ) are correlated across products for a firm (as in Bernard et al., 2011), intensive-margin improvements may lead to product changes. The idea is that the intensive-margin innovation then reduces marginal costs in other products and makes firms more willing to pay the per-product fixed cost for a new product. This correlation between products effectively blurs the line between intensive and extensive margin advances.

Before presenting the model's predictions for technological changes on the extensive margin, we clarify the distinction between two directions of change on the product side: vertical (within the same variety) versus horizontal (a new, imperfectly substitutable variety). In this class of models, vertical cost reductions and quality improvements within the same variety are essentially equivalent. In other words, the productivity term can be interpreted in terms of cost or within-variety quality; these interpretations are isomorphic to a change in units of account (Kugler and Verhoogen, 2012). This implies that technological changes increasing quality within a variety have the same predictions as cost-reducing changes, except for their effect on prices—prices decrease if the technology is cost-reducing and increase if it is quality-improving. In practice, distinguishing between vertical and horizontal quality changes is often difficult.

G.C Extensive Margin

Advances on the extensive margin enable expansion through the introduction of new varieties, allowing firms to produce new products. Unlike intensive margin changes, which occur within the production function, extensive margin changes affect the product-market side. A defining characteristic of this type of technological change is that outputs with different types are imperfect substitutes. Each variety is produced by a single firm—the most productive one—but firms differentiate themselves by offering multiple varieties. This dynamic was frequently highlighted by firms during our interviews.[61] [62]

We introduce the extensive margin advances by adapting from Melitz (2003). The firm can introduce a new variety by adopting a technology T_E. The technology requires a fixed entry cost f_E. Potential entrants to the new variety, both existing and new firms, face uncertainty about their productivity in the new variety. After the firm pays the entry cost, it observes its productivity φ for the new variety, drawn from a distribution $g(\varphi)$, with cumulative distribution $G(\varphi)$. The firm then decides whether to produce or exit the project. Melitz (2003) shows this decision is characterized by a cutoff productivity φ_E^* where the firm makes zero profits:

$$\pi\left(\varphi_E^*\right) = \frac{r\left(\varphi_E^*\right)}{\sigma} - wf = B\left(\varphi_E^*\right)^{\sigma-1} - wf = 0. \tag{20}$$

In equilibrium, the expected ex-ante profits equal zero due to free entry:

$$\int_0^\infty \pi(\varphi)dG(\varphi) = \int_{\varphi_E^*}^\infty \left[B\varphi^{\sigma-1} - wf\right] dG(\varphi) = wf_E. \tag{21}$$

Figure G1 visualizes the relationship between profits and productivity. Firms with $\varphi < \varphi_E^*$ would lose if they produced. They exit the project, receive $\pi(\varphi) = 0$ in that new variety, and cannot recover their entry cost. The subset of the firms that produce and have $\pi(\varphi) > wf_E$ make positive profits after the entry cost.

Firms that draw a high enough productivity after adopting an extensive margin technology introduce a new variety. This leads them to produce more and earn higher revenues (for clarity, we consider a simplified

[61] A new variety has several interpretations: a new product, a quality change not perfectly substitutable with quantity, re-purposing production to respond to changing demand, expansion to new markets, capturing a larger share of the value chain, etc. A new variety may be the same product but with an improved process that provides more reliable scheduling or a faster response time to orders, changing the aspects customers receive.

[62] The expansion of variety in consumer and intermediate goods plays a central role in many theoretical models of growth (Romer, 1990; Grossman and Helpman, 1991). The product view is closely related to Porter (1985): gaining competitive advantage through a quality-differentiation strategy instead of a cost-leadership strategy.

case of two products):

$$q = \begin{cases} q(\varphi_0) \\ q(\varphi_0) + E[q(\varphi)] \end{cases} \qquad r = \begin{cases} r(\varphi_0) & \text{if } T_E = 0 \\ r(\varphi_0) + E[r(\varphi)] & \text{if } T_E = 1, \end{cases} \tag{22}$$

and use more of the composite input:

$$x = \begin{cases} f + \frac{q_0}{\varphi_0} & \text{if } T_E = 0 \\ 2f + f_E + \frac{q_0}{\varphi_0} + \frac{q_1}{E[\varphi]} & \text{if } T_E = 1. \end{cases} \tag{23}$$

An extensive margin change, on average, predicts an increase in revenue and inputs but no changes in productivity, profits, or profit margin. The intuitive idea is that, conditional on drawing a high enough productivity, the new variety allows the firm to sell more, but ex-ante its productivity and profits, on average, remain unchanged due to the free-entry condition. Some new varieties are more profitable, while others are less so. Another distinct prediction of an extensive margin change is its potential effect on product composition. While a new variety does not necessarily mean a completely new product (e.g., it could involve faster response times), a new product serves as a sign of a new variety.

In our monopolistic-competition market structure, firms can expand either by improving productivity within a variety or by introducing a new variety, but they cannot expand without one of these actions. Introducing a new variety resembles a proportional scaling of the firm's size.

G.D Discussion

We close this section by discussing the model in the context of the firm subsidy program. In equilibrium without subsidies, the expected profits from adopting either type of technology are zero. Intuitively, one could argue that firms would have already adopted new technologies without subsidies if they were profitable. Winning a subsidy, however, reduces the cost of adopting new technology; ex-ante both for intensive and extensive margin technologies. In the model, this means that f_I (the cost of adopting an intensive margin technology) and f_E (the cost of adopting an extensive margin technology) are, on average, lower for subsidy winners than for non-winners, making technology adoption more attractive for subsidized firms.

Different types of technologies can incur different costs. Our fieldwork suggests that automation and major productivity improvements may require larger upfront investments than investments aimed at expansion. These higher fixed costs of automation, relative to the medium-scale grants provided, may drive firms to prioritize expansion (via extensive margin advances) over automation (via intensive margin advances) in our setting.

The benefits from adopting different types of technologies may also depend on the firm. In the model, intensive margin advances are generally more attractive to the more productive firms, as they scale the productivity term up by a constant factor $\iota > 1$. Intuitively, highly productive firms are larger within the same variety and benefit more from cost reductions. Conversely, cost-cutting is less attractive for smaller firms (those with lower within-variety productivity), while the expected profits from expanding into a new variety remain the same regardless of productivity in the current variety. In summary, we might expect larger, more productive firms to adopt more intensive margin technologies, and smaller, less productive firms to adopt more extensive margin technologies. Since our sample consists mostly of small- and medium-sized enterprises (SMEs), we could expect extensive margin advances to be more typical in our setting. This observation aligns with the text, survey, and trade journal evidence on firms' objectives, as discussed in Section VI.

When thinking about subsidies vs. technologies, the model's predictions under subsidies remain generally consistent with those discussed for both types of technologies, with one exception: The expected profits from adopting an extensive margin technology increase one-to-one with the subsidy. Since the expected profits from adopting a new extensive margin technology equal the adoption costs, winning a subsidy effectively allows the firm to capture the entire subsidy amount as profit by reducing adoption costs. This prediction is consistent with our empirical findings: The estimated profit effect aligns with the average subsidy size (see Table 4 and the related discussion in Section V).

How does the model help us understand the potential firm-level effects of adopting different types of technologies? Since we abstain from explicitly modeling the composite input as a function of different types of labor and other inputs, the model does not produce predictions on employment and skill demand. This omission reflects a deliberate choice: Based on our fieldwork, such effects are highly context-dependent. Explicitly including different labor inputs in the model would require taking a stance on how highly heterogeneous firms utilize these inputs in their production. More broadly, the model's predictions highlight that firms may react to technology subsidies by expansion and quality improvements, which do not always translate into predictable changes in labor inputs.

Outside of employment and skills, however, the model predicts distinct productivity effects depending on the type of adopted technology. Intensive margin technologies increase productivity uniformly, while extensive margin technologies predict, on average, no effect. This distinction helps rationalize our empirical finding of no effect on productivity: If our sample predominantly consists of firms adopting extensive margin technologies (as our supporting evidence suggests), we would expect to observe no changes in productivity.

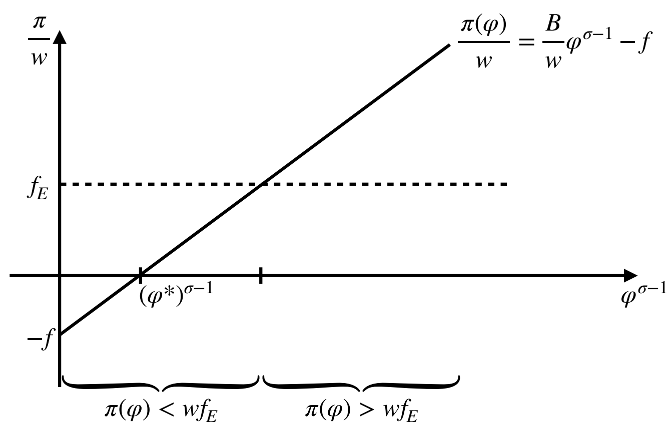


Figure G1: The Productivity Cutoff for the Extensive Margin Advances.

Notes: Illustration of the productivity cutoff after introducing a new product variety. Firms that draw productivities above the cutoff make positive profits, while firms below the cutoff find it optimal to exit and incur a loss equal to the entry cost. In equilibrium, the ex-ante expected profits are zero due to free entry. Adapted from Melitz and Redding (2014). Back to Section G.

H Dynamic Model

To clarify the source of variation in our identification strategies, we consider the forces that influence a firm's technology adoption and its factor demand. We proceed in two steps. In Step 1, we focus on the firm's technology-adoption decision. In Step 2, we consider the firm's conditional factor demand, treating the technology as a quasi-fixed factor; the idea is to show that we can trace the implications of the technology adoption problem for factors' relative demand. The framework is general to allow for the analysis of multiple types of technologies and factor inputs. The adoption model is adapted from Cooper et al. (1999).

H.A Step 1: Technology Adoption

In Step 1, we model the general technology-adoption problem of an individual firm. In the model, the firm makes the discrete choice between replacing existing technology with a new technology or continuing to use the old technology for another period. Consider a firm i that maximizes:

$$E_0 \sum_{t=0}^{\infty} B_t Y_t^i \tag{24}$$

subject to:

$$Y_t^i = A_t^i \theta_t^i F\left(T_t^i; X_t^i\right) - D_t^i \Theta_t^i \tag{25}$$

$$T_{t+1}^i = \begin{cases} (1-\delta) T_t^i & \text{if } D_t^i = 0 \\ \tau_{t+1}^i & \text{if } D_t^i = 1, \end{cases} \tag{26}$$

where $\tau_{t+1}^i = \mu_t^i \tau_t^i$ and $\mu_t^i \geq 1$ is the rate of exogenous technological progress.[63] The choice variable in this problem is D_t^i where $D_t^i = 1$ if the new technology T is adopted in period t.

The first equation (24) is the firm's objective function. The firm maximizes the discounted present value of profits, which are defined as output minus the adjustment costs. The discount rate is $B_t \in (0, 1)$.

The second equation (25) describes the production process and the adjustment costs. The function $F(\cdot)$ is increasing and concave in the level of technology. The output also depends on the state of productivity A_t^i. We assume that A follows a first-order Markov process $\Phi(A'|A)$. The model has two types of adoption costs. The first is a fixed adjustment cost (Θ_t^i). If the firm adopts the new technology ($D_t^i = 1$), it has to incur a cost Θ_t^i. It reflects the direct cost of the technology, such as its installation costs and other fixed adjustment costs. We assume that Θ_t^i is i.i.d. The second is the opportunity cost that is proportional to the production volume. It is characterized by θ_t^i that equals $\lambda_t^i \leq 1$ during an adoption period and 1 otherwise.[64] The intuition is that investment temporarily diverts resources away from production.

The third equation (26) describes the time path of the given technology. The technology frontier is τ_t. The firm's actual technology that is in-use is T_t^i. The in-use technology is typically less productive than the latest version because technology depreciates at an exogenous rate δ and because the latest technologies improve at rate μ_t^i. The firm can decide to adopt the latest version of the technology ($D_t^i = 1$); in that case its technology will be equal to τ_{t+1}^i in the next period. The gains to adoption reflect both technological progress (μ_t^i) and the rate of depreciation (δ).

[63] We allow the technological progress to contain an idiosyncratic and a deterministic common component to clarify the potential mechanisms. That is, we assume $\mu_t^i = \mu_t + \varepsilon_t^i$, where $\varepsilon_t^i \geq 0$.

[64] This implies that adjustment costs are heterogeneous across firms even if $\lambda_t^i = \lambda < 1$, i.e., equal for all firms i and periods t.

Under this framework, the firm's technology adoption reflects several forces:

1. Replacement cycle: The underlying deterministic replacement cycle—driven by depreciation (or aging) of capital δ and the exogenous technological progress μ_t—will imply that the older vintage of the capital, the more likely is replacement.

2. Shocks to technologies' costs: Idiosyncratic shocks to costs Θ_t^i affect the investment in a straightforward way: lowering the costs and increasing the likelihood of the investment.

3. Shocks to technological progress: Idiosyncratic shocks to technological progress, that is, shocks to μ_t^i via ε_t^i, increase the benefits from the technology investment and increase the likelihood of the investment.

4. Shocks to productivity: The response of investment to A_t^i depends on both the nature of the adjustment costs (λ_t^i and Θ_t^i) and the persistence of the shock ($\Phi(A'|A)$). The firm would prefer to replace machinery during a period where inputs are not very productive (reflecting $\lambda_t^i < 1$) and would also prefer to have a new machine available when productivity is high. To build intuition, suppose that adjustment costs are fixed. If A is i.i.d., investment is independent of A. But if a shock to A is informative of similar shocks in the future, then the investment is more likely when A is high—the firm invests now to benefit from the high productivity in the future.

We provide proofs and more detailed exposition in Section H.C.

In words, two forces determine a technology's productivity: the technology's age and a shock to total factor productivity. Given the state of productivity, the producer compares the discounted expected benefits of more productive technology relative to the current adoption costs. The gain to adoption is that a new version of the technology is more productive as it reflects some aspects of technological progress. There are two types of costs for replacement. First is the direct loss of output associated with the acquisition and installation of new capital goods. Second is that the process of installing the new machinery and retraining workers reduces productivity in the firm. The nature of the adjustment costs and the structure of the stochastic process governing the shocks jointly determine adoption timing.

The model assumes that small adjustments of technologies are either infeasible or undesirable. In particular, many technology-investment projects (e.g., the purchase of large machinery) are not possible in small quantities. In addition, the model assumes that the costs of adjusting the technologies stock may be non-convex. Consequently, at the firm or plant level, we may see periods of low technology investment activity followed by bursts of investment activity, i.e., investment spikes. Empirical observations support this view of technology adoption: We find that a significant fraction of technology investment activity at the firm level is associated with large variations in the technology stock, i.e., technology investment is typically a lumpy activity.

H.B Step 2: Conditional Factor Demand

In Step 2, we consider the firm's conditional factor demand, treating the technology as a quasi-fixed factor. This approach is closely related to the work by Berman et al. (1994), who treat machinery investments as quasi-fixed and invoke Shephard's lemma to justify their empirical specification. Cost-function estimates with quasi-fixed capital trace back to Caves et al. (1981). Our aim is to trace the implications of the technology adoption problem for factors' relative demand. The intuition is that technology is relatively more costly to adjust than labor.[65]

[65] Hamermesh (1989) analyzes the costs firms face in adjusting labor demand to exogenous shocks. The study argues that adjustment costs could be viewed as fixed and documents that labor adjustment tends to be lumpy.

The firm's production function is written as:

$$Y = F(T; X), \tag{27}$$

where T is the technology of our focus and X is a vector of multiple other factors. An element X_i is the quantity of factor i used in the production of a quantity Y of output. We assume F is strictly increasing with each of its arguments and strictly concave. We denote the relative price of factor i by $p_i > 0$. For the purposes of this analysis, these relative prices reflect potential relative productivity effects from technology T. The conditional factor demands are characterized as solutions to the cost-minimization function:

$$\min_{(X_1 \dots X_n)} \sum_{i=1}^{n} p_i X_i \quad \text{subject to} \quad F(T; X_1, ..., X_n) > Y. \tag{28}$$

The minimum value of the total cost is the cost function $C(p_1, ..., p_n, Y)$. Under this framework, it satisfies the standard properties of a cost function. It is increasing, homogeneous of degree 1, and concave in $(p_1, ..., p_n)$, and it satisfies the Shephard's lemma.

The Shephard's lemma gives us an analytical tool to interpret the relationship between factor demands and their prices. It states that:

$$\bar{X}_i = C_{p_i}(p_1, ..., p_n, Y), \tag{29}$$

where $\bar{X}_i$ denotes the factor demand for the factor X_i and C_{p_i} denotes the partial derivative of the cost function C with respect to price p_i. In other words, the cost function says that the conditional factor demands can be characterized through a shock to the price vector $(p_1, ..., p_n)$.

The expression (29) allows us to provide a theoretical basis for analyzing the effects of technology adoption on the demand for different types of labor. In this framework, technology's effect on labor demand is translated through its effect of the (potentially unobserved) prices of labor, which reflect the productivity of labor combined with the technology. For example, complementarity between technology and skills would mean that technology T would change the price vector $(p_1, ..., p_n)$ in a way that the factor demands $\bar{X}_i$ would shift toward high-skill labor $X_H \in X$.

H.C Details on Step 1: Technology Adoption

We consider the technology adoption (or replacement) problem of an individual firm with a given stock of technologies. This treatment is closely based on Cooper et al. (1999). The underlying technological progress in this economy makes the problem nonstationary. To analyze the problem, we normalize it to a stationary version. Define $x_t = X_t/\tau_t^i$ so that lowercase roman letters represent values which are normalized by the current value of the technology frontier. For simplicity, assume that the fixed adjustment cost is proportional to the technology frontier, i.e., $\Theta_t^i = \Theta^i \tau_t^i$ and that $F(\cdot)$ exhibits constant returns to scale. The problem is normalized as:

$$E_0 \sum_{t=0}^{\infty} \beta_t^i y_t^i \tag{30}$$

subject to:

$$y_t^i = A_t^i \theta_t^i t_t^i - D_t^i \Theta^i \tag{31}$$

$$t_t^i = \begin{cases} \rho_t^i t_t^i & \text{if } D_{t-1}^i = 0 \\ 1 & \text{if } D_{t-1}^i = 1. \end{cases} \tag{32}$$

In this normalized version, the discount rate (β_t^i) equals $B_t \mu_t^i$. We assume that the technological progress

(μ_t^i) is not too fast so that $\beta_t^i < 1$. We define $\rho_t^i = (1-\delta)/\mu_t^i \in [0,1]$ that reflects both depreciation and obsolescence. With this normalization, technology adoption ($D_t^i = 1$) implies that the state of the technology is 1 in the next period and a fraction ρ_t^i of its size in the previous period otherwise.

To analyze this problem, we use a dynamic programming approach. The state variables are the state of the technology stock (t) and the current period productivity shock (A). The value function $V(t, A)$ satisfies the functional equation:[66]

$$V(t,A) = \max\left[V^Y(t,A), V^N(t,A)\right], \tag{33}$$

where

$$\begin{array}{rcl} V^N(t,A) & = & AF(t) + \beta E_{A'|A} V(\rho t, A') \\ V^Y(t,A) & = & AF(t)\lambda - \Theta + \beta E_{A'|A} V(1, A'). \end{array} \tag{34}$$

The superscript Y refers technology adoption ($D_t^i = 1$) and N to no technology adoption ($D_t^i = 0$). The expectation over A' is taken using the conditional distributions $\Phi(A'|A)$. We assume shock follows a first-order Markov process. The productivity shock has two effects: a direct effect on current productivity and an indirect effect through information about future productivity shocks through $\Phi(A'|A)$. We assume shocks to the technological progress μ_t^i (ε_t^i) are i.i.d.The solution to the functional equation leads to adoption if and only if $V^Y > V^N$ given the state vector, $h = (t, A, \Theta)$. To close out the section, we note some key facts about the model's implications for the adoption decision.

Proposition 1. *There exists a solution to the functional equation.*

Proof. The solution's existence follows from Theorem 9.6 in Stokey et al. (1989) if $\beta < 1$.

□

Proposition 2. *The probability of adoption is decreasing in t.*

Proof. For a given value of productivity A let $t^*(A)$ satisfy $V^N(t, A) = V^Y(t, A)$ where:

$$V^N(t,A) \equiv At + \beta EV(\rho t, A') \tag{35}$$

$$V^Y(t,A) \equiv At\lambda - \Theta + \beta EV(1, A'). \tag{36}$$

Define $\Delta(t, A) = V^Y(t, A) - V^N(t, A)$. Using this object, it is sufficient to show that $\Delta(t, A)$ is decreasing in t. From (35) and (36):

$$\Delta(t,A) = At(\lambda - 1) - \Theta + \beta E\left[V(1,A') - V(\rho t, A')\right], \tag{37}$$

where $V(t, A) \equiv \max\left\{V^Y(t, A), V^N(t, A)\right\}$. The first term is negative and decreasing in t. The last part of this expression is also decreasing in t since $V(t, A)$ is an increasing function of t. Thus $\Delta(t, A)$ is decreasing in t.

□

Proposition 3. *The probability of adoption is decreasing in Θ.*

Proof. Using the definition of $\Delta(t, A; \Theta)$, we have:

$$\Delta(t,A;\Theta) = At(\lambda - 1) - \Theta + \beta E_{A'}\left[V(1,A';\Theta) - V(\rho t, A';\Theta)\right]. \tag{38}$$

[66] For expositional clarity, we drop the subscript t and the superscript i.

The term $\Delta(t, A; \Theta)$ is decreasing in Θ and thus the result is immediate.

$\square$

Proposition 4. *The probability of adoption is independent of A if $\Theta > 0$, $\lambda = 1$, and A is i.i.d.*

Proof. Using the definition of $\Delta(t, A)$, for the case of $\Theta > 0$ and $\lambda = 1$, we have:

$$\Delta(t, A) = -\Theta + \beta E_{A'}\left[V(1, A') - V(\rho t, A')\right]. \tag{39}$$

Since A is i.i.d., the right side is independent of the current realization of the shock. Thus the gains to replacement are independent of A.

$\square$

Proposition 5. *The probability of adoption is increasing in A if $\Theta > 0$, $\lambda = 1$, and $\Phi(A'|A)$ is decreasing in A.*

Proof. Using the definition of $\Delta(t, A)$, for the case of $\Theta > 0$ and $\lambda = 1$, we have:

$$\Delta(t, A) = -\Theta + \beta E_{A'|A}\left[V(1, A') - V(\rho t, A')\right]. \tag{40}$$

The expectation over A' is conditional on A so that the current state of productivity influences the replacement choice even though $\lambda = 1$. Since high values of A put, by assumption, more weight on high values of A', it is sufficient to show that $V(1, A) - V(t, A)$ is increasing in A for any t. This is, in turn, equivalent to the condition that:

$$\int_t^1 V_{tA}(z, A)dz > 0, \tag{41}$$

for all t. This condition is satisfied if $V_{tA}(t, A) > 0$ for all (t, A). From (35) and (36) this positive cross-partial condition holds when $\Theta > 0$ and $\lambda = 1$. To see this, note that by assumption, replacement will eventually occur so that (35) is a sequence of current period returns with positive cross partials between t and A. From (36), $V^Y(t, A)$ has a positive cross partial since the second term is independent of t.

$\square$