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

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Abstract

We present novel evidence on the effects of advanced technologies on employment, skill demand, and firm performance. The main finding is that advanced technologies led to increases in employment and no change in skill composition. Our main research design focuses on a technology subsidy program in Finland that induced sharp increases in technology investment in manufacturing firms. Our data directly measure multiple technologies and skills and track firms and workers over time. We demonstrate novel text analysis and machine learning methods to perform matching and to measure specific technological changes. To understand our findings, we outline a theoretical framework that contrasts two types of technological change: process versus product. We document that the firms used new technologies to produce new types of output rather than replace workers with technologies within the same type of production. The results contrast with the ideas that technologies necessarily replace workers or are skill biased.

Keywords: technology, labor demand, skills, industrial policy.

JEL Classification: J23, J24, O33, O25, H25.

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1 Introduction

A central question in the debate on the future of work is: What are the effects of advanced technologies on employment and skill demand? Two ideas often dominate the conversation. The first is that technologies replace workers (the Luddites; Keynes 1931; Brynjolfsson and McAfee 2014). The second is that technologies increase the demand for skills and can increase inequality—this is called the skill-biased technological change hypothesis (Griliches 1969; Welch 1970; Tinbergen 1975). Current research suggests that advanced technologies such as robots and ICT have been skill biased (Katz and Murphy 1992; Krusell et al. 2000; Autor et al. 2003; Acemoglu and Autor 2011; Akerman et al. 2015; Acemoglu and Restrepo 2020). But the evidence is limited because both measuring and identifying the effects of technologies are difficult.

This paper presents novel evidence on the effects of advanced technologies on employment, skill demand, and firm performance using new large-scale data and quasi-experimental designs. The context is manufacturing firms in Finland, 1994–2018. We focus on new production technologies, such as robots and computer numerical control (CNC) machines. Our novel data directly measure technologies, employment, and skills and track firms and workers over time. The main research design focuses on a technology subsidy program that induced sharp increases in technology investment in specific firms. The program provides direct funding for technology investment and is part of the European Structural and Investment Funds—one of the world's largest industrial policy programs. Our design compares close winners and losers of the technology subsidies using an event-study approach. We use novel text analysis methods on the application text data to compare close winners and losers (meaning that the firms had similar evaluation reports) and measure specific technological changes (Roberts et al. 2020). We complement our quantitative analysis with fieldwork: observing factories and interviewing CEOs, managers, workers, and subsidy administrators.

The first part of the paper reports results in sharp contrast with the ideas that technologies necessarily reduce employment or are skill biased. Technology investments induced by the subsidy program led to a 23% increase in employment, on average. But there were no differential changes in typical measures of skill bias: share of highly educated workers, average years of education, or production workers' share of employment. Zooming in to more detailed measures of skill composition—education and occupation groups, cognitive performance, and personality—we find generally zero effects. Several observations support the validity of our findings. The subsidy program induced a strong first stage: the firms showed a sharp rise in investments in technologies after winning technology subsidies. The firms had similar pre-trends in investment, employment, and skill composition before applying. Our results are robust to controlling for the evaluation texts of the subsidy applications using text analysis and other controls, including industry, firm size, and region trends. The results also hold when using alternative designs: a comparison to a matched non-applicant control group, a separate regression discontinuity (RD) design based on changes in the criteria defining a priority for small firms, and an event-study design without the subsidy program (Bessen et al. 2020). Our fieldwork supports these findings on the factory floor.

The second part of the paper explains the result that technologies did not replace workers or increase skill demand. To understand the findings, we outline a theoretical framework that contrasts two types of technological change: *process* versus *product*. The framework builds on Dixit and Stiglitz (1977) and Melitz (2003); we apply the ideas to a new context. Process refers to a productivity increase within an output variety, whereas product refers to expanding to new varieties. These two views predict different effects and can be tested empirically. The distinction is whether firms use new technologies to do the same thing at lower costs or do new things. The model clarifies that technologies may not necessarily be about changing the production process to replace workers or increase the demand for skills but creating new types of output. For example, automation is a process change, while the innovation of new goods is a product change (Klette and Kortum 2004; Acemoglu and Restrepo 2018).[1]

Based on the theoretical interpretation, we provide novel evidence documenting that the firms used technologies to create new products and services, not replace workers. Direct evidence shows that technology adoption led to more revenue, new products, and export growth. Text data from the subsidy program show that 91% of the firms described new products, response to changing demand, and other similar reasons for their technology investment. For example, the piston manufacturer included in the fieldwork invested in a new CNC machine and a robot to manufacture new, more effective pistons. Survey data from the EU's Community Innovation Survey (CIS) corroborate our observations: typical reasons for firms' process and product innovations are access to new markets, expanding product selection, and better quality—not typically to replace workers. We show the results also hold without the subsidy program, indicating that our results are more general.

To understand when and why to expect process versus product changes, we contrast two types of manufacturing: *mass production* (Taylor, 1911; Ford, 1922) versus *flexible specialization* (Piore and Sabel 1984; Milgrom and Roberts 1990). Mass production combines standardized products, high volumes, and process advances. Flexible specialization combines specialized products, low volumes, and product advances. While the two ideas—labor replacement and skill bias—are widely

[1] The concepts of process and product refer to the *uses* of technologies rather than physical *types* of technologies. Process, which is the idea that technological change lowers production costs, embeds the standard versions of labor replacement and skill bias. Conversely, product, which is the idea that technological change creates new output varieties, is present in standard growth models (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992) and in the management literature (Utterback and Abernathy 1975; Porter 1985).

accepted and used in the literature, research also recognizes that not all technological changes are labor replacing or skill biased. Most importantly, Piore and Sabel (1984) argue that a different set of technology–labor relations emerge in flexible manufacturing, most visible in technologically advanced small- and medium-sized enterprises that produce specialized products in small volumes to a changing market. In that context, and ours, the scope for specialization, low production volumes, and need for adaptation make it less profitable for firms to commit to the long-production runs of mass production and the fixed costs of process advances.[2] But our findings may not apply to non-specialized commodities, such as cement or steel, or high-volume assembly, where costs are critical. At the same time, the literature documents that manufacturing has widely evolved from mass production to flexible specialization (Dertouzos et al. 1989; Berger 2013).[3]

Two descriptive facts help position our findings into a broader context. First, the backdrop of our study is that the overall direction of manufacturing, including our treatment and control groups, is toward greater skill demand, seen in, for example, the rising share of educated workers. Because the skill trends are consistent with the rest of the world (Acemoglu and Autor 2011), we could have expected to find that new technologies were driving them at the firm level—but we did not. Our findings point to explanations for these skill trends other than the direct effects of adopting new technologies. Second, a critical aspect is that technology adopters are different from non-adopters. Growing firms typically invest in technologies, with and without subsidies. Our main design contrasts growing firms that plan to adopt new technologies. One firm gets the subsidy, the other does not, and that induces differences in technology adoption. This has two implications: 1) Our estimates capture the local average treatment effect (LATE) for firms close to investing in technologies. 2) Pre-screened but non-winning applicants provide a better control group than generic non-applicant firms because they have expressed an interest in technology adoption.

How broadly do the results apply? Our evidence is from Finland, where we can quantify the effects with high-quality data and research design. But the input we received from managers working in different contexts was that our observations apply more broadly in industrial manufacturing. There are still limitations. Our results do not directly apply to non-physical technological advances such as digitization or the internet, management practices such as lean manufacturing, R&D, technological advances in offices, historical eras, or the future. Our results and explanation focus on a firm-level mechanism. We do not exclude that micro-level technology could lead to macro-level skill bias or labor replacement (Oberfield and Raval 2021). We also do not claim that work does not

[2] Klette and Kortum (2004) and Akcigit and Kerr (2018) also relate the type of firm and innovation.

[3] Early research noted these changes first in Northern Italy, Germany, and Japan (Piore and Sabel 1984). Currently, the majority of Northern European manufacturing could be characterized as flexible specialization. For example, 90% of manufacturing employment in Finland is in non-commodity production under the Rauch (1999) classification. Bils and Klenow (2001) also document that US consumers have shifted away from standardized goods.

change: our qualitative evidence suggests it does, but that change does not imply labor replacement or skill bias by education, occupation, or cognitive performance.

Because our results challenge the two major ideas in the literature—that technologies replace labor or increase skill demand—it is critical to compare them to earlier research. We make two methodological contributions: We are the first to study the effects of technologies in manufacturing using a direct firm-level quasi-experiment, and our measurement is a major advance over earlier work because we directly measure the critical objects: technology, employment, and skills. Our results differ from the theoretical literature because it has focused more on process advances in mass production (Acemoglu and Restrepo 2018), while product advances are more common in our context. Our results are consistent with the non-quasi-experimental empirical studies that focus on similar technologies in manufacturing firms (Doms et al. 1997; Bartel et al. 2007; Aghion et al. 2020; Dixon et al. 2021; Koch et al. 2021) and qualitative evidence (Berger 2020). Complementary and simultaneous work by Curtis et al. (2021) documents that capital tax credits that favor capital investment raised labor demand in US manufacturing based on industry-level exposure. One interpretation is that their study detects similar local effects in the frontier sectors: their effects appear the largest in capital-intensive, skill-intensive, and robot-intensive subsectors of manufacturing. Potentially, capital subsidies made to frontier sectors are generally not applied to labor savings but rather market-share expansion among differentiated goods producers.[4]

Our analysis also contributes to the literature on industrial policy. We provide new estimates for one policy: a lump-sum transfer to increase technology adoption in manufacturing firms. The estimates help understand the broader question in growth and trade policy: What types of policies help firms grow? (Rodrik 2007). We find that the firms in our context use subsidies and technologies to achieve growth. To do so, they often scale up from idea to production. Our quantitative estimates suggest that 1 euro in technology subsidies led to 1.3 euros of technology investment. A typical EUR 100K subsidy led to 2.3 new jobs over the next 5 years. The cost per job was EUR 43K, close to the literature's average (Criscuolo et al. 2019).[5]

The paper proceeds in two parts. The first part presents the context, data, empirical strategies, and key results on employment, skill composition, and firm performance. The second part offers a theoretical interpretation based on process vs. product advances and then provides theory-motivated tests of that interpretation. Finally, we analyze robustness and conclude.

[4]Empirical studies also find different effects when focusing on 1) different types of technologies (especially digital technologies—the internet in Akerman et al. 2015 and ICT in Gaggl and Wright 2017), 2) replacement effects (Bessen et al. 2020), and 3) macro-level comparisons (Lewis 2011; Michaels et al. 2014; Acemoglu and Restrepo 2020).

[5]Recent research on industrial policy include Becker et al. (2010), Cerqua and Pellegrini (2014), Howell (2017), Criscuolo et al. (2019), Giorcelli (2019), Curtis et al. (2021), Howell et al. (2021), and Lane (2021). Technology subsidies and taxes are also actively debated (Acemoglu et al. 2020a; Costinot and Werning 2020; Guerreiro et al. 2021). We further review related research in Appendix H.

2 Context

We analyze the effects of advanced technologies in manufacturing firms in Finland, 1994–2018. Because we study technology investment with and without the subsidy program, we first outline the context common to all our analyses.

The technologies in our context are standard new production technologies in manufacturing: new CNC machines, robots, laser cutters, surface-treatment technologies, measurement devices, enterprise resource planning (ERP), computer-aided design (CAD) software, and similar technologies. The workers are primarily production workers (median 70%), for example, machinists, welders, and machine operators, typically with vocational training. The most represented industries are fabricated metal products and machinery. The firms are typically medium and small-sized (SMEs), but we also analyze large firms. Most firms are contract manufacturers that produce specialized intermediate goods in small batches, for example, pistons for engines, for large exporting firms. Figure 1 provides photographs of the typical technologies, workers, and firms in our sample.

Figure 2 documents that the overall direction of Finnish manufacturing is towards greater skill demands, seen in a rising share of educated labor and college income premium and a falling production-worker share. Finland's trends are consistent with the rest of the world (Acemoglu and Autor 2011), and the firm-level mechanisms we document might not be limited to Finland.

"Moore's Law for Pistons"

We conducted fieldwork to document the sample firms' technology adoption. The case of an industrial piston manufacturer clarifies our context.

The firm had invested in a new CNC machine, a robot arm, a measurement device, and new CAD software. When asked why they adopted the new technologies, the firm wanted to illustrate what they considered as the big picture of technological change in piston manufacturing: constant quality improvement. "With the old technologies, we couldn't make these pistons." Quality is essential for the piston manufacturer: pistons are only a fraction of an industrial engine's price, but if they break, it is expensive (see Kremer 1993 and Autor 2015 on the O-ring production function). Figure 3 shows the development of piston quality over the last 100 years. The firm called this the "Moore's law for pistons." The main effect of the new technology was that the firm could now produce new, larger, and more effective pistons. The firm stayed competitive and, as a result, has increased its revenue and employment.

The technology investment was associated with changes in production and work experience. Mainly those were "small, but important changes." For example, the new production design included a proprietary method of attaching the piston to the machining platform. The new production required some new skills: production workers needed to learn to use the robot and the CNC machine, and the R&D team had to learn to program with the new CAD software. The educational composition did not change as a result of the investment. But the educational composition in the firm has been increasing secularly over time.

The firm described operating in an environment where the market for each specific product is limited. They are de-facto monopolists (or oligopolists) in that market. They could not expand substantially within a product but could potentially expand by introducing a new product. All firms we studied explained essentially the same story, suggesting that the mechanisms could apply to other industrial and custom manufacturing firms.

3 Data

The first challenge in estimating the effects of technology on employment and skill demand is measurement. We directly measure the critical objects—technologies, work and skills, and firm performance—using novel high-quality data that track workers and firms over time.[6]

3.1 Technologies

We measure technologies using financial, text, customs, and survey data.

Financial Data[7] The primary source for measuring firms' technology investment is the Finnish Financial Statement Register. We measure firms' total investment and separately machinery and equipment and software. Statistics Finland collects the data directly, and the data cover all Finnish enterprises in almost all industries and our analysis years 1994–2018.

Text Data We develop a method to measure technologies using text data.[8] We measure overall technology investment, types of technologies, and uses of technologies directly at the firm level. The information on technologies' uses allows us to measure process vs. product advances.

The source for our text data is the ELY Center subsidy program, described in Section 4. The text data are unstructured and produced as a side product of the program. A technology subsidy

[6] We provide details on data in Appendix E. For consistent measurement, we harmonize the Finnish occupation, industry, and geography classifications. The novel crosswalks are available at economics.mit.edu/grad/tuhkuri/data.

[7] We deflate all monetary values in this paper to 2017 euros using the Statistics Finland CPI.

[8] Many policy programs and firms' decisions leave a trail of text records. Using this method, researchers can use text to produce data retrospectively without new data collection and when data would not be available otherwise. The novel part of our research is to measure technologies directly within firms. Recent research uses text data to measure technological changes, especially patents, in other ways (Alexopoulos 2011; Atalay et al. 2020; Autor et al. 2021; Dechezlepretre et al. 2021; Howell et al. 2021; Kogan et al. 2020; Mann and Puttmann 2021; Webb 2020).

application typically specifies the technology's *type* (e.g., a welding robot) and its *use* (e.g., weld longer seams). We focus on summary texts written by the program officers. The texts provide information on firms' actual plans because the technology plan is binding; the firms receive subsidies against verifiable costs. The full data contain 42,909 subsidy applications in different categories: technologies, exports, R&D, start-up, etc. Our method works in two steps:

Step 1: We code 21,210 randomly selected texts into categories based on pre-determined criteria, summarized in Table 1. We distinguish the type and use of technology because a firm can use the same technology for multiple purposes. Within technologies' uses, we code texts into applications intended to improve productivity within the same output variety (process) or produce new varieties (product). Within technologies' types, we code texts into automated vs. non-automated technologies (no active vs. an active user) and hardware vs. software (or both).

Step 2: We use machine learning to code the remaining 21,699 texts. We convert texts into a clean format, use the bag-of-words representation with TF-IDF weights, and support-vector machines (SVMs) for prediction. Figure E1 presents features that best predict the technology category. Table E1 provides summary information: our method achieves 95% accuracy in finding the technology applications from the pool of all applications. For the technology subcategories, we manually re-code all applications in the analysis sample to maximize precision.

Customs Data To measure the types of technologies, we also use customs data.[9] The data track technologies that firms import. Customs data record 621 different types of technologies in the 6-digit CN-classification system. We classify these technologies based on the physical type of machinery. The main distinction is between automated technologies vs. non-automated technologies. Automated technologies include, e.g., robots and CNC machines. Non-automated technologies include, e.g., non-automatic and hand-operated tools, hydraulic presses, and lifting equipment.

Survey Data To measure the uses of technologies, we also use survey data. The EU's Community Innovation Survey (CIS) provides firm-level information on the importance of different objectives for product and process innovations.

3.2 Work and Skills

We measure employment and wages from the registers maintained by Statistics Finland. The data allow us to track all individuals in Finland over time independently of their labor-market status. We link these data to multiple data sources on skills: education (level and type), school grades

[9]Recent research uses customs data to measure technology adoption; it is one of the few sources that track the types of technologies firms adopt (e.g., Acemoglu et al. 2020b; Acemoglu and Restrepo 2020, 2021).

(9th grade GPA and high-school exit exam), and cognitive performance and personality (test scores from universal male conscription). We measure occupations from employment registers at the 3-digit level in the ISCO classification system. To measure the task content of occupations, we use the European Working Conditions Survey (EWCS) that provides information on the tasks workers perform in their jobs, collected through face-to-face interviews every five years. We construct occupation-level measures of task intensity for routine, manual, cognitive, and social tasks.

3.3 Firm Performance

We assemble a large set of data on firm performance, including revenue, productivity, profits, exports, products, prices, marketing, and patents. The data track all firms over time.

The firm-performance measures, revenue and profits, are obtained from Finnish Financial Statement Register. We use two variables to measure productivity: revenue per worker and total factor productivity (TFP) estimated using the Cobb-Douglas production function.[10] We measure profits by the profit margin, defined as profits divided by revenue. We define the labor share as the wage bill divided by revenue. We winsorize firms' monetary values at the 5% level.

Exports are measured from Finnish Customs' Foreign Trade Statistics. We measure firms' products also from the Customs Register at the 6-digit CN classification. We focus on the number of products per firm and product turnover: introduced and discontinued products. We compute prices from the Customs Register and the Industrial Production Statistics, defining product-level prices as the product-level revenue divided by the number of units sold. Marketing expenditure data comes from the Financial Statement Register and patent data from Finnish Patent Database.

We measure firm subsidies from multiple registers. Two centralized systems (Yrtti 1 and 2) record the ELY Center subsidies. We gained access to these previously unstudied data that record the application process from submission to decision. We measure all other firm subsidies using the Statistics on Business Subsidies.

4 Research Design

The second challenge in estimating the effects of technology on employment and skill demand is identification. Our main research design is based on a technology subsidy program for manufacturing firms. Technology subsidies offer a valuable source of variation because they provide firms with a well-defined shock to the cost of technologies. We implement and validate an event-study design that compares close winning and losing firms of technology subsidies over time. The basis

[10] We obtain similar estimates using the Olley-Pakes and Levinsohn-Petrin methods (available upon request).

of the design is similar to Angrist (1998), Greenstone et al. (2010), and Kline et al. (2019).

A further novel aspect is that we use 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 reports into propensity scores that reflect the likelihood of receiving a subsidy and control for the scores to compare close winners and losers. Roberts et al. (2020) discuss text matching.

We present two alternative designs in the Appendix: 1) a regression discontinuity (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 address external validity). These designs complement our overall argument, and we refer to them in the analysis.

4.1 The Subsidy Program

The Program The technology subsidy program is administrated in Finland by the Centers for Economic Development, Transport and the Environment (the ELY Centers).[11] These centers promote regional business policy through various activities, including advisory, financing, and development services. Technology subsidies are part of a service called the Business Development Aid. The service provides funding for technology adoption, export promotion, R&D, and several smaller categories, such as starting a new company. It also supported firms during COVID-19. 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.

EU Context The program is part of the European Structural and Investment Funds (ESIFs), one of the world's largest industrial policy programs. ESIFs aim to support economic development across all EU countries, especially in remote regions. The 2014–2020 program budget was EUR 670 billion.[12] 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. The study speaks to the firm-level effects of the broader EU program.

The Program's Objectives The technology subsidies aim to promote the adoption of new technologies. The 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

[11] 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. ELY Centers are separate from Business Finland (previously TEKES), which provides funding for R&D.

[12] Source: ESI Funds Open Data Platform.

growth and structural change through industrial and regional policy (Rodrik 2007; Kekkonen 1952; Mitrunen 2021). The program follows the EU's technology neutrality principle—firms can choose their technology as long as it is new—and is not primarily about the direction of technology, e.g., automation vs. non-automation (Acemoglu 2002a).[13]

A Typical Case A typical technology subsidy is a EUR 100K cash grant paid toward technology costs. The technology is typically a new CNC machine, often combined with a robot, software, or measurement device. The firms are typically SMEs that manufacture fabricated metal products, e.g., parts for large industrial machinery. The subsidies provide funding for up to 35% of the investment, typically 15%. ELY Center pays the grant against verifiable technology costs. Subsidies of this size are audited, and approximately 30% of all ELY subsidies are audited.

The Selection Process The selection process works in three stages, illustrated in Figure 4.

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 can carry out the technology plan. Firms may decide to skip this stage, but that does not improve their chances of winning the subsidy (but it creates rejected applications from otherwise high-performing firms that are not, e.g., 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

[13] The standard economic rationales for the subsidies could be coordination problems, 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.

financial position. ELY 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. Other priorities also exist: firms satisfying the criteria for small firms and firms in remote regions are prioritized.[14] ELY Centers evaluate potential market distortions and sometimes reject applications if the subsidy negatively interferes with local competition. About 15% of applications are rejected.[15]

What Separates Winners from Losers? Text data allows us to read all 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 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 used 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 reasons for rejection; we address this concern in Section 7.

Comparing Subsidy Applicants to Average Manufacturers Table A1 compares the main sample to all Finnish manufacturing firms. Technology adopters are different from non-adopters. The subsidy sample firms are larger (despite being SMEs), more productive and profitable, and more educated. Importantly, technology adopters grow faster than average manufacturers. These observations highlight that non-winning applicants provide a better control group than average manufacturers because all applicants have indicated a strong interest in technology adoption. Our estimates capture the local treatment effect for firms close to investing in technologies.

Expected Effects on Technology Investment 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 reported in our interviews that subsidies affect investment because they lower the price of technology, including the associated

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

[15]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.

costs and the future risk of debt. Firms' managers and subsidy officers often mentioned the non-monetary costs of adopting new technology: mental investment and courage. They see the subsidy also as a tool to change the mindset to scale up from an idea to production.

We clarify the source of variation using a model adapted from Cooper et al. (1999) in Appendix G. 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 isolates the role of technology price shocks on technology investment.

4.2 Winners-Losers 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 the stacked event study:

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

where Y_{jt} is an outcome for firm j in year t, D_j is the treatment indicator, I_{jt}^{τ} is the event-time indicator for firm j's decision having occurred τ years ago, and the set $\mathcal{T} = \{-5, -4, \ldots, 4, 5\}$ 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.[16] 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 is the set of firm indicators, κ_t set of calendar-time t indicators, i.e., cohorts of applicant firms, and X_{jt}^{τ} 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

[16] Focusing on a control group that never receives treatment reduces the problems arising in the estimation of dynamic treatment effects when the comparison group consists of units that are treated at a different point in time and the event time is not explicitly defined for the control group (Sun and Abraham 2020; Goodman-Bacon 2021).

base clearly before the event to avoid contrasting the post-period to any anticipation effects (e.g., Ashenfelter's dip).[17] For clarity, we present all main estimates in reduced form (i.e., intention to treat, ITT).

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 and firm size, and calendar-time t fixed effects. We show the results are robust to different controls in the Appendix.

We construct the analysis sample in the following way. We first restrict to technology applications based on the text data. 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.[18] We exclude the largest 5% of applications because they tend to have poor control units. Finally, we restrict to a balanced sample over the five-year horizon.[19] The treatment group is defined by selecting the largest approved subsidy application for each firm. Event-time indicator $\tau = 0$ refers to the year the subsidy application was submitted. The control group is defined by the largest rejected application. Repeated applications for the same project are generally not allowed and untypical.

The ideal experiment that could capture the causal effects of technology on employment, skill demand, and firm performance would randomly assign technology to firms. While a perfect technology 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:

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

[17] Our results are robust to the choice of base year.

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

[19] 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 A14).

where Y_{1j} and Y_{0j} tell what happens if the firm 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 the subsidy but did not receive it. 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. Pre-screened non-winning applicants probably provide a better control group for technology adopters than conventional samples because, like subsidy winners, all applicants 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 (next section). Therefore, the remaining selection bias induced by the decision stage can be eliminated using regression techniques or matching using the information used in the decision process.

Table 2 reports summary statistics for the treatment and the 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. The pre-period differences between the treatment and control motivate our matching strategy in the next section.

An alternative 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, 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. 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 group also serves to assess whether the patterns in the losing firms are typical or specific to the losing applicants.

4.3 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 potentially related to the firm's future trajectory. Text matching methods allow us to control for these characteristics (see, e.g., Romer and Romer 2004; Roberts et al. 2020).

As our main text-matching method, we control 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:

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

The propensity score theorem (Rosenbaum and Rubin, 1983) states that, in principle, controlling for the probability of treatment allows to satisfy Assumption 1. Propensity scores are valuable in this context as a dimension-reduction tool as directly controlling for texts is not feasible.[20]

The subsidy records contain three types of texts that track the decision process: 1) application summary, 2) evaluation, and 3) decision texts. The application summary 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. These texts capture clearest the potential differences between the firms. Based on our interviews, the subsidy officers' goal is to present an unbiased evaluation.[21]

The text propensity score method works in three steps.

Step 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 information from the evaluations beyond clear markers of success or failure.

Step 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 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). Figure 5 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.[22]

Step 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

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

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

[22] 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.

probability weighting (IPW; Hirano et al. 2003).[23]

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 compute a similarity score directly between the texts' vector representations without projecting them first to a single-dimensional propensity score.[24] We construct a matched sample for the winners by selecting the nearest-neighbor with replacement from the losing firms. Table A2 reports the summary statistics for the cosine-similarity matched sample.

5 Estimates

This section provides the reduced-form estimates on employment and wages, skill composition, and firm performance using the primary research design. The main result is clear: we find no evidence of employment reduction or skill bias across a comprehensive set of skills and technologies. The estimates show that after winning a technology subsidy, firms invested sharply more in technologies, hired more workers, but did not change their skill composition. Before receiving a technology subsidy, the winning and losing firms had similar trends in technology investment, employment, and skill composition. The results are robust to controlling for the text propensity score and other controls. The RD and spikes designs in Appendices D and C confirm the results. The results are not limited to the subsidy program or SMEs.

The First Stage Figure 6 shows the first-stage event-study estimates β_τ from Equation 1. The outcome is technology investment. Winning a subsidy is associated with a sharp increase in technology investment. Before the subsidy application, the groups are on parallel trends. Figure A1 shows alternative first-stage estimates with all possible subsidies granted and received. It shows 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 3 reports the first stage estimates for the main versions of the winners-losers design, with and without text

[23] There are multiple ways to implement these steps: represent the text as data, model and estimate $p(W_j)$, and use $p(W_j)$ (Angrist and Pischke, 2009; Gentzkow et al., 2019). The results are broadly robust.

[24] A conceptual difference is that the propensity score measures the text's predictive power on treatment assignment, while cosine similarity measures the overall similarity between evaluation texts.

matching. The outcomes are technology subsidies, technology investment, and capital. The first stage is robust to controlling for the text propensity score.

Employment and Wages Figure 7 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 10 visualizes and Table 4 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. Our preferred specification with the propensity control indicates a statistically precise 23% increase in employment. The employment estimates are consistent with the idea that the advanced technologies were a complement to labor in this context.

Another way of measuring the potential replacement effects of advanced technologies is the labor cost share. It measures the share of revenue that a firm pays to workers. We find a precise zero estimate, reported in Table 4. We also generally find a zero effect on wages; in some specifications, there is a small, statistically insignificant negative effect.

The employment estimates are similar when using the matched non-applicant control group (Table 4 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 A3), different controls (Tables A4, A5), and are clearly present in the mean graphs that compare the treatment and control group means over time (Figure A12).

Skill Composition Figure 8 displays the event-study estimates for the main firm-level skill measures: average years of education, college-educated workers' share, and the production workers' share. We find no change in these measures, either before or after the technology subsidy. Figure 9 summarizes the estimates and Table 4 reports the numerical values. Our 95% confidence interval excludes over .15 year changes in the average years of education. The results are in contrast with the view that advanced technologies increase the share of more educated workers and decrease the share of production workers in manufacturing firms. 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 A2), occupation groups (Figure A3), cognitive performance (Figure A4), school performance (Figure A5), personality (Figure A6), demographics (Figure A7), and task composition (Figure A8). 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 .3 standard deviation lower than the average population, and the average 9th grade GPA is .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 (+.15 standard deviation). 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 .1 standard deviation (Figure A5), and the treatment effects on activity-energy, achievement aim, and sociability are .05 standard deviation (Figure A6). These are the traits the managers and workers we interviewed consistently mentioned to be complementary to new advanced technologies, as opposed to higher education or non-production occupations.[25]

Firm Performance Figure 10 visualizes and Table 4 reports the first-difference estimates from Equation 2 for measures of firm performance: revenue, labor productivity, total factor productivity, and the profit margin. We measure labor productivity as revenue per worker and total factor productivity from Cobb-Douglas production function estimation.[26] The robust finding is that technology subsidies and technology investment led to approximately 30% higher revenue in the five years after. However, we find no evidence of changes in productivity and the profit margin. This potentially surprising finding is consistent with Criscuolo et al. (2019), who study an investment subsidy program in UK manufacturing, and Cerqua and Pellegrini (2014), who focus on capital subsidies to businesses in low-performing regions. We provide an interpretation in Section 6.

Magnitudes Table 5 reports the first-difference estimates from Equation 2 with a continuous treatment variable, the subsidy granted in EUR. The estimates from our preferred specification indicate that 1 EUR in subsidies stimulated 1.3 EUR in machinery investment. The firms' revenue increased by 5 EUR per 1 EUR of subsidies.

Table 6 reports more detailed estimates on financial outcomes. The average profit margin is 5%. Winning a subsidy led to an increase in average gross profit by EUR 24K and financial costs by EUR 4K. The coefficients from continuous treatment are close to zero. There is a positive .05 effect on financial costs for each subsidy euro granted—that is, the firms carried additional financial

[25]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."

[26]TFP is not ideally suited to measure firm performance in our context because (as we will show in Section 6) the firms introduce new product varieties. Revenue per worker is robust to different production functions.

costs as a reaction to the subsidy. Because the baseline profitability is moderate in these firms, and they increase their revenue and employment in the same ratio and incur additional costs from the investment, winning a subsidy did not lead to a large increase in profits.

The employment increase is .23 jobs per EUR 10K subsidies, indicating a cost per job of EUR 43K (USD 49K). This number closely matches the numbers managers reported for machinery per worker in their plant in our interviews. Our estimate is 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 estimate of 27K USD at the firm level.

6 Mechanism

To recap the results: technology investment led to increases in employment and no changes in skill composition—in contrast with the ideas that technologies replace labor or are skill biased. This section offers a theoretical interpretation and then provides novel theory-motivated tests of that interpretation. We close by explaining when and why we expect to see these results.

6.1 Theoretical Framework: Process vs. Product

We outline a framework that contrasts two types of technological change: *process* versus *product*.[27] Process refers to productivity improvements within an output variety, product to the expansion of new varieties. The framework is standard (Dixit and Stiglitz 1977; Melitz 2003; Bustos 2011), but we apply it to a new context. The central element is imperfect substitutability between output varieties. The intuitive distinction is whether firms *use* new technologies to do the same thing at a lower cost or to do new things. We show that these two types of technological change predict different effects and can be empirically tested.

The core idea of the model can be simplified as a composite function:

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

The function highlights two types of technological change:

[27] We use the terms process vs. product, but other terms could convey the same idea: e.g., cost vs. differentiation (Porter 1985), secondary vs. primary (Saint-Paul 2002), or defensive vs. enterprise (e.g., Boone 2000). The critical distinction is whether technological change affects how the output is made versus how the customer receives it.

T_I **Process** (The Intensive Margin): This affects the production "recipe" f of how factors L are used in production activity. Example: a welding robot replaces human welder's tasks.

T_E **Product** (The Extensive Margin): This affects the "lens" F through which production is projected into markets. Example: a welding robot makes longer seams than a human welder.

6.1.1 Setup

Our basic setup is based on Melitz (2003) and Melitz and Redding (2014).[28] The market structure is monopolistic competition with product differentiation and increasing returns to scale at the firm level. The model specifies preference 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.

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

$$U = \sum_{j=0}^{J} \beta_j \log Q_j, \quad \sum_{j=0}^{J} \beta_j = 1, \beta_j \geq 0. \tag{6}$$

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:[29]

$$Q_j = \left[\int_{\omega \in \Omega_j} q_j(\omega)^{(\sigma_j - 1)/\sigma_j} d\omega \right]^{\sigma_j/(\sigma_j - 1)}, \quad \sigma_j > 1, j \geq 1. \tag{7}$$

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 $X_j = \beta_j Y$ 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:

$$q_j(\omega) = A_j p_j(\omega)^{-\sigma_j}, \quad A_j = X_j P_j^{\sigma_j - 1}, \tag{8}$$

[28] We aim to introduce the simplest model necessary to explain the findings, which captures the essence of a broad class of models featuring process vs. product type technological changes. 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 Hemous and Olsen (2021).

[29] 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). Our context is the technology adoption of intermediate-good producing firms that sell their outputs to final-good producing firms.

where P_j is the price index:

$$P_j = \left[\int_{\omega \in \Omega_j} p\left(\omega\right)^{1-\sigma_j} d\omega \right]^{1/(1-\sigma_j)}, \tag{9}$$

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.

Production Firms produce varieties using a composite input L_j with unit cost w_j in sector j. The firms 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 of a variety is:

$$l_j = f_j + \frac{q_j}{\varphi}. \tag{10}$$

Equilibrium 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:

$$p(\varphi) = \frac{\sigma}{\sigma - 1} \frac{w}{\varphi}. \tag{11}$$

That gives the equilibrium firm revenue:

$$r(\varphi) = Ap(\varphi)^{1-\sigma} = A \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} w^{1-\sigma} \varphi^{\sigma - 1}, \tag{12}$$

and the equilibrium firm profit becomes:

$$\pi(\varphi) = \frac{r(\varphi)}{\sigma} - wf = B\varphi^{\sigma-1} - wf, \quad B = \frac{(\sigma - 1)^{\sigma - 1}}{\sigma^{\sigma}} w^{1-\sigma} A. \tag{13}$$

6.1.2 Process

Process advances improve firms' productivity within a variety. This is the intensive margin: It allows firms to produce the same thing more efficiently. The change is on the factor-market side.[30]

We introduce the process advances as in Bustos (2011). The firm has a constant marginal cost

[30] The process efficiency motive is present in the models of specialization (Smith, 1776), labor-saving technologies (Marx, 1867), growth (Solow, 1956), routine-replacement (Autor, Levy and Murnane, 2003), tasks (Acemoglu and Autor, 2011), automation (Acemoglu and Restrepo, 2018), product and process (Utterback and Abernathy, 1975), and in the 'Schumpeterian models' (Grossman and Helpman, 1991; Aghion and Howitt, 1992).

$1/\varphi$ within a variety. It can adopt a technology T_I that reduces that cost. Figure 11 visualizes the idea. 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:

$$l = \begin{cases} f + \frac{q}{\varphi} & \text{if } T_I = 0 \\ f + f_I + \frac{q}{\iota\varphi} & \text{if } T_I = 1. \end{cases} \tag{14}$$

Process 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.

The predictions are summarized in Table 7.[31] Process-type change 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. A distinct prediction from the process-type technological change is zero effect on product composition. There is no similarly precise prediction on exports, which depends on whether the exports are new varieties or not. The prediction on prices is negative if the process change is a cost reduction and positive if it is a quality improvement.

The process view nests several standard models of technology and labor.[32] The predictions on employment, labor share, skill composition, and wages depend on the underlying structure of the process change. In the basic setup, firms use a composite factor L to produce the varieties. If that composite factor is only labor, the model predicts a reduction in the labor share as the firm takes wages as given and revenue per input increases. The models where technological change reduces costs and affects labor typically assume that technological change is "skill biased" in the sense that new technologies complement high-skill workers and increase their share of employment. If the technological change is automation (Acemoglu and Restrepo 2018), it replaces tasks performed by labor with capital and reduces the labor share.

6.1.3 Product

Product advances enable the production of new varieties. This is the extensive margin: It allows firms to produce new things and switch between varieties. The change is on the product-market side. Critical to this view of technological change is that outputs with different types are imperfect

[31] We derive these predictions in Appendix F.

[32] For example, the canonical (Tinbergen 1975; Katz and Murphy 1992), routine-replacement (Autor et al. 2003), and automation models (Acemoglu and Restrepo 2018).

substitutes. In our framework, there is only one dimension to improve productivity, but multiple dimensions to change product attributes. There is only one firm per variety (the most productive), but firms can differentiate through multiple varieties.[33] [34] [35]

We introduce the product advances by adapting from Melitz (2003). The firm can introduce a new variety by adopting a technology T_E. Figure 11 visualizes the idea. 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:

$$\pi\left(\varphi_E^*\right) = \frac{r\left(\varphi_E^*\right)}{\sigma} - wf = B\left(\varphi_E^*\right)^{\sigma-1} - wf = 0. \tag{15}$$

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

$$\int_0^\infty \pi(\varphi) dG(\varphi) = \int_{\varphi_E^*}^\infty \left[B\varphi^{\sigma-1} - wf\right] dG(\varphi) = wf_E. \tag{16}$$

We visualize the relationship between profits and productivity in Figure F1. 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.

The predictions from the product-type technological change are different from the process type. As shown in Table 7, product-type change predicts an increase in revenue but no changes in productivity and profit margin. The intuitive idea is that the new variety allows the firm to sell more, but its productivity and profit margin are still, on average, the same as before due to the free-entry condition. Some new varieties are more profitable, some less.

The next distinct prediction from the product-type technological change is the effect on the

[33] 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.

[34] 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.

[35] We distinguish two directions of change: vertical (within the same variety) vs. horizontal (a new, imperfectly substitutable variety). In this class of models, vertical cost reductions or quality improvements within the same variety are essentially equivalent. The reason is that the model assumes perfect substitution between quality and quantity within the same variety. The productivity term φ can be interpreted in terms of costs or within-variety quality; the interpretations are isomorphic to a change in units of account (Kugler and Verhoogen 2012).

product composition. While a new variety does not equal a new product (e.g., it could also be a faster response time), a new product is a signal of a new variety. Exports are also a signal of new varieties. If different markets have differentiated preferences, a new variety makes the firm more likely to export, export a larger share of its revenue, or export to a larger variety of destinations. If the new variety is a quality improvement, the predicted price effect is positive.

The predictions on employment, labor share, labor composition, and wages again depend on the underlying structure of the product change. But this time, the critical difference is that there is no unambiguous basis for expecting a sustained effect on the share or composition of labor. The skill or task composition might differ for a new variety, but that depends on the particular context. However, the basic structure predicts an increase in the use of the composite factor, generally employment (see also Harrison et al. 2014). The model predicts zero wage effects in a competitive labor market (for both technological advances) since wages are determined in the sectoral equilibrium and the firm is small relative to the market.

6.2 Evidence: Testing Process vs. Product

This section empirically tests whether the technological changes we observe are the process vs. product type. We document that they are primarily the product type. This observation helps explain the puzzling results of no labor replacement or skill bias. Firms used new technologies to create new types of output, not to replace workers.

We proceed in two steps. First, we directly measure the type of technological changes using our text and survey data. Second, guided by the framework, we consider a new set of outcomes that are critical signals that contrast process vs. product type change.

6.2.1 Directly Measuring the Type of Technological Change

We measure the type of technological change directly using text and survey data.

Text Data Text data allow us to read the sample firms' technology adoption plans. Based on our theoretical framework, we code the technology projects into process vs. product. Process refers to using technologies to produce the same type of output more efficiently, while product refers to using technologies to produce a new type of output or expand.

Figure 12 shows that 91% of projects in our sample are of the product type. These applications describe new products, access to new markets, responding to changing demand conditions, growth, or similar use for the technology. Only 9% of the texts do not describe such reasons. The technological changes we document are primarily product advances based on this measure, and our sample contains few purely process-type technological advances.[36]

While the sample is mostly product type, we estimate treatment effects separately for the two categories. We use the matched control group described in Section 4.2 because our control sample is small for both categories. Table A8 provides some evidence that product advances led to larger employment effects and no skill bias. Process advances led to smaller employment effects and some skill bias, .14 years, significant at the 10% level.

Survey Data We also measure the uses of technologies with survey data. The European Community Innovation Survey (CIS) asks our sample firms and other firms about the importance of different objectives for process and product innovations. The options include introducing a more extensive product selection, quality improvement, and lower labor costs.

Figure 13a shows that typical reasons for firms' process and product innovations are access to new markets, introducing a larger product selection, better quality, and larger capacity. Lower labor costs rank the 6th most important: only 20% of firms report that lowering labor costs is important for process and product innovation. Based on CIS data, we code the firm's technology project as the product type if the firm considers one of the product-type reasons (in black) important but does not consider lower labor costs important. Conversely, we code the technology project as the process type if lower labor costs (in grey) are important, but none of the product reasons are. Figure 13b shows that 97% of our technology-adoption cases are the product type. These numbers are similar when considering our spikes design sample, all manufacturing firms, or all Finnish firms, suggesting that the finding is not limited to the subsidy program. Our interviews with CEOs corroborate the observation from the survey data.[37]

6.2.2 Testing the Predictions with New Outcomes

Process and product type technological change predict different effects, summarized in Table 7. We use these predictions to distinguish them. So far, we have shown that the technological advances—either with or without the subsidies—led to increases in employment and revenue, no change in skill composition, the labor share, wages, productivity, or the profit margin. These empirical results are consistent with the product-type predictions but not with the process type.

[36] Our interviews suggest that while process-type advances exist, they are less likely to be physical machinery but new management styles such as lean manufacturing and digitization.

[37] Table A9 shows the estimates by the technology category using the survey data. We use a matched control group since the original control group's overlap with the survey is limited. The estimates for the product group are similar to the overall group. The process group is too small to estimate the results (marked by –).

Next, we provide evidence for new outcomes: exports, products, marketing, prices, and patents, all signals of product-type changes.

Figure 14 shows the event-study estimates with exporter indicator as the outcome. Subsidy winners are more likely to become exporters. Table 8 reports a treatment effect of 4 percentage points from the baseline of 28%. The effect on the exports' revenue share is .9 p.p. from the baseline of 5.2%. The winners also start exporting to .2 more regions, from 1.5 baseline.[38]

Table 8 reports the effects on products, measured from the customs data. The treatment effect is .15 products from the baseline of 1.55. We also observe an increase in the product *turnover*: the treatment firms both introduce and discontinue more products.

Figure 15 shows that subsidy winners are more likely to increase their marketing expenditure. The increased marketing signals that the firms intend to change how the customers perceive their output—a product-type change—not only their production costs.

Table 9 reports the treatment effects on prices. We measure prices from the Customs Register and the Industrial Production Statistics (a survey of manufacturing firms). We focus on product-level prices' unweighted average. We find a 29.1% increase in the customs data prices and 30.8% in the manufacturing survey. Price increases signal potential quality improvements.

Figure A11 shows the evolution of the subsidy applicant firms' patenting status. While suggestive evidence, we observe that patenting is concentrated in the periods before applying for subsidies and technology investment. This pattern of patenting is an additional signal that firms used the subsidies and technologies to scale up from an idea to production.

Some research proposes that exports and new products are also skill biased (Bernard and Jensen 1997; Xiang 2005; Matsuyama 2007). One reason we do not observe skill bias from exports or new products is that these changes—which we conceptualize as product advances—are a normal part of how these firms operate. We observe in our fieldwork that these manufacturers constantly identify shifts in demand and redeploy their productive resources to new uses using new technologies. Also the large-scale manufacturers combine economies of scale with flexibility, reflected in short production runs, product introductions, and sensitivity to customer needs. Earlier fieldwork by Dertouzos et al. (1989), Berger (2013), and Berger (2020) corroborates these observations.

6.3 Two Types of Manufacturing: Mass Production vs. Flexible Specialization

Our theoretical framework tells a tale of two types of technological change—process vs. product—and how they predict different effects that can be empirically distinguished. A central question created by our empirical analysis is: when and why is one more likely to occur than another?

[38]The export results are consistent with Lileeva and Trefler (2010) and Koch et al. (2021).

The technology adoption events in our data are almost entirely product rather than process-type changes. But both types may occur in reality, and some studies report examples of the latter when it comes to automation (e.g., Acemoglu and Restrepo 2020; Restrepo and Hubmer 2021). We explain next why our findings are distinctive but logical—and applicable to other settings where similar incentives for process vs. product type technology adoption prevail.

To do so, we contrast two types of manufacturing: mass production (Taylor 1911; Ford 1922) vs. flexible specialization (Piore and Sabel 1984; Milgrom and Roberts 1990). These two different *contexts* affect the incentives for the two types of technological change. Mass production is characterized by standardized products, high volumes, and a stable environment, and it makes process advances more likely. Flexible specialization is characterized by specialized products, low volumes, and an unstable environment. It makes product advances more likely.

Our results differ from the two views emphasized in the literature—that technologies replace labor or are skill biased—because the literature has focused more on process advances in mass production (e.g., Acemoglu and Restrepo 2018). In contrast, the flexible manufacturing system is more common among the firms we study. In our context, both small and large manufacturing firms produce specialized products in small batches. Examples include defense contractors building specialized equipment and industrial manufacturing firms producing new wind power stations. However, the findings may not apply to the mass production of non-specialized commodities, such as cement or steel, or high-volume assembly, where costs are critical.

A large literature documents that manufacturing has moved from mass production to new, more flexible, and specialized forms of production since the 1980s (e.g., Dertouzos et al. 1989; Berger 2013). These new forms of production emphasize quality and responsiveness to market conditions while utilizing technologically advanced equipment. Piore and Sabel (1984) call this change the second industrial divide, Kenney and Florida (1993) call it moving beyond mass production, and Milgrom and Roberts (1990) call it modern manufacturing. While different studies approach the topic from different angles, the common observation is that "the business environment is no longer conducive to producing standardized products for a stable market" (Piore 1994). One of the managers in Berger (2020) explained clearly: "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." Why did this change happen? The research suggests several reasons: consumers shifted away from standardized goods (Bils and Klenow 2001), globalization reduced the cost of specialization between firms (Berger and Center 2005), and new technologies reduced setup times and made it less costly to switch production between products (Bartel et al. 2007).

Next, we help understand when and why process vs. product type technological advances are more likely, and how this trade-off relates to the type of manufacturing—mass production vs. flexible specialization. We point out three central factors: scope for specialization, volume, and the need for adaptation that each affect the incentives for process vs. product type changes.[39]

Specialization The trade-off between process versus product advances depends on the scope for specialization. Firms in a sector with a higher scope for specialization are more likely to implement product advances, and a lower scope for specialization makes process advances more likely (see also Sutton 1998; Kugler and Verhoogen 2012). Intuitively, in sectors with a higher scope for specialization, firms may gain a competitive advantage by introducing a new good or changing their selection of goods. This contrasts with sectors that produce bulk goods, where the primary source of competitive advantage is cost. Scope for specialization comes most naturally in the framework from the elasticity of substitution σ_j in sector j: A higher elasticity magnifies the effects of productivity improvements on revenue and profitability (Appendix F). The intuition is that when the elasticity of substitution is high, demand is more responsive to price reductions, making process advances that reduce costs relatively more effective.

One measure to capture the scope for specialization is the Rauch (1999) index based on whether the good is a commodity.[40] Figure 16 shows that 91% of the firms are in an industry with a Rauch index over .5, indicating a high scope for specialization. Our main industries, fabricated metal products, machinery and equipment, and wood products, have an index of 1 and are fully specialized based on the Rauch index. Our sample does not include firms in non-specialized industries, such as cement, steel, or paper.[41] Specialized manufacturing is not limited to the subsidies design: the share of firms (and employees) in specialized vs. non-specialized industries is similar in the spikes design and Finnish manufacturing overall.

Table A11 reports further evidence: the number of firms by the scope for specialization and technology category. Less than 1% of our sample are process advances in non-specialized industries (e.g., cost reductions in steel manufacturing or automation in the paper industry). Consistent with our interpretation, product-type projects are more common in specialized sectors.[42]

[39]These are not the only factors that may influence the choice. Other relevant factors include: automation feasibility (Graetz and Michaels 2018; Acemoglu and Restrepo 2020), employment protection (Saint-Paul 2002; Manera and Uccioli 2021), complementary resources, such as venture capital, trade associations, and suppliers (Berger 2013; Gruber and Johnson 2019), and skill supply (Dertouzos et al. 1989; Berger 2013).

[40]Measures of the scope for specialization also include Gollop and Monahan (1991) and Sutton (1998).

[41]Dertouzos et al. (1989) emphasize that even in steel manufacturing, quality improvements are crucial.

[42]Table A10 provides treatment-effect estimates for specialized vs. non-specialized industries. The estimates are generally similar in both groups. Our interpretation is that because the clear pattern in our data is product-type technological change in specialized industries, it is unsurprising that we do not observe different effects in the small subsample of firms in the non-specialized industries.

Volume The trade-off between process vs. product depends on the production volume. In our interviews, most managers explained that they are specialized low-volume producers who invest in advanced technologies to make the products they sell to a few customers with unique demands. Our theoretical framework rationalizes why technology adoption events are more likely to be the product than process type in a low-volume context. In the framework, the amount of input required to produce volume q_j of a variety is:

$$l_j = f_j + \frac{q_j}{\varphi}, \tag{17}$$

where f is the fixed production cost and $1/\varphi$ is the constant marginal cost. The process-type technology adoption decision T_I is a tradeoff between an additional fixed cost f_I and a productivity increase to $\iota\varphi$. The high-volume producers benefit more from the productivity increase because the fixed cost is distributed over the higher volume. The low-volume producers benefit less from the productivity increase, but not from the introduction of new products. In our model, high-volume firms are also large firms with low marginal costs because, given the CES demand structure, firms' relative outputs and revenues inversely depend on their relative marginal costs.

Looking at the evidence, firms in our sample are mainly SMEs, as shown in Table 2, consistent with observing mainly product-type technology adoption events. Tables A6 and A7 describe the matched product and process samples. The groups are similar because our context is relatively uniform, but there are some relevant differences. Consistent with our interpretation, the product-type firms are smaller.

Adaptation Over time, the trade-off between process vs. product depends on the need for adaptation. Most firms we interviewed described operating in a changing environment where adaptability is important. One manufacturer described they could automate their assembly—currently done manually—but it would require them to commit to a specific model and set of parts to build it. This commitment was unattractive as they must update their model and parts frequently to stay competitive for their customers. In this context, the firm had more substantial incentives to use technologies to create new varieties than to improve its productivity within a variety. This need for adaptation arises from, for example, changes in consumer preferences, technological obsolescence, and cost competition. A firm we interviewed explained: "We cannot compete with the low-cost competitors. We need to offer unique goods and services."[43]

We conceptualize the need for adaptation as a death shock that occurs with an increasing

[43] Firms with limited capabilities to respond to cost competition may launch new varieties when faced with low-cost rivals (Porter, 1985; Aghion et al., 2005). This idea is consistent with Bloom et al. (2016) and Fieler and Harrison (2018), who document that import competition induced innovation and product differentiation. Bernard et al. (2010) analyze product switching as a source of reallocation within firms.

probability $\delta \in (0, 1)$, adapted from Melitz (2003):

$$\delta \in (0, 1), \quad \frac{\partial \delta}{\partial t} > 0. \tag{18}$$

The death shock increases the relative incentives for the product-type technology. It generates a discount factor for the value computation and reduces the net present value of future revenue in the given variety and, therefore, reduces the benefits from the process-type technological change. In contrast, with a new variety, the firm can start with a lower death risk.

Our text data directly records that firms invest in technologies to respond to changing demand. The need for adaptation also has two key empirical predictions: 1) we will observe a higher product turnover in addition to new products, and 2) we observe a negative trajectory for those firms that did not adopt the technology and a higher survival for those firms that did. Our evidence confirms both predictions (Table 8, Figures A12, A13).

7 Robustness

We conduct several robustness checks to evaluate the internal and external validity of our findings.

7.1 Internal Validity

Selection Bias A natural concern when estimating the impact of technology adoption is the bias due to a potential correlation between the adoption and unobserved characteristics of adopters. These concerns are less likely to be important in our setting because (as described in Section 4) we focus on variation induced by a technology subsidy program, where comparisons by adopter status are restricted to a sample of applicants to the program. Non-adopting applicants probably provide a better control group for adopters than conventional cross-section samples because, like adopters, 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 4, 5, A3, A4, and A5).

To directly investigate whether the rejected applications are a reasonable counterfactual for the approved applications, we read through all approved and rejected applications in the analysis sample. We found only 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. We also find similar effects when using a matched non-applicant control group (Appendix B). As a placebo test, we contrast the main control group to a matched non-applicant control group. 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 technology adopters. To address this concern, we can analyze trends in adopter firms without any control group. Figure A12 shows the evolution of treatment group means for machinery investment, 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. Trends in technology adopters do not support the view that advanced technologies reduced employment or significantly changed skill composition.

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 from our preferred specification indicate a -.004 change in the average years of education at the firm level, with a standard error of .075 years, meaning that we can exclude over .15 year increases in the average education. In comparison, the treatment and control firms increase their education on average over the 5-year event window by .4 years.

The small effects could be driven by small events. Several aspects suggest that this is not the reason for our findings: 1) A typical technology adoption event in the subsidy sample is EUR 100K, a doubled investment compared to an average year. The monetary value is a lower bound: the purchase price of the machinery is only part of the total cost, about 25% in the US manufacturing documented by Berger (2020). The rest of the cost is the machine bed, installation, and all the work needed to integrate the machinery into the plant. 2) The subsidy program requires that the technology investments represent significant technological advances to the firm. 3) We consider large technology investment events in the spikes design in Appendix C and find null effects on skill composition measured by education and occupation.

7.2 External Validity

There are several legitimate external validity concerns and alternative explanations for our findings and interpretation. To repeat here: we do not argue that our results apply everywhere. We document typical technological advances in manufacturing firms in Northern Europe. While we acknowledge that other technological advances exist, our fieldwork suggests we do not document a marginal phenomenon. Next, we respond to specific external validity concerns.

Concern 1: The subsidy program is biased toward employment and low-skill work. The observation behind this concern is, to some degree, correct. One of the objectives of the ELY Center subsidy program is to stimulate employment by supporting the adoption of advanced technologies in manufacturing firms. But several aspects support the view that the program's biases are not the primary source of our findings: 1) We find similar results also when evaluating technology adoption events without the subsidy program. 2) Interviews with managers document that the subsidy-supported technology adoption events are not notably different from typical technology adoption events. 3) Interviews with subsidy administrators document that significant technology projects are unlikely to be rejected because they would not stimulate positive employment effects.[44] 4) To address this concern systematically, we read all rejected applications and investigated whether they were rejected for employment-related reasons. In none of the applications was the concern about employment the main reason. Five reports mentioned employment, but the concerns were primarily about the potentially low first stage on technology investment; employment was secondary. Our findings are robust to excluding these applications. Text records also uncover that ELY Centers often interpret the employment effects compared to the counterfactual where the firm is not competitive in the market without the technology and would need to reduce employment; maintaining employment is seen as an increase. 5) The employment effects are not enforced: the firms are free to make their employment decisions after receiving the subsidy. 6) We have no evidence that the program intends to increase low-skill jobs; in fact, ELY Centers support hiring high-skill workers into manufacturing firms.

Concern 2: Workers are already skilled and learn new skills. This alternative explanation proposes that since workers are already skilled and learn new skills, we do not observe changes in skill composition even if technologies are skill biased. To some degree, this is true. Most workers in our sample have specialized training in production work and regularly participate in continuing vocational training (CVTS Survey 2015). All managers we interviewed reported that they combine

[44] Some insignificant technology projects get rejected because they are insignificant and unlikely to stimulate technological advances in production and employment effects.

technology adoption with worker training. New manufacturing technologies require new skills, but our observations from the field indicate that production workers are best suited to learn to use them. At the same time, the debate on skill bias has focused on the idea that advanced technologies replace production work and increase the relative demand for college-educated workers. We do not find evidence of either at the firm level.

Concern 3: The technologies are not typical advanced manufacturing technologies. A natural concern is that our estimates capture something other than the effects of standard advanced technologies in manufacturing, particularly that we miss the effects of automated technologies. To address this concern, we classify technologies into automated versus non-automated technologies using text and customs data, as described in Section 3. Automated technologies are considered automated in everyday language: e.g., robots, CNC machines, and conveyor belts. Non-automated are manually operated: e.g., non-automatic welding tools, hydraulic presses, and cutting machines. In our text data, non-automated refers to all applications not classified as automated. Figures A9 and A10 show the estimates of firm-level effects for automated vs. non-automated technologies. The effects are similar in both groups, and we still find employment increases and no changes in the skill composition from automated technologies. Finally, the spikes design captures major technology investment events in the industry and size range. While there may be different types of technology adoption events, our estimates capture the average of these events.

Concern 4: Credit constraints drive the employment and skill effects. One alternative explanation is that the effects are primarily about access to credit rather than technologies (an exclusion restriction concern). While credit constraints are likely to play a role in allowing the subsidies to induce firms to invest more, several arguments work against this explanation for the employment increases and skill null result: 1) We observe a strong first stage on technology investment. 2) We do not observe larger effects for the ex-ante more likely credit-constrained firms: small firms (Table A12) and firms with higher financial costs (Table A13). 3) We observe the same effects without the program in Appendix C.

Concern 5: Fixed costs in production lead to skill neutrality. One concern is that these firms could have non-homothetic production technologies where fixed and variable costs have different factor intensities (Flam and Helpman 1987). The fixed costs could be educated managers and technical staff, while the variable costs could be production workers. If the firms use technologies to expand, the increase in variable costs could mask the potential skill bias of technologies. This concern has a testable implication: it should be less important for large firms.

Small firms might primarily increase their variable costs, while we would expect that large firms would also need to scale their fixed costs. Table A12 reports the main estimates by firm size. We find no significant differences, suggesting that non-homothetic production is unlikely to be the cause for our findings.

Concern 6: Firm-level employment gains replace employment elsewhere. A firm's technology adoption may affect other firms, and the total employment and skill effects may differ from those reported here. Two aspects make estimating these effects challenging: 1) the firms are relatively small, and 2) they trade globally directly or indirectly through their customers; thus, externalities are likely to be minor. Theoretically, whether or not the technology adoption events replace employment elsewhere depends on the type of technology and the kind of externalities it induces. We document that our technological advances are the product type: the firms use technologies to produce new output types. These outputs are typically intermediate goods or machinery for final-good producing firms. In Romer (1990), this type of variety expansion generates growth—that is, some of the externalities may be positive. At the same time, new intermediate goods could replace previous vintages of intermediate goods as in the "Schumpeterian models" with quality improvements and creative destruction as in Grossman and Helpman (1991) and Aghion and Howitt (1992). Exploring these channels is a promising avenue for future research.[45]

8 Conclusion

This paper provides novel evidence on a classic question: What are the effects of advanced technologies on employment and skill demand? Our paper is the first to evaluate advanced manufacturing technologies' effects using a research design based on direct policy variation. Our novel administrative data allow us to measure firms' technology investment and workers' employment, wages, and skills precisely over time. To address external validity, we evaluate technology adoption events also without the program.

Our main finding is that advanced technologies, such as CNC machines, welding robots, and laser cutters, did not reduce employment, replace production workers, or increase the share of highly educated workers in industrial and custom manufacturing firms. We find that these technologies led to increases in employment and no change in skill composition. The findings are consistent across all estimation methods, with and without the subsidy program.

This paper proposes a simple explanation for the findings. We document that the firms used new technologies to produce new types of output, not replace workers with technologies. Direct

[45] Acemoglu et al. (2020b), Koch et al. (2021), and Oberfield and Raval (2021) analyze potential externalities.

evidence shows that technology adoption led to more revenue, new products, and new exports. Text analysis of firms' technology-adoption plans shows that they adopted new technologies to introduce new products, access new markets, respond to changing demand, and grow. To explain our findings, we outline a theoretical framework that contrasts two types of technological change: process versus product (e.g., Utterback and Abernathy 1975; Porter 1985). Process change refers to productivity improvements within an output variety; product expanding to new varieties (e.g., Dixit and Stiglitz 1977; Melitz 2003). Our evidence indicates that firms invested in advanced technologies to gain a competitive advantage by introducing new varieties. For example, the piston manufacturer we observed invested in new technologies to manufacture more effective pistons.

The results stand in contrast with the view that new technologies reduce employment or increase the share of highly educated workers in manufacturing firms. While no single study can be decisive, we review a body of evidence indicating that technology investments in manufacturing led to increases in employment and to no detectable changes in skill composition (e.g., Doms et al. 1997; Koch et al. 2021).

We do not argue that our results apply everywhere. We obtain our findings in a context where small and large manufacturing firms produce specialized products in small lot sizes. But the findings may not apply to non-specialized commodities, such as cement or steel, or high-volume assembly, where prices and costs are critical. Our results differ from the two views emphasized in the literature because it has focused more on process advances in mass production (e.g., Acemoglu and Restrepo 2018). In contrast, the flexible manufacturing system is more common among the firms we study. Qualitative evidence documents that a large part of manufacturing has evolved from mass production (Taylor, 1911; Ford, 1922) to flexible specialization (Piore and Sabel, 1984; Milgrom and Roberts, 1990). Currently, a large part of manufacturing is specialized.

Our results do not directly apply to non-physical technological advances, such as ICT or the internet (e.g., Autor et al. 2003; Akerman et al. 2015; Gaggl and Wright 2017), management practices, R&D, technological advances in offices, historical eras, or the future. Some technological advances have also replaced workers (e.g., Acemoglu and Restrepo 2020; Bessen et al. 2020), and our results do not challenge the view that skills and technologies are related (e.g., Lewis 2011). Our evidence from the field suggests that work and skill requirements change in subtle ways due to technology investment (as in Bartel et al. 2007).

Our results provide new evidence on the effects of one type of industrial policy: a lump-sum transfer to increase technology adoption in manufacturing firms (see also Criscuolo et al. 2019). Several researchers argue that lack of access to financial support limits the manufacturing sector's ability to scale up ideas into production (Dertouzos et al., 1989; Berger, 2013; Gruber and Johnson, 2019). We find that it is possible to stimulate technology investments by targeted subsidies and, by doing so, induce increases in employment, revenue, exports, and product variety.

Finally, our study makes some methodological contributions. We demonstrate novel methods to use text data in program evaluation. Many policy programs leave a trail of text records, and these texts allow measuring things that would otherwise be difficult to measure. We show how to use text data to measure variables of interest and perform matching. In the spirit of Roberts et al. (2020) and Mozer et al. (2020), we demonstrate how to craft a research design by controlling for program participants' underlying differences using text data. As new technologies have proliferated across firms, so, too, has the empirical literature on their effects. In light of the results reported here, some more conventional estimates of the effect of technologies in manufacturing firms do not appear to be too far off the mark (e.g., Doms et al. 1997).

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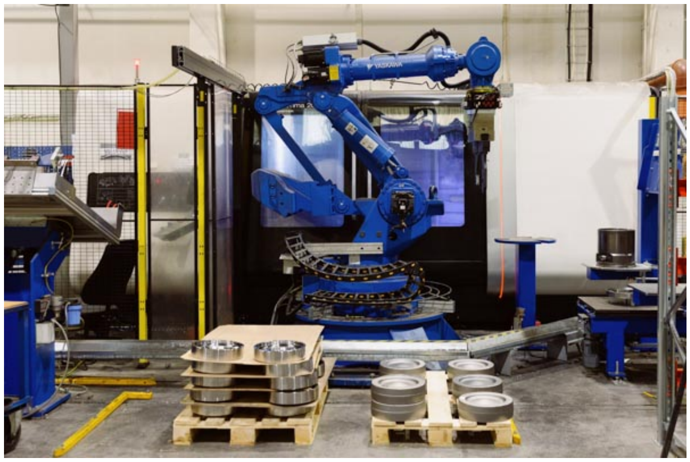
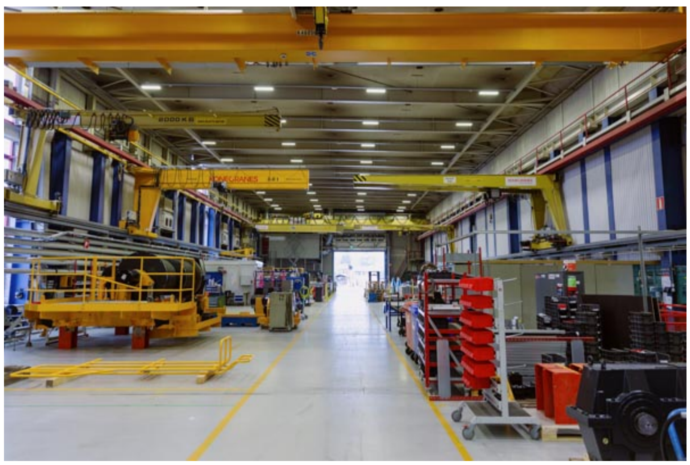
Main Figures and Tables



(a) CNC Machine and a Robot.

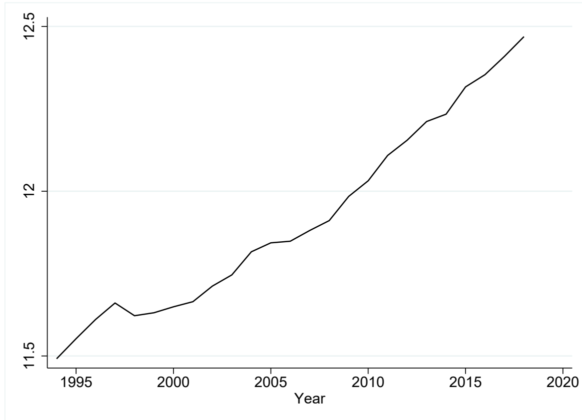


(b) Inside an Industrial Manufacturing Plant.

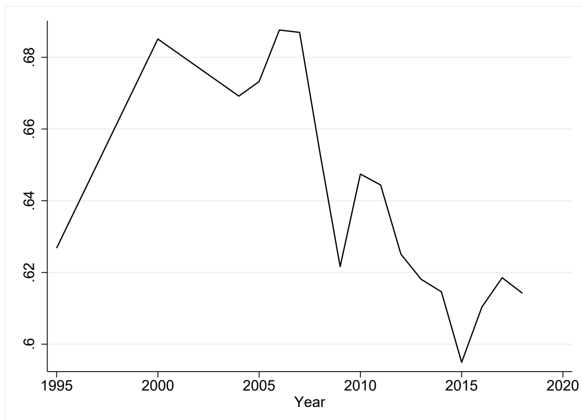
(c) Machine Operators and a Milling Machine.

Figure 1: Fieldwork: Documenting the Context.

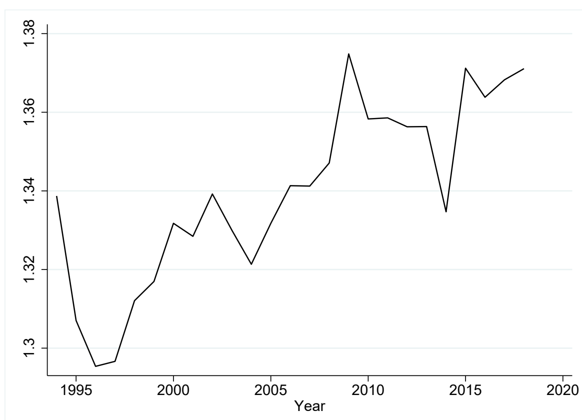
Back to Section 2.



(a) Average Years of Education.



(b) Production Worker Employment Share.



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

Figure 2: Manufacturing Skill Trends.

Notes: These figures document trends in Finnish manufacturing over 1994–2018. We restrict to firms with at least 3 workers. 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 2.

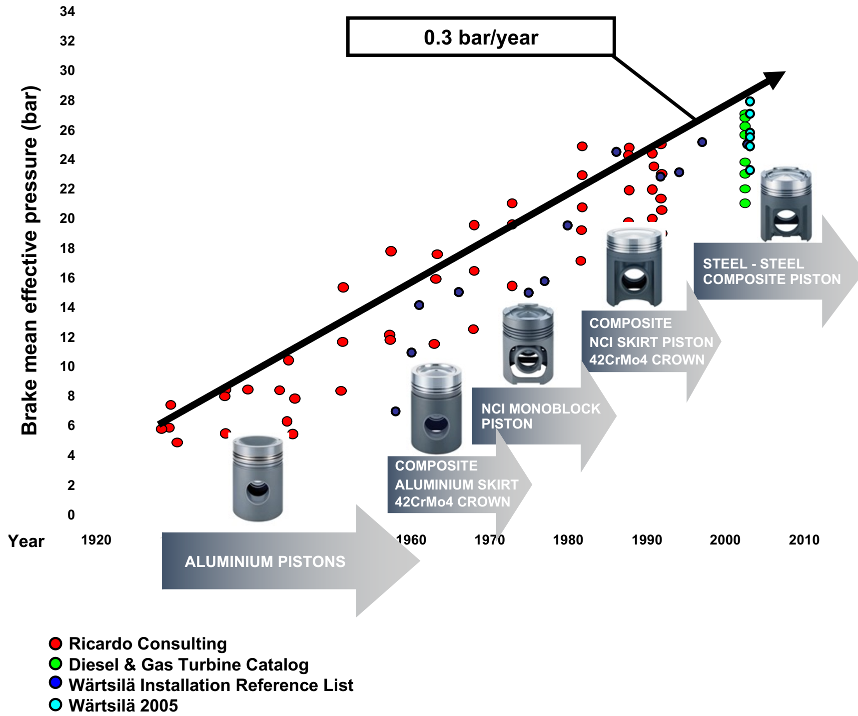


Figure 3: Moore's Law for Pistons: The Development Trend of Piston Materials Over 100 Years.

Back to Section 2.

Figure 4: The Subsidy Application Process.

Notes: Details in the main text. Back to Section 4.

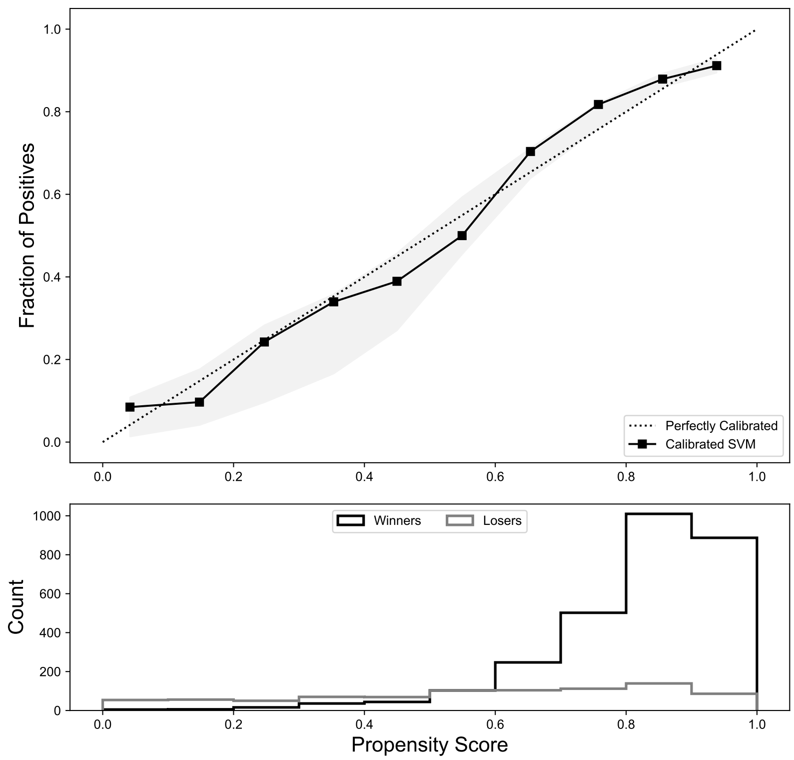


Figure 5: The Text Propensity Score Calibration Plot.

Notes: Upper panel: The predicted probabilities of subsidy receipt based on text data are on the x-axis, and the observed probabilities are 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 text and SVM. Standard errors are estimated by bootstrap. The predicted probabilities closely match the empirical probabilities. Lower panel: Distribution of the predicted values. Most of the applications have high predicted values reflecting the overall acceptance rate. Back to Section 4.3.

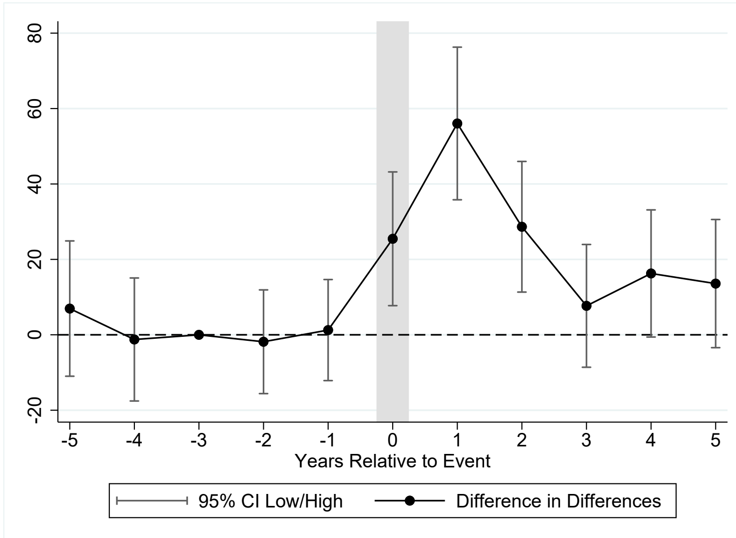


Figure 6: The First Stage: The Effect of Technology Subsidies on Machinery Investments.

Notes: Event-study estimates from Equation 1. The outcome is investment in machinery and equipment (in EUR 1000s) 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 130K effect on machinery investment. This event-study specification contains no controls in the term X^{τ}_{jt} of Equation 1. Back to Section 5.

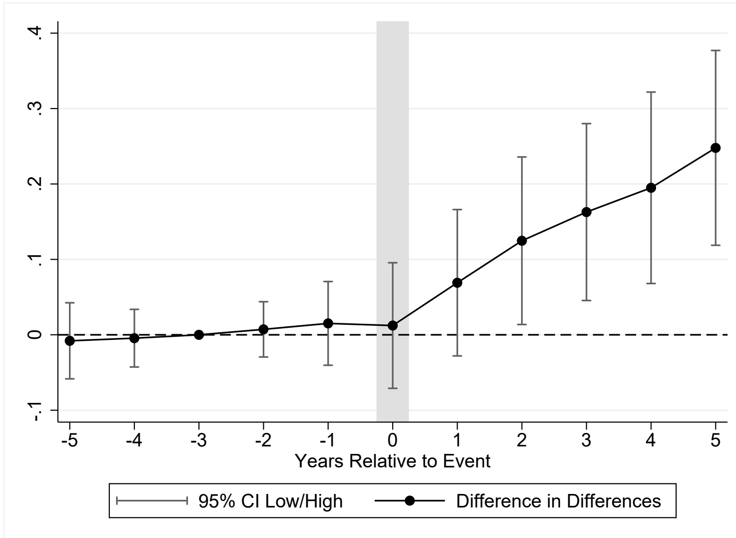
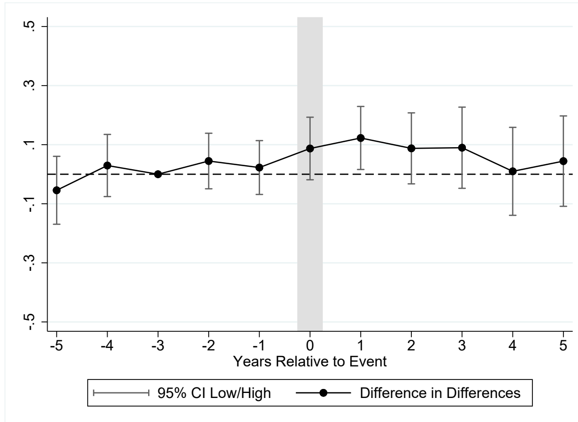
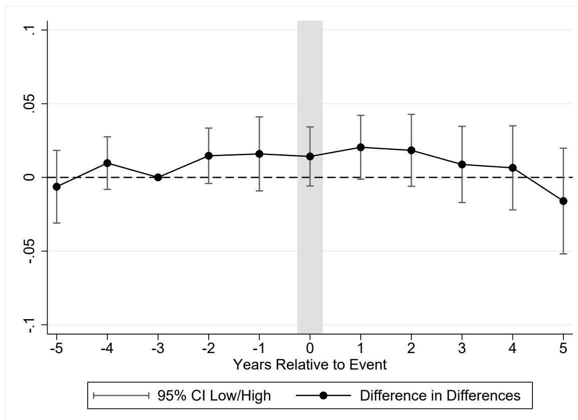


Figure 7: Employment Effects: The Effect of Technology Subsidies on Employment (in %).

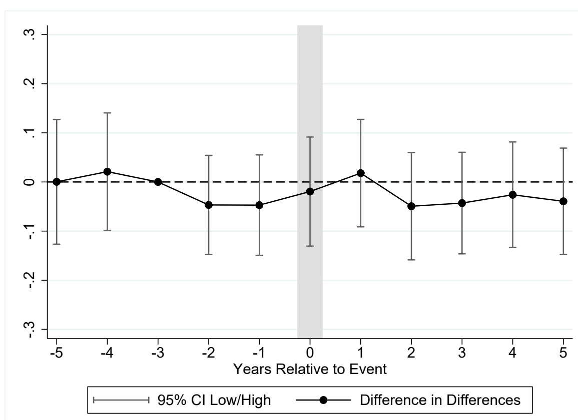
Notes: Event-study estimates from Equation 1. The outcome is employment relative to the base year $\tau = -3$. Event time $\tau = 0$ refers to the application year. The estimates indicate approx. 20% increase in employment. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section 5.



(a) Education Years.



(b) College-Educated Workers' Share.



(c) Production Workers' Share.

Figure 8: Skill Effects: Event-Study Estimates.

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^{τ}_{jt} of Equation 1.
Back to Section 5.

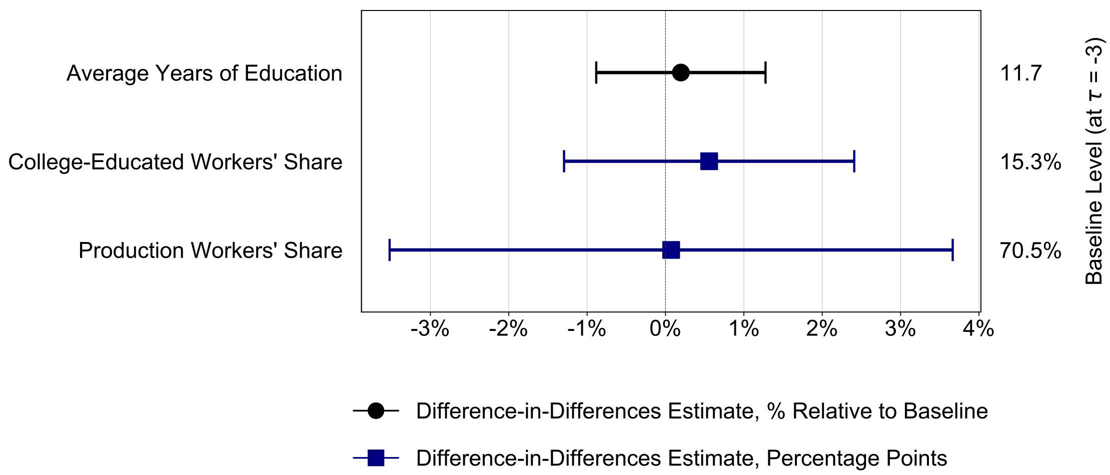


Figure 9: Skill Effects. The First-Difference Estimates.

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 of $\tau \in [2, 5]$. 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 5.

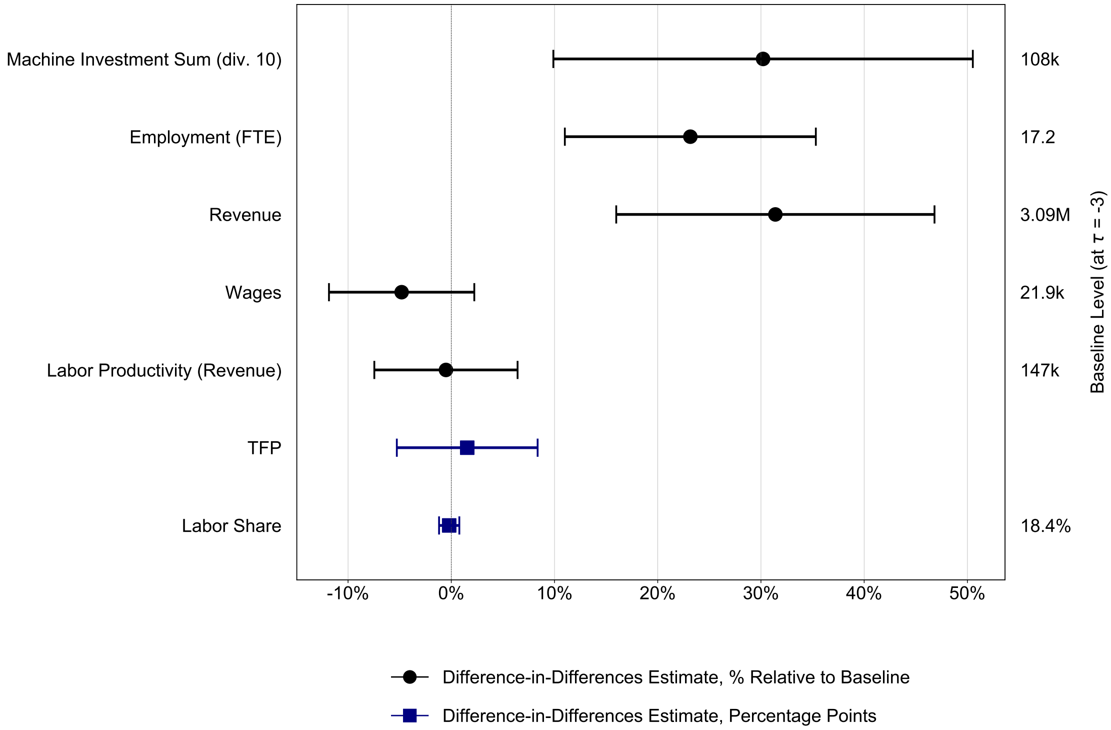


Figure 10: Firm-Level Effects.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. 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 sum of investment between $\tau \in [0, 2]$ and for other outcomes, the average of $\tau \in [2, 5]$. The specifications include two-digit industry and firm size as controls. Back to Section 5.

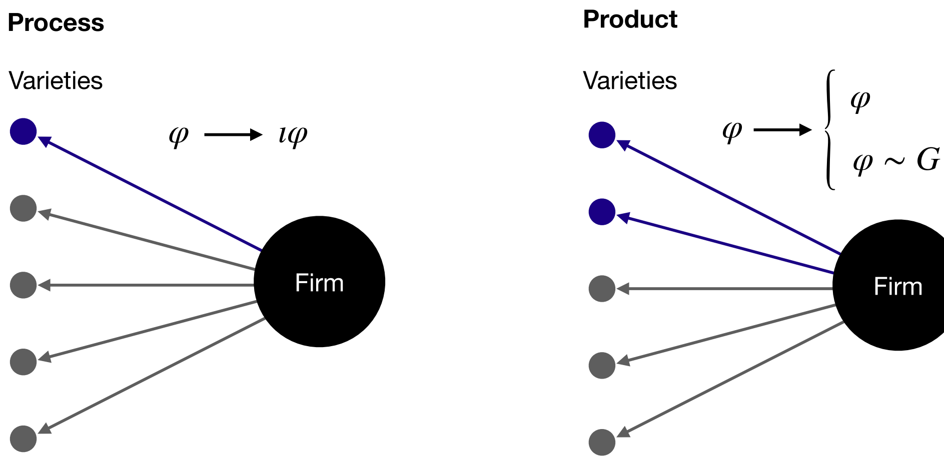


Figure 11: Process vs. Product.

Notes: Process refers to productivity improvements within an output variety, product to the expansion of new varieties. Details in the main text. Back to Section 6.

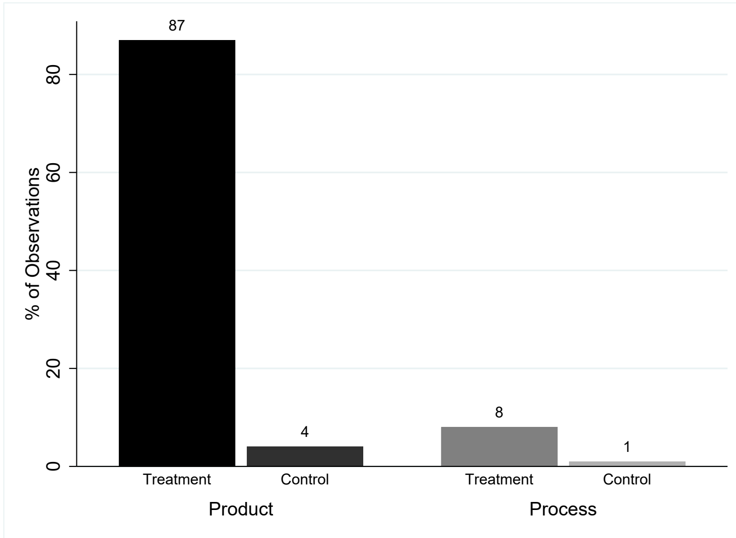
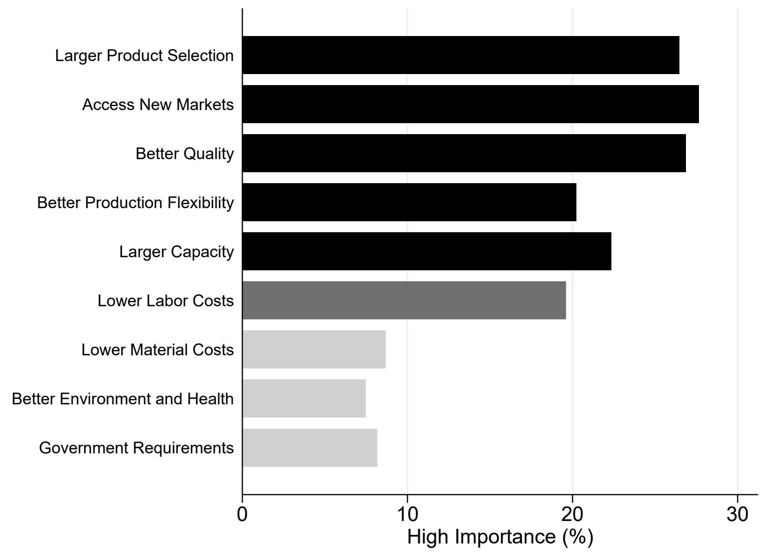
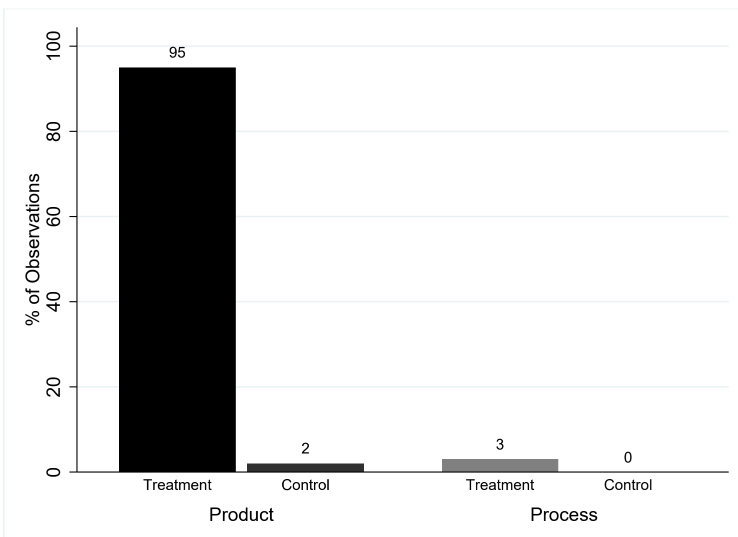


Figure 12: Technology Categories Measured from Text Data: Observations by Category.

Notes: Product refers to technology projects that aim to produce a new type of output. Process refers to technology projects that aim to produce the same type of output. The text data are text records from the subsidy program's administration, including each firm's application and evaluation texts. A trained panel performed the classification. Details in the main text. Back to Section 6.2.



(a) Specific Objectives.



(b) Aggregated Objectives.

Figure 13: Technology Categories Measured from the Survey Data: Observations by Category.

Notes: The European Community Innovation Survey (CIS) reports firms' views on the importance of different objectives for process and product innovations, including technology adoption. **Panel (a)** shows the share of firms in our main sample that report the objective is highly important. Variables are in thematic order (new varieties, expansion, costs, environment, and regulations). We use survey years 1996–2008. If the firm has responded to multiple rounds of CIS, we consider the closest survey to its technology-adoption event. **Panel (b):** Product refers to firms that reported that one of the first five objectives was important and lower labor costs were not. Process refers to firms that reported that lower labor costs were important but did not report any of the first five objectives as important. N = 510 (i.e., the number of main-sample firms also in CIS). Back to Section 6.2.

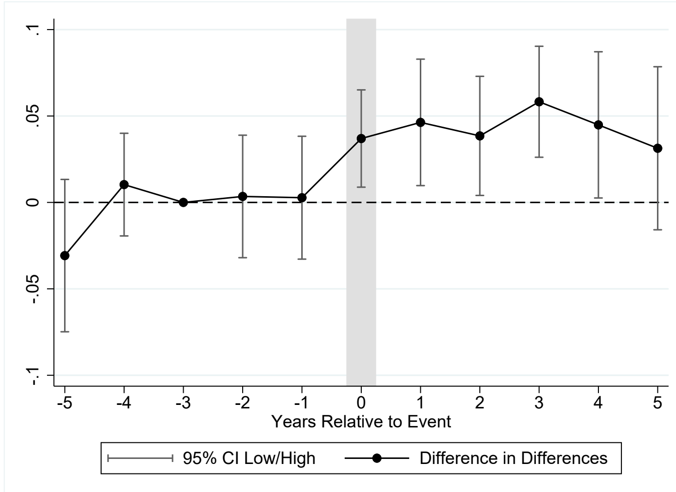


Figure 14: Export Effects: The Export Status.

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). Exports are measured from the Finnish Customs' Foreign Trade Statistics. 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 a single export event is over EUR 120K in value. This event-study specification contains no controls in the term X_{jt}^{τ} of Equation 1. Back to Section 6.2.

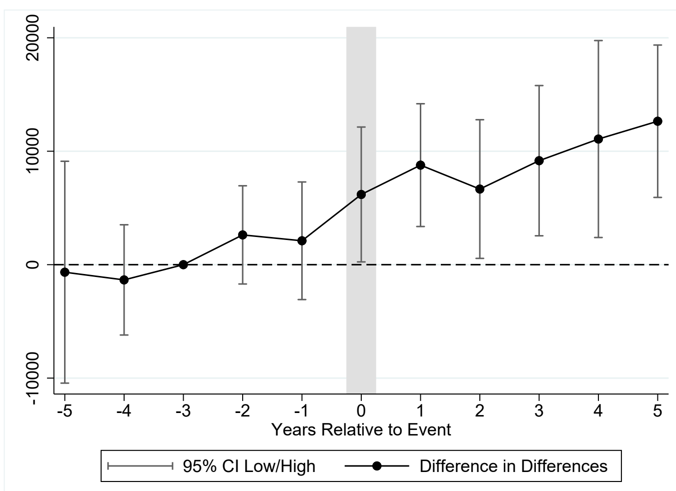


Figure 15: Marketing Effects: Marketing Expenditure.

Notes: Event-study estimates from Equation 1. The outcome is the firm's marketing expenditure, 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 6.2.

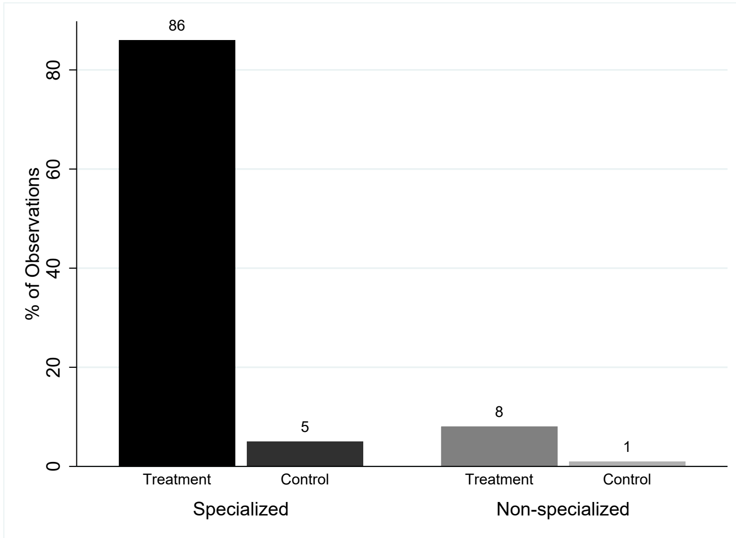


Figure 16: Specialized vs. Non-Specialized Industries: Observations by Category.

Notes: Specialized refers to industries producing non-commodities and non-specialized refers to industries producing commodities measured by the Rauch (1999) index. The distribution is similar when using Gollop and Monahan (1991) and Sutton (1998) indices. Back to Section 6.3.

Table 1: Technology Categories.

Classification	Description
Technologies	All technology investments and projects.
Uses of Technologies	
Process	Produce the same type of output using technologies.
Product	Produce a new type of output using technologies.
Types of Technologies	
Automated vs. non-automated	Technologies with no active user vs. an active user.
Hardware and/or software	Physical vs. non-physical technologies.

Notes: Technologies are measured from the financial, text, customs, and survey data. Uses of technologies are measured from the text data of the technology subsidy program and from the Community Innovation Survey (CIS). Types of technologies are measured from the text data and the customs data. The technology classes are described in Appendix E. Back to Sections 3 and 6.2.

Table 2: Summary Statistics: The Main Research Design (Winners vs. Losers).

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

Notes: All variables measured at $\tau = -3$. Machinery investment is measured from the financial statement register. Data on revenue, 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. Back to Section 4.2.

Table 3: The First Stage.

	(1) Granted Subsidy		(2) Machine Inv. (EUR K)		(3) Capital Stock (EUR K)	
Treatment	66.06***	70.22***	107.9***	100.4***	49.78**	41.60
	(3.119)	(4.907)	(17.53)	(21.90)	(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 control. To measure capital, we use the official records on firms' balance sheets. The post-period outcomes are sums between $\tau \in [0, 2]$. The specifications include two-digit industry and firm size as controls. Back to Section 5.

Table 4: Firm-Level Effects.

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	107.9***	100.3***	127.9***	0.232***	0.234**	0.217***	0.314***	0.333***	0.261***
	(17.53)	(21.90)	(6.556)	(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 a control. "Match" refers to estimation in the matched sample, where the control group is formed from matched non-applicant firms. **Panel A:** Machine 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 sum of investment between $\tau \in [0, 2]$ and for other outcomes, the average of $\tau \in [2, 5]$. Back to Section 5.

Table 5: Continuous Treatment Estimates.

	(1) Machine Inv.		(2) Employment		(3) Revenue	
Granted Subsidy	1.321***	1.262***	0.249***	0.230***	5.292***	4.973***
	(0.0806)	(0.0809)	(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 of $\tau \in [2, 5]$. The specifications include two-digit industry and firm size as controls. Back to Section 5.

Table 6: The Effects on Profits and Financial Costs.

Panel A: Win/Lose.

	(1) Profit Margin (%)	(2) Gross Profits	(3) Net Profits	(4) Fin. Costs
Treatment	0.121	24.49*	20.35*	4.133**
	(0.772)	(9.941)	(10.09)	(1.425)
Baseline	5.2	274.0	-16.07	290.1
N	2031	2031	2031	2031

Panel B: Continuous Treatment.

	(1) Gross Profits	(2) Net Profits	(3) Financial Costs
Granted Subsidy	-0.0353	-0.0878	0.0525***
	(0.0638)	(0.0646)	(0.00949)
Baseline	274,006	-16,074	290,080
N	2031	2031	2031

Standard errors in parentheses.

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

Notes: The effects on profits and financial costs. The baseline means are measured at $\tau = -3$. The profit margin is measured in percentage points. Gross and net profits refer to profits before and after financial costs. **Panel A**: The treatment is the win-lose status. The profits and financial costs are measured in EUR 1000s. **Panel B**: The treatment is the amount of subsidies the firm was granted. The coefficients are interpreted as the effect of one euro in subsidies on profits or financial costs, measured in euros. The baseline medians are 5.0% (profit margin), EUR 52K (gross profits), EUR 37K (net profits), and EUR 8.3K (financial costs). The specifications include two-digit industry and firm size as controls. Back to Section 5.

Table 7: Predictions from Process vs. Product Type Technological Changes.

Outcome	**Process**	**Product**
Revenue	↑	↑
Productivity	↑	0
Profit margin	↑	0
Products	0	↑
Export status and share	–	↑
Employment	–	↑
Labor share	↓	–
Skill composition	↑	–
Prices	↓ if cost ↑ if quality	0 ↑ if quality

Notes: Details in the main text. The symbol – refers to no clear prediction. Back to Section 6.1.

Table 8: Export and Product Effects.

	(1) Export Status	(2) Export Share	(3) Export Regions	(4) Products	(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)
Baseline	0.284	0.0523	1.498	1.546	0.498	0.539
N	2031	2031	2031	2031	2031	2031

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2 for the main research design (winners vs. losers). Exports and products are measured from the Finnish Customs' Foreign Trade Statistics. 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 a single export event is over 120K EUR in value. The specifications include two-digit industry and firm size as controls. Back to Section 6.2.

Table 9: Price Effects.

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

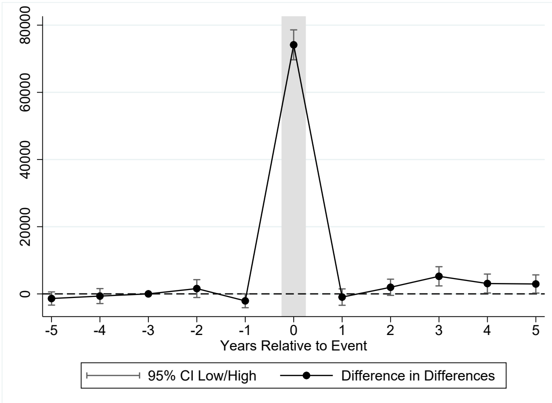
Standard errors in parentheses.

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

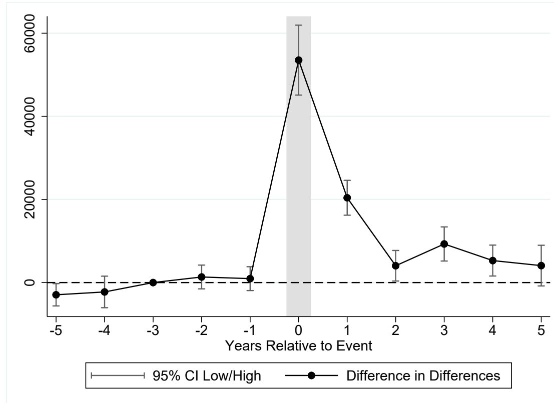
Notes: Difference-in-differences estimates from Equation 2 for the main research design (winners vs. losers). We winsorize price data at the 10% level within product and year. Prices are measured as product-level revenue divided by quantity from the Finnish Customs' Foreign Trade Statistics and the Industrial Production Statistics (a survey of manufacturing firms). The specifications include two-digit industry and firm size as controls. Back to Section 6.2.

Appendix

A The Winners-Losers Design: Supplementary Figures and Tables



(a) Granted.



(b) Received.

Figure A1: The First Stage: The Effect of Winning a Subsidy on Granted and Received Subsidies.

Notes: Event-study estimates from Equation 1. Panel (a): 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. Back to Section 5.

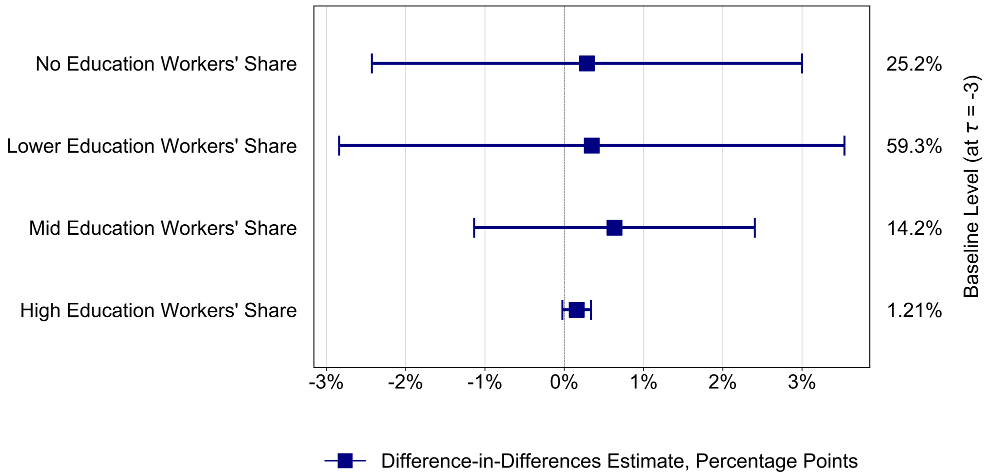


Figure A2: Skill Effects: Education Groups.

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 E. Back to Section 5.

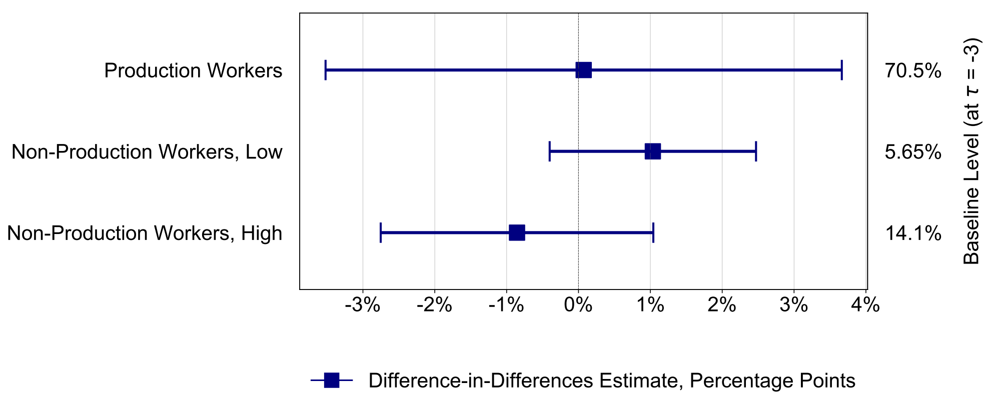


Figure A3: Skill Effects: Occupation Groups.

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 E. The shares do not sum to 100% because some workers do not have occupational info, i.e., the denominator includes all workers in the firm. Back to Section 5.

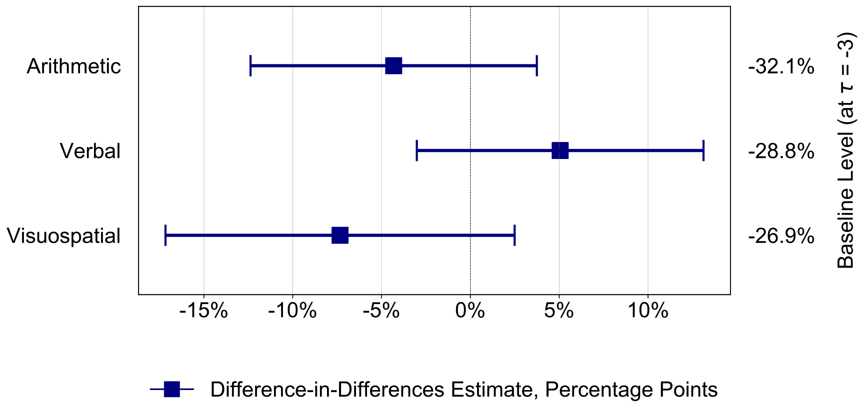


Figure A4: Skill Effects: Cognitive Performance.

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 Finnish Defence Forces. Back to Section 5.

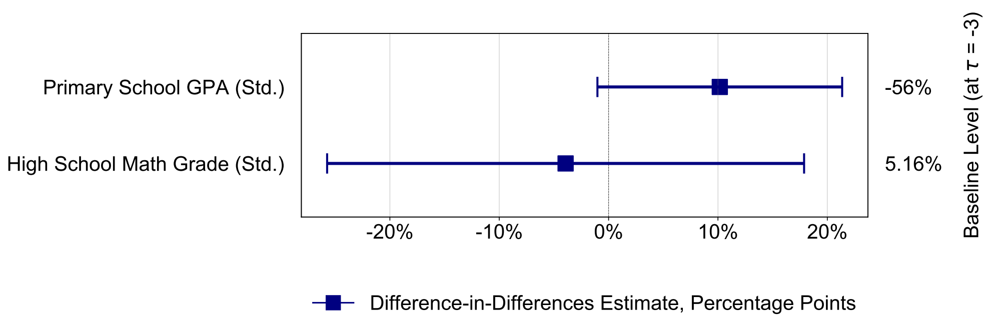


Figure A5: Skill Effects: School Performance.

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. Back to Section 5.

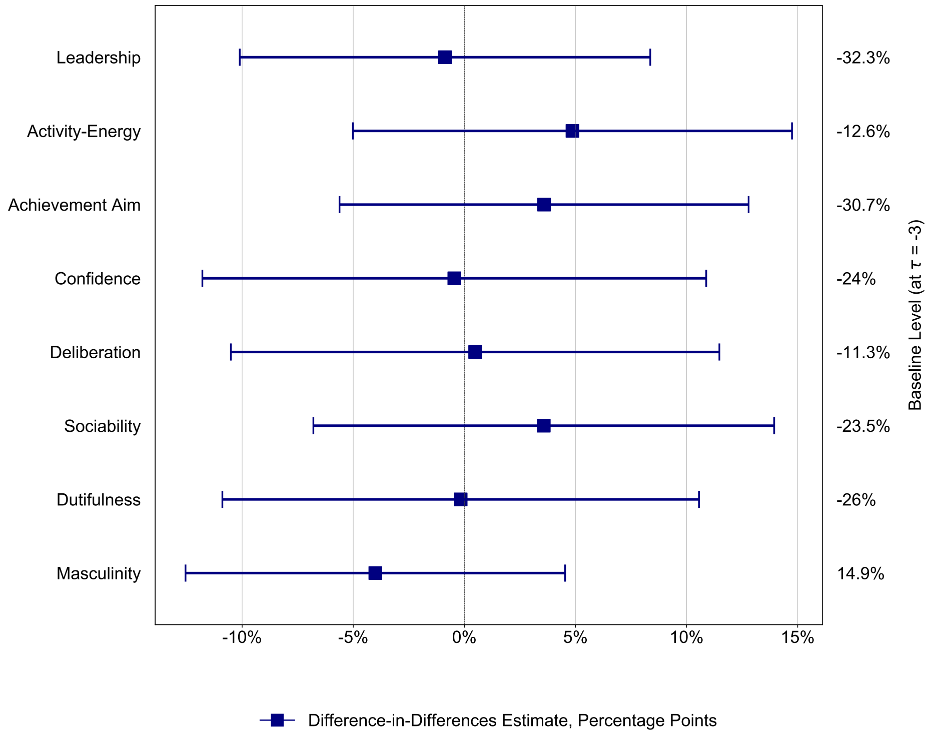


Figure A6: Skill Effects: Personality.

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. Back to Section 5.

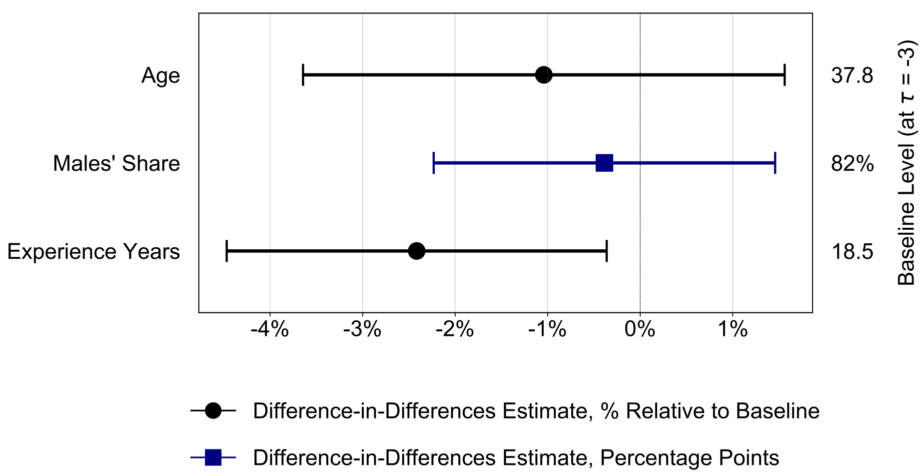
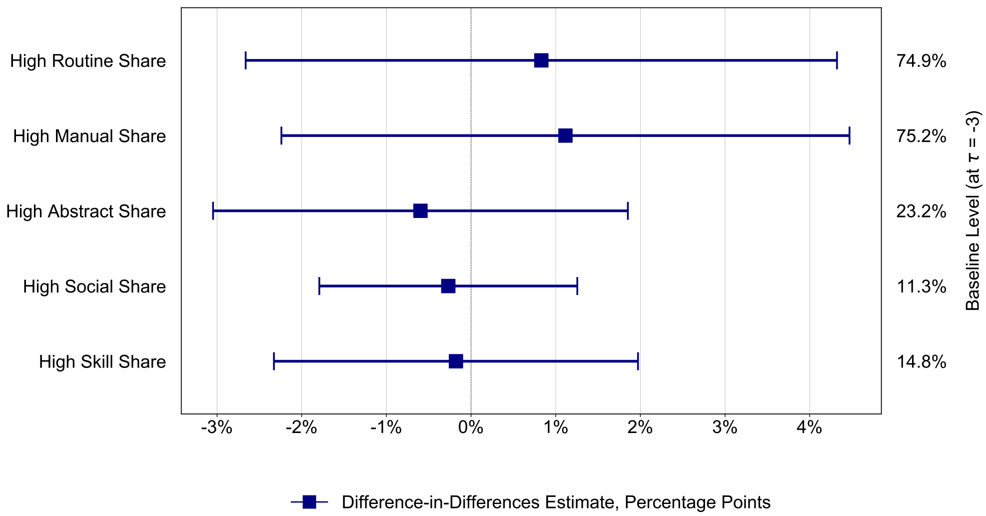


Figure A7: Skill Effects: Demographics.

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 Section 5.

Panel A: Above Median.



Panel B: Below Median.

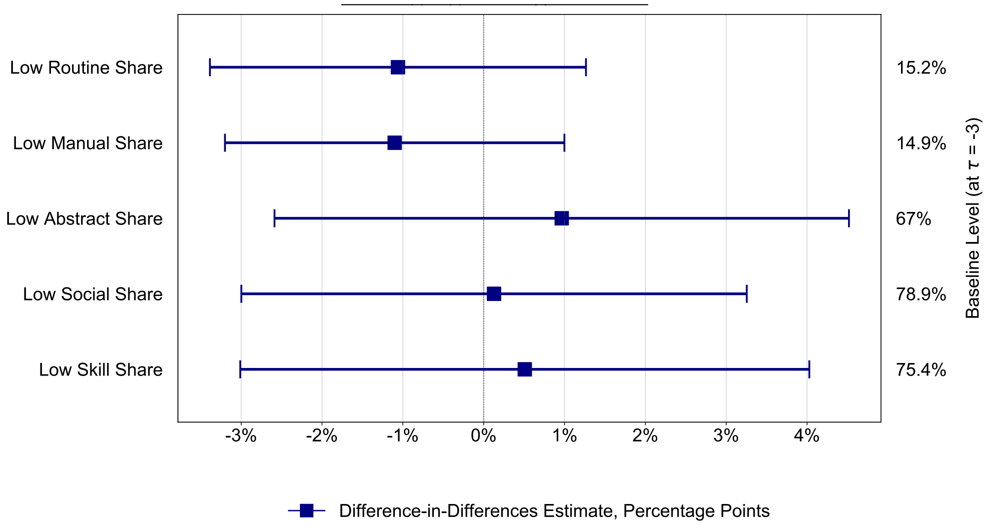


Figure A8: Skill Effects: Tasks.

Notes: Difference-in-differences estimates from Equation 2. The right-hand side reports means at $\tau = -3$. 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 shares do not sum to 100% because some workers do not have occupational info (the denominator includes all workers in the firm). The data are from the Finnish occupation registers and the European Working Conditions Survey (EWCS). Back to Section 5.

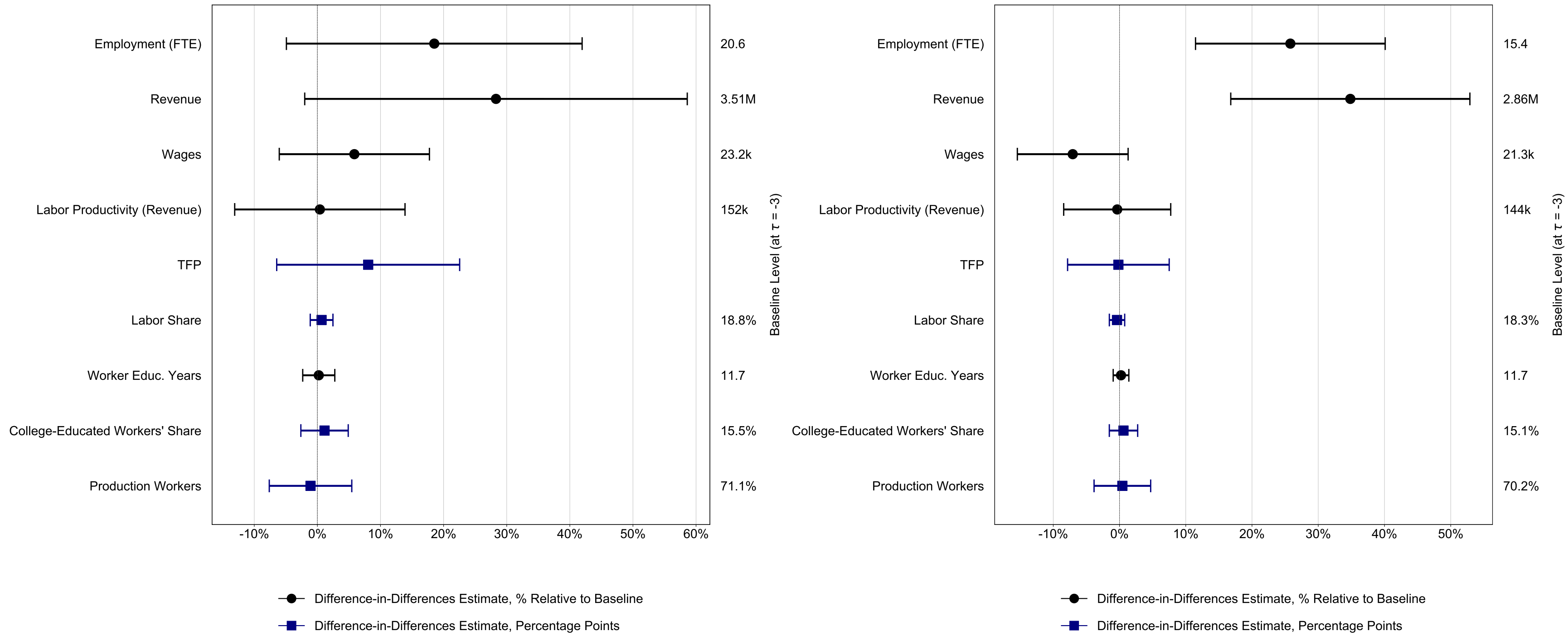


Figure A9: Automated (left) vs. Non-Automated (right) Technologies from Text Data.

Notes: Difference-in-differences estimates from Equation 2. Automated vs. non-automated technologies are measured from text data as described in Section 3 and Appendix E. Automated (N): Treatment 678, Control 30. Non-Automated (N): Treatment 1207, Control 116. Back to Section 7.

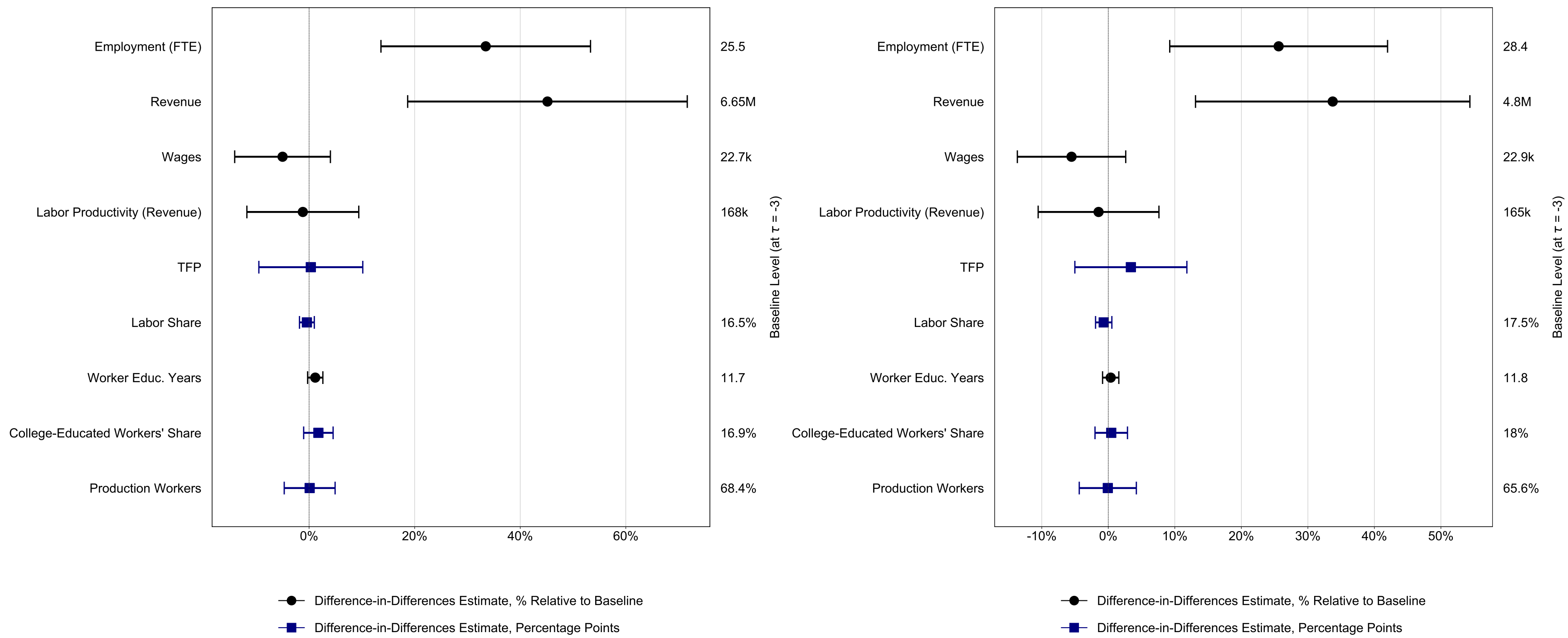


Figure A10: Automated (left) vs. Non-Automated (right) Technologies from Customs Data.

Notes: Difference-in-differences estimates from Equation 2. Automated vs. non-automated technologies are measured from customs data as described in Section 3 and Appendix E. 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 7.

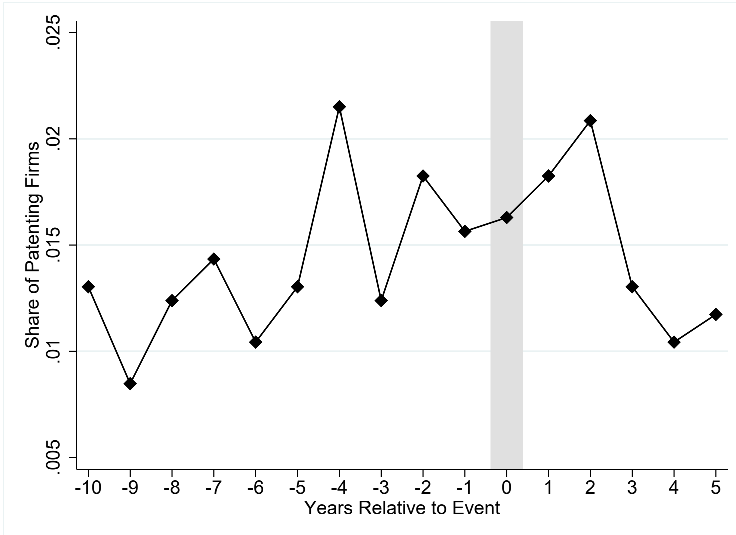
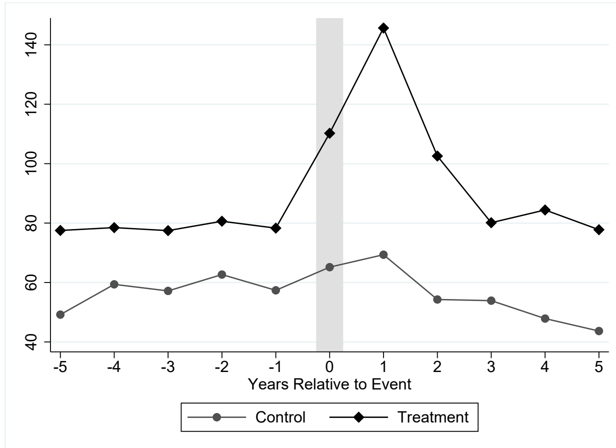
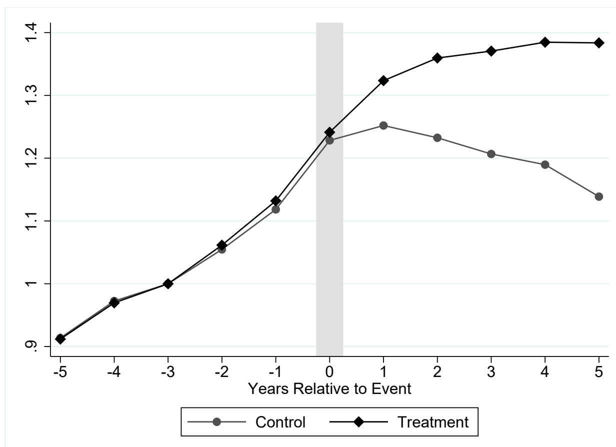


Figure A11: Patents: Share of Patenting Firms.

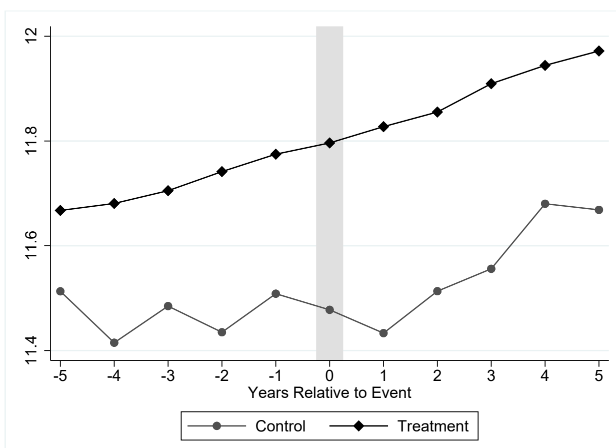
Notes: The share of patenting firms by year among subsidy applicant firms. Patent information comes from the Finnish Patent Database. Event time $\tau = 0$ refers to the subsidy application year. Back to Section 6.2.



(a) Machinery Investment.



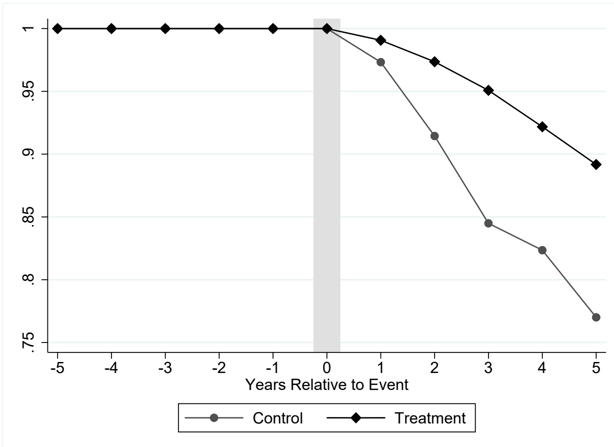
(b) Employment.



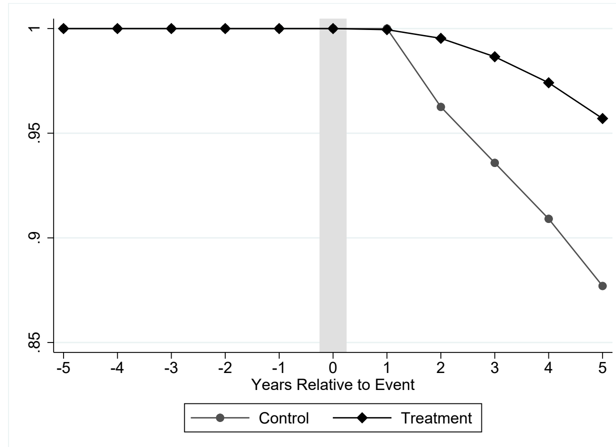
(c) Education Years.

Figure A12: Raw Means: Machinery Investment, Employment, and Education.

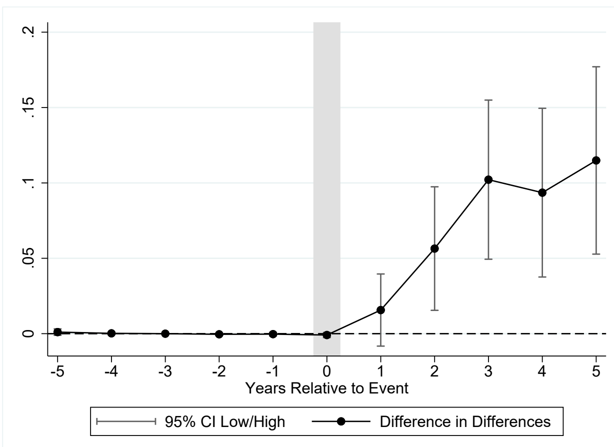
Notes: Means over time for the main treatment and control groups (winners vs. losers). Machinery investment in EUR, employment in % relative to $\tau = -3$, and education in years. The patterns in the main control group are similar to the patterns in a matched non-applicant control group as shown by Figure B1. Back to Section 7.



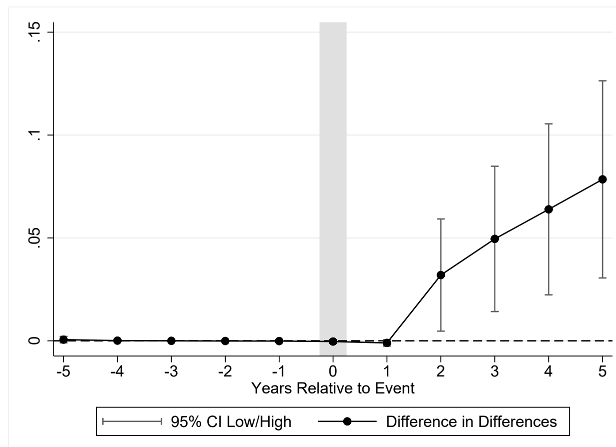
(a) Firm Survival Based on the Firm Register.



(b) Firm Survival Based on Worker Flows.



(c) Firm Survival Based on the Firm Register.



(d) Firm Survival Based on Worker Flows.

Figure A13: Firm Survival Effects.

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 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 A14. Back to Section 7.

Table A1: Summary Statistics: Benchmarking to All Manufacturing.

	Subsidy Sample				**Finnish Manufacturing**			
Variable	Mean	p10	Median	p90	Mean	p10	Median	p90
Revenue (EUR M)	2.66	1.96	2.56	3.77	2.03	1.89	2.01	2.27
Employment	16.25	12.76	16.11	19.07	12.35	11.63	12.52	13.06
Wages (EUR K)	26.25	19.98	25.88	32.83	26.95	21.13	26.94	32.16
Labor Productivity (EUR K)	150.30	131.20	147.80	171.08	140.55	125.82	142.72	152.31
Profit Margin (%)	5.55	3.10	5.56	7.63	4.47	2.94	4.56	5.84
Employment Change (%, Five Year)	57.72	40.70	50.81	84.15	48.11	34.52	44.24	82.17
Revenue Change (%, Five Year)	74.62	44.66	74.76	96.19	59.87	30.25	54.83	101.80
Subsidy Applied (EUR K)	110.48	86.74	107.61	149.45	4.80	3.38	4.68	6.20
Subsidy Granted (EUR K)	79.53	49.82	78.51	109.14	2.58	2.13	2.62	3.27
Educ. Years	11.79	11.57	11.77	12.07	11.64	11.49	11.60	11.84
College Share (%)	15.36	13.38	15.37	17.94	14.56	13.33	14.78	15.45
Production Worker Share (%)	70.70	66.37	69.99	74.87	69.33	66.76	69.12	72.67
Number of Observations	2031				260,220			
Number of Unique Firms	2031				18,501			
Number of Years	16				16			

Notes: 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 $\tau = -1$. Manufacturing means are measured for each firm in a given year and collapsed to a year-level mean for all manufacturing. These year-level means are averaged over 1994–2018. The median and the percentiles are at the year level. Subsidy applied, subsidy granted, college share, and production worker share are not winsorized, but all other outcomes are (at top and bottom 5% level). Back to Section 4.1.

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

	Treatment Group		**Control Group**		**Both**		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p
Revenue (EUR M)	2.26	4.44	1.68	3.85	0.13	0.72	4.68
Employment	15.77	26.04	11.15	24.65	1.10	5.90	27.40
Wages (EUR K)	21.24	8.15	19.28	10.29	6.73	21.27	29.23
Subsidy Applied (EUR K)	110.02	128.33	64.64	105.44	4.60	38.35	241.32
Subsidy Granted (EUR K)	78.31	99.14	0.00	0.00	0.00	0.34	124.65
Educ. Years	11.67	0.98	11.42	1.04	10.50	11.63	12.50
College Share (%)	15.18	16.75	11.05	16.30	0.00	10.30	33.33
Production Worker Share (%)	70.62	22.17	72.65	27.18	40.00	75.00	100.00
Observations	1508		1508		3016		

Notes: All variables measured at $\tau = -3$. Back to Section 4.3.

Table A3: 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	93.10***	0.242***	0.313**	-0.0480	-0.000144	-0.00883
	(19.93)	(0.0712)	(0.0956)	(0.0661)	(0.0105)	(0.0207)
Observations	1256	1256	1256	1160	1160	1161

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

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	159.6***	0.359***	0.458***	-0.0441	0.00547	-0.0276
	(22.81)	(0.0911)	(0.117)	(0.0848)	(0.0162)	(0.0300)
Observations	1812	1812	1812	1676	1676	1692

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

Panel C: Cosine Similarity.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Educ. Years	(5) College Share	(6) Production Worker Share
Treatment	103.9***	0.169***	0.195***	0.0133	-0.00224	-0.00769
	(14.90)	(0.0249)	(0.0335)	(0.0219)	(0.00542)	(0.00896)
Observations	3016	3016	3016	2678	2678	2678

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. Back to Section 5.

Table A4: Firm-Level Effects: 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	140.9***	0.185**	0.261***	-0.0553	-0.00559	-0.00242	0.0225	0.00480	-0.0235
	(25.76)	(0.0606)	(0.0770)	(0.0353)	(0.0341)	(0.00492)	(0.0599)	(0.00927)	(0.0359)
Controls 1	132.4***	0.219***	0.302***	-0.0499	-0.00379	-0.00247	0.0252	0.00587	-0.0263
	(26.17)	(0.0615)	(0.0779)	(0.0356)	(0.0351)	(0.00496)	(0.0611)	(0.00936)	(0.0357)
Controls 2	114.8***	0.232***	0.314***	-0.0481	-0.00516	-0.00202	0.0246	0.00557	-0.0256
	(23.99)	(0.0614)	(0.0779)	(0.0355)	(0.0350)	(0.00496)	(0.0611)	(0.00935)	(0.0357)
Controls 3	105.0***	0.249***	0.327***	-0.0385	-0.00670	-0.000862	0.0252	0.00572	-0.0255
	(23.96)	(0.0609)	(0.0773)	(0.0350)	(0.0349)	(0.00490)	(0.0612)	(0.00942)	(0.0363)
Controls 4	41.02	0.210***	0.284***	-0.0344	-0.00658	-0.000101	0.0247	0.00509	-0.0268
	(22.92)	(0.0607)	(0.0770)	(0.0351)	(0.0350)	(0.00493)	(0.0614)	(0.00946)	(0.0363)
Controls 5	36.43	0.221***	0.299***	-0.0319	-0.00474	-0.000143	0.0168	0.00482	-0.0275
	(22.65)	(0.0613)	(0.0776)	(0.0352)	(0.0350)	(0.00494)	(0.0619)	(0.00951)	(0.0366)
Observations	2031	2031	2031	1952	2031	2031	1884	1884	821

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 5.

Table A5: Continuous Treatment Estimates Controlling for the Subsidies Applied.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue	
Granted Subsidy	0.589***	0.613***	0.129**	0.140**	1.546	2.074*
	(0.153)	(0.163)	(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 over $\tau \in [0, 2]$. Other outcomes are averages over $\tau \in [2, 5]$. Back to Section 5.

Table A6: Product: Matched Sample Summary Statistics.

	Treatment Group		**Control Group**		**Both**		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p
Revenue (EUR M)	3.65	33.13	6.42	23.70	0.16	1.02	7.52
Employment	18.65	55.00	30.54	87.85	1.50	8.50	43.30
Wages (EUR K)	22.23	8.27	22.74	8.68	12.95	23.05	31.17
Subsidy Applied (EUR K)	111.99	128.51	3.13	23.43	0.00	4.03	182.69
Subsidy Granted (EUR K)	83.63	104.87	1.87	13.83	0.00	2.94	131.11
Educ. Years	11.71	1.00	11.62	1.04	10.50	11.70	12.67
College Share (%)	15.38	16.94	16.05	18.42	0.00	12.50	35.23
Production Worker Share (%)	70.81	21.92	67.97	24.67	37.50	72.34	100.00
Observations	1023		1023		2046		

Notes: All variables measured at $\tau = -3$. The treatment group is subsidy-winning firms that described product-type technological advances in their application text. The matched control group is searched from all non-applicant firms with balance sheet data. In this table, the subsidy applied and granted refer to all recorded subsidies; the matched control group does not apply or receive ELY Center subsidies. Back to Section 6.2.

Table A7: Process: Matched Sample Summary Statistics.

	Treatment Group		**Control Group**		**Both**		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p
Revenue (EUR M)	3.06	6.22	3.18	5.29	0.16	1.02	8.14
Employment	21.61	38.00	21.85	37.54	1.30	8.80	46.50
Wages (EUR K)	23.67	8.34	23.95	8.71	14.68	24.19	33.67
Subsidy Applied (EUR K)	77.50	95.55	13.12	59.09	0.00	4.16	141.99
Subsidy Granted (EUR K)	52.94	72.32	8.22	35.42	0.00	3.49	90.19
Educ. Years	11.57	0.95	11.53	0.93	10.50	11.68	12.52
College Share (%)	14.45	15.99	14.50	16.75	0.00	12.50	30.60
Production Worker Share (%)	69.48	20.42	70.32	22.70	50.00	71.43	100.00
Observations	99		99		198		

Notes: All variables measured at $\tau = -3$. The treatment group is subsidy-winning firms that described process-type technological advances in their application text. The matched control group is searched from all non-applicant firms with balance sheet data. In this table, the subsidy applied and granted refer to all recorded subsidies; the matched control group does not apply or receive ELY Center subsidies. Back to Section 6.2.

Table A8: The Effects by Technology Categories Measured from Text Data.

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

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity
Product	142.7***	0.210***	0.262***	-0.00270	0.0222
	(9.964)	(0.0235)	(0.0320)	(0.0122)	(0.0154)
Process	77.66***	0.0905	0.0783	-0.00154	-0.0515
	(22.95)	(0.0779)	(0.0759)	(0.0324)	(0.0483)
N, Product	2046	2046	2046	1963	2046
N, Process	198	198	198	192	198

Panel B: Skill Composition and The Labor Share.

	(1) Labor Share	(2) Educ. Years	(3) College Share	(4) Production Worker Share
Product	-0.00474	0.0227	0.00691	-0.0110
	(0.00264)	(0.0269)	(0.00422)	(0.00742)
Process	0.00583	0.137	0.00497	0.0101
	(0.00765)	(0.0809)	(0.0135)	(0.0211)
N, Product	2046	1905	1905	1921
N, Process	198	186	186	186

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2. Product (the extensive margin) refers to technology projects that aim to produce a new type of output. Process (the intensive margin) refers to technology projects that aim to produce the same type of output with new technologies. **Panel A:** Column 1 is in EUR K. Columns 2, 3, 4, and 5 are relative changes, e.g., 0.20 would refer to a 20% increase. **Panel B:** Columns 1, 3, and 4 (shares) are in percentage points. Column 2 (education) is in years. We use coarsened exact matching (CEM) to construct the control group. N refers to the number of matched observations. For machine investment, the post-period outcome is the sum of investment between $\tau \in [0, 2]$ and for other outcomes, the average of $\tau \in [2, 5]$. Back to Section 6.2.

Table A9: The Effects by Technology Categories Measured from Survey Data.

Panel A: Employment, Wages, and Firm Performance.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity
Product	311.5***	0.235**	0.364***	-0.00137	0.154*
	(62.75)	(0.0812)	(0.101)	(0.0296)	(0.0620)
Process	-	-	-	-	-
	-	-	-	-	-
N, Product	164	164	164	164	164
N, Process	6	6	6	6	6

Panel B: Skill Composition and the Labor Share.

	(1) Labor Share	(2) Educ. Years	(3) College Share	(4) Production Worker Share
Product	-0.0169*	0.0758	0.00812	-0.00478
	(0.00737)	(0.0679)	(0.0107)	(0.0184)
Process	-	-	-	-
	-	-	-	-
N, Product	164	163	163	163
N, Process	6	6	6	6

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2. The technology categories are measured from the European Community Innovation Survey (CIS). Product (the extensive margin) refers to technology projects that aim to produce a new type of output. Process (the intensive margin) refers to technology projects that aim to produce the same type of output with new technologies. The process sample is too small to perform estimation (denoted by –). **Panel A:** Column 1 is in EUR K. Columns 2, 3, 4, and 5 are relative changes, e.g., 0.20 would refer to a 20% increase. **Panel B:** Columns 1, 3, and 4 (shares) are in percentage points. Column 2 (education years) is in years. We use coarsened exact matching (CEM) 1:1. N refers to matched observations. Machine investment is the sum over $\tau \in [0, 2]$, other outcomes are averages over $\tau \in [2, 5]$. Back to Section 6.2.

Table A10: The Effects by Context Measured from the Rauch Index.

Panel A: Employment, Wages, and Firm Performance.

	(1) Machine Inv. (EUR K)	(2) Employment	(3) Revenue	(4) Wages	(5) Productivity
Specialized	147.9***	0.188***	0.216***	-0.00748	0.00401
	(8.141)	(0.0213)	(0.0272)	(0.0113)	(0.0134)
Non-Specialized	86.61*	0.132	0.171	0.0334	0.0122
	(42.06)	(0.0965)	(0.114)	(0.0386)	(0.0612)
N, Specialized	2704	2704	2704	2606	2704
N, Non-Specialized	248	248	248	242	248

Panel B: Skill Composition and the Labor Share.

	(1) Labor Share	(2) Educ. Years	(3) College Share	(4) Production Worker Share
Specialized	-0.00184	0.0247	0.00281	-0.00350
	(0.00219)	(0.0218)	(0.00361)	(0.00637)
Non-Specialized	-0.00149	-0.00469	-0.00735	0.0399
	(0.00988)	(0.107)	(0.0192)	(0.0251)
N, Specialized	2704	2539	2539	2584
N, Non-Specialized	248	236	236	239

Standard errors in parentheses.

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

Notes: Difference-in-differences estimates from Equation 2. **Panel A:** Column 1 is in EUR K. Columns 2, 3, 4, and 5 are relative changes, e.g., 0.20 would refer to a 20% increase. **Panel B:** Columns 1, 3, and 4 (shares) are in percentage points. Column 2 (education years) is in years. N refers to matched observations. We use coarsened exact matching 1:1 (CEM). Machine investment is the sum over $\tau \in [0, 2]$. Other outcomes are averages over $\tau \in [2, 5]$. Details in the main text. Back to Section 6.3.

Table A11: Technology Categories from Text Data vs. Rauch Index.

Class	Product	Process	Total
High Rauch Index	1019	89	1108
Low Rauch Index	98	15	113
Total	1117	104	1221

Notes: This 2x2 table reports the number of firms in the text categories and Rauch Index combinations. Product refers to technology projects that aim to produce a new type of output. Process refers to technology projects that aim to produce the same type of output with new technologies. High Rauch Index refers to specialized industries, Low Rauch Index refers to non-specialized industries. Back to Section 6.3.

Table A12: The Effects by Firm Size.

Panel A: Large Firms.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Productivity		(5) Labor Share		(6) College Share	
Treatment	83.88	68.81	0.305***	0.309**	0.264	0.494**	-0.136	0.0236	0.0133	-0.00853	-0.00893	-0.0159
	(69.06)	(88.72)	(0.0722)	(0.104)	(0.137)	(0.160)	(0.0834)	(0.0967)	(0.00981)	(0.0111)	(0.0167)	(0.0201)
Propensity Score		✓		✓		✓		✓		✓		✓
Observations	676	609	676	609	676	609	676	609	676	609	675	608

Panel B: Medium-Sized Firms.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Productivity		(5) Labor Share		(6) College Share	
Treatment	76.82*	87.38*	0.296***	0.280*	0.467***	0.399**	0.0707	0.0193	-0.0104	-0.0124	0.0185	0.0200
	(33.67)	(41.97)	(0.0858)	(0.113)	(0.114)	(0.150)	(0.0551)	(0.0718)	(0.00856)	(0.00969)	(0.0162)	(0.0213)
Propensity Score		✓		✓		✓		✓		✓		✓
Observations	685	603	685	603	685	603	685	603	685	603	683	601

Panel C: Small Firms.

	(1) Machine Inv. (EUR K)		(2) Employment		(3) Revenue		(4) Productivity		(5) Labor Share		(6) College Share	
Treatment	31.99*	28.23	0.330**	0.373**	0.355**	0.370*	-0.0410	-0.0956	0.00216	0.0162	0.00334	0.00373
	(13.48)	(18.09)	(0.103)	(0.121)	(0.125)	(0.148)	(0.0526)	(0.0615)	(0.00781)	(0.00927)	(0.0158)	(0.0192)
Propensity Score		✓		✓		✓		✓		✓		✓
Observations	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. 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 6.3.

Table A13: Credit Constraints: Robustness Checks.

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	113.3***	91.37***	0.276***	0.194*	0.313**	0.326**
	(25.88)	(23.11)	(0.0793)	(0.0959)	(0.105)	(0.114)
Observations	1016	1015	1016	1015	1016	1015

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

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	121.9***	78.93***	0.0676	0.384***	0.151	0.486***
	(25.97)	(23.58)	(0.0965)	(0.0687)	(0.125)	(0.0820)
Observations	1016	1015	1016	1015	1016	1015

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

Panel C: Controlling for Credit Constraint Measures.

	(1)			(2)			(3)		
	Machine Inv. (EUR K)			Employment			Revenue		
Treatment	107.9***	107.8***	108.3***	0.232***	0.242***	0.232***	0.314***	0.342***	0.314***
	(17.53)	(17.54)	(17.59)	(0.0614)	(0.0597)	(0.0614)	(0.0779)	(0.0721)	(0.0778)
Relative Debt		✓			✓			✓	
Average Financial Costs			✓			✓			✓
Observations	2031	2031	2031	2031	2031	2031	2031	2031	2031

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

Notes: The sample is the main analysis sample (subsidies design). Estimated effects on selected outcomes by the cost of capital (Panel A) and debt level (Panel B), and with credit-constraint 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.

Table A14: Robustness to a Non-Balanced 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	93.16***	103.4***	0.310***	0.268***	0.400***	0.364***	-0.0371	-0.0442	0.000834	-0.0125
	(17.22)	(20.09)	(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

Standard errors in parentheses.

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

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

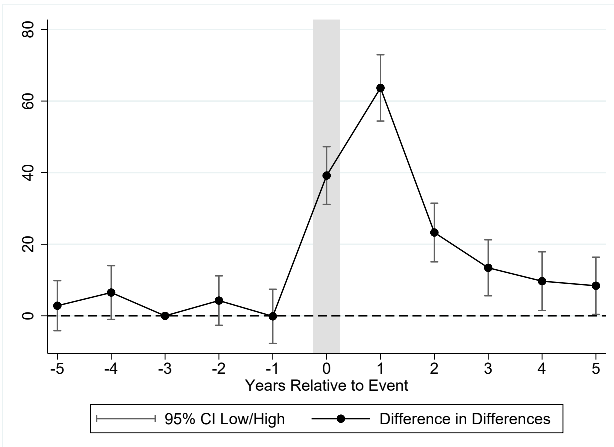
	(1) Productivity		(2) Labor Share		(3) Educ. Years		(4) College Share		(5) Production Worker Share	
Treatment	-0.00742	-0.0148	0.000989	0.00210	-0.0338	-0.0610	-0.00531	-0.00562	0.00735	-0.00679
	(0.0345)	(0.0417)	(0.00500)	(0.00620)	(0.0513)	(0.0649)	(0.00836)	(0.0106)	(0.0181)	(0.0213)
Propensity Score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

Standard errors in parentheses.

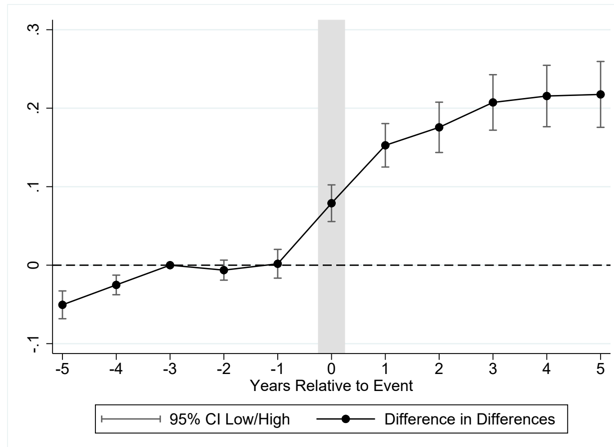
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is the main analysis sample (subsidies 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.

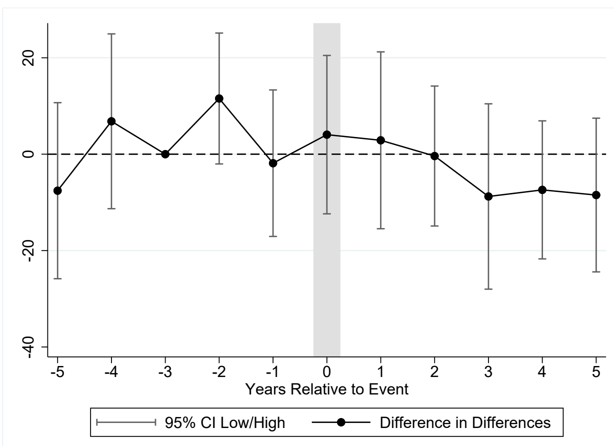
B The Winners-Losers Design: Matched Control Group



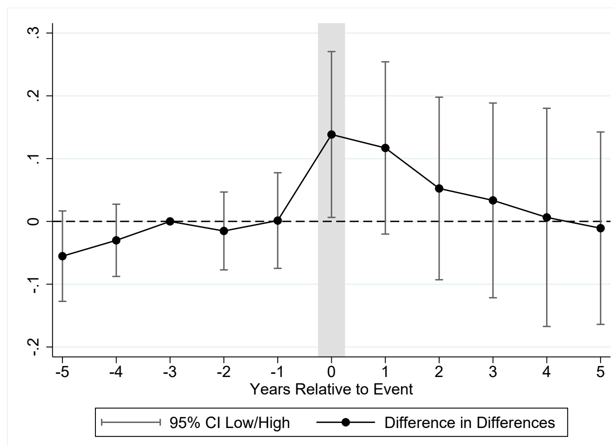
(a) Winners vs. Matched Control:
Machinery Investment.



(b) Winners vs. Matched Control:
Employment.



(c) Losers vs. Matched Control:
Machinery Investment



(d) Losers vs. Matched Control:
Employment.

Figure B1: The 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 Section 5.

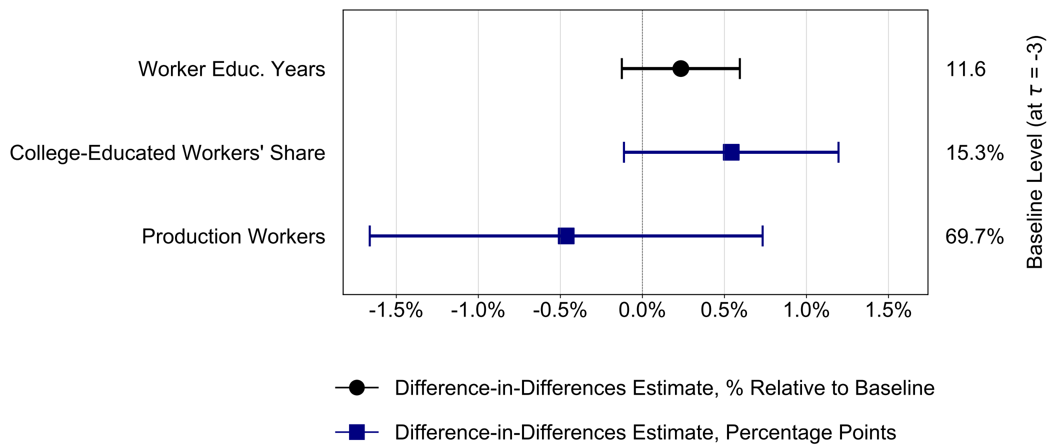


Figure B2: The Matched Control Group: Skill Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the main treatment group ("winners") to a matched control group. The right-hand side reports outcome means at $\tau = -3$. Back to Section 5.

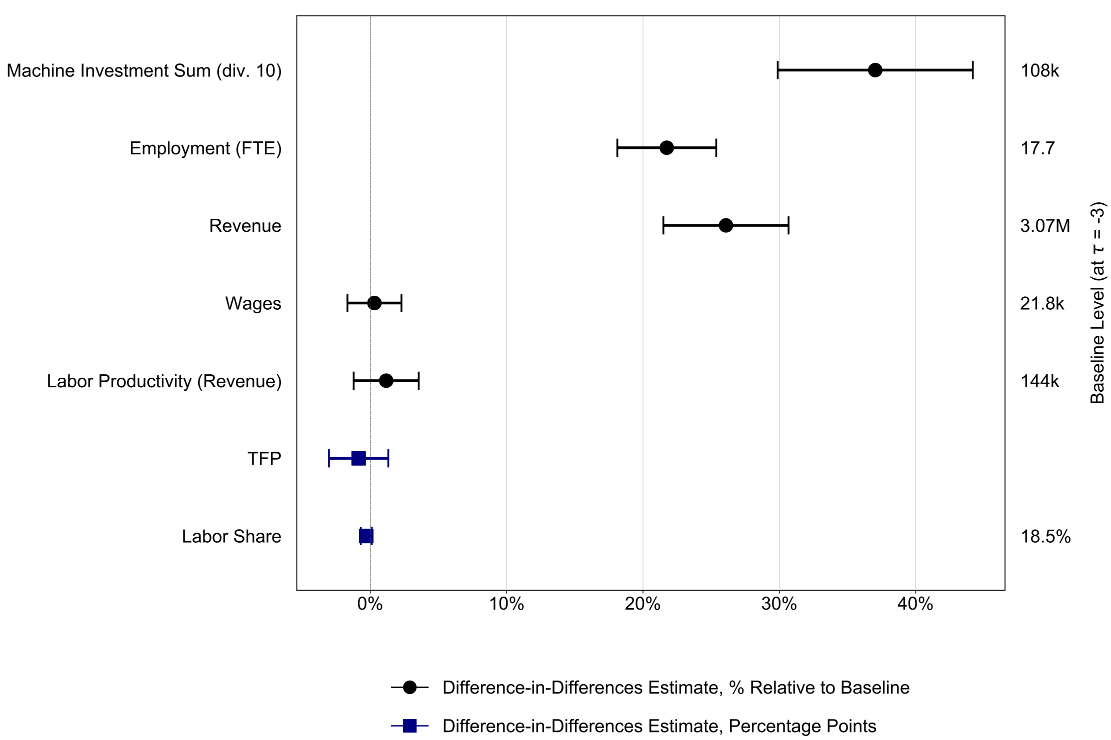


Figure B3: The Matched Control Group: Firm-Level Effects.

Notes: Difference-in-differences estimates from Equation 2. The estimates compare the main treatment group ("winners") to a matched control group. The right-hand side reports outcome means at $\tau = -3$. Back to Section 5.

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

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

Notes: All variables measured at $\tau = -3$. Back to Section 4.

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

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

Notes: All variables measured at $\tau = -3$. Back to Section 4.

C The 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. The spikes design 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 Hawkins et al. (2015) and Bessen et al. (2020). 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).

The Treatment Group We define the technology investment event, the spike, as an indicator that equals 1 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 4 (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 $\tau \in [-5, 8]$. 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.

The Matched Control Group To construct the control group, we match the spiking firms to non-spiking firms. To construct a 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 G. 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 4.2.

The First Stage Figure C2 shows the first stage. The outcome is technology investment. Treatment group firms invested 2 million EUR 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 theoretical framework that clarifies the source of variation in Appendix G, adapted from Cooper et al. (1999). The same model provides the basis also for the subsidies design, and we refer to it in Section 4.1. 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. The model produces a cutoff rule for the firm's optimal policy, where the firm adopts the technology if and only if the propensity $H \geq H^*$ for a cutoff H^* (Figure G1).

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).

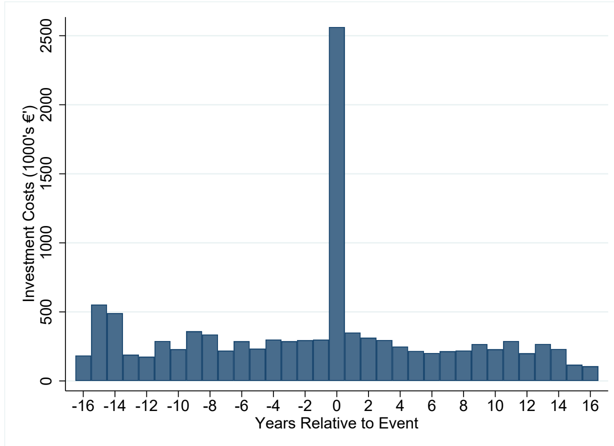


Figure C1: The Spikes Design. Machinery Investment.

Notes: Machinery investment in EUR 1000s. 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 G, technology investment is typically a spiky activity. Back to Section C.

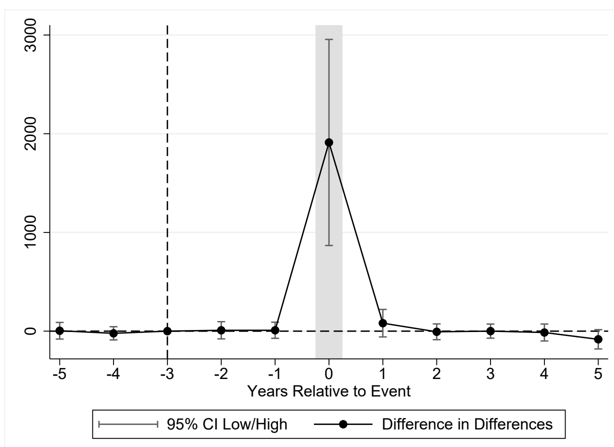
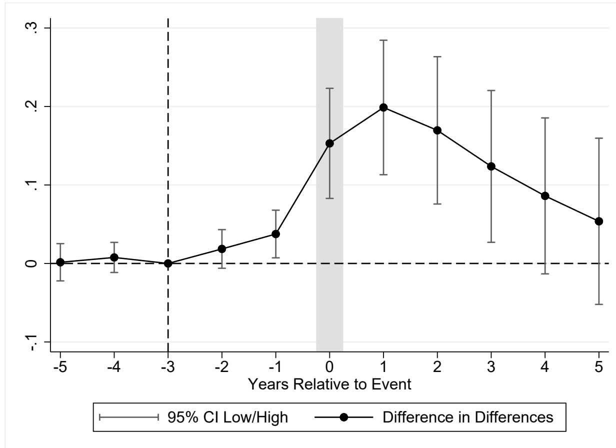
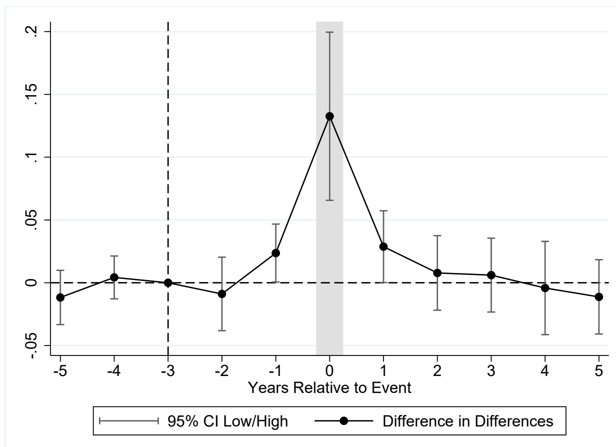


Figure C2: The Spikes Design. First Stage: Machinery Investment.

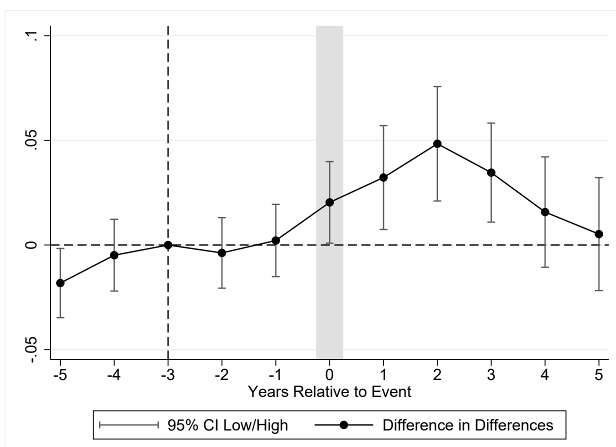
Notes: Event-study estimates from Equation 1. The outcome is machinery investment in EUR 1000s. Event time is normalized to zero in the year of the largest machinery investment. Back to Section C.



(a) Employment (%).



(b) Worker Entry Rate.



(c) Worker Exit Rate.

Figure C3: The Spikes Design. Employment Effects.

Notes: Event-study estimates from Equation 1. 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 rate is defined as the number of entering workers divided by employment in the base year $\tau = -3$. Exit rate is defined as the number of exiting workers divided by employment in the base year. Back to Section C.

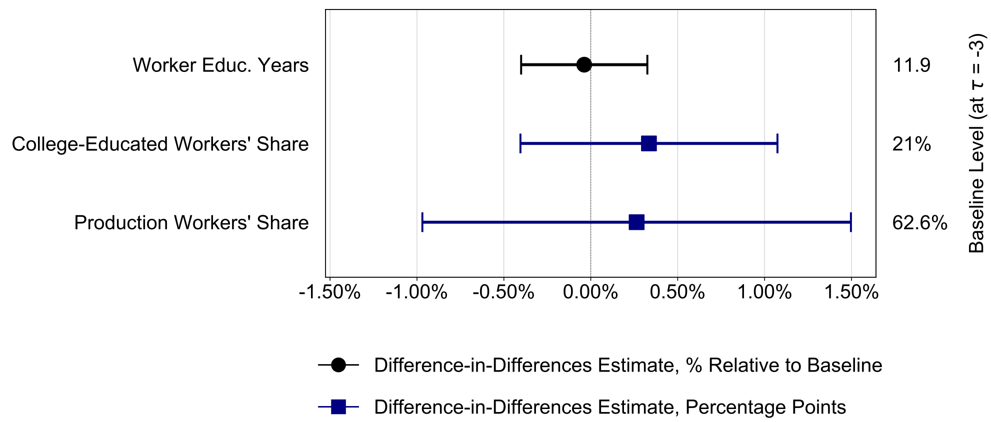


Figure C4: The Spikes Design: Skill Effects.

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.

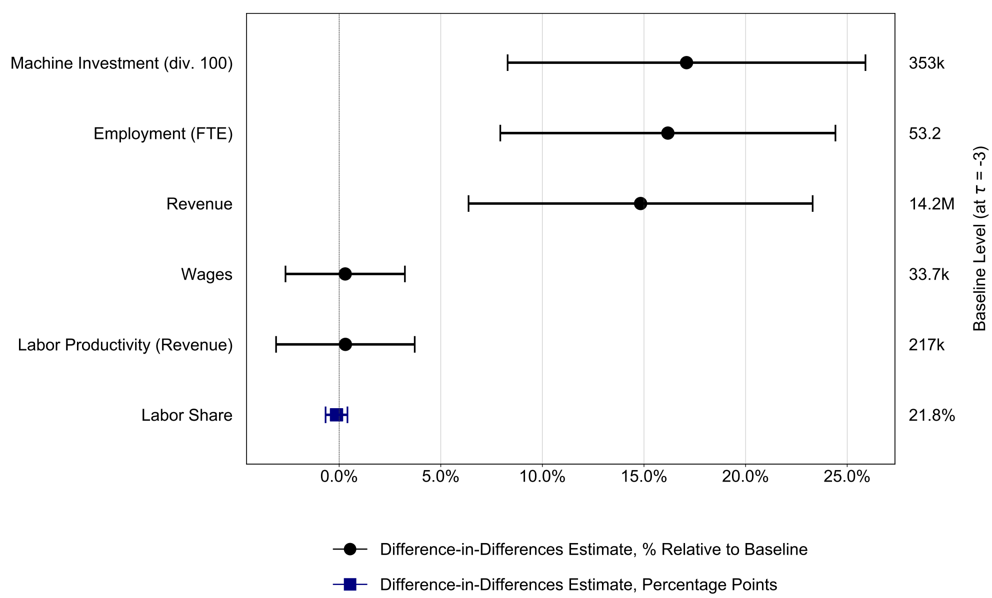


Figure C5: The Spikes Design: Firm-Level Effects.

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 $\tau = -3$. Back to Section C.

Table C1: The Spikes Design: Balance Table.

	Treatment Group		**Control Group**		**Both**		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	10p	Median	90p
Machinery Inv. (EUR K)	271.21	858.93	376.70	999.26	6.96	109.55	770.54
Revenue (EUR M)	14.48	30.10	14.12	69.98	1.29	4.85	26.97
Employment	51.66	68.29	53.67	71.11	11.10	28.30	119.20
Wages (EUR K)	33.68	9.26	33.75	8.21	25.12	32.56	43.20
Subsidy Applied (EUR K)	72.40	339.62	25.23	119.99	0.00	0.00	45.37
Subsidy Granted (EUR K)	41.15	173.02	16.07	81.71	0.00	0.00	23.17
Educ. Years	11.89	0.91	11.86	0.87	10.88	11.78	12.94
College Share (%)	21.24	16.70	20.90	14.95	5.56	17.65	40.91
Production Worker Share (%)	58.90	30.95	63.68	25.79	14.29	71.43	88.89
Observations	450		1593		2043		

Notes: All variables measured at $\tau = -3$ relative to the event. We use coarsened exact matching (CEM) with replacement. Back to Section C.

D The Regression Discontinuity 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. Buri (2017) discusses the policy change and the RD strategy. 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:

$$Y_i = \alpha + \beta E_i + f(z_{i,2004}) + \varepsilon_i \tag{19}$$

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 5 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 D2 shows the summary statistics for the RD sample firms.[46] As expected, the RD sample firms are larger than in the main design because, by definition, their revenue is around 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; 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 19 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.

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

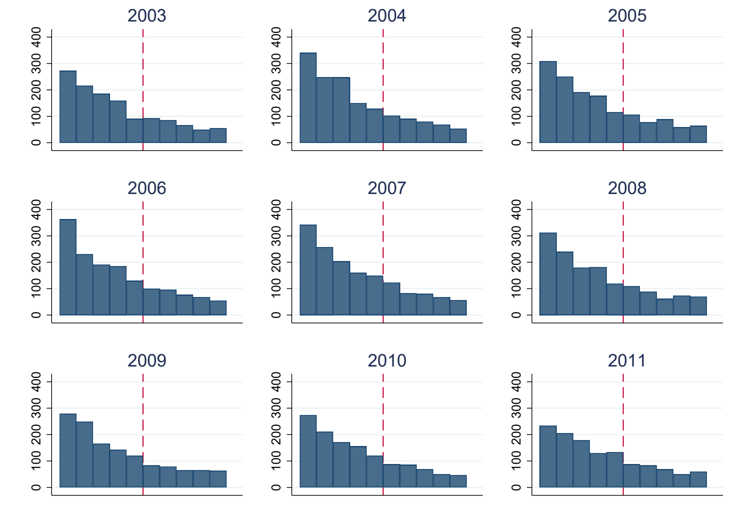


Figure D1: RD: The Number of Firms at the Balance-Sheet Threshold.

Notes: This figure shows the number of firms around the balance-sheet threshold for small firms announced in 2003, which came into effect in 2007. Back to Section D.

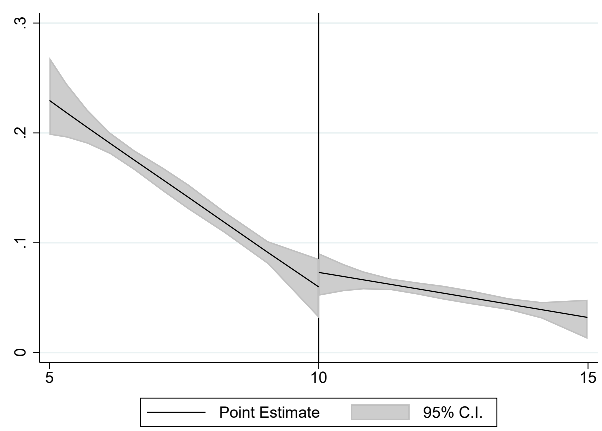


Figure D2: RD: The Density of Firms at the Balance-Sheet Threshold.

Notes: This figure visualizes the McCrary-test for our RD year. The horizontal axis is the firms' balance sheet in 2004 in millions of euros. The vertical axis denotes the density of observations. Back to Section D.

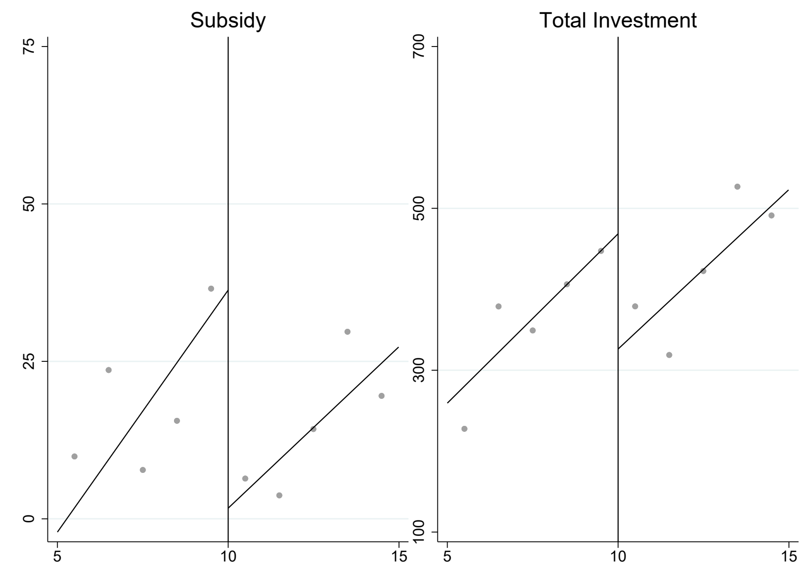


Figure D3: RD: The First Stage.

Notes: This figure shows the discontinuity at the balance-sheet threshold for 2007 investment subsidies (left) and total investment (right). The vertical axis is in thousands of euros, and the horizontal axis is in millions of euros. Back to Section D.

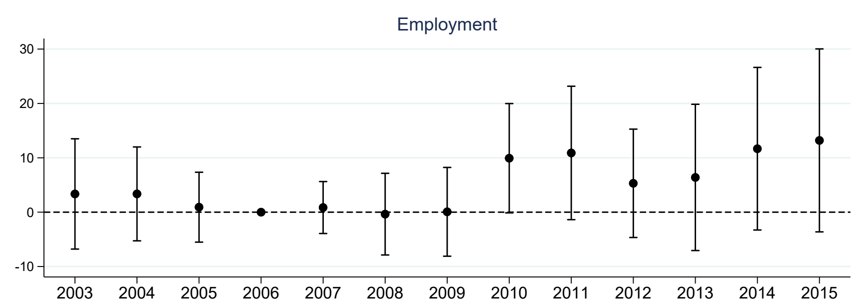


Figure D4: RD: Employment.

Notes: The estimates are from Equation 19. The outcome is the employment difference to base year 2006. The explanatory variable is the balance-sheet RD threshold indicator. 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.

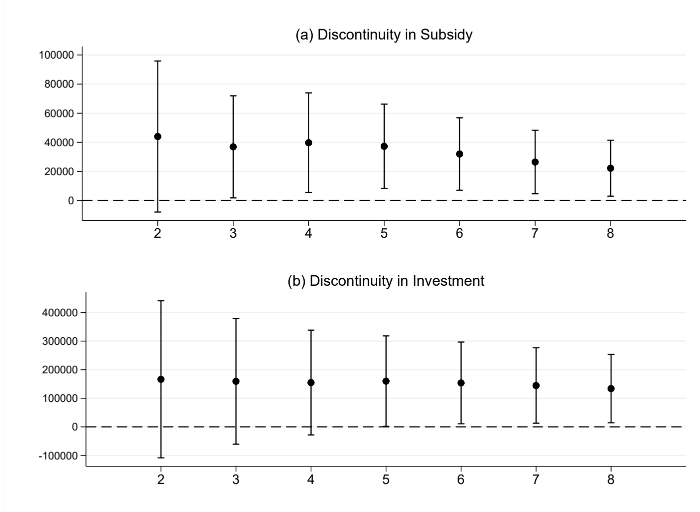


Figure D5: RD: Different Bandwidths.

Notes: The estimates are from Equation 19. The horizontal axis indicates the size 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.

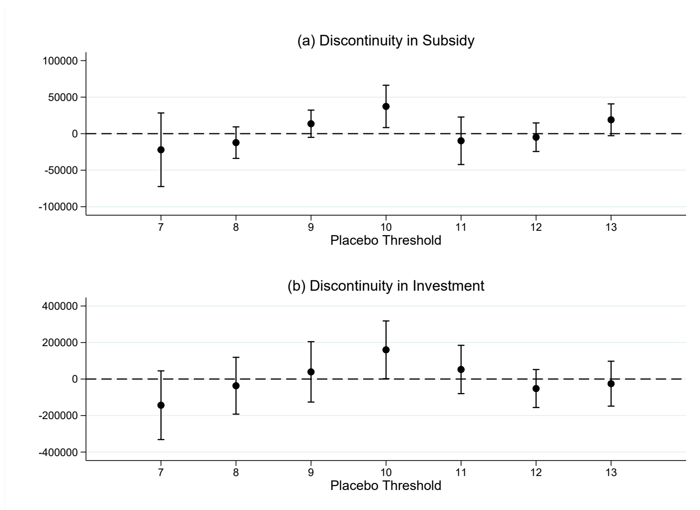
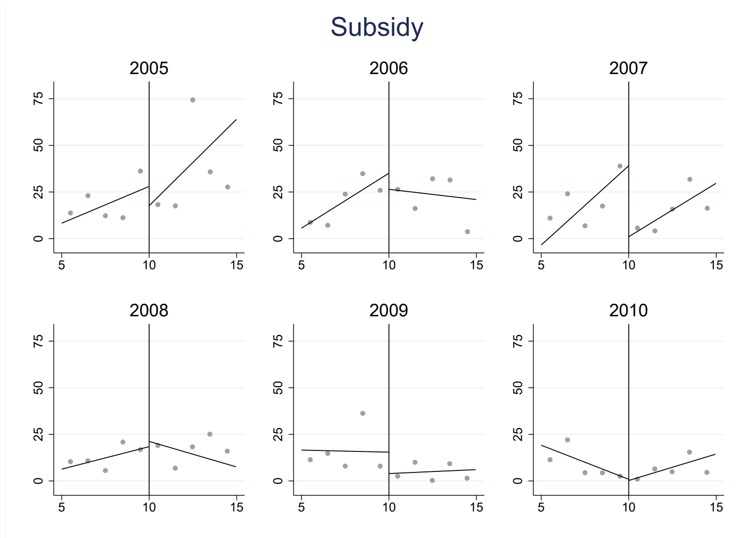
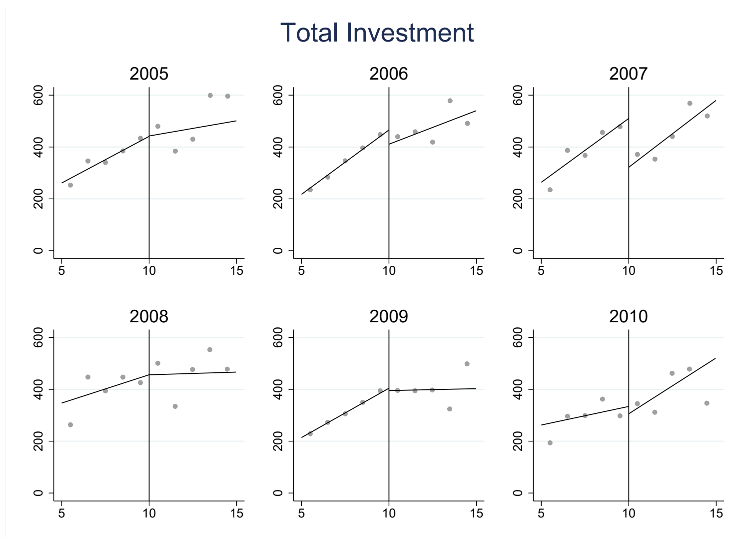


Figure D6: RD: Placebo Thresholds.

Notes: The estimates are from Equation 19. The outcome is investment subsidies in the upper panel and 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 effect should be at the real threshold 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: Placebo Years.

Notes: This figure shows the discontinuity at the balance-sheet threshold for investment subsidies (top) and total investment (bottom). The vertical axis is in thousands of euros, and the horizontal axis is in millions of euros. 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: Summary Statistics.

	Mean	Std. Dev	N
Employment	65.75	76.93	1269
Revenue (EUR M)	16.7	16.5	1273
Wages	34,700	16,900	1269
Production Worker Share	0.40	0.32	1271
College Share	0.37	0.26	1273
Total Investment	377,600	579,000	1273
Investment Subsidies	16,200	127,600	1273
Total Subsidies	23,900	124,600	1273
Subsidized Loans	168,500	1,055,500	1273

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

Table D2: RD: 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

Notes: The estimates are from Equation 19. The outcomes are pre-period averages over years 2000–2004. Standard errors in parentheses, clustered by three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Back to Section D.

Table D3: RD: The First Stage.

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

Notes: The estimates are from Equation 19. The outcomes are 2007 investment subsidies (left) and 2007 total investment (right). The values are in EUR K. Standard errors in parentheses, clustered by three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Back to Section D.

Table D4: RD: The Reduced-Form Estimates.

	(1) Employment	(2) Revenue	(3) Wages	(4) College Share	(5) Educ. Years	(6) Producion 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

Notes: The estimates are from Equation 19. The outcomes are defined in first differences. Standard errors in parentheses, clustered by three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Back to Section D.

E Data and Fieldwork

E.1 Data on Technologies

This section reports details on the technology categories primarily based on the text data.

E.1.1 Uses of Technologies

Process This category contains cases where the firm intends to use the technology to produce the same output type. The use of technologies to automate processes or increase automation in production is part of this category. Typical descriptions: an investment that makes operations more efficient, a productivity-enhancing investment, an investment that increases automation. These descriptions often include details, for example, which part of the production the firm intended to make more efficient. Some applications describe these advances as "solving bottlenecks," complementary to the other elements in the production.

Product This category contains cases where the firm intends to use the technology to produce a new output type. Typical descriptions: diversification of production, e.g., a new product, a new service, or a more comprehensive selection of services; improved production capabilities, e.g., the ability to work with or to manufacture larger items (very common), development of product features, such as increasing quality or the degree of processing, and transitioning to more environmentally sustainable production. This category also contains cases where the firm intends to use the technologies to expand or grow, as most of these cases also explicitly include a description of new types of customers, new output, or new capabilities.

Product and process are two opposites as to whether the improvement is within or between varieties. If the text does not specify the use of the technology on this margin, we code it as NA. Typical NA cases only specify the technology (e.g., a CNC machine) or provide limited information.

E.1.2 Types of Technologies

Automated vs. non-automated This category classifies cases where the technology requires no active user (automated) vs. an active user (non-automated). The classification is based on the specific technology or machinery described in the text and customs data. Automated machinery includes robots, CNC machines, automated conveyor belts, automated welding tools, etc. Non-automated machinery includes not explicitly automated machinery, for example, hand-operated tools, non-automatic welding tools, hydraulic presses, non-automatic machine tools, cutting machines, lifting equipment, pumps, furnaces, and sprayers.

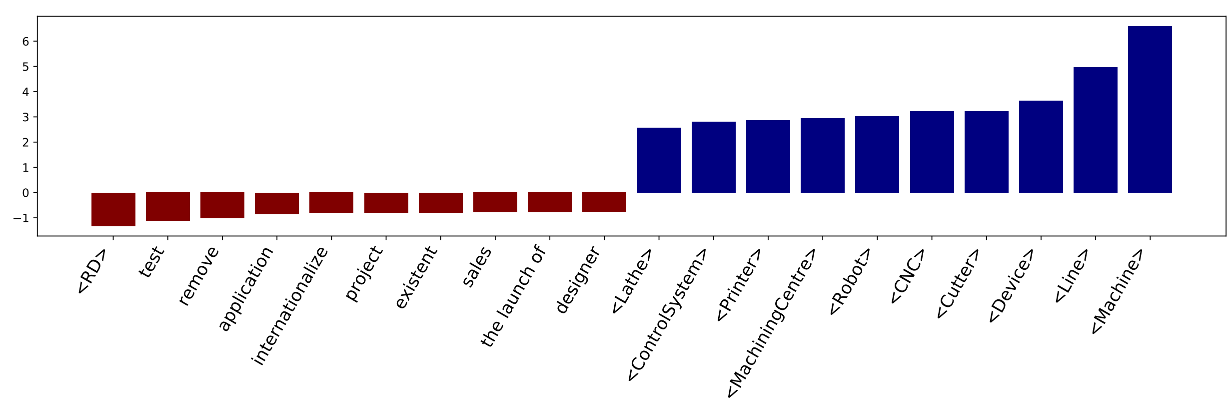
Hardware vs. software This category classifies cases where the technology is physical (hardware) or not physical (software). Typical hardware includes CNC machines, welding robots, laser cutters, bending presses, surface-treatment technologies, robot arms, conveyor belts, sensors, and measurement devices. Typical software includes enterprise resource planning (ERP), computer-aided design (CAD), and production-control software.

Table E1: Summary Statistics: Text-Category Predictions using SVM.

Class	Precision	Recall	F1-score	Test Support	Number of Cases
Not Technology (0)	0.97	0.96	0.96	1550	31022
Technology (1)	0.88	0.92	0.90	571	11887
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 E.

Figure E1: Predictive Features for Technology in the Text Data.



Notes: Top features for predicting technology texts. The y-axis refers to the feature weights from the SVM prediction. The features are translated into English from Finnish. Features in <> refer to compound terms combining similar spelling versions of the same term. Back to Section E.

E.2 Data on Work and Skills

We directly measure individual workers' employment, wages, education, grades, occupations, tasks, cognitive performance, and personality.

Employment and Wages We obtain employment and wage data from the registers maintained by Statistics Finland. The data contain the employment status, wages, and 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 the tax authorities) and direct data collection by Statistics Finland. These registers also record the individuals' age and gender.

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). 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).[47] We normalize both grade measures to have mean 0 and standard deviation 1 within cohorts.

Occupations and Tasks We measure occupations from the employment registers at the 3-digit level in the ISCO classification system. We 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).

To measure the task content of the occupations, we use the European Working Conditions Survey (EWCS). The survey provides information on the tasks workers perform in their jobs. The data are collected through face-to-face interviews every five years. Using these data, we construct occupation-level measures of task intensity for routine, manual, cognitive, and social tasks (see,

[47] We use 9th-grade GPA because only approximately 50% of Finns take the high-school exit exams.

Autor et al. 2003).[48] For example, an occupation is classified as highly routine if the workers in that occupation describe they often perform repetitive and monotonous tasks. The advantage of the EWCS data is that it is based on workers' descriptions of their work; it is available for a specific country and time and is consistent with the European occupational classification.

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 0 and standard deviation of 1 within cohorts. The FDF data are described in Izadi and Tuhkuri (2021a,b).

E.3 Data on Firms

We assemble a large set of data on firms, including the revenue, profits, exports, products, prices, and patents. The data track all firms over time.

Firm Performance The firm-performance measures, revenue, value-added, and profits, are obtained from the Finnish Financial Statement Register. We use two variables to measure productivity: revenue per worker and total factor productivity (TFP) estimated using the Cobb-Douglas production function. We measure profits primarily by the profit margin, defined as profits divided by the revenue. We define the labor share as the wage bill divided by the revenue. We winsorize firms' monetary values at the 5% level.

Exports Exports are measured from the Finnish Customs' Foreign Trade Statistics. We focus on the firms' export status (exporter vs. non-exporter), exports' share of the total revenue, and export destinations.

Products We measure firms' products from the Customs Register at the 6-digit CN classification. We focus on the number of products per firm and product turnover: the number of products introduced and discontinued.

[48] We use similar classifications as Kauhanen and Riukula (2019).

Prices We compute firms' product-level prices from the Customs Register and Industrial Production Statistics. We define product-level prices as the product-level revenue divided by the number of units sold. We harmonize the product categories to be consistent over time. We focus on firm-level average prices computed as an unweighted average. We winsorize price data at the 10% level within product and year.

Patents Patent information comes from the Finnish Patent Database. We focus on the number of new patent applications per firm.

Capital We measure capital from the official records on firms' balance sheets.

Industries We measure industries at a harmonized 2-digit level classification (based on NACE Rev. 2). Our primary industry-level variable is the industry's scope for quality differentiation, which we measure using Rauch (1999), Gollop and Monahan (1991), and Sutton (1998) indices. We also measure industries' automation intensity (Acemoglu and Restrepo, 2020), tradability (Mian and Sufi, 2014) and education level (similar to Ciccone and Papaioannou, 2009).

Subsidies We measure firm subsidies from multiple registers. Two centralized systems (Yrtti 1 and 2) record the ELY Center subsidies. We gained access to these previously unstudied data, which record the application process from submission to decision. We measure other firm subsidies using the Statistics on Business Subsidies data.

E.4 Fieldwork

We conducted fieldwork to understand the changes we document at the level of specific firms and workers. We visited our sample 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 4 hours at each manufacturing plant observing the production and conducting interviews. We also conducted five separate firm interviews (a total of 10 firms).

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; Berger 2013; Piore 2006). 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 30 to 18,000 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. 2019). 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 7 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.[49]

[49]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).

F Mechanism: Predictions

In this Appendix, we collect the predictions from process and product type technological change, adapted from Melitz and Redding (2014).

F.1 Predictions from the Process Type

Process-type technological change has several specific and measurable implications.

Revenue 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:

$$\frac{q(\varphi_1)}{q(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\sigma}, \quad \frac{r(\varphi_1)}{r(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\sigma-1}, \quad \varphi_1, \varphi_2 > 0 \tag{20}$$

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

$$\frac{r(\varphi)}{l(\varphi)} = \frac{w\sigma}{\sigma-1}\left[1 - \frac{f}{l(\varphi)}\right], \tag{21}$$

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

Profits Lower marginal-cost firms earn higher profits. As shown in the main text:

$$\pi(\varphi) = \frac{r(\varphi)}{\sigma} - wf = B\varphi^{\sigma-1} - wf, \quad B = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} w^{1-\sigma} A. \tag{22}$$

Prices The price effect depends on whether the productivity improvement refers to lower marginal costs or a higher quality within the variety. That comes from the fact that the CES preference representation implicitly imposes a choice of units to measure the quantity of each variety. Quantity and quality are perfect substitutes within a variety, and a marginal-cost reduction is equivalent to a quality improvement, up to a new price vector. Firms with lower costs charge lower prices because the equilibrium price for each variety is a constant mark-up over marginal cost, and firms with higher quality charge higher prices because the price for each variety can equivalently be expressed in terms of quality c:

$$p(\varphi)_{cost} = \frac{\sigma}{\sigma-1}\frac{w}{\varphi}, \quad p(\varphi)_{quality} = \frac{\sigma}{\sigma-1} cw. \tag{23}$$

Labor Share If the composite factor of production contains only labor, the structure of the model implies that lower marginal costs reduce the labor share because the firm takes wages w as given and revenue per input increases:

$$\frac{wl(\varphi)}{r(\varphi)} = \frac{\sigma - 1}{\sigma} \left[1 - \frac{f}{l(\varphi)}\right]^{-1}. \tag{24}$$

If the technological change is specifically automation as in Acemoglu et al. (2020b), it substitutes capital for tasks previously performed by labor and reduces the labor share of value added.

Employment and Labor Composition The firms use a composite factor of production L to produce the varieties. The underlying structure of the process change determines how it affects factor composition, including employment. The literature specifies different versions process-type change (e.g., Tinbergen 1975; Katz and Murphy 1992; Autor et al. 2003; Acemoglu and Restrepo 2018).[50]

In the models where technological change simultaneously reduces marginal costs and affects labor composition, technological change is typically assumed to be "skill biased," in the sense that new technologies are more complementary to high-skill workers.[51] The central prediction from these models is that if the firm adopts the technology ($T_I = 1$), the employment share of low-skill, routine, and production workers decreases:

$$s_{l^L}\left(T_I = 1\right) < s_{l^L}\left(T_I = 0\right), \text{ where } s_{l^L} = {l^L}/{\sum_i^{\mathcal{L}} l^i}. \tag{25}$$

[50]The distinction between cost and quality within the variety—while isomorphic in this framework—becomes relevant when considering the factor content of technologies. While the canonical, routine replacement, and automation models can be re-written so that instead of costs, technological change affects quality, their motivation is based on firms' cost-reduction intentions.

[51]In Autor et al. (2003) and Acemoglu and Autor (2011) the effect is mediated through tasks: technologies substitute for a set of tasks (e.g., routine or lower-complexity tasks), in which a set of workers (e.g., lower-skill workers) have a comparative advantage.

F.2 Predictions from the Product Type

Product-type technological change produces a set of distinct observable implications. For clarity, we consider a simplified case of two products.

Revenue Firms that introduce a new variety produce more and earn higher revenues:

$$q = \begin{cases} q\left(\varphi_0\right) \\ q\left(\varphi_0\right) + q\left(E\left[\varphi\right]\right) \end{cases} \qquad r = \begin{cases} r\left(\varphi_0\right) & \text{if } T_E = 0 \\ r\left(\varphi_0\right) + r\left(E\left[\varphi\right]\right) & \text{if } T_E = 1 \end{cases} \tag{26}$$

Products Firms that introduce a new variety produce a larger number of products:

$$\left|\Omega^i_{T_E=1}\right| > \left|\Omega^i_{T_E=0}\right|, \quad \omega \in \Omega \tag{27}$$

where $\left|\Omega^i_{T_E}\right|$ denotes the number of elements in the set of varieties produced by the firm i (measured as produced or exported products or, for example, patents).

Exports If different markets have differentiated preferences, a new variety makes it more likely that the firm starts exporting, exports a larger share of its revenue, or exports to a larger variety of destinations:

$$EXP^i_{T_E=1} > EXP^i_{T_E=0}, \tag{28}$$

where $EXP^i_{T_E}$ denotes the a measure of exporting activity by the firm i.

Inputs Firms that introduce a new variety use more inputs, such as labor:

$$l = \begin{cases} f + \frac{q_0}{\varphi_0} & \text{if } T_E = 0 \\ 2f + f_E + \frac{q_0}{\varphi_0} + \frac{q_1}{E[\varphi]} & \text{if } T_E = 1 \end{cases} \tag{29}$$

Productivity, Profits, and Prices The product-type technological change predicts, on average, zero effects on productivity, the profit margin, and prices because the expected productivity in the new variety is equal to the productivity in the existing variety. The new variety is not uniformly better than an existing variety but new and an imperfect substitute for the existing varieties. In our monopolistic-competition market structure, firms can expand either by improving productivity within a variety or by introducing a new variety, but the firms cannot expand without either action. On average, introducing a new variety appears as if the firm only scales proportionally in size. Zero effects on productivity, prices, and the profit margin combined with a positive effect on revenue are consistent with the new-varieties view.

Labor Composition, Labor Share, and Wages One critical difference between the process and product-type changes is whether technological change is likely to have distributional effects. The product view has no unambiguous basis for expecting a sustained effect on the labor composition or the labor share. The task or skill composition might be different for the new variety, but this likely depends on the particular context.[52] The model predicts zero effects on wages in a competitive labor market because wages are determined in the sectoral equilibrium, and the firm is small relative to the market.

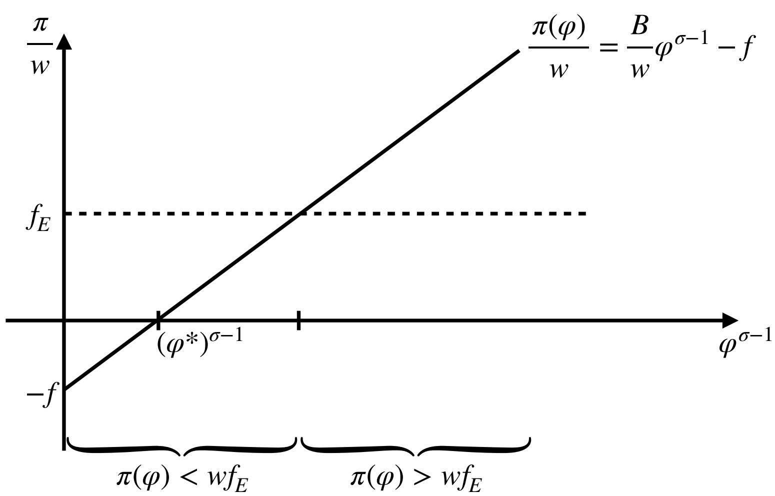


Figure F1: The Product Cutoff.

Notes: Adapted from Melitz and Redding (2014). Back to Section 6.

[52]In the Nelson and Phelps (1966) view, skills are complementary to the adoption of new technologies: New technologies could induce a temporary increase in skill demand, before or after the adoption event.

G Research Design: Theoretical Framework

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).

G.1 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:

$$E_0 \sum_{t=0}^{\infty} B_t Y_t^i \tag{30}$$

subject to

$$Y_t^i = A_t^i \theta_t^i F\left(T_t^i; L_t^i\right) - D_t^i \Theta_t^i \tag{31}$$

$$T_{t+1}^i = \begin{cases} (1-\delta)T_t^i & \text{if } D_t^i = 0 \\ \tau_{t+1}^i & \text{if } D_t^i = 1 \end{cases} \tag{32}$$

where $\tau_{t+1}^i = \mu_t^i \tau_t^i$ and $\mu_t^i \geq 1$ is the rate of exogenous technological progress.[53] 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 (30) 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 (31) 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,

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

its installation costs, other fixed adjustment costs, and a temporary output loss. 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.[54] The intuition is that investment temporarily diverts resources away from production.

The third equation (32) 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).

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

1. Replacement cycle: The underlying deterministic replacement cycle—driven by depreciation of capital δ and the common exogenous technological progress μ_t^i—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, increase the benefits from the technology investment and increase the likelihood of the investment.[55]

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 G.3. In the detailed version, we characterize the solution by a hazard function $H(t, A)$, the probability of adoption if the current technology stock is t and the state of productivity is A.

[54]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.

[55]Within the framework, this mechanism works analogously to the aging of technology.

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 nonconvex. 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.

G.2 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.[56]

The firm's production function is written as:

$$Y = F\left(T; L\right) \tag{33}$$

where T is the technology of our focus and L is a vector of multiple other factors. An element L_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 $W_i > 0$. For the purposes of this analysis, these relative prices reflect potential

[56] Hamermesh 1989analyzes 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.

relative productivity effects from technology T. The conditional factor demands are characterized as solutions to the cost-minimization function:

$$\min_{(L_1...L_n)} \sum_{i=1}^{n} W_i L_i \quad \text{subject to} \quad F(T; L_1...L_n) > Y \tag{34}$$

The minimum value of the total cost is the cost function $C(W_1...W_n, Y)$. Under this framework, it satisfies the standard properties of a cost function. It is increasing, homogeneous of degree 1, and concave in $(W_1...W_n)$, 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:

$$\bar{L}_i = C_{W_i}(W_1...W_n, Y) \tag{35}$$

where $\bar{L}_i$ denotes the factor demand for the factor L_i and C_{W_i} denotes the partial derivative of the cost function C with respect to price W_i. In other words, the cost function says that the conditional factor demands can be characterized through a shock to the price vector $(W_1...W_n)$.

The expression (35) 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 $(W_1...W_n)$ in a way that the factor demands $\bar{L}_i$ would shift toward high-skill labor $L_H \in L$.

G.3 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:

$$E_0 \sum_{t=0}^{\infty} \beta_t^i y_t^i \tag{36}$$

subject to:

$$y_t^i = A_t^i \theta_t^i t_t^i - D_t^i \Theta^i \tag{37}$$

$$t_t^i = \begin{cases} \rho t_t^i & \text{if } D_{t-1}^i = 0 \\ 1 & \text{if } D_{t-1}^i = 1 \end{cases} \tag{38}$$

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 states are the age of the technology stock (t) and the productivity shock (A). The value function $V(t, A)$ satisfies the functional equation:[57]

$$V(t, A) = \max \left[V^Y(t, A), V^N(t, A) \right] \tag{39}$$

where

$$\begin{aligned} V^N(t, A) &= AF(t) + \beta E_{A'|A,\varepsilon'} V(\rho t, A') \\ V^Y(t, A) &= AF(t)\lambda - \Theta + \beta E_{A'|A} V(1, A') \end{aligned} \tag{40}$$

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 Θ^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, $h = (t, A)$. We characterize the solution by a hazard function $H(t, A) \in [0, 1]$, the probability of adoption if the current technology stock is t and the state of productivity is A. The cutoff is visualized in Figure G1.[58]

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 $\beta < 1$. □

[57] For expositional clarity, we drop the subscript t and the superscript i.

[58] While given the state vector, the probability of an investment spike is deterministically either zero or one, this hazard is a useful object because the idiosyncratic shocks are generally not measured in the data.

Proposition 2. *$H(t, A)$ 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

$$V^N(t, A) \equiv At + \beta V(\rho t, A') \tag{41}$$

$$V^Y(t, A) \equiv At\lambda - \Theta + \beta EV(1, A') \tag{42}$$

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 (41) and (42):

$$\Delta(t, A) = At(\lambda - 1) - \Theta + \beta E_{A'}\left[V(1, A') - V(\rho t, A')\right] \tag{43}$$

where $V(t, A) \equiv \max\left\{V^Y(t, A), V^N(t, A)\right\}$. The first term is decreasing in t. The last part of this expression is also decreasing as t increases since $V(t, A)$ is an increasing function of t. Thus $\Delta(t, A)$ is decreasing in t. This proves that given the state of productivity A, the hazard $H(t, A)$ is decreasing in t. □

Proposition 3. *$H(t, A)$ is decreasing in Θ.*

Proof. Using the definition of $\Delta(t, A; \Theta)$, we have

$$\Delta(t, A; \Theta) = At(\lambda - 1) - \Theta + \beta E_{A'}\left[V(1, A'; \Theta) - V(\rho t, A'; \Theta)\right] \tag{44}$$

The term $\Delta(t, A; \Theta)$ is decreasing in Θ and thus the result is immediate. □

Proposition 4. *$H(t, A)$ 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

$$\Delta(t, A) = -\Theta + \beta E_{A'}\left[V(1, A') - V(\rho t, A')\right] \tag{45}$$

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. □

Proposition 5. *$H(t, A)$ 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

$$\Delta(t, A) = -\Theta + \beta E_{A'|A}\left[V(1, A') - V(\rho t, A')\right] \tag{46}$$

The expectation over A' is conditional on A so that the current state of productivity does influence 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

$$\int_t^1 V_{tA}(z, A)dz > 0 \tag{47}$$

for all t. This condition is satisfied if $V_{tA}(t, A) > 0$ for all (t, A). From (41) and (42) 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 (41) is a sequence of current period returns with positive cross partials between t and A. From (42), $V^Y(t, A)$ has a positive cross partial since the second term is independent of t. □

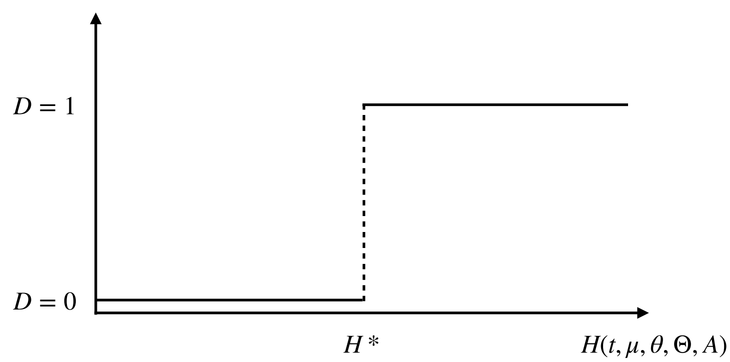


Figure G1: The Cutoff.

Notes: Threshold model. The technology adoption model rationalizes firms' spiky investment behavior. In the model, the firm makes a technology investment $D = 1$ if adoption likelihood H crosses a threshold.
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H Related Research

The Effect of Technology on Employment and Skill Demand This paper contributes to the active literature on the effects of technologies on employment and skill demand, surveyed by Acemoglu (2002b), Card and DiNardo (2002), and Acemoglu and Autor (2011), and specifically to the evidence on the effects of advanced technologies in manufacturing firms.

The closest papers to our research report similar findings. Doms et al. (1997) report little correlation between technology adoption and skill upgrading in US manufacturing, focusing on similar technologies (e.g., CNC machines and robots) and industries (e.g., fabricated metal products) as we do. Bartel et al. (2007) show that valve plants that adopted new IT-enhanced equipment shifted their business strategies toward producing more customized products, consistent with our interpretation and evidence. They report changes in machine operators' skill requirements, not in the traditional sense of replacing production workers or increasing the demand for formal education, but, for example, increased focus on setting up, monitoring, and correcting the new machinery, consistent with what we find in our fieldwork. Weaver and Osterman (2017) emphasize that most manufacturing work does not require high levels of formal education.

Additionally, Criscuolo et al. (2019) analyze the effects of an investment-support program in UK manufacturing using an instrumental variables (IV) strategy, and find evidence for a positive treatment effect on employment. Similarly, Curtis et al. (2021) find positive employment effects and no skill bias from a capital-investment tax policy in the US. Pavcnik (2003) documents that plants' adoption of foreign technology is not associated with skill upgrading, and Nilsen et al. (2009) find no evidence that investment spikes are associated with changes in the composition of the workforce. In recent work, Genz et al. (2021) report that the adoption of CNC machines and industrial robots led to increases in employment, including production workers, and did not coincide with a higher demand for more educated workers, and Koren et al. (2020) report positive wage effects on machine operators exposed to imported machinery. Extensive qualitative evidence corroborates these observations (e.g., Sohal 1996; Small 1999; Berger 2013, 2020).

Contemporary evidence on effects of robots and automation in firms supports our findings (Acemoglu et al., 2020b; Aghion et al., 2020; Bonfiglioli et al., 2020; Dixon et al., 2021; Eggleston et al., 2021; Koch et al., 2021; Stapleton and Webb, 2020). Most of it finds positive effects on employment, no negative effects on low-skill workers, and no major changes in skill composition.[59] Dixon et al. (2021) document that robot adoption is motivated by improving product and service quality, not reducing labor costs. Koch et al. (2021) report that the employment increases applied to

[59] Humlum (2019) provides a contrasting view that robot adoption affects firm-level skill composition.

all types of workers and provide evidence supporting the idea that exports facilitate the expansion effects of technologies. Aghion et al. (2020) report no different effects across skill groups. In contrast, Acemoglu et al. (2020b) estimate 0–1.6% declines in the production employment share while focusing on unskilled industrial jobs. The most significant difference between these studies is the result on the labor-cost share: e.g., Acemoglu et al. (2020b) and Koch et al. (2021) find labor share declines (3–5% and 5–7%), but Aghion et al. (2020) find no change. One way to reconcile these estimates is that the former two focus exclusively on robots, while the latter uses a broader measure of technologies. Robots specifically appear to reduce the labor share, while other advanced technologies appear to have neutral effects.[60]

Our results are different from some firm-level studies that focus on different types of technologies. Generally, the evidence suggests that investments in digital technologies may have been skill biased—in contrast to typical physical technology investments in manufacturing. For example, Akerman et al. (2015) study the regional rollout of broadband internet in Norway using a difference-in-differences design. More effective internet is a critical technological advance, but different from new manufacturing technologies, and we would expect potentially different effects. The estimates indicate that college-educated workers' wages and employment increased modestly in places that received faster internet. There were, on average, no negative effects on non-college and manual workers, but a small negative effect on high-school dropout and routine (cognitive) workers' wages. In another example, Gaggl and Wright (2017) estimate the effects of a temporary tax allowance on ICT investments, primarily software, in the UK using an RD design. They find that ICT subsidies induced increases in employment and wages. Workers performing non-routine cognitive tasks experienced the increases, routine cognitive workers experienced modest declines, and manual workers experienced no change. Furthermore, Bresnahan et al. (2002) report complementarities between skill and IT equipment, such as computers. Caroli and Van Reenen (2001) document that organizational change, Boler (2015) that R&D, and Leiponen (2005) and Lindner et al. (2021) that innovation is complementary to skills. The contrast to these papers highlights that distinct technological advances may induce distinct effects. Specifying the technologies in focus, as these papers do, is valuable for building cumulative evidence.

Our results are also different from studies that specifically focus on the replacement effects of technologies. These papers' results highlight that some technological changes may also replace workers. Bessen et al. (2020) study the effects of automation events on incumbent workers, measuring automation from firms' expenditures on third-party automation services. Our event-study design builds on their approach. The main difference is that their approach is designed to capture

[60]Similarly to Koch et al. (2021), we find zero effects on the labor share from advanced technologies.

the replacement effects; they isolate what happens to the incumbent workers when firms automate. They find that a large increase in automation expenditure makes workers more likely to separate from the firm. The effects are meaningful but modest in size: the average earnings loss is 2%. They detect no differences by wage groups, often used as a proxy for skill. In another study, Feigenbaum and Gross (2021) analyze the replacement of telephone operators for mechanical switching by AT&T in 1920–1940. This eliminated most of these jobs, did not reduce future cohorts' overall employment, but caused adverse effects on incumbent operators.

Our results are different from several macro-level studies. We organize the macro evidence into indirect and direct approaches. The indirect approaches include Katz and Murphy (1992); Beaudry et al. (2010); Lewis (2011); Acemoglu and Restrepo (2020); Dauth et al. (2021). These papers report skill bias from technological advances, partly for different reasons. The main argument in Katz and Murphy (1992) is that to reconcile the increased college wage premium with the increased supply of college-educated workers, substantial growth in the demand for more-educated workers is necessary. This demand growth is sometimes interpreted as skill-biased technological change. Similarly, Beaudry et al. (2010) and Lewis (2011) evaluate technology-skill complementarity using variation in skill supply. They find that the local skill supply predicts increases in technology adoption. This observation is consistent with our results, despite the seeming contradiction: Technology adoption may be easier in places with more high-skill workers, even if technologies do not directly affect skill composition within firms.[61] Acemoglu and Restrepo (2020) and Dauth et al. (2021) also analyze technology-skill complementarity indirectly at the local level in the US and Germany. They focus on the places' exposure to robots based on their pre-existing industry structure. This exposure approach has many clear advantages, including the possibility to analyze equilibrium effects, but the focus on variation stemming from pre-existing industries may leave out technologies' other effects than replacement, such as using technologies to launch new products.

The direct approaches include Berman et al. (1994); Autor et al. (1998); Krusell et al. (2000); Autor et al. (2003); Spitz-Oener (2006); Michaels et al. (2014), and Graetz and Michaels (2018). These papers also report skill bias from technological advances. Part of the direct macro evidence considers different technologies. Berman et al. (1994); Autor et al. (1998); Spitz-Oener (2006); Autor et al. (2003), and Michaels et al. (2014) focus on the effects of ICT, especially computers. Another part, e.g., Krusell et al. (2000) and Graetz and Michaels (2018), considers similar technologies to our study and still finds skill bias. While we do not have a complete explanation for

[61] This interpretation is consistent with the technology view emphasized by Nelson and Phelps (1966); Welch (1970); Schultz (1975), where education fosters the process of technology adoption and with models of directed technological change (Acemoglu, 1998, 2002a). The interpretation is also consistent with Doms et al. (1997), who find that plants that adopted more technologies employed more educated workers *before* adoption.

the difference, micro and macro estimates may be different and still consistent with each other for several reasons, for example, due to externalities (see, e.g., Oberfield and Raval 2021) or if technologies induce broad economy-wide changes.[62] Exploring these channels is a promising avenue for future research.

To summarize the evidence from the prior literature, we make six observations:

1. According to contemporary evidence, technology investments in manufacturing have not appeared to cause adverse effects to workers generally.

2. Advanced technologies in manufacturing, such as CNC machines, appear to have caused increases in employment and no changes in the skill composition at the firm level.

3. Robots, specifically, also appear to have caused increases in employment and no significant skill bias at the firm level but may have reduced the labor-cost share.

4. Digital technologies—ICT, computers, software, and the internet—appear to have been skill biased for cognitive work at the micro and macro levels.

5. Some technological advances, such as automation consulting services, appear to have caused some worker displacement.

6. Local skill supply appears to foster technology adoption.

Our results corroborate 1–3 and are consistent with 4–6. These conclusions are tentative due to the still limited evidence.

The Effects of Industrial Policy Our analysis contributes to the literature on industrial policy. By industrial policy, we refer to policies that stimulate specific economic activities and promote economic development. These policies are common. For example, EU countries spent EUR 134.6 billion on government subsidies to the private sector (designated as state aid) in 2019, about .81 % of the EU's GDP (The EU State Aid Scoreboard, 2020). The objectives and effects of industrial policy are debated (Lane, 2020).

This paper focuses on a particular type of firm subsidy: a lump-sum transfer to increase technology adoption in manufacturing. Manufacturing subsidies are widespread (see, e.g., Gruber and

[62] These reasons include: 1) externalities, e.g., in the product market, the intermediate input market, the factor market, or due to technological externalities, 2) compositional effects, e.g., through expansion and contraction of firms and industries, 3) technologies creating new areas in the economy, e.g., video games, the Apollo program, or Google, and 4) technologies directly inducing macro-level changes, e.g., self-booking platforms displacing travel agents, the internet changing job search, or technologies inducing broad organizational and cultural changes. The papers addressing externalities and compositional effects include Acemoglu et al. (2020b); Aghion et al. (2020); Humlum (2019); Koch et al. (2021); Restrepo and Hubmer (2021), and Oberfield and Raval (2021).

Johnson 2019) but understudied. Berger (2013) argues that these types of programs have contributed to the productivity and growth opportunities in German SME manufacturing, and lack of them may contribute to the relatively low productivity growth of US manufacturing. Our evidence from Finland shows that it is possible to increase technology adoption by targeted subsidies and, by doing so, induce increases in the subsidized firms' employment, revenue, and exports.

Empirical challenges in the industrial policy literature are similar to those in the literature on technology and work. There are different types of industrial policies in different contexts, and evaluating them is challenging. This paper provides new quasi-experimental estimates of firm subsidies' effects in a specific context. In addition to the research we mentioned earlier, Takalo et al. (2013) and Einio (2014) analyze Finnish R&D subsidies.

Production and Innovation Our analysis relates to the research on firms' product and export choices, intermediate inputs, and innovation.

Recent research documents that becoming an exporter stimulates technology adoption and product-quality upgrading in firms (Verhoogen, 2008; Lileeva and Trefler, 2010; Bustos, 2011; Kugler and Verhoogen, 2012). Our research finds that technology adoption also induces firms to become exporters and introduce new product varieties—the complementarity between technology and exporting appears to operate in both directions.

Access to new machinery is an example of access to new intermediate inputs. Existing research finds that access to new imported inputs fosters introducing new product varieties and productivity (Goldberg et al., 2010; Koren et al., 2020). Our research corroborates the result on product varieties. In related work, Bernard et al. (2010, 2011) analyze the role of product switching as a source of reallocation within firms, and Hausmann et al. (2007) consider product-specialization patterns' implications for growth.

Our theoretical framework builds on the literature on heterogeneous firms and trade, reviewed by Melitz and Redding (2014). We use modeling techniques from Bustos (2011) to capture the technology-adoption decisions by heterogeneous firms. We find that the monopolistic competition view of the industrial manufacturing market is consistent with our quantitative and qualitative evidence. More generally, our research provides empirical evidence to enrich the models of firm-level technological change and innovation (e.g., Hopenhayn 1992; Ericson and Pakes 1995; Klette and Kortum 2004; Acemoglu et al. 2018; Kerr et al. 2020).[63]

[63] Back to Section 1.