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Fredrik Heyman, Pehr-Johan Norbäck and Lars Persson

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

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Fredrik Heyman
Research Institute of Industrial Economics (IFN) and Lund University

Pehr-Johan Norbäck
Research Institute of Industrial Economics (IFN)

Lars Persson
Research Institute of Industrial Economics (IFN), CEPR and CESifo

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Abstract

We construct an oligopolistic model with heterogeneous firms where new automation technologies displace workers. We show that both leading and laggard firms increase their productivity when automating—but only laggards increase employment of automation-susceptible workers. We test the model's predictions using Swedish matched employer–employee data combined with a novel firm-level automation measure of worker exposure to new technologies. Our empirical results strongly support a relationship between workforce exposure to automation and productivity that varies by firm type. Consequently, a diversity of firm types may function as insurance against excessive labor demand reductions in periods of fast technological change.

Keywords: Automation; Robotics; Job displacement; Firm Heterogeneity; Productivity; Matched employer–employee data

JEL classification: D2; J24; L2; O33

*Research Institute of Industrial Economics (IFN), P.O. Box 55665, SE-102 15 Stockholm, Sweden. Email: fredrik.heyman@ifn.se, pehr-johan.norback@ifn.se, and lars.persson@ifn.se. Fredrik Heyman gratefully acknowledges financial support from the Johan and Jakob Söderbergs Stiftelse and the Torsten Söderbergs Stiftelse. All authors gratefully acknowledge financial support from the Marianne and Marcus Wallenberg Foundation and the Jan Wallander och Tom Hedelius Stiftelse. We have benefited from the feedback provided by participants at seminars and conferences.

1. Introduction

Firms are increasingly able to automate job tasks using advances in robotics, machine learning and other forms of artificial intelligence (AI). Examples include coordinating production and transportation, picking orders in a warehouse and providing automated customer service. Recent studies show that new automation technologies affect firms and workers in different ways. For instance, Graetz and Michaels (2018) use the variation in robot usage across industries in different countries and find that industrial robots increase productivity and wages but reduce the employment of low-skill workers. Acemoglu and Restrepo (2020) rely on the same IFR data and find robust adverse effects of robots on employment and wages in the US commuting zones most exposed to automation by robots. Webb (2019) uses the overlap between the text of job task descriptions and the text of patents to construct a measure of the exposure of tasks to automation. When applying his method to software and industrial robots, he finds that occupations highly exposed to automation technologies have seen a decline in employment and wages. Webb (2019) also uses his approach to predict the impact of AI, finding that, in contrast to software and robots, AI is directed toward high-skilled tasks.

However, firms' incentives to automate likely differ substantially across different types of firms. Indeed, Syverson (2011), in his overview article, concludes that significant and persistent differences in productivity levels across businesses are ubiquitous and, to a large extent, depend on firm asymmetries in firm-specific assets. Management has been shown to significantly impact productivity (Bloom and Van Reenen, 2007; Gibbons and Henderson, 2012; Giorcelli, 2019). OECD (2021) finds that workforce composition accounts for nearly one-third of the labor productivity gap between medium- and top-performing firms within the same sector. However, workforce composition in combination with traditionally measured capital still accounts for only a portion of the productivity differences, leaving a significant share unexplained. This unexplained share may be related to differences in hard-to-measure firm-specific capital and interactions between different types of capital. The success of implementing new technologies thus likely depends on firm-specific assets, which to a considerable extent today consist of intangible assets such as workforce skill level, blueprints, patents and company culture inside the firm (Haskel and Westlake, 2017). Employees and firm-specific capital are thus closely intertwined. Therefore, firms endowed with different combinations of firm-specific capital may implement new technologies differently, which may have an impact on their productivity performance.

However, knowledge of how firm heterogeneity affects the implementation of automation technologies is scarce. For instance, do firms with highly educated employees and managers and firms with less educated employees and managers implement automation technologies differently, and how may this affect productivity and occupational dynamics? The purpose of this paper is to enhance our knowledge on these matters.

To capture these elements in an automation-driven industrial restructuring process, we take as our starting point that firms differ in their possession of firm-specific assets. Today, these firm-specific assets are, to a significant extent, intangibles such as software, data, blueprints, patents, trademarks, organization, and employee training. We refer to firms with low amounts of firm-specific assets as "laggard firms" and firms with high amounts of firm-specific assets as "leading firms". We assume that organizing and managing firm-specific assets requires skilled labor and that ownership of more firm-specific assets requires more skilled labor. Firms are active in imperfectly competitive product markets and can invest in new automation technologies to automate their production and displace less educated production workers.

We show that only laggard firms increase the hiring of production workers when investing in the new automation technology. The reason is that increasing investment in new automation technology has two effects on the demand for production workers. First, the implementation of the new automation technology reduces per unit output demand for production workers—this is the *displacement effect*. However, there is also a second effect—the *output expansion effect*—that increases the demand for production workers. For leading firms, the displacement effect dominates the output expansion effect, and demand for production workers falls. The reason is that leading firms have larger output and, hence, more people employed and have more to gain from implementing the new labor-saving automation technology.[1] For laggard firms, the displacement effect is weaker: their inherently lower output and employment reduce their incentives to invest substantially in the new automation technology. For laggard firms, the output effect then dominates, increasing the demand for production employees.

We then proceed to test these predictions on Swedish matched employer–employee data. Sweden has been at the forefront of implementing new automation technology in its business sector. Sweden is, therefore, a suitable country to study the influence of new automation technology on labor demand and productivity on a larger scale. Our analysis uses comprehensive and detailed Swedish matched employer–employee data from 1996 to 2015. The use of detailed information on firms, plants, and individuals working for the firms makes it possible to analyze issues related to implementing new automation technology on job and productivity dynamics in greater detail than most other international studies have done.

While our data contain abundant information on firms and their employees, we—like the authors of most other related studies—do not have access to detailed information on firms' investments in automation technologies. We therefore adopt an indirect estimation strategy. We first calculate a novel measure of a firm's workforce automation probabilities based on the estimated automation probabilities at the occupational level derived by Frey and Osborne (2017) and Webb (2019). This firm-specific measure reveals the extent to which a firm's workforce can be replaced by automation in general or through the use of software and robots. We then use this firm-level exposure measure to identify how the implementation of automation technology affects the occupational mix and productivity development in different types of firms.

We note that our theoretical model predicts that only laggard firms increase their hiring of production workers while all firms increase their productivity when implementing new automation

[1] Using a new module in the Annual Business Survey covering firms across all US sectors, Acemoglu et al. (2021) show that the largest firms in an industry are 1.7 times more likely to use automation technologies than the median firm.

technologies. This suggests that exposure to automation and productivity should be positively correlated in laggard firms. In contrast, in leading firms, automation and productivity should be negatively correlated. How then do we identify laggard and leading firms? From the theory, firm heterogeneity is determined by firms' different possession of firm-specific assets or intangible assets such as patents, management, know-how or employee training and experience. Leaders are thus firms with large amounts of firm-specific assets, whereas laggards are firms with small amounts of firm-specific assets. Under the assumption that firm-specific assets require skilled labor to be efficiently used, we show that leading firms—for which exposure to automation and productivity should be negatively correlated—are firms with high workforce skill intensity, while laggard firms—for which exposure to automation and productivity should be negatively correlated—are firms with low skill intensity.

To explore these predictions, we estimate panel data models with firm fixed effects (which control for unobserved differences in firm-specific assets), regressing productivity on firms' exposure to automation and the interaction between exposure to automation and the share of skilled workers (plus additional controls). By exploiting the within-firm variation, we estimate the partial correlation between employees' exposure to automation and productivity arising from firms' unobserved investments in automation, which—according to our theory—should differ by firm type.

The empirical results give strong support for our theoretical prediction of a correlation between productivity and workforce exposure to automation that varies by firm type. We find that an increase in the exposure to automation is associated with an increase in productivity in laggard firms, i.e., firms for which the share of skilled labor is sufficiently small. In leading firms, i.e., firms with a sufficiently high skill share, a decrease in exposure to automation is associated with an increase in productivity. Put differently, the estimates imply that in laggard firms, an increase in productivity is associated with a shift in the mix of workers toward occupations more susceptible to automation. In leading firms, the increase in productivity is associated with a shift in the mix of workers *from* occupations more susceptible to automation *toward* occupations less susceptible to automation.

To deal with the potential endogeneity associated with the relation between productivity and workforce automation probabilities, we use aggregate changes in the employment structure and workforce automation probabilities at the national level (Finland and Sweden) as a shift-share instrument for firm-level workforce automation probabilities. When using this instrument, we find that the IV results are similar to the OLS results in that productivity and exposure to automation are positively (negatively) correlated when the skill share is sufficiently low (high). There is also consistency in the estimates. Almost regardless of specification (OLS or IV) or the chosen measure of exposure to automation, we find a stable range of cutoffs in skill intensity, where laggard firms are found to be firms in which less than 40% to 60 % of employees have tertiary education while leaders are firms with skill intensities above this range. We also explore other measures of firm heterogeneity, such as the (average) age of workers or their (average) work experience. We then find a positive correlation between productivity and exposure to automation in firms with younger or less experienced workers (laggard firms), while this correlation is negative for firms with older or more experienced workers (leading firms).

In the final part of the paper, we investigate how product market competition affects our results. We show that when competition in the product market intensifies, the output expansion effect in laggard firms may subside due to aggressive competition from leading firms. The strong expansion of output in leading firms may induce laggard firms to reduce their employment of production workers. However, aggressive expansion of output in leading firms requires increased employment, which increases the incentive to invest in more automation—and, therefore, both leading and laggard firms may reduce production employment in the process. Using the product market competition measure developed by Boone (2008a,b), we explore how stronger product market competition affects our empirical results. As predicted, we find that our benchmark results of productivity and exposure to automation being positively correlated in laggard firms—but negatively correlated in leading firms—hold up in industries with a low level of competition while this correlation essentially disappears in industries with higher level of competition.

The paper proceeds as follows. Section 2 describes the related literature. Section 3 presents the theoretical model that we use to examine how investment in automation technologies affects leading and laggard firms' productivity and occupational dynamics and to derive predictions for our empirical analyses. In Section 4, we conduct the empirical analysis. Section 5 extends the benchmark monopoly model to an oligopoly setting. Finally, Section 6 concludes the paper. In the appendix, we present several extensions to the model, e.g., relaxing some of the assumptions made in the benchmark model.

2. Related literature

Our paper relates to the literature that examines the impact of investments in automation technologies on employment. Worker displacement plays a central role in this literature, as machines take over tasks previously performed by humans (Autor et al. 2003; Acemoglu and Autor 2011; Benzell et al. 2016; Susskind 2017; Acemoglu and Restrepo 2018a,b, 2019a,b). In their overview article Aghion et al. (2022) describe two different views on how automation may affect employment. One approach focuses on that firm automation will reduce employment (a negative "direct effect"), even if new jobs are created because of declining equilibrium wages induced by job destruction (a positive "indirect effect"). A second approach stresses that automating firms increases their productivity. This enables them to reduce their prices and increase the demand for their products, resulting in higher employment (a positive "direct effect"), potentially at the expense of employment in their competitors (a negative "indirect effect" through business stealing). Bessen (2019) proposes a demand satiation model that can explain the growth and subsequent decline in employment over time when a new technology is introduced. Hubmer and Restrepo (2021) develop a heterogenous firm model showing that a positive technology shock can reduce the aggregate labor share while the median firm's labor share rises. Large firms find it profitable to automate, but due to the fixed cost of adoption, the median firm does not.

We contribute to this literature theoretically by proposing a model where heterogenous firms invest in automation technologies that substitute for labor used in production. We show that both leading and laggard firms invest in automation in response to new technological opportunities and increase their productivity. However, only laggard firms increase their hiring of workers susceptible to automation. In laggard firms, the increase in labor demand from output expansion dominates the reduction in labor demand from displacement. The reason is that the smaller initial size of a laggard firm limits the incentives to investment in automation and, therefore, the output expansion effect dominates the displacement effect. However, when product market competition intensifies, the output expansion effect is weakened in laggard firms, and investments in automation may lead to lower production employment in both leading and laggard firms.

We also make an empirical contribution to the literature. The empirical work on the implications of investments in automation for labor demand has thus far focused mainly on robotics. Using IFR data similar to those in Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), Dauth et al. (2021) analyze Germany. They find no evidence that robots cause total job losses but do find that they affect employment composition. Koch et al. (2019) show that firms that adopt robots experience net employment growth relative to firms that do not, and Dixon et al. (2019) find that a firm's employment growth increases in its robot stock. Humlum (2019) uses Danish firm-level robot data and finds that increased robot usage leads to an expansion of output, layoffs of production workers, and increased hiring of advanced employees. Aghion et al. (2020) use microdata on the French manufacturing sector and estimate a positive impact of automation on employment, including for unskilled industrial workers. Moreover, they find positive employment responses to automation only in industries that face international competition. Hirvonen et al. (2022) examine a technology subsidy program in Finland that induced increases in technology investment, showing that firms used new technologies to produce new products rather than to replace workers.

We contribute by proposing a new firm-level measure of workforce exposure to automation technologies based on the work by Webb (2019) and Frey and Osborne (2017). This measure enables us to examine the effects of improved automation opportunities on different types of firms. Our proposed firm-level measure also allows us to test our predictions on firms in all sectors of the economy—not only in manufacturing, where robot data is mainly available. We find support for the predictions derived in our proposed theoretical model in detailed matched employer–employee data for Sweden spanning the period 1996–2015, using a shift-share IV design to address endogeneity problems. In particular, we show that the (within-firm) correlation between productivity and employment in occupations susceptible to automation depends on firm type—where productivity and employment in occupations susceptible to automation is only positively correlated in laggard firms. However, this pattern also depends on the intensity of product market competition and, in particular, when competition in the product market becomes tough, the employment creating effect in laggard firms is weakened.

3. A simple model of investment in automation technologies with leaders and laggards

To examine how firm heterogeneity and market power affect the productivity and occupational dynamics associated with investments in automation technology, we develop a simple partial equilibrium model in which (i) firms in imperfectly competitive markets invest in automation technologies that displace (less educated) production workers, (ii) firms are heterogenous in their possession of preexisting firm-specific assets, and (iii) the usage of firm-specific assets requires skilled labor to be used efficiently.

3.1. Preliminaries

3.1.1. Consumers

Consider an industry with n firms indexed $i = \{1, 2, ...n\}$, each producing a single differentiated product. A representative consumer has quadratic quasi-linear preferences over consumption of the n products and the consumption of an outside good:

$$U(\mathbf{q},m) = \sum_{i=1}^{n} a_i q_i - \frac{1}{2}\left[\sum_{i=1}^{n} q_i^2 + 2\lambda \sum_{i=1}^{n}\sum_{j\neq 1}^{n} q_i q_j\right] + q_0, \tag{3.1}$$

where $a_i > 0$ is a firm-specific demand parameter, q_i is the consumption of product i, q_0 is the consumption of the outside good, and $\lambda \in [0, 1]$ captures the degree of product differentiation.

The representative consumer faces the budget set

$$\sum_{i=1}^{n} P_i q_i + q_0 = m, \tag{3.2}$$

where m is exogenous consumer income and P_i is the price of product i. The price of the outside good is normalized to unity. Solving for the amount of consumption of the outside good, q_0, from the budget constraint (3.2), the direct utility in (3.1) can be rewritten as

$$U(\mathbf{q},m) = \sum_{i=1}^{n} (a_i - P_i)\, q_i - \frac{1}{2}\left[\sum_{i=1}^{n} q_i^2 + 2\lambda \sum_{i=1}^{n}\sum_{j\neq i}^{n} q_i q_j\right] - m. \tag{3.3}$$

Taking the first-order condition for utility maximization, $\frac{\partial U}{\partial q_i} = 0$, we obtain the inverse demand facing each firm:

$$P_i = a_i - q_i - \lambda \sum_{j\neq i}^{n} q_j, \qquad i = \{1, 2, ...n\}\,. \tag{3.4}$$

3.1.2. Firms

Now consider firms. Let us first simplify such that each producer is a monopolist in its variety i. Setting $\lambda = 0$ in (3.4), the maximization problem of firm i is

$$\begin{aligned}
\max_{\{q_i,k_i\}} \pi_i &= \underbrace{P_i(q_i)\cdot q_i}_{\text{Revenues}} - \underbrace{w_L \cdot L_i(q_i,k_i)}_{\text{Wage costs: production}} - \underbrace{C(k_i)}_{\text{Investment costs}} - \underbrace{w_H\cdot(f_i+\phi k_i)}_{\text{Wage costs: management}}, && (3.5)\\
s.t &: P_i(q) = a_i - q_i,\ a_i = a(I_i),\ a'(I_i) > 0. && (3.6)\\
&: L_i(q,k) = l_i(k_i)\cdot q_i, && (3.7)\\
&: l_i(k_i) = c_i - \gamma k_i,\ \gamma > 0,\ c_i = c(I_i),\ c'(I_i) < 0. && (3.8)\\
&: C(k_i) = \frac{\mu}{2}k_i^2,\ \mu > 0. && (3.9)\\
&: f_i = f(I_i),\ f'(I_i) > 0, \phi \geq 0. && (3.10)
\end{aligned}$$

The first row depicts the *direct profit* that the firm is maximizing by optimally choosing output, q_i, and the amount of automation technology, k_i: The first term is the firm's revenues, $P_i(q_i)\cdot q_i$; the second term depicts costs for labor used in production, $w_L \cdot L_i(q_i,k_i)$, where w_L is the exogenous wage for production workers (given from the labor market) and $L_i(\cdot)$ is the number of unskilled (or less skilled) production workers; and the third term depicts investment costs for the automation technology, $C(k_i)$. Several things can be noted.

An important component of the labor cost to produce q_i units of output is the per unit requirement of labor, $l_i(k_i)$, since the total number of production workers needed is $L_i(q_i,k_i) = l_i(k_i)q_i$ from (3.7). As shown in (3.8), if the firm invests more in automation technology k_i, this will reduce the number of production workers needed to produce one more unit at rate γ. From (3.9), the investment is associated with a quadratic installation cost, $C(k_i) = \frac{\mu}{2}k_i^2$.

Firm heterogeneity is captured by assuming that firms differ in initial firm-specific assets (Williamson (1979) and Hart and Moore (1990)), I_i, from previous (exogenous) investments in brands, organization and management, training of labor, patents and trademarks, etc. Firm-specific assets have become more important in the business sector over recent decades as investments in intangible assets have increased in importance and are now more important than tangible assets (Corrado et al. (2022)). Intangible investments are, to a large extent, sunk and thus, again to a large extent, firm specific (Haskel and Westlake (2017)). Access to preexisting firm-specific assets confers several advantages on a firm: First, consumers' willingness, a_i, in the inverse demand function (3.6) is increasing in the amount or quality of these firm-specific assets, $da_i/dI_i = a'(I_i) > 0$. Moreover, access to more or better firm-specific assets reduces the firm's unit labor requirement (3.8), $dc_i/dI_i = c'(I_i) < 0$. As we will show below, access to initial firm-specific assets I_i also plays an important role in the firm's incentives to invest in new firm-specific automation technology, k_i.

The final term in (3.5), $w_H \cdot (f_i + \phi k_i)$ reflects fixed costs in terms of skilled labor, where w_H is the wage of skilled labor. First, there is a fixed input requirement of skilled labor, f_i, which we can think of as management leading the firm's operations. We make the intuitive assumption that handling more firm-specific assets requires more skilled labor in management positions, i.e., $f_i = f(I_i)$ with $f'(I_i) > 0$ in (3.10). Moreover, ϕ units of skilled labor are required per unit of investment in the new automation technology, k_i. For expositional reasons but without loss of generality, however, we will derive most of our results assuming that $\phi = 0$. As we show in Section 3.5.3, the model's main predictions still hold if we assume that investments in new technology also require skilled workers, $\phi > 0$.

The exogenous industry variables γ and μ characterize the efficiency and the cost of automation technology. It is then useful to define the following exogenous variable, which we denote the *return to investing in automation*[2]:

$$\eta = \frac{\gamma^2}{\mu}. \tag{3.11}$$

Intuitively, the return to investing in automation technology is higher when this technology is more efficient in replacing labor (i.e., when γ is higher) and when it becomes less expensive to invest in automation technology (i.e., when μ is lower). The variable η is a useful tool to study how firms' investments in new automation technology affect productivity and employment of workers susceptible to being replaced by the new automation technology.

To proceed, we normalize the wage for production workers to unity, $w_L = 1$. We start the analysis by assuming that each firm is a monopolist, i.e., $\lambda = 0$. In Section 5, we extend the analysis to allow for the impact of competition in the product market, $\lambda \in (0, 1]$. We return to the profit maximization problem for firms in (3.5). Consider the following setting: In stage 1, a firm invests in the new automation technology, k_i. In stage 2, given its investments in technology, k_i, the firm sells q_i units of its product to consumers. To solve (3.5), we use backward induction.

3.2. Stage 2: Product market

To further ease notation, we normalize the wage for production workers to unity, $w_L = 1 < w_H$. Using the inverse demand (3.6), the unit labor requirement (3.6) and the investment cost for the automation technology (3.9) in (3.5), we obtain

$$\max_{\{q_i\}} \pi_i = \underbrace{(a_i - q_i)q_i}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i)\, q_i}_{\text{Low skilled wage costs}} - \underbrace{\frac{\mu}{2}k_i^2}_{\text{Installation cost}} - \underbrace{w_H \cdot f_i}_{\text{High skilled wage costs}}. \tag{3.12}$$

The optimal output is given from the first-order condition:

$$\frac{\partial \pi_i}{\partial q_i} = P_i - q_i - (c_i - \gamma k_i) = 0, \qquad i = \{1, 2, ...n\} \tag{3.13}$$

with the associated second-order condition $\frac{\partial^2 \pi_i}{\partial q_i^2} = -2 < 0$.

[2] Leahy and Neary (1996, 1997) and Neary (2002) also make use of this definition.

From (3.13), we can solve for the optimal output:

$$q_i^*(k_i) = \frac{a_i - (c_i - \gamma k_i)}{2}. \tag{3.14}$$

To ensure that the firm produces output even without investments in the new technology, we assume that $a_i > c_i$. Note that the firm will produce more output q_i^* when it has invested more in the automation technology, k_i. To explore this mechanism in greater detail, it is instructive to rewrite the first-order condition into the familiar form equating marginal revenue (MR_i) and marginal cost (MC_i), with marginal revenue expressed as a function of a firm's price elasticity of demand, $El_{P_i}q_i = \frac{dq_i}{dP_i}\frac{P_i}{q_i}$

$$\underbrace{P_i\left[1 - \frac{1}{El_{P_i}q_i}\right]}_{MR_i} = \underbrace{c_i}_{MC_i}. \tag{3.15}$$

A firm with market power chooses output such that the price elasticity of demand is larger than unity, i.e., $El_{P_i}q_i > 1$. This fact implies that if increased investments in automation technology induce a firm to reduce its product market price, the increase in demand causes output to rise. In the analysis below, we will examine (i) whether the output expansion effect can compensate for the replacement effect, i.e., whether labor demand can increase when investments in automation technology increase, and (ii) if so, in which firm type this mechanism is at play.[3]

3.3. Stage 1: Investing in the automation technology

How much does a firm then invest in the automation technology, k_i? Substituting the optimal quantity, $q_i^*(k_i)$, from (3.13) into (3.12), we obtain

$$\max_{\{k_i\}} \pi_i(k_i) = \underbrace{[a_i - q_i^*(k_i)]\, q_i^*(k_i)}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i)\, q_i^*(k_i)}_{\text{Low Skilled Wage cost}} - \underbrace{\frac{\mu}{2}k_i^2}_{\text{Installation cost}} - \underbrace{w_H \cdot f_i}_{\text{High Skilled Wage cost}}. \tag{3.16}$$

Using the envelope theorem, the first-order condition is

$$\frac{\partial \pi_i(k_i)}{\partial k_i} = \gamma q_i^*(k_i^*) - \mu k_i^* = 0. \tag{3.17}$$

From (3.17), we can link the optimal level of investments in the automation technology, k_i^*, to optimal output $q_i^*(k_i^*)$:

$$k_i^* = \frac{\gamma}{\mu} \cdot q_i^*(k_i^*). \tag{3.18}$$

Combining (3.11), (3.14) and (3.18), we can solve for the equilibrium level of automation technology, $k_i^*(\eta)$:

[3] Bessen (2019) shows that labor demand in the textile industry in the 19th century grew for an extended period despite considerable improvements in productivity from labor-saving technologies. He also develops a model that explains this pattern by a highly elastic demand for textiles.

$$k_i^*(\eta) = \frac{\gamma}{\mu} \cdot \frac{a_i - c_i}{2 - \eta} > 0, \tag{3.19}$$

where it is easily verified that $2 - \eta > 0$ is required from the second-order condition associated with (3.16). It is useful to note the synergy arising in (3.19). As emphasized by Jonathan Haskel and Stian Westlake in their 2017 book "Capitalism without Capital", an important feature in the model is the synergies arising between a firm's investments in new intangibles assets in the firm of the new technology k_i and the quality or size of its existing intangibles I_i (as captured by consumer willingness to pay $a_i = a(I_i)$ and the firm's labor demand requirement $c_i = c(I_i)$). Thus, a firm that is equipped with more and/or better preexisting intangible assets, I_i, and has a higher margin, $a_i - c_i$, also invests more in new intangible assets in terms of terms of the automation technology, $\frac{dk_i^*(\eta)}{dI_i} = \frac{\gamma}{\mu} \cdot \frac{a'(I_i)-c'(I_i)}{2-\eta} > 0$, since $a'(I_i) > 0$ and $c'(I_i) < 0$.

Combining (3.6)-(3.8), (3.18) and (3.19), we can finally solve for a firm's equilibrium quantity, $q_i^*(\eta)$, equilibrium price, $P_i^*(\eta)$, equilibrium unit requirement, $l_i^*(\eta)$, and equilibrium labor demand, $L_i^*(\eta)$, all as functions of the return to investing in automation technology, η:

$$\begin{aligned}
q_i^*(\eta) &= \frac{a_i - c_i}{2 - \eta} > 0, && (3.20)\\
P_i^*(\eta) &= a_i - q_i^*(\eta) = \frac{a_i + c_i - a_i\eta}{2-\eta} > 0, && (3.21)\\
l_i^*(\eta) &= c_i - \eta \cdot q_i^*(\eta) = c_i \cdot \frac{2 - \frac{a_i}{c_i}\eta}{2-\eta} > 0, && (3.22)\\
L_i^*(\eta) &= l_i^*(\eta) \cdot q_i^*(\eta) = c_i \cdot \frac{(a_i - c_i)\left(2 - \frac{a_i}{c_i}\eta\right)}{(2-\eta)^2} > 0, && (3.23)
\end{aligned}$$

where we assume that the return to investing in automation technology is not excessively high to ensure that the unit labor requirements for all firms are always strictly positive, i.e., $\eta \in [0, \eta_i^{\max})$ for $\forall i$, where $\eta_i^{\max} = \frac{2c_i}{a_i}$. Furthermore, the return to investing in the new technology is capped by the restriction that the product market price for all firms be strictly positive, i.e., $a_i + c_i - a_i\eta > 0$, for $\forall i$.

3.4. Comparative statics: Increasing return to investing in automation technology

Suppose that technological developments increase automation possibilities by increasing the *return to investing in automation technology*, η, defined in (3.11). How does this affect firms in terms of investments in automation technology, labor productivity and employment of production workers?

3.4.1. Impact on investments in automation technology

From (3.19), we have the following straightforward result:

Lemma 1. *The amount of automation technology investment by firm $k_i^*(\eta)$ is strictly increasing in the return to investing in new automation technology η (either because the new technology becomes less expensive, $(\mu \downarrow)$, or because the new technology becomes more efficient, $(\gamma \uparrow)$).*

Intuitively, an increased return to investing in automation technology increases the level of automation technology used in equilibrium.

3.4.2. Impact on labor productivity and value added per employee

Labor productivity Increased investments spurred by a higher return to investment in the automation technology should increase productivity in the firm. We define labor productivity as output per worker, which we label $v_i^*(\eta)$. Using (3.7), we have

$$v_i^*(\eta) = \frac{\overbrace{q_i^*(\eta)}^{\text{Output}}}{\underbrace{\underbrace{L_i^*(\eta)}_{\text{Production}} + \underbrace{f_i}_{\text{Nonproduction}}}_{\text{Total employment}}} = \frac{1}{\underbrace{l_i^*(\eta) + \frac{f_i}{q_i^*(\eta)}}_{\text{Total unit labor requirement}}}. \tag{3.24}$$

Taking logs in (3.24) and differentiating with respect to η, we can derive the following elasticity expressions, which show how an increase in the return to investing in automation technology affects labor productivity:

$$\frac{dv_i^*(\eta)}{d\eta}\frac{\eta}{v_i^*(\eta)} = \frac{\frac{f_i}{L_i^*(\eta)} \cdot \overbrace{\left(\frac{dq_i^*(\eta)}{d\eta}\frac{\eta}{q_i^*(\eta)}\right)}^{\text{Output expansion effect :}(+)} - \overbrace{\left(\frac{dl_i^*(\eta)}{d\eta}\frac{\eta}{l_i^*(\eta)}\right)}^{\text{Replacement effect:}(-)}}{1 + \frac{f_i}{L_i^*(\eta)}} > 0. \tag{3.25}$$

The expression in (3.25) shows that labor productivity is strictly increasing in the return to investing in automation technology from two distinct effects: an *output expansion effect* (weighted by relative employment) and a *replacement effect.*

The *output expansion effect* is strictly positive since, from (3.20), we have

$$\frac{dq_i^*(\eta)}{d\eta} \cdot \frac{\eta}{q_i^*(\eta)} = \frac{\eta}{2-\eta} > 0. \tag{3.26}$$

The *replacement effect* is strictly negative since, from (3.22), we have

$$\frac{dl_i^*(\eta)}{d\eta}\frac{\eta}{l_i^*(\eta)} = -\frac{2\eta}{c_i}\frac{a_i - c_i}{(2-\eta)\left(2 - \frac{a_i}{c_i}\eta\right)} < 0. \tag{3.27}$$

Intuitively, when the return to investment, η, increases, firms respond by investing more in the automation technology, i.e., $\frac{dk_i^*(\eta)}{d\eta} > 0$ from Lemma 1. This reduces the unit labor requirements $l_i^*(\eta)$ from (3.8), reducing marginal costs, which, in turn, increases output $q_i^*(\eta)$ from (3.14). With larger output and fewer workers needed to produce each unit of output, labor productivity is raised.

We summarize these results as follows:

Proposition 1. *An increase in the return to investing in the automation technology strictly increases labor productivity,* $\frac{dv_i^*}{d\eta}\frac{\eta}{v_i^*} > 0$.

Value added per worker For the empirical analysis presented in the next section, we do not have data on unit labor requirements and output levels (typically not observed in firm-level data). We do have data on firms' revenues and costs. We therefore use value added per employee as our productivity measure. How is this alternative measure affected when the return to investing in automation technology becomes more profitable?

Let $VAL_i^*(\eta)$ denote the reduced-form value added per employee, and let $R_i^*(\eta) = P_i^*(\eta) \cdot q_i^*(\eta)$ denote revenues. Without materials in our model, value added per worker can then be written as the average revenue per total labor hour used:

$$VAL_i^*(\eta) = \frac{\overbrace{R_i^*(\eta)}^{\text{Revenues}}}{\underbrace{L_i^*(\eta) + f_i}_{\text{Total employment}}} = \frac{\overbrace{P_i^*(\eta)}^{\text{Average revenue}}}{\underbrace{l_i^*(\eta) + \frac{f_i}{q_i^*(\eta)}}_{\text{Total unit labor requirement}}}. \tag{3.28}$$

where we use (3.7) in the last term.

Taking logs in (3.28) and again differentiating with respect to η, we obtain

$$\frac{dVAL_i^*(\eta)}{d\eta}\frac{\eta}{VAL_i^*(\eta)} = \underbrace{\frac{dv_i^*(\eta)}{d\eta}\frac{\eta}{v_i^*(\eta)}}_{\text{Labor productivity effect: } (+)} + \underbrace{\frac{dP_i^*(\eta)}{d\eta}\frac{\eta}{P_i^*(\eta)}}_{\text{Price effect: (-)}}. \tag{3.29}$$

Thus, the percentage change in value added per employee from a 1% increase in the return to investing in automation technology is simply the percentage change in the unit labor requirement net of the percentage change in the product market price. We already know from (3.25) that the labor productivity effect is strictly positive from the combined influence of the labor replacement and output expansion effects. However, from the output expansion effect being strictly positive in (3.26), there must be a reduction in the product market price from (3.6). From (3.21), we can show that the price effect is negative:

$$\frac{dP_i^*(\eta)}{d\eta}\frac{\eta}{P_i^*(\eta)} = -\frac{a_i - c_i}{(2-\eta)(a_i + c_i - a_i\eta)}\eta < 0. \tag{3.30}$$

In sum, a higher return to investing in automation technology increases a firm's labor productivity; however, the higher return also reduces the price of the firm's good or service. We show in the appendix that the labor productivity effect still dominates and that value added per employee increases in the return to investment in automation technology, i.e., $\frac{dVAL_i^*(\eta)}{d\eta}\frac{\eta}{VAL_i^*(\eta)} > 0$ in (3.29).

To summarize:

Corollary 1. *An increase in the return to investing in the automation technology also strictly* *increases value added per employee,* $\frac{dVAL_i^*}{d\eta}\frac{\eta}{VAL_i^*} > 0$.

3.4.3. Impact on employment

How is employment affected when investments in automation technology become more profitable? Since the employment of nonproduction workers is by assumption fixed (this assumption is relaxed in the next section), we can focus on the impact of production workers who are susceptible to being replaced by technology. Taking logs of the reduced-form employment, $L_i^*(\eta) = l_i^*(\eta) \cdot q_i^*(\eta)$, and then differentiating with respect to the return, η, we obtain

$$\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} = \left(\underbrace{\frac{dl_i^*(\eta)}{d\eta} \cdot \frac{\eta}{l_i^*(\eta)}}_{\text{Displacement effect (-)}} + \underbrace{\frac{dq_i^*(\eta)}{d\eta} \cdot \frac{\eta}{q_i^*(\eta)}}_{\text{Output effect (+)}} \right). \tag{3.31}$$

More profitable investment opportunities in labor-saving automation technology imply that fewer workers are needed per unit of output produced but also that more workers are needed because output increases: From the *displacement effect* in (3.27), we know that a higher return, η, leads to a lower unit labor requirement, $\frac{dl_i^*(\eta)}{d\eta}\frac{\eta}{l_i^*(\eta)} < 0$. However, improving technological opportunities also increases output, that is, from the *output expansion effect* in (3.26), $\frac{q_i^*(\eta)}{d\eta}\frac{\eta}{q_i^*(\eta)} > 0$.

Which of these two opposing forces—the *displacement effect* or the *output expansion effect*—dominates? Inserting (3.31) and (3.26) into (3.31) and simplifying, we obtain

$$\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} = 2 \cdot \frac{\left(2 - \frac{a_i}{c_i}\left(1 + \frac{\eta}{2}\right)\right)}{(2-\eta)\left(2 - \frac{a_i}{c_i}\eta\right)} \gtreqless 0. \tag{3.32}$$

From (3.32), we can solve for the critical return to investing in the new technology, η_i^L, at which demand for production labor does not change, i.e., $\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} = 0$, that is:

$$\eta_i^L = \frac{4}{(a_i/c_i)}\left(1 - \frac{1}{2}\frac{a_i}{c_i}\right). \tag{3.33}$$

The two expressions above suggest that the impact of investments in new technology on the demand for production workers depends on the firm type, related to firms' endowment of intangible assets, I_i: Leading firms' endowment with more and better firm-specific intangible assets provides these firms with a higher consumer willingness to pay, a_i, and a lower unit requirement for production workers, c_i. Conversely, laggard firms with fewer intangible assets require more production workers (i.e., have a higher unit requirement, c_i) and have customers with a lower willingness to pay (i.e., a lower a_i).

From (3.32) and (3.33), we can state our main proposition:

Proposition 2. *The following holds:*

1. (**Laggard firm**) *If* $\frac{a_i}{c_i} \in (1,2)$ holds, *an increase in the return to investing in automation technology* $d\eta > 0$ *leads to:*

   a.) *An increase in employment,* $\frac{dL_i^*(\eta)}{d\eta}\frac{\eta}{L_i^*(\eta)} > 0$, *if* $\eta \in [0, \eta_i^L)$.

   b.) *No change in employment,* $\frac{dL_i^*(\eta)}{d\eta}\frac{\eta}{L_i^*(\eta)} = 0$, *if* $\eta = \eta_i^L$.

   b.) *A decline in production employment,* $\frac{dL_i^*(\eta)}{d\eta}\frac{\eta}{L_i^*(\eta)} < 0$, *if* $\eta \in (\eta_i^L, \eta_i^{\max})$.

2. (**Leading firm**) *If* $\frac{a_i}{c_i} > 2$, *an increase in the return to investing in automation technology,* $d\eta > 0$, *always reduces employment,* $\frac{dL_i^*(\eta)}{d\eta}\frac{\eta}{L_i^*(\eta)} < 0$.

Let us explain the intuition behind Proposition 2. Since the Output expansion effect, i.e., the elasticity $\frac{dq_i^*(\eta)}{d\eta} \cdot \frac{\eta}{q_i^*(\eta)}$, is *independent* of firm characteristics (cf Equation 3.26), the heterogenous employment of the different firm types in Proposition 2 can be fully understood from the displacement effect, $\frac{dl_i^*}{d\eta}\frac{\eta}{l_i^*(\eta)}$. It is then useful to rewrite the displacement effect as follows:

$$\frac{dl_i^*}{d\eta}\frac{\eta}{l_i^*(\eta)} = -\frac{q_i^*(\eta)}{l_i^*(\eta)} \cdot \left(\frac{2}{2-\eta}\right) < 0, \tag{3.34}$$

where we have used (3.22) and (3.26).

Faced with weak consumer demand (i.e., low a_i) and weak cost efficiency (i.e., high c_i), laggard firms choose lower output, $q_i^*(\eta)$ (cf Equation 3.20). This implies a weak incentive to invest in the new automation technology since any reduction in the unit labor requirement affects few units of output (cf Equation 3.18). The low investments in the labor-saving technology then translate into a high unit labor requirement, $l_i^*(\eta)$ (cf Equation 3.8). As shown in (3.34), at a low output level and high unit labor requirement (i.e., at a low ratio $q_i^*(\eta)/l_i^*(\eta)$), the displacement effect is weakened. The output expansion effect therefore dominates in (3.31), and substitutable production employment increases despite increased investments in labor-saving automation technology. The employment locus for a laggard firm, $L_i^*(\eta)|_{\frac{a_i}{c_i}\in(1,2)}$, is shown in Figure 3.1, where a higher return to investing in automation technology increases production employment as long as the initial return η is not too high.

In contrast, under greater consumer demand (i.e., a higher a_i) and higher cost efficiency (i.e., a lower c_i), leading firms produce more output, providing a stronger incentive to invest in labor-saving technology, which, ultimately, yields a low unit labor requirement. From (3.34), at a high level of production and a low unit labor requirement (i.e., at a high ratio $q_i^*(\eta)/l_i^*(\eta)$), the displacement effect is now strengthened: The output expansion effect is now dominated by the displacement effect in (3.31), and substitutable production employment declines when investments in labor-saving automation technology increase. The employment response for a leading firm is illustrated by the employment locus $L_i^*(\eta)|_{\frac{a_i}{c_i}>2}$ in Figure 3.1. In contrast to in the laggard firm, a higher return to investment in automation technology η always reduces employment in the leading firm.

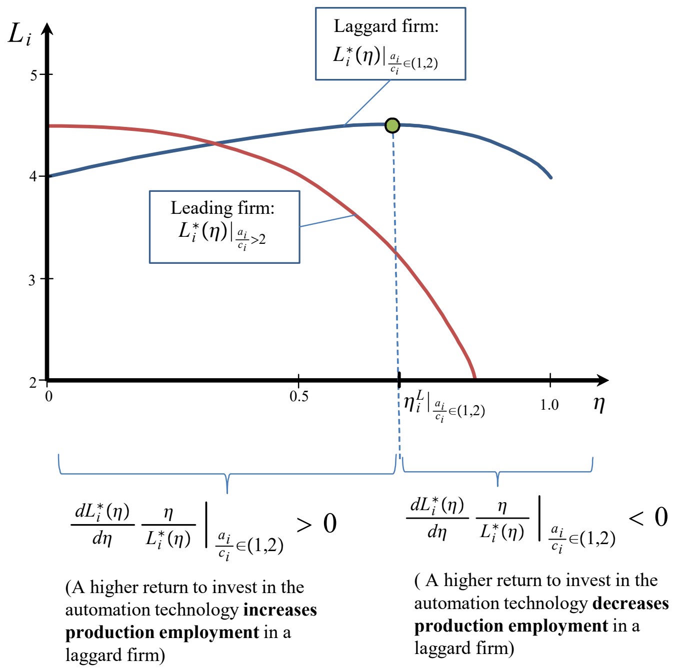

Figure 3.1: Illustrating how the relationship between the number of production workers, L_i^*, and the return to investing in the automation technology, η, differs by firm type. Parameter values are $a = 6$ and $c = 3$ for a leading firm and $c = 4$ for a laggard firm.

3.5. Empirical predictions

Let us now derive empirical predictions from the model to be tested in the next section.

3.5.1. Productivity and production employment

Combining Propositions 1 and 2, we can make a prediction on how productivity (as measured by value added per employee) and production employment are related when firms increase their investments in the automation technology.

Lemma 2. ***(Productivity and production employment)*** *Suppose that the return to investing in automation technology, η, increases. Firms then respond by increasing their investments in automation technology, $k_i^*(\eta)$. Then:*

(i) *For a laggard firm, $\frac{a_i}{c_i} \in (1, 2)$, given that the return to investment is not too high, $\eta \in [0, \eta_i^L)$, increased investment in the new automation technology leads to a positive correlation between production employment, $L_i(\eta)$, and value added per employee, $VAL_i(\eta)$, as increased investment in new automation technology boosts both production employment and productivity.*

(ii) *For a leading firm, $\frac{a_i}{c_i} > 2$, increased investment in the new automation technology leads to a negative correlation between production employment, $L_i(\eta)$ and labor productivity, $VAL_i(\eta)$.*

Part (ii) states that in more efficient leading firms, there is a negative correlation between production worker employment and productivity. In these firms, the displacement effect of the new technology dominates the output expansion effect in (3.31), and labor demand falls when productivity increases. In contrast, Part (i) states that in less efficient laggard firms, the correlation between labor productivity and the employment of production workers (who are substitutable by automation investments) is positive. That is, increasing firm-level productivity is associated with higher employment of production workers—in the latter type of firm, the output expansion effect of increased automation investments dominates the displacement effect in Equation (3.31).

These predictions are illustrated in Figures 3.3 and 3.2, where the top panels show a firm's investments in automation technology, $k_i^*(\eta)$, the middle panels depict its labor productivity, $v_i^*(\eta)$, and the bottom panels depict its production employment, $L_i^*(\eta)$. As shown by the horizontal axis, all three endogenous variables are functions of the return to investment in the automation technology, η. The lower panels in Figures 3.3 and 3.2 are emphasized to illustrate that, in the empirical analysis in the next section, we can only observe employment and productivity—we do *not* observe the actual investments in new automation technology shown in the top panel when we go to the data.

In Section 4, we will test the predictions from the model on the relationship between labor productivity and employment. How do we deal with the problem that the investments in new technology is hard to measure in the data? We assume a process whereby automation possibilities increase over time, i.e., the return to investing in new automation technologies ,η, rises over time. In *leading firms*, increasing (unobserved) investments in the new automation technology lead to higher productivity associated with falling production employment. From the two lower panels in Figure 3.3, this produces a negative correlation between labor productivity and production employment. In contrast, from the lower panels in Figure 3.2, increasing (unobserved) automation investment produces a positive correlation between labor productivity and production employment in *laggard firms*. How can we then identify leading firms and laggard firms in the data?

3.5.2. Identification of leaders and laggards in the data

Firm heterogeneity—and hence our distinction between leading and laggard firms—is determined by firms' endowments of initial firm-specific assets, I_i, through their effect on the demand and cost parameters a_i and c_i in Lemma 2. Firm-level microdata do not generally contain detailed information on firm-specific assets due to the problem of valuing such assets (see Haskel and Westlake, 2017). The Swedish micro firm-level data that we use in the next section are no exception to this rule. How then can we identify firm types in the data?

To identify leaders and laggards in the data, we use the skill intensity of a firm. This identification strategy is illustrated in the three panels contained in Figure 3.4. In panel (i) of Figure 3.4, we depict consumers' relative willingness to pay, $\frac{a_i}{c_i}$, as a function of firm i's firm-specific assets, I_i. Recall that willingness to pay, $a_i = a(I_i)$, is increasing in I_i, $a'(I_i) > 0$, and the unit production labor requirement, $c_i = c(I_i)$, is decreasing in I_i, $c'(I_i) < 0$. As shown in panel (i), the ratio

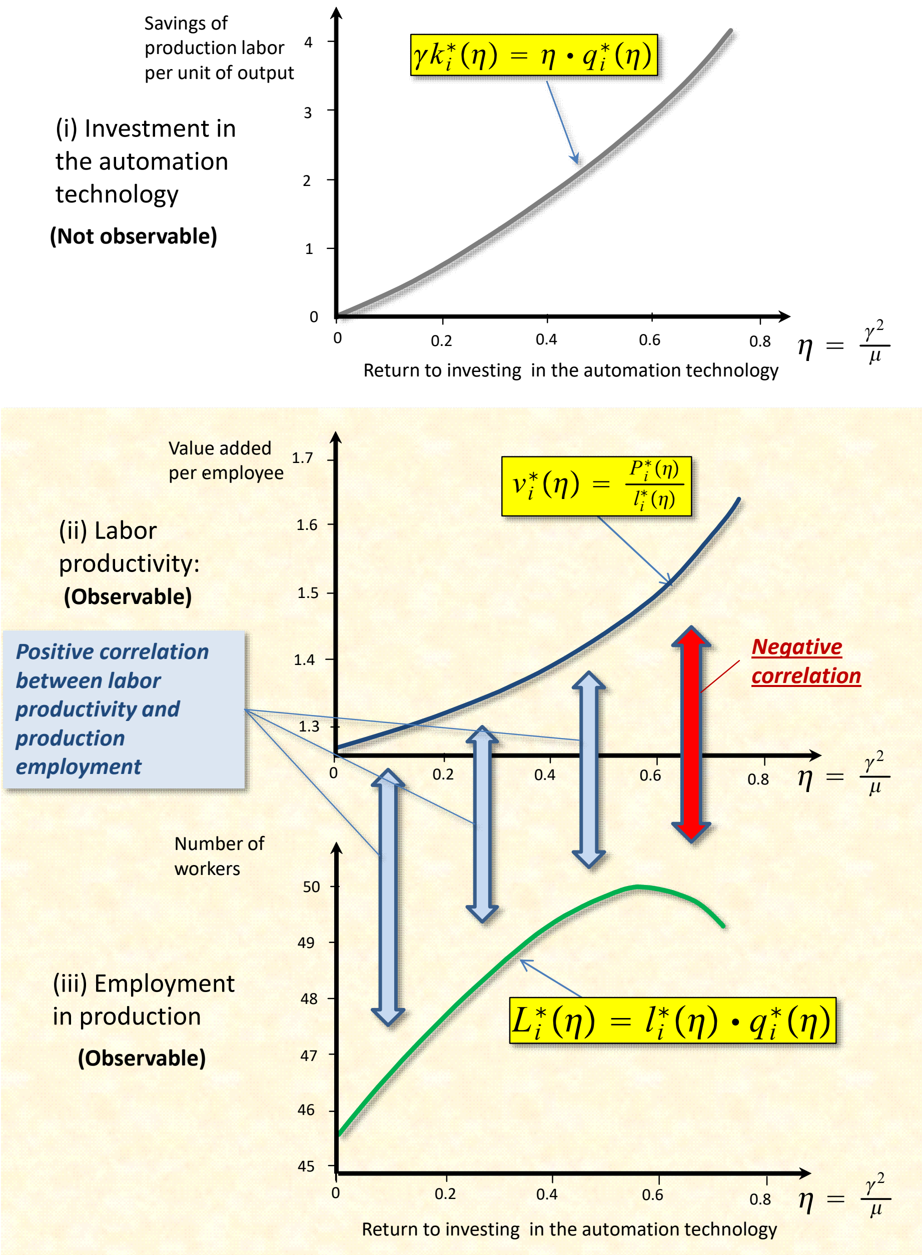

Figure 3.2: Labor productivity and production employment in a *"laggard firm"*, $\frac{a_i}{c_i} \in (1, 2)$: The top panel (i) shows how investments in the new automation technology, k_i^*, increase when the return, η, increases. The investments, k_i^*, are not observed in the data. Panels (ii) and (iii) then show how the unobserved investments in new the new technology, k_i^*, can cause a positive correlation between production worker employment, $L_i^*(\eta)$, and productivity, $v_i^*(\eta)$, which can be *observed* in the data.

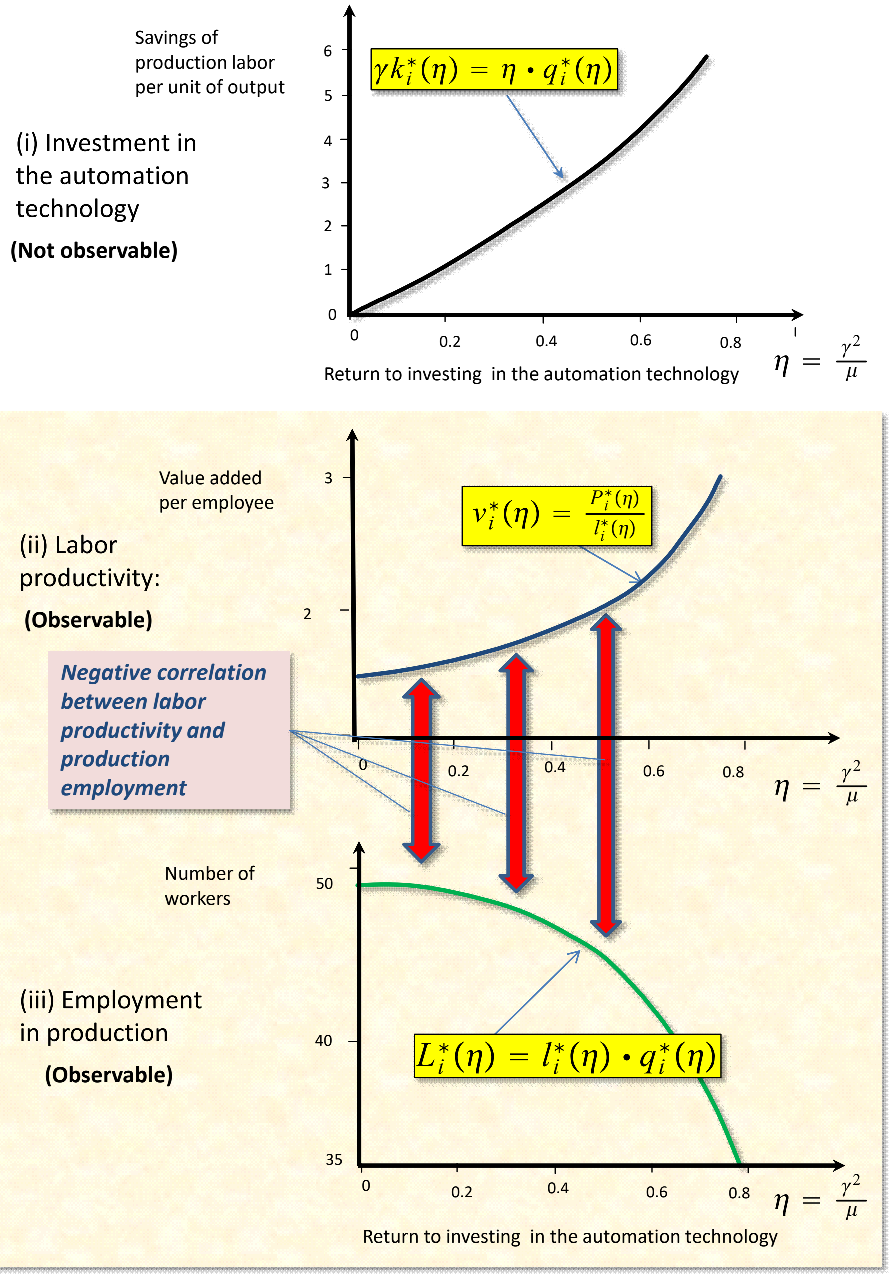

Figure 3.3: Labour productivity and production employment in a *"leading firm"*, $\frac{a_i}{c_i} > 2$: The top panel (i) shows how investments in the new automation technology, k_i^*, increase when the return η, increases. The investments, k_i^*, are not observed in the data. Panels (ii) and (iii) then show how the unobserved investments in the new technology, k_i^*, cause a *negative* correlation between production worker employment $L_i^*(\eta)$ and productivity $v_i^*(\eta)$, which can be *observed* in the data.

$\frac{a_i}{c_i} = \frac{a(I_i)}{c(I_i)}$, or the "relative willingness to pay", must then increase in I_i. By calculation,

$$\frac{d}{dI_i}\left(\frac{a(I_i)}{c(I_i)}\right) = \frac{1}{c(I_i)}\left[\underset{(+)}{a'(I_i)} - \frac{a(I_i)}{c(I_i)}\cdot \underset{(-)}{c'(I_i)}\right] > 0. \tag{3.35}$$

Recall from Proposition 2 that the amount of production labor $L_i^*(\eta)$ used in a laggard firm increases with investments in new automation technology when the return to investing in automation rises, $\frac{dL_i^*(\eta)}{d\eta}\cdot\frac{\eta}{L_i^*} > 0$. The reason is that consumers' relative willingness to pay in this case is sufficiently low, $\frac{a_i}{c_i} \in (1,2)$. Conversely, in a leading firm for which $\frac{a_i}{c_i} > 2$, production labor employment declines following investments in the new technology, $\frac{dL_i^*(\eta)}{d\eta}\cdot\frac{\eta}{L_i^*} < 0$. Note that since the relative willingness to pay, $\frac{a_i}{c_i} = \frac{a(I_i)}{c(I_i)}$, is an increasing function of the amount of firm-specific assets, I_i, from (3.35), we can solve for the critical level of firm-specific assets at which production labor employment does not change when investment in new automation technology occurs—i.e., when the displacement effect of investments in new automation technology is completely offset by the increase in labor demand from the output expansion effect. As shown in panel (i), this level of firm-specific assets, $\tilde{I}$, is given from the equality $\frac{a(\tilde{I})}{c(\tilde{I})} = 2$. Leaders and laggards can now be distinguished from their endowment of firm-specific assets, I_i. This is shown in panels (i) and (ii) in Figure 3.4 and illustrated for two different firms: Firm 1 has abundent firm-specific assets, $I_1 > \tilde{I}$, while Firm 2 has less firm-specific assets at its disposal, $I_2 < \tilde{I}$. Since $\frac{a(I_2)}{c(I_2)} < 2$ holds, it follows that Firm 2 is a *laggard firm,* for which $\frac{dL_2^*(\eta)}{d\eta}\cdot\frac{\eta}{L_2^*} > 0$. Conversely, since $\frac{a(I_1)}{c(I_1)} > 2$ holds, it follows that Firm 1 is a *leading firm,* for which $\frac{dL_1^*(\eta)}{d\eta}\cdot\frac{\eta}{L_1^*} > 0$.

Thus, laggards possess a low and leaders a high amount of firm-specific assets, I_i. How can we use this to associate leaders and laggards with skill intensity of workers at the firm level? Recall that the number of skilled workers needed in a firm's operations depends on the amount of firm-specific assets in the firm, i.e., $f_i = f(I_i)$. We can then write a firm's skill intensity as a function of its possession of firm-specific assets:

$$s_i^*(I_i) = \frac{f_i}{L_i^* + f_i} = \frac{f(I_i)}{L_i^*(\eta, I_i) + f(I_i)}, \tag{3.36}$$

where we also write the number of production workers as a function of both the relative return to investing in new technologies and the amount of existing intangible assets, $L_i^*(\eta, I_i)$. To proceed, we make the following identifying assumption:

Assumption 1: *The share of high-skilled workers is monotonously increasing in the amount of firm-specific assets in a firm:* $\frac{ds_i^*(I_i)}{dI_i} > 0$.

Assumption 1 always holds if production worker employment is decreasing in the amount of available firm-specific assets, $\frac{dL_i^*}{dI_i} < 0$, since the number of skilled workers required is monotonously increasing in the amount of firm-specific assets, $\frac{df_i}{dI_i} = f'(I_i) > 0$. However, the sign of $\frac{dL_i^*}{dI_i}$ is, in general, ambiguous. Straightforward differentiation shows that an increase in a firm's firm-specific assets will again increase production worker labor demand from an output expansion effect,

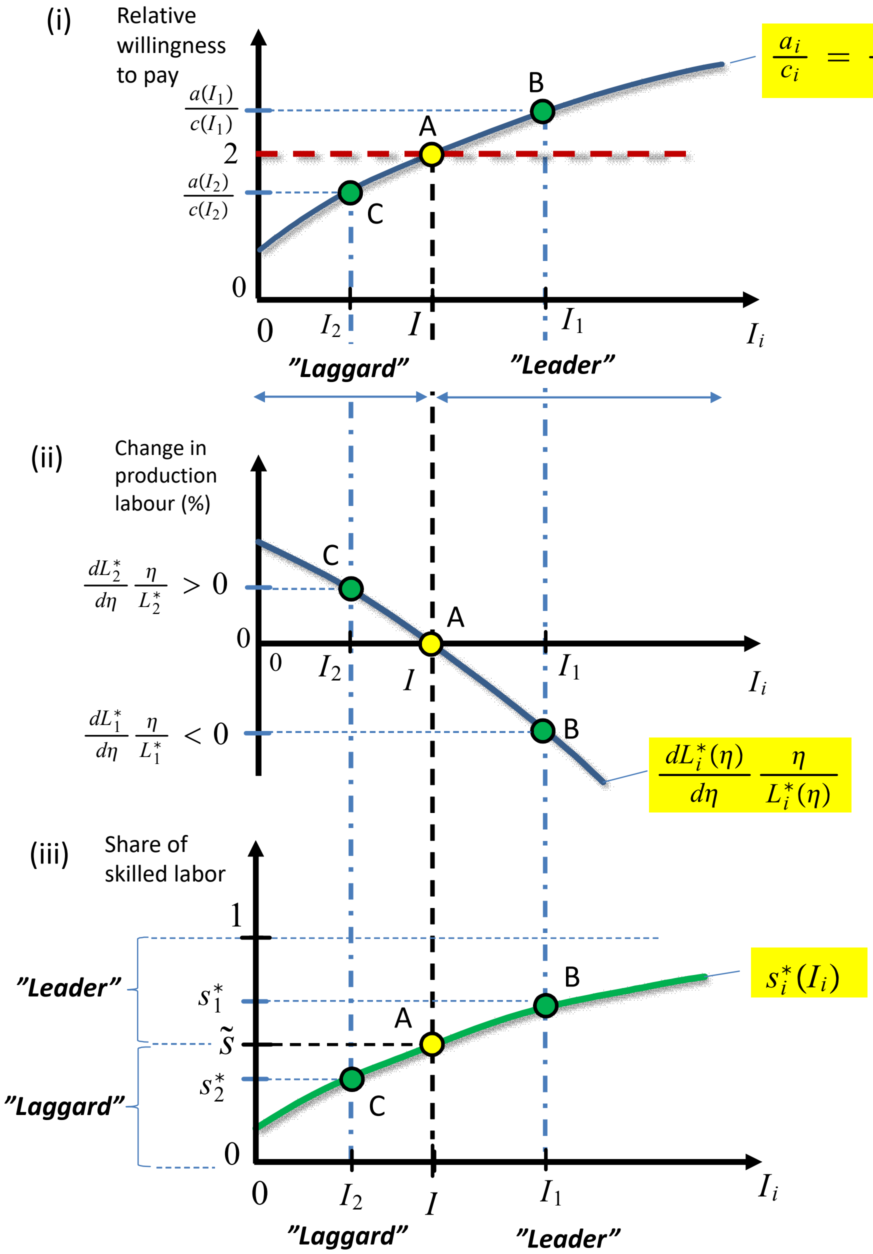

Figure 3.4: Identifying leading firms and laggard firms from their skill intensity. Panels (i) and (ii) show how leading and laggard firms are identified from their endowment of firms-specific assets I_i. Panel (iii) then shows how the endowment of firms-specific assets, I_i, which is unobserved in the data, is mapped to skill intensity, s_i^*, which is observed in the data.

while reducing it from a displacement effect: If the latter effect dominates, the firm's demand for production worker labor declines, $\frac{dL_i^*}{dI_i} < 0$; if the former effect dominates, production worker labor demand increases, $\frac{dL_i^*}{dI_i} > 0$. If $\frac{dL_i^*}{dI_i} > 0$, Assumption 1 requires $f'(I_i) > 0$ to be sufficiently large.

Given that Assumption 1 holds, we can find a *unique observable skill share*, $\tilde{s}$, corresponding to a *unique unobservable possession of firm-specific assets*, $\tilde{I}$, for which leading firms are firms with a skill share above $\tilde{s}$ and laggard firms are firms with skill share below this threshold. This mapping is illustrated in panel (iii) in Figure 3.4: Note that Firm 1, the leading firm with $I_1 > \tilde{I}$, must have a skill intensity above the threshold, i.e. $s_1 > \tilde{s}$. Conversely, Firm 2, the laggard firm with $I_2 < \tilde{I}$, must have a skill intensity below the threshold, i.e. $s_2 < \tilde{s}$. Invoking Lemma *2* finally gives us our main empirical prediction that we will test empirically in the next section:

Prediction 1: *Suppose that Lemma 2 holds. Then, from Assumption 1, it follows that:*

(i) *In a laggard firm,* $s_i^* < \tilde{s}$, if the return to investment is not too high, $\eta \in [0, \eta^L)$, *(unobservable) increased investments in the new automation technology should lead to a positive correlation between (observable) production employment,* $L_i(\eta)$, *and (observable) value added per employee,* $VAL_i(\eta)$, *as increased investment in new automation technology increases both production employment and productivity.*

(ii) *In a leading firm,* $s_i^* > \tilde{s}$, *(unobservable) increased investments in the new automation technology should lead to a negative correlation between (observable) production employment,* $L_i(\eta)$, *and (observable) value added per employee,* $VAL_i(\eta)$, *as increased investment in new automation technology reduces production employment while increasing productivity.*

3.5.3. Investments in new automation technology and the demand for skilled labor

For ease of exposition, we assumed, in the main analysis, that the use of skilled nonproduction workers is not directly related to investments in new automation technology. Suppose now that $\phi > 0$ so that skilled workers are also needed for each unit of investment in new automation technology, k_i, in addition to the fixed requirement, f_i. A firm's cost of skilled nonproduction workers is then $w_H \cdot (f_i + \phi k_i)$ as in (3.5). Let us now argue that Assumption 1 and Prediction 1 are also applicable in this more elaborate setting.

Return to Figure 3.4 and first consider the two upper panels. By definition, the relative willingness to pay, $\frac{a_i}{c_i}$, is an increasing function of firm-specific assets, I_i. Tedious but straightforward calculations also show that Lemma 2 holds in this setting (albeit under mild additional conditions). Hence, there exists a unique level of firm-specific assets, $\tilde{I}$, such that that laggard firms (for which $\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} > 0$) are firms with a possession of a low amount of firm-specific assets, $I_i < \tilde{I}$, and leading firms (for which $\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} < 0$) are firms with a possession of a high amount of firm-specific assets, $I_i > \tilde{I}$. Prediction 1 states that laggard firms are identified as firms with a low skill share, $s_i^* < \tilde{s}$, and leading firms are associated with high skill share, $s_i^* > \tilde{s}$. As shown in panel (iii), this requires that a firm's skill share, s_i^*, be increasing in its possession of firm-specific assets, I_i. The share of skilled workers defined in (3.36) can now be written as:

$$s_i^*(\eta, I_i) = \frac{f(I_i) + \phi k_i^*(\eta, I_i)}{L_i^*(\eta, I_i) + \phi k_i^*(\eta, I_i)}. \tag{3.37}$$

It can be shown that $k_i^*(\eta, I_i) = \frac{\gamma}{\mu}\frac{1}{(2-\eta)}\left(a(I_i) - c(I_i) - 2\phi\frac{w_H}{\gamma}\right)$ and that the amount of skilled labor needed to handle the investment in new technology, $\phi k_i^*(\eta, I_i)$, is increasing in I_i. Let $S_i^*(\eta, I_i) = f(I_i) + \phi k_i^*(\eta, I_i)$,and then it follows that (3.37) becomes $s_i^*(\eta, I_i) = S_i^*(\eta, I_i)/(L_i^*(\eta, I_i) + S_i^*(\eta, I_i))$. Taking logs and differentiating in I_i, we then obtain

$$\frac{ds_i^*}{dI_i}\frac{I_i}{s_i^*} = (1 - s_i^*)\left(\underbrace{\frac{dS_i^*}{dI_i}\frac{I_i}{S_i^*}}_{(+)} - \frac{dL_i^*}{dI_i}\frac{I_i}{L_i^*}\right). \tag{3.38}$$

Hence, as in the main setup, we cannot unambiguously determine how an increase in the possession of firm-specific assets affects the skill share—this depends on how the possession of a greater amount of firm-specific assets affects the employment of production workers, which, in turn depends on parameter values and assumptions on functional forms.

To proceed, we assume that Assumption 1 holds and, hence, that Prediction 1 applies. We now turn to the empirical analysis examining whether our theoretical predictions are consistent with our data on productivity and employment dynamics in the Swedish business sector.

4. Empirical analysis

The aim of our empirical section is to estimate how investments in new automation technology affect the relationship between the employment of workers susceptible to being replaced by new technology and productivity. The challenge is to examine this relationship without detailed information on firms' investments in new automation technology and sources of firm heterogeneity.

This section first describes the data and our method of measuring worker susceptibility to automation and firm heterogeneity. In the next section, we present the estimation equation and explain how we capture the model's prediction of how firm heterogeneity affects the correlation between productivity and the employment of workers susceptible to being replaced by automation technology. We then present our empirical results.

4.1. Data

We base our analysis on detailed, register-based, matched employer–employee data from Statistics Sweden (SCB). The database comprise firm, plant and individual data, which are linked with unique identification numbers and cover the period from 1996 to 2015. Specifically, the database consists of the following parts.

(i) Individual data The worker data contain Sweden's official payroll statistics based on SCB's annual salary survey and are supplemented by a variety of registry data. They cover detailed information on a representative sample of the labor force, including full-time equivalent wages, work experience, education, gender, occupation, employment, and demographic data, among other characteristics. Occupations are based on the Swedish Standard Classification of Occupations (SSYK96), which in turn is based on the International Standard Classification of Occupations (ISCO-88). Occupations in ISCO-88 and SSYK96 are grouped based on the similarity of skills required to fulfill the duties of the jobs.

(ii) Firm data The firm data contain a large amount of firm-level information, including detailed accounts, productivity, investments, capital stocks, profits, firm age, and industry affiliation, among other characteristics. The dataset includes all firms with production in Sweden, and in our analysis, we use firms with at least ten employees.

(iii) Plant data The plant data contain detailed plant-level information such as employee demographics, salaries, education, and codes for company mergers, closures, formations, and operational changes. The dataset covers all plants in Sweden. Plant-level data are aggregated to the firm level.

4.2. A firm-level measure of exposure to automation

Our first task is to construct a measure of production workers' susceptibility to replacement by automation, i.e., L_i^* in the theoretical model. To obtain a firm-level measure of how susceptible the workers in our Swedish firms are to new technologies, we assume that firms can employ workers from Swedish SSYK96 occupations at the 2-digit level, where each occupation j is associated with an automation probability, $Exposure_j$, which is an automation probability converted from Webb (2019) and Frey and Osborne (2017). We use four different measures of automation risk, which are described in more detail below. For each of these four measures, we then derive the *workforce exposure to automation* in firm i at time t, $Exposure_{it}^{\tau}$, as

$$Exposure_{it}^{\tau} = \sum_{j=1}^{J} \sigma_{ijt} \cdot Exposure_j^{\tau}, \tag{4.1}$$

where σ_{ijt} is the share of employees in firm i in occupation j at time t, which is used as a weight for the automation probability of workers in a particular occupation, $Exposure_j$. The average risk—or average exposure—to automation is thus formed by multiplying the share of employees in an occupation, $\sigma_{ijt} \in [0, 1]$, by the automation probability of that occupation, $Exposure_j$, and then summing over all occupations j that are represented within firm i. Since the probability of automation for an occupation, $Exposure_j$, is a time-invariant measure, all variation over time in the exposure to automation—or average risk of automation—in a firm, $Exposure_{it}$, originates from changes in the composition of occupations, σ_{ijt}. Note that an increase in $Exposure_{it}$ must be due to a change in the composition of employees within the firm toward occupations that have a higher probability of automation. Conversely, a decrease in $Exposure_{it}$ must be due to a change in the composition of employees within the firm such that a smaller share of employees is found in occupations with a lower probability of being automated.

4.2.1. Frey and Osborne (2017)

Our first measure of firm-level exposure, $Exposure_{it}$, makes use of Frey and Osborne (2017). They compute the probability that a job will be replaced by computers or robots, hence quantifying occupation-specific automation probabilities, $Exposure_j$. They predict the computerization probabilities for 702 US occupations, where the predicted risk can be interpreted as the risk that an occupation will be automated within 10 to 20 years. The authors use an objective and a subjective assessment of the occupation-specific automation probability. The objective assessment is based on combinations of required knowledge, skills and abilities for each occupation and ranks the occupations' likelihood of automation based on this. The subjective ranking categorizes (a subset of the) occupations on the basis of the different tasks that they entail. The assessments are based on the occupational characteristics and qualifications in the O*NET database, developed by the US Department of Labor. The O*NET database covers around 1,000 occupations, and for each occupation, there are 300 variables.[4] To obtain a probability measure for each occupation, Frey and Osborne use a Gaussian process classifier to identify factors that increase or reduce the ability to computerize a profession. Based on this analysis, the authors provide an occupation-specific automation probability (see Frey and Osborne (2017) for further details).

They then proceed to calculate the automation probabilities for US SOC2010 occupational classifications. This classification is not used in either Sweden or the EU, and there is no direct translation from the SOC2010 to its Swedish counterpart SSYK96. We therefore translate the US classifications to the European occupational code, ISCO08, which in turn can be translated to SSYK96. The US code is more detailed than both the EU and Swedish occupational classifications; i.e., some European codes include several US occupations (and vice versa in some cases). We account for this by using occupational employment weights from the United States Bureau of Labor Statistics (BLS) and from Statistics Sweden when there is no 1:1 relationship between US and European occupations. Furthermore, we use the new Swedish occupational classification SSYK2012 for translating ISCO08 to SSYK96. While SSYK2012 is almost identical to ISCO08, differences exist; in these cases, we use different methods to convert the occupational codes. The occupations most susceptible to automation include machine operators and assemblers and various office clerks, while workers faced with low automation risk include managers of small enterprises, science professionals and legislators and senior officials.

Recall from Section 3.5.2 and Prediction 1 that we showed how the share of skilled workers could be used to identify firm types. Firms with a high share of skilled workers, $s_i^* > \tilde{s}$, were

[4] The variables describe the daily work, skills and interests of the typical employee. These descriptive variables are organized into six different main areas: characteristics of the performer, performer requirements, experience requirements, occupation-specific information, labor characteristics and occupational requirements.

identified as “leading firms" and firms with a low share of skilled workers, $s_i^* > \tilde{s}$, were identified as “laggard firms" (we will estimate the cutoff $\tilde{s}$ in the next section). In the matched employer–employee data, we calculate skill intensity as the share of employees in a firm with tertiary education, labeled $Skill\_share_{it}$. Panel (i) in Figure 4.1 depicts the correlation between our exposure measure calculated from Frey and Osborne's measures of occupation automation risks, $Exposure_{it}$, and firms' skill intensity, $Skill\_share_{it}$, in 2015. Firm size in terms of the log number of employees is indicated by the size of the circle surrounding each observation. Note that the firm-level exposure to automation and the share of skilled workers are negatively correlated. This is consistent with Assumption 1 of more or better access to *preexisting* intangible assets or firm-specific assets being associated with more use of skilled workers and less use of workers susceptible to automation.[5]

4.2.2. Webb (2019)

We also construct three other firm-level exposure measures from the index of job exposure to automation developed by Michael Webb to calculate our exposure measure (see Webb (2019) for details). These measures are based on quantifying overlaps between patent descriptions and specific texts of job descriptions. We make use of the data from Webb (2019) on robot, software and AI technologies. To assess how occupations are affected by these technologies, the method identifies what the technologies can do and then calculates the degree to which specific occupations involve performing similar tasks. The extent to which occupations require job tasks similar to what the technologies can do based on patent text are what determines exposure to automation based on the different technologies. As for the measure by Frey and Osborne (2017), Webb (2019) uses the O*NET database as source of information on job tasks and occupations. The finalized measure of occupational exposure to automation for a specific technology is expressed as the intensity of patenting activity in a specific technology (robots, software and AI) directed toward the tasks in that occupation. The automation exposure measures are expressed as score percentiles for each occupation. An occupation's overall score is calculated as the average of its task scores. To translate the data from Webb to the Swedish occupational system, we apply the same method that we use for the Frey and Osborne (2017) measure of automation described above.

Panel (ii) in Figure 4.1 depicts the correlation between Webb's occupational measure of exposure to robots and firms' skill intensity. Note that we again find that this firm-level exposure to automation and the share of skilled workers are negatively correlated, consistent with Assumption 1, with a higher endowment of intangible assets increasing a firm's skill intensity while reducing the demand for labor susceptible to automation. Panel (iii) derives the same scatterplot but now with Webb's occupational measure of exposure to software. The negative correlation between firm-level exposure to automation from the use of software and the share of skilled labor is still present but less accentuated. Finally, in panel (iv), we depict the correlation in 2015 between firm-level exposure

[5] Going back to the theory, again let I_i be the amount of preexisting intangibles in firm i. Let S_i be the number of skilled workers in firm i, and let L_i be the number of production workers susceptible to automation from investments in new technology. Assumption 1 with $\frac{ds_i^*}{dI_i}\frac{I_i}{s_i^*} > 0$ is then fulfilled from $\frac{dS_i^*}{dI_i}\frac{I_i}{S_i^*} > 0$ and $\frac{dL_i^*}{dI_i}\frac{I_i}{L_i^*} < 0$ in (3.38).

to automation from AI and skill intensity. Note that there is a clear positive correlation between these two variables. The theory in the previous sections does not rule out such a pattern, which could arise if a larger firm endowment of intangibles increases both skill intensity and demand for labor susceptible to automation through AI.[6] However, we do not stress this interpretation since our model does not allow skilled labor to be replaced by new technology. At the same time, we do not believe that AI replacing skilled labor is an important mechanism in our data, which cover Swedish firms during the period 1996–2015. It is not likely that AI was used to any larger extent even at the end of this period.

Figure 4.2 finally explores how the different measures of $Exposure_{it}$ changed over the period 1996–2015 in firms in the Swedish business sector with at least ten employees. For all four measures, we observe declining average automation risks. Looking at the Frey and Osborne (2017) measure, labeled Auto, we find that it decreased by approximately 5 percentage points.[7] For the measures based on Webb (2019), we see that the largest decline (approximately 5 percentage points) occurred for occupations exposed to robots. Overall, Figure 4.2 indicates a shift in the distribution of occupations in terms of exposure to automation. This is likely a result of the structural change in the Swedish labor market that started in the 1990s. Overall, the pattern emerging from Figure 4.2 appears to show that overall employment in low-risk occupations has declined—at least as a share of total employment.

Finally, before presenting the econometric analysis, we present in Table 1 some descriptive statistics at the firm level on our data and variable definitions. We note that the pattern observed in Figure 4.2 above can also be seen in the table when we inspect the mean values with corresponding standard deviations. All firm-level measures of exposure to automation decreased during our sample period. This implies that the workforce of Swedish firms has gradually changed toward occupations with less exposure to automation and is further evidence of a technology-driven structural change observed at the firm level. We can also see from Table 1 that there has been strong human capital upgrading, measured in terms of both the share of employees with university education and the mean schooling of individual workers. The table also includes some firm-level measures of the routineness and offshorability of the workforce that we will use in a robustness analysis. Comparing 2015 with 1996, we note that the firm-level means of both routine task intensity (RTI) and offshorability decreased during this period.[8] Finally, we note that for the period 1996–2015, we observe an increase in both labor productivity and capital intensity and a higher mean number of employees at the firm level.

[6] Again let I_i be the amount of preexisting intangibles in firm i. Let S_i be the number of skilled workers in firm i, and let L_i be the number of production workers susceptible to automation from investments in new technology. Assumption 1 with $\frac{ds_i^*}{dI_i}\frac{I_i}{s_i^*} > 0$ is then fulfilled from $\frac{dS_i^*}{dI_i}\frac{I_i}{S_i^*} > 0$ and $\frac{dL_i^*}{dI_i}\frac{I_i}{L_i^*} > 0$ in (3.38), but where $\frac{dS_i^*}{dI_i}\frac{I_i}{S_i^*} > \frac{dL_i^*}{dI_i}\frac{I_i}{L_i^*} > 0$.

[7] See Gardberg et al. (2002) for an analysis on the relationship between occupational automation probabilities based on Frey and Osborne (2017) and employment dynamics in Sweden over nearly two decades.

[8] See Section 4.4.2 for details about these measures.

(i) **Auto exposure** (y-axis) and skill share (x-axis)

(ii) **Robot exposure** (y-axis) and skill share (x-axis)

(iii) **Software exposure** (y-axis) and skill share (x-axis)

(iiv) **AI exposure** (y-axis) and skill share (x-axis)

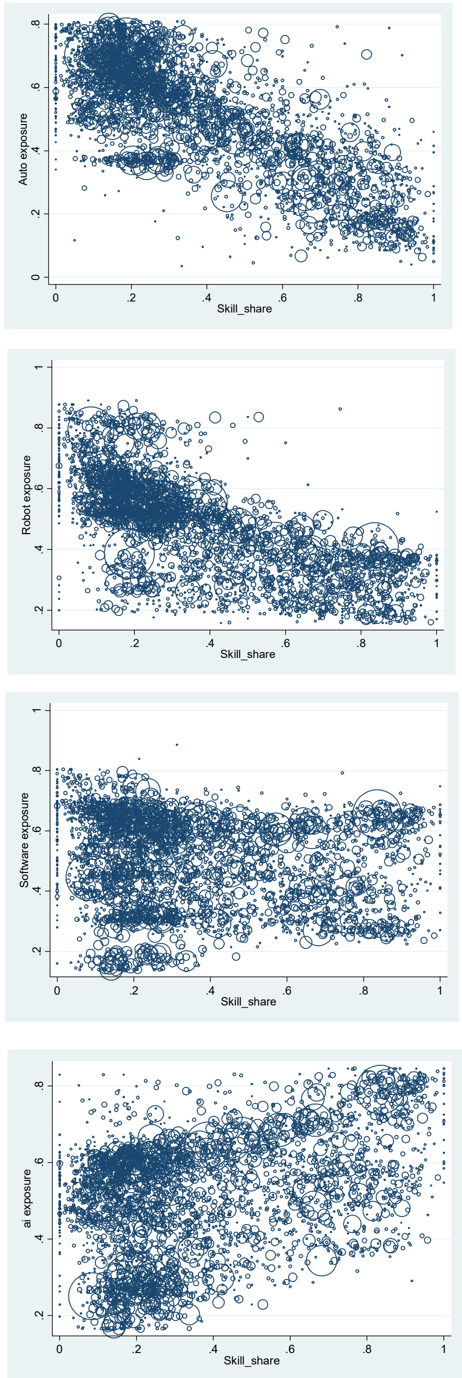

Figure 4.1: Scatterplots of firms' combinations of share of skilled workers, $Skill\_share_{it}$, and workforce exposure to automation, $Exposure_{it}$, measured from Frey and Osborne, 2017 (Auto) and Webb, 2020 (Robots,Software and AI). Data from 2015.

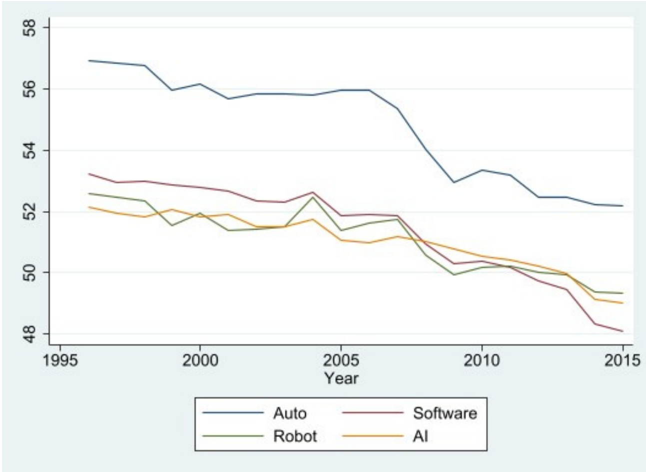

Figure 4.2: Firm-level evolution of four exposure measures, 1996–2015. Auto (based on Frey and Osborne, 2017) and Robot, Software and AI (based on Webb, 2020).

Table 1

4.3. Specification

We estimate the following specification:

$$\begin{aligned}\log(VA_{it}/L_{it}) \quad = \quad & \alpha + \underset{(+)}{\beta} \cdot Exposure_{it} + \underset{(-)}{\vartheta} \cdot Share\_skilled_{it} \times Exposure_{it} \\ & \underset{(+)}{\zeta} \cdot Share\_skilled_{it} + \varphi \cdot \log L_{it} + \rho \cdot \log(K_{it}/L_{it}) + \phi_i + \psi_t + \varepsilon_{it}. \quad (4.2)\end{aligned}$$

The dependent variable in (4.2) is the log of value added per employee in firm i at time t, $\log(\frac{VA_{it}}{L_{it}})$, which is our measure of productivity.[9] Value added is calculated as the output value minus the costs of purchased goods and services, excluding wages and other personnel costs.

Our main variables of interest are $Exposure_{it}$, which again denotes the workforce's exposure to automation in firm i at time t, and $Share\_skilled_{it} \times Exposure_{it}$, its interaction with the share of skilled workers, defined as the share of employees with university education. We also include $Share\_skilled_{it}$ as a separate regressor. We control for the log of a firm's tangible capital intensity $\log(K_{it}/L_{it})$ and log firm size, $\log L_{it}$. All specifications include firm fixed effects, ϕ_i, to control for unobserved firm-level heterogeneity in productivity arising from differences in firms' intangible assets I_i. With the firm-specific effects in (4.2), we are thus using the within-firm variation over time to explore the relationship between a firm's productivity and its workforce's exposure to automation and the way in which this relationship is affected by the firm's type. We also include year fixed effects that account for common shocks, ψ_t. Finally, ε_{it} is the error term. To allow for within-firm

[9] Value added per employee is a commonly used measure of productivity and is easily comparable across countries.

correlation over time, standard errors are adjusted for clustering at the firm level.

We want to infer how productivity and workforce exposure to automation are related in a setting where firms' investments in new technology cannot be observed. As we have shown in Prediction 1 in the previous section, we can infer this relationship from the partial correlation between productivity and exposure to automation in our panel regression. Take the derivative of (4.2) with respect to the workforce exposure to automation, $Exposure_{it}$, to obtain:

$$\frac{\partial \log (VA_{it}/L_{it})}{\partial Exposure_{it}} = \underset{(+)}{\beta} + \underset{(-)}{\vartheta} \cdot Share\_skilled_{it}. \tag{4.3}$$

Note that Prediction 1 demands that $\beta > 0$ and $\vartheta < 0$: This implies a positive partial correlation between exposure to automation and productivity for laggard firms, that is, $\frac{\partial \log(VA_{it}/L_{it})}{\partial Exposure_{it}} > 0$ for $Share\_skilled_{it} < -\frac{\beta}{\vartheta} > 0$, and a negative partial correlation between exposure to automation and productivity for leading firms, i.e., $\frac{\partial \log(VA_{it}/L_{it})}{\partial Exposure_{it}} < 0$ for $Share\_skilled_{it} > -\frac{\beta}{\vartheta} > 0$.[10] Recall the intuition behind these correlations. Over time, the return to investing in automation increases. In laggard firms, the increase in firm-level productivity from increased (unobserved) investments in automation is associated with higher employment of substitutable production workers (proxied here by the exposure variable) as the output expansion effect dominates the displacement effect from investment in new technology. In contrast, in leading firms, the output expansion effect is dominated by the displacement effect. In leading firms, increasing firm-level productivity from (unobservable) investments in the automation technology is now associated with lower employment of substitutable production workers (again proxied by the exposure variable).

4.4. Results

4.4.1. Benchmark results

As a first test, it is useful to start by estimating (4.2) while excluding the interaction term, $Share\_skilled_{it} \times Exposure_{it}$. The results for this restricted model are shown in columns 1, 3, 5 and 7 in Table 2. Column 1 shows that the estimated coefficient on exposure to automation, $Exposure_{it}$, is statistically insignificant for the Frey and Osborne (2017) automation measure (Auto). This is also the case for the exposure to AI measure from Webb (2019), as shown in column 7. These results may not be surprising since—as shown by the theory—the relationship between exposure to automation and labor productivity should differ between firm types. This heterogeneity is not accounted for when laggard and leader firms are pooled into a single relationship, as shown in Prediction 1. However, turning to exposure to robots and exposure to software, columns 3 and 5 do show a positive and significant correlation between these types of exposure measures and productivity. The latter results indicate that the positive correlation between exposure to automation in laggard firms and productivity appears to dominate in the data.

Table 2

[10] Note that we can think of $-\frac{\beta}{\vartheta}$ as an estimate of $\tilde{s}$ in Prediction 1.

In columns 2, 4, 6 and 8 in Table 2, we turn to the full specification in (4.2), which allows for heterogeneity across firms by allowing the relationship between exposure to automation to differ between laggards and leaders. The results show that for all the exposure measures except exposure to AI, the correlations are in accordance with Prediction 1. Starting with the direct impact of Frey and Osborne's general exposure to automation, we now find that the direct estimate is positive and statistically significant (i.e., $\hat{\beta} > 0$). Importantly, its interaction with the share of skilled labor is negative and statistically significant (i.e., $\hat{\vartheta} < 0$). The coefficient on the share of skilled workers is positive and statistically significant (i.e., $\hat{\zeta} > 0$). This is also expected given the assumption in the theory and Assumption 1 that higher skill intensity is associated more intangible

We obtain qualitatively similar results for exposure to robots and software; i.e., we find that the direct effects of these exposure measures are positive and statistically significant and that the interaction terms are also negative and statistically significant. However, as can be seen in column 8, we find no impact of exposure to AI on productivity—either directly or interacted with the share of skilled workers. As we noted in the previous section, this may be expected since AI was not implemented during the period that we study. In fact, the lack of results on exposure to AI may be interpreted as a simple placebo test. In the following, we will focus on the first three exposure measures (Auto, Robot and Software).

As further evidence for Prediction 1, panel (i) in Figure 4.3 shows the predicted partial correlation in (4.3), $\frac{\partial \log(VA_{it}/L_{it})}{\partial Exposure_{it}} = \hat{\beta} + \hat{\vartheta} \cdot Share\_skilled_{it}$ for all our exposure measures except AI. Irrespective of the measure, in firms with a sufficiently low skill intensity (laggard firms), labor productivity and exposure to automation are positively correlated. In firms with a sufficiently high skill intensity (leading firms), labor productivity and exposure to automation are negatively correlated.

It is again worthwhile to explain the interpretation of these correlations. Since (4.3) is estimated with firm fixed effects, the within-firm estimates in (4.2) mirror a process whereby the return to investing in new technology increases, spurring firms to invest in new automation technology. In laggard firms, the resulting technology-induced increase in productivity is associated with hiring more workers susceptible to automation (increasing our exposure measures), whereas in leading firms, the corresponding increase in productivity is associated with shedding workers susceptible to automation (decreasing our exposure measures). The theory again suggest that the positive partial correlation in laggard firms occurs because the output expansion effect of investments in new technology dominates the substituting effect while the opposite holds in leading firms.

Panel (i) in Figure 4.3 also depicts the skill share cutoff at which we can distinguish leading and laggard firms in the data. According to the Frey and Osborne's measure of exposure (Auto), the estimates tell us that firms with a skill share less than approximately 0.4 (calculated as $-\hat{\beta}/\hat{\vartheta} = x/y \approx 0.4$ from column 2 in Table 2) are laggard firms, which is also the approximate cutoff if we use Webb's software measure. Webb's robots measure gives a slightly higher cutoff of approximately 0.6.

Finally, panel (ii) in Figure 4.3 then shows the contours of predicted productivity from (4.2)

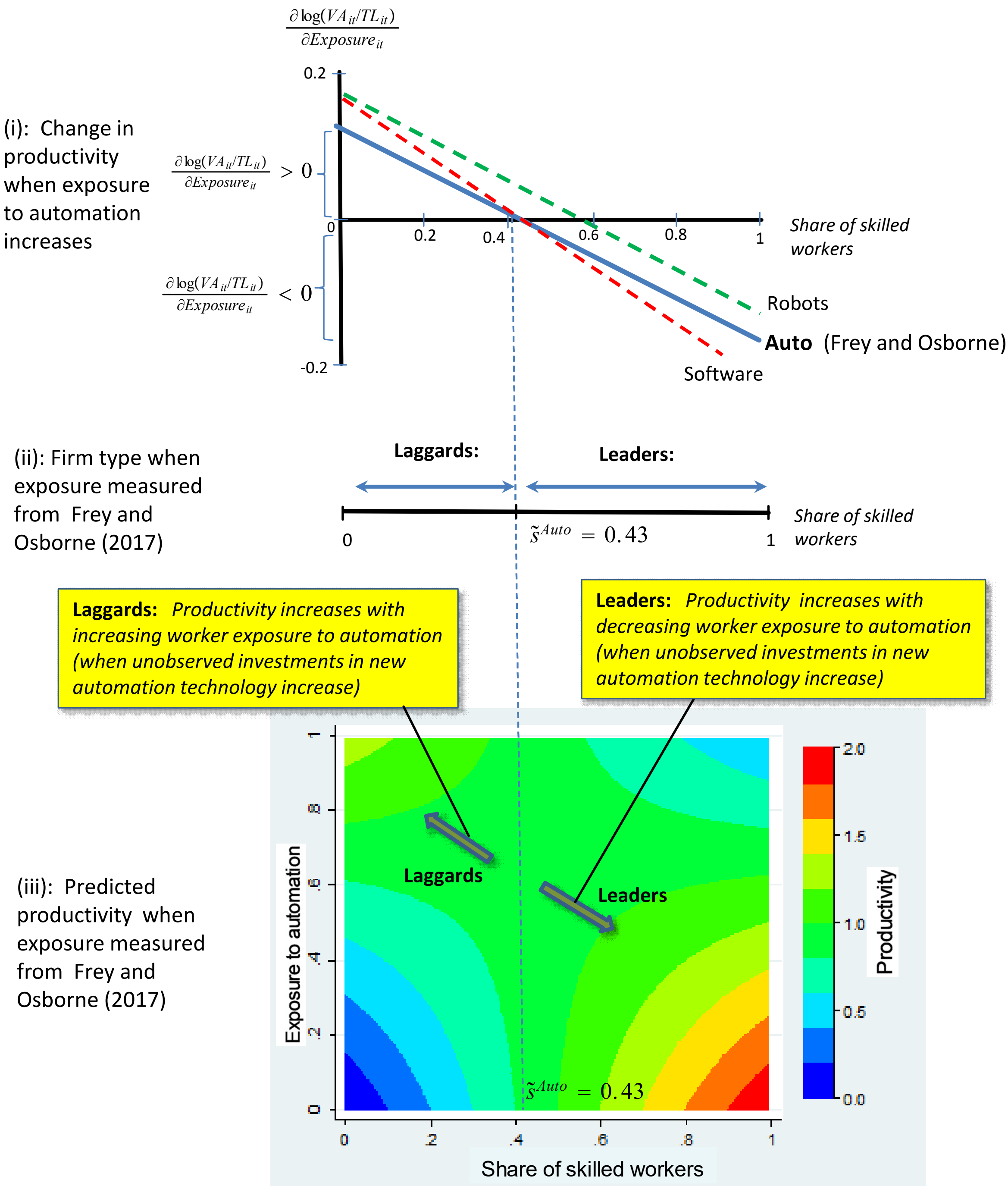

Figure 4.3: Illustrating regression results in Table 2. Panel (i) depicts the predicted cutoffs in skill intensity, $-\hat{\beta}/\hat{\vartheta}$, which distinguishes laggard and leading firms, from specifications (2), (4) and (6) of (4.2). Panel (ii) depicts predicted productivity as a function of our firm-level exposure to automation (measured from Frey and Osborne, 2017) and firm-level skill intensity from Table 2, specification (2).

plotted over a firm's skill share (x-axis) and the Frey–Osborne measure of workers' exposure to automation (y-axis) using the data for 2015. Laggard firms (those with a skill intensity less than approximately 0.4) show increasing productivity in the northwest direction, while leading firms show increasing productivity in the southeast direction. When new technology becomes cheaper and more available, laggard firms increase their investments, leading to a workforce composition skewed toward workers with a high exposure to automation with reduced skill intensity. For leading firms, the opposite process occurs: the increase in productivity from investments in new technology is associated with a workforce with lower exposure to automation and increased skill intensity.

4.4.2. Other measures of firm heterogeneity and worker exposure to automation

From the theory, we showed how one can use skill intensity as a proxy for firm heterogeneity arising from varying access to intangible or firm-specific assets. In this section, we examine alternative measures of firm types and exposure to automation.

In Table 3, we sequentially add other measures of firm heterogeneity and interact these with the average automation risk. We start by using employees' average work experience in years, Exp_{it}, and then their average age, Age_{it}. We add these variables separately to the benchmark specification (4.2), and we also do so for their interaction with the average exposure to automation, $Exposure_{it}$. These alternative proxies for heterogeneity based on employment composition reveal a pattern similar to that associated with our main heterogeneity measure based on the share of workers with tertiary education. Interestingly, it is in firms with workers who have less work experience and who are younger where we find that shifting employment toward high-exposure occupations is associated with higher labor productivity (i.e., based on $-\hat{\beta}/\hat{\vartheta}$, the cutoff in experience is approximately 22 years and the cutoff in age is approximately 41 years). In unreported specifications, we also experiment with other measures of firm heterogeneity such as firm age. Here, in line with the results on the average age of employees, we find that in younger firms, an increase in automation exposure is positively correlated with increased productivity.

Table 3

In Table 4, we check the robustness of our measure of the workforce's exposure to automation, $Exposure_{it}$, by adding alternative measures of job tasks and then interacting these variables with our main measure of firm heterogeneity, $Share\_skilled_{it}$. We here take as our starting point several measures of job task characteristics that have been used in the literature on the impact of automation. We first use RTI, a measure that is also based on occupational characteristics and qualifications from the O*NET database and developed by the US Department of Labor. This measure has been used by, for example, Autor and Dorn (2013) and Goos et al. (2014). Weighting occupations by their employment shares, we calculate a firm-level measure of routineness, RTI_{it}, in the same way as in (4.1). We also calculate firm-level averages of the level of routine cognitive tasks, RC_{it}, nonroutine manual tasks, NMR_{it}, and routine manual tasks, MR_{it}. Finally, in the same way, we compute a measure of average offshorability, $Offshore_{it}$, which has been used in, for instance, Goos et al. (2014) and was originally constructed by Blinder and Krueger (2013).[11] The results for exposure to robots are presented in Table 4. The corresponding results for exposure to software and the Frey and Osborne measure of automation are presented in the appendix (see Tables A1 and A2).

Remarkably, as shown in Table 4, the interactions of these alternative job characteristics with our skill measure for firm heterogeneity are consistently statistically insignificant, while our exposure to robots variable and its interaction is consistently estimated with good precision. Table 4 thus gives us more confidence in our estimates using the workforce's exposure to automation.[12]

Table 4

4.4.3. The use of ICT

As noted, we have no direct data on firms' investments in the new technology but argue that the correlations presented thus far between the firms' workforce exposure to automation and labor productivity arise because firms make unobserved investments in automation technology. However, we can indirectly capture some of the variation in new investments by exploring the return to investing in new technologies at the industry level, which are likely correlated with investments in automation technologies (i.e., the industry-level variable η in the theory section), using data from EUKLEMS.

To this end, we use data on the IT, ICT and software usage of Swedish firms at the two-digit industry level. To identify industries with significant variation in the return to investing in automation technology, we distinguish between industries where, for example, ICT usage was low at the beginning of the studied period 1996–2015 versus industries where ICT usage was already high at the beginning of the period. Similarly, we distinguish between industries where the use of, e.g., ICT grew considerably over the period and those with less growth. Our industry data from the EUKLEMS database are based on the version "EUKLEMS2011cap". By using this version of EUKLEMS, we are able to correctly merge the industries in our Swedish data with EUKLEMS. We use several industry measures from EUKLEMS. These include the share of the total real fixed capital stock that amounts to ICT assets, the corresponding share that amounts to software and the corresponding investment shares based on ICT and software real gross fixed capital formation. The results are very similar, regardless of which measurement we use.

In Table 5, we reestimate the benchmark specification (4.2) based on the intensity with which firms in different industries use ICT (share of total capital stock). We begin by examining initial use

[11] This measure is also available at the two-digit SSYK96 level.

[12] The results for the Frey and Osborne automation measure are identical to the results in Table 4 (see the online appendix Table A1). The estimates on exposure and its interaction with the high-skilled share are unaffected by the addition of other job task measures. However, it seems that the results for the exposure to software measure are more similar to those for the other added job task measures. As can be seen in the online appendix Table A2, the interaction term between exposure to software and high-skilled share now turns statistically insignificant, although the direct effect of exposure to software is still positive and statistically significant.

of ICT by industry. In columns 1–2, this is measured in a preperiod, 1993–1995, and in columns 3–4, it is measured at the initial year of our analysis, 1996. In columns 5–6, we instead study changes over time, measured as the change in ICT usage at the industry level during the period that we study.[13]

Inspecting Table 5, we note that the main results in Table 2 for the Frey and Osborne measure of automation originate from firms in industries that have a low initial share of ICT usage, independent of how we measure initial use. This is seen in the results for firms in industries with low ICT usage in the period before our period begins (column 1) and in industries with a low ICT share in 1996, which is the first year of our data (column 3). We find similar results in industries where ICT use increased considerably (column 6). For these industries, we again find that for firms with a low share of skilled workers (laggards), there is a positive and statistically significant correlation between the workforce's exposure to automation and labor productivity whereas this correlation is reversed in firms with a high share of skilled workers (i.e., leaders in our terminology). For exposure to robots and exposure to software, the patterns are somewhat different. For exposure to robots, we also have that the results from Table 2 originate from industries with a high change in ICT during the period that we study (column 6). However, when we compare firm in industries with a low or high ICT share in the beginning of the period, it seems that the results are driven by high-ICT industries (columns 2 and 4). Similar results on initial ICT are also seen in the specifications using exposure to software (the lowest panel in Table 5).

In Table A3 in the appendix, we also find the same patterns when we differentiate industries according to their gross investments in ICT.

Table 5

4.4.4. Endogeneity

In the theoretical model, we showed how investments in automation technology (unobserved in the data) imply a positive correlation between productivity and production employment in laggard firms. In leading firms, however, investments in automation technology imply a negative correlation between productivity and production employment. We found support for these predictions in the data: in firms in which workers without tertiary education predominate, productivity and exposure to automation are positively correlated; in firms dominated by workers with tertiary education, we found a negative correlation.

To overcome the potential endogeneity problems affecting the OLS estimates, we need to construct instruments that are positively correlated with a firm's workforce exposure to automation but that do not directly affect firm productivity. To do so, we use a shift-share instrument ap-

[13] Due to a change in industry classification in EUKLEMS during our sample period, we are not able to use a consistent industry series. We therefore base our analysis on changes over time at the industry level during the period 1996–2007. Note that this has to do with our division of industries but that we are still able to use the firm data for the entire period 1996–2015 though we again base the changes at the industry level on a somewhat shorter time window.

proach. Our IV approach is related to the analysis in, e.g., Hummels et al. (2014) and Davidson et al. (2017) on globalization and labor market outcomes. They use weighted averages of world import demand (WID) as an instrument for firm export shares, acknowledging that firm export behavior could be endogenously determined.

Adapting this approach to our research question, we use the following instrument for the firm-level measure of exposure to automation:

$$Exposure\_instr_{it} = \sum_{j=1}^{J} s_{ijt_0} \cdot Aut_j \cdot (L_{jt} - L_{ijt}) . \tag{4.4}$$

In (4.4), s_{ijt_0} is the share of workers in firm i in occupation j in the first year in which firm i is present during the period 1996–2013. We also use the share in $t-1$ as an alternative measure, denoted s_{ijt-1}. The variable $L_{jt} = \Sigma_i L_{ijt}$ is the total number of workers in occupation j in the Swedish business sector at time t, where L_{ijt} is the number of workers in firm i in occupation j at time t. Thus, the variation over time in the instrument $Exposure\_instr_{it}$ essentially stems from how employment in different occupations evolves over time at the national level (excluding employment in the own firm), L_{jt}. Since firms employ different types of workers, they are differentially affected by changes in aggregate employment. This is our identifying assumption in (4.4). Moreover, the shocks to aggregate employment are external to individual firms and unlikely to be correlated with unobserved firm characteristics that may affect productivity.

As discussed in, e.g., Autor et al. (2013) on the impact of Chinese import competition and in Acemoglu and Restrepo (2020) and Dauth et al. (2021) on the impact of robot adoption, there is potentially a concern that the shift-share variable is correlated with domestic demand shocks. To address this endogeneity problem, we use data on changes in aggregate employment at the national level in Finland instead of Sweden. Finland is a country neighboring Sweden with a business sector that shares similar levels of technological advancements. Thus, instead of using data from Sweden on aggregate employment at the national level (L_{jt}), we use data from Finland. More specifically, we use data from the ILO on aggregate changes in the share of employees in different occupations in Finland.

The IV results are presented in Tables 6 and 7 for the three measures of exposure to automation. Table 6 shows regressions where $Exposure\_instr_{it}$ acts as an instrument for $Exposure_{it}$ but where the interaction term, $Exposure_{it} \times Share\_skilled_{it}$, is not instrumented. In Table 7, we estimate (4.2) with $Exposure\_instr_{it}$ as an instrument for $Exposure_{it}$ and using $Exposure\_instr_{it} \times Share\_skilled_{it}$ as an instrument for the interaction variable $Exposure_{it} \times Share\_skilled_{it}$. For each exposure measure, we present results where the share s_{ijt_0} is held constant in the first year of appearance in the data (first column) and specifications where s_{ijt_0} is replaced with s_{ijt-1} (second column). In all specifications, we use $\log Exposure\_instr_{it}$ as an instrument for $Exposure_{it}$ in (4.2). Regardless of specification, we first note that the instrument $Exposure\_instr_{it}$ is significantly and positively correlated with $Exposure_{it}$ in the first stage (see Tables 6b and 7b). These first-stage estimates show that $Exposure\_instr_{it}$ is significantly and positively correlated with firm exposure to automation, implying that firms tend to have a workforce with a higher mean automation probability when the aggregate national occupational structure is higher.

Tables 6a and 7a report the two-stage least squares (2SLS) results. Starting with Table 6a, the estimates indicate that the results are qualitatively similar to our benchmark results in Table 2, though the coefficient estimates are somewhat larger. The specifications in columns 1, 3 and 5 hold the share s_{ijt_0} constant in the first year of appearance in the data and use $\log Exposure\_instr_{it}$ as an instrument for $Exposure_{it}$ in (4.2). Similar second-stage estimates are also found in columns 2, 4 and 6, where s_{ijt_0} is replaced with s_{ijt-1}.

Tables 6a and 6b

Our results in Table 6a show that the IV estimates for $Exposure_{it}$ are significantly larger than the corresponding OLS (FE) estimates. The same is true for the interaction term $Exposure_{it} \times Share\_skilled_{it}$. However, taking into account the cutoffs that define laggard and leading firms, our IV estimates are in accordance with both our theoretical predictions and our OLS estimates. This can be seen by comparing the calculated cutoffs in Tables 2 and 6a. For instance, the OLS and the IV estimates using the Webb robot exposure measure imply a cutoff range between 0.42 and 0.47. As illustrated, in in Figure 4.3(i), this implies that in laggard firms with a skill share less than approximately 40%, labor productivity and exposure to automation are positively correlated. In leading firms with a higher skill share above approximately 40%, productivity and exposure to automation are instead negatively correlated.

In Table 7a, we estimate (4.2) with $Exposure\_instr_{it}$ acting as an instrument for $Exposure_{it}$ and $Exposure\_instr_{it} \times Share\_skilled_{it}$ acting as an instrument for the interaction variable $Exposure_{it} \times Share\_skilled_{it}$. The results are similar to the ones in Table 6a and confirm how the relationship between exposure to automation and productivity differs between laggard and leading firms.

Tables 7a and 7b

5. The impact of product market competition

We derived our theoretical results under the simplifying assumption of monopoly. What happens if we allow for oligopolistic competition between firms? We may then suspect that the output expansion effect of laggard firms is weakened when product market competition is intensified. This may alter our observation that laggard firms can play an important role in sustaining employment in times of fast technological development.

To examine the impact on our results from allowing for oligopolistic interaction, we solve the model allowing the production differentiation parameter in (3.4) to be in the range $\lambda \in [0, 1]$. Recall that $\lambda = 0$ implies that each firm is a monopolist. Then, note that $\lambda \in (0, 1)$ implies a differentiated Cournot model and $\lambda = 1$ implies Cournot competition in homogeneous goods. It is tedious, but straightforward, to solve the product market interaction (stage 2) and the investment game (stage 1), and we relegate this to the online appendix (Section A.2). For expositional reasons, in the next section, we will illustrate the main results for Cournot duopoly.

5.1. Illustration: Cournot duopoly

Let us use the solution to the full model in the online appendix for $n = 2$ and simplify such that $a_i = a$. This implies that firm heterogeneity stems solely from the production worker input requirement, c_i. Let $i, j = \{1, 2\}$ index the firm, where Firm 1 is more efficient than Firm 2, i.e., $c_2 > c_1 > 0$. The solution to the Cournot duopoly model with endogenous investments in the new automation technology can be written as follows:

$$\begin{aligned}
q_i^*(\eta) &= \frac{(a - c_i - \lambda Q^*(\eta))}{\left(2 - \lambda - \eta\left(1 + \frac{\lambda}{(4-\lambda)(2-\lambda)}\right)\right)}, && (5.1)\\
Q^*(\eta) &= q_1^*(\eta) + q_2^*(\eta) = \frac{2a - (c_1 + c_2)}{\left(\frac{(2-\lambda)(4-\lambda)}{2(1-\lambda)+2-\lambda}\right) - \eta\left(1 + \frac{\lambda}{(4-\lambda)(2-\lambda)}\right)} && (5.2)\\
P_i^*(\eta) &= a - q_i^*(\eta) - \lambda q_j^*(\eta),\ i, j = \{1, 2\},\ i \neq j, && (5.3)\\
l_i^*(\eta) &= c_i - \eta q_i^*(\eta)\left(1 + \frac{\lambda}{(4-\lambda)(2-\lambda)}\right), && (5.4)\\
L_i^*(\eta) &= l_i^*(\eta)\, q_i^*(\eta), && (5.5)\\
k_i^*(\eta) &= \frac{\gamma}{\mu} q_i^*(\eta)\left(1 + \frac{\lambda}{(4-\lambda)(2-\lambda)}\right), && (5.6)\\
v_i^*(\eta) &= \frac{P_i^*(\eta)\, q_i^*(\eta)}{L_i^*(\eta) + f_i}. && (5.7)
\end{aligned}$$

5.1.1. The output expansion effect and product market competition

Recall that the impact on the number of production workers needed when a firm increases its investments in the new automation technology is given from the output expansion effect, which increases the demand for workers, and the labor displacement effect, which reduces the demand for production workers. A necessary condition for employment of production workers to increase when a firm increases its investments in labor saving technology is that the output expansion effect be positive. More intense product market competition may weaken the laggard firm's ability to sustain employment of production workers when the rewards to investment in new automation technologies are high.

To highlight how the output expansion effect is affected by the intensity of product market competition, assume homogeneous goods, $\lambda = 1$, substitute (5.2) into (5.1) and differentiate in η, to obtain

$$\frac{dq_i^*}{d\eta} = 12\frac{(9-24\eta)a + (36-24\eta)c_j - (45-48\eta)c_i}{(3-4\eta)^2(9-4\eta)^2}. \tag{5.8}$$

From (5.8), we have the following Lemma:

Lemma 3. *Assume that $n = 2$ and $\lambda = 1$ (Cournot-duopoly with homogeneous goods). Let $\tilde{c}_2(c_1, \eta)$ be defined from $\frac{dq_2^*(\eta, \tilde{c}_2(c_1,\eta), c_1)}{d\eta} = 0$, and let $\check{c}_2(c_1, \eta)$ be defined from $q_2^*(\eta, \check{c}_2(c_1, \eta), c_1) = 0$. The following then holds:*

(i) F*or $c_2 \in (c_1, \tilde{c}_2(c_1, \eta))$, the output expansion effect for the laggard firm, Firm 2, is positive: $\frac{dq_2^*}{d\eta} > 0$.*

(ii) *For $c_2 \in (\tilde{c}_2(c_1, \eta), \check{c}_2(c_1, \eta))$, the output expansion effect for the laggard firm, Firm 2, is negative:$\frac{dq_2^*}{d\eta} < 0$.*

(iii) *The output expansion effect for the leading firm, Firm 1, is always positive:$\frac{dq_1^*}{d\eta} > 0$.*

The message from Lemma 3 is that when Firm 2 (the laggard firm) is sufficiently less efficient than Firm 1 (the leading firm), the output expansion effect for the laggard becomes negative. The reduction in output for the laggard firm stems from the well-known strategic effect in oligopolistic markets: as the leading firm becomes increasingly aggressive, taking advantage of its initial advantage in terms firm-specific assets, the laggard firm scales back to prevent a drastic fall in the price of its product. Lemma 3 thus highlights that the main result in Prediction 1—that both productivity and employment of workers susceptible to automation can increase in tandem for laggard firms when firms increase investments in a new automation technology—may not hold in an environment with strong product market competition.

To explore this further, Figure 5.1 depicts four panels: Panels (i) and (ii) show contour plots of productivity and employment of production workers in the *laggard firm*, $v_2^*(\eta)$ and $L_2^*(\eta)$; Panels (iii) and (iv) show contour plots of productivity and employment of production workers in the *leading firm*, $v_1^*(\eta)$ and $L_1^*(\eta)$. In each panel, the horizontal axis shows the return to investing in the new automation technology η, while the vertical axis shows the intensity of product market competition, as measured by the product differentiation parameter, λ. Recall that each firm is a monopolist when $\lambda = 0$ and is engaged in Cournot competition with homogenous goods when $\lambda = 1$. To compare with the outcome under monopoly in the benchmark model, we also choose the input requirements in accordance with Prediction 1, i.e., $\frac{a}{c_2} \in (0, 2]$ and $\frac{a}{c_1} > 2$. Several observations follow from Figure 5.1.

Illustrating the model under differentiated Cournot duopoly. Parameter values such that Firm 1 is the leader and Firm 2 the laggard with: $c_1 = 4.2$, $c_2 = 6$, $f_1 = 0.2$, $f_2 = 0.1$ and $a = 10$. In the left column, panel (i) depicts the laggard's productivity v_2^* and panel (ii) depicts the laggards production employment L_2^*, both as functions of competition λ (vertical axis) and the return to invest in new technology η (horizontal axis). In the right column, panel (iii) depicts the leader's productivity v_1^* and panel (iv) depicts the leader's production employment L_1^*, again as functions of competition λ and the return to invest in new technology η.

First, if product market competition is weak (i.e., when λ is low), the lower part of panels (i) and (ii) show that Prediction 1 extends into oligopoly: In the laggard firm, the increased return to investing in automation η leads to increased productivity, $v_2^*(\eta)$, and increased employment of

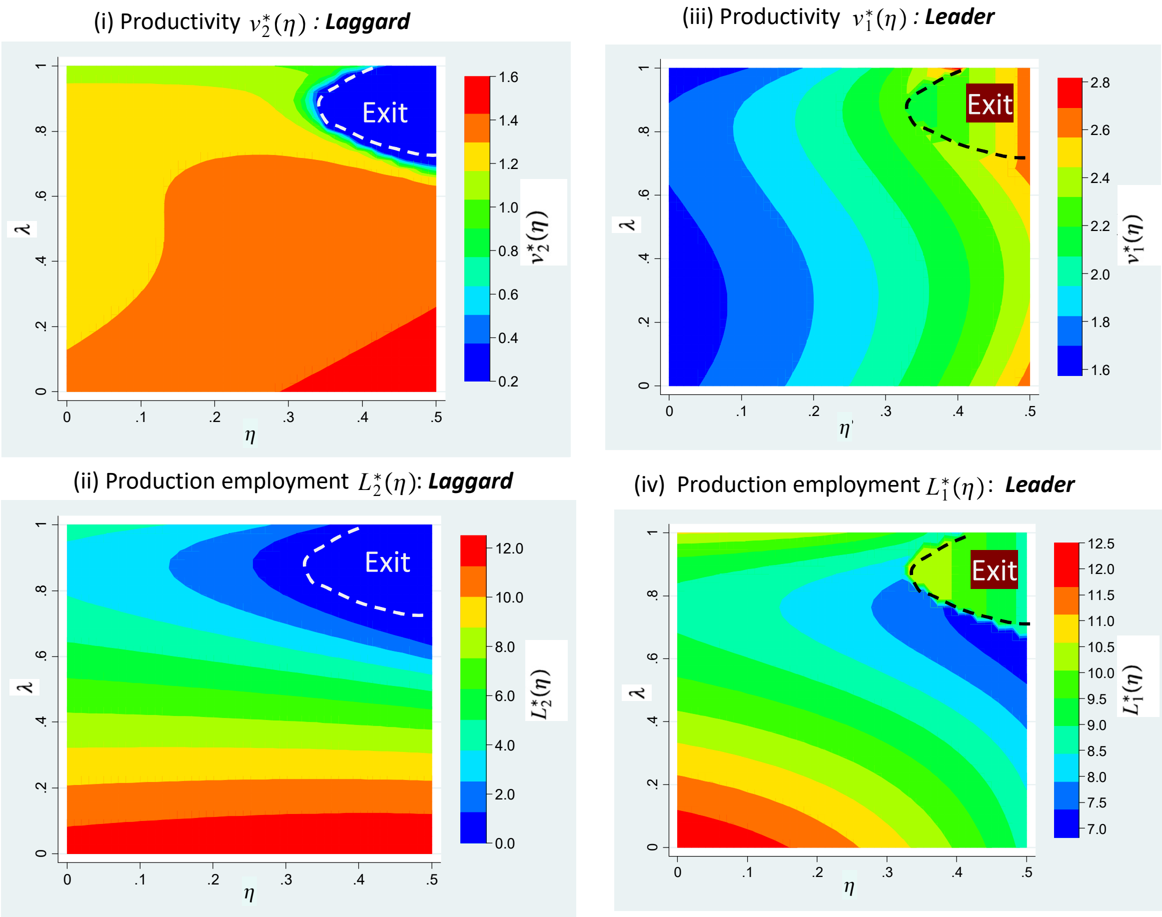

Figure 5.1: Illustrating the model under differentiated Cournot duopoly. Parameter values such that Firm 1 is the leader and Firm 2 the laggard with: $c_1 = 4.2$, $c_2 = 6$, $f_1 = 0.2$, $f_2 = 0.1$ and $a = 10$. In the left column, panel (i) depicts the laggard's productivity v_2^* and panel (ii) depicts the laggards production employment L_2^*, both as functions of competition λ (vertical axis) and the return to invest in new technology η (horizontal axis). In the right column, panel (iii) depicts the leader's productivity v_1^* and panel (iv) depicts the leader's production employment L_1^*, again as functions of competition λ and the return to invest in new technology η.

production workers, $L_2^*(\eta)$. In the leading firm in panels (iii) and (iv), the lower part of these diagram reveals that higher returns to investing in the new technology instead lead to increased productivity, $v_1^*(\eta)$, and reduced employment of production workers, $L_1^*(\eta)$.

Second, at a higher intensity of product market competition (i.e., when high λ is high), the output expansion effect is weakened in the laggard firm. This implies that the increased productivity associated with an increase in the return to investment in automation η is associated with lower employment levels for production workers. Thus, productivity and production employment become negatively correlated in the laggard firm. When the intensity of product market competition increases, further increasing the return to invest in automation η leads to shrinking employment of production workers in the laggard firm, combined with declining productivity.

Third, a combination of increased intensity of product market competition and an increased return to investment in the automation technology may even induce the laggard firm to exit. This is shown in the northeast part of panels (i) and (ii). As shown in panels (iii) and (iv), exit by the laggard firm pushes up both productivity and employment of production workers in the leading firm.

To summarize:

Proposition 3. *Suppose that the market structure is a Cournot duopoly with differentiated or homogenous products, i.e.,* $n = 2$ *and* $\lambda \in (0, 1]$. *Then:*

(i) *Prediction 1 holds if the intensity of product market competition is not too high: In laggard firms, both productivity and employment of production workers then increase when the return to investments in the new automation technology increases, while for leading firms, the increase in productivity is associated with lower employment of production workers.*

(ii) *When the intensity of product market competition is sufficiently high, an increased return on investment in the new automation technology is associated with several different correlations between productivity and employment of production workers. For instance, in laggard firms, both productivity and employment of production workers can fall when the return on investment in automation technology increases.*

As illustrated in Figure 5.1, when the intensity of product market competition is high, the relationship between how productivity and employment of production workers develops when new automation technology is implemented is involved. This result suggests that Prediction 1 should primarily hold in industries with low-intensity product market competition.

To explore this finding empirically, we rerun specification 4.2 for three subsamples depending on the intensity of product market competition in different industries. Following Boone (2008a,b), we define increased product market competition as changes in industry characteristics that increase the relative profitability of more efficient firms in an industry. This formalization of the intensity of product market competition has the advantage of being consistent with different types of structural changes in an industry such as reduced entry barriers, reduced product differentiation and market integration. The Boone measure has been used extensively in the finance literature, and it is produced by the World Bank as a measure of banking competition.[14] Details on how the Boone measure of product market competition is estimated can be found in Section A.3 in the appendix.

To examine how the estimated Boone measure is related to our predictions, we divide firms in industries into three groups based on the intensity of product market competition at the industry level (low, medium and high). We then examine the relationship between exposure to automation and productivity for each group of industries. The results are shown in Table 8.

Table 8

We start by looking at exposure to automation based on Frey and Osborne (2017) and exposure to robots based on Webb (2019). In line with Proposition 3(i) and (ii), we find that $Exposure_{it}$ is positive and significant and that $Share\_skilled_{it} \times Exposure_{it}$ is negative and significant only for industries with a low intensity of product market competition (the 25% of industries with the lowest-intensity product market competition). The latter finding is consistent with the results illustrated in the move to the right in panels (i) and (ii) for low-intensity product market competition in Figure 5.1. Thus, the basic results in Table 2 seem to originate from firms in industries with low-intensity product market competition. Columns 7–9 in Table 8 present the corresponding results for the exposure to software measure. For this measure, we do not find any clear pattern, so in line with results above, we find different results for exposure to software than for the other two measures.

5.2. Discussion

To summarize, we have shown that we can derive qualitatively similar results with several firms competing in the same product market under strategic interaction as in the monopoly setup. It is outside the scope of the paper to undertake a complete theoretical welfare analysis of the automation technology–driven creative destruction process. However, Figure 5.1 illustrates that a country with business sectors characterized by diversity in firm types might face a smoother automation-driven creative destruction process. Countries with highly competitive product markets may face a harsh creative destruction process when new technologies emerge. This effect is illustrated in Figure 5.1, for the case with high-intensity product market interaction where the employment of production workers decreases substantially when new technologies emerge. While leading firms are the engines of creating prosperity and welfare for society, a diversity of firm types may function as insurance against excessive reduction in labor demand in occupations where workers are replaced by automation technology. Business sectors with a few large, highly efficient firms may show high productivity growth but might be susceptible to socially excessive temporary unemployment. Business sectors with many small and inefficient firms might be more stable in labor demand but may hamper productivity growth and lead to a suboptimal growth rate.

Moreover, Figure 5.1 illustrates some potentially significant policy insights. When the intensity

[14] See http://www.worldbank.org/en/publication/gfdr/background/banking-competition.

of product market competition is high, laggard firms might lose substantial market share and even be forced out of the market when the pace of automation technology change is high (when η is high). If the welfare cost of an increased job destruction rate is high, this suggests that a laxer merger policy might be called for during periods of rapid technological change. In particular, the failing firm defense in merger law might be used in a forward-looking way (Persson 2005) to ensure a smoother creative destruction process. Our analysis suggests that policymakers should consider these forces when balancing the pros and cons of merger regulations.

6. Conclusion

In this paper, we have investigated how automation affects productivity and the occupational mix for different types of firms. We develop a model in which (i) firms in imperfectly competitive markets can invest in new automation technology that can displace production workers, (ii) we distinguish between leading firms that have access to high-quality firm-specific capital and laggard firms that lack such assets, and (iii) firms can change their occupational mix between production workers and other employees. Under plausible assumptions regarding how profits depend on automation technology, we show that increased automation possibilities lead to all firms increasing their productivity. Nevertheless, only laggard firms may increase employment of workers susceptible to automation. Moreover, we show that when technology development has advanced considerably and when product market competition is stiff, laggard firms face reduced productivity and decrease their employment of workers susceptible to automation.

Using Swedish matched employer–employee data, we find strong empirical evidence for these predictions. In particular, we find a negative correlation between productivity and the share of employees in occupations susceptible to automation for firms with a high share of high-skill workers but a negative correlation for firms with a low share of high-skill workers. To address a potential endogeneity problem, we apply a shift-share instrument approach, where the variation over time in our instrument essentially stems from how the employment of different occupations evolves over time at the aggregated level. Our main results hold when we use our proposed instrument.

Our empirical findings indicate that leading and laggard firms react differently to new automation technologies with respect to their hiring of workers in occupations susceptible to automation. This suggest that countries with business sectors characterized by diversity in firm types might face a smoother automation-driven creative destruction process. Such diversity of firm types may function as insurance against excessive reduction in labor demand in occupations where workers are replaced by automation technology in periods of rapid technological change. Business sectors with a few large, highly efficient firms may display high productivity growth but might suffer from excessive temporary unemployment. However, business sectors with too many small and inefficient firms might be more stable in terms of labor demand but may hamper productivity growth.

Sweden may be an interesting example in that it might achieve the appropriate balance during the automation-driven creative destruction process that has occurred in recent decades. We have described this process in several papers (Heyman, Norbäck and Persson 2019a, b). Sweden is also one of the few countries that have been able to combine relatively high productivity growth with a high labor participation rate in the private sector and rising wages. Policies such as tax reforms conducive to a level playing field between large incumbent firms and young small firms were implemented in Sweden in 1990 and might be of particular value during periods of rapid technological change. Indeed, our results suggest that a crucial element in achieving balanced automation-driven industrial restructuring is that leading firms replace workers in occupations susceptible to automation with automation technologies while laggard firms, in contrast, tend to hire employees in such occupations.

The intensity of product market competition also affects the pace of the creative destruction process. We show that we can derive qualitatively similar results with several firms competing in the same product market under strategic interaction. However, we also show that when competition in the product market is tough, laggard firms might be forced out of the market. This finding suggests that laxer merger policy might be called for during periods of rapid technological change. Our analysis suggests that policy-makers should consider these forces when balancing the pros and cons of merger regulations.

Interfering with firms' choice of pace in their implementation of new automation technologies could also result in welfare losses by reducing the rate of creative destruction in the economy below the socially optimal level. Fine-tuning the level of implementation of automating technologies may well be beyond the government's ability due to information frictions and other practical concerns. Government intervention seeking to reduce the speed of bankruptcies might, however, be a desirable measure in a period of rapid technological change. Such a policy can ensure that laggards do not exit the markets at an excessively fast pace (although whether such interventions solve more problems than they create is an open question due to the moral hazard problems involved). An alternative way to mitigate the adverse consequences of implementing automation technology may be to introduce measures that reduce the cost of reskilling activities for workers. This policy might increase the expected returns from skill formation and improve political support for technology transformation, which could increase the economy's total surplus.

Finally, the firm heterogeneity emphasized in this paper comes in many different shapes. An exciting avenue for further research would be to examine how different forms of ownership may affect productivity and employment patterns when automation technology is implemented. Regional heterogeneity may also be significant in how a country's automation technology industrial restructuring evolves and warrants further investigation.

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Table 1: Definitions and descriptive statistics (firm-level means and standard deviations). Firms with at least 10 employees, 1996–2015

Firm variables:	Definition	1996–2015	1996	2015
Value added per employee	Sales-operational expenses excluding wages/No. of employees	0.59 (0.53)	0.44 (0.27)	0.72 (0.61)
Capital intensity	Net property, plant and equipment/No. of employees	0.88 (4.09)	0.32 (0.89)	0.90 (4.12)
No. of employees	No. of employees	256 (992)	287 (1,300)	309 (973)
Individual level-based variables:				
Auto	Exposure to automation	0.56 (0.17)	0.57 (0.16)	0.52 (0.18)
Robot	Exposure to robots	0.51 (0.17)	0.52 (0.17)	0.48 (0.17)
Software	Exposure to software	0.52 (0.17)	0.52 (0.15)	0.50 (0.15)
AI	Exposure to AI	0.51 (0.14)	0.51 (0.14)	0.52 (0.15)
Share high skilled	Share of employees with tertiary education	0.26 (0.24)	0.18 (0.20)	0.36 (0.26)
Schooling	Individual grouping of schooling, ranging from 1 to 7	3.60 (0.78)	3.13 (0.73)	4.04 (0.73)
Labor market experience	Age minus number of years of schooling minus seven	22.29 (5.75)	21.97 (5.74)	22.37 (5.68)
Age	Age of employees	40.80 (5.50)	39.76 (5.38)	41.53 (5.50)
RTI	Routine task intensity (RTI) index	0.03 (0.54)	0.12 (0.56)	-0.04 (0.51)
Offshorability	Offshorability index	0.14 (0.83)	0.20 (0.89)	0.15 (0.78)

Note: All monetary variables are in 1995 SEK. RTI and Offshorability are based on the years 1996–2013. See Section 4.1 for details about the variables.

Table 2: Automation probability and productivity, 1996–2015. Basic regressions based on exposure to automation, exposure to robots and exposure to software at 2-digit level

	Auto		Robot		Software		AI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure	0.034	0.126***	0.088**	0.167***	0.104**	0.173***	0.060	0.086
	(0.037)	(0.045)	(0.034)	(0.043)	(0.041)	(0.050)	(0.050)	(0.065)
Exposure × Share_skilled		-0.292**		-0.389**		-0.300*		-0.095
		(0.133)		(0.178)		(0.171)		(0.193)
Share_skilled	0.053	0.190**	0.061	0.221**	0.050	0.193**	0.041	0.092
	(0.055)	(0.092)	(0.056)	(0.104)	(0.057)	(0.096)	(0.056)	(0.105)
Log Capital Intensity	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Firm Size	-0.129***	-0.129***	-0.130***	-0.129***	-0.129***	-0.129***	-0.128***	-0.128***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Cutoff:$= -\frac{\widehat{\beta}}{\widehat{\vartheta}}$		0.43		0.42		0.58		
R-squared	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073
Observations	75,829	75,829	75,829	75,829	75,829	75,829	75,829	75,829
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. The cutoff is calculated from equation 4.2. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Automation probability and productivity, 1996–2015. Basic regressions based on exposure to automation, exposure to robots and exposure to software at 2-digit level

	Auto		Robot		Software	
	Mean experience	Mean age	Mean experience	Mean age	Mean experience	Mean age
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.317***	0.658***	0.224**	0.424**	0.293***	0.563**
	(0.095)	(0.171)	(0.106)	(0.189)	(0.111)	(0.202)
Experience	0.004		-0.000		0.000	
	(0.002)		(0.002)		(0.002)	
Exposure × Experience	-0.014***		-0.007*		-0.009**	
	(0.004)		(0.004)		(0.005)	
Age		0.005*		0.000		0.001
		(0.003)		(0.003)		(0.001)
Exposure × Age		-0.016***		-0.009**		0.012**
		(0.004)		(0.005)		(0.005)
Observations	74,829	74,829	74,829	74,829	74,829	74,829
R-squared	0.074	0.074	0.074	0.074	0.074	0.074
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), and Software is exposure to software (Webb, 2020). Mean experience is mean labor market experience at the firm level, and Mean Age is mean age of the workforce at the firm level. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Automation probability and productivity, 1996–2013. Impact of other job task characteristics on exposure to robots (Webb, 2020) at 2-digit level

	RTI	Offshorability	Routineness	Routine cognitive	Routine manual	Nonroutine manual
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.176***	0.192***	0.179***	0.208***	0.175***	0.217***
	(0.046)	(0.046)	(0.046)	(0.058)	(0.046)	(0.055)
Exposure × Share_skilled	-0.394**	-0.431**	-0.415**	-0.476**	-0.436**	-0.539**
	(0.200)	(0.207)	(0.200)	(0.230)	(0.205)	(0.248)
RTI	0.007					
	(0.011)					
RTI ×Share_skilled	-0.040					
	(0.042)					
Offshorability		0.014*				
		(0.007)				
Offshorability ×Share_skilled		-0.010				
		(0.037)				
R			0.012			
			(0.019)			
R ×Share_skilled			-0.035			
			(0.087)			
RC				0.032		
				(0.039)		
RC ×Share_skilled				-0.075		
				(0.111)		
RM					0.014	
					(0.021)	
RM ×Share_skilled					0.019	
					(0.120)	
NRM						-0.029
						(0.023)
NRM ×Share_skilled						0.097
						(0.113)
Observations	69,116	69,116	69,116	69,116	69,116	69,116
R-squared	0.064	0.064	0.064	0.064	0.064	0.064
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Exposure is is firm-level exposure to robots (Webb, 2020), Share_skilled is the share of employees with university education, RTI is the routine task intensity (RTI) index, Offshorability is the offshorability index, R is routine, RC is routine cognitive, RM is routine manual, and NRM is nonroutine manual, all measured as means at the firm level of the firm's workforce. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Automation probability and productivity, 1996–2015. By capital share in ICT at the industry level based on exposure at 2-digit level

	Low ICT share (pre-means)	High ICT share (pre-means)	Low ICT share (1996)	High ICT share (1996)	Low ICT share change	High ICT share Change
	(1)	(2)	(3)	(4)	(5)	(6)
			Auto			
Exposure	0.183***	0.048	0.203***	0.043	0.112**	0.142**
	(0.058)	(0.067)	(0.059)	(0.066)	(0.055)	(0.068)
Exposure × Share_skilled	-0.444*	-0.149	-0.569**	-0.101	-0.197	-0.431**
	(0.229)	(0.164)	(0.229)	(0.164)	(0.161)	(0.211)
Observations	34,004	41,825	32,974	42,855	42,615	33,214
R-squared	0.088	0.063	0.093	0.060	0.062	0.091
			Robot			
Exposure	0.102**	0.231***	0.112**	0.235***	0.177***	0.136**
	(0.052)	(0.071)	(0.052)	(0.071)	(0.058)	(0.058)
Exposure × Share_skilled	-0.130	-0.601**	-0.251	-0.544**	-0.324	-0.441*
	(0.241)	(0.244)	(0.243)	(0.244)	(0.253)	(0.238)
Observations	34,004	41,825	32,974	42,855	42,615	33,214
R-Squared	0.088	0.063	0.093	0.061	0.062	0.091
			Software			
Exposure	0.104*	0.203**	0.118**	0.213**	0.170***	0.133*
	(0.058)	(0.080)	(0.058)	(0.083)	(0.059)	(0.079)
Exposure × Share_skilled	0.397	-0.547**	0.336	-0.562***	-0.247	-0.419
	(0.318)	(0.218)	(0.314)	(0.217)	(0.204)	(0.313)
Observations	34,004	41,825	32,974	42,855	42,615	33,214
R-Squared	0.089	0.063	0.093	0.061	0.062	0.091
Firm controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. ICT share at the industry level is the share of the total real fixed capital stock that amounts to ICT assets. Firms are divided into two groups according to their pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 6a: IV regressions 1996–2015 based on auto/Webb robot/Webb software at 2-digit level. Exposure instrumented (aggregate changes in the share of employees by occupation in Finland)

	Auto		Robot		Software	
	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	1.228*	2.670***	0.807	1.278***	1.128*	2.777***
	(0.746)	(0.942)	(0.507)	(0.348)	(0.629)	(0.806)
Exposure × Share_Skilled	-1.949*	-4.188***	-1.741	-2.715***	-2.127*	-5.090***
	(1.163)	(1.483)	(1.064)	(0.761)	(1.176)	(1.468)
Share_skilled	1.121*	2.332***	0.859*	1.292***	1.114*	2.554***
	(0.628)	(0.811)	(0.484)	(0.358)	(0.573)	(0.727)
Cutoff: $= -\frac{\widehat{\beta}}{\widehat{\vartheta}}$	0.63	0.64	0.46	0.47	0.53	0.54
Observations	54,594	52,791	54,594	52,791	54,594	52,791
R-squared	0.059	0.007	0.066	0.055	0.061	0.007
Firm controls	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. Gross investments in ICT at the industry level are based on real gross fixed capital formation. Firms are divided into two groups according to pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. The cutoff is calculated from equation 4.2. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 6b: IV first-stage regressions 1996–2015. Exposure instrumented

	Auto		Robot		Software	
	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure_instr	0.007***	0.007***	0.010***	0.015***	0.009***	0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Exposure × Share_skilled	1.554***	1.557***	2.052***	2.043***	1.841***	1.808***
	(0.024)	(0.026)	(0.043)	(0.045)	(0.039)	(0.042)
Share_skilled	-0.844***	-0.847***	-0.941***	-0.937***	-0.907***	-0.891***
	(0.015)	(0.016)	(0.020)	(0.021)	(0.021)	(0.022)
Observations	54,594	52,791	54,594	52,791	54,594	52,791
F test	30.38	26.09	36.34	127.9	31.67	36.08
Firm controls	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. Gross investments in ICT at the industry level are based on real gross fixed capital formation. Firms are divided into two groups according to pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 7a: IV regressions 1996–2015 based on auto/Webb robot/Webb software at 2-digit level. Exposure and interaction term instrumented (aggregate changes in share of employees by occupation in Finland)

	Auto		Robot		Software	
	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	1.399**	1.955***	0.969***	1.010***	1.513***	2.049***
	(0.591)	(0.558)	(0.354)	(0.255)	(0.495)	(0.530)
Exposure × Share_skilled	-2.743***	-2.242***	-2.638***	-1.300*	-5.035**	-2.046*
	(0.807)	(0.672)	(1.020)	(0.778)	(2.124)	(1.094)
Share_Skilled	1.475***	1.395***	1.221***	0.719**	2.509**	1.087**
	(0.435)	(0.395)	(0.442)	(0.338)	(1.036)	(0.535)
Cutoff: $= -\frac{\hat{\beta}}{\hat{\vartheta}}$	0.51	0.66	0.36	0.49	0.30	0.57
Observations	54,594	52,791	54,594	52,791	54,594	52,791
R-squared	0.054	0.035	0.062	0.060	0.042	0.031
Firm controls	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. Gross investments in ICT at the industry level are based on real gross fixed capital formation. Firms are divided into two groups according to pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. The cutoff is calculated from equation 4.2. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 7b: IV first stage regressions 1996–2015. Exposure and interaction term instrumented

	Auto		Robot		Software	
	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1	Share based on first year	Share based on t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure_instr	0.006***	0.007***	0.014***	0.024***	0.014***	0.013***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Exposure_instr × Share_skilled	0.025***	0.040***	0.007	0.007	-0.006	0.006
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.005)
Share_skilled	-0.123***	-0.058**	-0.150***	-0.147***	-0.059**	-0.010
	(0.029)	(0.027)	(0.025)	(0.024)	(0.029)	(0.024)
Observations	54,594	52,791	54,594	52,791	54,594	52,791
F test	20.78	56.11	20.81	91.12	16.46	33.14
Firm controls	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. Gross investments in ICT at the industry level are based on real gross fixed capital formation. Firms are divided into two groups according to pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Automation probability and productivity, 1996–2015. Differences across product market competition. Based on Boone means over the period

	Auto			Robot			Software		
	Below p25	Between p25 and p75	Above p75	Below p25	Between p25 and p75	Above p75	Below p25	Between p25 and p75	Above p75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exposure	0.177**	0.036	0.267	0.254***	0.034	0.550*	0.306***	0.037	0.612**
	(0.085)	(0.059)	(0.243)	(0.085)	(0.051)	(0.289)	(0.094)	(0.059)	(0.282)
Exposure × Share_skilled	-0.524***	0.332	-1.122	-0.644***	0.272	-2.636	-0.479**	0.222	-3.813*
	(0.178)	(0.220)	(1.819)	(0.232)	(0.227)	(2.065)	(0.213)	(0.245)	(2.150)
Share_skilled	0.198**	-0.087	0.265	0.240**	-0.045	0.958	0.204*	-0.045	1.856
	(0.095)	(0.148)	(1.166)	(0.110)	(0.142)	(1.190)	(0.113)	(0.137)	(1.268)
R-squared	0.076	0.078	0.056	0.076	0.078	0.059	0.076	0.078	0.059
Observations	24,061	41,299	10,469	24,061	41,299	10,469	24,061	41,299	10,469
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. Gross investments in ICT at the industry level are based on real gross fixed capital formation. Firms are divided into three groups according to Boone. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

A. Online appendix (not for publication)

A.1. Proof of (3.29) being strictly positive

Note that value added per employee in our model can be written as

$$VAL_i^*(\eta) = \frac{R_i^*(\eta)}{L_i^*(\eta) + f_i} = \frac{P_i^*(\eta) q_i^*(\eta)}{l_i^*(\eta) q_i^*(\eta) + f_i} = \frac{P_i^*(\eta)}{l_i^*(\eta) + \frac{f_i}{q_i^*(\eta)}}. \tag{A.1}$$

To show that $\frac{dVAL_i^*(\eta)}{d\eta}\frac{\eta}{VAL_i^*(\eta)} > 0$, we need to show that $\frac{dVAL_i^*(\eta)}{d\eta} > 0$. First, invert (A.1) to obtain

$$\frac{1}{VAL_i^*(\eta)} = \frac{l_i^*(\eta)}{P_i^*(\eta)} + \frac{f_i}{R_i^*(\eta)}. \tag{A.2}$$

Then, define

$$\tilde{v}_i^*(\eta) = \frac{R_i^*(\eta)}{L_i^*(\eta)} = \frac{P_i^*(\eta)}{l_i^*(\eta)}. \tag{A.3}$$

Combining (3.30), (3.34) and (A.3), we obtain

$$\underbrace{\frac{d\tilde{v}_i^*(\eta)}{d\eta}\frac{\eta}{\tilde{v}_i^*(\eta)}}_{\text{Productivity effect}} = \underbrace{\frac{dP_i^*(\eta)}{d\eta}\frac{\eta}{P_i^*(\eta)}}_{\text{Price effect}} - \underbrace{\frac{dl_i^*(\eta)}{d\eta}\frac{\eta}{l_i^*(\eta)}}_{\text{Displacement effect}} = \left(\underbrace{\frac{a_i}{c_i}\cdot\frac{a_i - c_i}{\left(2 - \frac{a_i}{c_i}\eta\right)(a_i + c_i - a_i\eta)}\eta}_{(+)}\right) > 0. \tag{A.4}$$

Now, use (3.20) and (3.21) to have

$$R_i^*(\eta) = P_i^*(\eta) q_i^*(\eta) = \left(\frac{a_i + c_i - a_i\eta}{2-\eta}\right)\left(\frac{a_i - c_i}{2 - \eta}\right) = (a_i - c_i)\frac{a_i + c_i - \eta a_i}{(\eta - 2)^2}. \tag{A.5}$$

Taking the derivative of (A.5), we obtain

$$\frac{\partial R_i^*(\eta)}{\partial \eta} = (a_i - c_i)\frac{2c_i - \eta a_i}{(2-\eta)^3} > 0. \tag{A.6}$$

Since $R_i^*(\eta)$ is strictly decreasing in η from (A.6), $\frac{f_i}{R_i^*(\eta)}$ must be strictly decreasing in η. Moreover, since $\tilde{v}_i^*(\eta) = \frac{P_i^*(\eta)}{l_i^*(\eta)}$ is strictly increasing in η from (A.4), it follows that $\frac{1}{VAL_i^*(\eta)}$ in (A.2) is strictly declining in η. However, then $VAL_i^*(\eta)$ must be strictly increasing in η, which implies that $\frac{dVAL_i^*(\eta)}{d\eta}\frac{\eta}{VAL_i^*(\eta)} > 0$.

A.2. The Cournot model

In this section, we solve the differentiated product Cournot model for $n \geq 2$ firms.

A.2.1. Stage 1: Product market competition

To highlight the effect of competition, the profit maximization problem for firm i is

$$\max_{\{q_i,k_i\}} \pi_i = \underbrace{P_i q_i}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i)\, q_i}_{\text{Labor (high risk) costs}} - \underbrace{\frac{\mu}{2} k_i^2}_{\text{Installation costs}} - w_H f_i. \tag{A.7}$$

Let us simplify such that $a_i = a$ so that c_i is the source of heterogeneity in intangible assets among firms. The inverse demand is then

$$P_i = a - q_i - \lambda \sum_{j \neq i}^{n} q_j, \tag{A.8}$$

where $\lambda \in [0,1]$ gives the (inverse) level of intensity of product market competition. For $\lambda = 0$, each firm has a monopoly, whereas for $\lambda = 1$, there is Cournot competition in homogeneous goods. For $\lambda \in (0,1)$, there is Cournot competition in differentiated goods.

The first-order condition in stage 1, $\frac{\partial \pi}{\partial q_i} = 0$, is then

$$P_i - (c_i - \gamma k_i) - q_i = 0, \quad \{i = 1, 2, 3, ...i, ..., n\}. \tag{A.9}$$

From (A.9) and (A.8), we then have

$$q_i^* = \frac{a - c_i + \gamma k_i - \lambda Q}{2 - \lambda} \tag{A.10}$$

since $2 - \lambda > 0$.

Let $C = \sum_{j=1}^{n} c_j$ be the “aggregate marginal cost" in the industry, and let $K = \sum_{i=1}^{n} k_i$ be the total number of robots in the industry. Summing (A.10) over all n firms, we can solve for total output as

$$Q^* = \frac{na - C + \gamma K}{2 - \lambda + n\lambda}, \tag{A.11}$$

where $2 - \lambda + n\lambda > 0$.

Combining (A.10) and (A.11), the Cournot output for firm i can be written

$$q_i^* = (a - c_i + \gamma k_i) \tfrac{(n+2-2\lambda)}{(n+2-\lambda)(2-\lambda)} - \tfrac{\lambda}{(n+2-\lambda)(2-\lambda)} \left(\sum_{j \neq i} (a - c_j + \gamma k_j) \right), \tag{A.12}$$

where $n + 2 - 2\lambda > 0$.

From (A.12), it us useful to note that

$$\frac{dq_i^*}{dk_i} = \frac{\gamma (n + 2 - 2\lambda)}{(n + 2 - \lambda)(2 - \lambda)} > 0, \tag{A.13}$$

$$\frac{dq_i^*}{dk_j} = -\frac{\gamma\lambda}{(n + 2 - \lambda)(2 - \lambda)} = \frac{dq_j^*}{dk_i} < 0. \tag{A.14}$$

A.2.2. Stage 2: Investments

Now turn to stage 1. From (A.12), we can write the stage 1 profit as a function of k_i:

$$\max_{\{k_i\}} \pi_i(k_i) = \left(\underbrace{a - q_i^*(k_i) - \lambda \sum_{j \neq i} q_j^*(k_i)}_{P_i} - (c_i - \gamma k_i) \right) q_i^*(k_i) - \mu \frac{k_i^2}{2}. \tag{A.15}$$

From (A.15) and (A.14) and applying the envelope theorem, we have

$$\begin{aligned} \frac{d\pi_i^*}{dk_i} &= \frac{\partial \pi_i}{\partial k_i} + \sum_{j \neq i} \frac{\partial \pi_i}{\partial q_j} \frac{dq_j^*}{dk_i} = 0, \\ &= \underbrace{\gamma q_i^* - \mu k_i}_{\frac{\partial \pi_i}{\partial k_i}} + \sum_{j \neq i} \underbrace{(-q_i^*)}_{\frac{\partial \pi_i}{\partial q_j}} \underbrace{\left(\frac{-\gamma\lambda}{(n+2-\lambda)(2-\lambda)} \right)}_{\frac{dq_j^*}{dk_i}} = 0. \end{aligned} \tag{A.16}$$

From (A.16), we obtain

$$k_i^* = \frac{\gamma}{\mu} \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right) q_i^*, \tag{A.17}$$

where $1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} > 1$ if $\lambda > 0$.

Substituting (A.17) into (A.12) and using symmetry, and then summing over all n firms, we find that total output is

$$Q^*(\eta) = \frac{an - C}{\left(\frac{(2-\lambda)(n-\lambda+2)}{n(1-\lambda)+2-\lambda} \right) - \eta \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right)}. \tag{A.18}$$

Then, inserting (A.17) into (A.10), we can solve for equilibrium output for firm i as a function of the total quantity in (A.18):

$$q_i^*(\eta) = \frac{(a - c_i - \lambda Q^*(\eta))}{\left(2 - \lambda - \eta \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right) \right)}. \tag{A.19}$$

It then follows from (A.17) that firm i's unit labor requirement, labor demand, product market price and labor productivity are, finally,

$$
\begin{aligned}
l_i^*(\eta) &= c_i - \gamma k_i^*(\eta) = c_i - \eta q_i^*(\eta)\left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)}\right) && \text{(A.20)}\\
L_i^*(\eta) &= l_i^*(\eta)\, q_i^*(\eta) && \text{(A.21)}\\
P_i^*(\eta) &= a - (1-\lambda)\, q_i^*(\eta) - \lambda Q^*(\eta) && \text{(A.22)}\\
\tilde{v}_i^*(\eta) &= \frac{P_i^*(\eta)\, q_i^*(\eta)}{l_i^*(\eta)\, q_i^*(\eta)} = \frac{P_i^*(\eta)}{l_i^*(\eta)}. && \text{(A.23)}
\end{aligned}
$$

A.3. The Boone elasticity

Measuring product market competition is no easy task. The level of product market competition is affected by the number of firms in the market, the degree of product differentiation, the level of tacit or explicit collusion between firms, and whether firms compete on prices or quantities. The empirical literature has attempted to measure competition using aggregate measures such as the Herfindahl index or the aggregate market share of the largest firms in the industry. These measures have been subject to substantive criticism. For instance, an industry with two firms may be very competitive if the two firms are competing intensely on prices. However, an industry with ten firms may exhibit little competition if firms sell products that consumers do not perceive to be close substitutes or if the firms collude.

We use the measure of product market competition developed by Boone (2008a,b). It has been used extensively in the finance literature, and it is produced by the World Bank as a measure of banking competition.[15] Boone's measure of competition focuses on how firm profits react to changes in marginal cost, positing that in a more competitive industry, firms should, on average, react more negatively to shocks to own costs. Boone's profit elasticity is estimated in each industry r and year t from the following firm-level regression:

$$
\log(\pi_{jt}) = \mu_j + \mu_t + C_{rt} \times \log(AVC_{jt}) + \varepsilon_{jt}, \tag{A.24}
$$

where π_{jt} is the profit of firm j in industry r in year t. Profits are measured as the log of value added net of the firm's wage bill. Ideally, we would use the log of a firm's marginal cost as a regressor to obtain the profit elasticity with respect to costs, C_{rt}. However, due to the problem of isolating marginal costs in accounting data, we need to use the average variable cost (measured as a firm's total wage bill plus the cost of materials as a share of total sales). We also control for unobserved heterogeneity by adding firm-specific effects, μ_j, and time-specific effects, μ_t. Note that a higher estimated elasticity (higher absolute value), C_{rt}, indicates that the industry is characterized by a higher degree of competition. Thus, our measured source of variation in the intensity of product market competition comes from yearly changes in how sensitive profits are to cost changes at the industry level.

[15] See http://www.worldbank.org/en/publication/gfdr/background/banking-competition. See also Heyman et al. (2013) for another study that uses the Boone measure of product market competition.

Online Appendix: Additional tables

Table A1: Automation probability and productivity, 1996–2013. Impact of other job task characteristics on exposure to automation (Frey and Osborne, 2017) at 2-digit level

	RTI	Offshorability	Routineness	Routine cognitive	Routine manual	Nonroutine manual
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.170***	0.125**	0.205***	0.137***	0.138**	0.142***
	(0.051)	(0.053)	(0.057)	(0.048)	(0.055)	(0.048)
Exposure × Share_skilled	-0.363**	-0.335**	-0.480***	-0.374**	-0.382**	-0.355**
	(0.161)	(0.162)	(0.166)	(0.158)	(0.169)	(0.156)
RTI	-0.017					
	(0.011)					
RTI ×Share_skilled	0.012					
	(0.042)					
Offshorability		0.005				
		(0.008)				
Offshorability ×Share_skilled		-0.004				
		(0.036)				
R			-0.046**			
			(0.023)			
R ×Share_skilled			0.108			
			(0.089)			
RC				-0.056**		
				(0.030)		
RC ×Share_skilled				0.121		
				(0.095)		
RM					-0.006	
					(0.024)	
RM ×Share_skilled					0.077	
					(0.126)	
NRM						0.032*
						(0.019)
NRM ×Share_skilled						-0.034
						(0.091)
Observations	69,116	69,116	69,116	69,116	69,116	69,116
R-squared	0.064	0.064	0.064	0.064	0.064	0.064
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Exposure is firm-level exposure to automation (Frey and Osborne, 2017), and Share_skilled is the share of employees with university education. RTI is the routine task intensity (RTI) index, Offshorability is the offshorability index, R is routine, RC is routine cognitive, RM is routine manual, and NRM is nonroutine manual, all measured as means at the firm level of the firm's workforce. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Automation probability and productivity, 1996–2013. Impact of other job task characteristics on exposure to software (Webb, 2020) at 2-digit level

	RTI	Offshorability	Routineness	Routine cognitive	Routine manual	Nonroutine manual
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.196***	0.189***	0.191***	0.179***	0.185***	0.184***
	(0.054)	(0.055)	(0.053)	(0.056)	(0.054)	(0.052)
Exposure × Share_skilled	-0.307	-0.322	-0.296	-0.289	-0.290	-0.286
	(0.192)	(0.197)	(0.191)	(0.198)	(0.193)	(0.192)
RTI	0.009					
	(0.011)					
RTI ×Share_skilled	-0.052					
	(0.043)					
Offshorability		0.001				
		(0.008)				
Offshorability ×Share_skilled		0.018				
		(0.090)				
R			0.003			
			(0.020)			
R ×Share_skilled			-0.041			
			(0.090)			
RC				-0.020		
				(0.032)		
RC ×Share_skilled				0.017		
				(0.101)		
RM					0.018	
					(0.022)	
RM ×Share_skilled					-0.027	
					(0.123)	
NRM						0.024
						(0.019)
NRM ×Share_skilled						-0.048
						(0.093)
Observations	69,116	69,116	69,116	69,116	69,116	69,116
R-squared	0.064	0.064	0.064	0.064	0.064	0.064
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Exposure is is firm-level exposure to software (Webb, 2020), Share_skilled is the share of employees with university education, RTI is the routine task intensity (RTI) index, Offshorability is the offshorability index, R is routine, RC is routine cognitive, RM is routine manual, and NRM is nonroutine manual, all measured as means at the firm level of the firm's workforce. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Automation probability and productivity, 1996–2015. By capital share in ICT at the industry level based on exposure at 2-digit level

	Low ICT share (pre-means)	High ICT share (pre-means)	Low ICT share (1996)	High ICT share (1996)	Low ICT share change	High ICT share Change
	(1)	(2)	(3)	(4)	(5)	(6)
			Auto			
Exposure	0.201***	0.048	0.201***	0.048	0.137	0.061
	(0.063)	(0.063)	(0.063)	(0.063)	(0.092)	(0.062)
Exposure × Share_skilled	-0.776***	-0.062	-0.776***	-0.062	0.013	-0.269**
	(0.261)	(0.155)	(0.261)	(0.155)	(0.508)	(0.133)
Observations	30,783	45,046	30,783	45,046	31,646	44,183
R-squared	0.089	0.065	0.089	0.065	0.060	0.089
			Robot			
Exposure	0.138**	0.179***	0.138**	0.179***	0.175**	0.122**
	(0.061)	(0.063)	(0.061)	(0.063)	(0.081)	(0.051)
Exposure × Share_skilled	-0.340	-0.430**	-0.340	-0.430**	-0.368	-0.315*
	(0.315)	(0.216)	(0.315)	(0.216)	(0.488)	(0.174)
Observations	30,783	45,046	30,783	45,046	31,646	44,183
R-Squared	0.088	0.065	0.088	0.065	0.060	0.089
			Software			
Exposure	0.127**	0.172**	0.127**	0.172**	0.182**	0.133*
	(0.064)	(0.076)	(0.064)	(0.076)	(0.081)	(0.068)
Exposure × Share_skilled	0.327	-0.473**	0.327	-0.473**	-0.493	-0.210
	(0.387)	(0.202)	(0.387)	(0.202)	(0.510)	(0.183)
Observations	30,783	45,046	30,783	45,046	31,646	44,183
R-Squared	0.089	0.065	0.089	0.065	0.060	0.089
Firm controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is logged value added per employee. Firm controls are logged capital per employee and logged number of employees. Auto is firm-level exposure to automation (Frey and Osborne, 2017), Robot is exposure to robots (Webb, 2020), Software is exposure to software (Webb, 2020), and Share_skilled is the share of employees with university education. ICT share at the industry level is the share of the total real fixed capital stock that amounts to ICT assets. Firms are divided into two groups according to pre-means (in the period 1993–1995), the first year in the sample period (1996) and based on changes during the period 1996–2007. See Section 4.1 and Table 1 for details about the variables. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.