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Artificial Intelligence, Robotics, Work and Productivity: The Role of Firm Heterogeneity

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Artificial intelligence, Robotics, Work and Productivity: The role of Firm Heterogeneity*

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Abstract

We propose a model with asymmetric firms where new technologies displace workers. We show that both leading (low-cost) firms and laggard (high-cost) firms increase productivity when automating but that only laggard firms hire more automation-susceptible workers. The reason for this asymmetry is that in laggard firms, the lower incentive to invest in new technologies implies a weaker displacement effect and thus that the output-expansion effect on labor demand dominates. Using novel firm-level automation workforce probabilities, which reveal the extent to which a firms' workforce can be replaced by new AI and robotic technology and a new shift-share instrument to address endogeneity, we find strong empirical evidence for these predictions in Swedish matched employer-employee data.

Keywords: AI&R Technology; Automation; Job displacement; Firm Heterogeneity; Matched employer-employee data

JEL classification: J7, L2, M5

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1. Introduction

Firms are increasingly able to automate job tasks using advances in robotics, machine learning and other forms of artificial intelligence. Examples include coordinating production and transportation, picking orders in a warehouse and performing automated customer service. We will refer to this technology as Artificial Intelligence and Robotics (AI&R) technology. Recent studies show that AI&R technology affects firms and workers. 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.

However, firms' incentives to automate will likely differ substantially across different types of firms. Indeed, Syverson (2011), in his overview article, concludes that large and persistent differences in productivity levels across businesses are ubiquitous and to a large extent depend on firm-specific assets. Berlingieri et al. (2017) provide evidence on the increasing dispersion in wages and productivity using microaggregated firm-level data from 16 countries. These results notwithstanding, we have little systematic knowledge about how different types of firms may implement these new AI&R technologies and how this may affect productivity and hirings and firings in different types of firms. The purpose of this paper is to provide more knowledge on these matters.

To capture these elements in an AI&R-driven industrial restructuring processes, we propose a model in which firms differ in their inherent productivity due to different firm-specific assets such as patents, know-how or human capital. We refer to firms with inherently high productivity as leading firms and firms with inherently low productivity as laggard firms. Firms competing in imperfectly competitive product markets may then use advances in AI&R technology to automate their production and displace labor in the production process. We refer to this labor type as production employees.

We show that only laggard firms increase the hiring of production employees when investing in the new AI&R technology. The reason is that increasing investment in the new AI&R technology has two effects on the demand for production employees. First, the implementation of the new AI&R technology reduces per unit of output demand for production employees—this is the *displacement effect*. However, there is also a second effect—the *output effect*—that increases the demand for production employees. For laggard firms, the *output effect* dominates the *displacement effect*, since their inherently lower output reduces their incentives to invest significantly in the new AI&R technology.

We then turn to our empirical analysis. Sweden has been at the forefront of the implementation of new AI&R technology in its business sector. Sweden is, therefore, a suitable country to study the influence of new AI&R technology on labor demand and productivity on a larger scale. Our analysis uses comprehensive and detailed Swedish matched employer-employee data from 1996 to 2013. The use of detailed information on firms, plants, and individuals working for the firms makes it possible to analyze issues related the impact of the implementation of new AI&R technology on

job and productivity dynamics in greater detail than is possible in most other international studies.

The starting point in our empirical analysis is that the implementation of AI&R technology will affect firms' behavior in terms of their investments in the new technology, the composition of workers in different occupations, and performance in terms of productivity. However, lacking information on investments in AI&R technology, we first calculate a novel measure of a firm's workforce automation probabilities, which is based on estimated automation probabilities at the occupational level derived by Frey and Osborne (2017). This firm-specific measure reveals the extent to which a firm's workforce can be replaced by new AI&R technology. We then use this measure to identify how the implementation of AI&R affects the occupational mix and productivity development in different types of firms.

To this end, we first note that our model predicts that only laggard firms increase their hiring of production workers, but all firms increase productivity when implementing AI&R technology. This prediction implies that only in laggard firms will an increase in the firms' exposure to automation be positively correlated with increased productivity—in leading firms, an increase in firm exposure to automation will be negatively correlated with increased productivity.

To test these predictions, we estimate panel data models with firm fixed effects, regressing productivity on firms' exposure to automation, their share of skilled workers and the interaction between the exposure to automation and the skill share (plus additional controls). From the theory, we can show that a high skill share of the workforce (i.e. a high share of employees with a university degree) is associated with leading firms, while a low skill share is associated with laggard firms. As predicted from the theory, our basic OLS estimates show that an increase in the automation probability—or exposure to automation—is associated with an increase in productivity in laggard firms, i.e. firms for which the skill share is sufficiently small. As also predicted, in leading firms, i.e. firms in which the skill share is high, an increase in the exposure to automation is associated with a reduction in productivity.

As our theory suggests, it is likely that we have an omitted variable problem associated with the relation between productivity and workforce automation probabilities: The AI&R technology will not only affect productivity through its effect via hiring and firing but also directly through an efficiency effect. To address this potential endogeneity problem, we use aggregate changes in the employment structure and workforce automation probabilities as a shift-share instrument for firm-level workforce automation probabilities. When using this instrument, we find that IV results are remarkably similar to the OLS results in that productivity and exposure to automation are positively (negatively) correlated when the skill share is sufficiently low (high).

Our paper relates to the literature that examines the impact of investment in AI&R technology 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; Acemoglu and Restrepo 2018a,b, 2019a,b; Benzell et al. 2016; Susskind 2017). The empirical work on the implications of AI&R technology investments on labor demand has thus far mostly focused on robotics. Using similar IFR data as in Graetz and Michaels (2018) and Acemoglu and Restrepo

(2020), Dauth et al. (2017) analyze Germany. They find no evidence that robots cause total job losses but that they do affect the composition of aggregate employment. While industrial robots have a negative impact on employment in the manufacturing sector, there is a positive and significant spillover effect as employment in the non-manufacturing sectors increases. They also report that robots raise labor productivity. Some recent papers take the analysis to the firm level. 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. Finally, Aghion et al. (2020) use microdata on the French manufacturing sector. Based on event studies and a shift-share IV design, their estimated impact of automation on employment is positive, even for unskilled industrial workers. Moreover, the industry-level employment response to automation is positive and significant only in industries that face international competition.

We contribute to this literature by proposing a model of automation with heterogeneous firms. We show that both leading and laggard firms increase productivity when automating, but only laggard firms increase the hiring of automation-susceptible employees.¹ The reason is that laggard firms have low investment incentives, which results in a small displacement effect, and the output-expansion effect will therefore dominate. Seamans and Raj (2020) summarize the recent literature on AI, labor and productivity and highlight the lack of firm-level data on the greater use of AI. We contribute to this literature by proposing a new measure of workforce exposure to AI&R in a firm based on the work by Frey and Osborne (2017). This enables us to examine the effects on firms of different types and the role of market structure in AI&R investments on a more general level. We find support for these mechanisms in detailed matched employer-employee data for Sweden spanning the period 1996-2013, using a shift-share IV design to address endogeneity problems. In particular, we find that leading and laggard firms will have different productivity developments and in particular behave differently in their hiring of employees in occupations susceptible to automation.

This paper also contributes to the literature on technological development and productivity development, which has demonstrated that measured productivity growth over the past decade has slowed significantly (Syverson, 2017). Productivity differences between frontier firms and average firms in the same industry have been increasing in recent years (Andrews et al., 2016; Furman and Orszag, 2015). Moreover, a smaller number of superstar firms are gaining market share (Autor et al., 2017), while workers' earnings are increasingly tied to firm-level productivity differences (Song et al., 2015). We contribute to this literature by examining the effects of AI&R investments on firms of different types. We show that both leading firms (low-cost firms) and laggard firms (high-cost firms) increase productivity when implementing AI&R technology but that only laggard firms hire more automation-susceptible workers.

¹Besen (2019) proposes a demand satiation model that can explain the growth and subsequent decline in employment over time when a new technology is introduced.

The paper proceeds as follows. Section 2 presents the theoretical model that we use to examine how investment in AI&R technology affects leading and laggard firms' productivity and employment development and to derive predictions for our empirical analyses. In Section 3, we conduct the empirical analysis. Section 4 discusses the policy implications. Finally, Section 5 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. The model

2.1. Preliminaries

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

$$U(\mathbf{q}, m) = \sum_{i=1}^n a_i q_i - \frac{1}{2} \left[\sum_{i=1}^n q_i^2 + 2\lambda \sum_{i=1}^n \sum_{j \neq i}^n q_i q_j \right] + q_0, \quad (2.1)$$

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

$$\sum_{i=1}^n P_i q_i + q_0 = m, \quad (2.2)$$

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 (2.2), the direct utility in (2.1) can be rewritten as

$$U(\mathbf{q}, m) = \sum_{i=1}^n (a_i - P_i) q_i - \frac{1}{2} \left[\sum_{i=1}^n q_i^2 + 2\lambda \sum_{i=1}^n \sum_{j \neq i}^n q_i q_j \right] - m. \quad (2.3)$$

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

$$P_i = a_i - q_i - \lambda \sum_{j \neq i}^n q_j, \quad i = \{1, 2, \dots, n\}. \quad (2.4)$$

Let us simplify such that each producer is a monopolist on its variety i . Setting $\lambda = 0$ in (2.4), the

maximization problem of firm i is

$$\max_{\{q_i, k_i\}} \pi_i = \underbrace{P_i(q_i) \cdot q_i}_{\text{Revenues}} - \underbrace{w \cdot L_i(q_i, k_i)}_{\text{Wage costs from production}} - \underbrace{C(k_i)}_{\text{Installation costs}} - \underbrace{vf_i}_{\text{Fixed cost}}, \quad (2.5)$$

$$s.t. : P_i(q) = a_i - q_i, \quad (2.6)$$

$$: L_i(q, k) = l_i(k_i) \cdot q_i, \quad (2.7)$$

$$: l_i(k_i) = c_i - \gamma k_i, \quad \gamma > 0, \quad c_i < a_i \quad (2.8)$$

$$: C(k_i) = \frac{\mu}{2} k_i^2, \quad \mu > 0, \quad (2.9)$$

The first row depicts the *direct profit* that the firm is maximizing by optimally choosing output, q_i , and the amount of AI&R 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, $w \cdot L_i(q_i, k_i)$, where w is the exogenous wage for production workers (given from the labor market), and $L_i(\cdot)$ is the number of unskilled production workers; the third term depicts installation costs for the AI&R technology, $C(k_i)$; and the last term depicts the wage costs for a fixed number of (high skilled) workers needed to use AI&R technology, vf_i .

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 is $L_i(q_i, k_i) = l_i(k_i)q_i$ from (2.7). As shown in (2.8), if the firm invests more in AI&R technology k_i , this will reduce the number of production workers needed to produce one more unit at rate γ . Finally, from (2.9), there are quadratic installation costs for the AI&R technology, $C(k) = \frac{\mu}{2} k_i^2$.

The exogenous industry variables γ and μ characterize the efficiency and the cost of AI&R technology. It is then useful to define the following exogenous variable, which we will denote the *return to investing in the AI&R technology*²

$$\eta = \frac{\gamma^2}{\mu}. \quad (2.10)$$

Intuitively, the return to investing in AI&R 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 AI&R technology (i.e., when μ is lower). The variable η will be a useful tool to study how investments in AI&R technology affect productivity and the composition of employment within firms.

To proceed, we normalize the wage for production workers to unity, $w = 1$. In the Appendix, we show that this normalization does not qualitatively affect our results. As we will discuss below, in the Appendix, we also provide an extension of the model where the demand for skilled workers increases with investments in the AI&R technology. Additionally, the Appendix also contains an extension where we allow for the impact of competition in the product market.

We now return to the profit maximization problem for firms in (2.5). Consider the following

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

setting: In stage 1, a firm invests in the new AI&R 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 (2.5), we use backward induction.

2.2. Stage 2: Product market

Using the inverse demand (2.6), the unit labor requirement (2.6) and the investment cost for the AI&R technology (2.9) in (2.5), we obtain

$$\max_{\{q_i\}} \pi_i = \underbrace{(a_i - q_i)q_i}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i)q_i}_{\text{Wage costs}} - \underbrace{\frac{\mu}{2}k_i^2}_{\text{Installation cost}} - \underbrace{vf_i}_{\text{Fixed costs}}. \quad (2.11)$$

The optimal output is given from the first-order condition

$$\frac{\partial \pi_i}{\partial q_i} = P_i - q_i - (c_i - \gamma k_i) = 0, \quad i = \{1, 2, \dots, n\} \quad (2.12)$$

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

From (2.12), we can solve for the optimal output

$$q_i^*(k_i) = \frac{a_i - (c_i - \gamma k_i)}{2}. \quad (2.13)$$

To ensure that the firm produces output—even without investments in the new technology—we will assume that $a_i > c_i$. Note that the firm will produce more output q_i^* when having invested more in the AI&R 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, $El_{P_i} q_i = \frac{dq_i}{dP_i} \frac{P_i}{q_i}$

$$\underbrace{P_i \left[1 - \frac{1}{El_{P_i} q_i} \right]}_{MR_i} = \underbrace{c_i}_{MC_i}. \quad (2.14)$$

A firm with market power will choose 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 AI&R technology induce a firm to reduce its product market price, the increase in demand will cause the output to rise. In the analysis below, we will examine (i) whether the output expansion effect can compensate for the replacement effect, i.e., if labor demand can increase when investments in AI&R technology increase, and (ii) if so, in which firm type this mechanism is at play.³

³Bessen (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.

2.3. Stage 1: Investing in the AI&R technology

How much will a firm then invest in the AI&R technology, k_i ? Substituting the optimal quantity, $q_i^*(k_i)$, from (2.12) into (2.11), we obtain

$$\max_{\{k_i\}} \pi_i(k_i) = \underbrace{[a_i - q_i^*(k_i)] q_i^*(k_i)}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i) q_i^*(k_i)}_{\text{Wage cost}} - \underbrace{\frac{\mu}{2} k_i^2}_{\text{Installation cost}} - \underbrace{v f_i}_{\text{Fixed cost}}. \quad (2.15)$$

Using the envelope theorem, the first-order condition is

$$\frac{\partial \pi_i(k_i)}{\partial k_i} = \gamma q_i^*(k_i^*) - \mu k_i^* = 0. \quad (2.16)$$

From (2.16), we can link the optimal level of investments in the AI&R technology, k_i^* , to optimal output $q_i^*(k_i^*)$

$$k_i^* = \frac{\gamma}{\mu} \cdot q_i^*(k_i^*). \quad (2.17)$$

Combining (2.10), (2.13) and (2.17), we can solve for the equilibrium level of AI&R technology, $k_i^*(\eta)$

$$k_i^*(\eta) = \frac{\gamma}{\mu} \cdot \frac{a_i - c_i}{2 - \eta} > 0, \quad (2.18)$$

where it is easily checked that $2 - \eta > 0$ is required from the second-order condition associated with (2.15).

Combining (2.6)-(2.8), (2.17) and (2.18), 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 the equilibrium labor demand, $L_i^*(\eta)$, all as functions of the return to investing in AI&R technology, η .

$$q_i^*(\eta) = \frac{a_i - c_i}{2 - \eta} > 0, \quad (2.19)$$

$$P_i^*(\eta) = a_i - q_i^*(\eta) = \frac{a_i + c_i - a_i \eta}{2 - \eta} > 0, \quad (2.20)$$

$$l_i^*(\eta) = c_i - \eta \cdot q_i^*(\eta) = c_i \cdot \frac{2 - \frac{a_i}{c_i} \eta}{2 - \eta} > 0, \quad (2.21)$$

$$L_i^*(\eta) = l_i^*(\eta) \cdot q_i^*(\eta) = c_i \cdot \frac{(a_i - c_i) \left(2 - \frac{a_i}{c_i} \eta\right)}{(2 - \eta)^2} > 0. \quad (2.22)$$

where we assume that the return to investing in AI&R 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 restricting the product market price for all firms to be strictly positive, i.e., $a_i + c_i - a_i \eta > 0$, for $\forall i$.

2.4. Comparative statics: Increasing return to investing in AI&R technology

Suppose that technological developments increase automation possibilities by increasing *the return to investing in AI&R technology*, η , defined in (2.10). How will this affect firms in terms of investments in AI&R technology, labor productivity and the employment of production workers?

2.4.1. Impact on investments in AI&R technology

From (2.18), we have the following straightforward result:

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

Intuitively, increased return to investing in AI&R technology increases the level of AI&R technology used in equilibrium.

2.4.2. Impact on labor productivity and value added per employee

Labor productivity Increased investments spurred by a higher return to investment in the AI&R technology should increase productivity in the firm. We define labor productivity as output per worker, which we will label $v_i^*(\eta)$. Using (2.7), we have

$$v_i^*(\eta) = \frac{\overbrace{q_i^*(\eta)}^{\text{Output}}}{\underbrace{L_i^*(\eta) + f_i}_{\text{Total employment}}} = \frac{1}{\underbrace{l_i^*(\eta) + \frac{f_i}{q_i^*(\eta)}}_{\text{Total unit labor requirement}}}. \quad (2.23)$$

Taking logs in (2.23) and differentiating with respect to η , we can derive the following elasticity expressions, which show how an increase in the return to investing in AI&R technology affects labor productivity

$$\frac{dv_i^*(\eta)}{d\eta} \frac{\eta}{v_i^*(\eta)} = \frac{\frac{f_i}{L_i^*(\eta)}}{1 + \frac{f_i}{L_i^*(\eta)}} \cdot \frac{\overbrace{\left(\frac{dq_i^*(\eta)}{d\eta} \frac{\eta}{q_i^*(\eta)}\right)}^{\text{Output expansion effect : (+)}} - \overbrace{\left(\frac{dl_i^*(\eta)}{d\eta} \frac{\eta}{l_i^*(\eta)}\right)}^{\text{Replacement effect : (-)}}}{1 + \frac{f_i}{L_i^*(\eta)}} > 0 \quad (2.24)$$

The expression in (2.24) shows that labor productivity is strictly increasing in the return to investing in AI&R 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 (2.19), we have

$$\frac{dq_i^*(\eta)}{d\eta} \cdot \frac{\eta}{q_i^*(\eta)} = \frac{\eta}{2 - \eta} > 0. \quad (2.25)$$

The *replacement effect* is strictly negative, since from (2.21), we have

$$\frac{dl_i^*(\eta)}{d\eta} \frac{\eta}{l_i^*(\eta)} = -\frac{2\eta}{c_i} \frac{a_i - c_i}{(2 - \eta) \left(2 - \frac{a_i}{c_i} \eta\right)} < 0 \quad (2.26)$$

Intuitively, when the return to investment, η , increases, firms respond by investing more in the AI&R technology, i.e., $\frac{dk_i^*(\eta)}{d\eta} > 0$ from Lemma 1. This reduces the unit labor requirements $l_i^*(\eta)$ from (2.8), reducing marginal costs, which, in turn, increases output $q_i^*(\eta)$ from (2.13). 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 AI&R technology strictly increases labor productivity, $\frac{dv_i^*}{d\eta} \frac{\eta}{v_i^*} > 0$*

Value added per worker In the empirical analysis presented in the next section, we will not have data on unit labor requirements and output levels (typically not observed in firm-level data). We will have data on firms' revenues and costs. We will therefore use value added per employee as our productivity measure. How is this alternative measure affected when the return to investing in AI&R 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:

$$VAL_i^*(\eta) = \frac{\overbrace{R_i^*(\eta)}^{\text{Revenues}}}{\underbrace{L_i^*(\eta) + f_i}_{\text{Total employment}}} = \frac{\overbrace{P_i^*(\eta)}^{\text{Average revenue}}}{\underbrace{l_i^*(\eta) + \frac{f_i}{q_i^*(\eta)}}_{\text{Total unit labor requirement}}} \quad (2.27)$$

where we use (2.7) in the last term.

Taking logs in (2.27) and again differentiating with respect to η , we obtain

$$\frac{dVAL_i^*(\eta)}{d\eta} \frac{\eta}{VAL_i^*(\eta)} = \underbrace{\frac{dv_i^*(\eta)}{d\eta} \frac{\eta}{v_i^*(\eta)}}_{\text{Labor productivity effect: (+)}} + \underbrace{\frac{dP_i^*(\eta)}{d\eta} \frac{\eta}{P_i^*(\eta)}}_{\text{Price effect: (-)}}. \quad (2.28)$$

Thus, the percentage change in value added per employee from a one-percent increase in the return to investing in AI&R 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 (2.24) 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 (2.25), there must be a reduction in the product market price from (2.6). From (2.20), we can show

that the price effect is negative

$$\frac{dP_i^*(\eta)}{d\eta} \frac{\eta}{P_i^*(\eta)} = -\frac{a_i - c_i}{(2 - \eta)(a_i + c_i - a_i\eta)} \eta < 0. \quad (2.29)$$

In sum, a higher return to investing in AI&R 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 value added per employee will increase in the return to investment in AI&R technology, i.e., $\frac{dVAL_i^*(\eta)}{d\eta} \frac{\eta}{VAL_i^*(\eta)} > 0$ in (2.28).

Value added per employee will, of course, underestimate the true increase in labor productivity from new technologies. In our setting, this is not a serious problem since our focus is on inferring whether productivity improvements from AI&R investments can occur with rising employment in occupations susceptible to automation and—if so—in which type of firms this arises. To summarize:

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

2.4.3. Impact on employment

How is employment affected when investments in AI&R technology become more profitable? Since the employment of non-production workers is by assumption fixed (this assumption is relaxed in the next section), we can focus on the impact of production workers that 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

$$\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} = \left(\underbrace{\frac{dl_i^*(\eta)}{d\eta} \cdot \frac{\eta}{l_i^*(\eta)}}_{\text{Displacement effect (-)}} + \underbrace{\frac{dq_i^*(\eta)}{d\eta} \cdot \frac{\eta}{q_i^*(\eta)}}_{\text{Output effect (+)}} \right). \quad (2.30)$$

More profitable investment opportunities in labor-saving AI&R technology implies that fewer workers are needed per unit of output produced—however, more workers are also needed because output increases: From the *displacement effect* in (2.26), 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 (2.25), $\frac{dq_i^*(\eta)}{d\eta} \frac{\eta}{q_i^*(\eta)} > 0$.

Which of these two opposing forces—the *displacement effect* or the *output-expansion effect*—dominates? Inserting (2.30) and (2.25) into (2.30) and simplifying, we obtain

$$\frac{dL_i^*(\eta)}{d\eta} \cdot \frac{\eta}{L_i^*} = 2 \cdot \frac{\left(2 - \frac{a_i}{c_i} \left(1 + \frac{\eta}{2}\right)\right)}{(2 - \eta) \left(2 - \frac{a_i}{c_i} \eta\right)} \stackrel{>}{\leq} 0. \quad (2.31)$$

To infer the sign of the employment effect, we employ the following definition:

Definition 1. Firm i is a "laggard firm" if it has a relatively high innate cost, i.e., $\frac{a_i}{c_i} \in (1, 2)$. In contrast, Firm i is a "leading firm" if it has a relatively low innate cost, i.e., $\frac{a_i}{c_i} > 2$.

We can then state the following proposition:

Proposition 2. Define the cutoff $\eta_i^L = \frac{4}{(a_i/c_i)} \left(1 - \frac{1}{2} \frac{a_i}{c_i}\right)$. Then, the following holds:

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

- 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 AI&R technology, $d\eta > 0$, always reduces employment, $\frac{dL_i^*(\eta)}{d\eta} \frac{\eta}{L_i^*(\eta)} < 0$.

Let us explain the intuition in 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 (c.f. Equation 2.25), the heterogenous employment of the different firm types in Proposition 2 can be 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:

$$\frac{dl_i^*}{d\eta} \frac{\eta}{l_i^*(\eta)} = -\frac{q_i^*(\eta)}{l_i^*(\eta)} \cdot \left(\frac{2}{2-\eta}\right) < 0 \quad (2.32)$$

where we have used (2.21) and (2.25).

Faced with weak consumer demand (i.e., low a_i) and weak cost efficiency (i.e., high c_i), laggard firms will choose a lower output, $q_i^*(\eta)$ (c.f. Equation 2.19). This implies a weak incentive to invest in the new AI&R technology since any reduction in the unit labor requirement will affect few units of output (c.f. Equation 2.17). The low investments in the labor-saving technology then translate into a high unit labor requirement, $l_i^*(\eta)$ (c.f. Equation 2.8). As shown in (2.32), at a low output level and high unit labor requirements (i.e., at a low ratio $q_i^*(\eta)/l_i^*(\eta)$), the displacement effect is weakened. The output-expansion effect therefore dominates in (2.30), and substitutable production employment increases despite increased investments in labor-saving AI&R technology. The employment locus for a laggard firm, $L_i^*(\eta)|_{\frac{a_i}{c_i} \in (1, 2)}$, is shown in Figure 2.1, where a higher return to investing in AI&R 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 (2.32), 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

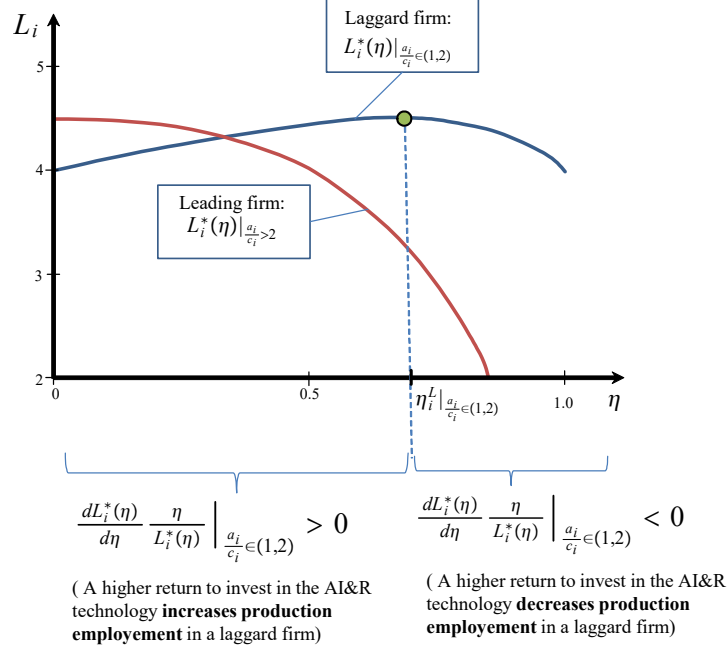


Figure 2.1: Illustrating Proposition 2. Parameter values are $a = 6$ and $c = 3$ for a leading firm and $c = 4$ for a laggard firm.

effect is now strengthened: The output expansion effect is now dominated by the displacement effect in (2.30), and substitutable production employment declines when investments in labor-saving AI&R 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 2.1. In contrast to a laggard firm, a higher return to investment in AI&R technology η always reduces employment in the leading firm.

2.5. Empirical predictions

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

2.5.1. Labor productivity and employment susceptible to automation

Combining Propositions 1 and 2, our first prediction concerns how productivity (as measured by value added per employee) and production employment are related when firms increase their investments in the AI&R technology.

Prediction 1: *Suppose that the return to investing in AI&R technology, η , increases. Firms will then respond by increasing their investments in AI&R 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, $\eta \in [0, \eta^L)$, increased investment in the new AI&R technology lead to a positive correlation between production employment, $L_i(\eta)$, and value added per employee, $VAL_i(\eta)$, as increased investment in new AI&R technology boosts both employment and productivity.*

- (ii) For a "leading firm", $c_i < \frac{a_i}{2}$, increased investment in the new AI&R 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 (2.30), 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 for AI&R 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 AI&R investments dominates the displacement effect in Equation (2.30).

These predictions are illustrated in Figure 2.2 and Figure 2.3, where the top panels show a firm's investments in AI&R 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 AI&R technology, η . The top panels in Figure 2.2 and Figure 2.3 are shaded to illustrate that we—in the empirical analysis in the next section—do not observe the actual AI&R investments.

Thus, we will test the predictions from the model from the relationship between labor productivity and employment. We then assume a process whereby automation possibilities increase over time, i.e., the return to investing in new AI&R technologies, η , rises over time. In leading firms, increasing (unobserved) investments in the new AI&R technology lead to higher productivity associated with falling production employment. From the two lower panels in Figure 2.2, this produces a negative correlation between labor productivity and production employment. In contrast, from the lower panels in Figure 2.3, increasing (unobserved) AI&R investment produces a positive correlation between labor productivity and production employment in laggard firms.

2.5.2. Firm heterogeneity

Prediction 2.5.1 tells us that the correlation between productivity and the employment of production workers should differ between firm types: In laggard firms, productivity and the employment of production workers susceptible to automation are positively correlated; when laggards respond to better automation possibilities by investing more in new technology, increased productivity is accompanied by increased employment in production. However, in leading firms, the increase in productivity—spurred by increased investments in new technology—entails reduced production employment.

How can we then identify firm types in data without detailed firm-level information on costs and demand (i.e., the parameters a_i and c_i)? Our main proxy for firm type in the empirical analysis will be the share of skilled workers in a firm, under the assumption that leading firms should be firms with higher skill intensity and laggard firms should be firms with lower skill intensity. Suppose that production workers are essentially less skilled workers. From the assumption of a fixed number of

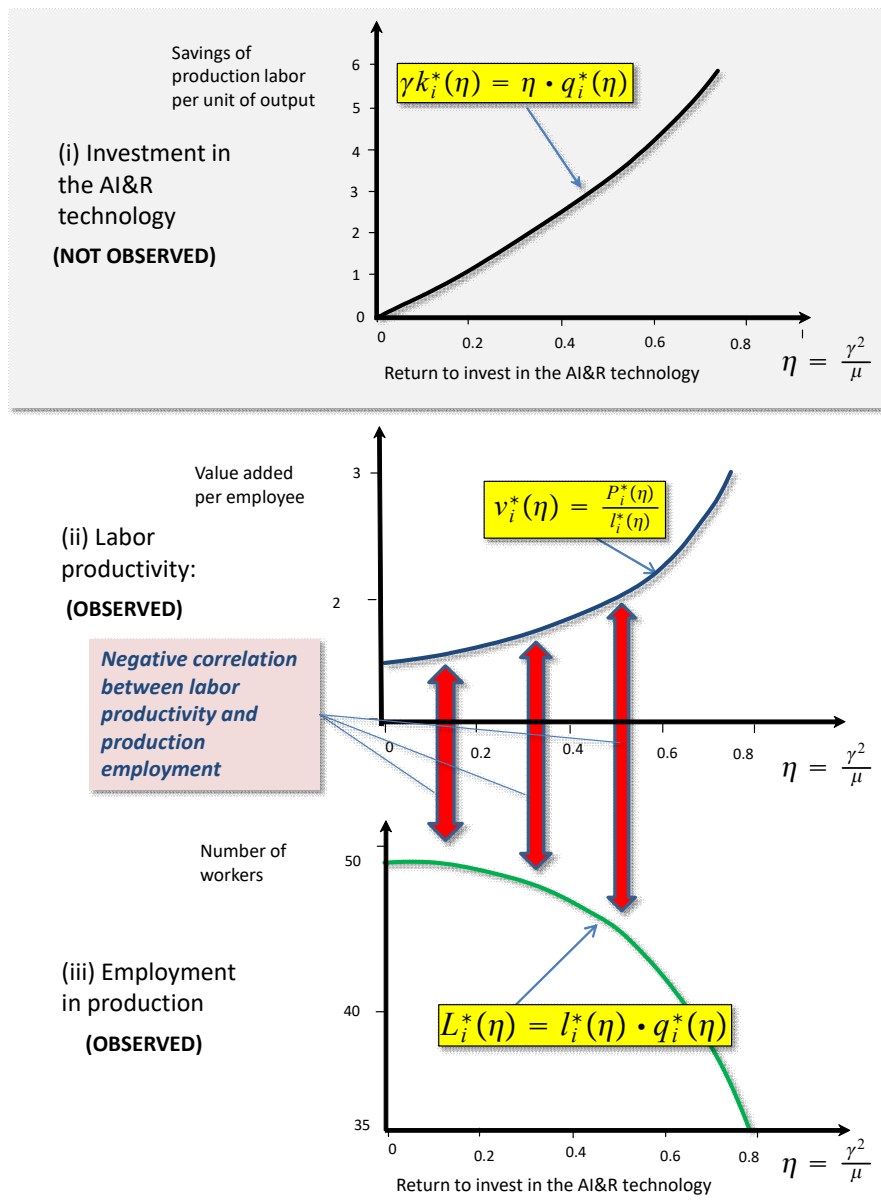


Figure 2.2: Illustrating a negative correlation between production worker employment and productivity.

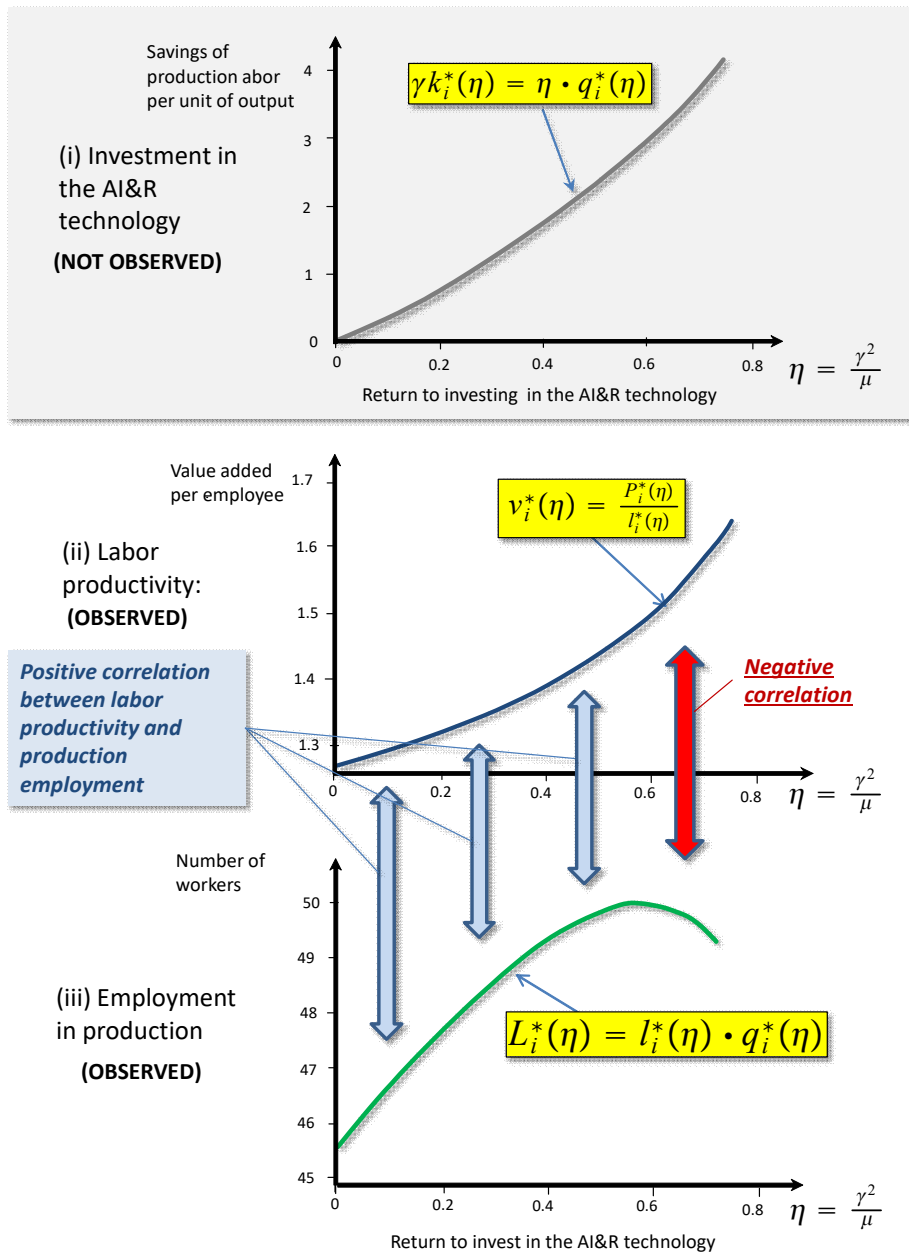


Figure 2.3: Illustrating a positive correlation between production worker employment and productivity.

high-skilled non-production workers, f_i , the share of high-skilled workers in firm employment in the model is simply

$$s_i^*(\eta) = \frac{f_i}{L_i^*(\eta) + f_i}. \quad (2.33)$$

From Proposition 2 and (2.33), it follows that when the return to investment in new technologies η becomes sufficiently high, leading firms will have a higher skill intensity than laggard firms: $L_i^*(\eta)$ is declining in leading firms, while $L_i^*(\eta)$ is increasing in laggard firms (unless η becomes too high). By taking logs in (2.33) and differentiating with respect to η , we can examine how skill shares change when the return to investment in the new technology increases

$$\frac{ds_i^*(\eta)}{d\eta} \frac{\eta}{s_i^*(\eta)} = -\frac{dL_i^*(\eta)}{d\eta} \frac{\eta}{L_i^*(\eta)} \cdot (1 - s_i^*(\eta)). \quad (2.34)$$

Thus, when the return to investing in AI&R technology η increases, the percentage change in the share of skilled workers, $\frac{ds_i^*(\eta)}{d\eta} \frac{\eta}{s_i^*(\eta)}$ and the percentage change in production worker employment, $\frac{dL_i^*(\eta)}{d\eta} \frac{\eta}{L_i^*(\eta)}$, move in opposite directions.

The inverse relationship in (2.34) leads to our second prediction:

Prediction 2: *Suppose that Prediction 1 holds and $s_i^*(\eta) > 0$. Then, from (2.34), it follows that:*

- (i) *In a "laggard firm", $\frac{a_i}{c_i} \in (1, 2)$, if the return to investment is not too high, $\eta \in [0, \eta^L)$, increased investments in the new AI&R technology lead to a negative correlation between skill intensity $s_i^*(\eta)$ and value added per employee, $VAL_i(\eta)$.*
- (ii) *In a "leading firm", $\frac{a_i}{c_i} > 2$, the increased investments in the new AI&R technology lead to a positive correlation between skill intensity $s_i^*(\eta)$ and value added per employee, $VAL_i(\eta)$.*

On a final note, Predictions 1 and 2 build on a very simple structure of a firms' workforce composition, in particular assuming a fixed labor requirement of skilled non-production workers and variable employment of less skilled production workers. A more elaborate assumption would be to assume that the cost of skilled non-production workers is $v \cdot (f_i + \phi k_i)$, so that an additional $\phi > 0$ of skilled workers are needed for each unit of investment in AI&R technology, k_i , in addition to the fixed requirement, f_i . In Appendix A.2, we show how Predictions 2.5.1 and 2.5.2 also hold when increased investment in AI&R technology also increases non-production high-skilled workers, under mild restrictions on ϕ .

3. Empirical analysis

Our aim in the empirical section is to estimate how AI&R technology investments affect productivity and the relationship between productivity and the employment of workers susceptible to being replaced by AI&R technology. The challenge is to examine these relationships without detailed information on firms' investments in AI&R technology and firms' demand and cost conditions.

This section first describes the data and how we measure 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 the AI&R technology. We then present our empirical results.

3.1. Data

We base our analysis on detailed, register-based, matched employer-employee data from Statistics Sweden (SCB). The database comprises firm, plant and individual data, which are linked with unique identification numbers and cover the period from 1996 to 2013. 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 (Hoffmann, 2004).

(ii) Firm Data The firm data contain a large amount of firm-level data, 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 at the firm level.

3.1.1. Firm heterogeneity

Section 2.5.2 showed how we can use the share of skilled workers as a proxy for firm type: Firms with a higher share of skilled workers are to a higher degree "leading firms"; firms with a lower share of skilled workers are to a higher degree "laggard firms" (we explain the exact cutoff in the next section). From the matched-employer employee data, we thus calculate the share of employees in a firm with tertiary education, labelled $Skill_share_{it}$. As a robustness check, we will also explore a number of other variables to measure firm heterogeneity, such as the mean years of schooling of a firm's employees, the mean age of the employees, and the firm's age.

3.1.2. Workers' susceptibility to substitution

In the empirical analysis, we need a firm-level measure that captures how new technologies affect firms' decisions to hire workers susceptible to automation. To highlight the results, we made some simple assumptions regarding labor inputs in our theoretical model—essentially, less skilled blue-collar workers can be replaced by labor-saving automation (the use of the AI&R technology), whereas white-collar workers either cannot be replaced (as they are used in fixed numbers), or they are in higher demand when automation increases. In the empirical analysis, we need a firm-level measure that captures how firms hire workers in many occupations that differ in susceptibility to automation.

Frey and Osborne (2017) compute the probability that a job will be replaced by computers or robots. 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 they entail. The assessments are based on occupational characteristics and qualifications in the O*NET database, developed by the US Department of Labor. The O*NET database covers almost 1,000 occupations, and for each occupation, there are 300 variables. 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. 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).

Frey and Osborne calculate these automation probabilities for the US SOC2010 occupational classification. This classification is not used in Sweden, nor in the EU, and there is no direct translation from the SOC2010 classifications to the Swedish counterpart SSYK96 (ISCO-88). To make use of the automation probabilities provided by Frey and Osborne, we first translate the US classifications to the European occupational code, ISCO08, which in turn can be translated to the Swedish SSYK96 code.⁴ Given that our data on occupations at the SSYK96 level are available for the years 1996-2013, our empirical analysis will be based on this time period. The occupations most susceptible to automation include machine operators and assemblers and various office clerks, while

⁴There are a few issues with this translation. 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 SCB, 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.

low automation risk jobs include managers of small enterprises, science professionals and legislators and senior officials.

To obtain a firm-level measure of how susceptible workers in our Swedish firm are to automation, we assume that firms can employ workers from $j = \{1, 2, 3, \dots, J\}$ SSSYK96 occupations at the 3-digit level ($J = 109$), where each occupation j is associated with an automation probability, $Auto_j$, which is the converted automation probability from Frey and Osborne (2017). We then calculate *the workforce exposure to automation* in firm i at time t , $Auto_{it}$, as

$$Auto_{it} = \sum_{j=1}^J \sigma_{ijt} \cdot Auto_j \quad (3.1)$$

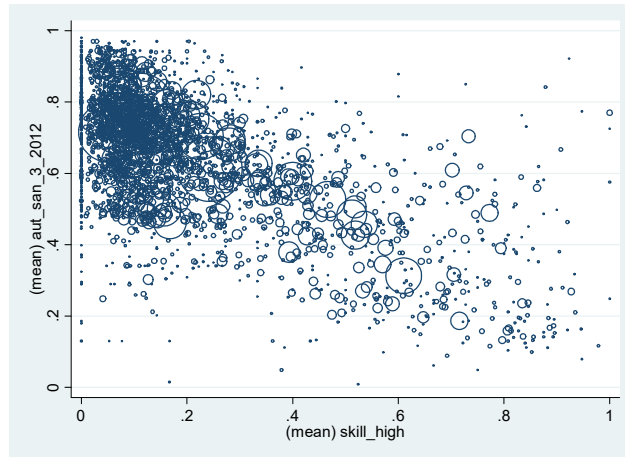
where σ_{ijt} is the share of employees in firm i in occupation j at time t , which is used as a weight for the automation probability for workers in a particular occupation, $Auto_j$. The average risk—or the average exposure—to automation is thus formed by multiplying the share of employees in an occupation, $\sigma_{ijt} \in [0, 1]$, by the automation probability of that occupation, $Auto_j$, and then summing over all occupations j that are represented within firm i . Since the probability of automation for an occupation, $Auto_j$, is a time-invariant measure, all variation over time in the exposure to automation—or average risk of automation—in a firm, $Auto_{it}$, will originate from changes in the composition of occupations, σ_{ijt} .

Note that an increase in $Auto_{it}$ must be due to a change in the composition of employees within the firm towards occupations that have a higher probability of automation—in the simple theory, this would capture "laggard firms" increasing their employment of production workers. Conversely, a decrease in $Auto_{it}$ must be due to a change in the composition of employees within the firm such that a smaller share of employees are found in occupations that have a lower probability of being automated—in theory, this would correspond to "leading firms" decreasing their employment of production workers in the theoretical model.

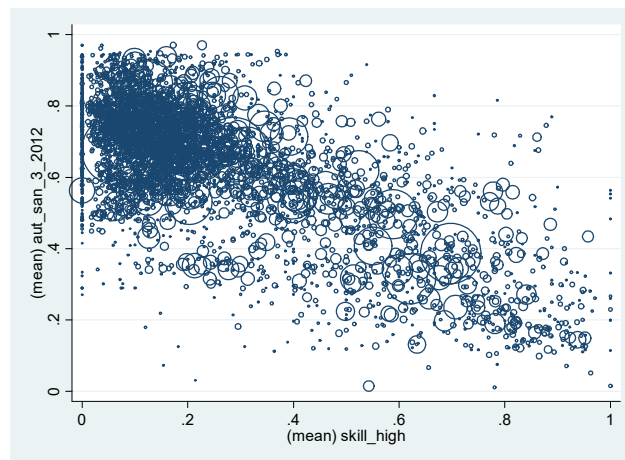
From the theory, we should also expect a negative correlation between $Auto_{it}$ and $Skill_share_{it}$. A potential concern regarding the execution of the empirical analysis is a perfect negative correlation between these variables. However, this seems unfounded given multiple types of occupations (where there are also many occupations that require higher education that have relatively high risk of automation). To illustrate this, in Figure 3.1, we plot—for the years 1996, 2004 and 2013—each firm's combinations of the share of skilled workers, $Skill_share_{it}$, on the x-axis and workforce exposure to automation, $Auto_{it}$, on the y-axis for Swedish firms with at least ten employees. Firm size in terms of the log number of employees is indicated by the size of the circle surrounding each observation.

Several observations emerge from the three panels in Figure 3.1. First, while workforce exposure to automation and the share of skilled workers are negatively correlated, there is far from a perfect negative correlation. Second, in particular, at the beginning of our period of study, many firms cluster in the area up to the top left with a workforce with high exposure to automation and a lower share of skilled workers. These firms are candidates for the "laggard firm" category in our

(i) The year 1996



(i) The year 2004



(i) The year 2013

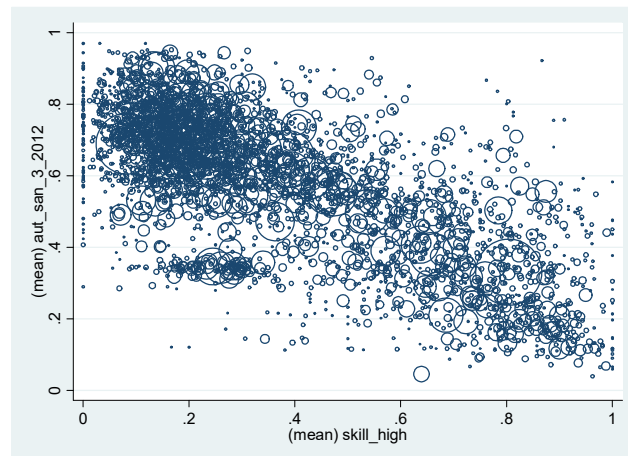


Figure 3.1: Scatterplots of firms' combinations of share of skilled worker, $Skill_share_{it}$, and workforce exposure to automation, $Auto_{it}$, 1996, 2004 and 2013.

theory, while firms located down to the right in each panel would broadly fit into the "leading firm" category. Finally, when comparing distributions over the years, we can detect a movement of the distribution down to the right, towards firms with higher skill shares and lower exposures to automation, with larger firms becoming more frequent in this region. This is what we should expect from conventional wisdom regarding skill-biased technological change. However, by no means does the cluster of firms with high exposure to automation and low skill share vanish. In fact, the latter cluster appears to be the largest and most dense in all three observed years. It is also interesting to further examine how exposed employment in the business sector has been to automation over time.

Figure 3.2 explores how the distribution of total employment changed over the period 1996-2013, dividing workers into three groups based on the estimated automation probabilities associated with a worker's occupation (based on the 3-digit classification):

- The "Low" group contains workers in occupations with a Frey-Osborne automation probability below 30 percent.
- The "Medium" group includes occupations with a Frey-Osborne automation probability above 30 percent but less than 70 percent.
- The "High" group contains occupations with a Frey-Osborne automation probability above 70 percent.

Figure 3.2 shows the development over time for workers in firms in the Swedish business sector with at least ten employees. The figure shows that the proportion of employment in the low-risk group has increased by approximately 7 percentage points. We also note that the share of jobs in the high-risk group decreased by approximately 9 percentage points, but most of this decline takes place in the period before 2009—after 2009, during the recovery from the financial crises, the share of employment with high-risk occupations levels out. Overall, Figure 3.2 indicates a shift in the disturbance 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. Taken together, the pattern emerging from Figures 3.1 and 3.2 appears to show that overall employment in low-risk occupations declines—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. From the table, we note that the pattern observed in Figure 3.2 above at the worker level can also be seen at the firm level. Our firm-level measure of exposure to automation decreased during our sample period, from a mean of 0.66 in 1996 to 0.59 in 2013. This implies that the workforce of Swedish firms has gradually changed towards occupations with less exposure to automation and is further evidence of a AI&R-driven structural change observed at the firm level. We can also see from Table 1 that there has been strong human capital upgrading, measured both in terms of the share of employees with university education and based on the mean schooling of individual workers. The table also presents firm-level

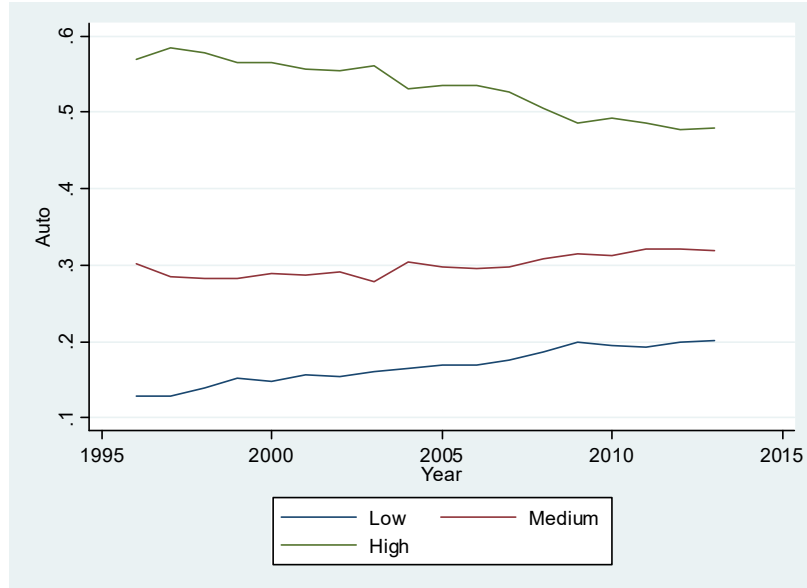


Figure 3.2: Employment shares in three groups based on automation probabilities, 1996-2013.

measures of the routineness and offshorability of the workforce. Comparing 2013 with 1996, we note that firm-level means of both RTI (routine task intensity) and offshorability decreased during this period.⁵ Finally, we note that over the period 1996-2013, we observe an increase in both labor productivity and capital intensity and a higher mean number of employees at the firm level.

Table 1

3.2. Empirical specification

We will estimate the following specification:

$$\begin{aligned} \log(VA_{it}/L_{it}) = & \alpha + \beta \cdot Auto_{it} + \zeta \cdot Share_skilled_{it} + \vartheta \cdot Share_skilled_{it} \times Auto_{it} \\ & + \varphi \cdot \log L_{it} + \rho \cdot \log(K_{it}/L_{it}) + \phi_i + \psi_t + \varepsilon_{it}. \end{aligned} \quad (3.2)$$

The dependent variable in (3.2) is the log of value added per employee in firm i at time t , $\log v_{it} = \log(\frac{VA_{it}}{L_{it}})$, which is our measure of productivity.⁶ 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 $Auto_{it}$, which again denotes the workforce's *exposure to automation* in firm i at time t ; *the share of skilled workers* in the firm, $Share_skilled_{it}$; and the interaction $Share_skilled_{it} \times Auto_{it}$. The share of skilled workers is defined as the share of employees with university education. We also control for the log of a firm's capital intensity

⁵See Section 3.3.2 for details about these measures.

⁶Value added per employee is a commonly used measure of productivity and is easily comparable across countries.

$\log(K_{it}/L_{it})$ and \log firm size $\log L_{it}$. All specifications include firm fixed effects, ϕ_i , to control for unobserved firm-level heterogeneity in productivity (i.e., the firm-specific demand and cost parameters in the model, a_i and c_i) and year fixed effects that account for common shocks, ψ_t . Finally, ε_{it} is the error term. To allow for within-firm correlation over time, standard errors are adjusted for clustering at the firm level. Let us now discuss expected signs of our main variables of interest in (3.2).

3.2.1. Testing Prediction 1

As discussed in Section 2.5.2, Proposition 2 and Equation (2.34) imply that a low skill share should be associated with laggard firms and how a higher skill share is associated with leading firms: In laggard firms, production employment increases when the return to investing in new technology increases, driving down the skill share; in leading firms, production employment declines when the return to investing in new technology increases, driving up the skill share.⁷ Using our variable $Auto_{it}$, which measures how firms change their employment of workers susceptible to automation together with the the share of skilled workers firms, $Share_skilled_{it}$, we can use this information to test Prediction 1 as follows.

First, differentiate (3.2) with respect to the workforce exposure to automation, $Auto_{it}$ to obtain:

$$\frac{\partial \log(VA_{it}/TL_{it})}{\partial Auto_{it}} = \beta + \vartheta \cdot Share_skilled_{it}, \quad (3.3)$$

In the limiting case of a *laggard firm*, we have

$$\underbrace{\lim_{Share_skilled_{it} \rightarrow 0} \left(\frac{\partial \log(VA_{it}/TL_{it})}{\partial Auto_{it}} \right)}_{\text{"Laggard"}} = \beta \underset{(+)}{> 0} \quad (3.4)$$

In laggard firms—i.e., firms with a low skill intensity—increased (unobserved) investments in AI&R technology is associated with increased hirings of workers with a high risk of automation. Since investments in new technology increase productivity, productivity and work force exposure to automation should be positively correlated, i.e., we expect $\beta > 0$ in (3.4).

⁷This can be formalized. To ensure that leading firms always have a higher skill intensity than laggard firms, assume that higher quality firm-specific assets associated with higher consumer demand (a_i) and lower cost (c_i) are related to more intense use of high-skilled non-production labor in terms of the fixed number of non-production high-skilled workers, f_i . Let $f_i = f(\frac{a_i}{c_i}) > 0$ with $f'(\frac{a_i}{c_i}) > 0$. Let $f(\frac{a_i}{c_i} \in (1, 2))$ denote the fixed number of non-production high-skilled workers in a laggard firm and let $f(\frac{a_i}{c_i} > 2)$ denote the fixed number of non-production high-skilled workers in a leading firm. Then, at $\eta = 0$, if $\frac{f(\frac{a_i}{c_i} > 2)}{f(\frac{a_i}{c_i} \in (1, 2))} > \frac{L_i^*(0|\frac{a_i}{c_i} > 2)}{L_i(0|\frac{a_i}{c_i} \in (1, 2))}$ holds, leading firms will always have strictly higher skill intensity than laggard firms, i.e., $s_i^*(\eta|\frac{a_i}{c_i} > 2) > s_i^*(\eta|\frac{a_i}{c_i} \in (1, 2))$.

In the limiting case, for a *leading firm*, we have

$$\underbrace{\lim_{Share_skilled_{it} \rightarrow 1} \left(\frac{\partial \log(VA_{it}/TL_{it})}{\partial Auto_{it}} \right)}_{\text{"Leader"}} = \underbrace{\beta}_{(+)} + \underbrace{\vartheta}_{(-)} < 0. \quad (3.5)$$

In leading firms—i.e., firms with a high skill intensity—increased (unobserved) investments in AI&R technology also raise productivity, but in contrast this process now comes with fewer high-risk workers being employed. This will now cause productivity and work force exposure to automation to be negatively correlated, i.e., we expect $\vartheta < 0$ and $\beta + \vartheta < 0$ in (3.5).

Given the estimates of $\beta > 0$ and $\vartheta < 0$, we can derive a cutoff to empirically *distinguish* the two firm types: Setting $\frac{\partial \log(v_{it})}{\partial Auto_{it}} = 0$ in (3.3), we can find the skill share of a marginal firm, $\tilde{s} = -\frac{\beta}{\vartheta} \in (0, 1)$. We can get then classify firms with skill shares below \tilde{s} as "laggard firms" (i.e., firms for which $\frac{\partial \log(v_{it})}{\partial Auto_{it}} > 0$). And we can classify firms with skill shares above \tilde{s} as "leading firms" (i.e., firms for which $\frac{\partial \log(v_{it})}{\partial Auto_{it}} < 0$).

3.2.2. Testing Prediction 2

We can also test Prediction 2 in a similar way. Differentiating (3.3) with respect to $Share_skilled_{it}$, we obtain

$$\frac{\partial \log(VA_{it}/TL_{it})}{\partial Share_skilled_{it}} = \zeta + \vartheta \cdot Auto_{it}. \quad (3.6)$$

In the limiting case for a leading firm, we first have

$$\underbrace{\lim_{Auto_{it} \rightarrow 0} \left(\frac{\partial \log(VA_{it}/TL_{it})}{\partial Share_skilled_{it}} \right)}_{\text{"Leader"}} = \underbrace{\zeta}_{(+)} > 0. \quad (3.7)$$

Again, in a leading firm, investments in AI&R technology raise productivity and reduce employment in high-risk jobs. Since the share of skilled workers and employment in high-risk jobs are negatively correlated (but not perfectly, as shown in the three panels of Figure 3.1), this will imply a positive correlation between the share of skilled workers and productivity, i.e., we predict that $\zeta > 0$ in (3.7).

In the limiting case for a laggard firm, we finally obtain

$$\underbrace{\lim_{Auto_{it} \rightarrow 1} \left(\frac{\partial \log(v_{it})}{\partial Share_skilled_{it}} \right)}_{\text{"Laggard"}} = \underbrace{\zeta}_{(+)} + \underbrace{\vartheta}_{(-)} < 0. \quad (3.8)$$

Again, since investments in AI&R technology lead to increased productivity in tandem with the employment of workers who have a high risk of automation in laggard firms, the share of skilled workers will be negatively correlated with productivity, i.e., we predict that $\zeta + \vartheta < 0$. Setting $\frac{\partial \log(VA_{it}/TL_{it})}{\partial Share_skilled_{it}} = 0$ in (3.6) and solving for the marginal firm $\tilde{Auto} = -\frac{\zeta}{\vartheta} \in [0, 1]$, we have a second

identifying condition for firm types where firms with $Auto_{it} > \tilde{Auto}$ are considered as laggard firms, and firms with $Auto_{it} < \tilde{Auto}$ are leading firms.

3.3. Empirical results

3.3.1. Benchmark results

Let us start by estimating in (3.2) when excluding the interaction term, $Share_skilled_{it} \times Auto_{it}$. The results for this restricted model are shown in column one of Table 2. We find that the coefficient on the exposure to automation, $Auto_{it}$ is statistically insignificant. This may be expected since—as shown by the theory—the relationship between exposure to automation and labor productivity should differ between firm types, and this heterogeneity is not accounted for when pooling firm types in a single relationship.

Table 2

In column two in Table 2, we turn to the results for the full specification in (3.2) which allows for firm heterogeneity. We find that the coefficient of $Auto_{it}$, $\hat{\beta}^{OLS}$, to be positive and statistically significant. The coefficient on the interaction with the skill share, $Share_skilled_{it} \times Auto_{it}$ $\hat{\vartheta}^{OLS}$, is negative and statistically significant. Substituting these estimated coefficients into (3.3), we obtain:

$$\frac{\partial \log\left(\frac{VA_{it}}{L_{it}}\right)}{\partial Auto_{it}} = \begin{cases} \hat{\beta}^{OLS} + \hat{\vartheta}^{OLS} \cdot Share_skilled_{it} > 0 \text{ if } Share_skilled_{it} \in [0, 0.42), \\ \quad (+) \quad \quad \quad (-) \\ \hat{\beta}^{OLS} + \hat{\vartheta}^{OLS} \cdot Share_skilled_{it} < 0 \text{ if } Share_skilled_{it} \in (0.42, 1]. \\ \quad (+) \quad \quad \quad (-) \end{cases} \quad (3.9)$$

Expression (3.9) provides evidence for Prediction 1: Productivity as measured by value added per employee is increasing in the exposure to workforce automation when the share of skilled workers is low (i.e., when the skill share is less than 42%, i.e., $\tilde{s} = -\frac{\hat{\beta}^{OLS}}{\hat{\vartheta}^{OLS}} = 0.42$). However, productivity declines when the exposure to workforce automation increases, namely, when the share of workers with tertiary education is sufficiently high (i.e., higher than 42%).

Recall the intuition behind these results: We imagine a process whereby—over time—AI&R technologies become increasingly available and more profitable. Investments in AI&R technology increase, but this is not observed in the data (see the top panels in Figure 2.2 and Figure 2.3). The AI&R technology causes productivity in all types of firms to rise. Since the output-expansion effect trumps the labor-replacement effect in laggard firms, employment of production workers susceptible to being replaced by the new technology increases. Therefore, investments in AI&R technology cause a positive correlation between labor productivity and high-risk production employment (see the middle and bottom panels in Figure 2.3). In contrast, in leading firms, the replacement effect dominates the output expansion effect, causing the employment of production workers susceptible to automation to decline. Investments in the AI&R technology then cause a negative correlation between labor productivity and production employment in leading firms (see the middle and bottom

panels in Figure 2.2.

In column two in Table 2, we see that the estimated coefficient for the share of skilled workers, $Share_skilled_{it}$, $\hat{\zeta}^{OLS}$, is positive and statistically significant. Combining this finding with the negatively estimated—and statistically significant—coefficient for the interaction variable, $\hat{\vartheta}^{OLS}$, we also find support for Prediction 2

$$\frac{\partial \log\left(\frac{VA_{it}}{L_{it}}\right)}{\partial Share_skilled_{it}} = \begin{cases} \hat{\zeta}_{(+)}^{OLS} + \hat{\vartheta}_{(-)}^{OLS} \cdot Auto_{it} > 0 \text{ if } Auto_{it} \in [0, 0.75), \\ \hat{\zeta}_{(+)}^{OLS} + \hat{\vartheta}_{(-)}^{OLS} \cdot Auto_{it} < 0 \text{ if } Auto_{it} \in (0.75, 1]. \end{cases} \quad (3.10)$$

where $\tilde{Auto} = -\frac{\hat{\zeta}}{\hat{\vartheta}} = 0.75$.

Figure 3.3 provides some further support for the theoretical predictions. In the top panel, we reproduce panel (iii) in Figure 3.1. Again, this panel depicts each firm’s combination of skill share, $Skill_share_{it}$, on the x-axis, and its work force exposure to automation, $Auto_{it}$, on the y-axis. The data include all Swedish firms with at least ten employees in 2013 (with the size of a circle again indicating the size of a firm in terms of the log number of employees). We indicate the regions over which productivity rises and falls with the exposure to automation, obtained using the implied cutoff $\tilde{s} = 0.42$ from (3.9). In firms with skill shares below \tilde{s} , productivity increases when automation exposure increases (as the firms shift employment towards high-risk occupations). However, in firms with skill shares above $\tilde{s} = 0.42$, productivity increases with declining automation risk (as the firm shifts employment out of high-risk occupations). We can also use (3.10) to delineate the regions where productivity increases with the skill share. This occurs when the exposure to automation is below $\tilde{Auto} = 0.75$, while productivity decreases with the share of skilled workers when the exposure is above the latter cutoff. Note that a large share of the observations fall into the top-left quadrant (with $s_{i,2013} < \tilde{s}$ and $Auto_{i,2013} > \tilde{Auto}$) and in the lower-right quadrant (with $s_{i,2013} > \tilde{s}$ and $Auto_{i,2013} < \tilde{Auto}$). From Predictions 1 and 2, we can characterize these firms as laggard firms and leading firms, respectively. In line with the theory, we find almost no observations in the upper-right corner, although there is a cluster of observations in the lower-left corner, in line with Prediction 1—but not Prediction 2.

Turning to the lower panel, we use contour plots to flesh out how productivity varies over exposure to automation, $Auto_{it}$, and skill share, $Skill_share_{it}$, using the estimated OLS coefficients $\hat{\beta}^{OLS}$, $\hat{\vartheta}^{OLS}$ and $\hat{\zeta}^{OLS}$. Two features of increasing productivity stand out: Productivity increases in the southeast direction—with increasing skill shares and declining exposure to automation—but also in the northwest direction—with declining skill shares and increasing exposure to automation.

The increase in productivity in the southeast direction corresponds to what the theory predicts for leading firms: At higher (unobserved) investments in new technology, productivity rises when using a mix of workers with more education and lower automation risk. The increase in productivity in the northeast direction, on the other hand, corresponds to what the theory predicts for laggard firms: Here, productivity rises when shifting employment towards a mix of less skilled workers with

higher automation risk. While productivity peaks for both less efficient laggard and leading firms, we find—consistent with the theory—that the highest productivity is reached in more efficient leading firms.

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

Thus far, we have measured skill intensity as a proxy for firm heterogeneity and average work force exposure to automation as a measure of the risk of being replaced by new technology. In this section, we examine alternative measures of firm type and worker exposure to automation.

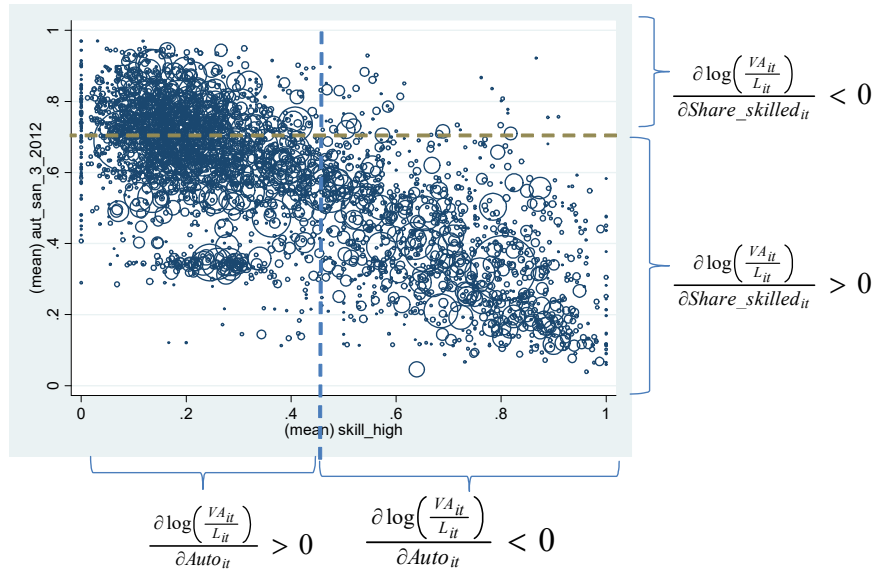
In the remaining columns of Table 2, we sequentially add other measures of firm heterogeneity and interact these with the average automation risk. We start by using a schooling measure, Sch_{it} , which uses a seven-degree scale to measure the level of education of the workers in a firm.⁸ We also compute the average working experience in terms of years for the employees, Exp_{it} , and the average age of the employees, Age_{it} . We add these variables separately to the benchmark specification (3.2), and we also do so for their interaction with the average risk of automation, $Auto_{it}$. These alternative proxies for heterogeneity in terms of the composition of employment reveal a similar pattern as our main measure of heterogeneity in terms of the share of workers with tertiary education, $Share_skilled_{it}$. Interestingly, it is in firms with workers who are younger, have less schooling and less work experience where we find that shifting employment towards high-risk occupations is associated with higher labor productivity. In unreported specifications, we also experimented with other measures of firm heterogeneity such as firm size and firm age. Here, we found no effect on the interaction of firm size and the average automation risk. However, in line with the results on the average age of employees, we found that in younger firms, an increase in automation risk was positively correlated with increased productivity.

In Table 3, we check the robustness of our measure of the workforce’s exposure to automation, $Auto_{it}$, 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 Autor (2013), Autor and Dorn (2013), Autor et al. (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 (3.1). We also calculate firm-level averages of the level of routine cognitive tasks, RC_{it} , non-routine cognitive tasks, NRC_{it} , non-routine 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).⁹ Remarkably, as shown in Table 3, the

⁸The individual schooling variable is based on seven education levels, ranging from less than high school to a doctoral degree.

⁹This measure is also available at the two-digit SSSYK96 level.

(i) Partial correlations and observations in 2013



(i) Predicted labor productivity as a function of exposure to automations and the share of skilled workers

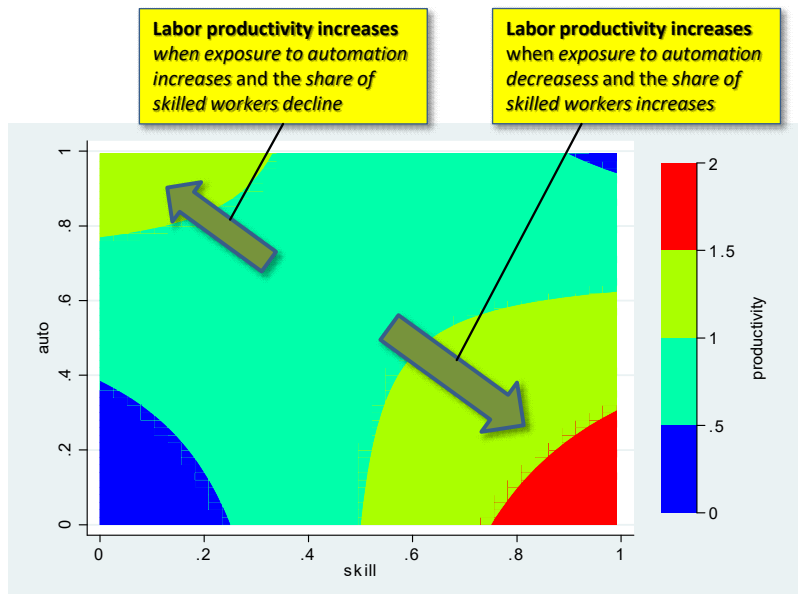


Figure 3.3: Illustrating Predictions 1 and 2.

interactions of these alternative job characteristics with our skill measure for firm heterogeneity are consistently insignificant, while our preferred automation risk variable and its interaction is consistently estimated with good precision. Table 3 thus gives us more confidence in our estimates using the workforce's exposure to automation.

Table 3

3.3.3. 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 invest in unobserved investments in AI&R 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 that are likely correlated with investments in AI&R 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 AI&R technology, we distinguish between industries where, say, ICT usage was low at the beginning of the studied period 1996-2013 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 has grown considerably over the time 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 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 4, we re-estimate the benchmark specification (3.2) based on the intensity with which firms in different industries use ICT (share of total capital stock). We begin by examining initial use 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 we study.¹⁰

Inspecting Table 4, we note that the main results in Table 2 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 one) and in industries with a low ICT share in 1996, which the first year of our data (column 3).

¹⁰Due 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 we are still able to use the firm data for the entire period 1996-2013 but again base changes at the industry level on a somewhat shorter time window.

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). This pattern is indeed what we should expect if these industries had more growth in the return to investing in AI&R technology (η).

In Table 5, we also find the same patterns when we differentiate industries according to their gross investments in ICT. In unreported results, we find similar results when we differentiate industries according to the use of IT and software.¹¹

Table 4 and Table 5

3.3.4. Endogeneity

In the theoretical model, we showed how investments in AI&R technology (unobserved in the data) implied a positive correlation between productivity and production employment in "laggard firms". In leading firms, however, investments in AI&R technology (unobserved in the data) implied 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 were 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 approach. 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.

Adapted to our research question, we will use the following instrument for the firm-level measure of exposure to automation:

$$Auto_instr_{it} = \sum_{j=1}^J \sigma_{ijt_0} \cdot Aut_j \cdot (L_{jt} - L_{ijt}). \quad (3.11)$$

In (3.11), σ_{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 of σ_{ijt_0} . $L_{jt} = \sum_i L_{ijt}$ 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 $Auto_instr_{it}$ will essentially stem from how the employment of different

¹¹These results are available from the authors upon request.

occupations evolves over time at the national level, L_{jt} (excluding employment in the own firm). This is our identifying assumption in (3.11). The variation in L_{jt} stems from the fact that different firms employ different occupations and hence firms will be differentially affected by changes in aggregate employment at the national level. Moreover, the shocks to aggregate employment are external to individual firms and unlikely to be correlated with unobserved firm characteristics that may affect productivity.¹²

The IV results are presented in Table 6. The main specification in columns one and two holds the share s_{ijt_0} constant the first year of appearance in the data and uses $\log Auto_instr_{it}$ as an instrument for $Auto_{it}$ in (3.2). The next specification in columns three and four repeats this without taking the log of $Auto_instr_{it}$. Finally, in columns 5-8, we repeat this procedure, but now s_{ijt_0} is replaced with s_{ijt-1} . Regardless of specification, we first note that the instrument $Auto_instr_{it}$ is significantly and positively correlated with $Auto_{it}$ in the first stage (columns 1, 3, 5 and 7). These first-stage estimates show that $Auto_instr_{it}$ 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.

In column 2, we report the two-stage least square (2SLS) estimates when shares are based on the first year in which a firm is present in the data. Our estimates indicate that the results are qualitatively similar to our benchmark results in Table 2, although the coefficient estimates are larger. Similar second-stage estimates are also found in columns 4, 6 and 8.

Table 6

Our results in Table 6 show that the IV estimates for $Auto_{it}$ are significantly larger than the corresponding OLS (FE) estimates. As will be discussed below, our IV estimates are, however, in accordance with our theoretical predictions and are economically reasonable. The higher IV estimates suggest that workforce composition changes are a more important driver of productivity effects from AI&R technology investment than picked up by our OLS (FE) estimates. Furthermore, it is essential to note that the IV estimates capture the average effect of firm exposure to automation on productivity for the subsample of firms that have engaged in more automation (see, e.g., Imbens and Angrist 1994 for a discussion of the local average treatment effect). Hence, the productivity effect from having the right workforce composition may be more substantial for this subsample of firms ("compliers") than for other firms.

From the IV estimates in column 2 in Table 6, in a similar way as in 3.9, we can compute the

¹² $Auto_instr_{it}$ captures the fluctuations in employment conditions that are time varying and specific to each firm. The variation in $Auto_instr_{it}$ stems from the fact that different firms employ different types of workers, and hence firms will be differentially affected by changes in aggregate employment. Moreover, these changes are external to individual firms and unlikely to be correlated with unobserved firm characteristics.

following:

$$\frac{\partial \log \left(\frac{VA_{it}}{L_{it}} \right)}{\partial Auto_{it}} = \begin{cases} \hat{\beta}_{(+)}^{IV} + \hat{\vartheta}_{(-)}^{IV} \cdot Share_skilled_{it} > 0 \text{ if } Share_skilled_{it} \in [0, 0.63), \\ \hat{\beta}_{(+)}^{IV} + \hat{\vartheta}_{(-)}^{IV} \cdot Share_skilled_{it} < 0 \text{ if } Share_skilled_{it} \in (0.63, 1]. \end{cases} \quad (3.12)$$

Thus, from (3.9) and (3.12), it follows that both the OLS and IV estimates support the theoretical prediction of a positive correlation between a firm's workforce exposure to automation and productivity for laggard firms and a negative correlation for leading firms. We also note that the estimated cutoff, \tilde{s} , is estimated at 0.42 in the OLS specification and 0.63 in the IV specification, lending further confidence to our estimates. In Table 7, we estimate (3.2) with $Auto_instr_{it}$ acting as an instrument for $Auto_{it}$ and $Auto_instr_{it} \times Share_skilled_{it}$ acting as an instrument for the interaction variable $Auto_{it} \times Share_skilled_{it}$. While some specifications are less precisely estimated, the results in Table 7 confirm the heterogeneity in (3.12).

Table 7

Finally, we have also applied the system generalized method of moments (GMM) approach developed by Arellano and Bover (1995) and Blundell and Bond (1998). The system GMM estimator, building on one equation in level and one in differences, improves efficiency by using more instruments as compared to the difference GMM developed by Arellano and Bond (1991). More precisely, the system GMM estimator uses first-differenced and level versions of the estimating equation, where lagged values and lagged differences can serve as valid instruments. The differentiated instruments are assumed to be uncorrelated with the unobserved fixed effects, implying that first differentiated variables can act as instruments for variables in levels, i.e., instrumenting levels with differences.

Results from GMM may be sensitive to the choice of instruments and the choice of variables being instrumented (Fajnzylber and Maloney 2001). We test the joint validity of the instruments with the Sargan–Hansen test and also show tests for up to the 4:th order of serial correlation of the residuals of the first-differenced equation.

Results are presented in Tables A1 and A2 in Appendix 1 and show specifications with different lag structures. Table A1 show results where $Auto_{it}$ is instrumented with $Auto_instr_{it}$ and in Table A2 we follow Table 7 and estimate (3.2) with $Auto_instr_{it}$ acting as an instrument for $Auto_{it}$ and $Auto_instr_{it} \times Share_skilled_{it}$ acting as an instrument for the interaction variable $Auto_{it} \times Share_skilled_{it}$. Results from the GMM estimations are similar to the results presented above. Again, we find that the estimated coefficient of $Auto_{it}$, $\hat{\beta}^{OLS}$, is positive and statistically significant and that the estimated coefficient on the interaction with the skill share, $Share_skilled_{it} \times Auto_{it}$ $\hat{\vartheta}^{OLS}$, is negative and statistically significant. Substituting the estimated coefficients from column

1 in the GMM Table A1 into (3.3), we obtain:

$$\frac{\partial \log\left(\frac{VA_{it}}{L_{it}}\right)}{\partial Auto_{it}} = \begin{cases} \hat{\beta}_{(+)}^{OLS} + \hat{\vartheta}_{(-)}^{OLS} \cdot Share_skilled_{it} > 0 \text{ if } Share_skilled_{it} \in [0, 0.61), \\ \hat{\beta}_{(+)}^{OLS} + \hat{\vartheta}_{(-)}^{OLS} \cdot Share_skilled_{it} < 0 \text{ if } Share_skilled_{it} \in (0.61, 1]. \end{cases} \quad (3.13)$$

This is quantitatively very similar to what we obtained in the IV regressions presented above, again lending support for Prediction 1.

3.3.5. Further evidence

The OLS and IV estimates from the interacted model reveal a positive correlation between a firm's workforce exposure to automation and productivity in low-skill-intensive firms and a corresponding negative correlation in high-skill-intensive firms. From our proposed model, these correlations mask a relationship where low-skill "laggard" firms respond to (unobserved) increased investments in new technology by shifting their employment mix towards high-risk occupations, while in high-skill-intensive leading firms, the increased use of newer technology is to a greater extent replacing workers at a high risk of automation.

Let us further illustrate this heterogeneous response to unobserved investments in new technology between different types of firms. To this end, let us compare the time pattern of the within-firm productivity and the within-firm exposure to automation for firms with different skill compositions.

In a first step, we residualize value added per worker by first estimating

$$\log\left(\frac{VA_{it}}{L_{it}}\right) = \alpha + \rho \cdot \log(K_{it}/L_{it}) + \varphi \cdot \log L_{it} + \phi_i + \varepsilon_{it}, \quad (3.14)$$

Note that we have excluded the time dummies, the share of skilled workers and the exposure to automation. We then compute the residuals: $E[\hat{\varpi}_{it}^{Auto}|t]$

$$\hat{\varepsilon}_{it}^{\log(VA/L)} = \log\left(\frac{VA_{it}}{L_{it}}\right) - \left[\hat{\alpha} + \hat{\rho} \cdot \log(K_{it}/L_{it}) + \hat{\varphi} \cdot \log L_{it} + \hat{\phi}_i\right] \quad (3.15)$$

In a second step, we residualize the exposure to automation by running the regression

$$Auto_{it} = \chi_0 + \chi_1 \cdot \log(K_{it}/L_{it}) + \chi_2 \cdot \log L_{it} + \chi_i + \varpi_{it}. \quad (3.16)$$

and then compute the residuals

$$\hat{\varpi}_{it}^{Auto} = Auto_{it} - [\hat{\chi}_0 + \hat{\chi}_1 \cdot \log(K_{it}/L_{it}) + \hat{\chi}_2 \cdot \log L_{it} + \hat{\chi}_i] \quad (3.17)$$

We can now compare the within-firm variation in productivity $\hat{\varepsilon}_{it}^{\log(VA/L)}$ with the within-firm variation in the exposure to automation $\hat{\varpi}_{it}^{Auto}$ for different skill groups.

The three top panels in Figure 3.4 depict yearly binscatter plots of value added per employee, as

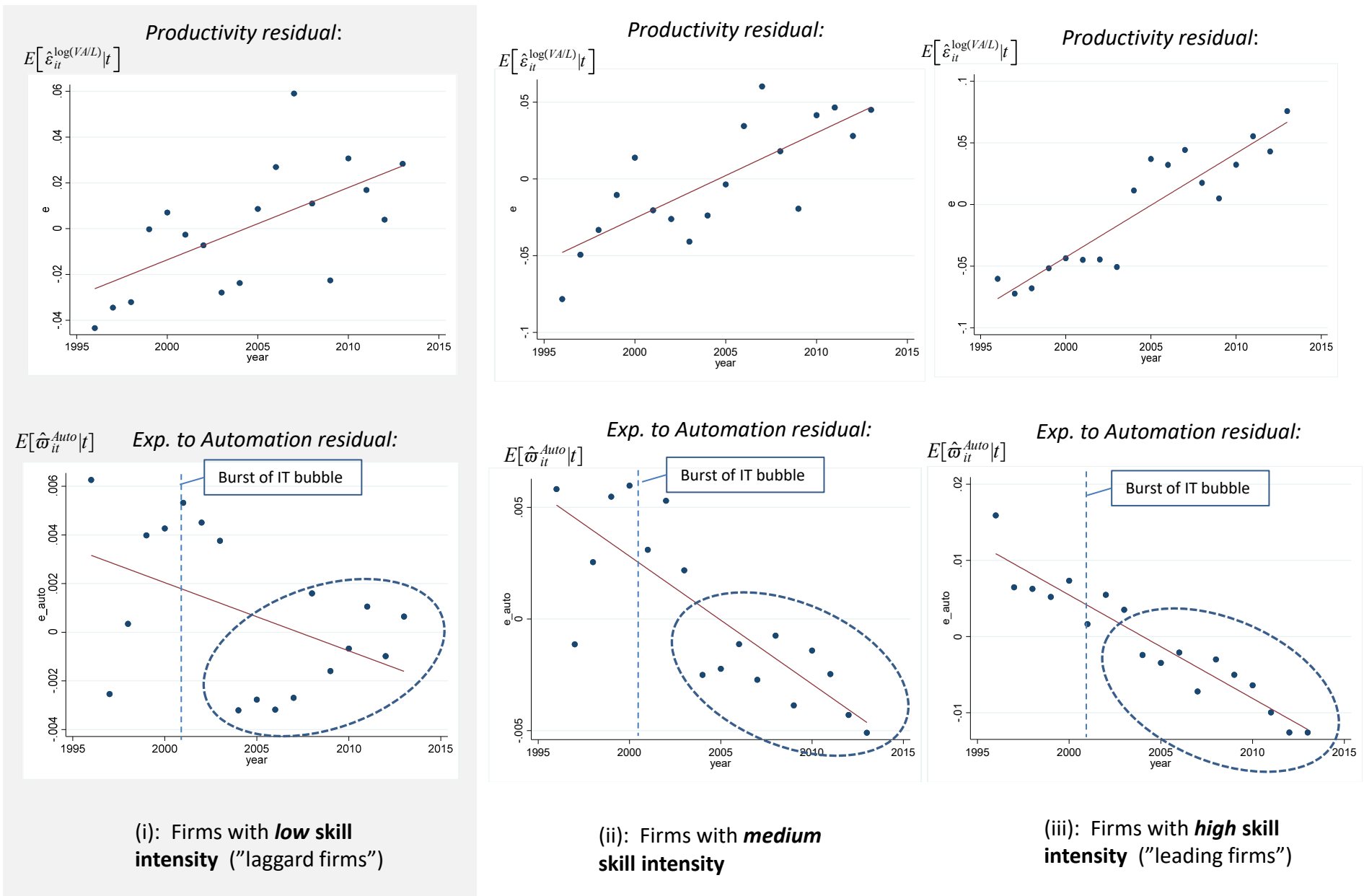


Figure 3.4: Comparing the within-firm variation in productivity from (3.15) with the within-firm variation in exposure to automation in (3.17), for different skill groups

measured by the residual $\hat{\varepsilon}_{it}^{\log(VA/L)}$, for three groups of firms ranked in terms of their skill intensity: For each year in the data, the low-skill group consists of the 25 percent of firms with lowest skill share; the high-skill group consists of the 25% firms with the highest skills share, and the middle group contains the remaining firms. The top panels illustrate that labor productivity broadly has an upward trend over time, albeit with considerably short-term variation in recessions and booms and with low- and medium-skilled firms being considerably more affected by the business cycle than high-skilled firms.

The three lower panels in Figure 3.4 show similar yearly binscatter plots of the exposure to automation in terms of the residual $\hat{\omega}_{it}^{Auto}$ over time. If we first focus on firms with a high share of workers with tertiary education, comparing the top and the bottom panels for the high-skilled group reveals a negative correlation between the trends in labor productivity and exposure to automation. This is in line with the prediction from the theory illustrated in Figure 2.2: In leading firms, investments in new technology increase productivity, but this is associated with shifting the mix of workers from high-risk to low-risk occupations. The correlation between the time variation in labor productivity and exposure to automation appears to also be negative in the middle skill group. However, here, we also note a large discrete decline in exposure to automation in the aftermath of the IT crash in 2001. Medium-skilled firms appear to have shifted employment out of high-risk occupations under the major restructuring taking place during this period. However, during the recovery years, firms also appear to have continued to shift out of high-risk occupations.

Finally, regarding low-skilled firms, there is again a discrete decrease in exposure to automation during the slump occurring in the years after 2001. In contrast to the other two skill groups, during the recovery, we see that firm exposure to automation is rising as a consequence of shifting the mix of employees towards workers in occupations with higher automation risks. The latter finding is also in line with the prediction from the theory illustrated in Figure 2.3: In low-skilled laggard firms, investments in new technology increase productivity, and this process is associated with shifting the mix of workers toward high-risk occupations.

4. Conclusion and Policy discussion

In this paper, we have investigated how AI&R-based 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 AI&R 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 AI&R technology, we have shown 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 have shown that when technology development has proceeded considerably and when the intensity of product market competition is stiff, laggard firms will face reduced productivity and will decrease the 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 positive correlation for firms with a low share of high-skill workers. We also find that these results originate from industries where technology investments increased substantially during the period of study. To address the endogeneity problem, we apply a shift-share instrument approach, where the variation over time in our instrument will essentially stem from how the employment of different occupations evolves over time at the national level. Our main results also hold when we use our proposed instrument.

Our empirical findings indicate that leading and laggard firms react differently to new technologies with respect to their hiring of workers in occupations susceptible to automation. This suggests that countries with business sectors characterized by diversity in firm types might face a smoother AI&R-driven creative destruction process. Diversity of firm types may function as insurance against excessive reduction in labor demand in occupations where workers are replaced by AI&R technology. Business sectors with few large highly efficient firms will be conducive to high productivity growth but might cause 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; 2019b). 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 median 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, which might be of particular value during periods of rapid technological change. Indeed, our results suggest that a crucial element in achieving balanced AI&R-driven industrial restructuring is that leading firms replace workers in occupations susceptible to automation with AI&R technologies. In contrast, laggard firms tend to hire employees in such occupations.

The intensity of product market competition will also affect the pace of the creative destruction process. In the appendix, we show that we can derive qualitatively identical results with several firms competing in the same product market under strategic interaction. However, we also show that when more firms compete in the product market, 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. In particular, the failing firm defense in merger law might be used in a forward-looking way (Persson 2001) to ensure a smoother creative destruction process. 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 when implementing new AI&R 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 AI&R implementation 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 the laggards are not exiting the markets at too fast a 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 AI&R 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, firm heterogeneity emphasized in the 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 AI&R technology is implemented. Regional heterogeneity may also be significant in how a country's AI&R technology industrial restructuring evolves and warrants further investigation.

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Tables

Table 1: Definitions and descriptive statistics (firm-level means and standard deviations). Firms with at least 10 employees, 1996–2013.

<i>Firm variables:</i>	Definition	1996–2013	1996	2013
Value added per employee	Sales-operational expenses excluding wages / No. of employees	0.58 (0.52)	0.44 (0.27)	0.66 (0.56)
Capital intensity	Net property, plant and equipment)/ No. of employees	0.87 (0.41)	0.32 (0.89)	0.92 (0.45)
No. of employees	No. of employees	252 (994)	287 (1,300)	307 (985)
<i>Individual level-based variables:</i>				
Auto	Exposure to automation	0.63 (.19)	0.66 (.18)	0.59 (.20)
Share high skilled	Share of employees with tertiary education	0.25 (.24)	0.18 (.20)	0.35 (.26)
Schooling	Individual grouping of schooling, ranging from 1 to 7	3.56 (0.77)	3.13 (0.73)	3.99 (0.74)
Labor market experience	Age minus number of years of schooling minus seven	22.25 (5.75)	21.93 (5.7)	22.30 (5.65)
Age	Age of employees	40.7 (5.47)	39.71 (5.34)	41.37 (5.42)
RTI	Routine Task Intensity (RTI) index	0.29 (0.54)	0.12 (0.56)	-0.39 (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. See Section 4.1 for details about the variables.

Table 2: Automation probability and productivity, 1996-2013. Basic regressions.

	Basic spec.	Share skilled	Mean schooling	Mean experience	Mean age
	(1)	(2)	(3)	(4)	(5)
Auto	0.032 (0.038)	0.124*** (0.045)	0.285** (0.127)	0.281*** (0.096)	0.596*** (0.170)
Share_skilled	0.064 (0.060)	0.221** (0.101)			
Auto × Share_skilled		-0.293** (0.127)			
Sch			0.053* (0.028)		
Auto × Sch			-0.067* (0.035)		
Exp				0.003 (0.003)	
Auto × Exp				-0.013*** (0.004)	
Age					0.004 (0.003)
Auto × Age					-0.015*** (0.004)
Log Capital intensity	0.069*** (0.005)	0.069*** (0.005)	0.069*** (0.005)	0.068*** (0.005)	0.069*** (0.005)
Log Firm size	-0.126*** (0.011)	-0.126*** (0.011)	-0.127*** (0.011)	-0.131*** (0.011)	-0.132*** (0.011)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R-squared	0.064	0.064	0.064	0.065	0.065
Observations	69,156	69,156	69,156	69,156	69,156

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, Share_skilled is share of employee with university education, Sch is mean schooling at the firm-level based on grouping of education levels, Exp is mean labor market experience at the firm-level, 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 3: Automation probability and productivity, 1996-2013. Impact of other job task characteristics.

	RTI	Offshorability	Routineness	Routine cognitive	Routine manual	Non-routine manual	Non-routine cognitive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Auto	0.136*** (0.047)	0.113** (0.048)	0.147*** (0.047)	0.130*** (0.046)	0.117** (0.047)	0.126*** (0.045)	0.100** (0.050)
Auto × Share_skilled	-0.291** (0.128)	-0.284** (0.130)	-0.341*** (0.127)	-0.327*** (0.126)	-0.302** (0.130)	-0.298** (0.126)	-0.274** (0.127)
RTI	-0.011 (0.011)						
RTI × Share_skilled	0.002 (0.043)						
Offshorability		0.006 (0.008)					
Offshorability × Share_skilled		-0.007 (0.036)					
R			-0.026 (0.020)				
R × Share_skilled			0.057 (0.088)				
RC				-0.063** (0.030)			
RC × Share_skilled				0.133 (0.095)			
RM					0.003 (0.021)		
RM × Share_skilled					0.044 (0.123)		
NRM						0.031 (0.019)	
NRM × Share_skilled						-0.036 (0.091)	
NRC							-0.025 (0.028)
NRC × Share_skilled							0.022 (0.094)
Firm controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	69,106	69,106	69,106	69,106	69,106	69,106	69,106
R-squared	0.064	0.064	0.064	0.064	0.064	0.064	0.064

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, Share_skilled is share of employee with university education, RTI is Routine Task Intensity (RTI) index, Offshorability is Offshorability index, R is Routine, RC is Routine Cognitive, RM is Routine Manual, NRM is Non-Routine Manual, NRC is Non-Routine Cognitive, 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 4: Automation probability and productivity, 1996-2013. By capital shares in ICT at the industry 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	0.146** (0.059)	0.120* (0.069)	0.161*** (0.060)	0.102 (0.067)	0.107** (0.054)	0.151** (0.076)
Share_skilled	0.394*** (0.140)	0.131 (0.127)	0.438*** (0.144)	0.097 (0.127)	0.165 (0.131)	0.308** (0.154)
Auto × Share_skilled	-0.481** (0.198)	-0.212 (0.155)	-0.553*** (0.200)	-0.160 (0.155)	-0.191 (0.147)	-0.425** (0.215)
Firm controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	31,306	37,850	30,337	38,819	38,738	30,418
R-squared	0.080	0.053	0.083	0.052	0.053	0.082

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, and Share_skilled is share of employee 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 (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 5: Automation probability and productivity, 1996-2013. By gross investments in ICT at the industry level.

	Low ICT (pre-means)	High ICT (pre-means)	Low ICT (1996)	High ICT (1996)	Low ICT change	High ICT change
	(1)	(2)	(3)	(4)	(5)	(6)
Auto	0.152** (0.062)	0.111* (0.067)	0.152** (0.062)	0.111* (0.067)	0.081 (0.081)	0.096 (0.067)
Share_skilled	0.519*** (0.162)	0.121 (0.122)	0.519*** (0.162)	0.121 (0.122)	-0.005 (0.341)	0.184** (0.086)
Auto ×Share_skilled	-0.753*** (0.235)	-0.125 (0.148)	-0.753*** (0.235)	-0.125 (0.148)	0.216 (0.450)	-0.317** (0.129)
Firm controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	28,224	40,932	28,224	40,932	29,219	39,937
R-squared	0.080	0.056	0.080	0.056	0.052	0.080

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, and Share_skilled is share of employee 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 (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 6: Automation probability and productivity. IV regressions 1996-2013. Auto instrumented.

	IV (in logs)		IV		IV (in logs)		IV	
	Share based on first year		Share based on t-1		Share based on t-1			
	1:st stage	2SLS	1:st stage	2SLS	1:st stage	2SLS	1:st stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Auto		1.601*		1.975**		2.091***		2.227***
		(0.876)		(0.971)		(0.701)		(0.761)
Share_skilled	-0.937***	1.594*	-0.938***	1.947**	-0.941***	2.060***	-0.939***	2.189***
	(0.019)	(0.833)	(0.019)	(0.913)	(0.020)	(0.686)	(0.020)	(0.733)
Auto × Share_skilled	1.541***	-2.502*	1.541***	-3.083**	1.548***	-3.294***	1.547***	-3.507***
	(0.026)	(1.369)	(0.026)	(1.507)	(0.027)	(1.109)	(0.027)	(1.201)
log(Auto_instr)	0.006***				0.007***			
	(0.001)				(0.001)			
Auto_instr			0.001***				0.001***	
			(0.000)				(0.000)	
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	48,617	48,617	48,617	48,617	47,550	47,550	47,550	47,550
R-squared		0.037		0.023		0.014		0.007
F-test	20.16		30.73		28.98		52.36	

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, Share_skilled is share of employee with university education. See Section 4.1 and Table 1 for details about the variables. For the IV estimates in this table, we instrument for Auto using Auto_instr described in Section 4.3.3. The shares are in columns 1-4 based on the first year we observe the firms and in columns 5-8 on t-1. Auto_instr are in logs in columns 1-2 and 5-6 and in non-log forms in columns 3-4 and 7-8. The first-stage regressions include the instrument, firm controls, and firm and year fixed effects. 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 7: Automation probability and productivity. IV regressions 1996-2013. Both Auto and Auto interacted with skill shares instrumented.

	IV (in logs)		IV		IV (in logs)		IV	
	Share based on first year				Share based on t-1			
	1:st stage	2SLS	1:st stage	2SLS	1:st stage	2SLS	1:st stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Auto		1.180** (0.517)		1.123* (0.589)		4.049** (1.652)		0.951** (0.406)
Share_skilled × Auto3		-1.294 (0.901)		-0.376 (1.045)	0.978*** (0.031)	-7.692** (3.122)		-0.468 (0.592)
Share_skilled	-0.344*** (0.058)	0.937* (0.524)	-0.233*** (.019)	0.494 (0.588)		5.301** (2.138)	-0.276*** (0.019)	0.485 (0.372)
log(Auto_instr)	0.008*** (0.003)				0.046*** (0.003)			
log(Auto_instr) × Share_skilled	0.015** (0.006)				-0.126*** (0.008)			
Auto_instr			0.002*** (0.000)				0.001*** (0.000)	
Auto_instr × Share_skilled			0.002 (0.001)				0.006*** (0.001)	
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	48,617	48,617	48,617	48,617	47,550	47,550	47,550	47,550
R-squared		0.048		0.041		-0.152		0.048
F-test	23.42		25.71		155.84		113.93	

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, Share_skilled is share of employee with university education. See Section 4.1 and Table 1 for details about the variables. For the IV estimates in this table, we instrument for Auto and Auto × Share_skilled using Auto_instr and Auto_instr × Share_skilled as described in Section 4.3.3. The shares are in columns 1-4 based on the first year we observe the firms and in columns 5-8 on t-1. Auto_instr are in logs in columns 1-2 and 5-6 and in non-log forms in columns 3-4 and 7-8. The first-stage regressions include the instrument, firm controls, and firm and year fixed effects. 1:st stage for Auto are presented in the table. 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. Appendix (not for publication)

A.1. Proof of (2.28) being strictly positive

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

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

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 get

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

Then, define

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

Combining (2.29), (2.32) and (A.3), we get

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

Now use (2.19) and (2.20), to have

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

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

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

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 . But 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. Skilled workers used in proportion to investments in the AI&R technology

Replacing vF_i in (2.5) with $v(F_i + \phi k_i)$, and repeating the steps in stage 1 and stage 2, the optimal investment in the AI&R technology now become

$$k_i^*(\eta) = \frac{\gamma}{\mu} \cdot \frac{a_i - c_i - 2\frac{v\phi}{c_i}}{(2 - \eta)}. \quad (\text{A.7})$$

It is then straightforward to solve for the remaining endogenous variables expression in $k_i^*(\eta)$, i.e. $q_i^*(\eta) = \frac{\mu k_i^*(\eta)}{\gamma} + \frac{\phi v}{\gamma}$, $P_i^*(\eta) = a - q_i^*(k^*)$, $l_i^*(\eta) = c_i - \gamma k_i^*(\eta)$, $L_i^*(\eta) = l_i^*(\eta) q_i^*(\eta)$. The share of skilled labor in (2.33) is

$$s_i^*(\eta) = \frac{F_i + \phi k_i^*(\eta)}{L_i^*(\eta) + F_i + \phi k_i^*(\eta)}. \quad (\text{A.8})$$

Taking logs in (A.8), differentiating in η and rewriting, the elasticity in (2.34) can be written

$$\frac{ds_i^*}{d\eta} \frac{\eta}{s_i^*} = \left(\frac{dL_i^*(\eta)}{d\eta} \frac{\eta}{L_i^*(\eta)} - \phi \cdot \frac{dk_i^*(\eta)}{d\eta} \frac{\eta}{F_i + \phi k_i^*(\eta)} \right) \cdot (1 - s_i^*(\eta)) \quad (\text{A.9})$$

Comparing (2.34) and (A.9), it follows that Prediction 2 will still hold if ϕ is limited in size, that is, if skilled workers are not essential in the production process. At higher values of ϕ , however, signing (A.9) is more involved and Prediction 2 may not hold. For laggard firms, hirings of production workers can increase with increasing investments in the AI&R technology, but this may arise with an increasing skill share.

A.3. Competition

Let us now show that we can derive qualitatively the same results with several firms competing in the same product market under strategic interaction. Let $a_i = a$ and $w = 1$, The profit maximization problem for firm i is

$$\max_{\{q_i, k_i\}} \pi_i = \underbrace{P_i q_i}_{\text{Revenues}} - \underbrace{(c_i - \gamma k_i) q_i}_{\text{labor (high risk) costs}} - \underbrace{\frac{\mu}{2} k_i^2}_{\text{Installation costs}} \quad (\text{A.10})$$

where c_i is general cost of firm i and, hence, the source of heterogeneity among firm, and the inverse demand is

$$P_i = a - q_i - \lambda \sum_{j \neq i}^n q_j \quad (\text{A.11})$$

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

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

$$P_i - (c_i - \gamma k_i) - q_i = 0, \quad \{i = 1, 2, 3, \dots, n\}. \quad (\text{A.12})$$

From (A.12) and (A.11), we then have

$$q_i^* = \frac{a - c_i + \gamma k_i - \lambda Q}{2 - \lambda}, \quad (\text{A.13})$$

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 total number of robots in the industry. Summing (A.13) over all n firms, we can solve for total output as

$$Q^* = \frac{na - C + \gamma K}{2 - \lambda + n\lambda}, \quad (\text{A.14})$$

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

Combining (A.13) and (A.14), the Cournot output for firm i can be written

$$q_i^* = (a - c_i + \gamma k_i) \frac{(n+2-2\lambda)}{(n+2-\lambda)(2-\lambda)} - \frac{\lambda}{(n+2-\lambda)(2-\lambda)} \left(\sum_{j \neq i} (a - c_j + \gamma k_j) \right), \quad (\text{A.15})$$

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

From (A.15), it is useful to note that

$$\frac{dq_i^*}{dk_i} = \frac{\gamma(n+2-2\lambda)}{(n+2-\lambda)(2-\lambda)} > 0, \quad (\text{A.16})$$

$$\frac{dq_i^*}{dk_j} = -\frac{\gamma\lambda}{(n+2-\lambda)(2-\lambda)} = \frac{dq_j^*}{dk_i} < 0. \quad (\text{A.17})$$

Stage 2: Investments in robots Now turn to stage 1. From (A.15), we can write the stage 1 profit as a function of k_i

$$\max_{\{k_i\}} \pi_i(k_i) = \left(\underbrace{a - q_i^*(k_i) - \sum_{j \neq i} q_j^*(k_i)}_{P_i} - (c_i - \gamma k_i) \right) q_i^*(k_i) - \mu \frac{k_i^2}{2}. \quad (\text{A.18})$$

From (A.18) and (A.17) and applying the envelope theorem, we have

$$\begin{aligned} \frac{d\pi_i^*}{dk_i} &= \frac{\partial \pi_i}{\partial k_i} + \sum_{j \neq i} \frac{\partial \pi_i}{\partial q_j} \frac{dq_j^*}{dk_i} = 0, \\ &= \underbrace{\gamma q_i^* - \mu k_i}_{\frac{\partial \pi_i}{\partial k_i}} + \sum_{j \neq i} \underbrace{(-q_i^*)}_{\frac{\partial \pi_i}{\partial q_j}} \underbrace{\left(\frac{-\gamma \lambda}{(n+2-\lambda)(2-\lambda)} \right)}_{\frac{dq_j^*}{dk_i}} = 0. \end{aligned} \quad (\text{A.19})$$

From (A.19), we get

$$k_i^* = \frac{\gamma}{\mu} \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right) q_i^*, \quad (\text{A.20})$$

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

Substituting (A.20) into (A.15) and using symmetry, and then summing over all n firms, we find that total output is

$$Q^*(\eta) = \frac{an-C}{\left(\frac{(2-\lambda)(n-\lambda+2)}{n(1-\lambda)+2-\lambda} \right) - \eta \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right)}. \quad (\text{A.21})$$

Then, inserting (A.20) into (A.13), we can solve for equilibrium output for firm i as a function of the total quantity in (A.21)

$$q_i^*(\eta) = \frac{(a - c_i - \lambda Q^*(\eta))}{\left(2 - \lambda - \eta \left(1 + \frac{(n-1)\lambda}{(n+2-\lambda)(2-\lambda)} \right) \right)}. \quad (\text{A.22})$$

It then follows from (A.20) that firm i 's unit labor requirement, labor demand, product market price and labour productivity are, finally

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

Panels a.) and b.) show how previous results extend when the model is turned into monopoly ($\lambda = 0$): The laggard firm, Firm 4, has labor productivity and employment positively correlated with both increasing robot investments, while the leading firm, Firm 1, has these variables negatively correlated. Panels c.) and d.) shows that when four heterogenous firms compete in Cournot (with differentiated goods), Firm 1 still has negative correlation between value-added per employe and the number of production workers. Firm 4 still has a positive correlation between value-added per employe and the number of production workers—but this positive correlation

emerges from both value added per employe and the number of production workers falling in η . This stems from a very strong price effect under strong competition and greater scope to invest in robots.

Appendix

Table A1: Automation probability and productivity, 1996-2013. System GMM specifications. Auto instrumented.

	Orthogonal lag 2-	Orthogonal lag 3-	Orthogonal lag 4-	Orthogonal lag 2-4
	(1)	(2)	(3)	(4)
Share_skilled	5.201*** (0.603)	5.833*** (0.784)	6.125*** (0.858)	5.227*** (0.622)
Auto	5.422*** (0.636)	6.099*** (0.830)	6.413*** (0.910)	5.438*** (0.657)
Auto × Share_skilled	-8.590*** (0.995)	-9.649*** (1.300)	-10.137*** (1.424)	-8.627*** (1.025)
Firm controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	69,156	69,156	69,156	69,156
Sargan	0.874	0.968	0.976	0.162
Hansen	0.595	0.710	0.718	0.181
AR(1)	0	0	0	0
AR(2)	0.00004	0.00003	0.00002	0.00004
AR(3)	0.250	0.249	0.250	0.249
AR(4)	0.206	0.178	0.166	0.203

Notes: AR (1) - AR (4) are tests for 1:st up to 4:th order autocorrelation (reported p-values). Hansen is a test for over identifying restrictions (reported p-values). Results from system GMM estimations. Absolute t-values within parentheses, based on robust Windmeijer (2005) corrected second step standard errors. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Automation probability and productivity, 1996-2013. System GMM specification. Both Auto and Auto interacted with skill shares instrumented.

	Orthogonal lag 2-	Orthogonal lag 3-	Orthogonal lag 4-	Orthogonal lag 2-4
	(1)	(2)	(3)	(4)
Share_skilled	3.922*** (0.472)	4.062*** (0.559)	3.950*** (0.609)	4.329*** (0.508)
Auto	5.007*** (0.669)	5.439*** (0.876)	5.874*** (0.999)	5.630*** (0.783)
Auto × Share_skilled	-6.045*** (0.802)	-6.168*** (0.931)	-5.752*** (1.012)	-6.678*** (0.838)
Firm controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	69,156	69,156	69,156	69,156
Sargan	0.702	0.816	0.955	0.112
Hansen	0.171	0.181	0.293	0.105
AR(1)	0	0	0	0
AR(2)	0.00004	0.00003	0.00002	0.00003
AR(3)	0.222	0.209	0.182	0.208
AR(4)	0.270	0.258	0.260	0.241

Notes: AR (1) - AR (4) are tests for 1:st up to 4:th order autocorrelation (reported p-values). Hansen is a test for over identifying restrictions (reported p-values). Results from system GMM estimations. Absolute t-values within parentheses, based on robust Windmeijer (2005) corrected second step standard errors. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.