THE EFFECTS OF IT INVESTMENTS AND SKILLED LABOR ON FIRMS' VALUE ADDED

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Abstract

Investments in information technologies (IT) and skilled labor are often highlighted as central for firms wishing to improve their performance. However, what mechanisms enable these investments to improve firm performance? The literature suggests two such channels: the production frontier of upgrading the input factors and the technical efficiency of exploiting the input factors in a more efficient way. We study these channels for increasing firms' value added in a stochastic frontier model. Notably, we find that investments in IT and skilled labor improve firms' value added, but they do so through different channels. Multi-purpose hardware investments mainly improve efficiency in concert with other input factors, while investments in application-oriented software and skilled labor generally work by raising the production frontier itself.

Keywords: IT-investments, skilled labor, production frontier, technical efficiency, stochastic frontier model

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1. Introduction

Many studies have examined the influence of investments in IT and skilled labor on various aspects of industry and firm performance. This widespread interest is reflected in numerous meta-analyses conducted at different points in time (e.g., Kohli and Devaraj, 2003; Sabherwal and Jeyaraj, 2015; Acemoglu and Restrepo, 2018; Raisch and Krakowski, 2021). While the early literature was rather inconclusive about the effects of investments in IT and skilled labor on firm performance, recent research has more consistently found positive effects. This is particularly evident in studies conducted at the firm level using productivity measures. As Aral and Weill (2007, p. 763) summarize: "Recently, more precise measurements have demonstrated a convincing (albeit varied) positive relationship among IT investments, economic productivity and business value."

One key insight is that the effects of investments in IT and skilled labor on a firm's performance are manifold and can occur through different channels (Bresnahan, Brynjolfsson, & Hitt, 2002; Pieri, Vecchi, & Venturini, 2018). In this paper, we focus on firm performance in terms of the firm's value added—the difference between the revenues received from the sale of its output and the costs of the input factors used in production. Firms' investments in IT and labor affect the value added through two distinct channels—the *production frontier* and *technical efficiency*.[1] The production function expresses the relationship between the quantity of output and the different

[1] For a comprehensive discussion of other channels that may affect performance, such as technological change over time and spillover effects among firms, see Pieri et al. (2018).

quantities of inputs used in the production process (Greene, 2008). It depends on the state of technology, such that adopting new technologies may shift the frontier upwards due to transformations in the production process that allow for a greater or similar output to be produced with fewer inputs. We denote this channel as the production frontier. In contrast, technical efficiency refers to the ability of firms to produce maximal output from a given set of inputs (Greene, 2008). Therefore, affecting the value added through the production frontier implies changing the input factors by, for instance, upgrading or substituting them, while improved technical efficiency requires different and better usage of the existing input factors by, for instance, changing the organization or its business model. For example, if a robot is used as a substitute for humans but process is not changed, we have a case of changes in the production frontier. However, if the robot collaborates with humans (i.e., "cobots") and, thereby, alters the process, then the task is conducted more efficiently by using the mutual strengths of the robot and the humans, which affects technical efficiency.

IT investments and skilled labor have the potential to affect the production frontier by serving as key input factors (e.g., Acemoglu & Autor, 2011). They can also improve the efficiency of input factor use. IT, especially hardware, is viewed as a general-purpose technology that allows for new, innovative, and more efficient ways of exploiting existing resources (Majumdar, Carare, & Chang, 2009).

This distinction between two possible channels for improving firms' value added leads to a central question: *How do investments in IT and skilled labor affect firms' value added?* In other words, do IT investments and skilled labor mainly act as input factors (i.e., the effect occurs through the production frontier), or as enablers of more efficient utilization of the existing input factors (i.e., the effect occurs through improved technical efficiency)?

The literature recognizes the lack of focus on this question as a significant gap in our knowledge. For instance, Aral and Weill (2007, p. 763) highlighted: “Although this research provides evidence of a general relationship between IT and organizational performance, our knowledge of the specific factors driving these general results remains quite limited.”

The mechanisms that enable investments in IT and skilled labor to affect performance have attracted scholarly attention in studies conducted on different levels (see Pieri, Vecchi, & Venturini, 2018, for a comprehensive study on the country level). For instance, Becchetti, Bedoya, and Paganette (2003) and Castiglione (2012) conducted econometric studies on the firm level. In this paper, we also focus on the firm level and, in line with the extant literature, we employ a stochastic frontier approach that allows us to separate and simultaneously estimate the production frontier and technical-efficiency effects of investments in IT and skilled labor.

Notably, researchers have thus far tended to study IT investments as a homogenous type of investment, although specific components of IT, such as hardware and software, might affect firms’ value added in different ways (Bloom, Garicano, Sadun, and Van Reenen, 2014). Therefore, we disaggregate IT investments and look at their individual effects. More specifically, we investigate how investments in hardware, software, and skilled labor affect firms’ value added. We address the gaps in the literature by examining the following question: *Do investments in hardware, software, and skilled labor affect value added in the same way or through different channels?*

Our empirical analysis is based on unique, longitudinal data on Danish firms collected by Statistics Denmark and matched at the employer-employee level. The panel dataset, which contains 8,889 firm-year observations covering eight years from 2009 to 2016, offers detailed information on firms’ investments and outcomes.

As such, we make three main contributions in this paper. First, we examine the channels through which investments in IT and skilled labor affect value added. Thus, we extend our theoretical knowledge on the drivers and mechanisms underpinning firms' value added. Second, we scrutinize the interplay among hardware, software, and skilled labor in determining value added at the firm level. Third, we test hypotheses at the firm level using a unique employer-employee dataset representative of Danish firms with details on investments and performance over a span of eight years.

The remainder of the paper is structured as follows. First, we outline the study's theoretical framework and review the extant literature on the effects of IT and skills on firm performance. This enables us to identify gaps in our knowledge and propose hypotheses. Thereafter, we outline our methodological approach, including details on our data and measurements. Finally, we report the results of our empirical tests and conclude with an interpretation of the main findings.

2. Theoretical framework

The impact of investments in IT and skilled labor on firm performance has been the subject of numerous inquiries and a large body of empirical work. Inconclusive evidence from early studies (see Kohli and Devaraj, 2003, for a comprehensive review) suggested that these investments had no effects or even negative effects on different performance measures, resulting in a "productivity paradox" (Brynjolfsson, 1993). These findings were later attributed to measurement errors and misspecifications of empirical models (Brynjolfsson & Hitt, 1996; Brynjolfsson & Yang, 1996), and they were eventually rejected (Dedrick, Gurbaxani, & Kraemer, 2003).

More recent studies have tended to find positive effects of investments in IT and skilled labor on firm performance (e.g., Brynjolfsson & Hitt, 2000; Stiroh, 2002). These effects have been documented in systematic and meta-analytic reviews of the business value of implementing IT (e.g., Ada, Sharman, & Balkundi, 2012; Cardona, Kretschmer, & Strobel, 2013; Lim, Dehning, Richardson, & Smith, 2011; Melville, Kraemer, & Gurbaxani, 2004). This line of research concludes that productivity-based dependent variables, like firms' value added, are better suited for capturing the business value of IT because they are less affected by external confounding factors (such as economic cycles or new trends among customers).

However, conflicting findings still exist. For example, Sabherwal and Jeyaraj (2015) do not find a productivity-associated payoff from IT investments, while Liang et al. (2010) uncover only a weak positive association between IT and productivity. Moreover, Ko and Osei-Bryson (2004) conclude that the positive impact of IT investments on productivity is not uniform but rather conditional on complementary factors. The latter result suggests that investments in IT and skilled labor largely affect the efficiency of firms through complementarity with other factors in the firm. Brynjolfsson and Hitt (2003, p. 794) also highlight the efficiency effect, proposing that: "Rather than merely substituting a cheaper input (e.g., computers) for another input (e.g., labor) in the context of a fixed production process, companies can combine computers with other innovations to fundamentally change their production process." For IT to act as a general-purpose technology, it needs to be implemented along with certain organizational changes (Brynjolfsson & Hitt, 2000). In other words, the efficiency benefits of investments in IT and skilled labor emerge when changes in relevant organizational processes and investments in employee training occur concurrently (Bresnahan et al., 2002; Corrado, Haskel, & Jona-Lasinio, 2017).

The recent discussion in the literature on the human-machine interface in IT highlights a similar distinction between two broad applications: automation and augmentation (Raisch & Krakowski, 2021). Automation implies that IT takes over the tasks of a human, thereby triggering a change in the production frontier, while augmentation means that humans collaborate closely with IT to perform tasks, which leads to more efficient use of the input factors.

As such, the literature offers evidence of a performance effect of investments in IT and skilled labor that is channeled through the production frontier and through technical efficiency. However, there is little evidence on the strength and complementarity of these ways of affecting firms' value added.

Before outlining our theoretical model and hypotheses on these relationships, we present stylized examples of firms investing in IT and skilled labor in order to illustrate the focal issues of this study. Imagine a firm that produces fast-moving consumer goods and has semi-automated production with many machines that work separately from each other. These machines require physical inspections and supervision on the spot, which is time consuming. Therefore, the firm invests in digitalizing the entire production process and connecting all of the machines to the internet. The long-term vision is to create a digital twin of the physical production process (Martinelli, Mina, & Moggi, 2021). The investments relate to hardware (e.g., servers, laptops, and robots) and software (e.g., specific programs for managing and connecting the machines) as well as employee training and upgrading of employees' skills. Such investments typically affect the production frontier because the new input factors (i.e., hardware, software, and skills) generate more output than the old input factors. In other words, the new production factors are simply faster and more effective than the old ones at conducting the same tasks. Additional benefits relate to the possibilities that the digitalization of the production process creates, as the machines can now be managed from a distance. Furthermore, digitalization provides the data needed to trace and track the production flow and obtain a better overview of the whole production process, which results in more innovative and efficient use of the input factors. The question is whether the main effect on the firm's value added occurs because of the upgraded input factors or because of the new, more efficient ways of exploiting the input factors.

Another example is a firm that invests in installing sensors in the final product (i.e., the consumer good) that measure the products' use and fitness (i.e., the "internet of things"). This involves investments in standard hardware (e.g., sensors) and software for capturing, collecting, and analyzing the data from the sensors. Investments in employees with the skills needed to, for instance, develop and run the firm-specific software are also essential. In this case, the bulk of the investments goes into developing software and upgrading the employee's skills. Here, the effect on value added is expected to follow from changes in customer-facing activities (like the business model) with more focus on services and ongoing product upgrades (e.g., by exploiting the rich data on the product's uses). This stylized example, which is more focused on software and skilled labor, raises the questions of what channel or mechanism turns the investments into more value added.

In the following, we develop hypotheses on how the different elements of hardware, software, and skilled labor, channeled through the production frontier and/or technical efficiency, affect firms' value added.

2.1. Effects of hardware, software, and skilled labor on the production frontier

IT investments and the composition of employees' skills are separate but interdependent choices that determine organizational outcomes. In other words, firms can choose to invest in IT without increasing the share of skilled labor or vice versa. Although IT capital and skilled labor are viewed as separate production factors in economics, both are necessary inputs for achieving desired outcomes due to their complementary nature. This is emphasized by Boothby, Dufour, and Tang (2010), who conclude that firms that simultaneously invest in new IT and skills are more productive than firms that only invest in IT (Bharadwaj, 2000; Saunders & Brynjolfsson, 2016).

Along these lines, numerous researchers have examined the link between the quality of labor (as reflected in education, training, overall experience, and firm tenure) and firm outcomes.

Although this stream of literature is too extensive to cover here, a subset of this research looks at the impact of skilled labor on productivity measures (see Abowd, Kramarz, & Margolis, 1999; Acemoglu & Autor, 2011; Raisch & Krakowski, 2021, for reviews). Some of these studies use matched employer-employee datasets, which allows for the tracking of individual workers across firms and over time, and thereby improves our understanding of the impact of labor quality. For example, Ilmakunnas, Maliranta, and Vainiomäki (2004) use matched data on Finnish firms to show that productivity increases with employee education. Fox and Smeets (2011) arrive at the same conclusion using Danish data. Accordingly, we propose the following hypothesis on the input factors of IT capital and skilled labor:

> *Hypothesis 1: Investments in hardware, software, and skilled labor, channeled through the production frontier, increase firms' value added.*

In our stylized firm, this is the pure effect of performance that comes from faster, better, and more efficient hardware, software, and skilled labor. Achieving this effect might involve something as simple as introducing better tablets, word-processing programs, and accounting software, or hiring more highly skilled employees who perform the same tasks but produce greater output.

2.2. Effects of hardware, software, and skilled labor on technical efficiency

Many economists argue that skills and IT are complementary and mutually reinforcing (e.g., Acemoglu, 2003). Accordingly, IT investments must be complemented by highly skilled labor to enable digital business transformation (Tambe & Hitt, 2014). As Bresnahan et al. (2002, p. 369) highlight, "skilled labor is complementary with a cluster of three distinct changes at the firm level: information technology, new work organization, and new products and services." From this perspective, the expected efficiency payoffs of investments in IT and skilled labor are conditional upon complementary organizational changes, which might include empowering employees to take the initiative in applying their knowledge, redistributing work tasks based on abilities, introducing talent-management practices, and improving communication and knowledge sharing within and among teams. Along these lines, recent research on the labor effects of IT investments posits that relatively routine and well-structured tasks can be automated, while more complex tasks cannot. Moreover, more complex and ambiguous tasks can be addressed through augmentation, where humans' unique capabilities, such as intuition and common-sense reasoning, are combined with IT abilities (Raisch and Krakowski, 2021). On a more general level, this speaks to the concept of the "duality of technology," which highlights that technology is both shaped by and shapes human action, such that the interaction between people and technology is ongoing and dynamic (Orlowski, 1992).

The key point is that hardware, software, and skilled labor are not only inputs in the production function. To varying degrees, they are also general-purpose resources that can be used to increase the value and effectiveness of other inputs (i.e., by increasing technical efficiency). Along these lines, we propose the following:

Hypothesis 2: Investments in hardware, software, and skilled labor, channeled through technical efficiency, increase firms' value added.

In our stylized firm, this boils down to the many opportunities that investments create to use existing resources in new and smarter ways. Such uses might include new business models (e.g., the "internet of things"), new ways of organizing tasks, and the empowering of employees (e.g., the digitalization of the production process) (see Nasiri, Ukko, Saunila, & Rantala, 2020; Sestino, Prete, Piper, & Guido, 2020).

2.3. Interaction effects between IT and skilled labor on firms' value added

Highly skilled labor is a segment of the workforce that has accumulated specialized know-how and experience. It is generally characterized by higher education and advanced training. Highly skilled employees are typically well equipped to undertake more complex cognitive, creative, and innovative tasks that go beyond simple or routine job functions. The promises offered by IT can most effectively be converted into real benefits when combined with human intelligence. IT's ability to quickly conduct simple tasks often acts as a complement to human judgement in decision-making. Such analytical judgements are often carried out by highly skilled labor. Highly skilled employees typically undertake non-routine tasks that are not well defined and cannot easily be programmed into algorithms, while less-skilled employees tend to perform routine tasks that are well defined, can be expressed in mathematical rules, and are programmable (Raisch and Krakowski, 2021). As such, they can typically be handled by IT at a reasonable cost (Bresnahan et al., 2002). Similarly, when studying the labor effects of IT investments, Autor, Levy, and Murnane (2003, p. 1322) highlight the aspect of complementarity and conclude that "computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules, while complementing workers in executing nonroutine tasks demanding flexibility, creativity, generalized problem-solving capabilities, and complex communications."

Therefore, enhancing the pool of highly skilled employees implies the enrichment of the quality of human capital as well as an influx of new knowledge and "smarter" ways of working, resulting in efficiency gains (see Abowd et al., 1999; Acemoglu & Autor, 2011; Raisch and Krakowski, 2021, for literature reviews on the link between labor quality and efficiency). As such, an increase in highly skilled labor (as a complement to IT) should reduce time spend on routine tasks, thereby making the production process more productive and efficient. Thus, we propose:

Hypothesis 3: Increasing the share of highly skilled employees reinforces the positive relationship between investments in IT and firms' value added.

In our stylized firm, this implies that investments in hardware and software will be more beneficial for both the production frontier and technical efficiency if they go hand-in-hand with the upgrading of employees' skills.

2.4. Different effects of investments in hardware and software on firms' value added

A few studies have disaggregated investments in IT and skilled labor into their different elements to investigate their nature and separate effects on firm performance. However, most studies have treated IT investments as an aggregate, uniform asset. As a result, "we know little about the relative performance contributions of different types of IT investments and whether different IT investments impact different aspects of firm performance" (Aral and Weill, 2007, p. 763). Nevertheless, a few notable studies have analyzed the impact of different types of IT investments. Bloom et al. (2014) criticize most studies on information and communication technology (ICT) for treating it as an aggregate capital stock. These authors make a critical distinction between information technology (mainly software oriented) and communications technology (more hardware oriented). They show that these two distinct types of ICT affect firm organization differently, as information technology tends to promote decentralization, while communication technology stimulates the centralization of decision-making in firms. Along the same lines, Balsmeier and Woerter (2019) differentiate between machine-based digital technologies (e.g., robots and 3D printing) and non-machine-based digital technologies (e.g., enterprise resource planning and social media). They find dissimilar employment effects of applying these different types of IT. Becchetti et al. (2003) analyze the impact of investments in software and telecommunications on firm productivity and efficiency in a sample of 4,000 Italian firms from 1995 to 1997. They show that the effect of investments in IT on firm performance can be more clearly detected if those investments are divided into software and telecommunications investments. They find that telecommunications investments positively affect the creation of new products and processes, while software investments increase average productivity.

Based on the few studies that have investigated the effects of IT investments on a more disaggregated level, firms appear to benefit unequally from different IT investments. Hardware-oriented investments improve internal processes (e.g., product and process innovation), resulting in more efficient use of available resources, while software-oriented investments have a more direct effect on firm productivity.

As such, both hardware and software investments are expected to improve firm performance, but the mechanisms behind their effects on firms' value added may not be the same, as the nature of hardware and software investments differs. Thus, we offer a finer level of granularity by separately examining the effect of hardware and software. Hardware (e.g., tablets, laptops, servers, sensors, and robots) is defined as "an artifact whose functions are realized in processes that directly or indirectly bring about the results of some calculation" (Duncan, 2017, p. 27), while software (e.g., programs for managing hardware and communication) is "a specification that consists of one or more programming language instructions and whose concretization is embodied by an artifact that is designed so that a physical machine may read the concretized instructions" (Duncan, 2017, p. 27). In other words, hardware refers to the physical devices that execute the instructions specified in the different layers of software. Hardware provides the basic physical architecture of the IT platform to which layers of software are added. As such, IT platforms have a hierarchical structure with hardware at the lowest level, as it is more general and multi-purpose in nature. Above the hardware, we find different layers of software, from the operating system to the programming language to specific software applications that become increasingly application oriented (Castrillon et al., 2018). Although hardware is generally standardized across firms (e.g., the same types of robots or sensors across firms), the specific dedication of the hardware (e.g., a specific task conducted by the robot) is programmed into the software. Hardware alone might be of limited use if it is not programmed for a specific business purpose using relevant software. Software, on the other hand, is typically more application oriented. This is, in particular, the case for software in the upper layers that is suited to (firm-)specific uses. Skilled employees make the specific dedication happening given their high-level competencies.

Thus, we expect hardware investments to have broader uses and to potentially be more complementary with other factors, which will result in an efficiency effect. Therefore, we expect hardware investments to channel their effect on firms' value added through efficiency effects to a larger extent than the two other input factors. Software and skilled labor are more related to final applications and should, therefore, be more likely to affect firms' value added through changes in the input factors (i.e., the production frontier). We consequently propose the following hypothesis:

> *Hypothesis 4: Investments in hardware affect firms' value added through the efficiency channel, while software and skilled labor affect firms' value added through the production frontier.*

In the stylized firm, this would be reflected in fact that the investments in hardware (e.g., new robots) do not just serve as a substitute for labor (i.e., the existing input factor) but alter the entire process so that the existing labor can work more efficiently (e.g., on other tasks that make better use of their skills). Software and skilled labor are closer to the actual application, as in the case of programming the robot for a specific task in the process and using skilled labor to manage the firm-specific processes. In so doing, these factors do not alter the entire process, but upgrade the input factors and eventually increase the stylized firm's value added.

3. Methodology

3.1. Sample and data

The sample was constructed from several firm-level and individual-level datasets obtained from Statistics Denmark. First, we used data from the survey on ICT expenditures to construct the measures of annual hardware and software investments. The ICT survey covers private enterprises based in Denmark with more than 10 full-time employees. The survey uses a stratified simple random sampling approach to select respondents from the population of Danish enterprises based on their business activities (as captured by the NACE code) and the number of employees. Strata weights are estimated and applied to the enterprises' responses to ensure that they are statistically representative of different industries and firm sizes.

Second, to construct measures of employees' skills, we added individual-level data on education and employment gathered from several datasets that are collected annually by the Statistical Business Register. We drew on employment history to link individuals to firms. We then aggregated individual-level data to the respective firm level to construct a measure of the proportion of the workforce with an academic education.

In addition, we included financial information on enterprises in Denmark from all sectors and industries, which is also gathered on a yearly basis by the Statistical Business Register. After merging all relevant databases, we had an unbalanced panel dataset spanning eight years from 2009 to 2016. The dataset contained 8,889 firm-year observations covering 2,098 firms, with an average of 4.2 observations per firm.

3.2. Analytical approach and measures

The literature review highlights the lack of research that explicitly examines how IT investments and employees' skills independently affect firms' production frontiers and efficiency. We employ a stochastic frontier modelling approach to expand this line of inquiry, as this approach allows us to simultaneously estimate the production frontier and efficiency effects on firms' value added. The basic premise of stochastic frontier analysis (SFA) is to compare the relationship between a set of inputs and an output used in the production process against the maximum output attainable from each input level, presented as the production frontier (Greene, 2008). In this approach, the production frontier is estimated as the maximum theoretically attainable output in the sample given available inputs, while the distance to the frontier reflects the firm's inefficiency (or the reverse of the efficiency effect) (Kumbhakar, Wang, & Horncastle, 2015). Firms that operate on the production frontier are fully efficient, while firms that operate beneath the frontier are relatively inefficient.

In line with prior literature (Brynjolfsson & Hitt, 2003; Castiglione, 2012), we specify the basic production process of the firm (i) as a function that connects its output (Q) to two inputs: capital (K) and labor (L). Specifically, in our baseline specification, output (Q) refers to value added, capital (K) refers to total assets,[2] and labor (L) refers to the number of employees. The stochastic nature of the frontier model is represented by two random components that define firm-varying effects: the error term v_i, which refers to the idiosyncratic component, and the term u_i, which refers to inefficiency (Battese & Coelli, 1992). Subsequently, using a Cobb-Douglas logarithmic specification, the baseline estimated stochastic frontier model can be expressed as:

$$logQ_i = \beta_0 + \beta_1 \, ln(K_i) + \beta_2 \, ln(L_i) + v_i + u_i. \; (1)$$

Firms' production processes are often affected by heterogeneity in the sample. Therefore, the random components v_i and u_i can be heteroskedastic. Stochastic frontier models allow for the incorporation of variance in the idiosyncratic component (v_i) and inefficiency (u_i) as a linear

[2] The measure of total assets excludes any IT-related capital (see Table 1 for exact operationalization).

function of a set of covariates. In addition, we observe that the firms in our sample differ in terms of age. Assuming that this variation introduces heteroskedasticity into the idiosyncratic error, we extend our baseline production function by including firm-level explanatory variables that could influence firms' productivity potential in the variance function for the idiosyncratic error. Specifically, we include *firm age* as a proxy for the level of resources and maturity, as follows:

$$v_i = \partial_0 + \partial_1 firm\ age_i. \text{ (1.1)}$$

We then extend Equation 1 by adding IT-related capital and labor, which are also expected to affect firms' productivity. We disaggregate firm-level spending on IT into *hardware investments* and *software investments*. The variable *highly skilled employees* is the share of the workforce with a tertiary, or academic, education (Balsmeier & Woerter, 2019), including bachelor's, master's, and PhD degrees.[3] As additional controls, we include *year dummies* and a proxy for industry concentration, namely the Herfindahl-Hirschman Index. We are dealing with a fixed effects model and industry does not vary over years for a given firm. As we want to account for heterogeneity across industries over years, we compute a concentration measure for industry competitiveness for each sub-NACE category:[4]

$$logQ_i = \beta_0 + \beta_1 \, ln(K_i) + \beta_2 \, ln(L_i) + \beta_3 \, ln(hardware_i) +$$
$$\beta_4 \, ln(software_i) + \beta_5 \, ln(skilled\ labor_i) + controls + v_i + u_i. \text{ (2)}$$

While controlling for the parameters of the production frontier (H1) and idiosyncratic error, we extend Equation 2 by adding an inefficiency equation. In the first step in Equation 3, we add the

[3] On average, around 20% of the individuals in our dataset had a tertiary degree.

[4] The manufacturing category includes manufacturing (C) and utilities and construction (D, E, F). The services category includes wholesale and retail trade (G), transportation and storage (H), accommodation and food service activities (I), and other service activities (N, Q, S). The advanced services category includes information and communication (J), financial and insurance activities (K), real-estate activities (L), and professional, scientific, and technical activities (M).

IT-related variables in the variance function for the inefficiency component (H2). In the second step in Equation 3, we add their interaction terms to test for complementarity effects (H3):

$$u_i = \partial_0 + \partial_1 \, ln(hardware_i) + \partial_2 \, ln(software_i) + \partial_3 \, ln(skilled\ labor_i). \quad (3)$$

The variables used in the analysis are summarized in Table 1.

INSERT TABLE 1 ABOUT HERE

Table 2 depicts a correlation matrix as well as the means and standard deviations of all variables used in the analysis. The average annual software investment of DKK 2,972 in the period is slightly higher than the comparable investment in hardware of DKK 2,462.

INSERT TABLE 2 ABOUT HERE

In summary, our analytical approach offers several advantages relative to alternative analytical methods and, thereby, extends prior research. First, it allows IT and skills to concurrently affect the production frontier as well as increase or decrease firms' efficiency. As such, we empirically investigate the simultaneous effects of IT investments and skills on the production frontier and efficiency, which enables us to detect potential interdependencies between the focal predictors (i.e., complementarity or substitution effects). Furthermore, we include predictors of idiosyncratic error terms to control for heterogeneity in the sample. This minimizes the likelihood of confounding the estimates.

We conducted our analysis using a large-scale panel dataset. To select a feasible analytical method, we compared OLS with stochastic frontier models (SFM) for panel datasets and calculated the modified Wald statistic for group-wise heteroskedasticity in the residuals after a fixed effect regression model. With a p-value < 0.001, we rejected the null hypothesis that there was no heteroscedasticity when fitting with OLS. Therefore, we concluded that an SFM accounting for heteroskedasticity would be a better fit. Second, we conducted a Hausman's test to determine whether a fixed-effects or a random-effects model specification would provide more efficient estimates. The Hausman test indicated that our data would be adequately modeled by a fixed-effects model, with a test statistic rejecting an initial hypothesis of superiority of the random-effects model at p < 0.001. To generate robust coefficients for our model, we used a fixed-effects stochastic frontier model. Specifically, we estimated the parameters of a Cobb-Douglas production function using a pairwise difference estimator with normal-exponential distribution (Belotti and Ilardi, 2018) and employing a stochastic frontier true fixed effects model. This allowed random components to be heteroskedastic, and to be expressed as a function of both time-invariant and time-variant exogenous explanatory variables.

Common correlated effects are always a concern in such analyses. We therefore tested for cross-sectional dependence for the baseline model by reporting the CD statistic. The CD statistic has the value 0.980 and a corresponding p-value of 0.327. With a p-value above the threshold (0.005) for the CD statistic, we cannot reject the null hypothesis. Therefore, we do not find evidence of cross-dependency in our panel dataset.

4. Results

4.1. Results of the main models

Model 1 in Table 3 shows the estimation of a two-factor baseline effect on the production frontier while controlling for heteroskedasticity in the idiosyncratic error term (Equation (1)). The results of the estimation procedure confirm that both labor (L) and capital (K) are statistically significant determinants of value added (Q). The extension of Model 1 for σ_v shows that using firm age as a predictor does not reduce idiosyncratic error. A strongly significant constant in the equation for σ_u indicates the presence of inefficiency. This insight further proves that the stochastic frontier model is an appropriate empirical choice (as opposed to an OLS model with normal errors as an alternative approach).

Model 2 demonstrates that hardware investments (β = 0.006, p = 0.001), software investments (β = 0.002, p = 0.054), and skilled labor (β = 0.176, p = 0.016) have positive and significant effects on the production function. This indicates that, as expected, all three input factors raise the production frontier and, eventually, increase firms' value added. The substantial increase in log likelihood from Model 1 to Model 2 is also noteworthy. When investments in IT and skilled labor are plugged into the inefficiency equation (Model 3), the results reveal that hardware investments positively affect efficiency by decreasing the inefficiency component σ_u (∂ = -0.040, p = 0.001), while the effect of hardware investments is no longer significant in determining the production frontier. Simultaneously, software investments (∂ = 0.013, p = 0.003) and skilled labor (∂ = 0.240, p = 0.001) are positively associated with inefficiency. In the production frontier model, the effects of these two variables remain positive and significant.

In Model 4, we present the results of the SFM containing the interaction terms in the inefficiency equation. For two continuous variables, their interaction indicates that the slope of the relationship between the independent and dependent variable varies (i.e., increases or decreases) according to the level of the moderator variable. Our model predicts that a one-unit increase in firms' skilled labor implies a lower effect of hardware investments on inefficiency (∂ = -0.095, p = 0.001), or higher efficiency. At the same time, a one-unit increase in firms' skilled labor implies a greater influence of software investments on inefficiency (∂ = 0.079, p = 0.001), or less efficiency.

INSERT TABLE 3 ABOUT HERE

We can summarize the results of the hypothesis testing. Hypothesis 1, which predicts that all three input factors increase firms' value added through the production frontier, is generally supported. Skilled labor has a particularly significantly positive effect on the production frontier that cuts across all models. The results related to Hypothesis 2 on the efficiency effects are more mixed, as the hypothesis is supported by investments in hardware, but not by investments in software and skilled labor. However, when we add the moderation effects (Hypothesis 3), the interaction between hardware investments and skilled labor is highly significant in increasing the efficiency, and the interaction between software investments and skilled labor also increases inefficiency.

Overall, the results clearly indicate that while all three input factors increase firms' value added, they do so in different ways. Investments in hardware, software, and skilled labor all contribute by increasing the production frontier (i.e., by upgrading to better, more productive input factors). At the same time, hardware investments affect firms' value added through efficiency and they do so in interaction with skilled labor. Hardware investments both raise the production frontier and increase efficiency, but the stronger effect comes through efficiency when hardware provides opportunities to introduce, for instance, different ways of organizing tasks or new business models. This is similar to using hardware investments for augmentation rather than automation.

4.2. Robustness checks

We conducted various robustness tests (see the Appendix). First, in Appendix A, we report the marginal effects of each covariate after Model 4. The coefficients in Model 4 represent the predicted change in the outcome variable given a one-unit change in the independent variable(s). Conversely, the average marginal effect measures the impact—in absolute terms—that a one-unit change in one variable has on the outcome variable while all other variables are held constant. The signs of the coefficients and the marginal effects are consistent with Model 4 (Table 3). We find a negative coefficient for both software and hardware investments in the inefficiency equation, which means that our model predicts that such investments decrease inefficiency when controlling for the effects of all other variables. The marginal effects of software and hardware on inefficiency correspond to -0.009 and -0.012, respectively, which suggests that the higher these investments are, the lower is inefficiency (see Appendix A for more details). Interestingly, we find that given a higher share of skilled employees, the average marginal effect on inefficiency is positive (0.380), with hardware weakening (-0.095) this positive effect and software investments strengthening (0.079) it. This means that IT investments in hardware can boost human capital and skills in firms by increasing efficiency, but that software investments are not always immediate and direct catalyzers in terms of encouraging skilled employees to improve efficiency and, ultimately, firms' value added.

Second, in Appendix B, we report the results of the Model 4 with different specifications. In line with prior research (Brynjolfsson and Hitt, 2003), we use value added as the measure of output, as this specification produces more robust estimates than turnover. However, as a robustness check, we run an alternative specification (Model 4.1) with turnover as the dependent variable. We obtained similar results, although investments in software had a significant positive effect on efficiency. Model 4.2 also includes the squared terms of IT investments and skilled labor as a consistency check. We observed that two of the squared terms are significant. However, even with the added squared terms, the main results remained the same. Model 4.3 reports the SFM model that includes a time-trend variable instead of year dummies. We found that the effect of the time trend was positive and significant in the production frontier equation, and it did not affect the coefficients of other predictors in the model. Model 4.4 specifies the same variables for the model specification as Model 4 in Table 3, but with a different specification of the initial values (the statistical software used a random method) to rule out the possibility that the results depend on the chosen initial values.

In addition, we conducted robustness checks to test whether capital deepening,[5] rather than investments in year t, drives our effects. More specifically, we constructed a new assets measure that excluded one-year lagged hardware and software investments. Model 4.5 shows consistent evidence that the results remain unchanged, even when accounting for prior investments.

Due to data availability, we used total assets as a proxy for capital in the main analysis. We therefore conducted a robustness check using estimated fixed assets as an alternative input in the specified production function. Fixed assets were derived as a proportion of total assets for each of the 10 industries used in the analysis. We obtained industry-level data from Statistics Denmark on total and fixed assets for the period 2009 to 2016. We calculated the average proportion of fixed to total assets and applied it as a multiplier to the value of firms' total assets to approximate fixed assets. An alternative production function (with fixed assets as an input) resulted in estimates that were largely in line with our primary specification.

5. Discussion and conclusion

From the literature, we know that investments in IT and skilled labor are positively related to firm performance. However, our knowledge of the specific channels and mechanisms that drive these findings remains limited. This issue is particularly important because investments in IT and skilled labor play different roles, as input factors raise the production frontier as well as interact with other input factors to increase efficiency.

[5] We would like to thank one of the anonymous reviewers for this suggestion.

All three input factors have positive effects on firms' value added, but the channels through which they do so differ. Our results show that investments in hardware, software, and skilled labor all have positive effects that raise the production frontier and, eventually, increase firms' value added, which is in line with previous results (e.g., Abowd et al., 1999; Acemoglu & Autor, 2011; Falk, 2005; Marsh, Rincon-Aznar, Vecchi, & Venturini, 2017; Sánchez, Minguela Rata, Rodríguez Duarte, & Sandulli, 2006). However, when exploring the efficiency mechanism, we find that investments in hardware have a significant positive effect on efficiency, while their impact on the production frontier deteriorates. In contrast, for software and skilled labor, the positive effects on the production frontier remain, while the effect on efficiency turns insignificant or even negative. Finally, when the interaction effects are added, our results indicate that a combination of investments in hardware and skilled labor complements efficiency. As such, our results extend the literature on organizational complementarity between IT and skills (e.g., Bresnahan et al., 2002; Giuri, Torrisi, & Zinovyeva, 2008; Moshiri & Simpson, 2011).

Our results paint a picture in which hardware is a more general-purpose technology that works best in combination with other input factors, like skilled labor. Investments in hardware, such as improvements in the platform or the infrastructure, may create opportunities to change the way things are done as well as the company's internal organization. Such changes eventually increase firm efficiency. We have illustrated this using a stylized firm in which the digitalization of machines triggers many other changes in the firm, like more efficient supervision of machines and at a distance, or the building of a digital twin of the production process in which everything can be traced and optimized. As such, hardware seems to mainly act as a catalyzer that increases the efficiency of other input factors in the firm and, thereby, affects firms' value added.

As such, the path from investments in hardware to firms' value added differs from the path from investments in software and skilled labor to firms' value added. Investments in software and skilled labor take the high road and raise the production frontier, while investments in hardware take a more scenic path along which they interact with the surroundings and improve efficiency. We argue that the reason for this difference in how the effects of the investments are channeled is that hardware involves more standardized and multi-purpose assets (i.e., computers or robots are not developed for individual firms), while firm-specific aspects are found in the software skills of employees and are closer to the application level. Skilled labor has experience and capabilities that are more firm specific in the sense that their value is higher in a specific firm context. To some extent, this is also the case for software investments that are more firm specific and application oriented. In other words, investments in hardware might be equally useful in another firm, as hardware can relatively easily be reprogrammed and dedicated to other uses, while investments in skilled labor and software will be unique for a particular firm to a greater extent.

The results relate to the discussion on IT applications for automation versus augmentation (Raisch & Krakowski, 2021), as automation is reflected in the production frontier, while augmentation affects efficiency. This study adds that, in the context of Danish firms, investments in hardware seem to be more closely related to the augmentation of the existing ways of conducting tasks. They also create opportunities for collaboration between machines and humans, as indicated by the significant interaction effect between investments in hardware and skilled labor. Compared to hardware, investments in software seem to be more related to the improvement or substitution of existing input factors in order to conduct the same tasks better and faster, as when introducing administrative systems that digitalize existing processes without altering them.

On a more general level, our results also relate to the discussion of the “duality of technology” (Orlikowski, 1992). This study has shown that both hardware and software have a duality, which is captured by the two channels, where they both substitute for other input factors and complement and interact with other input factors to increase efficiency. However, while both have duality, investments in software tend to be more substitutive investments, while hardware investments tend to be more complementary. We suggest that additional studies should be conducted to further disaggregate investments in hardware and software (e.g., into the different layers) and that data should be collected from other countries to further investigate this duality.

Our paper makes several theoretical and methodological contributions that advance the literature on how investments in IT and skills affect firms' value added. First, we separate and unfold the channels and mechanisms that enable these investments to improve firms' value added. More specifically, we show that the mechanisms differ for investments in hardware, software, and skilled labor. The implication is that pooling the mechanisms together or studying more aggregated categories, like total ICT investments, might result in misleading findings (as highlighted, e.g., by Bloom et al., 2014). In addition, we need to disaggregate investments into categories that reflect the roles they play in firms. In this regard, the distinction between specialized, firm-specific resources and multi-purpose resources is only the beginning.

In terms of methodology, we applied the state-of-art methodology of stochastic frontier models, which allowed us to separate the two confounding mechanisms of the production frontier and efficiency. Few studies have applied such models to firm-level data, but our analysis focused on a large and unique firm-level dataset (8,889 firm-year observations covering eight years) that was representative of Danish firms with more than 10 employees.

Our study also has significant managerial implications. Notably, it supports the view that investments in IT and skilled labor have an effect on firms' value added that goes beyond their direct effects as input factors. This is particularly true for hardware, as it has the characteristics of a general-purpose technology. The implication is that the optimal performance of hardware investments is achieved when changes related to hardware are combined with changes in the ways things are done (e.g., changes in the organization, the upgrading of skills, employee empowerment, or changes in business models). Hardware investments often make such changes possible, and the best outcomes of such investments can be achieved if these possibilities are pursued in concert with hardware investments. Investments in software and skilled labor also positively affect firms' value added, but as better and faster input factors.

The limitations of this study point to avenues for future research related to the disaggregation of the hardware and software categories, each of which captures elements that have different effects on firms' value added. For instance, consider the software category, which includes software for controlling and managing internal processes (e.g., enterprise resource planning, digital twins) and for external communication with customers (e.g., social media, the internet). These two subcategories might have different effects in terms of substitution and complementarities. Similarly, the effects could vary in the hardware category, which includes everything from computers to robots and sensors to 3D-printing. Future studies should aim to conduct similar analyses on more disaggregated levels and in countries other than Denmark, thereby allowing for comparative analyses.

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Table 1: Summary of variables

Variable	***Measurement***	***Source***
Output (value added)	The difference between the value of goods produced and the value of goods consumed in the production of products or services, in DKK, log-transformed	Register data
Capital (assets)	The value of buildings, machinery, fixtures, patents, licenses, and long-term investments of a financial nature minus investments in hardware and software, in DKK, log-transformed	Register data
Labor (number of employees)	The number of people employed by the firm including the owner(s), log-transformed	Register data
Hardware investments	Annual expenditures on computers, monitors, printers, and network equipment, in DKK, log-transformed	Survey
Software investments	Annual expenditures on standard software (software that requires little or no customization), in DKK, log-transformed	Survey
Highly skilled labor	The share of employees who hold a bachelor’s, master’s, or PhD degree as a percentage of the firm’s total labor force	Register data
Firm age	Number of years since the firm’s foundation, log-transformed	Register data
Year dummies	Year dummies for each year in the period between 2009 and 2016	Register data
Industry Herfindahl-Hirschman Index	Continuous variable representing the concentration of the market calculated as the sum of the squares of the firms’ sizes based on market shares	Register data

Table 2: Descriptive statistics and correlations

Descriptive Statistics

Variable	Obs.	Mean
Value-added	8947	255,189.2
Assets	8947	475,948.03
Employees	8947	423.543
Hardware investments	8947	2,462.112
Software investments	8947	2,971.71
Highly skilled employees	8947	.279
Firm age	8947	27.139
Industry Herfindahl-Hirschman Index	8947	.041

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Ln value-added	1.000							
(2) Ln assets	0.571***	1.000						
(3) Ln employees	0.872***	0.501***	1.000					
(4) Ln hardware investments	0.561***	0.365***	0.471***	1.000				
(5) Ln software investments	0.475***	0.313***	0.400***	0.588***	1.000			
(6) Highly skilled employees	0.054***	-0.095***	-0.161***	0.250***	0.215***	1.000		
(7) Firm age	0.219***	0.243***	0.178***	0.129***	0.135***	-0.051***	1.000	
(8) Industry Herfindahl-Hirschman Index	-0.042***	-0.039***	-0.017	-0.087***	-0.061***	-0.056***	-0.074***	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Results of the stochastic frontier model (full sample)

	Model 1	Model 2	Model 3	Model 4
Production frontier (DV = ln (value-added))				
Ln assets	0.009***	0.009***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.001]	[0.001]	[0.001]	[0.001]
Ln employees	0.722***	0.722***	0.717***	0.718***
	(0.010)	(0.010)	(0.010)	(0.010)
	[0.001]	[0.001]	[0.001]	[0.001]
Industry Herfindahl-Hirschman Index	0.359	0.365	0.340	0.348
	(0.210)	(0.207)	(0.217)	(0.215)
	[0.088]	[0.078]	[0.117]	[0.105]
Year dummies	Yes	Yes	Yes	Yes
Ln hardware investments		0.006***	0.001	0.002
		(0.002)	(0.002)	(0.002)
		[0.001]	[0.470]	[0.307]
Ln software investments		0.002	0.004**	0.003**
		(0.001)	(0.001)	(0.001)
		[0.054]	[0.002]	[0.004]
Highly skilled employees		0.176*	0.235**	0.230**
		(0.073)	(0.077)	(0.076)
		[0.016]	[0.002]	[0.003]
Inefficiency equation (DV = ln (σ_u))				
Ln hardware investments			-0.040***	-0.012
			(0.006)	(0.009)
			[0.001]	[0.193]
Ln software investments			0.013**	-0.009
			(0.004)	(0.007)
			[0.003]	[0.161]
Highly skilled employees			0.240**	0.380*
			(0.075)	(0.164)
			[0.001]	[0.021]
Ln hardware investments # highly skilled employees				-0.095***
				(0.024)
				[0.001]
Ln software investments # highly skilled employees				0.079***
				(0.021)
				[0.001
Constant	-1.588***	-1.590***	-1.483***	-1.530***
	(0.014)	(0.014)	(0.039)	(0.052)
	[0.001]	[0.001]	[0.001]	[0.001]
Idiosyncratic error equation (DV = ln (σ_v))				
Firm age	-0.866	-0.779	-0.853	-0.772
	(0.761)	(0.783)	(0.592)	(0.630)
	[0.255]	[0.320]	[0.150]	[0.221]
Constant	-2.239	-2.452	-2.056	-2.293
	(1.537)	(1.700)	(1.232)	(1.399)
	[0.145]	[0.149]	[0.095]	[0.101]
No. observations	8922	8917	8917	8917
No. firms	2104	2103	2103	2103
Log likelihood	-2200.947	-2148.320	-2081.038	-2054.829

** p < 0.05, ** p < 0.01, *** p < 0.001. First line = coefficient, second line in parenthesis = standard error, third line in brackets = p-values*

Appendix A: Marginal effects after Model 4

Production frontier equation	
Ln assets	0.009***
	(0.002)
	[0.001]
Ln employees	0.718***
	(0.010)
	[0.001]
Ln hardware investments	0.002
	(0.002)
	[0.307]
Ln software investments	0.003**
	(0.001)
	[0.004]
Highly skilled employees	0.230**
	(0.076)
	[0.003]
Industry Herfindahl-Hirschman Index	0.348
	(0.215)
	[0.105]
Inefficiency equation	
Ln hardware investments	-0.012
	(0.009)
	[0.193]
Ln software investments	-0.009
	(0.007)
	[0.161]
Highly skilled employees	0.380*
	(0.164)
	[0.021]
Ln hardware investments # highly skilled employees	-0.095***
	(0.024)
	[0.001]
Ln Software investments # highly skilled employees	0.079***
	(0.021)
	[0.001]
Idiosyncratic error equation	
Firm age	-0.772
	(0.630)
	[0.221]
N	8917

First line = coefficient, second line in parentheses = t-statistics, third line in brackets = p-values.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B: Robustness tests

	Model 4.1	Model 4.2	Model 4.3	Model 4.4	Model 4.5
	DV= ln(Turnover)	DV= ln(Value Added)			
Production frontier (DV = ln (value-added))					
Ln assets	0.008***	0.009***	0.009***	0.009***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Ln ($assets_t$ – $software_{t-1}$ – $hardware_{t-1}$)					0.027***
					(0.005)
Ln employees	0.684***	0.721***	0.723***	0.718***	0.704***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)
Ln hardware investments	0.001	0.001	0.002	0.002	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Ln software investments	0.000	0.003*	0.003**	0.003**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Highly skilled employees	0.378***	0.193*	0.238**	0.230**	0.317***
	(0.068)	(0.078)	(0.076)	(0.076)	(0.092)
Industry Herfindahl-Hirschman Index	0.836***	0.345	0.324	0.348	0.329
	(0.176)	(0.214)	(0.204)	(0.215)	(0.246)
Time trend	-	-	0.020***	-	
			(0.001)		
Year dummies	Yes	Yes	-	Yes	Yes
Inefficiency equation (DV = ln (σu))					
Ln hardware investments	-0.018**	-0.014	-0.012	-0.012	-0.004
	(0.006)	(0.017)	(0.009)	(0.009)	(0.013)
Ln software investments	-0.030***	-0.067***	-0.009	-0.009	-0.007
	(0.007)	(0.013)	(0.007)	(0.007)	(0.008)
Highly skilled employees	0.944***	1.608***	0.380*	0.380*	0.457
	(0.116)	(0.266)	(0.164)	(0.164)	(0.252)
Ln hardware investments # highly skilled employees	-0.097***	-0.077**	-0.097***	-0.095***	-0.110***
	(0.022)	(0.025)	(0.024)	(0.024)	(0.033)
Ln software investments # highly skilled employees	0.036	0.059**	0.080***	0.079***	0.087***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.026)
Ln hardware investments (sq)		-0.001			
		(0.002)			
Ln software investments (sq)		0.007***			
		(0.001)			
Ln highly skilled employees (sq)		-1.677***			
		(0.276)			
Idiosyncratic error equation (DV = ln (σv))					
Firm age	-1.132	-0.766	-0.889	-0.772	-1.655***
	(0.809)	(0.519)	(0.763)	(0.630)	(0.480)
No. observations	8991	8917	8917	8917	5904
No. firms	2115	2103	2103	2103	1341
Log likelihood	1270.952	-1955.827	-2098.245	-2054.829	-963.812

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *First line = coefficient, second line in parenthesis= SEs.*