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The Effects of Digitalization on Production

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Abstract

How does digitalization transform the macroeconomic production function? Within an endogenous technology choice framework, we find that sectors with more digital capital exhibit a higher elasticity of substitution between value-added and intermediate inputs and within value-added, between capital and labor. The shift in the elasticity of substitution is consistent with a higher complementarity of input-specific productivities. We also find that digitalization contributes to Hicks-neutral technical change in value added. Not all types of digital capital have a significant impact on the production function.

Keywords: Digitalization, Elasticity of substitution, Productivity, Endogenous technology choice, Technology frontier.

JEL codes: E23, E25, O33

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1 Introduction

Digital technology is pervasive in the production processes of industrial and service sectors, and its continuous development as a general-purpose technology has had a transformative impact on society.[1] Despite these facts, our knowledge and understanding of the effect of digital technology on the macroeconomy are still rather limited. In this paper, we focus on the effects of digitalization on the supply side. Specifically, we ask how digitalization alters production possibilities by examining how digital intensity affects the key parameters of sectoral production functions, namely the elasticity of substitution and productivity. Such effects can change fundamental properties of the economy's growth trajectory and its dynamic adjustment to sectoral shocks.

We shed some light on this question by combining sectoral production and input data with a theory of factor demand that accounts for endogenous technology choice. The latter is an essential ingredient for understanding changes in the way inputs such as labor and capital are used to produce. The mere possibility of choosing efficiency for each input enhances the elasticity of substitution between factors as firms can choose the more appropriate technologies. Moreover, it makes clear that technological innovation can have an impact on production by changing the trade-off between the efficiencies of different inputs. The technology frontier is of central importance in this respect. We provide further motivation for the existence of such a frontier in the Appendix of the paper using a task-based model.

While the empirical specification is formulated based on the model implications for input demand, the effects of digital intensity on production are yet to be determined by the data. We proxy digitalization using capital-related measures. The level of digitalization in a specific sector is measured as the share of digital capital in overall capital - that is, digitalization is regarded as the process when non-digital capital gets substituted for or complemented by digital capital.[2] The capital-based measure allows us to further differentiate between the effects of three types of digital capital - information technology

[1] See e.g. Bresnahan (2002) for the classification of digitalization as general-purpose technology.

[2] This definition assumes that digitalization is a broad and profound change in the production structure. We acknowledge that it may not encompass all types of digitalization, but we assess it as reasonable approximation for our purposes. The installation of digital capital is always concomitant with a transformation of the interaction between capital and labor, which might - but does not necessarily have to - lead to the displacement of labor. For example, sending a letter via email (using digital capital - a computer) has replaced a physical letter on paper (using non-digital capital - a typewriter), but a person writing the letter is necessary in any case. Also, ordering food online as opposed to ordering it by phone changes the nature of interaction between labor and capital, but it still requires the same amount of labor (a person placing the order).

(IT), communication technology (CT) and software and databases (SoftDB).[3] Distinguishing between these types of capital is important, because they have exhibited different growth rates over the last decades, while they can have different effects on the interaction between inputs.

Using an instrumental variables approach, we find that digitalization has a positive impact on the elasticity of substitution. A 1% increase in the information technology capital share raises the elasticity of substitution between capital and labor by 0.095 and the elasticity between value-added and intermediate inputs by 0.131. Our estimates of the effect of digitalization on the elasticity of substitution between capital and labor are robust to accounting for the level of development. Moreover, the results are robust to using alternative measures of digital intensity and alternative instruments. A second key takeaway from our results is that the effects are not uniform across the different components of digital technologies that we consider. Only IT intensity significantly increases the elasticity of substitution between capital and labor. The elasticity of substitution between value-added and intermediate inputs is increasing in both IT and SoftDB capital intensities. CT intensity appears to be insignificant in all of our empirical specifications.

Interpreted through the lens of the model, empirical results suggest that digital innovation through information technology and software and databases makes input-specific technologies more complementary. Hence, digitalization channels innovations towards Hicks-neutral technical change. In line with this interpretation, we also find that a higher investment intensity in SoftDB leads to a similar increase in labor augmenting and capital augmenting productivity. These results are verified using independently constructed total factor productivity measures from KLEMS.

Furthermore, we exploit the structure of the model to back out the implied technology frontiers for labor and capital, and for valued added and intermediate inputs.

The rest of the paper is structured as follows: Section 2 contextualizes our research in existing literature. Section 3 describes the theoretical and the empirical methodology. Section 4 presents the results and demonstrates the shifts in technology frontiers due to digitalization. Section 5 concludes. Appendix A includes a further description of the data, model derivations, additional empirical results and a description of the sector codes in the KLEMS database.

[3] The definitions of the different types of digital capital are based on the KLEMS database: IT = Computer hardware, CT = Telecommunications equipment, SoftDB = Computer software and databases.

2 Related literature

The literature on digitalization mostly focuses on the question of its impact on productivity. It generally agrees that digital technologies have had a positive impact[4], yet with a decreasing pace after around the year 2000[5]. The reason for the limited overall benefits of digital technologies are explained as "one time event" (Gordon (2017)), diminishing returns of IC technologies on productivity growth (Gordon (2015)) or a weaker growth in capital deepening (Ollivaud, Guillemette, and Turner (2016)). The effects may vary on the analyzed time frame (Cette, Clerc, and Bresson (2015), Van Ark (2016)) or IT measurements applied (Acemoglu, Dorn, Hanson, Price, et al. (2014)). In addition, productivity gains may be different for routine and non-routine/abstract tasks (e.g. Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006)).

In line with the above mentioned literature, we find positive effects of digitalization on labor and capital productivity growth, but this effect depends on the digital capital type and is only significant for SoftDB. Thus, we agree that the specification of digitalization is decisive for the measured effects and their interpretation. The distinct effects of different capital types (IT, CT and SoftDB) in this paper are an indication for the complex operating mode of digitalization.

Regarding the general effects of technical change on elasticities of substitution, Knoblach and Stöckl (2020) show that elasticity of substitution is not an immutable parameter but is shapeable by technology and subject to technical and non-technical factors. Oberfield and Raval (2021) demonstrate that the U.S. aggregate capital-labor elasticity of substitution is not constant but evolves over time. Moreover, the level of development, specifically the capital-labor ratio, has an effect on the aggregate EOS. This effect depends primarily on the quantity of capital and is not dependent of the type of capital, i.e. whether capital is digital or non-digital capital. The sign and size of the effect depends on specifications of the production structure, i.e. on the mobility of primary inputs between sectors and on the level of substitutability of intermediate inputs in the production of final goods (cf. Miyagiwa and Papageorgiou (2007), Papageorgiou and Saam (2008) and Xue and Yip (2013)).

A microfoundation for the adaptation of the EOS after technical change is given by the endogenous technology choice literature. In this setup, firms are able to choose produc-

[4]See e.g. Van Reenen, Bloom, Draca, Kretschmer, Sadun, Overman, and Schankerman (2010), Bresnahan, Brynjolfsson, and Hitt (2002), Stiroh et al. (2001), Van Ark (2016)

[5]See e.g. Stiroh (2002),Brynjolfsson and Hitt (2003), Gordon (2015), Cette, Clerc, and Bresson (2015), Graetz and Michaels (2018), Gallipoli and Makridis (2018), Dauth, Findeisen, Suedekum, and Woessner (2021), Byrne, Oliner, and Sichel (2013)

tivity factors (technologies) endogenously from all optimal available technologies, which are allocated on a technology frontier. The curvature of the frontier is a measure for the elasticity of substitution between technologies, which is linked to the elasticity of substitution between inputs. A general description of this approach can be found in Jones (2005), León-Ledesma and Satchi (2019), Growiec (2008), Growiec (2013), Growiec (2018) and Growiec (2008). Caselli and Coleman (2006) applies this approach to the usage of capital in high- and low-income countries and the question of complementarity to high- and low-skilled labor. We deploy the endogenous technology choice framework in our theoretical model to digitalization and differentiate in our empirical model between digital and non-digital capital.

While this approach has the advantage of keeping the nature of technical change general and omitting assumptions about specific characteristics of technologies, an alternative framework for thinking about the effects of technical change on the elasticity of substitution is to assume certain technical features. In the case of automation, Alonso, Berg, Kothari, Papageorgiou, and Rehman (2022) presumes in a quantitative model a higher elasticity of substitution for automated production structures. Also, Adachi (2021) specifies the analysis on automation and uses US data on robot imports to estimate a higher elasticity of substitution between robots and labor as compared to general capital goods. In the same vain, Eden and Gaggl (2018) specifies a quantitative model in which ICT capital interacts differently with routine and non-routine labor. Using an exogenous fall in the relative price of ICT capital and an exogenous increase in the depreciation rate, the paper argues through simulation that the concominant rise in the relative demand for ICT capital leads to an increase in the overall EOS between capital and labor as ICT capital has a relatively higher EOS with labor.

Automation itself can be modelled using a task-based approach, which especially allows to disentangle the displacement effect (using capital instead of labor for a specific task) and the productivity effect (higher demand for labor due to higher overall productivity) (Acemoglu and Restrepo (2019) and Acemoglu and Restrepo (2018a)). Furthermore, the literature differentiates between routine tasks (when computers are able to substitute for labor) and non-routine tasks (when computers complement labor). Autor, Levy, and Murnane (2003) finds that automation leads to measurable changes in the composition of job tasks. In Appendix A3, we apply the task-based approach to digitalization and provide a formal link between the model of technology choice and the task-based setup often used in automation-related literature. Specifically, we show that while in the task-based approach the allocation of tasks to inputs is determined in equilibrium, different allocations correspond to tracing a technology frontier. We derive the corresponding convexity of this frontier and characterize which factors determine this convexity.

Moreover, while the literature on automation often focuses on the displacement effect, we regard digitalization as a broader technical development, which also encompasses non-automated digital production processes. In line with the literature on high complementarities between digital and human capital[6], digitalized work may include non-routine or creative tasks. In this context, the incentives for firms to digitalize are to increase labor productivity with a complementary use of digital capital instead of replacing labor with capital. Therefore, our analysis allows for a very heterogenous group of tasks and of digital technologies and also provides empirical evidence for different types of digital capital.

3 Methodology

We will rely on a quasi-structural approach to identify unobserved elements of the production process. Below we present the theoretical setup, the econometric model, data and measurements and discuss identification.

3.1 Theoretical Setup

The theoretical model we employ is simple enough so that it is amenable to direct empirical analysis using a standard input demand model. At the same time, it allows for the possibility that technological shifts can affect production endogenously.

We assume a multisector economy with supplier-customer relations between all sectors, i.e. the final output of each sector is used both for private consumption and also for further processing in other sectors (intermediate goods). Production in each sector is the result of two different layers of choice. The first layer of choice takes technology as given, while the second layer allows for technology choice.

The first layer is akin to a standard optimization problem of the representative firm in sector i. It engages in a two-stage budget allocation, where it initially decides how much to produce internally and how much to procure as intermediate inputs, and then, given a determined allocation for value-added production, it chooses how much capital and

[6]Literature has studied the effects of digitalization - and more recently of automation - on the labor share and skills and has found a high level of complementarity between digital tasks and human capital. (e.g. Spitz-Oener (2006), Autor, Levy, and Murnane (2003), Autor (2015)). Our findings corroborate their results and provide a theoretical microfoundation for an increased complementarity of productivities in digitalized production processes.

labor to employ. Intermediate goods are assumed to be the total quantity of other sectors' output used in a sector's production as specified in the KLEMS database (cf. Section 3.3).

While the above decisions are ultimately about quantities, the resulting choice for each input is combined with a corresponding efficiency unit. Hence, in the second layer of choice, we allow for input-specific productivities that are partially chosen by firms at each step of production. For factor inputs such as labor and capital, choosing productivity can be formally linked to choosing which production tasks are best performed by different types of labor and capital. We illustrate such a link in Appendix A3 using a task assignment model. In the automation literature, equilibrium determines a threshold for tasks over which tasks cannot be automated (see i.e. Acemoglu and Restrepo (2018a,b)). This yields an efficiency term for aggregate capital and labor. We illustrate that such aggregate efficiency terms arise also in a more general setting where technologies do not necessarily automate tasks but allow for complementarities between types of labor and capital. Importantly, we derive the implicit aggregate efficiency frontier between labor and capital and clarify how technical change can affect it. Nevertheless, for our purposes, it is sufficient to directly study the trade-off between different levels of labor and capital productivities and how firms allocate these appropriately.[7]

The maintained production setup implies that changes in the demand for the final sectoral output or in the supply of inputs to production (primary factors, productivity parameters, intermediate inputs) change optimal input quantities and endogenous productivities in both nested production functions (value added and final output).

In the upper nesting, final output $(y_{i,t})$ is produced employing sectoral i's value added $(VA_{i,t})$ and the intermediate good $(X_{i,t})$ as follows:

$$y_{i,t} = \left((1-\lambda_i) \left(\nu_{i,t}^{VA} e^{z_{i,t}^{VA}} VA_{i,t} \right)^{\frac{\tilde{\sigma}_i - 1}{\tilde{\sigma}_i}} + \lambda_i \left(\nu_{i,t}^{X} e^{z_{i,t}^{X}} X_{i,t} \right)^{\frac{\tilde{\sigma}_i - 1}{\tilde{\sigma}_i}} \right)^{\frac{\tilde{\sigma}_i}{\tilde{\sigma}_i - 1}} \tag{1}$$

where λ_i and $\tilde{\sigma}_i$ are the share parameter of the effective intermediate input and the elasticity of substitution (EOS), respectively. In the lower nesting, the production function for value-added in sector i is as follows:[8]

$$VA_{i,t} = \left(\alpha_i (\nu_{i,t}^{k} e^{z_{i,t}^{k}} k_{i,t})^{\frac{\tilde{\gamma}_i - 1}{\tilde{\gamma}_i}} + (1-\alpha_i)(\nu_{i,t}^{l} e^{z_{i,t}^{l}} l_{i,t})^{\frac{\tilde{\gamma}_i - 1}{\tilde{\gamma}_i}} \right)^{\frac{\tilde{\gamma}_i}{\tilde{\gamma}_i - 1}} \tag{2}$$

[7] A framework which is useful to think about this issue is the one developed in the endogenous technology choice literature, such as Jones (2005), Caselli and Coleman (2006), Growiec (2013), Growiec (2018) and León-Ledesma and Satchi (2019). In this strand of literature, firms are considered to choose both the factor combination as well as factor-specific productivities (technologies).

[8] This nested structure of CES production functions avoids issues with elasticity interpretation arising in production functions with more than two inputs, see e.g. Sato (1967).

where $\alpha_{i,t}$ and $\tilde{\gamma}_{i,t}$ are the share parameter of effective capital and the EOS between effective capital and effective labor, respectively. Both the capital and labor inputs refer to sector-specific aggregates, and can consist of qualitatively different units. More specifically, the capital stock k_i consists of digital and non-digital capital, while l_i can consist of workers with different skills. Effective units are the result of firm decisions about the employment of inputs as well as their productivity $(e^{z^{VA}_{i,t}}, e^{z^{X}_{i,t}}, e^{z^{k}_{i,t}}, e^{z^{l}_{i,t}})$, up to an exogenous component $(\nu^{VA}_{i,t}, \nu^{X}_{i,t}, \nu^{k}_{i,t}, \nu^{l}_{i,t})$.

Finally, the exogenous productivity processes $(\nu^{VA}_{i,t}, \nu^{X}_{i,t}, \nu^{k}_{i,t}, \nu^{l}_{i,t})$ follow an idiosyncratic but deterministic growth path:[9]

$$ln(v)^q_{i,t} = ln(v)^q_{i,t-1} + g^q_i, \quad \text{for} \quad q \in \{VA, X, k, l\}$$

We follow the expenditure minimization (dual) approach as we do not have to specify the demand side of the market, and can therefore accommodate imperfect competition in product markets as well as price rigidities.[10] Conditional on technology, the cost-minimizing choices for $(k_{i,t}, l_{i,t})$ and $(VA_{i,t}, X_{i,t})$ yield standard relative demand functions for each nest, where $\left(p^{VA}_{i,t}, p^{X}_{i,t}, w_{i,t}, p^{k}_{i,t}\right)$ are the corresponding input prices:

$$\frac{\alpha_i}{1-\alpha_i}\left(\frac{k_{i,t}}{l_{i,t}}\right)^{-\frac{1}{\tilde{\gamma}_i}}\left(\frac{\nu^k_{i,t}e^{z^k_{i,t}}}{\nu^l_{i,t}e^{z^l_{i,t}}}\right)^{1-\frac{1}{\tilde{\gamma}_i}} = \frac{p^k_{i,t}}{w_{i,t}} \tag{3}$$

$$\frac{1-\lambda_i}{\lambda_i}\left(\frac{VA_{i,t}}{X_{i,t}}\right)^{-\frac{1}{\tilde{\sigma}_i}}\left(\frac{\nu^{VA}_{i,t}e^{z^{VA}_{i,t}}}{\nu^X_{i,t}e^{z^X_{i,t}}}\right)^{1-\frac{1}{\tilde{\sigma}_i}} = \frac{p^{VA}_{i,t}}{p^X_{i,t}} \tag{4}$$

Since the input choices of the firms are conditional on the technology combinations, we call the resulting production functions conditional production functions.[11] Each combination of technologies defines a specific production function that firms can choose and for which they have to select combinations of inputs according to their cost minimization objective. We next characterize the optimal choice of input-specific technologies and the implications for observable factor demand.

[9] We follow the literature in assuming a specific functional form for the exogenous productivity processes as joint identification of the bias in technical progress and the EOS is impossible (Diamond, McFadden, and Rodriguez, 1978).

[10] Another advantage of estimating production related parameters using optimization conditions instead of directly estimating the production function is the robustness of the results to the presence of normalization. Please see Appendix A6 in the Appendix.

[11] This type of production function is also called local production function (as in Growiec (2018)) or short-run production function (as in León-Ledesma and Satchi (2019)).

3.1.1 Technology choice

New technologies can only be adopted once they have been invented and become part of a technology menu. The technology frontier consists of the most efficient feasible technology combinations. For empirical tractability, we assume that this process of innovation is exogenous to the model.[12]

Specifically, we assume that the set of technologies that firms can choose from are specified in the technology frontier (cf. Caselli and Coleman (2006) and Growiec (2008)):

$$\left(e^{z^k_{i,t}}\right)^{\omega_i^{k/l}} + \theta_i^{k/l}\left(e^{z^l_{i,t}}\right)^{\omega_i^{k/l}} = B^{k/l} \tag{5}$$

$$\left(e^{z^{VA}_{i,t}}\right)^{\omega_i^{VA/X}} + \theta_i^{VA/X}\left(e^{z^X_{i,t}}\right)^{\omega_i^{VA/X}} = B^{VA/X} \tag{6}$$

where B defines the overall level of productivity, and ω and θ change the shape and thus the trade-off between both productivities.[13] The invention of new digital technologies is an exogenous change to the technology frontier, which results in a new set of techniques. Depending on the type of innovation, these new techniques might allow firms to exploit new trade-offs between input-specific productivities, which can alter the level and curvature of the technology frontier.[14]

The cost-minimizing choice for productivities $(e^{z^{VA}_{i,t}}, e^{z^X_{i,t}}, e^{z^k_{i,t}}, e^{z^l_{i,t}})$ yields optimal relative productivities as follows, with a similar expression for $\left(\frac{e^{z^{VA}_{i,t}}}{e^{z^X_{i,t}}}\right)$:

$$\left(\frac{e^{z^k_{i,t}}}{e^{z^l_{i,t}}}\right)^{\omega_i^{k/l}-\frac{\tilde{\gamma}_i-1}{\tilde{\gamma}_i}} = \frac{\alpha_i}{1-\alpha_i}\theta_i^{k/l}\left(\frac{\nu^k_{i,t}k_{i,t}}{\nu^l_{i,t}l_{i,t}}\right)^{\frac{\tilde{\gamma}_i-1}{\tilde{\gamma}_i}} \tag{7}$$

For interior choices ($\omega > \frac{\tilde{\gamma}}{\tilde{\gamma}-1}$), if labor and capital are gross substitutes, then the relative endogenous productivities are increasing functions of the relative factor supplies as well as the relative exogenous productivities. Hence, holding everything else constant, higher relative exogenous productivity in one factor translates to higher relative endogenous productivity in the same factor. The opposite holds when labor and capital are gross complements; firms will choose to enhance the productivity of the factor which is rela-

[12] Such innovation can of course subsume digital technical change, which can manifest itself in an exogenous fall in the production cost for digital capital and hence a higher value share of digital capital in all sectors. The qualitative change in the composition of capital will affect the aggregate efficiency factor of this input. Similar effects can arise for the other inputs as well.

[13] ω, θ and B are exogenous parameters and strictly positive.

[14] In Appendix A9, we show that such aggregate productivity trade-offs arise in a microfounded model of task assignment.

tively scarce in terms of efficient units.

Combining equation (7) and the corresponding one for value-added and intermediate inputs with the relative demand equations for factors in (3)-(4) and imposing that the relative share parameters and the frontier relative share are identical i.e. $\frac{\alpha_i}{1-\alpha_i} = \theta_i^{l/k}$, the relative demand equation for capital and labor is as follows

$$\begin{aligned} ln\left(\frac{k_{i,t}}{l_{i,t}}\right) &= \frac{\omega_{i,t}^{k/l}\tilde{\gamma}_i - (\tilde{\gamma}_i - 1)}{\omega_i^{k/l} - (\tilde{\gamma}_i - 1)} ln\left(\frac{\alpha_i}{1-\alpha_i}\right) - \frac{\omega_i^{k/l}\tilde{\gamma}_i - (\tilde{\gamma}_i - 1)}{\omega_i^{k/l} - (\tilde{\gamma}_i - 1)} ln\left(\frac{p_{i,t}^k}{w_{i,t}}\right) \\ &\quad + \frac{\omega_i^{k/l}(\tilde{\gamma}_i - 1)}{\omega_i^{k/l} - (\tilde{\gamma}_i - 1)} ln\left(\frac{\nu_{i,t}^k}{\nu_{i,t}^l}\right) \qquad (8) \\ &= \gamma_i ln\left(\frac{\alpha_i}{1-\alpha_i}\right) - \gamma_i ln\left(\frac{p_{i,t}^k}{w_{i,t}}\right) + (\gamma_i - 1)(g_i^k - g_i^l)t \qquad (9) \end{aligned}$$

where $\gamma \equiv \frac{\omega^{k/l}(\tilde{\gamma}-1)}{\omega^{k/l}-(\tilde{\gamma}-1)}$ is the mapping that relates the conditional elasticity $(\tilde{\gamma})$ to the unconditional elasticity (γ), the latter being the reduced form parameter. We have also normalized initial productivities to be equal, $\nu_{i,0}^k = \nu_{i,0}^l$.[15]

For interior technology choices, relative factor demands for inputs which are gross substitutes are decreasing in relative prices, while exogenous biased technical progress increases further the demand for the more productive input. Inspecting the mapping from the conditional to the unconditional elasticity, we can see that the only way in which the technology frontier, and thus digitalization, can affect the unconditional EOS between factors is through its curvature, ω:

$$\gamma_i = \frac{\omega_i^{k/l}\tilde{\gamma}_i - (\tilde{\gamma}_i - 1)}{\omega_i^{k/l} - (\tilde{\gamma}_i - 1)} = \tilde{\gamma}_i + \frac{(\tilde{\gamma}_i - 1)^2}{\omega_i^{k/l} - (\tilde{\gamma}_i - 1)} \qquad (10)$$

In an interior solution, allowing firms to choose technologies results in additional responsiveness to changes in the relative factor prices, and hence a higher unconditional EOS compared to the conditional EOS between factors.

The resulting specification in (9) clarifies that the elasticity of substitution can be heterogeneous across sectors (or time) because technologies are different or because the EOS between labor and capital for a fixed technology is different. Since our aim is to quantify the effects of the former, we have to allow for such effects in our econometric specification, which we now turn to.

[15] For more information on the calculations, see Appendix A2. An analogous calculation holds for the relative demand for value-added and intermediate inputs.

3.2 Econometric Model

Given the availability of panel data at the country-sector level, we can exploit both the time-series dimension to control for unobserved fixed effects, and both the times series and cross-sectional dimensions to identify the marginal effects of digital intensity on the elasticities of substitution. Hence, using data on relative quantities and prices for the factors of production, we can in principle proceed with estimating the production coefficients from the corresponding reduced form model.

There are nevertheless two key challenges that we need to address. The first challenge is that relative prices are endogenous due to the presence of unobserved demand and supply shocks. In order to identify the true slope of these relative demand curves we need to resort to some form of exogenous variation to supply, such as a relative marginal cost shifter. Following the industrial organization literature (see e.g. Hausman (1996) and Nevo (2001)), we will utilize relative prices of the same aggregate goods in other geographic markets (in our case U.S. data), which can be considered as proxies of relative marginal costs, while we also discuss later how we deal with the possibility of common shocks between the US and Europe. The second challenge has to do with identifying the effect of digitalization on these coefficients. We will directly allow them to be functions of covariates $\mathcal{X}_{i,t}$, which will include measures of digital intensity. Allowing for functional coefficients results in the following econometric specification for equation (9):

$$ln\left(\frac{k_{i,t}}{l_{i,t}}\right) = c_0(\mathcal{X}_{i,t}) + c_1(\mathcal{X}_{i,t})ln\left(\frac{p^k_{i,t}}{w_{i,t}}\right) + c_2(\bar{\mathcal{X}}_{i,t})t + \epsilon_{i,t} \tag{11}$$

where $\bar{\mathcal{X}}_{i,t}$ is the time average of covariates $\mathcal{X}_{i,t}$. Using a Taylor expansion around $\tilde{\mathcal{X}}$, the centered values of vector $\mathcal{X}$, and denoting by $(c^T_{0,j}, c^T_{1,j}, c^T_{2,j})^T$ the vector of Taylor coefficients for the j_{th} order, the resulting empirical specification is as follows, where we estimate $(c^T_{0,1}, c_{1,0}, c^T_{1,1}, c_{2,0}, c^T_{2,1})$, the reduced form coefficients, using a within group estimator.[16]

[16] While we have estimated specifications up to second order, in most cases only linear terms are significant, if any. We thus only present the first order terms of the approximation. Employing semi-parametric methods to estimate these functions could be an alternative approach (see e.g. Hastie and Tibshirani (1993); Durlauf, Kourtellos, and Minkin (2001) for reduced form and Cai, Das, Xiong, and Wu (2006) for instrumental variable varying coefficient models). Due to the relatively large number of covariates, and more importantly, our desire to leverage conventional methods for testing for weak identification and instrument exogeneity with panel data, we choose a global approximation to these functions and not a local approximation, which is implied by the use of kernel methods in the aforementioned approaches.

$$
\begin{aligned}
ln\left(\frac{k_{i,t}}{l_{i,t}}\right) &= c^{i}_{0,0} + c^{T}_{0,1}\tilde{\mathcal{X}}_{i,t} + c_{1,0}ln\left(\frac{p^{k}_{i,t}}{w_{i,t}}\right) + c^{T}_{1,1}\tilde{\mathcal{X}}_{i,t} \otimes ln\left(\frac{p^{k}_{i,t}}{w_{i,t}}\right) \\
&\quad + c_{2,0}t + c^{T}_{2,1}\bar{\mathcal{X}}_{i,t} \otimes t + u_{i,t} \qquad (12)
\end{aligned}
$$

Hence, the implied estimate for the linearized form of the EOS between capital and labor is equal to $\hat{\gamma}_{i,t} = c_{1,0} + c^{T}_{1,1}\tilde{X}_{i,t}$, while the relative growth rate of productivities is equal to $\hat{g}^{VA/X}_{i} := g^{VA}_{i} - g^{X}_{i} = c_{2,0} + c^{T}_{2,1}\bar{\mathcal{X}}_{i,t}$.

Share parameters $\alpha_{i,t}$ are recovered using

$$
ln\left(\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\right) = \frac{1}{\hat{\gamma}_{i,t}} ln\left(\frac{k_{i,t}}{l_{i,t}}\right) + ln\left(\frac{p^{k}_{i,t}}{w_{i,t}}\right) - \frac{\hat{\gamma}_{i,t}-1}{\hat{\gamma}_{i,t}}\left[(\hat{g}^{k}_{i} - \hat{g}^{l}_{i})t\right] \qquad (13)
$$

which is computed at the estimated elasticities and growth rates, and re-projecting on covariates $\tilde{\mathcal{X}}_{i,t}$ using a fixed effects estimator to purge $c^{i}_{0,0}$ and $u_{i,t}$. A similar approach is followed for estimating $(\sigma_{i,t}, \lambda_{i,t}, g^{VA/X}_{i})$.[17]

This econometric approach can be further rationalized by expanding equation (10) around $\tilde{\gamma}_i = \bar{\gamma}$ and $\omega_i = \bar{\omega}$, where we get that

$$
\gamma_i \approx \frac{\bar{\omega}^{k/l}\bar{\gamma} - (\bar{\gamma}-1)}{\bar{\omega}^{k/l} - (\bar{\gamma}-1)} - \frac{\bar{\omega}^{k/l}(\bar{\gamma}-1)^2}{(\bar{\omega}^{k/l} - (\bar{\gamma}-1))^2}\tilde{\tilde{\omega}}^{k/l}_{i} + \frac{(\bar{\omega}^{k/l})^2\bar{\gamma}}{(\bar{\omega}^{k/l} - (\bar{\gamma}-1))^2}\tilde{\tilde{\gamma}}_i \qquad (14)
$$

where $\tilde{\tilde{\omega}}$ is the deviation of ω from $\bar{\omega}$ and $\tilde{\tilde{\gamma}}$ is the deviation of $\tilde{\gamma}$ from $\bar{\tilde{\gamma}}$. An identical expression may be derived for the value-added-intermediate inputs elasticity. Technology-related factors that can potentially shift the unconditional elasticity will be part of $\tilde{\tilde{\omega}}$, while non-technology related factors will be related to $\tilde{\tilde{\gamma}}_t$. For example, if $\tilde{\tilde{\omega}}_{i,t} = \beta_1\tilde{\mathcal{X}}^{1}_{i,t}$ and $\tilde{\tilde{\gamma}}_{i,t} = \beta_2\tilde{\mathcal{X}}^{2}_{i,t}$, then the relevant reduced form coefficients identified in our empirical specification $(c_{1,1})$ are pinned down by $-\beta_1\frac{\bar{\omega}^{k/l}(\bar{\gamma}-1)^2}{(\bar{\omega}^{k/l}-(\bar{\gamma}-1))^2}$ and $-\beta_2\frac{(\bar{\omega}^{k/l})^2\bar{\gamma}}{(\bar{\omega}^{k/l}-(\bar{\gamma}-1))^2}$. The empirical results presented in Tables 1 and 2 directly report the estimates of the latter.

3.3 Data and Measurements

We employ (unbalanced) panel data from the EU KLEMS Growth and Productivity accounts, which includes yearly observations in 1995-2017 of 1- or 2-digit sectors for 28 European economies, including the UK.[18] We aim to analyze the effect of digitalization

[17] In order to signify that parameters are functions of covariates, for brevity, we add a time index (t) in addition to the sector index (i).

[18] Data are publicly available and can be obtained here. See also O'Mahony and Timmer (2009) for methodology.

on different sectors, so our unit of analysis, indexed by i, is at the country-industry level.[19] Intermediate inputs are calculated in KLEMS by applying supply and use tables (SUTs) for each sector, which trace the supply and use of all commodities in the economy and thus indicate the composition of each sector's intermediate input. Similarly, SUTs contribute to the calculation of the components of value added in each sector. [20]

While price indices for value-added, gross output and intermediate goods are readily available, we need to impute the sectoral wage rates and the rental rates of capital. We recover the price of capital by dividing the estimated capital compensation by the chain linked volume of the capital stock since $CAP_{i,t} = p^k_{i,t} K_{i,t}$. In EU KLEMS, $p_{k,i,t}$ is computed using the user cost of capital formula (see e.g. Jorgenson (2005)), which takes into account both the nominal rate of return, the rate of depreciation and changes in the price of investment per industry. Similarly, we impute wages by dividing labor compensation to hours worked for the employed. It is also worth noting that our theoretical model is entirely consistent with the KLEMS measurement methodology.[21] The only difference is that we allow for input-specific productivities, while KLEMS assumes total factor productivities for gross output and value added correspondingly.[22]

We measure digitalization using three complementary measures that summarize the intensity of use of such technologies in the production process: the lagged share of the Information Technology (IT) capital stock to the total capital stock, and the corresponding capital stock shares for Communication technology (CT) and Software and Databases (SoftDB).[23] Our classification is based on capital as opposed to labor, which is sometimes used in related literature (see e.g. Gallipoli and Makridis (2018)) as we do not have infor-

[19] We exclude sectors which may include non-market activities such as public sector, education, health and home production. We also excluded the real estate sector due to large swings in prices. In Appendix A4 we report the corresponding sectors we use.

[20] Cf. Timmer, O'Mahony, and Van Ark (2007).

[21] The KLEMS methodology employs a translog production function, which can approximate any production function which is homogeneous of degree one, as in our case. More particularly, sectoral output growth is expressed as follows:

$$\Delta lnY_{i,t} = v_x \Delta lnX_{i,t} + v_K \Delta lnK_{i,t} + v_L \Delta lnL_{i,t} + \Delta lnA_{i,t} \tag{15}$$

$$\equiv v_x \Delta lnX_{i,t} + v_{VA} \Delta lnVA_{i,t} + \Delta lnA^Y_{i,t} \tag{16}$$

where v_j are values shares, $v_{VA}\Delta lnVA_{i,t} \equiv v_K \Delta lnK_{i,t} + v_L \Delta lnL_{i,t} + \Delta lnA^{VA}_{i,t}$, and $\Delta lnA_{i,t} \equiv \Delta lnA^Y_{i,t} + \Delta lnA^{VA}_{i,t}$. Intermediate input measures can be further decomposed into energy, materials and services, and are constructed using supply and use tables from the National Accounts, and are available for many countries after 1995, which is the starting point of our sample (O'Mahony and Timmer, 2009).

[22] This difference does not affect the estimation of the elasticities as they are based on relative demand equations where TFP cancels out by construction, and not on the assumed production function.

[23] For information about the shares IT, CT and SoftDB in overall capital, refer to Table 5 for sectoral information and Table 6 for country shares in Appendix A5. Figures 4 and 3 in the same appendix show histograms of sectoral and country intensities.

mation on the share of IT related occupations in the KLEMS database. The approach is nevertheless similar, as we are looking at the digital intensity of one of the main factors of production to characterize the digital intensity of the production process.[24] Focusing on capital has also the advantage of looking at more granular classifications such as IT, CT and SoftDB. In the case of SoftDB, we also investigate the share of investments in SoftDB out of total investment because we consider data as highly depreciable, and hence past data might have little added value for production in the current period.

Expressing digitalization related capital as a fraction of the total capital stock is important for distinguishing between economic growth due to capital deepening, which may naturally lead to an increase in the use of digital technologies, and the qualitative effect of structural change due to digital transformation. For more details on measurement please refer to Appendix A1.

Beyond IT, CT and SoftDB, in the set of covariates $\mathcal{X}_{i,t}$ used for modeling the varying coefficients, we control both for technological and non-technological factors that might influence the EOS. A prime non-technological factor that affects the EOS at highly aggregated sectoral levels is the level of development, as measured by the lagged capital to labor ratio. As mentioned in the introduction, the level of development can have positive or negative effects on the EOS, depending on primary factor mobility and substitutability between intermediate inputs and final goods. For technological factors, we control for factors that do have a large technological component that is nevertheless not focused on digital technology, such as investment and capital intensity in research and development (R&D).

3.4 Identification

Given the final model specification in (11), the errors $u_{i,t}$ are likely to contain input demand disturbances that we have not explicitly modelled, such as other stochastic relative input demand shocks and wedges. In related literature (Atalay, 2017; Miranda-Pinto and Young, 2022) researchers derived estimating equations based on total output, where total factor productivity (TFP) was part of the error, and a prime source of endogeneity as final output prices are correlated with TFP shocks. This necessitated the use of demand shifters such as military spending as instruments. In our case we use *relative* factor demand equations for estimating the elasticities of substitution. Any common component of input-specific productivities which would feature as a total factor productivity shock

[24] In Appendix A1, we employ the data used by Gallipoli and Makridis (2018) and show that their IT intensity index, which is based on occupation-level data, is correlated with IT capital expenditures. We use the latter to construct the measure of IT digital intensity.

cancels out in (9).

Moreover, our estimating equations feature relative input demand shocks. Hence, identification necessitates the use of relative input supply shifters as instruments. For this purpose, we utilize (lagged) relative prices in the United States, both for the labor to capital price ratio and the value-added to intermediate input price ratio. Variation in relative prices in the US should capture variation in relative marginal costs of production for these inputs which can have a common component with those in Europe. A justification for a strong common component would be the common outsourcing of material and other inputs to East Asian countries such as China. At the same time, relative input prices in the US should be uncorrelated with sectoral relative input demand disturbances in Europe. This would be less likely in the presence of global demand disturbances that affect relative input demand in the US and in Europe. A specific example of this is the presence of input financing frictions where the distortion to the relative price of value-added and intermediate goods in the US may be correlated with the distortion in Europe. We control for such disturbances using time fixed effects and the CBOE Volatility index (VIX) in alternative specifications. The identifying assumption is that controlling for time fixed effects or the VIX is sufficient to purge this common component.[25] We present estimates in both cases, with qualitatively similar results. Another source of endogeneity which is specific to the capital to labor demand equation is that we allow for the lagged level of development (capital to labor ratio) to affect the EOS. Due to within differencing to remove fixed effects, the error becomes correlated with the interaction term between relative prices and the lagged capital to labor ratio. We instrument the latter using the corresponding variable in the US.

We test both for instrument relevance and instrument exogeneity. For both demand equations and all the reported specifications, we fail to reject the overidentifying restric-

[25] As an example of why controlling for time fixed effects is sufficient, consider the value-added - intermediate input choice, where limited commitment places an upper bound on how much of the firm revenue (η) may be used to buy inputs. This leads to a constraint of the form $\zeta_1 VA_i P_i^{VA} + \zeta_2 X_i P_i^X \leq \eta p_{i,t} y_{i,t}$, where η is the share of revenue that can be used to finance expenditure proportions ζ_1 on value-added and ζ_2 on intermediate inputs respectively (See e.g. Bigio and La'O (2020); Miranda-Pinto and Young (2022).) In our case this yields a relative demand equation which is distorted by the Lagrange multiplier $\mu_{i,t}$ only if $\zeta_1 \neq \zeta_2$:

$$\frac{1-\lambda_i}{\lambda_i}\left(\frac{VA_i}{X_i}\right)^{-\frac{1}{\sigma_i}}\left(\frac{\nu_{i,t}^{VA}}{\nu_{i,t}^{X}}\right)^{1-\frac{1}{\sigma_i}} = \frac{p_i^{VA}}{p_i^X} + \frac{1-\zeta_1\mu_{i,t}}{1-\zeta_2\mu_{i,t}} \tag{17}$$

A log-linear approximation yields a distortion equal to $(\zeta_2-\zeta_1)\bar{\mu}\tilde{\mu}_{i,t}$. Absent significant heterogeneity in $(\zeta_2-\zeta_1)\bar{\mu}$, time fixed effects absorb the common variation in $\mu_{i,t}$ due to global disturbances, while idiosyncratic effects are absorbed by the error and are by construction uncorrelated across country-sectors.

tions and reject underidentification. We have assessed the robustness of our results with respect to weak identification by employing identification robust inference procedures which are consistent with heteroscedasticity and autocorrelation in the errors (see Finlay, Magnusson, and Schaffer (2013)). We report robust confidence sets based on inverting the Conditional Likelihood Ratio test which has been shown to have good power properties when the number of endogenous regressors increases (Moreira, 2003).

4 Empirical Results

We next present and discuss the empirical results for all production function parameters. As a brief preview of the results, the main message is that only IT intensity increases all elasticities of substitution, while data intensity appears to be important for the value-added-intermediate input elasticity, as well as productivity in value-added. Importantly, CT intensity is not significant in any of the specifications.

4.1 Elasticities of Substitution

Table 1 presents the estimates for the elasticity of substitution between capital and labor. The constant component of the elasticity (which corresponds to $c_{1,0}$ in specification 12) yields a value for γ close to 0.184, which is consistent with estimates in the literature (Gechert, Havranek, Irsova, and Kolcunova, 2022) and implies gross complementarity between labor and capital. IT capital intensity has a significantly positive impact, as a 1% increase in intensity is associated with a 0.095 increase in the elasticity. CT intensity and Software-database intensity have no significant impact. As we mentioned earlier in the paper, we also find that the level of development (lagged capital to labor ratio) is also associated with a higher EOS, with a similar impact to IT intensity.

To investigate further the heterogeneity of these estimates within sectors, we estimate specification (2) for service and non-service sectors. Restricting the sample to service sectors yield similar estimates for the constant, IT and Development level components (0.205, 0.051 and 0.109 respectively). For the non-service sectors the corresponding estimates are 0.196, 0.061 and 0.102 (please see Table 4 in Appendix A4 for the classification). We furthermore check the robustness of our results along several dimensions. Most important are specifications (5) and (6), where in (5) we change our definition of IT intensity to a definition based on skills by measuring the proportion of high-skilled labor at the sectoral level, while in (6) we use relative prices from Japan instead of the US as an instrument. In both cases, the results for digital intensity are qualitatively similar.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital to Labor ratio $\left(\frac{k}{l}\right)$					
$\frac{w}{p^k}$	0.059	0.184	0.183	0.123	0.167	0.111
	[-0.100,0.218]	[0.089,0.279]	[0.087,0.279]	[-0.033,0.280]	[0.075,0.260]	[-0.046,0.268]
		(0.041, 0.327)				
IT share $\times \left(\frac{w}{p^k}\right)$	0.137	0.095	0.092		0.123	0.124
	[-0.009,0.283]	[0.048,0.142]	[0.046,0.139]		[0.003,0.244]	[0.062,0.186]
		(0.039,0.184)				
CT share $\times \left(\frac{w}{p^k}\right)$	-0.001					
	[-0.007,0.005]					
Inv. share $\times \left(\frac{w}{p^k}\right)$						
SoftDb	0.020					
	[-0.106,0.147]					
R&D	0.006					
	[-0.069,0.081]					
Cap. share $\times \left(\frac{w}{p^k}\right)$						
SoftDb	-0.035					
	[-0.149,0.080]					
R&D	-0.005					
	[-0.013,0.004]					
Devel. Level$\times \left(\frac{w}{p^k}\right)$	0.099	0.101	0.099		0.036	0.112
	[0.043,0.154]	[0.064,0.139]	[0.059,0.140]		[0.002,0.007]	[0.082,0.143]
		(0.030, 0.171)				
VIX	0.026	0.005	5.190	2.356	-0.032	0.011
	[-0.015,0.070]	[-0.016,0.026]	[-1.775,12.160]	[-0.777,5.489]	[-0.059,-0.004]	[-0.018,0.040]
No. Observations	3481	4153	4153	5323	1371	4690
Country-Sector Fixed Effects	✓	✓	✓	✓	✓	✓
Time Fixed Effects	-	-	✓	✓	-	-
Underidentification test (p-value)	0.0011	0.0023	0.0000	0.0000	0.0512	0.0119
J test (p-value)	0.8259	0.8222	-	-	0.7349	0.0581

Table 1: Impact of Digitalization on the EOS between k and l. For brevity we do not present interaction terms of digital intensities with time, as well as other controls. Specification (1) includes all interaction terms of relative prices with factors that can potentially affect the elasticity (IT, CT, SoftDb and Research intensity, Level of Development), interaction terms of the constant and time trend with the aforementioned factors, and linear-quadratic terms in the VIX. Spec. (2) drops jointly insignificant terms while Specification (3) includes time-fixed effects instead of the VIX. Spec. (4) reports the estimates obtained without controlling for digitalization-related heterogeneity. Spec. (5) re-estimates spec. (2) using a skills-based definition of IT intensity. Spec. (6) uses relative prices from Japan as an instrument for European relative prices. All specifications report conventional 95% confidence sets (CS) in []. For the benchmark spec. (2), in (,) we report the projection of the robust CS based on inverting the Conditional LR test.

	(1)	(2)	(3)	(4)	(5)	(6)
	Value added to Intermediate Inputs ratio $\frac{VA}{X}$					
$\frac{p^X}{p^{VA}}$	0.468	0.584	0.610	0.683	-0.080	0.258
	[0.255,0.682]	[0.428,0.740]	[0.444,0.776]	[0.532,0.834]	[-0.354,0.195]	[-0.029,0.545]
		(0.415, 0.752)				
IT share $\times \left(\frac{p^X}{p^{VA}}\right)$	0.144	0.131	0.131		-0.469	0.174
	[0.020,0.268]	[0.023,0.239]	[0.022,0.239]		[-0.945,0.008]	[-0.011,0.360]
		(0.011, 0.367)				
CT share $\times \left(\frac{p^X}{p^{VA}}\right)$	-0.057					
	[-0.147,0.033]					
Inv. share $\times \left(\frac{p^X}{p^{VA}}\right)$						
SoftDb	-0.123					
	[-0.350,0.103]					
R&D	0.166	0.148	0.146		-0.007	0.236
	[0.050,0.281]	[0.038,0.258]	[0.037,0.256]		[-0.158,0.143]	[0.088,0.383]
		(0.029, 0.270)				
Cap. share $\times \left(\frac{p^X}{p^{VA}}\right)$						
SoftDb	0.301	0.183	0.187		-0.054	0.289
	[0.134,0.467]	[0.092,0.274]	[0.096,0.277]		[-0.265,0.156]	[0.142,0.436]
		(-0.024,0.282)				
R&D	0.007	0.008	0.008		0.004	0.006
	[0.003,0.012]	[0.004,0.010]	[0.004,0.012]		[-0.001,0.010]	[0.001,0.013]
		(0.032, 0.242)				
		(0.003, 0.012)				
Devel. Level$\times \left(\frac{p^X}{p^{VA}}\right)$	0.082					
	[-0.044,0.208]					
VIX	0.020	0.020	-0.047	-0.005	0.011	0.023
	[0.003,0.037]	[0.004,0.037]	[-0.393,0.299]	[-0.211,0.200]	[-0.024,0.047]	[0.001,0.045]
No. Observations	3765	3765	3765	4475	1320	4281
Country-Sector Fixed Effects	✓	✓	✓	✓	✓	✓
Time Fixed Effects	-	-	✓	✓	-	-
Underidentification test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0006	0.0001
J test (p-value)	0.2978	0.2532	0.2545	-	0.5344	0.1957

Table 2: Impact on the Elasticity of Substitution between VA and X. Please see Table 1 for details regarding specifications (1) to (6).

Similar to Table 1, Table 2 shows that a larger share of IT-related capital stocks brought forward from the last period positively affect the EOS between value-added and intermediate inputs. In particular, the marginal effect is estimated to be relatively large (0.131).[26] Furthermore, there is some evidence that a higher intensity in SoftDB and R&D is positively associated with the EOS. Sectors in which the existing capital share of IT technology as well as R&D investment share is higher, have higher substitution possibilities between production that takes place within the firm and production outsourced to other firms. Despite allowing for heterogeneity in σ, the constant coefficient component is also significant (0.584), indicating that part of this elasticity could be due to other factors that do not vary across time and space. Switching down heterogeneity yields an EOS of 0.683. Again, restricting the sample to service sectors yields similar estimates for the constant, IT, SoftDB and Research capital intensities (0.410, 0.200, 0.319 and 0.179 respectively). For the non-service sectors the corresponding estimates are 0.493, 0.145, 0.270 and 0.157

Finally, we have performed similar robustness checks as in Table 1. Using a skill-based definition does not yield a statistically significant effect of IT intensity, yet we take this result as non-conclusive as sectoral data on skills are only available after 2008 and not for all sectors, resulting in a smaller sample. Using Japanese data for constructing the instrument yields the same empirical insights as our main specification (2).

4.2 Productivity

Given the estimates of the elasticities of substitution, the share parameters and the relative growth rates of productivities, we use the corresponding production functions and the process for each productivity to back out their levels and growth rates.[27] Table 3 reports the results for each input-specific productivity we recovered using our approach, as well as the estimates based on the total factor productivity in value-added provided in the KLEMS database. A higher share of investment in software and databases leads to higher labor and capital productivity growth, while higher capital intensity in information and communications technology does not seem to positively contribute to input-specific productivity growth. [28]

Assuming that the endogenous and exogenous productivities of our theoretical model have similar attributes, our results in Table 3 support the finding of high complementarity

[26]The underidentification test (Kleibergen-Paap rk LM statistic) has p-value = 0.0000 and the Hansen J-statistic has p-value = 0.2532.

[27]Please see Appendix A2 for the way we recover unobserved productivities.

[28]The same holds for value-added productivity growth, although the result is statistically significant once we drop the insignificant lagged values of productivity growth.

between productivities. Because digitalization has almost the same impact on the growth rates of labor and capital productivity, their ratio must remains fairly constant with higher levels of digital intensity.

Furthermore, we also find that intermediate inputs' productivity growth is positively affected by a higher share of research and development in capital brought forward, while there are negative effects of research investment intensity, possibly due to organizational inertia due to necessary investment-related organizational adjustments, which entail temporary inefficiencies in production.

Our results are indeed conditional on the way we recover these unobserved productivities and our prior estimates of the model parameters. We have nevertheless checked the robustness of our finding by utilizing the sectoral total factor productivity measure which is available in the KLEMS database, and we find very similar results in the case of software and database investment intensity. Total factor productivity growth is also increasing in the corresponding investment intensity in software and databases.

While the finding that IT intensity is not significant but SoftDB intensity is may be surprising at first sight, we interpret this as evidence that the installation of digital hardware alone cannot account for an increase of productivity, but it is the effective use of it through software and data that drives productivity gains. Allowing for an interaction between IT intensity and SoftDB capital intensity yields a statistically significant coefficient for the KLEMS-TFP data, which corroborates our earlier claim about complementarities between the installation of hardware and its use. There is nevertheless no further strong evidence of this complementarity in the (more noisy) input-specific productivity measures.[29]

4.3 Share Parameters

In our extensive estimation exercises, we have additionally investigated whether the share parameters are affected by digitalization, with little evidence of such a relationship. We relegate these results to Table 7 in Appendix A7. The constant estimates for α and λ are 0.3154 and 0.5720 respectively.

[29] In alternative specifications, we have investigated for complementarity between SoftDB and IT in both the capital and the investment shares. We found some evidence of complementarity in the investment share for the productivity growth of capital, yet the result was non-robust to accounting for such complementarities in the capital share.

	$\Delta\nu^{VA}$	$\Delta\nu^{X}$	$\Delta\nu^{L}$	$\Delta\nu^{K}$	$\Delta\nu^{VA}_{KLEMS,TFP}$
IT share	0.047	0.040	-0.030	-0.097	0.011
	[-0.074,0.168]	[-0.057,0.137]	[-0.114,0.053]	[-0.294,0.101]	[-0.017,0.039]
CT share	0.069	0.073	-0.026	-0.035	-0.007
	[-0.046,0.183]	[-0.050,0.195]	[-0.055,0.004]	[-0.074,0.005]	[-0.029,0.016]
Inv. share					
R& D	-0.189	-0.186	0.005	0.018	0.005
	[-0.339,-0.040]	[-0.332,-0.041]	[-0.014,0.024]	[-0.004,0.039]	[-0.009,0.018]
SoftDb	0.028	0.017	0.033	0.030	0.029
	[-0.030,0.087]	[-0.038,0.071]	[0.009,0.056]	[0.000,0.059]	[0.005,0.053]
SoftDb $\times$ IT share					0.008
					[-0.007,0.024]
Cap. share					
R&D	0.114	0.112	0.039	0.006	0.015
	[0.003,0.225]	[0.016,0.208]	[0.006,0.071]	[-0.033,0.045]	[-0.009,0.039]
SoftDb	-0.066	-0.072	0.021	0.013	0.029
	[-0.160,0.028]	[-0.154,0.011]	[-0.027,0.069]	[-0.045,0.072]	[-0.002,0.060]
SoftDb $\times$ IT share					0.022
					[0.007,0.038]
Devel. Level	-0.103	-0.070	0.165	0.255	0.175
	[-0.347,0.141]	[-0.283,0.142]	[-0.008,0.339]	[0.051,0.465]	[0.080,0.270]
VIX	-0.043	-0.038	-0.067	-0.063	-0.061
	[-0.092,0.007]	[-0.081,0.006]	[-0.100,-0.034]	[-0.100,-0.026]	[-0.075,-0.047]
No.of Obs.	3607	3606	4288	4043	4646
C-S F.E.	✓	✓	✓	✓	✓
$\geq$ 2 lags	✓	✓	✓	✓	✓
t & t^2	✓	✓	✓	✓	✓

Table 3: Impact of Digitization on Input Specific Productivity Growth. The Table presents the results of regressing the imputed input-specific productivity growth and the KLEMS TFP growth data on the same set of covariates employed in Tables 1 and 2. Estimates are obtained using the Arellano-Bond estimator. All specifications report conventional 95% confidence sets in [.]. The input-specific productivity growth series are obtained using the estimates of $(c_{2,0}, c_{2,1})$ in equation 12 and the corresponding production function. Please see Appendix A2 for more details.

4.4 Digitalization and Shifting Technology frontiers

We employ the structure of the model to back-out the implied shifts in the technology frontier. As evident from (14) and the discussion that follows, the estimated reduced form coefficients for each elasticity relevant factor are nonlinear functions of $(\bar{\omega}^{k/l}, \bar{\gamma})$ and $(\bar{\omega}^{VA/X}, \bar{\sigma})$ respectively, as the structural coefficients that relate $(\tilde{\bar{\omega}}^{k/l}_{i,t}, \tilde{\bar{\gamma}}_{i,t})$ and $(\tilde{\bar{\omega}}^{VA/X}_{i,t}, \tilde{\bar{\sigma}}_{i,t})$ to those factors. This relationship is useful for deriving the corresponding estimates of

$\omega_{i,t}$, which are used in Figure 1 for illustration purposes.

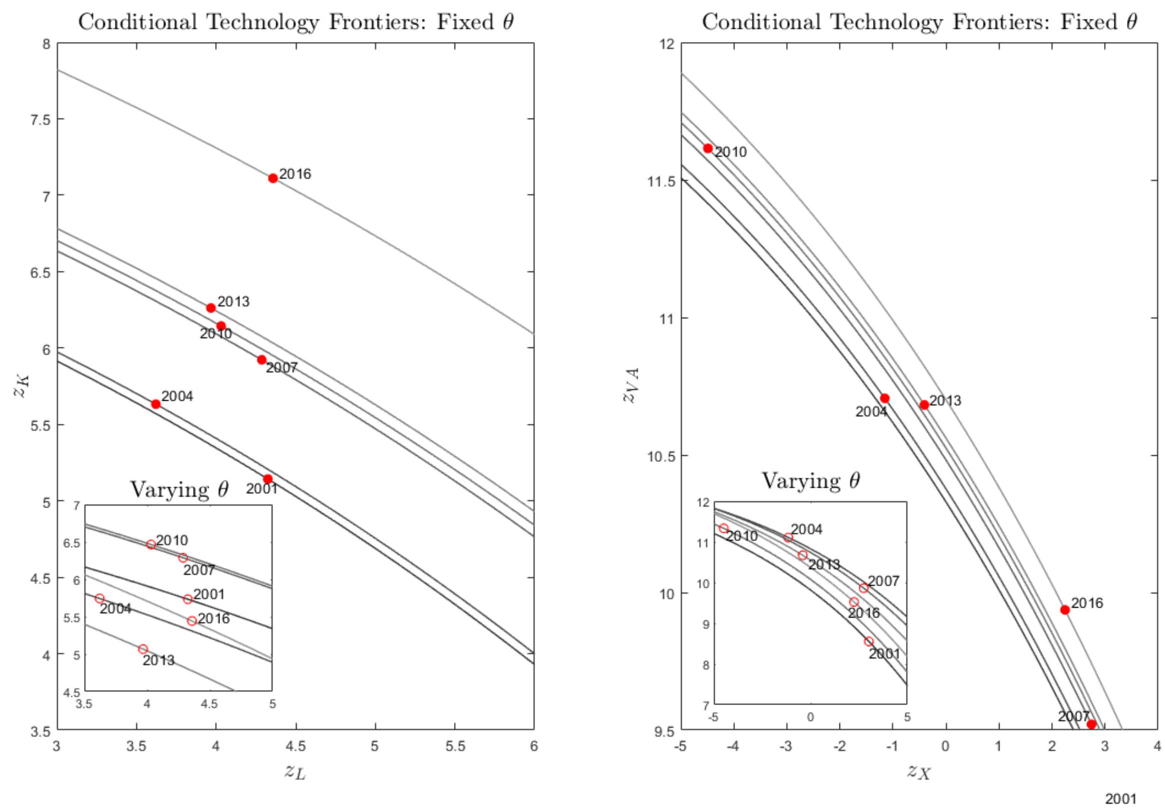

Figure 1: We plot the log-linear approximations to the average technology frontiers (across country-sector), for capital-labor (left) and value-added and intermediate inputs (right), $v_{K,t} \approx -\frac{\bar{\theta}_t^{K/L}}{\bar{\omega}_t^{K/L}\bar{B}}(e^{v_{L,t}})^{\bar{\omega}_t^{K/L}} + \frac{1}{\bar{\omega}_t^{K/L}} log(\bar{B})$ and $v_{VA,t} \approx -\frac{\bar{\theta}_t^{VA/X}}{\bar{\omega}_t^{VA/X}\bar{B}}(e^{v_{L,t}})^{\bar{\omega}_t^{VA/X}} + \frac{1}{\bar{\omega}_t^{VA/X}} log(\bar{B})$, for every three years in the sample. The main plots calibrate θ to its average value over time, while the sub-plots allow for θ to vary and depict the sample realizations. $(\theta_i^{K/L}, \theta_i^{VA/X})$ are obtained using (α_i, λ_i). In both cases $\bar{B}$ is normalized as it is not identified.

In particular, we have employed the reduced form estimates obtained from the relative demand equations to back out the implied estimates of $\bar{\gamma}$ and $\tilde{\gamma}_{i,t}$ using that $\tilde{\gamma}_{i,t} \approx \bar{\gamma} \exp\left(\frac{\bar{\omega}^{[k/l^2]}}{(\bar{\gamma}^{k/l} - (\bar{\gamma}-1))^2}\tilde{\tilde{\gamma}}_{i,t}\right)$ and the estimates of $\omega_{i,t}^{k/l}$ using that $\omega_{i,t}^{k/l} = \frac{(\gamma_{i,t}-1)(\tilde{\gamma}_{i,t}-1)}{\gamma_{i,t}-\tilde{\gamma}_{i,t}}$.[30]

Figure 1 displays the conditional effects on the technology frontiers between labor and capital as well as between value-added and intermediate inputs. We plot the average (over country-sector) log-technology frontiers for every three years in our sample. We focus on the effects of digitalization and keep those of non-digital factors constant (we

[30]Since $\tilde{\tilde{\gamma}}_{i,t}$ depends on several non-technology factors, i.e. m factors, the reduced form estimates can identify only $m-1$ coefficients. Hence the coefficient of the first factor is normalized to one.

also keep θ constant). Digitalization lowers ω and hence shifts these log-frontiers to the right and makes them more convex. If we allow θ to vary, the technology frontiers shift more randomly, but the effects of IT and SoftDB are still the dominant factor (inner plots).

For a given conditional EOS between factors, a higher convexity of the technology frontier leads to more complementary technologies. Hence the choice of technologies matters more for the overall substitution between inputs, increasing the unconditional EOS. This effect holds irrespective of whether the factors are complements or substitutes in the conditional production function.

Further insights on what drives complementarities in technologies can be gained by thinking about task assignments for inputs. As we show in Appendix A3, higher complementarity between aggregate productivities of labor and capital can be the result of a less pronounced comparative advantage of labor over capital in producing (previously) labor intensive tasks. As an example, consider the case of a hospital, where certain tasks are only completed by a medical doctor, while others by a combination of a nurse and equipment. Technological innovation that results into new digital equipment can enable the nurse to complete some of the tasks that only the medical doctor could previously do, due to her expertise. In this case, tasks that were previously done by high-skilled labor are now completed by lower skilled labor together with a more efficient (digital) equipment. This corroborates the idea that technological innovations are not limited to automation, but bring in other organizational changes that alter the trade-offs between technologies.

4.5 Further Discussion

The empirical results have some additional implications for understanding technologically biased technical change and the labor share of income. As can be seen from rearranging the relative demand equations for capital and labor, explaining the decline in the relative share of value-added by which labor is remunerated falls on either relative productivity growth or the decline in the price of investment goods, such as in Karabarbounis and Neiman (2013).

$$ln\left(\frac{k_{i,t}p^k_{i,t}}{l_{i,t}w_{i,t}}\right) = \gamma_i ln\left(\frac{\alpha_i}{1-\alpha_i}\right) + (1-\gamma_i) ln\left(\frac{p^k_{i,t}}{w_{i,t}}\right) + (\gamma_i - 1)\left[(g^k_i - g^l_i)t\right]$$

The evidence suggests that productivity gains, at least for the type of digital technology we are looking at, are unlikely to contribute to a decline in the labor share as the effect we find are uniform across labor and capital productivity growth. Nevertheless, since digitalization increases γ_i, it unconditionally decreases the labor share through the first term (as the share parameters are not affected), and at the same time it *dampens* the effects of the decline in the price of investment goods. We believe that this is an additional source of variation to the labor share that should be taken into account when discussing the implications of digitalization.[31] How much this contributes to the overall effect is of course an interesting question that goes beyond the scope of this paper. The literature on the decline of the labor share is vast, and involves several nuances, both theory and measurement related (see e.g. Grossman and Oberfield (2021)). We thus view our evidence on this debate as suggestive and complementary.

5 Conclusion

We find that digitalization has a significant impact on the macroeconomic production function. Our endogenous technology choice framework shows that a higher IT intensity makes input-specific productivities more complementary. The corresponding shifts in the technology frontier allow firms to re-optimize their production processes with more appropriate technologies, which increases the EOS between value-added and intermediate goods and the EOS between capital and labor. A higher EOS can be consequential for both the labor share as well as the propagation of sectoral shocks in the economy.

Further evidence suggests that higher data intensity positively contributes to the growth rate of Hicks-neutral productivity in value-added. We conclude that different types of digital intensity matter for alternative components of the production function. It is therefore important to disentangle the effects of different types of digital technologies both for the design of policy measures and the assessment of their likely effects.

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[31] Note that while we do not explicitly account for markups, we expect the effect on the relative expenditure share to be relatively muted. Markups contribute to a decline in both labor and capital shares (see e.g.De Loecker, Eeckhout, and Unger (2020)).

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Appendix

A1: Further description of data and transformations

KLEMS (2019) provides data on chain-linked volumes (reference year 2010) for capital stocks of ten different asset categories per industry: Computing equipment K_{IT}, Communications equipment K_{CT}, Computer software and databases K_{SoftDB}, Transport Equipment K_{TraEq}, Machinery and Equipment $K_{OMAchOther}$, Total Non-residential investment K_{OCon}, Residential structures $K_{RStruct}$, Cultivated assets K_{Cult}, Research and development K_{RD}, Other IPP assets K_{IPP}. The total index K_{GFCG} is then constructed using the Törnqvist index as follows, $\Delta ln(K_{GFCG}) = \sum_{i=j..n} \bar{v}_i \Delta ln(K_j)$, where $\bar{v}_j$ are the weights given by the average of current and lagged nominal expenditure shares of each type of capital where $\bar{v}_j = 0.5(v_{j,t} + v_{j,t-1})$ and $\sum_{j=1..10} \bar{v}_j = 1$. The measures of digital intensity we use are then given by $\frac{K_{IT}}{K_{GFCG}}$, $\frac{K_{CT}}{K_{GFCG}}$, $\frac{K_{SoftDB}}{K_{GFCG}}$ and correspondingly, our measure of R&D intensity is $\frac{K_{RD}}{K_{GFCG}}$. The same approach is followed for investment intensities. Instead of $ln\left(\frac{K_{IT}}{K_{GFCG}}\right)$, one possibility would be to use the expenditure share $v_{i,t}$ (which is provided in the KLEMS (2022) release.). Nevertheless, neither the current nor the lagged expenditure shares are consistent measures of intensity. The former because it incorporates changes in current prices, and the latter because they feature lagged quantities. Ideally, one would like to use the expenditure share using current quantities at constant prices. This is then almost equivalent to utilizing the ratio of the volume index for a particular asset to the total index. The chain linked volumes for each individual asset type are by construction independent of current prices, and hence any change in the intensity will be due to a change in the quantity. Correspondingly, since the change of K_{GFCG} from period $t-1$ to period t is by construction a geometric average over the individual asset types, an increase in $ln\left(\frac{K_{IT}}{K_{GFCG}}\right)$ will reflect an increase in K_{IT} relative to other asset types.

Relation to existing measures of digital intensity

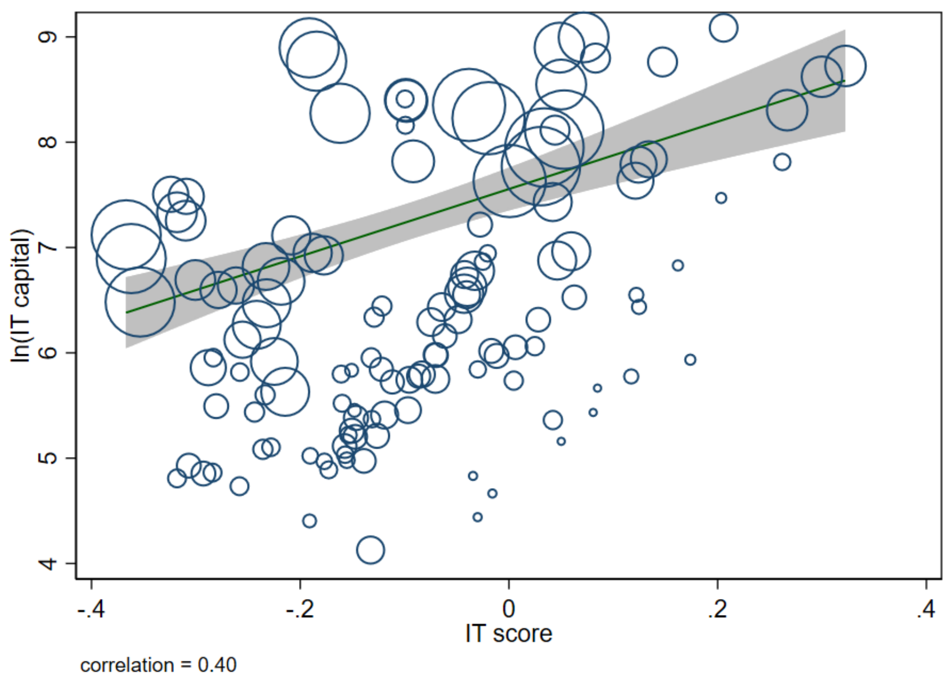

Figure 2: Correlation of IT capital expenditures and the measure of digitalization in Gallipoli and Makridis (2018).

A2: Estimating labor and capital productivities for $t > 0$

Given the relative growth rate estimates and the normalization of initial relative productivity to one, we compute relative productivity: $e^{z_{i,t}} = e^{gt}$. Using the (normalized) value-added production function, we back out $e^{z^l_{i,t}-\bar{z}^l_i}$ and $e^{z^k_{i,t}-\bar{z}^k_i}$:

$$
\begin{aligned}
\frac{VA_{i,t}}{\bar{VA}} &= (\alpha(e^{z^k_{i,t}-\bar{z}^k_i}\frac{k_{i,t}}{\bar{k}_i})^{\frac{\gamma-1}{\gamma}} + (1-\alpha)(e^{z^l_{i,t}-\bar{z}^l_i}\frac{l_{i,t}}{\bar{l}_i})^{\frac{\gamma-1}{\gamma}})^{\frac{\gamma}{\gamma-1}} \\
&= e^{z^l_{i,t}-\bar{z}^l_i}\frac{l_{i,t}}{\bar{l}_i}\left(\alpha\left(e^{z_{i,t}-\bar{z}_i}\frac{k_{i,t}}{l_{i,t}}\frac{\bar{k}_i}{\bar{l}_i}\right)^{\frac{\gamma-1}{\gamma}} + 1-\alpha\right)^{\frac{\gamma}{\gamma-1}}
\end{aligned}
$$

and thus, $e^{z^l_{i,t}-\bar{z}^l_i} = (VA_{i,t}/\bar{VA}_i)/\left(\frac{l_{i,t}}{\bar{l}_i}\left(\alpha\left(e^{z_{i,t}-\bar{z}_i}\frac{k_{i,t}}{l_{i,t}}\frac{\bar{k}_i}{\bar{l}_i}\right)^{\frac{\gamma-1}{\gamma}} + 1-\alpha\right)^{\frac{\gamma}{\gamma-1}}\right)$. Using $e^{z^k_{i,t}-\bar{z}^k_i} = e^{g_i(t-\bar{t})}e^{z^l_{i,t}-\bar{z}^l_i}$, we back out capital productivity. The same approach is followed for backing out the productivities of valued added and intermediate inputs.

A3: Input Specific Productivity and Task Assignment.

Consider a model of production where final sectoral output is produced using a CES aggegate of tasks with unit measure:

$$
Y \;=\; A\left(\int_0^1 y(j)^{\frac{\zeta-1}{\zeta}}dj\right)^{\frac{\zeta}{\zeta-1}} \tag{18}
$$

Profit maximization yields that demand for task j is pinned down by $y(j) = A^{\zeta-1}Yp(j)^{-\zeta}$. Correspondingly, each task j can be produced with just labor, or a Leontieff form of production using labor and capital.

We allow for potentially different types of labor that can accomplish tasks above or below j. We nevertheless don't take a stance on whether l and l_k correspond to low-skill or high-skill workers. It can very well be that either low skilled or high skilled labor complements capital, depending on the available technology.

For a given technology, there is a threshold task $j = J \in (0,1)$ over which tasks are better produced by labor only,(l_n), while for the rest of the tasks the representative firm uses a fixed combination of labor (l_k) and capital (k):

$$
y(j) \;=\; \begin{cases} \xi_n(j)l_n(j) & j > J \\ \min(\xi_k(j)l_k(j), \eta(j)k(j)) & j \le J \end{cases} \tag{19}
$$

We also assume that $\frac{\xi_n(j)}{\eta(j)}$ is increasing in j.

An example for this production function would be medical tasks in hospitals, which could either be done by a doctor (l_n) or by a nurse (l_k). Digital devices (k) can enable the nurse to do certain tasks that were previously dependent on the doctor's decisions (e.g.

monitoring the heath condition of patients, deciding upon giving drugs based on blood test results etc.). Once these digital devices have been introduced, the nurse is able to use the devices in a complementary manner and take the responsibilities for additional tasks. Consequently, J shifts upward.

Correspondingly, in a competitive setting, the price of each task is set equal to the minimum unit cost of production which is equal to

$$p(j) \quad = \quad \begin{cases} \frac{W_n}{\xi_n(j)} & j > J \\ \frac{W_k}{\xi_k(j)} + \frac{R}{\eta(j)} & j \leq J \end{cases} \tag{20}$$

Note that the actual threshold determined in equilibrium $(J^{\star})$ might be different than J. The equilibrium threshold takes into account factor prices as well, and hence the unit cost of production. There is a threshold $\tilde{J} : \frac{W_n}{\xi_n(\tilde{J})} = \frac{W_k}{\xi_k(\tilde{J})} + \frac{R}{\eta(\tilde{J})}$, where it is efficient that tasks $j : j > \tilde{J}$ are produced only with labor. If $\tilde{J} > J$, the assignment is constrained by existing technology. Hence, it is understood that $J^{\star} = min(\tilde{J}, J)$.

For a given quantity of tasks demanded, the demand for each input is as follows:

$$l_n(j) \quad = \quad \frac{y(j)}{\xi_n(j)} = \frac{Y}{\xi_n(j)} A^{\zeta-1} \left(\frac{W_n}{\xi_n(j)}\right)^{-\zeta} \tag{21}$$

$$l_k(j) \quad = \quad \frac{y(j)p(j)}{W_n + R\frac{\xi_n(j)}{\eta(j)}} = Y(A\xi_n(j))^{\zeta-1} \left(W_k + R\frac{\xi_n(j)}{\eta(j)}\right)^{-\zeta} \tag{22}$$

$$k(j) \quad = \quad = l_k(j)\frac{\xi_k(j)}{\eta(j)} = Y(A\xi_n(j))^{\zeta-1} \left(W_k + R\frac{\xi_n(j)}{\eta(j)}\right)^{-\zeta} \frac{\xi_k(j)}{\eta(j)} \tag{23}$$

Assuming that labor and capital are sector-specific, a local market equilibrium where $\int_{J^{\star}}^{1} l_n(j)dj = L_n$, $\int_0^{J^{\star}} l_k(j)dj = L_k$ and $\int_{J^{\star}}^{1} k(j)dj = K$ yields that:

$$W_n \quad = \quad \left(\frac{Y}{L_n}\right)^{\frac{1}{\zeta}} A^{1-\frac{1}{\zeta}} \left(\int_{J^{\star}}^{1} \xi_n(j)^{\zeta-1} dj\right)^{\frac{1}{\zeta}} \tag{24}$$

$$W_k \quad = \quad \left(\frac{Y}{L_k}\right)^{\frac{1}{\zeta}} A^{1-\frac{1}{\zeta}} \left(\int_0^{J^{\star}} \left(1 + \frac{R\xi_k(j)}{W_k\eta(j)}\right)^{-\zeta} dj\right)^{\frac{1}{\zeta}} \tag{25}$$

$$R \quad = \quad \left(\frac{Y}{K}\right)^{\frac{1}{\zeta}} A^{1-\frac{1}{\zeta}} \left(\int_0^{J^{\star}} \left(\frac{W_k}{R} + \frac{\xi_k(j)}{\eta(j)}\right)^{-\zeta} \frac{\xi_k(j)^{\zeta}}{\eta(j)} dj\right)^{\frac{1}{\zeta}} \tag{26}$$

Using that $W_k L_k + W_n L_n + RK = PY$ and imposing that the final good is the numeraire, yields the price index:

$$A^{1-\zeta} = \int_{J^\star}^{1} \left(\frac{W_n}{\xi_n(j)}\right)^{1-\zeta} dj + \int_{J^\star}^{1} \left(\frac{W_k}{\xi_n(j)}\right)^{1-\zeta} \left(1+\frac{R\xi_n(j)}{W_k\eta(j)}\right)^{-\zeta} dj + \int_{J^\star}^{1} \left(\frac{R}{\eta(j)}\right)^{1-\zeta} \left(1+\frac{W_k\eta(j)}{R\xi_n(j)}\right)^{-\zeta} dj$$

Combining the equilibrium prices with the price index yields the CES production function for aggregates:

$$Y^{1-\frac{1}{\zeta}} = A^{1-\frac{1}{\zeta}} \left[\left(\int_{J^\star}^{1} \xi_n(j)^{\zeta-1} dj\right)^{\frac{1}{\zeta}} L_n^{1-\frac{1}{\zeta}} + \left(\int_0^{J^\star} \left(\frac{\xi_k(j)^{\zeta-1}}{\left(1+\frac{R\xi_k(j)}{W_k\eta(j)}\right)^{\zeta}}\right) dj\right)^{\frac{1}{\zeta}} L_k^{1-\frac{1}{\zeta}} + \left(\int_0^{J^\star} \left(\frac{\eta(j)^{\zeta-1}}{\left(1+\frac{W_n\eta(j)}{R\xi_k(j)}\right)^{\zeta}}\right) dj\right)^{\frac{1}{\zeta}} K^{1-\frac{1}{\zeta}} \right]$$

where we can write

$$Y^{1-\frac{1}{\zeta}} = A^{1-\frac{1}{\zeta}} \left[\left(\int_{J^\star}^{1} \xi_n(j)^{\zeta-1} dj\right)^{\frac{1}{\zeta}} L^{1-\frac{1}{\zeta}} + \left(\int_0^{J^\star} \left(\frac{\eta(j)^{\zeta-1}}{\left(1+\frac{W_k\eta(j)}{R\xi_k(j)}\right)^{\zeta}}\right) dj\right)^{\frac{1}{\zeta}} K^{1-\frac{1}{\zeta}} \right]$$

with L being the CES aggregate of L_n and its efficiency equivalent L_k:

$$L^{1-\frac{1}{\zeta}} := L_n^{1-\frac{1}{\zeta}} + \left(\frac{\int_0^{J^\star} \left(\frac{\xi_k(j)^{\zeta-1}}{\left(1+\frac{R\xi_k(j)}{W_k\eta(j)}\right)^{\zeta}}\right) dj}{\int_{J^\star}^{1} \xi_n(j)^{\zeta-1} dj} \right)^{\frac{1}{\zeta}} L_k^{1-\frac{1}{\zeta}}$$

Finally, letting

$$e^{z_L} := \left(\int_{J^\star}^{1} \xi_n(j)^{\zeta-1} dj\right)^{\frac{1}{\zeta-1}}, \quad e^{z_K} := \left(\int_0^{J^\star} \left(\frac{\eta(j)^{\zeta-1}}{\left(1+\frac{W_k\eta(j)}{R\xi_k(j)}\right)^{\zeta}}\right) dj\right)^{\frac{1}{\zeta-1}}$$

yields

$$Y^{1-\frac{1}{\zeta}} = A^{1-\frac{1}{\zeta}} \left[(e^{z_L}L)^{1-\frac{1}{\zeta}} + (e^{z_K}K)^{1-\frac{1}{\zeta}} \right]$$

Note that for simplicity, we have assumed away the existence of intermediaries. Nevertheless, this approach could be extended to allow for intermediaries as well.

A3.1 The implicit Technology Frontier

We are now ready to show how a technology frontier arises in the equilibrium of this model. In particular, we directly explore the slope of this frontier, whose elasticity will be related to convexity, and hence complementarity of these technologies. When there is no technological constraint ($J^{star} = \tilde{J}$), the slope of the log-frontier is as follows:

$$slope\left(\frac{z_K}{z_L}\right) := \frac{dz_K}{dz_L} = \frac{\frac{dz_K}{dJ^\star}}{\frac{dz_L}{dJ^\star}} = -\left(\frac{e^{z_K}}{e^{z_L}}\right)^{1-\zeta}\left(\frac{\eta_{J^\star}}{\xi_{J^\star}}\right)^{\zeta-1}\left(1+\frac{W_k\eta(J^\star)}{R\xi_k(J^\star)}\right)^{-\zeta} \tag{27}$$

$$= -\frac{L_n}{K}\frac{\xi(J^\star)}{\eta(J^\star)} \tag{28}$$

where the last line uses that at $J^\star$, $1+\frac{W_k\eta(J^\star)}{R\xi_k(J^\star)} = \frac{W_n\eta(J^\star)}{R\xi(J^\star)}$, and that $\frac{W_n}{R} = \left(\frac{K}{L_n}\right)^{\frac{1}{\zeta}} e^{(z_L-z_K)\frac{\zeta-1}{\zeta}}$. The slope of the frontier is negative, which implies that there is a trade-off between the two aggregate labor and capital productivities. Different equilibrium levels of $J^\star$ will determine this trade-off *along* the frontier. If $J^\star = J$, then current technology imposes a constraint on that frontier. Technological innovations, which include but are not limited to automation, can induce a shift in J, which will allow obtaining points further along the *same* factor frontier. Thus, technical change enables firms to choose new technologies on another conditional production function. By moving along the technology frontier, the EOS increases from the conditional towards the unconditional one.

Moreover, a measure of convexity of the log-frontier introduced by León-Ledesma and Satchi (2019) is the elasticity of the slope of the log-frontier with respect to $\frac{z_K}{z_L}$,

$$\delta := \frac{slope'\Big(z_K - z_L\Big)}{slope\Big(z_K - z_L\Big)} = -\left(\frac{\partial(z_K - z_L)}{\partial J^\star}\right)^{-1}\left(\frac{\partial ln\left(\frac{\xi(J^\star)}{\eta(J^\star)}\right)}{\partial J^\star}\right) \tag{29}$$

Both the first term and second terms in brackets are positive, as an increase in threshold $J^\star$ increases z_K and decreases z_L, while $\frac{\xi_n(j)}{\eta(j)}$ is increasing in j by the comparative advantage of labor (l). Hence, the log-frontier is concave, as is the model of technology choice we employ in the main body of the paper.

It is then clear that a higher convexity must be the result of the comparative advantage of l_n over k (and hence l_k) becoming less pronounced, or the effects on relative productivity becoming more pronounced. Technological innovations can have such an effect either through an explicit shift in J and therefore $J^\star$, or through other exogenous structural changes that affect comparative advantage. This corroborates the idea that technological innovations are not limited to automation, but bring in other organizational changes that change the trade-offs between technologies.

In our setting, since we do not employ an analysis at the task level, an equivalent way of modeling the equilibrium determination of $J^\star$ is to allow firms to directly choose it amongst all permissible levels of j along the frontier. The same calculation yields that convexity in our case is pinned down by:

$$\delta := \frac{slope'\Big(z_K - z_L\Big)}{slope\Big(z_K - z_L\Big)} \quad = \quad \frac{\omega\theta e^{(-\omega-1)(z_K - z_L)}}{-\theta e^{-\omega(z_K - z_L)}} e^{z_K - z_L} = -\omega \tag{30}$$

A4: Explanation of sectors

Code	Explanation	S
A	Agriculture, forestry & fishing	
B	Mining & quarrying	
D-E	Electricity, gas & water supply	✓
F	Construction	
I	Accomodation & food service activities	✓
K	Financial & insurance activities	✓
L	Real estate activities	✓
M-N	Professional, scientific, technical, admin. & support service activities	✓
R	Arts, entertainment & recreation	✓
S	Other service activities	✓
10-12	Food products, beverages & tobacco	
13-15	Textiles, wearing apparel, leather & related products	
16-18	Wood & paper products; printing & reprod. of recorded media	
19	Coke & refined petroleum products	
20-21	Chemicals & chemical products	
22-23	Rubber & plastics products, & other non-metallic mineral products	
24-25	Basic metals & fabricated metal products (excl. machinery & equip.)	
26-27	Electrical & optical equipment	
28	Machinery & equipment n.e.c.	
29-30	Transport equipment	✓
31-33	Other manufacturing; repair & installation of machinery & equipment	✓
45	Wholesale & retail trade & repair of motor vehicles & motorcycles	✓
46	Wholesale trade, except of motor vehicles & motorcycles	✓
47	Retail trade, except of motor vehicles & motorcycles	✓
49-52	Transport & storage	✓
53	Postal & courier activities	✓
58-60	Publishing, audiovisual & broadcasting activities	✓
61	Telecommunications	✓
62-63	IT & other information services	✓

Table 4: Sector codes, names & classification as service sector (S)

A5: Shares of digital capital types in overall capital

	Intensities		
Code	Information Technology	Communications Technology	Databases and Software
A	0,004253	0,0010234	0,0014143
B	0,0077766	0,0039974	0,0053481
C10-C12	0,0107238	0,006219	0,0177819
C13-C15	0,0125911	0,0034936	0,029158
C16-C18	0,0137761	0,0088125	0,0192843
C19	0,0053049	0,0073741	0,0126016
C20	0,0071038	0,0152717	0,0147406
C20-C21	0,0054727	0,012895	0,017749
C21	0,0046682	0,0068411	0,0208358
C22-C23	0,0134607	0,0061375	0,0195104
C24-C25	0,008547	0,0078541	0,0193133
C26	0,0219624	0,0148604	0,0723233
C26-C27	0,0175541	0,012431	0,0646179
C27	0,0111281	0,0105202	0,0467235
C28	0,0107818	0,0096089	0,0510598
C29-C30	0,0064563	0,0118472	0,029536
C31-C33	0,0141074	0,007993	0,0535963
D	0,0061376	0,0116058	0,0091
E	0,0034602	0,002207	0,0064929
F	0,0199727	0,0085336	0,0200736
G45	0,0186795	0,009214	0,0164421
G46	0,0369193	0,0135821	0,0469053
G47	0,0317989	0,0117243	0,0236333
H49	0,0081865	0,0106475	0,0053906
H50	0,0074767	0,005658	0,0033922
H51	0,0112966	0,0172487	0,0181651
H52	0,0049014	0,0102961	0,0053065
H53	0,0230998	0,054194	0,0501782
I	0,0159736	0,0089399	0,0112556
J58-J60	0,0442202	0,0398583	0,139925
J61	0,0248976	0,1979001	0,0556065
J62-J63	0,1406515	0,040945	0,3060345
K	0,0471777	0,0117678	0,1161901
M-N	0,0327934	0,0164067	0,0571099
R	0,0152655	0,0092689	0,0173999
S	0,0199397	0,0067417	0,0460683

Table 5: Average intensities per sector in 2017

Country	Information Technology	Communications Technology	Databases and Software
Austria	0.0115	0.0298	0.0313
Belgium	0.0185	0.0311	0.0198
Czechia	0.0162	0.00543	0.0181
Germany	0.0211	0.0203	0.0214
Denmark	0.0203	0.00716	0.0337
EU	0.00581	0.0306	0.0104
Greece	0.0231	0.0271	0.016
Spain	0.00588	0.0246	0.0372
Finland	0.00703	0.0111	0.0331
France	0.00377	0.0183	0.0992
Hungary	-	-	0.0152
Italy	0.00893	0.0147	0.0519
Latvia	0.0121	0.0128	0.00386
Luxembourg	0.0247	0.0112	0.0105
Netherlands	0.0126	0.00197	0.0496
Serbia	0.00639	0.0256	0.0528
Slovenia	0.00776	0.00376	0.0125
Slovakia	0.0144	0.0135	0.00975
UK	0.00977	0.00618	0.0349
US	0.00792	0.0228	0.0302

Table 6: Average intensities per country in 2017

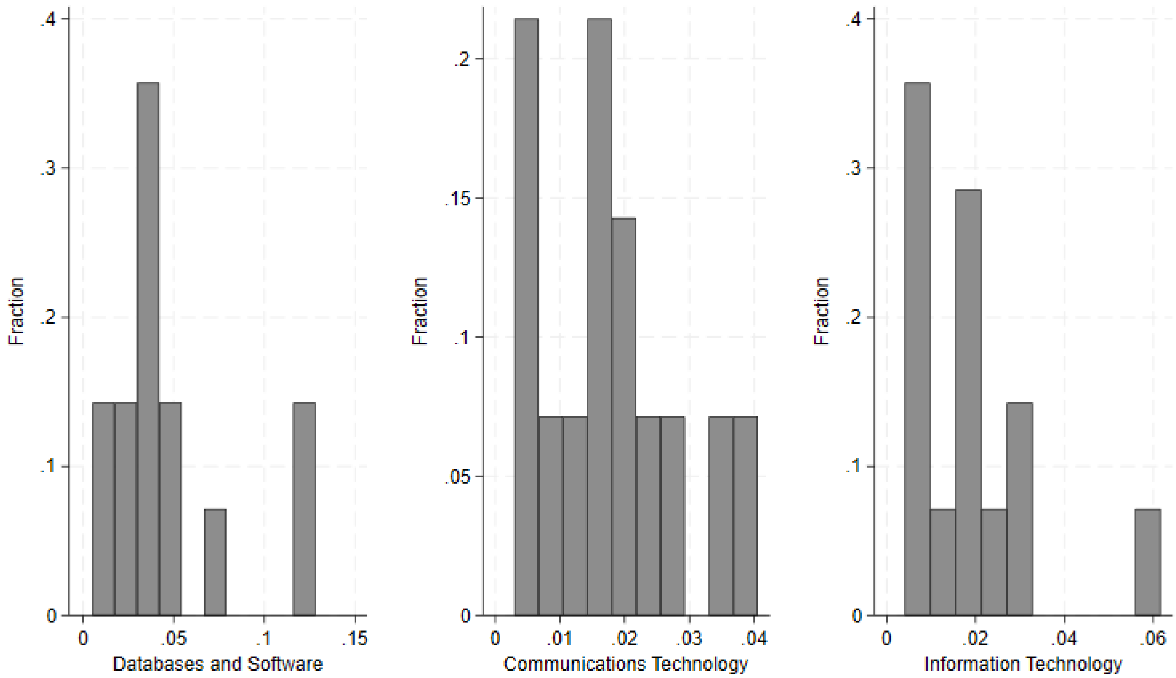

Figure 3: Histogram of Sectoral Intensities (Average over Countries)

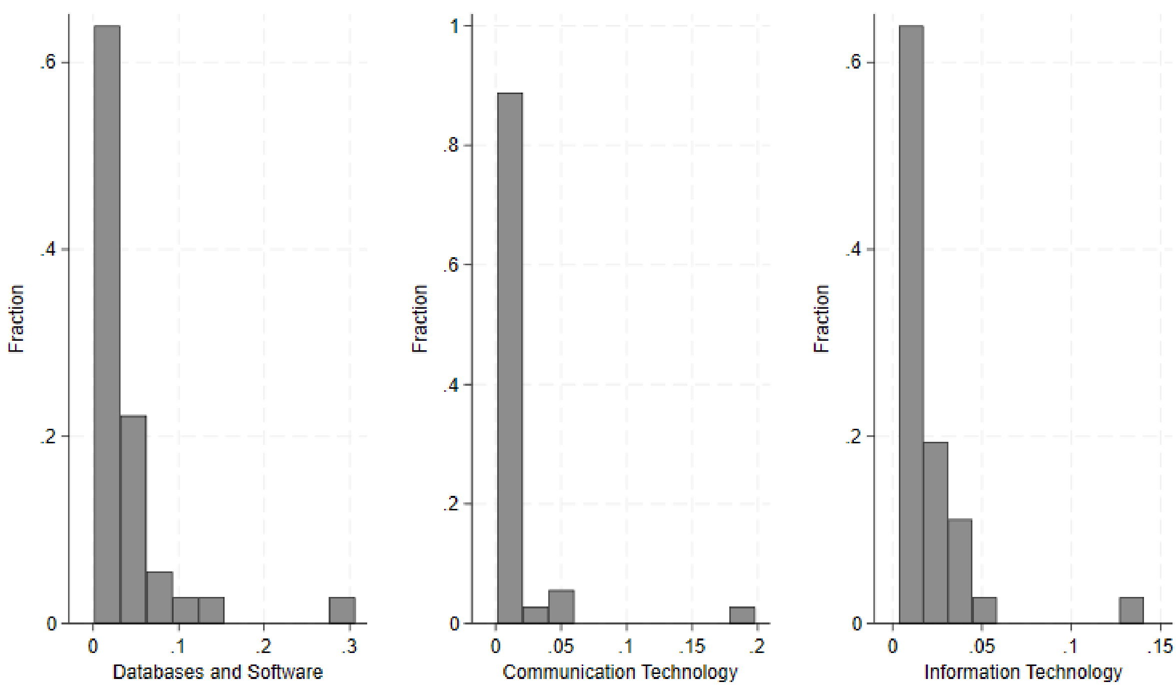

Figure 4: Histogram of Country Intensities (Average over Sectors)

A6: Estimation with a normalized production function

It can be shown that the first order conditions under normalization are

$$
\begin{aligned}
ln\left(\frac{k_{i,t}}{l_{i,t}}\right) &= (1-\gamma_{i,t})ln\left(\frac{\bar{k}_{i,t}}{\bar{l}_{i,t}}\right) - (g_i^k - g_i^l)\bar{t} + \gamma_{i,t} ln\left(\frac{\bar{\alpha}_{i,t}}{1-\bar{\alpha}_{i,t}}\right) \\
&\quad -\gamma_{i,t} ln\left(\frac{p_{i,t}^k}{w_{i,t}}\right) + (\gamma_{i,t}-1)\left[\left(z_{i,0}^k - z_{i,0}^l\right) + (g_i^k - g_i^l)t\right]
\end{aligned}
\tag{31}
$$

where $(\bar{k}_{i,t}, \bar{l}_{i,t}, \bar{\alpha}_{i,t}, \bar{t})$ are the normalization points. Since in the non-normalized case we have already controlled for the potential covariates related to the relative share, which are the same for $\gamma_{i,t}$, the regression estimates are robust to the presence of the additional terms $(1-\gamma_{i,t})ln\left(\frac{\bar{k}_{i,t}}{\bar{l}_{i,t}}\right) - (g_i^k - g_i^l)\bar{t}$.

A7: Effects of Digital Intensity on Share Parameters

	$\ln\left(\frac{\alpha}{1-\alpha}\right)$	$\ln\left(\frac{1-\lambda}{\lambda}\right)$
Constant	-0.775	-0.290
	[-1.904,0.355]	[-0.707,0.128]
IT share	0.328	0.0218
	[-0.0520,0.707]	[-0.133,0.176]
CT share	0.228	-0.0367
	[-0.131,0.588]	[-0.116,0.0428]
Inv. share:		
R&D	0.0178	0.0249
	[-0.114,0.150]	[-0.126,0.176]
SoftDb	0.142	-0.104
	[-0.0454,0.330]	[-0.192,-0.0153]
Cap. share:		
R&D	0.0485	0.190
	[-0.378,0.475]	[-0.0522,0.431]
SoftDb	-0.205	-0.105
	[-0.477,0.0663]	[-0.356,0.146]
No. Observations	2609	2433
Country-Sector F.E. and 4 lags	✓	✓

Table 7: This table reports the estimation results for the impact of digital intensities on relative share parameters (α, λ).