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Digitalization and Resilience to Disaggregate Shocks

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Abstract

How does digital technology affect the transmission of idiosyncratic shocks to the gross domestic product? We show that shock amplification depends on the elasticity of substitution and the relative abundance of inputs. Using an IV approach, we find a positive effect of digital intensity on substitution elasticities between capital and labor and between value-added and intermediate inputs, respectively. We interpret our empirical results through the lens of the technology choice literature, attributing the effect to a change in the curvature of the technology frontier. We show that whether a higher elasticity of substitution dampens the propagation of sectoral shocks or not depends on a simple sufficient statistic, the relative abundance of intermediate inputs. Based on the latter, our estimates suggest that many sectors in selected European economies amplify shocks after digitalization, with a deteriorating trend in resilience between 1995 and 2017.

Keywords: Digitalization, Productivity, Elasticity of substitution, Domar weights, Resilience, Production Networks.

JEL codes: E1, E23, E25, O33

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1 Introduction

Digital technology is omnipresent 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 about its effects on the macroeconomy is still scant. A substantial research effort has been devoted to understanding the effects of information technology and automation on growth, and yet the evidence is mixed. The literature agrees that digital technologies have had a positive impact on productivity, with a decreasing pace after around the year 2000 (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)). The existence and strength of the effects of digitalization on productivity might depend on the measures used (Acemoglu, Dorn, Hanson, Price, et al. (2014)), their precision (Byrne, Fernald, and Reinsdorf, 2016) and the analyzed time frame (Van Ark (2016)).

Setting aside these measurement issues, the fact that total factor productivity growth has shown a rapid decline after its initial takeoff while digital intensity in production has exhibited a secular rise may invite alternative and complementary interpretations of the way technical change can have an impact on the economy. As we will argue, one such relatively unexplored alternative is macroeconomic resilience, defined as the ability of a system to mitigate the effects of an adverse disaggregated shock. A recent strand of literature has investigated the extent to which digitalization could mitigate disruptions based on sectoral responses to the pandemic. Using firm-level data from developing countries, Comin, Cruz, Cirera, Lee, and Torres (2022) shows that a higher pre-pandemic level of digitalization has mitigated some of the initial negative impact on firms' sales during the early stage of the Covid shock. Complementary work has investigated the post-shock adoption of digital technologies to alleviate the negative economic impact (e.g. Apedo-Amah, Avdiu, Cirera, Cruz, Davies, Grover, Iacovone, Kilinc, Medvedev, Maduko, et al. (2020), Bloom, Valero, and Van Reenen (2021) and Bellmann, Bourgeon, Gathmann, Kagerl, Marguerit, Martin, Pohlan, and Roth (2021)).

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

This recent evidence raises some fundamental questions regarding the effects of technical change on the macroeconomy that go beyond the transition we have observed in recent years. In this paper, we take a new view and investigate which factors determine macroeconomic resilience, how digitalization may be mapped to these factors, and how data can be brought to bear on this question.

A suitable measure to quantify resilience and hence the overall effects of disaggregated shocks in a multi-sectoral economy is the Domar weight. The larger the Domar weight of a specific sector, the more severe are GDP adjustments and thus the smaller is economic resilience. We build our analytical model on Acemoglu, Akcigit, and Kerr (2016) and generalize the results to a CES production function. Consistent with Baqaee and Farhi (2019), Domar weights are no longer constant and solely dependent on the parameters of a production function. Instead, input expenditure shares - a central component of Domar weights - may vary. Compared to the Cobb Douglas case, a higher expenditure share for intermediate inputs implies an amplification of a shock and vice versa. In turn, the expenditure share itself depends on two production parameters - the share parameter and the elasticity of substitution - as well as the relative abundance of inputs. An immediate empirical question is whether digitalization can have an impact through these components.

Using an instrumental variables approach, we find that digitalization has a significantly positive impact on the elasticity of substitution between capital and labor and between value-added and intermediate inputs, respectively. These results corroborate the claim that the elasticity of substitution is not an immutable parameter but is shapeable by technology, amongst other factors (Knoblach and Stöckl, 2020). Oberfield and Raval (2021) finds that the elasticity of substitution evolves over time, although they find a slight negative trend since the 1970s. Moreover, our result that digitalization increases the elasticity of substitution between capital and labor provides further empirical support to assumptions made in the recent literature on automation (see e.g. Alonso, Berg, Kothari, Papageorgiou, and Rehman (2022)). Using data on robot imports, Adachi (2021) estimates a higher elasticity of substitution between robots and labor, as compared to general capital goods. This further supports our general findings, as robots is a specific type of digital capital that combines both hardware and software.

In addition, 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. We thus confirm Miyagiwa and Papageorgiou (2007)'s conclusion that the aggregate elasticity of substitution between capital and labor is positively related to the level of economic development. Digitalization's effect cannot be simply captured by the overall level of development, which we take as a sign of a deeper mechanism in place. We interpret our empirical results through the lens of the technology choice literature by Jones (2005); Caselli and Coleman (2006); Growiec (2008, 2013, 2018) and León-Ledesma and Satchi (2019), which motivates an endogenous evolution of the elasticity of substitution based on technological change. More specifically, we argue that digitalization has an impact on the curvature of the technology frontier, altering the substitutability of input-specific technologies.

Moreover, we revisit our theoretical model to investigate the consequences of a higher elasticity of substitution on Domar weights. We find that the effect on resilience depends on the quantity ratio of intermediate inputs to value-added and can thus be shock-reinforcing or -dampening. We quantify the impact of a higher elasticity of substitution on resilience for several sectors in selected European economies and find that for most of the sectors resilience decreases. This effect is largely uniform across countries, reinforcing the idea that it largely depends on technologies with a strong sector-specific component rather than a country-specific idiosyncratic characteristic. We furthermore illustrate that there is a general trend towards less resilience between 1995 and 2017. Sectors that would have been classified as becoming more resilient with digitalization in the 1990s are gradually becoming less resilient with digitalization post-2000.

Another key takeaway from our empirical results is that the effects are not uniform across different components of digital technologies. We distinguish between information technology (IT), communication technology (CT) and software-databases (SoftDB), whose capital stock intensity has exhibited different growth rates over the last decades (see Figure 1). Among these three categories, only IT intensity significantly increases the elasticity of substitution between capital and labor, while both IT and SoftDB capital intensities contribute to an increase in the elasticity of substitution between value-added and intermediate inputs.

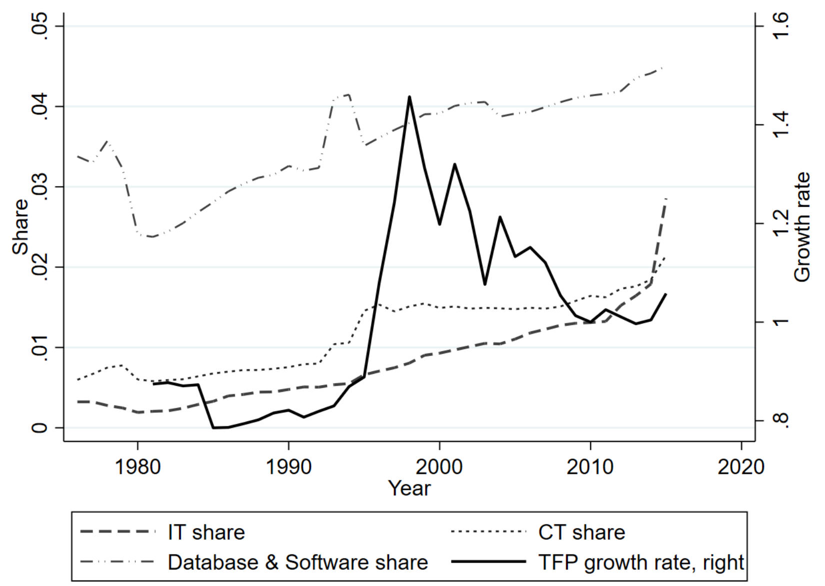

Figure 1: All series are computed using the EU KLEMS (2019). Total Factor Productivity growth is available from the database and computed as the residual from a translog specification of the production function. We compute capital stock intensity by dividing the capital stock per asset type (IT, CT, SoftDB) to the total stock (chain linked volumes).

Furthermore, we find that a higher investment intensity in data and software leads to an increase in labor augmenting and capital augmenting productivity.

The paper is structured as follows: Section 2 presents the general equilibrium model and the corresponding Domar weight. Sections 3 and 4 describe the empirical methodology and present the results. Section 5 investigates the impact of the elasticity of substitution on the Domar weight, the relevant conditions for amplification/dampening, and the corresponding empirical application. Section 6 provides a microfoundation for the empirical results on the elasticity of substitution and connects this to our empirical results regarding digitalization. Section 7 concludes.

2 Theory

In this section we develop the theoretical framework within which we will define resilience and how it depends on the production structure of the economy. We focus on the simplest possible structure that is general enough to illustrate the mechanisms in place. We will thus focus on an efficient economy setup with a representative household and n productive sectors, each populated by a representative producer.

2.1 General Equilibrium Model

2.1.1 Production and Factor Demand

Firms in each sector employ labor and intermediate goods to produce final output, where intermediate goods are combined to an intermediate composite using a Cobb-Douglas production function. Final output is a constant elasticity of substitution (CES) aggregate of value-added, which is labor intensive, and the intermediate goods composite as follows:

$$\begin{aligned} y_{i,t} &= e^{z_{i,t}} \left((1-\lambda_i) l_{i,t}^{\frac{\sigma_i - 1}{\sigma_i}} + \lambda_i \left[\prod_{j=1..n} x_{i,j}^{\alpha_{i,j}} \right]^{\frac{\sigma_i - 1}{\sigma_i}} \right)^{\frac{\sigma_i}{\sigma_i - 1}} \\ &= e^{z_{i,t}} \left((1-\lambda_i) l_{i,t}^{\frac{\sigma_{i,t} - 1}{\sigma_i}} + \lambda_i X_{i,t}^{\frac{\sigma_i - 1}{\sigma_i}} \right)^{\frac{\sigma_i}{\sigma_i - 1}} \end{aligned} \tag{1}$$

where $\sigma_i \in [0, \infty)$ is the elasticity of substitution between the labor and the intermediate good bundle and $(\lambda_i, \{\alpha_{i,j}\}_{j=1..n})$ are the share parameters for the bundle and its sub-components respectively. Productivity is assumed to be Hicks neutral. Due to perfect competition in product markets the producers of the sector's final good take the price of their own good $(p_{i,t})$ as given and choose labor and intermediate inputs to maximize profits according to

$$\max_{l_{i,t}, x_{j,i}} p_{i,t} y_{i,t} - w_{i,t} l_{i,t} - \sum_{j=1..n} p_{j,t} x_{i,j} \tag{2}$$

where $p_{j,t}$ is the price paid for the goods produced by producer j and $w_{i,t}$ is the wage paid for labor services. Correspondingly, the total cost of intermediate inputs is such that $\sum_{j=1..n} p_j x_{i,j} = p_i^X X_i$. At the optimal choice of each producer i, the marginal product of each input is equal to its real price as follows:

$$\begin{aligned}(1-\lambda_i)\left(\frac{l_{i,t}}{y_{i,t}}\right)^{-\frac{1}{\sigma_i}} e^{z_{i,t}\left(\frac{\sigma_i-1}{\sigma_i}\right)} &= \frac{w_{i,t}}{p_{i,t}} \qquad (3)\\ \lambda_{i,t}\left(\frac{X_{i,t}}{y_{i,t}}\right)^{-\frac{1}{\sigma_{i,t}}} e^{z_{i,t}\left(\frac{\sigma_{i,t}-1}{\sigma_{i,t}}\right)} &= \frac{p^X_{i,t}}{p_{i,t}} \qquad (4)\end{aligned}$$

and the expenditure share of each $x_{i,j}$ is pinned down by $\frac{p_{j,t}}{p_i^X}\frac{x_{i,j}}{X_i} = \alpha_{i,j}$. Combining the first order conditions (3) and (4), we get that that relative demand between labor and the intermediates bundle is

$$\frac{X^d_{i,t}}{l^d_{i,t}} = \left(\frac{1-\lambda_i}{\lambda_i}\frac{p^X_{i,t}}{w_t}\right)^{-\sigma_i} \qquad (5)$$

The larger the elasticity of substitution σ_i the larger will be the adjustment to relative demand due to a change in relative prices.

2.1.2 Household Consumption and Labor Supply

The representative agent chooses how much to work and consume by maximizing utility according to

$$\begin{aligned}\max_{l_{i,t},c_{i,t}} \quad & \gamma(l_t)\prod_{i=1..n} c_{i,t}^{\beta_i} \qquad (6)\\ s.t. \quad & \sum_{i=1..n} p_{i,t}c_{i,t} = \sum_{i=1..n} w_{i,t}l_{i,t}\\ & \sum_{i=1..n} l_{i,t} = l_t\end{aligned}$$

where $\gamma(l_t)$ is disutility from hours worked and consumption utility is a Cobb-Douglas aggregate over goods produced from sectors $i = 1..n$, with $\sum_{i=1..n}\beta_i = 1$. In each period, the household decides how much consumption to allocate in each good and how much to work in each sector. Combining the first order conditions for goods i and j yields that their relative expenditure is pinned down by

$$\frac{p_{i,t}c_{i,t}}{p_{j,t}c_{j,t}} = \frac{\beta_i}{\beta_j} \qquad (7)$$

Correspondingly, the expenditure share for good j is pinned down by [2]

$$\frac{p_{j,t}c_{j,t}}{\sum_{i=1..n} wl_{i,t}} = \beta_j \tag{8}$$

In Appendix A1., we show that aggregate labor supply l_t by the representative household in this economy will be constant.

2.1.3 Competitive Equilibrium

Goods markets: Each sector's output can be used either for consumption or as intermediate good in the production of another sector:

$$y_{i,t} = c_{i,t} + \sum_{j=1..n} x_{j,i} \tag{9}$$

Labor markets: With a constant aggregate supply and full mobility of labor, wages are equalized across industries.[3] Hence, the common wage w is determined by aggregate demand and supply of labor while equilibrium hours worked in each industry will be pinned down by labor demand:

$$\bar{l}^s = \sum_{i=1..n} l_i^d$$

2.1.4 Aggregate Demand

Final demand, which will be equal to the Gross Domestic Product, is measured by the constant returns aggregator over individual goods at the optimal household choice:

$$Y_t = \prod_{i=1..n} \left(c_{i,t}^{\star}\right)^{\beta_i}$$

2.2 Shock propagation and GDP resilience

Shock propagation in a multi-sector model is channeled by inter-sectoral demand and supply as well as by consumption behavior. A well known result by Hulten (1978) states that the first order impact on GDP of a productivity shock in sector j

[2] Relaxing the unit elasticity of substitution between goods would also introduce interesting non-linearities on the consumption side but this goes beyond the scope of this paper.

[3] Please see Appendix A1.

can be summarized by the sector's Domar weight, which is the sales share of sector i in total consumption (GDP):

$$\frac{dln(Y)}{dz_{j,t}} = \frac{p_{j,t}y_{j,t}}{\sum_{i,t} p_{i,t}c_{i,t}} \tag{10}$$

This is a non-parametric result as it holds for a general class of constant returns to scale production functions, while it is exact when production functions have unit elasticity of substitution such as in the Cobb-Douglas case. In the latter case, the sales share and the input-output matrix is constant.[4] What this implies is that the transmission mechanism of the shock is constant, shutting down interesting non-linearities. In our setup, the CES form of the production function leads to a non-constant transmission mechanism, and hence resilience will be affected by inter-sectoral trade and sectoral production possibilities. The following result derives the Domar weight consistent with the general equilibrium model presented above.

Proposition 1: *In a multisectoral economy with CES production functions and competitive markets, the Domar weight of each sector equals:*

$$\frac{p_{j,t}y_{j,t}}{\sum_{i,t} p_{i,t}c_{i,t}} = \beta_j + \sum_{i=1..n} \beta_i \alpha_{i,j} \frac{y_{i,t}}{c_{i,t}} \phi_{i,t}$$

where

$$\phi_{i,t} \equiv \frac{\lambda_i}{\lambda_i + (1-\lambda_i)\left(\frac{l_{i,t}}{X_{i,t}}\right)^{\frac{\sigma_i - 1}{\sigma_i}}} = \frac{p^X_{i,t}X_{i,t}}{w_t l_{i,t} + p^X_{i,t}X_{i,t}}$$

is the expenditure share of intermediate goods.

Proof: Please see Appendix A1.

The impact of a sectoral Hicks neutral shock on GDP is thus equal to

$$\frac{dln(Y)}{dz_{j,t}} := \mathcal{D}_{j,t} = \beta_j + \sum_{i=1..n} \alpha_{i,j}\phi_{i,t}\mathcal{D}_{i,t} \tag{11}$$

The Domar weight $(\mathcal{D}_{j,t})$ depends on the constant consumption share β_j, which measures the direct impact of a shock to sector j, and the indirect effects of the shock to other sectors, which are customer industries of sector j. Supply shocks

[4] Baqaee and Farhi (2019) have generalized Hulten (1978)'s result to second order effects and highlighted the importance of the microeconomic details of the production structures.

propagate only downstream and upstream suppliers remain unaffected[5]. More compactly, the vector of sectoral Domar weights $\mathbf{D}_t$ is determined as follows

$$\mathbf{D}_t = (I - \mathbf{A}\boldsymbol{\Phi}_t)^{-1}\mathbf{b} \tag{12}$$

where $\mathbf{A}\boldsymbol{\Phi}_t$ is the state dependent input-output matrix.[6]

When the production function takes the Cobb-Douglas form, the expenditure share in Proposition 1 is constant and equal to the share parameter, λ_i. In this case the Domar weight does not depend on labor or intermediate goods supply $(l_{i,t}, X_{i,t})$, which implies the absence of higher order effects. When the elasticity of substitution between labor and intermediate goods deviates from unity, the propagation of the shock is no longer deterministic. It is therefore important to analyze how the propagation of the shock differs from the Cobb Douglas case and under which conditions the propagation is relatively muted or amplified.

Since the expenditure share of intermediate goods is equal to λ_i in the Cobb-Douglas specification, it is immediate that the propagation of the shock is smaller (larger) when the expenditure share is smaller (larger) than λ_i. Expressing $\phi_{i,t}$ in terms of the relative expenditure share and rearranging, we must have that dampening (amplification) holds when the marginal rate of technical substitution (MRTS) is lower (higher) than the one that corresponds to the Cobb-Douglas case:

$$MRTS \equiv \frac{\frac{\partial y_{i,t}}{\partial x_{i,t}}}{\frac{\partial y_{i,t}}{\partial l_{i,t}}} \lesseqgtr \frac{\lambda_i}{1-\lambda_i}\frac{l_{i,t}}{X_{i,t}} \tag{13}$$

This is also a non-parametric result, which if specialized to the CES production function, it boils down to whether the following conditions are satisfied:

$$\left(\frac{\sigma_i - 1}{\sigma_i}\right) ln\left(\frac{X_{i,t}}{l_{i,t}}\right) \lesseqgtr 0$$

When $\sigma_i = 1$, the relative abundance of the two factors is irrelevant for the propagation of the shock and symmetrically, when $X_{i,t} = l_{i,t}$, the elasticity of substitution is also irrelevant. Otherwise, when both σ_i and $X_{i,t}/l_{i,t}$ deviate from unity, the am-

[5]See also Acemoglu, Akcigit, and Kerr (2016) for upstream vs. downstream propagation.

[6]We define the I-O matrix as the matrix of expenditure shares of intermediate inputs, which are by construction equal to the expenditure share of the intermediate composite $\phi_{i,t}$ weighted by $\alpha_{i,j}$.

plification or dampening depends on the interplay between the curvature of the production isoquant and the relative abundance of the two factors. In Table 1 we spell out the conditions for amplification ($\phi > \lambda$) or dampening ($\phi < \lambda$).

	$\frac{X_{i,t}}{l_{i,t}} > 1$	$\frac{X_{i,t}}{l_{i,t}} < 1$
$\sigma_i < 1$	$\phi_{i,t} < \lambda_i$	$\phi_{i,t} > \lambda_i$
$\sigma_i > 1$	$\phi_{i,t} > \lambda_i$	$\phi_{i,t} < \lambda_i$

Table 1: Amplification versus Dampening

To build intuition, we consider these cases in Figure 2, which presents the isoquants that correspond to a CES production function with gross substitutability (blue) and gross complementarity (red). The Cobb Douglas case would be a horizontal line, representing the case in which the relative cost share stays constant - independently of $ln(X/L)$.

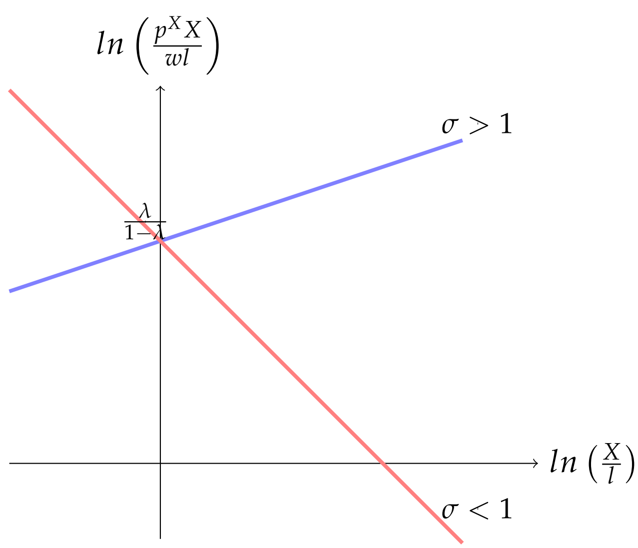

Figure 2: When $\sigma > 1$, the relative cost share $\frac{p^X X}{wl}$ is an increasing function of relative quantity, as a higher relative quantity does not decrease much the marginal rate of technical substitution, and hence the relative cost increases. When $\sigma < 1$, a higher relative quantity decreases the marginal rate of technical substitution more than proportionately, and hence the relative cost decreases. When $\sigma = 1$, the relative cost share is constant at $(\lambda/(1-\lambda))$ for all values of the relative quantities.

If inputs are gross substitutes, a producer tries to maximize the use of the cheaper input and minimize the use of the more expensive factor. If $X > l$, intermediate products are relatively less expensive, an increase of p^X would still yield the producer to demand as much as possible X, which results in a larger exposure to the intermediate factor and thus increases the Domar weight. On the contrary, if $X < l$, intermediate inputs are relatively more expensive, a shock results in a decrease in demand, resulting in a reduction of the Domar weight.

3 Empirical Methodology

In the previous section, we have shown that the production parameters that influence Domar weights are the elasticity of substitution and the share parameter. In this section we empirically explore the effects of digitalization on these parameters. We will therefore allow the latter to vary over time and space. As a byproduct of our empirical approach, we also explore the effects of digitalization on input-specific productivities. By employing standard production theory, we will rely on a quasi-structural approach to identify unobserved elements of the production process. In contrast to the theoretical model, in this section we generalize the production structure by accommodating for input-specific productivities, as well as a value-added production function that utilizes capital. This allows for a more realistic specification that is in line with the way the data we use were constructed.

Production in Sector i, $y_{i,t}$, is described by a two level constant elasticity of substitution (CES) production function as follows[7]:

$$y_{i,t} := \left((1-\lambda_{i,t})(\nu_{i,t}^{VA} VA_{i,t})^{\frac{\sigma_{i,t}-1}{\sigma_{i,t}}} + \lambda_{i,t}(\nu_{i,t}^{X} X_{i,t})^{\frac{\sigma_{i,t}-1}{\sigma_{i,t}}} \right)^{\frac{\sigma_{i,t}}{\sigma_{i,t}-1}} \tag{14}$$

where $VA_{i,t}$ is value-added and $X_{i,t}$ are intermediate inputs in the higher level nesting. $\lambda_{i,t}$ and $\sigma_{i,t}$ are the share parameter of *effective* intermediate inputs and the elasticity of substitution, respectively. In turn, in the lower level nesting, value-added itself is a result of firm decisions about the employment of capital and labor.

[7] 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).

In particular, the production function for value-added is as follows:

$$VA_{i,t} = \left(\alpha_{i,t} (\nu^k_{i,t} k_{i,t})^{\frac{\gamma_{i,t}-1}{\gamma_{i,t}}} + (1-\alpha_{i,t})(\nu^l_{i,t} l_{i,t})^{\frac{\gamma_{i,t}-1}{\gamma_{i,t}}} \right)^{\frac{\gamma_{i,t}}{\gamma_{i,t}-1}} \tag{15}$$

where $\alpha_{i,t}$ and $\gamma_{i,t}$ are the share parameter of *effective* capital and the elasticity of substitution between effective capital and labor, respectively. Finally, $(\nu^{VA}_{i,t}, \nu^X_{i,t}, \nu^k_{i,t}, \nu^l_{i,t})$ are the factor specific productivities which are assumed to follow an idiosyncratic but deterministic growth path: $ln(v)^q_{i,t} = ln(v)^q_{i,t-1} + g^q_i, \quad \text{for} \quad q \in \{VA, X, k, l\}$. [8]

3.1 Two stage budgeting

Instead of relying on a primal approach, we follow the expenditure minimization (dual) approach. This has several advantages, including the fact that we do not have to specify the demand side of the market $(y^d_{i,t})$, and can therefore accommodate imperfect competition in product markets as well as price rigidities.

More particularly, each representative firm in sector j engages in a two stage budget allocation, where it first decides about 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 labor to employ. Analytically, the representative firm chooses inputs to minimize total costs:

$$\begin{aligned} \min_{VA, X_t} \quad & p^{VA}_{i,t} VA_{i,t} + p^X_{i,t} X_{i,t} \\ s.t. \quad & y_{i,t} \geq y^d_{i,t} \end{aligned} \tag{16}$$

where $p^{VA}_{i,t} VA_{i,t} + p^X_{i,t} X_{i,t}$ is the total cost of production. Dividing the first and the second first order conditions, we get

$$\frac{1-\lambda_{i,t}}{\lambda_{i,t}} \left(\frac{VA_{i,t}}{X_{i,t}} \right)^{-\frac{1}{\sigma_{i,t}}} \left(\frac{\nu^{VA}_{i,t}}{\nu^X_{i,t}} \right)^{1-\frac{1}{\sigma_{i,t}}} = \frac{p^{VA}_{i,t}}{p^X_{i,t}} \tag{17}$$

Given an optimal choice for $VA_{i,t}$, denoted by $VA^{opt}_{i,t}$, the representative firm solves

[8] 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 elasticity of substitution is impossible (Diamond, McFadden, and Rodriguez, 1978).

the following second stage problem:

$$\min_{k_{i,t},l_{i,t}} \quad w_{i,t}l_{i,t} + p^k_{i,t}k_{i,t} \qquad (18)$$
$$s.t. \quad VA_{i,t} \geq VA^{opt}_{i,t}$$

Dividing the first order condition with respect to capital and labor yields

$$\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\left(\frac{k_{i,t}}{l_{i,t}}\right)^{-\frac{1}{\gamma_{i,t}}}\left(\frac{\nu^K_{i,t}}{\nu^l_{i,t}}\right)^{1-\frac{1}{\gamma_{i,t}}} = \frac{p^k_{i,t}}{w_{i,t}} \qquad (19)$$

Expressions (19) and (17) are going to form the basis of our empirical approach. Taking logs results in the following relative input demand functions, where we have normalized initial productivities to be equal, $z^k_{i,0} = z^l_{i,0}$ and $z^{VA}_{i,0} = z^X_{i,0}$:

$$ln\left(\frac{k_{i,t}}{l_{i,t}}\right) = \gamma_{i,t}ln\left(\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\right) - \gamma_{i,t}ln\left(\frac{p^k_{i,t}}{w_{i,t}}\right) + (\gamma_{i,t}-1)(g^k_i - g^l_i)t \qquad (20)$$

$$ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) = \sigma_{i,t}ln\left(\frac{1-\lambda_{i,t}}{\lambda_{i,t}}\right) - \sigma_{i,t}ln\left(\frac{p^{VA}_{i,t}}{p^X_{i,t}}\right) + (\sigma_{i,t}-1)(g^{VA}_i - g^X_i)t \qquad (21)$$

Relative factor demands for inputs are therefore decreasing in relative prices. If inputs are gross substitutes, then biased technical progress increases further the demand of the more productive input.

4 Econometric Model

Given data on relative quantities and prices for the factors of production, we can in principle proceed with estimating the 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 marginal costs. The second challenge has to do with controlling the dimensions of these coefficients, as it is infeasible to estimate elasticities and value shares that vary over time and space in an unrestricted way. Since we are mostly interested in identifying the effect of digitalization on these coefficients, we will directly allow coefficients to be functions of covariates $\mathcal{X}_{i,t}$.

Allowing for functional coefficients results in the following econometric specification for equation (21):

$$ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) = c_0(\mathcal{X}_{i,t}) + c_1(\mathcal{X}_{i,t})ln\left(\frac{p^{VA}_{i,t}}{p^{X}_{i,t}}\right) + c_2(\bar{\mathcal{X}}_{i,t})t + \epsilon_{i,t} \tag{22}$$

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: [9]

$$\begin{aligned} ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) &= c^i_{0,0} + c^T_{0,1}\tilde{\mathcal{X}}_{i,t} + c_{1,0}ln\left(\frac{p^{VA}_{i,t}}{p^{X}_{i,t}}\right) + c^T_{1,1}\tilde{\mathcal{X}}_{i,t} \otimes ln\left(\frac{p^{VA}_{i,t}}{p^{X}_{i,t}}\right) \\ &\quad + c_{2,0}t + c^T_{2,1}\bar{\mathcal{X}}_{i,t} \otimes t + u_{i,t} \end{aligned}$$

We estimate the reduced form coefficients $(c^T_{0,1}, c_{1,0}, c^T_{1,1}, c_{2,0}, c^T_{2,1})$ using a within group estimator. Hence, the implied estimate for the linearized form of the elasticity of substitution between value added and intermediate inputs is equal to $\sigma_{i,t} = c_{1,0} + c^T_{1,1}\tilde{X}_{i,t}$, while the relative growth rate of productivities is equal to $g^{VA/X}_i := g^{VA}_i - g^X_i = c_{2,0} + c^T_{2,1}\bar{\mathcal{X}}_{i,t}$. Share parameters $\alpha_{i,t}$ are recovered using that

$$ln\left(\frac{1-\lambda_{i,t}}{\lambda_{i,t}}\right) = \frac{1}{\sigma_{i,t}}ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) + ln\left(\frac{p^{VA}_{i,t}}{p^{X}_{i,t}}\right) - \frac{\sigma_{i,t}-1}{\sigma_{i,t}}\left[(g^{VA}_{i,t} - g^{X}_{i,t})t\right] \tag{23}$$

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 $(\gamma_{i,t}, \alpha_{i,t}, g^{k/l}_i)$ in equation (20).

[9] 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.

4.1 Data and Measurements

We utilize country-industry data from the European Union capital, labor, energy, materials, and service inputs database (also known as the EU KLEMS Growth and Productivity accounts, see e.g. O'Mahony and Timmer (2009)). Our unit of analysis, indexed by i, is at the country-industry level.[10] 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 $CAP_{j,t} = p^k_{j,t} K_{j,t}$. In EU KLEMS, $p_{k,j,t}$ 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.

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). 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 information 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. 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, resulting in a situation in which data from the last periods might have little value for production in the current period.[11]

[10] 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.

[11] The depreciation rate of SoftDB in KLEMS is similar to that of IT capital, but this is an average rate and includes software, which to our assessment has a lower depreciation rate than data.

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 the Appendix A3. In the set of covariates $\mathcal{X}_{i,t}$ used for modeling the varying coefficients, we control for factors that might influence the elasticity of substitution at highly aggregated sectoral levels (at one/two digits). Such factors can be the level of development, as measured by the lagged capital to labor ratio, or exogenous business cycle developments, as captured by the CBOE Volatility index (VIX).

Both factors reflect the idea that the aggregate elasticity of substitution in a one- or two-digit industry will be influenced by intersectoral substitution in three- and higher digit industries as a result of adjustments in consumption due to growth or economic fluctuations (see e.g. Knoblach and Stöckl (2020)). Furthermore, we control for other technological factors such as investment in research and development by including them as additional terms that interact with relative input prices.

4.2 Identification

Given the final model specification in (22), 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 arising from input financing frictions. An example of the latter arises in the value-added - intermediate input choice, where limited commitment places an upper bound on how much of the firm revenue (η_i) may be used to buy inputs. This leads to a constraint of the form $\zeta_{1,i} VA_i P_i^{VA} + \zeta_{2,i} X_i P_i^X \leq \eta_i p_{i,t} y_{i,t}$, where η_i is the share of revenue that can be used to finance expenditure proportions $\zeta_{1,i}$ on value-added and $\zeta_{2,i}$ on intermediate inputs respectively.[12] In our case this yields a relative demand equation distorted by the Lagrange multiplier μ_i

$$\frac{1-\lambda_i}{\lambda_i}\left(\frac{VA_i}{X_i}\right)^{-\frac{1}{\sigma_i}}\left(\frac{\nu_{i,t}^{VA}}{\nu_{i,t}^{X}}\right)^{1-\frac{1}{\sigma_i}} = \frac{p_i^{VA}}{p_i^X} + \frac{1-\zeta_{1,i}\mu_i}{1-\zeta_{2,i}\mu_i} \tag{24}$$

[12] See e.g. Bigio and La'O (2020) and Miranda-Pinto and Young (2022).

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 cancels out in 20 and 21.[13]

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 from 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 unlikely 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 if input financing frictions as in (24), where the distortion to the relative price of value-added and intermediate goods in the US will be correlated with the distortion in Europe. We control for such disturbances using time fixed effects and the VIX in alternative specifications. The identifying assumption is that controlling for time fixed effects or the VIX is sufficient to purge this common component.

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 elasticity of substitution. 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.

[13]The only exception is the wedge of an input financing friction such as (24), which would respond to a common input-specific shock in value-added and intermediate inputs if $\zeta_{1,i} \neq \zeta_{2,i}$.

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 restrictions and underidentification.[14]

4.3 Elasticities of Substitution and Digitalization

Table 2 presents the estimates for the elasticity of substitution between capital and labor. The constant component of the elasticity yields a value for γ close to 0.191, 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 0.089 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 elasticity of substitution, with a similar impact to IT intensity. The mean estimate in the benchmark specification (2) is 0.096. 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 (0.191, 0.073 and 0.111 respectively). For the non-service sectors the corresponding estimates are 0.222, 0.076 and 0.089 (please see Table 5 for the classification).

Similar to the elasticity of substitution between capital and labor, the next set of empirical results show that a larger share of Information Technology related capital stocks brought forward from the last period have a positive effect on the elasticity of substitution between value-added and intermediate inputs. In particular, the marginal effect is estimated to be relatively large (0.128). Furthermore, there is some evidence that a higher intensity in SoftDB and R&D are positively associated with the elasticity of substitution.

[14]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).

	(1)	(2)	(3)	(4)
	Capital to Labor ratio $\left(\frac{k}{l}\right)$			
$\frac{w}{p^k}$	0.159^{**}	0.191^{***}	0.177^{***}	0.101
	[0.052,0.266]	[0.105,0.277]	[0.095,0.259]	[-0.065,0.266]
		(0.0939, 0.334)		
IT share $\times \left(\frac{w}{p^k}\right)$	0.083^{*}	0.089^{***}	0.094^{***}	
	[0.003,0.164]	[0.049,0.128]	[0.053,0.136]	
		(0.044,0.169)		
CT share $\times \left(\frac{w}{p^k}\right)$	0.000918			
	[-0.002,0.004]			
Inv. share $\times \left(\frac{w}{p^k}\right)$				
S&D	-0.0133			
	[-0.098,0.072]			
Cap. share $\times \left(\frac{w}{p^k}\right)$				
S&D	-0.005			
	[-0.079,0.070]			
Devel. Level$\times \left(\frac{w}{p^k}\right)$	0.093^{***}	0.096^{***}	0.107^{***}	
	[0.053,0.133]	[0.066,0.126]	[0.072,0.143]	
		(0.053,0.152)		
VIX^2	0.069^{*}	0.056^{**}		
	[0.010,0.128]	[0.015,0.097]		
No. Observations	4371	4371	4371	4580
Count.-Sec. F.E.	✓	✓	✓	✓
Time FE	-	-	✓	✓
Constant γ	-	-	-	✓

Table 2: Impact of Digitalization the Elasticity of Substitution between k and l. For brevity we do not present the estimates on the interaction terms of digitalization intensities with the constant and with time. Specification (1) includes all relevant interaction terms. Specification (2) drops jointly insignificant terms while Specification (3) includes time fixed effects instead of the VIX. Specification (4) reports the estimates obtained without controlling for digitalization related heterogeneity. For the benchmark specification 2, in $(,)$ we report the projection of the robust 90% confidence set based on inverting the Conditional Likelihood ratio test .

	(1)	(2)	(3)	(4)
	Value added to Intermediate Inputs ratio			
$\frac{p^X}{p^{VA}}$	0.399***	0.534***	0.554***	0.662***
	[0.244,0.554]	[0.380,0.688]	[0.392,0.716]	[0.473,0.851]
		(0.386, 0.681)		
IT share $\times \left(\frac{p^X}{p^{VA}}\right)$	0.061	0.128*	0.129*	
	[-0.064,0.186]	[0.007,0.249]	[0.008,0.249]	
		(0.005, 0.3138)		
CT share $\times \left(\frac{p^X}{p^{VA}}\right)$	-0.015			
	[-0.108,0.078]			
Inv. share $\times \left(\frac{p^X}{p^{VA}}\right)$				
S&D	-0.095			
	[-0.305,0.116]			
Cap. share $\times \left(\frac{p^X}{p^{VA}}\right)$				
S&D	0.136	0.099	0.102*	
	[-0.023,0.295]	[-0.00001,0.198]	[0.005,0.200]	
		(-0.041, 0.25)		
R&D $\times \left(\frac{p^X}{p^{VA}}\right)$	0.143*	0.139*	0.138*	
	[0.028,0.260]	[0.025,0.253]	[0.025,0.251]	
		(0.032, 0.242)		
VIX	0.013	0.018*		
	[-0.003,0.029]	[0.002,0.033]		
No. Observations	4106	4106	4106	4106
C-S Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	-	-	✓	✓
Constant Elasticity	-	-	-	✓

Table 3: Impact on the Elasticity of Substitution between VA and X.

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. The rise of IT technology has enabled firms to outsource part of their production process to other more efficient or specialized firms, while R&D is likely to have a positive effect on the extensive margin i.e. the number of firms which are more prepared to change this feature of their production process, and the number of firms which are ready to provide such goods and services as intermediate inputs. Symmetrically, what this implies is that should the price of doing so rises due to e.g. a negative productivity shock, firms will more likely substitute away from intermediate goods and services.

Finally, despite allowing for heterogeneity in σ, the constant coefficient component is also significant (0.534), 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 elasticity of substitution of 0.662, while the mean estimate in the benchmark specification with heterogeneity (specification 2) is 0.534.

4.3.1 Share Parameters

In our extensive estimation exercises, we have also investigated whether the share parameters are affected by digitalization, with no apparent evidence of such a relationship. We relegate these results to Table 1 in the Online Appendix. The constant estimates for α and λ are 0.3318 and 0.5744 respectively.

4.3.2 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.[15] Table 4 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. While this finding 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. Furthermore, we also find that

[15] Please see Appendix A4 for the way we recover unobserved productivities.

intermediate inputs' productivity growth is positively affected by a higher share of research and development in capital brought forward.[16]

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 capital intensity in software and databases.

The empirical results can thus be summarized as follows: The intensity of digitalization as measured by the information technology share has an impact on the elasticity of substitution between capital and labor and between value-added and intermediate inputs, while higher intensity in software and databases has a uniform impact on labor and capital productivities.

Focusing on the effects on the elasticities of substitution between factor inputs, the empirical evidence suggests that digitalization is one of the sources of structural change in the productive structure of the economy. In the rest of the paper we will analyze the implications of this change for the ability of the productive structure to mitigate the effects of sectoral shocks, while we will also provide a microfoundation that can potentially explain the empirical relationship between digital intensity and the elasticity of substitution.

Before doing so, we briefly comment on some other implications that our estimates have for understanding technologically biased technical change and the labor share of income. 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 at best. As can be seen from rearranging the relative demand equations for capital and labor,

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

explaining the decline in the relative share of value-added by which labor is re-

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

	Δz^{VA}	Δz^{X}	Δz^{L}	Δz^{K}	$\Delta z^{VA}_{KLEMS,TFP}$
IT cap.	0.150	0.066	0.010	0.005	0.006
	[-0.06,0.36]	[-0.03,0.16]	[-0.05,0.07]	[-0.06,0.07]	[-0.024,0.037]
CT cap.	0.003	-0.047	-0.045	-0.038	-0.008
	[-0.205,0.206]	[-0.18,0.08]	[-0.11,0.02]	[-0.09,0.01]	[-0.03,0.05]
Inv. share					
R& D	-0.066	-0.038	0.0153	0.007	0.003
	[-0.14,0.02]	[-0.09,0.01]	[-0.01,0.04]	[-0.01,0.02]	[-0.01,0.02]
S&D	-0.081	0.006	0.020*	0.025*	0.030*
	[-0.26,0.09]	[-0.03,0.04]	[0.001,0.04]	[0.004,0.05]	[0.01,0.05]
Cap. share					
R&D	0.133	0.122*	0.011	0.024	0.011
	[-0.01,0.28]	[0.02,0.23]	[-0.02,0.04]	[-0.01,0.06]	[-0.01,0.04]
S&D	-0.037	-0.028	0.00724	-0.002	0.036*
	[-0.12,0.04]	[-0.07,0.02]	[-0.04,0.05]	[-0.05,0.05]	[0.01,0.07]
VIX	-0.127	0.049	-0.054***	-0.057***	-0.061***
	[-0.48,0.22]	[-0.06,0.16]	[-0.07,-0.04]	[-0.08,-0.03]	[-0.08,-0.05]
Devel. Lev.	1.337	0.147	0.286**	0.258**	0.149**
	[-1.28,3.95]	[-0.25,0.55]	[0.09,0.48]	[0.06,0.45]	[0.05,0.25]
No.of Obs.	3602	3590	4768	4528	4646
C-S F.E.	✓	✓	✓	✓	✓
$\geq$ 2 lags	✓	✓	✓	✓	✓
t & t^2	✓	✓	✓	✓	✓

Table 4: Impact of Digitization on Input Specific Productivity Growth.

munerated falls on either relative productivity growth or the decline in the price of investment goods, such as in Karabarbounis and Neiman (2013). Our empirical results suggest 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. In addition, since digitalization increases $\gamma_{i,t}$, it unconditionally decreases the labor share through the first term as the share parameters are not affected, while 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 and automation. How much this contributes to the overall effect is of course an interesting question that goes beyond the scope of this paper. Finally, note that while we do not explicitly account for markups, since markups do contribute to a decline in both labor and capital shares (see De Loecker, Eeckhout, and Unger (2020) for example), we expect the effect on the relative expenditure share to be relatively muted.

5 Elasticity of substitution and resilience

In light of the empirical results of the previous section, we revisit our analytical model of Section 2 and study the impact of a higher elasticity of substitution on Domar weights, and hence the effect of a higher elasticity of substitution on the propagation of a sectoral TFP shock to GDP. The fact that our empirical results for the impact of digitalization on both γ and σ are qualitatively and quantitatively similar makes our analytical model sufficient for this kind of exercise. Hence, we consider capital as an intermediate input in this model.[17]

Based on Proposition 1, we can see that the question whether an increase in $\sigma_{i,t}$ propagates or dampens the effect of shocks depends on the change of $\phi_{i,t}$, which is the expenditure share of the intermediate good composite. Therefore, we focus on how this expenditure share is affected by a higher elasticity of substitution:

Proposition 2: *In the same economy as in Proposition 1, the impact of a marginal increase of sectoral elasticity of substitution is equal to:*

$$\frac{\partial \mathbf{D}_t}{\partial \sigma_j} = (I - \mathbf{A}\mathbf{\Phi}_t)^{-1}\mathbf{A}\frac{\partial \mathbf{\Phi}_t}{\partial \sigma_j}(I - \mathbf{A}\mathbf{\Phi}_t)^{-1}\mathbf{b} \tag{25}$$

where the *jth* column of $\frac{\partial \mathbf{\Phi}_t}{\partial \sigma_j}$ is nonzero, with its *kth* element equal to

$$\alpha_{j,k}\frac{d\phi_{j,t}}{d\sigma_{j,t}} \quad = \quad -\alpha_{j,k}\frac{\phi_{j,t}^3}{1-\phi_{j,t}}\frac{1}{\sigma_{j,t}}\ln\left(\frac{l_{j,t}}{X_{j,t}}\right)$$

Proof: Please see Appendix A2.

[17] This is consistent with the literature see e.g. Baqaee and Farhi (2019); Acemoglu, Akcigit, and Kerr (2016); Baqaee and Rubbo (2022).

While the magnitude of the effect does depend on structural parameters, its sign does not, as it only depends on whether $(l_{i,t}/X_{i,t})$ is smaller or larger than unity. If production is labor intensive, $(l_{i,t}/X_{i,t}) > 1$, shock propagation will be dampened after an increase of the elasticity of substitution. If production uses comparably little labor, $(l_{i,t}/X_{i,t}) < 1$, an increase in the elasticity of substitution augments shock propagation in the economy. The intuition for these results can be found by considering the relative expenditure share between intermediate inputs and value-added, as $\phi_{i,t}$ is a monotone function of this share:

$$ln\left(\frac{X_{i,t}p^X_{i,t}}{l_{i,t}w_{i,t}}\right) = ln\left(\frac{\lambda_{i,t}}{1-\lambda_{i,t}}\right) + \left(1-\frac{1}{\sigma_{i,t}}\right) ln\left(\frac{X_{i,t}}{l_{i,t}}\right) \tag{26}$$

When intermediate inputs are relatively abundant, their marginal product relative to that of value-added is low. An increase in the elasticity of substitution enables the producer to use relatively more of the cheaper input (intermediate inputs) and maximize the impact of the more expensive factor (labor), which is going to tilt the share of total expenditure towards intermediate inputs, decreasing resilience by increasing the exposure to the shocked sector. Conversely, when labor is relatively abundant, an increase in the elasticity of substitution tilts the share of total expenditure to labor and thus decreases the exposure to the shocked sector.

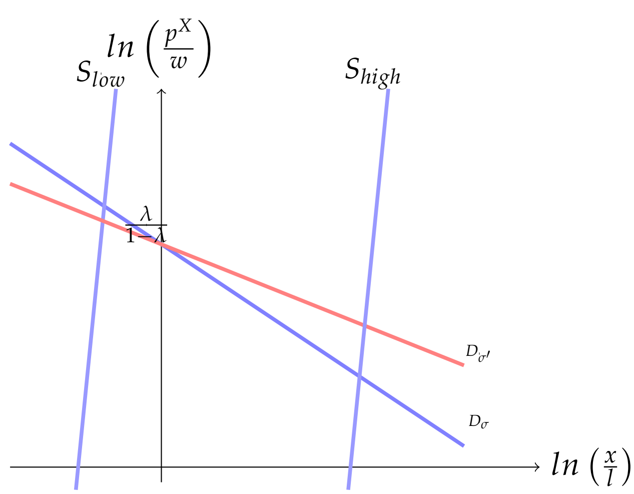

Figure 3: An increase in σ to σ' twists the relative demand curve. The position of the relative supply curve is critical for the effect on relative prices and quantities.

Figure 3 describes the effects of an increase in the elasticity of substitution on the sectoral demand schedule and thus on equilibrium values for relative quantities and price levels. We assume equilibrium values for the use of labor and intermediate inputs in all other sectors, exposing the analyzed sector to different supply curves for the factors. In the case of labor abundance (S_{low}), an increase of the elasticity tilts the demand curve of the specific sector from blue to red and thus decreases both the equilibrium values for relative quantities and relative prices. The expenditure share of intermediate inputs falls. Conversely, a relatively high supply of intermediate inputs (S_{high}) yields a higher expenditure share.

5.1 Example economy

Despite the differences in sectoral levels of digitalization, all sectors tend to digitalize further. If all sectors feature a higher level of digitalization, what will be the effect on resilience? Will higher elasticities of all sectors have an impact on resilience? As an example, consider an economy with three sectors and a network structure as shown in Figure (4). Sector 1 is sole customer to sector 2, and sector 3 is sole customer to sector 1.

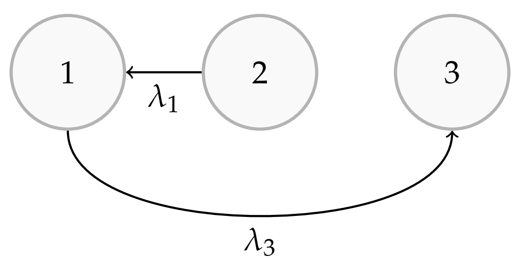

Figure 4: Roundabout Economy with no links between sector 2 and 3

Sectoral production functions are thus given as follows:

$$
\begin{aligned}
y_1 &= e^{z_1}\left((1-\lambda_1)l_1^{\frac{\sigma_1-1}{\sigma_1}} + \lambda_1 x_2^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}} \\
y_2 &= e^{z_2}\left((1-\lambda_2)l_2^{\frac{\sigma_2-1}{\sigma_2}} + \lambda_2\right)^{\frac{\sigma_2}{\sigma_2-1}} = e^{z_2}l_2 \\
y_3 &= e^{z_3}\left((1-\lambda_3)l_3^{\frac{\sigma_3-1}{\sigma_3}} + \lambda_3 x_1^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}}
\end{aligned}
$$

Taking the example of a shock to sector 1, the sectoral Domar weight is equal to

$$\mathcal{D}_1 = \frac{dln(Y)}{dz_1} = \beta_1 + \beta_3 \frac{\lambda_3}{\lambda_3 + (1-\lambda_3)\left(\frac{l_3}{x_3}\right)^{\frac{\sigma_3 - 1}{\sigma_3}}} \tag{27}$$

Due to the downstream-propagation of the shock, the indirect effect captures the sales of sector 1 to sector 3. Hence, the level of digitalization of sector 3 affects the domar weight of sector 1 by means of its elasticity of substitution. The change in sector 1's Domar weight then equals

$$\frac{d\mathcal{D}_1}{d\sigma_3} = \frac{\frac{dln(Y)}{dz_1}}{d\sigma_3} = \beta_3 \frac{d\phi_1}{d\sigma_3} = -\beta_3 \frac{(\phi_3)^3}{1-\phi_3} \frac{1}{\sigma_3} ln\left(\frac{l_3}{x_3}\right) \tag{28}$$

Consequently, higher levels of digitalization in sectors 1 (the shocked sector) and sector 2 (supplying sector 1) have no effect on resilience. Only if sector 3 (supplied by sector 1) enhances its level of digitization, resilience will be higher or lower, depending on the relative quantities in production.

5.2 Sectoral results

The analytical result in Proposition 2 proves to be useful, in the sense that determining whether a sector amplifies or dampens supply shocks when it is more digitalized depends on a simple sufficient statistic that does not depend on estimated parameters. We next use this to classify sectors in our dataset by calculating relative quantities of value-added and of the intermediate composite, $ln(VA_i/X_i)$ for each sector in each country.

Figure 5 plots $ln(X_i/VA_i) = -ln(VA_i/X_i)$, where the vertical axis varies over country and the horizontal axis varies over sectors.[18] For the sector classification, please refer to Table 5 in Appendix A6. All negative values have a dark shade, meaning that $\phi_i(\sigma_i)$ decreases with an increasing level of the elasticity of substitution. In these cases, a higher level of digitalization increases economic resilience. All lighter shades represent country-sector combinations with an increasing $\phi_i(\sigma_i)$, meaning that the higher elasticity of substitution increases the Domar weight of the corresponding industry in the specific country.

[18] Data on shorter time periods can be seen in the Online appendix.

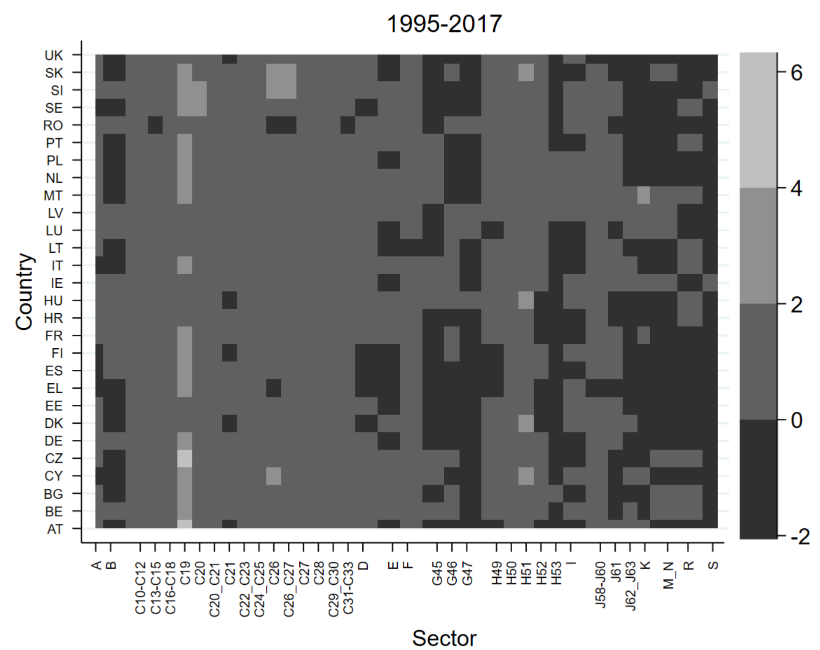

Figure 5: Relative Intensity of Intermediate Inputs ln $\left(\frac{X}{VA}\right)$

The sign of $ln(X_i/VA_i)$ is positive for most 2-digit sectors, resulting in a reinforcing effect after a shock and lower resilience. 1-digit sectors show smaller values, which results from the fact that intermediate goods within a 1-digit sector are omitted whenever sectors are subsumed within one sector. Thus, the overall impact is dependent on the level of aggregation. If firm-level data is regarded as a first choice regarding the measurement of resilience, we can infer from our data that the effect of digitalization on resilience will be mostly negative.

Generally, most sectors have quite homogeneous signs of $ln(X/VA)$ across countries, which reiterates the fact that resilience of sectors should be rather dependent on the type of industry and not on country-specific characteristics. Overall, we can conclude from our results that an increase in unconditional elasticities has a mixed impact on resilience.

5.2.1 Decreasing resilience over time

The evolution of the relative abundance of intermediate inputs to value-added over time gives an indication of how the impact of higher digitalization on resilience changes. Figure 6 shows an increase of the ratio $ln(X_i/VA_i)$ over time

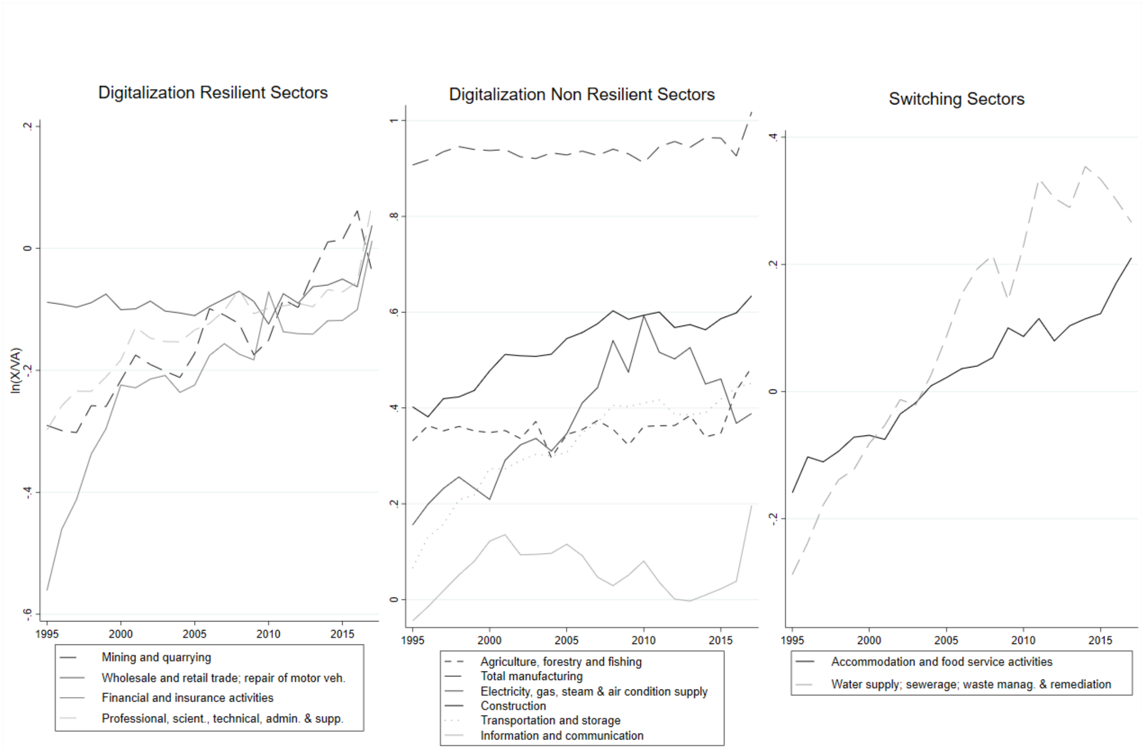

Figure 6: Sectors and Resilience over time

and thus a trend towards lower resilience in most sectors, especially those with negative values of $ln(X/VA)$ at the beginning of the time horizon. Noticeable exceptions are the wholesale sector, "total manufacturing", "agriculture, forestry and fishing" and "information and communication". Their ratio of $ln(X/VA)$ remained rather constant across time. Three of these sectors are non-resilient sectors, i.e. sectors with an amplifying effect to shocks if their level of digitalization gets increased. Generally, we can classify the sectors as resilient sectors with $ln(X/VA) < 0$, which are mainly service sectors. The group of non-resilient sectors ($ln(X/VA) > 0$) consists of mainly sectors with industrial production. Sectors which start with a dampening effect and show an amplifying effect at the end of the sample ("switching sectors") include both services and industrial production.

We conclude that resilience decreased over time as a consequence of changes in the elasticity of substitution, which are partially attributed to digitalization given our earlier empirical results. Idiosyncratic shocks had more impact on GDP in 2017 compared to 1995. Consequently, a shock to an economy with a higher level of digitalization resulted in larger consequences for GDP in 2017 than in 1995.

6 Technology and the elasticity of factor substitution

Given the evidence that digitalization changes production structures and, more precisely, it increases the flexibility of economies to choose between inputs to production, we attempt to provide a coherent theoretical explanation in this section. Our empirical measure of digitalization is its share in different types of capital stocks, which is a result of adoption and utilization of digital technologies that become available for commercial and industrial purposes. This is akin to a quality adjustment in the composition of the capital stock that does not alter the total index, and hence the model presented earlier in the paper can be considered as a reduced form of a deeper mechanism in place. The notion of a quality adjustment in inputs can be rationalized by the choice of technologies from a technology menu, which is changing because of the introduction of new digital technologies. 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 to be used in production as well as their augmentation by factor specific productivities. The latter are chosen from a technology frontier, which consists of the most efficient feasible combinations.

While technology is fixed in the very short run, it is more likely that in the longer run firms will be able to optimally choose the technology they use. We think of the introduction of new digital technologies as a force that changes the form of the technology menu. Importantly, the literature has shown that the optimal choice of technologies leads to an endogenous determination of the elasticity of substitution between inputs. We deem that this framework provides a solid basis for providing microfoundations to our empirical findings. Note that in contrast to León-Ledesma and Satchi (2019), we do not attribute the increase in the elasticity of substitution to the increased flexibility in technology choice over the long run, but we rather consider changes in the technology frontier themselves. We think of the latter as a more plausible explanation of our empirical findings.

Consider a representative firm of sector i having the possibility to choose their inputs for different sets of technologies. In our setup, this translates to a choice over value-added (labor) and intermediate inputs for different factor augmenting productivities $e^{z^{VA}_{i,t}}$ and $e^{z^{X}_{i,t}}$ respectively. 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 profit maximization problem. Since the choices of the firms are conditional on the technology combinations, we call these production functions conditional production functions.[19] Some of the conditional production functions will be chosen by firms, whereas others are not optimal and thus will not be applied. The set of all optimal conditional production functions defines the unconditional production function.[20] This function constitutes an envelope of all choices of optimal conditional production functions and describes the production function firms can choose if they are able to decide about both technologies and input quantities.

The set of technologies that firms can choose from are specified in the technology frontier in $\left(e^{z^{VA}_{i,t}}, e^{z^{X}_{i,t}}\right)$-space (cf. Caselli and Coleman (2006) and Growiec (2008)), where ω, θ and B are exogenous parameters and strictly positive:

$$\left(e^{z^{VA}_{i,t}}\right)^{\omega_{i,t}} + \theta_{i,t}\left(e^{z^{X}_{i,t}}\right)^{\omega_{i,t}} = B_{i,t} \tag{29}$$

B defines the overall level of productivity, whereas ω and θ change the shape and thus the trade-off between both productivity parameters. Digitalization is an exogenous change to the technology frontier and can have an impact on all three parameters. It results in a new set of techniques, which changes the trade-off between all existing technologies and thereby alters the level and curvature of the technology frontier. Rearranging terms of the technology frontier yields

$$\left(e^{z^{VA}_{i,t}} B_{i,t}^{-\frac{1}{\omega_{i,t}}}\right)^{\omega_{i,t}} + \theta_{i,t}\left(e^{z^{X}_{i,t}} B_{i,t}^{-\frac{1}{\omega_{i,t}}}\right)^{\omega_{i,t}} = 1 \tag{30}$$

We assume $e^{\tilde{z}^{VA}_{i,t}} = e^{z^{VA}_{i,t}} B_{i,t}^{-\frac{1}{\omega}}$ and $e^{\tilde{z}^{X}_{i,t}} = e^{z^{X}_{i,t}} B_{i,t}^{-\frac{1}{\omega}}$ to separate exogenous total factor productivity, $B_{i,t}^{\frac{1}{\omega}}$, and the productivities that can be chosen endogenously by firms in the model, $e^{z^{VA}_{i,t}}$ and $e^{z^{X}_{i,t}}$. The latter conforms to the trade-off of technologies

[19] 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)).

[20] Equivalent to global production function (Growiec (2018)) or long-run production function (León-Ledesma and Satchi (2019))

based on the endogenous choice framework introduced above. Furthermore, we allow for factor specific exogenous productivity shocks $\nu_{i,t}^{VA}$ and $\nu_{i,t}^{X}$ respectively. The conditional production function of becomes

$$y_{i,t} := B_{i,t}^{\frac{1}{\omega_{i,t}}} \left((1-\lambda_{i,t}) \left(\nu_{i,t}^{VA} e^{\tilde{z}_{i,t}^{VA}} VA_{i,t} \right)^{\frac{\tilde{\sigma}_{i,t}-1}{\tilde{\sigma}_{i,t}}} + \lambda_{i,t} \left(\nu_{i,t}^{X} e^{\tilde{z}_{i,t}^{X}} X_{i,t} \right)^{\frac{\tilde{\sigma}_{i,t}-1}{\tilde{\sigma}_{i,t}}} \right)^{\frac{\tilde{\sigma}_{i,t}}{\tilde{\sigma}_{i,t}-1}} \tag{31}$$

This approach enables us to measure the resilience of an industry j after an exogenous shock to TFP of another sector ($B_{i,t}^{\frac{1}{\omega}}$) while taking both exogenous productivity shifts and endogenous technology choice into account. The latter is essential since the digitalization-induced change of the elasticity of substitution requires the inclusion of a technology frontier. In this case, the cost minimizing choice for $(e^{\tilde{z}_{i,t}^{VA}}, e^{\tilde{z}_{i,t}^{X}}, e^{\tilde{z}_{i,t}^{k}}, e^{\tilde{z}_{i,t}^{l}})$ endogenizes the relative productivities as follows:

$$\left(\frac{e^{z_{i,t}^{VA}}}{e^{z_{i,t}^{X}}} \right)^{\omega_{i,t}^{VA/X} - \frac{\tilde{\sigma}_{i,t}-1}{\tilde{\sigma}_{i,t}}} = \frac{1-\lambda_{i,t}}{\lambda_{i,t}} \theta_{i,t}^{X/VA} \left(\frac{\nu_{i,t}^{VA} VA_{i,t}}{\nu_{i,t}^{X} X_{i,t}} \right)^{\frac{\tilde{\sigma}_{i,t}-1}{\tilde{\sigma}_{i,t}}} \tag{32}$$

$$\left(\frac{e^{z_{i,t}^{k}}}{e^{z_{i,t}^{l}}} \right)^{\omega_{i,t}^{k/l} - \frac{\tilde{\gamma}_{i,t}-1}{\tilde{\gamma}_{i,t}}} = \frac{\alpha_{i,t}}{1-\alpha_{i,t}} \theta_{i,t}^{l/k} \left(\frac{\nu_{i,t}^{k} k_{i,t}}{\nu_{i,t}^{l} l_{i,t}} \right)^{\frac{\tilde{\gamma}_{i,t}-1}{\tilde{\gamma}_{i,t}}} \tag{33}$$

The relative factor demand equations are similar to those in Section 2. Substituting equations (32) and (33) in the relative demand equations for factors and assuming that the relative share parameters and the frontier relative share are identical i.e. $\frac{\lambda_{i,t}}{1-\lambda_{i,t}} = \theta_{i,t}^{X/VA}$ and $\frac{\alpha_{i,t}}{1-\alpha_{i,t}} = \theta_{i,t}^{l/k}$, the relative demand equations for factors are as follows, and are identical to (20) and (21) (please see A5 for the derivation):

$$\begin{aligned} ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) &= \frac{\omega_{i,t}^{VA/X}\sigma_{i,t} - (\sigma_{i,t}-1)}{\omega_{i,t}^{VA/X} - (\sigma_{i,t}-1)} ln\left(\frac{1-\lambda_{i,t}}{\lambda_{i,t}}\right) - \frac{\omega_{i,t}^{VA/X}\sigma_{i,t} - (\sigma_{i,t}-1)}{\omega_{i,t}^{VA/X} - (\sigma_{i,t}-1)} ln\left(\frac{p_{i,t}^{VA}}{p_{i,t}^{X}}\right) \\ &\quad + \frac{\omega_{i,t}^{VA/X}(\sigma_{i,t}-1)}{\omega_{i,t}^{VA/X} - (\sigma_{i,t}-1)} ln\left(\frac{\nu_{i,t}^{VA}}{\nu_{i,t}^{X}}\right) \end{aligned} \tag{34}$$

$$\begin{aligned} ln\left(\frac{k_{i,t}}{l_{i,t}}\right) &= \frac{\omega_{i,t}^{l/k}\gamma_{i,t} - (\gamma_{i,t}-1)}{\omega_{i,t}^{l/k} - (\gamma_{i,t}-1)} ln\left(\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\right) - \frac{\omega_{i,t}^{l/k}\gamma_{i,t} - (\gamma_{i,t}-1)}{\omega_{i,t}^{l/k} - (\gamma_{i,t}-1)} ln\left(\frac{p_{i,t}^{k}}{w_{i,t}}\right) \\ &\quad + \frac{\omega_{i,t}^{l/k}(\gamma_{i,t}-1)}{\omega_{i,t}^{l/k} - (\gamma_{i,t}-1)} ln\left(\frac{\nu_{i,t}^{k}}{\nu_{i,t}^{l}}\right) \end{aligned} \tag{35}$$

6.1 Digitalization and the technology frontier

Based on the description of the technology frontier above, we now link digitalization to changes in the technology frontier and thus to increases of the unconditional elasticity of substitution, which is the relation we have analyzed in our empirical work.[21] We define the reduced form for unconditional elasticities as σ and ω as

$$\begin{aligned}\sigma_{i,t} &= \frac{\omega_{i,t}^{VA/X}\tilde{\sigma}_{i,t}-(\tilde{\sigma}_{i,t}-1)}{\omega_{i,t}^{VA/X}-(\tilde{\sigma}_{i,t}-1)}=\tilde{\sigma}_{i,t}+\frac{(\tilde{\sigma}_{i,t}-1)^2}{\omega_{i,t}^{VA/X}-(\tilde{\sigma}_{i,t}-1)}\\ \gamma_{i,t} &= \frac{\omega_{i,t}^{l/k}\tilde{\gamma}_{i,t}-(\tilde{\gamma}_{i,t}-1)}{\omega_{i,t}^{l/k}-(\tilde{\gamma}_{i,t}-1)}=\tilde{\gamma}_{i,t}+\frac{(\tilde{\gamma}_{i,t}-1)^2}{\omega_{i,t}^{l/k}-(\tilde{\gamma}_{i,t}-1)}\end{aligned}$$

The only way in which the technology frontier, and thus digitalization, can affect the unconditional elasticity of substitution between factors is through its curvature, ω. The conditional elasticities of substitution, $\tilde{\sigma}_{i,t}$, are based on existing technologies and cannot be affected by the introduction of new technologies. Provided that $\omega^{l/k} > (\tilde{\gamma}-1)$ and $\omega^{VA/X} > (\tilde{\sigma}-1)$ (which guarantees an interior solution for productivities), the mere presence of curvature in the technology frontier (imperfect substitution or complementarity between technologies) implies a higher unconditional elasticity of substitution between factors. An increase in the curvature (lower ω), creates more complementarity between technologies and hence an even higher elasticity of substitution between factors.

In Figure 7 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. Clearly, digitalization shifts these log-frontiers to the left and thus lowers ω. For a given conditional elasticity of substitution between factors, a lower curvature of the technology frontier leads to more flexibility in technology choice and hence increases the unconditional elasticity of substitution, whether factors are complements or substitutes. The figures visualize the positive impact of digitalization on the technology frontier's curvature and thus on the unconditional elasticity of substitution between value-added and intermediate inputs as well as between labor and capital. More generally, the technology frontiers shift randomly due to other factors that affect ω or θ. The inner plots show that a varying θ may also affect the log-frontiers.

[21] For a relation of the below elasticities to our econometric model, please refer to Appendix A7.

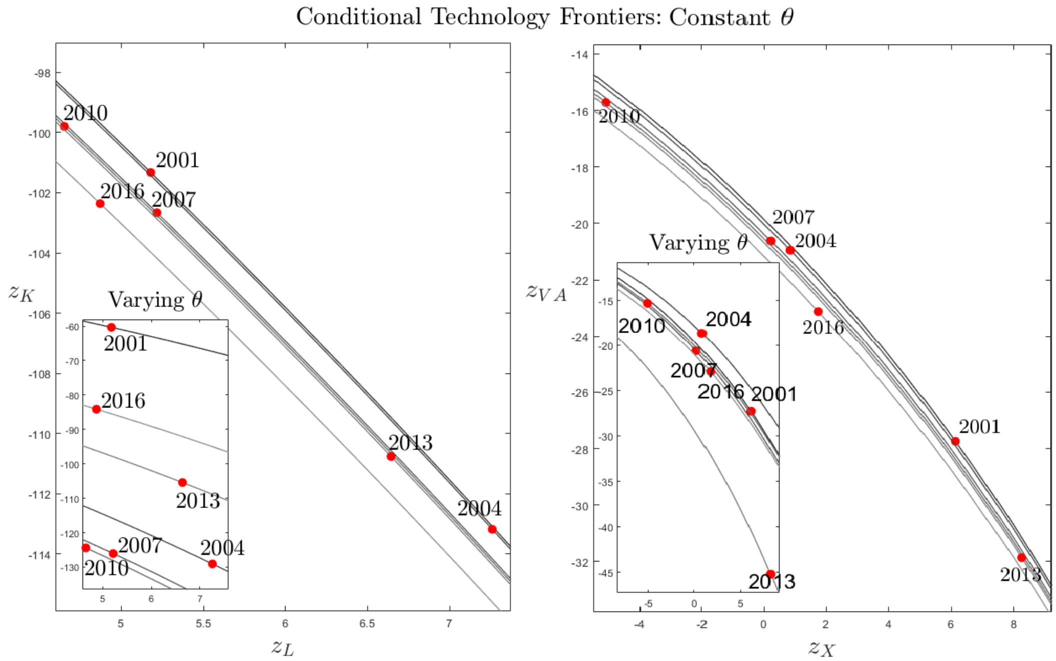

Figure 7: Shifting technology frontiers for capital-labor (left) and value-added and intermediate inputs (right)

The interpretation of complementarity of technologies is analogous to that of input factors: The relative quantities (in case of input factors) or productivities (in case of technologies) must remain fairly constant (within a small range of flexibility). Consequently, digitalization must either have a uniform impact on both productivity parameters within a production function (or their growth rates) or have no impact on either productivity parameter. A significant impact of digitalization on only one factor productivity would be inconsistent with the finding that digitalization fosters the complementarity of technologies. Assuming that the endogenous and exogenous productivities have similar attributes, our results in Table 4 support the finding of high complementarity between productivity parameters. Because digitalization has almost the same impact on the growth rates of labor and capital productivity, this ensures that their ratio remains fairly constant with higher levels of digital intensity. Furthermore, digitalization has no impact on the productivity growth rates of value-added and the intermediate good, which excludes the case of higher substitutability between technologies due to a higher level of digitalization.

7 Conclusion

In this paper, we have shown that digitalization has a significant impact on the macroeconomic production function that goes beyond productivity growth. A standard question explored in the literature is whether digitalization affects the latter. We provide evidence that higher data intensity in digitalization positively contributes to the growth rate of Hicks-neutral productivity in value-added. We nevertheless also find that higher IT intensity increases the elasticity of substitution between value-added and intermediate goods and the elasticity of substitution between capital and labor. Different types of digital intensity matter for alternative components of the production function.

We have shown that a higher elasticity of substitution does not always warrant a more resilient economy. A central result of the paper is that this crucially depends on the relative abundance of value-added. Based on this sufficient statistic, we find that many sectors in selected European economies amplify shocks after digitalization, with a deteriorating trend in resilience between 1995 and 2017.

Our results point toward several directions that deserve further research. Since the relative abundance of inputs decides on the impact of a higher elasticity of substitution on resilience, it is worthwhile to investigate the role of barriers to trade between sectors and limited mobility of primary factors such as capital and labor. Finally, our analytical results focused on the contemporaneous impact of digitalization. A higher elasticity of substitution between capital and labor should impact the propagation of shocks to different sectors across time. This necessitates studying resilience in a model with capital accumulation. We leave this interesting extension for immediate future work.

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Appendix

A1: Household optimization

$$\begin{aligned} \max_{l_{i,t}, c_{i,t}} \quad & \gamma(l_t) \prod_{i=1..n} c_{i,t}^{\beta_i} \\ s.t. \quad & \sum_{i=1..n} p_{i,t} c_{i,t} = \sum_{i=1..n} w l_{i,t} \\ & \sum_{i=1..n} l_{i,t} = l_t \end{aligned} \tag{36}$$

First order conditions:

$$l_{i,t} \quad : \quad \gamma'(l_t) \prod_{i=1..n} c_{i,t}^{\beta_{i,t}} = \lambda_{i,t} w_{i,t} \tag{37}$$

$$c_{i,t} \quad : \quad u(c1, c_2, ..., l_t)\beta_{i,t} = -\lambda_{i,t} p_{i,t} c_{i,t} \tag{38}$$

Combining two first order conditions for goods i and j, we have that $p_{i,t}c_{i,t} = p_{j,t}c_{j,t}\frac{\beta_{i,t}}{\beta_{j,t}}$, and summing over i, using that $\sum_{i=1..n} \beta_{i,t} = 1$ and the budget constraint, we get that $\sum_{i=1..n} w_{i,t} l_{i,t} = \frac{p_{j,t}c_{j,t}}{\beta_{j,t}}$, and therefore $p_{i,t}c_{i,t} = \beta_{i,t} \sum_{i=1..n} w_{i,t} l_{i,t}$. Plugging this back to the first order condition for good i, the lagrange multiplier is pinned down by $\lambda_{i,t} = -u(c_1, c_2, ..., l_t) \left(\sum_{i=1..n} w_{i,t} l_{i,t}\right)^{-1}$. Multiplying 37 with

$l_{i,t}$ and summing over i yields $\sum_{i=1..n} l_{i,t}\gamma'(l_t)\prod_{i=1..n} c_{i,t}^{\beta_{i,t}} = \lambda_{i,t}\sum_{i=1..n} l_{i,t}w_{i,t}$ and thus $l_t\gamma'(l_t) = -\gamma(l_t)$. Aggregate labor supply is therefore constant, $l_t = \bar{l}_t$. Furthermore, using that $l_t\gamma'(l_t) = -\gamma(l_t)$ in $\gamma'(l_t)\prod_{i=1..n} c_{i,t}^{\beta_{i,t}} = \lambda_{i,t}w_{i,t}$ yields that $w_i = \bar{l}_t \sum w_i l_{i,t}$, which implies that wages are equalized across sectors due to unrestricted mobility.

A2: Results on the Domar weight

Proof of Proposition 1. Using 7 and 8, the sales share is equal to:

$$\frac{p_{j,t}y_{j,t}}{\sum_{i,t} p_{i,t}c_{i,t}} = \beta_{j,t}\frac{y_{j,t}}{c_{j,t}} \tag{39}$$

Using the goods market equilibrium, and dividing by $c_{j,t}$:

$$\begin{aligned}
\frac{y_{j,t}}{c_{j,t}} &= 1 + \sum_{i=1..n} \frac{x_{i,j}}{c_{j,t}} &(40)\\
&= 1 + \sum_{i=1..n} \alpha_{i,j}\lambda_{i,t}\left(\frac{\beta_{i,t}y_{i,t}}{\beta_{j,t}c_{i,t}}\left(\frac{X_{i,t}}{y_{i,t}}\right)^{(1-\frac{1}{\sigma_{i,t}})} e^{(z_{i,t}(\frac{\sigma_{i,t}-1}{\sigma_{i,t}})}\right) &(41)\\
&= 1 + \sum_{i=1..n} \alpha_{i,j}\lambda_{i,t}\left(\frac{\beta_{i,t}y_{i,t}}{\beta_{j,t}c_{i,t}}\left(\frac{X_{i,t}e^{z_{i,t}}}{y_{i,t}}\right)^{(1-\frac{1}{\sigma_{i,t}})}\right)\\
&= 1 + \sum_{i=1..n} \alpha_{i,j}\lambda_{i,t}\left(\frac{\beta_{i,t}y_{i,t}}{\beta_{j,t}c_{i,t}}\left(\lambda_{i,t} + (1-\lambda_{i,t})\left(\frac{l_{i,t}}{X_{i,t}}\right)^{\frac{\sigma_{i,t}-1}{\sigma_{i,t}}}\right)^{-1}\right) &(42)\\
&= 1 + \sum_{i=1..n} \alpha_{i,j}\left(\frac{\beta_{i,t}}{\beta_{j,t}}\frac{p^X_{i,t}X_{i,t}}{w_t l_{i,t} + p^X_{i,t}X_{i,t}}\right)\frac{y_{i,t}}{c_{i,t}} &(43)
\end{aligned}$$

where we used that $\frac{x_{i,j}p_{j,t}}{p_{i,t}y_{i,t}} = \lambda_{i,t}\alpha_{j,i,t}\left(\frac{X_{i,t}}{y_{i,t}}\right)^{(1-\frac{1}{\sigma_{i,t}})} e^{z_{i,t}^{\frac{\sigma_{i,t}-1}{\sigma_{i,t}}}}$, (5) and (7).

Proof of Proposition 2. The derivative of the vector of Domar weights follows directly from rules of matrix differentation. Focusing on the derivative of the expenditure share, and dropping subscripts to ease notation, denote the relative expenditure share by $\phi = \left(\lambda + (1-\lambda)\left(\frac{l}{X}\right)^{\frac{\sigma-1}{\sigma}}\right)^{-1}$. Then,

$$\begin{aligned}
\frac{\partial\phi}{\partial\sigma} &= -\lambda\left(\lambda + (1-\lambda)\left(\frac{l}{X}\right)^{\frac{\sigma-1}{\sigma}}\right)^{-2} \times \qquad (44)\\
&\quad -\phi^2\frac{1-\lambda}{\lambda}\left(\frac{\sigma-1}{\sigma}\frac{\partial\left(\frac{l}{X}\right)}{\partial\sigma}\left(\frac{l}{X}\right)^{-\frac{1}{\sigma}} + \left(\frac{l}{X}\right)^{\frac{\sigma-1}{\sigma}}\frac{1}{\sigma^2}ln\left(\frac{l}{X}\right)\right)\\
&= -\phi^2\frac{1-\lambda}{\lambda}\left(\frac{l}{X}\right)^{1-\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\frac{\partial ln\left(\frac{l}{X}\right)}{\partial\sigma} + \frac{1}{\sigma^2}ln\left(\frac{l}{X}\right)\right) \qquad (45)\\
&= -\phi^2\frac{1-\lambda}{\lambda}\left(\frac{l}{X}\right)^{1-\frac{1}{\sigma}}\left(\frac{1}{\sigma}ln\left(\frac{l}{X}\right)\right) \qquad (46)
\end{aligned}$$

where the last line uses (5).

A3: 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, $\Delta ln(K_{GFCG}) = \sum_{i=1..n}\bar{v}_i\Delta ln(K_i)$, where $\bar{v}_i$ are the weights given by the average of current and lagged nominal expenditure shares of each type of capital where $\bar{v}_i = 0.5(v_{i,t} + v_{i,t-1})$ and $\sum_{i=1..10}\bar{v}_i = 1$. 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.

A4: Estimating labor and capital productivities, $t > 0$

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 $e^{z^k_{i,t}-\bar{z}^k_i}$:

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

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.

A5: Microfounded relative demand equations

The relative demand equations for inputs are as follows:

$$\frac{1-\lambda_{i,t}}{\lambda_{i,t}}\left(\frac{VA_{i,t}}{X_{i,t}}\right)^{-\frac{1}{\sigma_{i,t}}}\left(\frac{\nu^{VA}_{i,t}e^{z^{VA}_{i,t}}}{\nu^X_{i,t}e^{z^X_{i,t}}}\right)^{1-\frac{1}{\sigma_{i,t}}} = \frac{p^{VA}_{i,t}}{p^X_{i,t}} \tag{47}$$

$$\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\left(\frac{k_{i,t}}{l_{i,t}}\right)^{-\frac{1}{\gamma_{i,t}}}\left(\frac{\nu^k_{i,t}e^{z^k_{i,t}}}{\nu^l_{i,t}e^{z^l_{i,t}}}\right)^{1-\frac{1}{\gamma_{i,t}}} = \frac{p^k_{i,t}}{w_{i,t}} \tag{48}$$

Substituting equations (32) and (33) above we get that

$$
\begin{aligned}
ln\left(\frac{VA_{i,t}}{X_{i,t}}\right) &= \frac{\omega_{i,t}^{VA/X}\sigma_{i,t}}{\omega_{i,t}^{VA/X}-(\sigma_{i,t}-1)}ln\left(\frac{1-\lambda_{i,t}}{\lambda_{i,t}}\right)+\frac{\sigma_{i,t}-1}{\omega_{i,t}^{VA/X}-(\sigma_{i,t}-1)}ln(\theta_{i,t}^{X/VA}) \\
&\quad -\frac{\omega_{i,t}^{VA/X}\sigma_{i,t}-(\sigma_{i,t}-1)}{\omega_{i,t}^{VA/X}-(\sigma_{i,t}-1)}ln\left(\frac{p_{i,t}^{VA}}{p_{i,t}^{X}}\right)+\frac{\omega_{i,t}^{VA/X}(\sigma_{i,t}-1)}{\omega_{i,t}^{VA/X}-(\sigma_{i,t}-1)}ln\left(\frac{\nu_{i,t}^{VA}}{\nu_{i,t}^{X}}\right) \\
ln\left(\frac{k_{i,t}}{l_{i,t}}\right) &= \frac{\omega_{i,t}^{l/k}\gamma_{i,t}}{\omega_{i,t}^{l/k}-(\gamma_{i,t}-1)}ln\left(\frac{\alpha_{i,t}}{1-\alpha_{i,t}}\right)+\frac{\gamma_{i,t}-1}{\gamma_{i,t}-(\gamma_{i,t}-1)}ln(\theta_{i,t}^{l/k}) \\
&\quad -\frac{\omega_{i,t}^{l/k}\gamma_{i,t}-(\gamma_{i,t}-1)}{\omega_{i,t}^{l/k}-(\gamma_{i,t}-1)}ln\left(\frac{p_{i,t}^{k}}{w_{i,t}}\right)+\frac{\omega_{i,t}^{l/k}(\gamma_{i,t}-1)}{\omega_{i,t}^{l/k}-(\gamma_{i,t}-1)}ln\left(\frac{\nu_{i,t}^{k}}{\nu_{i,t}^{l}}\right)
\end{aligned}
$$

If we further assume that $\frac{\lambda_{i,t}}{1-\lambda_{i,t}} = \theta_{i,t}^{X/VA}$ and $\frac{\alpha_{i,t}}{1-\alpha_{i,t}} = \theta_{i,t}^{l/k}$ then these demand equations simplify to (34) and (35).

A7: Relation of micro-founded elasticity of substitution to econometric model

Expanding $\sigma_{i,t} = \frac{\omega_{i,t}\tilde{\sigma}_{i,t}-(\tilde{\sigma}_{i,t}-1)}{\omega_{i,t}-(\tilde{\sigma}_{i,t}-1)}$ around $\tilde{\sigma}_{i,t} = \bar{\sigma}$ and $\omega_{i,t} = \bar{\omega}$, we get that

$$
\sigma_{i,t} \approx \frac{\bar{\omega}^{VA/X}\bar{\sigma}-(\bar{\sigma}-1)}{\bar{\omega}^{VA/X}-(\bar{\sigma}-1)} - \frac{\bar{\omega}^{VA/X}(\bar{\sigma}-1)^2}{(\bar{\omega}^{VA/X}-(\bar{\sigma}-1))^2}\hat{\omega}_{i,t} + \frac{\bar{\omega}^{[}VA/X^2]\bar{\sigma}}{(\bar{\omega}^{VA/X}-(\bar{\sigma}-1))^2}\hat{\sigma}_{i,t}
$$

where $\hat{\omega}$ is the deviation of ω from $\bar{\omega}$ and $\hat{\sigma}$ is the deviation of $\tilde{\sigma}$ from $\bar{\bar{\sigma}}$. An identical expression may be derived for the capital-labor elasticity. All factors relating to digital technology will be part of $\hat{\omega}_t$ and non- digital technology related factors will be related to $\hat{\sigma}_t$. This is a microfounded version of the expansion we adopted for the functional coefficients in the empirical specification. The estimated reduced form coefficients for each factor are nonlinear functions of $(\bar{\omega}, \bar{\sigma})$ and the structural coefficients that relate $(\hat{\sigma}_{i,t}, \hat{\omega}_{i,t})$ to those factors e.g. $\hat{\omega}_{i,t} = \alpha_1 IT\ share + \alpha_2 CT\ share$. For illustration purposes, we have employed the reduced form estimates obtained from the relative demand equations to back out the implied estimates of $\bar{\sigma}$ and $\tilde{\sigma}_{i,t}$ using that $\sigma_{i,t} \approx \bar{\sigma}\exp\left(\frac{\bar{\omega}^{[}VA/X^2]}{(\bar{\omega}^{VA/X}-(\bar{\sigma}-1))^2}\hat{\sigma}_{i,t}\right)$ and the corresponding estimates of $\omega_{i,t}$ using that $\omega_{i,t} = \frac{(\sigma_{i,t}-1)(\tilde{\sigma}_{i,t}-1)}{\sigma_{i,t}-(\tilde{\sigma}_{i,t})}$. Since $\hat{\sigma}_{i,t}$ 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.

A6: Tables

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

Online Appendix to: Digitalization and Resilience to Disaggregate Shocks

Florentine Schwark* Andreas Tryphonides**

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Abstract

This Appendix contains further empirical results on (a) the evolution of resilience over subsamples and the econometric estimates on the relative share parameters and (b) a note on the robustness to normalization in the production function for econometric estimates for the relative demand equations.

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(a) Further empirical results

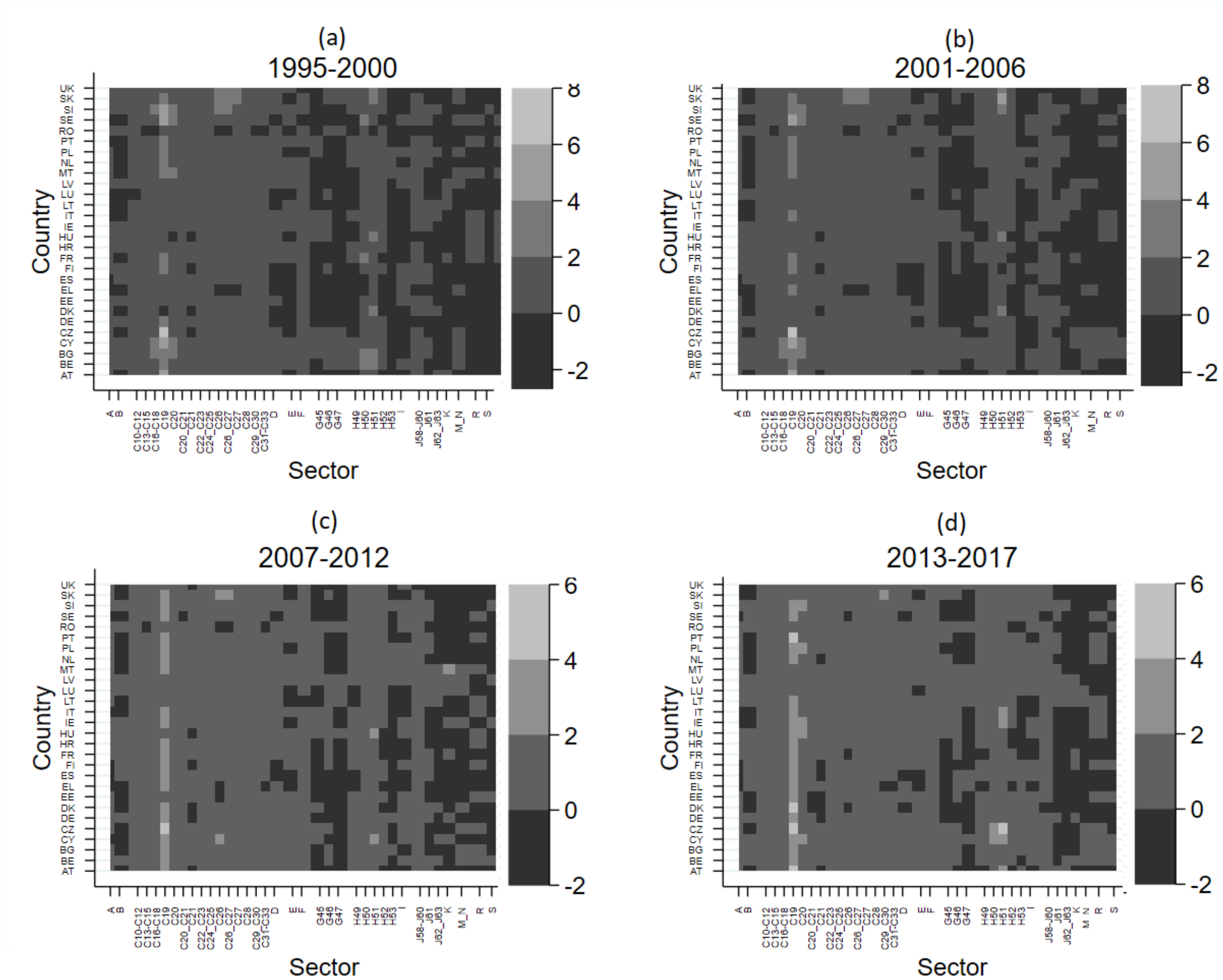

Figure 1: Evolution of relative intensity of intermediate inputs $ln\left(\frac{X}{VA}\right)$ over subsamples.

		$\ln\left(\frac{\alpha}{1-\alpha}\right)$	$\ln\left(\frac{1-\lambda}{\lambda}\right)$
t		0.0587	0.0437*
		[-0.0261,0.144]	[0.00263,0.0847]
IT share		0.215	0.0211
		[-0.0562,0.486]	[-0.100,0.143]
IT share ^{2}		0.0675	-0.00218
		[-0.0329,0.168]	[-0.0356,0.0312]
CT share		0.415	-0.0155
		[-0.0137,0.843]	[-0.101,0.0697]
CT share ^{2}		0.0876	0.0117
		[-0.0247,0.200]	[-0.0160,0.0394]
Inv. share:	R&D	0.0557	-0.00123
		[-0.0781,0.189]	[-0.0817,0.0792]
	S&D	-0.0115	-0.0130
		[-0.179,0.156]	[-0.0901,0.0642]
Inv. share ^{2}:	R&D	0.00870	-0.0295
		[-0.0223,0.0397]	[-0.0609,0.00196]
	S&D	-0.0911*	-0.000398
		[-0.179,-0.00281]	[-0.0413,0.0405]
Cap. share:	R&D	0.198	0.103
		[-0.174,0.569]	[-0.0715,0.278]
	S&D	-0.248	-0.0336
		[-0.763,0.266]	[-0.138,0.0705]
Cap. share ^{2}:	R&D	0.0462	0.0114
		[-0.0232,0.116]	[-0.0612,0.0841]
	S&D	-0.0319	-0.00204
		[-0.132,0.0680]	[-0.0480,0.0439]
Constant		-0.708	-0.333
		[-1.543,0.127]	[-0.935,0.269]
No. Observations		2744	2696
Country-Sector F.E. and ≥ 2 lags		✓	✓

Table 1: Impact of Digitization on relative share parameters (α, λ).

(b) Estimation with a normalized production function

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

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

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 $(1-\gamma_{i,t})ln\left(\frac{\bar{k}_{i,t}}{\bar{l}_{i,t}}\right) - (g_i^k - g_i^l)\bar{t}$.