# Digitalization, Factor-Bias Productivity, and the Labor Share*

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**Abstract**

We examine how digitalization affects factor-neutral and factor-nonneutral productivity and the labor share of income. To do this, we develop a novel method for estimating factor-augmenting productivity within a translog production function that relaxes the assumption of homothetic separability and permits unrestricted interactions among inputs — departing from the CES-based approaches that dominate the existing literature. Applying the framework to an unbalanced panel of 2,795 Spanish manufacturing firms across 10 industries (2000–2019), we find that digitalization raises both labor-augmenting productivity (3.4%) and Hicks-neutral productivity (2.9%) at the aggregate level, though the labor-augmenting channel is considerably more heterogeneous across industries. Digitalization also increases the labor share by approximately 2.7 percentage points, consistent with the capital–labor complementarity we document in the aggregate elasticity estimates. These findings suggest that digital adoption in manufacturing need not come at the expense of labor's share of income.

**Keywords**: Digitalization, Factor-Augmenting Productivity, Labor Share, Translog Production Function, Markups, Spanish Manufacturing

**JEL Classification No.**:

## 1 Introduction

The digitalization of productive activities has accelerated rapidly in recent years, particularly in developed economies and in emerging markets such as China and Brazil. Firms are increasingly replacing manual control with digital technologies, including industrial robots, numerically controlled machines, and machine learning and artificial intelligence (AI) systems, in the production of goods and services. Beyond production, firms have expanded their adoption of digital technologies for commercial transactions, selling

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products directly to buyers through websites and engaging in e-commerce for both sales and procurement, both business-to-business and business-to-consumer.

Emerging evidence suggests that AI and digitalization improve productivity and enhance firms' ability to charge prices above marginal cost, thereby increasing markups. While a large body of literature has examined the impact of digitalization on total factor productivity, relatively few studies have focused on its effect on factor-augmenting productivity. Moreover, the intensification of digitalization across firms and industries has coincided with a decline in labor's share in developed economies and an increase in labor's share in developing economies, raising important questions about the channels through which digitalization shapes the distribution of income between labor and capital.

A declining labor share is widely regarded as a contributing factor to rising income inequality, given that capital ownership tends to be more concentrated than labor income (International Labour Organization, 2019; Autor et al., 2020). Many U.S. workers are concerned that AI will take away their jobs; about 52% of U.S. workers surveyed in 2024 expressed concern that AI would negatively affect their jobs (Lin & Parker, 2025; Acemoglu et al., 2026). Understanding the channels through which digitalization affects the labor share is therefore important for assessing its distributional consequences. The literature on the relationship between digitalization and the labor share also remains sparse. In developing economies, Liu et al. (2025) and Li et al. (2024) examine the impact of digital technologies on the labor share in China, finding a positive effect.

In developed economies, however, existing studies have focused exclusively on individual components of digitalization. Acemoglu & Restrepo (2019) use internet technology as their measure of digitalization and find a positive effect on labor income shares, while Fu et al. (2021) similarly employ internet development and document a universal positive effect on the labor share of income. Alexopoulos & Cohen (2016) examine the role of robots and find a negative effect on the labor income share. Regarding artificial intelligence, Binder & Bound (2019) find a positive effect on the labor income share, whereas Bessen (2019) finds that AI induces a short-term reduction in the labor share. A notable limitation of these studies is that each relies on a single dimension of digitalization, whether internet penetration, robotics, or artificial intelligence, to proxy for the broader phenomenon of digital transformation. To the best of our knowledge, no prior study has examined the multidimensional nature of digitalization and its effects on labor share in a developed economy.

Descriptive evidence from Spanish manufacturing firms motivates our empirical analysis. The average labor share is relatively stable at about 0.25 in the early 2000s, rises sharply to a peak of roughly 0.29 around 2010, and then trends downward through the late 2010s, reaching a low near 0.24 before ending around 0.25–0.26 by 2020 (see Figure 1). Over the same period, the composite digitalization index increases markedly from approximately 0.42 in the early 2000s to about 0.62 by 2020, with a pronounced early jump (to roughly 0.59) and a mid-2010s peak close to 0.65 (see Figure 2). However, disaggregating labor costs reveals a more nuanced story. Average labor hours decline substantially from about 340,000 hours in the early 2000s to roughly 220,000–230,000 hours by 2020, while average wages per hour increase

steadily from about 14.5 to approximately 22 over the same period (see Figures 3 and 4). The magnitude of the decline in labor hours dominates the increase in hourly wages, helping to explain the downward drift in the labor share after its 2010 peak.

This pattern is consistent with a labor-augmenting channel, as digitalization increases worker productivity, reducing the labor hours required to produce the same output, even as firms pay higher hourly wages to the remaining, more productive workers. The continued decline in the labor share, despite rising wages, indicates that productivity gains, as reflected in reduced labor hours, outpace wage increases. This evidence points toward complementarity between capital and labor rather than high substitutability. When capital and labor are complements, firms cannot readily replace workers with machines; instead, digitalization enhances each worker's productivity, allowing firms to achieve similar or higher output with fewer but higher-paid workers operating increasingly sophisticated capital equipment.

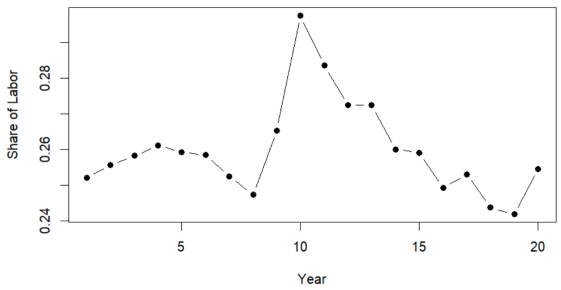



Figure 1: Labor Share ($s_L$) Over Time

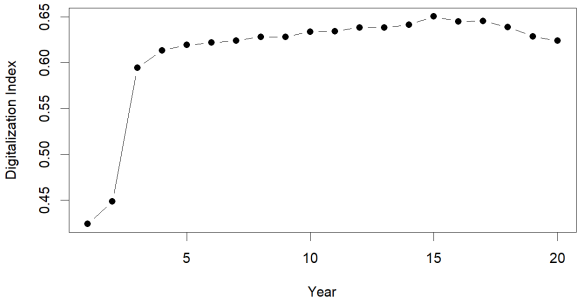



Figure 2: Digitalization Index Over Time

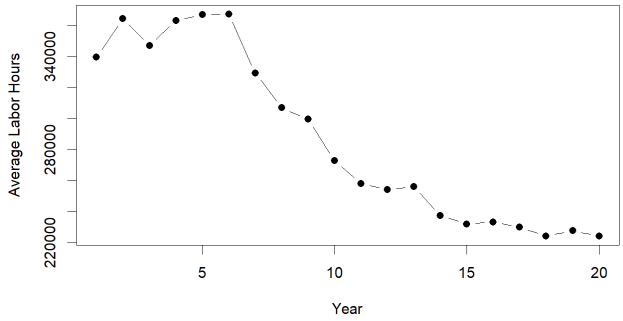



Figure 3: Average Labor Hours Over Time

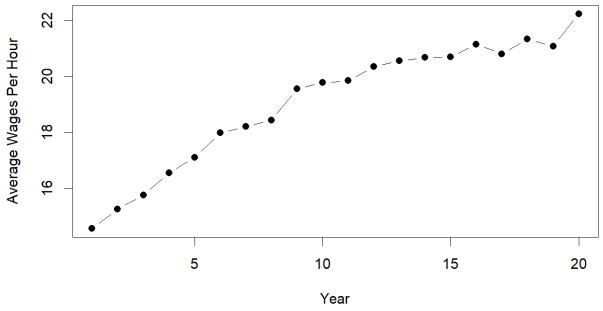



Figure 4: Average Wages Per Hour Over Time

In the production function literature, the estimation of factor-augmenting productivity has predominantly relied on the constant elasticity of substitution (CES) specification. While widely used, the CES framework imposes restrictive assumptions; it does not permit interactions among inputs and assumes a homogeneous elasticity of substitution across all factor pairs. These restrictions are at odds with empirical evidence that inputs interact and that substitution possibilities may vary across factor combinations. A small number of studies have adopted the translog production function, which offers greater flexibility by accommodating input interactions. However, even within this framework, existing approaches impose

restrictions on the interaction structure among inputs to achieve parameter identification. A common restriction is the assumption of homothetic separability between capital and other inputs, which constrains the interaction among capital, labor, and materials in the production function.

The central questions motivating this study are as follows. What is the impact of digitalization on labor productivity and Hicks-neutral productivity in a developed economy? What is the effect of a multidimensional digitalization index on labor share? How should one estimate production technology when inputs are permitted to interact in the absence of homothetic separability? These are the key questions this study seeks to answer.

To investigate these issues, we propose an approach to estimating factor-nonneutral productivity without assuming homothetic separability and endogenize digitalization to examine its effects on both factor-neutral and factor-nonneutral productivity. We model labor and materials as quasi-fixed inputs that adjust within the production period, following the standard treatment in Olley & Pakes (1996) and Levinsohn & Petrin (2003). This specification is particularly appropriate for Spanish manufacturing, where labor market institutions facilitate rapid workforce adjustments through temporary contracts. As documented by Bentolila (2012), temporary employment constitutes a substantial share of manufacturing employment in Spain, with firms adjusting these contracts in response to short-run productivity and demand shocks. Materials, aggregating intermediate consumption, primarily energy and raw materials, similarly exhibit low adjustment costs and respond to within-period optimization decisions. Capital, by contrast, is modeled as a state variable predetermined at the beginning of the production period.

Our findings yield several important results regarding the structure of production, the role of digitalization, and the dynamics of the labor share in Spanish manufacturing. With respect to the production technology, the output elasticities indicate that materials constitute the predominant input, followed by labor, with capital contributing the least to output growth. This ordering is consistent across most industries and underscores the materials-intensive nature of the manufacturing sector. The markup estimates reveal that firms price moderately above marginal cost, as evidenced by mean markups exceeding unity across all industries, suggesting that Spanish manufacturing operates under imperfect competition characterized by modest but economically meaningful market power.

Turning to the productivity effects of digitalization, the estimated coefficients on digitalization in the labor-augmenting productivity process are positive for most industries, indicating that digital adoption enhances the effective quality of labor in most sectors. A small number of industries, however, exhibit negative estimates, suggesting that the capacity of digitalization to augment labor productivity is not uniform and depends on sector-specific production characteristics. The Hicks-neutral channel yields more uniformly positive results, with digitalization contributing to broad-based efficiency improvements in nearly all industries, the sole exception being Chemical Products.

Regarding labor share, our decomposition results indicate that digitalization has a positive effect on labor share in most industries. This finding implies that digital technologies in the manufacturing sector increase labor's contribution to total revenue, thereby reducing income inequality. The positive

effect of digitalization on the labor share operates through improvements in worker performance and productive capacity enabled by digital tools. The labor-augmenting component of technical change, by contrast, reduces the labor share. As labor-augmenting productivity rises, fewer hours of labor are required to complete a given production process, thereby reducing the share of revenue accruing to labor even as the effective quality of each labor unit improves. The decomposition further reveals that the principal drivers of the observed decline in the labor share are materials intensity and labor-augmenting productivity growth, both of which reduce the relative contribution of labor to output and, consequently, its share of total income.

A large body of work on firm-level productivity has focused on factor-neutral productivity. Classic contributions include Olley & Pakes (1996) (OP), Levinsohn & Petrin (2003) (LP), Ackerberg et al. (2015) (ACF), Gandhi et al. (2020) (GNR). These studies employ control-function approaches to address the endogeneity of unobserved productivity, using investment, materials, or other intermediate inputs as proxies; GNR, by contrast, uses the input share to identify a subset of parameters and relies on timing assumptions about productivity dynamics to identify the remainder. In contrast, empirical work on factor-augmenting productivity is relatively limited but growing. A key motivation is that estimating only factor-neutral productivity, while ignoring the possibility that technical change may be biased toward particular inputs, can distort inference about productivity and its evolution. Much of the existing literature on biased technical change relies on CES structures and often assumes homothetic separability of capital from other inputs (Doraszelski and Jaumandreu, 2018). More recent studies, such as Malikov et al. (2020) and Doraszelski & Jaumandreu (2019), adopt translog production functions but still impose homothetic separability on the capital input, restricting its interaction with other factors.

The contributions of this paper are twofold, spanning both methodology and empirical application. On the methodological side, we develop a new framework to estimate factor non-neutral productivity within a translog technology without imposing homothetic separability, accommodating both perfectly competitive and imperfectly competitive product markets. Under imperfect competition, we recover markups using the demand elasticity estimated from the demand function. The identification of the production-function parameters proceeds in three stages. In the first stage, we estimate demand to obtain the inverse demand elasticity. In the second stage, we use this inverse elasticity as a scaling factor in the system of input-share equations derived from profit maximization, thereby identifying all parameters associated with the material and labor share equations and a subset of parameters associated with the elasticity of capital. In the third stage, we identify the remaining parameters governing capital elasticity. Under perfect competition, markups equal one, and the inverse demand elasticity equals zero, simplifying identification to a two-stage procedure: we first estimate the system of share equations to identify a subset of the production function parameters, then estimate the remaining parameters in a second stage. Our use of Spanish manufacturing data is motivated by the richness and accessibility of the digitalization variables in the Encuesta sobre Estrategias Empresariales (ESEE) dataset.

On the empirical side, we examine how digitalization affects labor-augmenting productivity, factor-

neutral productivity, and markups. We also examine the effect of digitalization on the labor share using both our structural approach and panel fixed effects. We then quantify the extent to which labor-augmenting productivity contributes to the decline in the labor share over time and assess the role of digitalization in accelerating this decline by affecting labor-augmenting productivity.

The remainder of the paper is organized as follows. Section 2 documents trends in digitalization and the labor share across sub-industries within the Spanish manufacturing sector. Section 3 reviews the related literature. Section 4 describes the data and details the construction of key variables, including output and input prices and the digitalization measure. Section 5 introduces our model for estimating factor-neutral production technology. Section 6 discusses identification and estimation. Section 7 presents the empirical results. Finally, Section 8 concludes with policy implications.

## 2 Trends in Digitalization and Labor Share

The complementarity between human workers and digital technologies, including industrial robots, numerically controlled machinery, and artificial intelligence systems, has the potential to enhance labor productivity by accelerating skill acquisition and augmenting human capabilities, thereby elevating the labor share of income. A growing body of empirical work supports this view. Liu et al. (2025) and Li et al. (2024), among others, provide evidence that digitalization contributes positively to the labor share, particularly through channels that improve worker efficiency and expand employment opportunities in technology-adopting firms. [1] Acemoglu et al. (2026) offers a complementary perspective through the concept of pro-worker AI, in which technological adoption is deliberately directed toward augmenting human labor. Their emphasis on the direction of technological change aligns closely with our empirical strategy, which estimates factor-biased technical change within a translog production function framework to quantify how digitalization alters the relative productivity of labor, capital, and materials in Spanish manufacturing firms.

[1] We develop the theoretical foundations for this argument within a factor-augmenting production function framework in a companion paper Musbaudeen & Kumbhakar (2026).

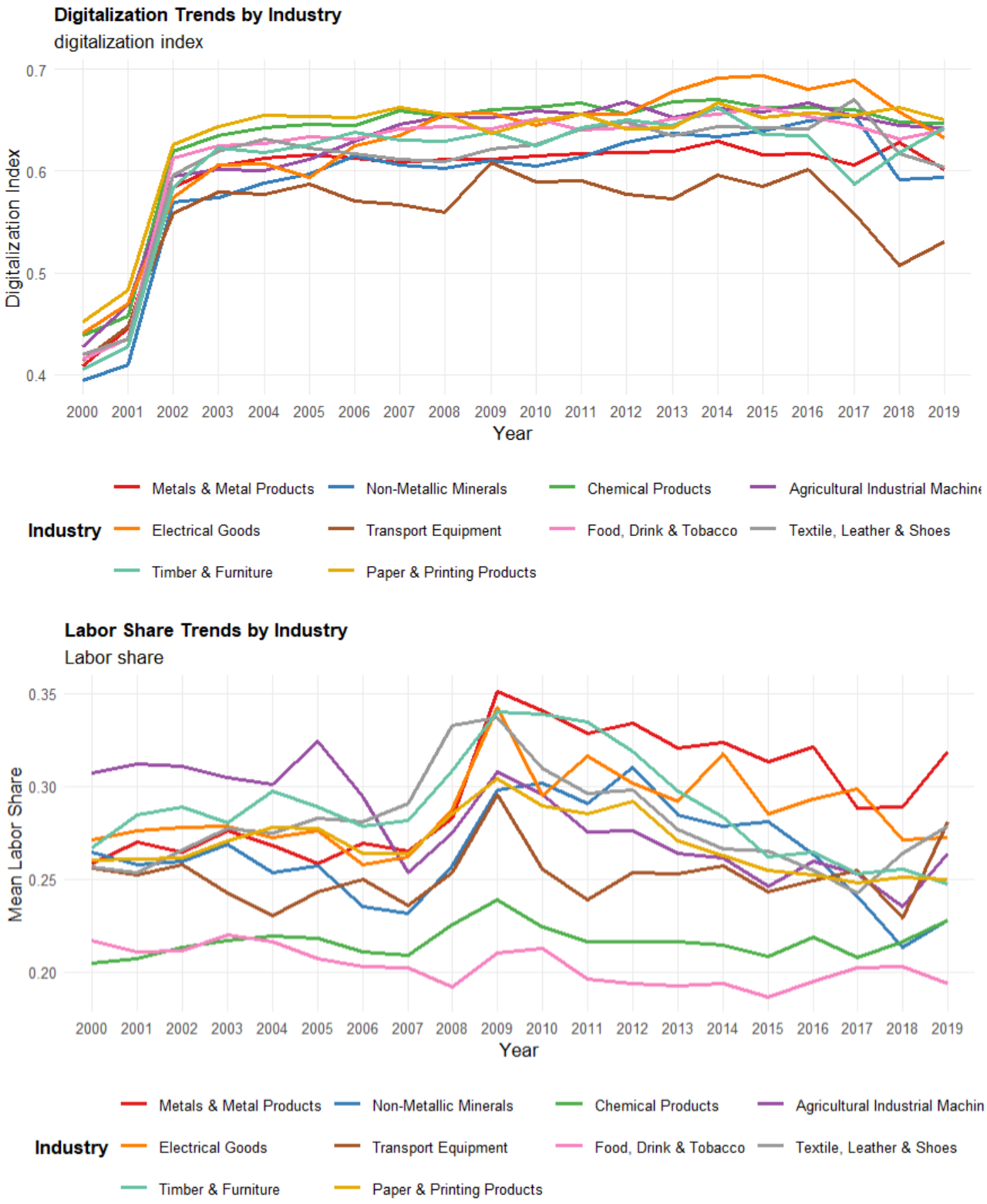



Figure 5: Digitalization and Labor Share Trends (2000–2019). Data sourced from the ESEE manufacturing survey.

Figure 5 depicts the evolution of mean labor shares across ten manufacturing sub-industries in

Spain over the period 2000 to 2019. Several notable patterns emerge. First, there is a pronounced countercyclical spike in labor shares around 2008-2009, coinciding with the onset of the Global Financial Crisis. This spike is particularly sharp in Metals and Metal Products, Non-Metallic Minerals, and Electrical Goods, where labor shares rose to approximately 0.33-0.35. This pattern is consistent with the well-established empirical regularity that labor shares tend to rise during recessions as output contracts more rapidly than wages and employment adjust downward.

Second, following the crisis-induced spike, most industries exhibit a gradual decline in labor shares through the early 2010s, reflecting the prolonged adjustment period associated with the European sovereign debt crisis and the subsequent labor market reforms enacted in Spain in 2012. The post-crisis trajectory is not uniform across industries, however. Chemical Products and Food, Drink, and Tobacco consistently maintain the lowest labor shares throughout the sample period, hovering between 0.20 and 0.24, indicating their capital- and materials-intensive production structures. In contrast, Agricultural and Industrial Machinery and Textile, Leather, and Shoes display persistently higher labor shares, generally exceeding 0.28, reflecting their greater reliance on labor as a factor of production.

Third, the latter portion of the sample period, from 2015 to 2019, reveals a degree of convergence across most industries, with labor shares clustering in the range 0.25 to 0.28. A notable exception is Food, Drink, and Tobacco, which continues to exhibit the lowest labor share, declining to approximately 0.19 by 2019. The general downward trend in labor shares across most sub-industries over the two decades is consistent with broader macroeconomic evidence of declining labor shares in advanced economies. It motivates the central inquiry of this paper regarding the role of digitalization in driving factor-biased technical change.

Figure 5 also presents the corresponding trends in the digitalization index. The most striking feature of the figure is the rapid and broadly synchronized increase in digitalization across all industries between 2000 and 2005, during which the index rose from approximately 0.40 to 0.60. This initial surge reflects the diffusion of foundational digital technologies, such as internet connectivity, email, and basic enterprise resource planning systems, across the Spanish manufacturing sector in the early 2000s.

Following this initial convergence, the digitalization trajectories begin to diverge across industries from approximately 2005 onward. Chemical Products and Metals and Metal Products emerge as the most digitally advanced sub-industries, with indices ranging from 0.68 to 0.70 by the mid-2010s. These sectors, characterized by complex supply chains and process-intensive production, likely benefit disproportionately from digital tools for quality control, inventory management, and automated production monitoring. Electrical Goods and Agricultural and Industrial Machinery also exhibit relatively high levels of digitalization, consistent with their technological proximity to information and communication technologies. At the lower end, Food, Drink, and Tobacco and Textile, Leather, and Shoes exhibit somewhat slower digitalization trajectories, though they nonetheless reach index values above 0.60 by the end of the sample period. The more modest digital adoption in these industries may reflect their smaller average firm sizes, lower skill intensity, and production processes that are less amenable to digital

automation.

An important observation from the joint reading of the two figures is the suggestive inverse relationship between digitalization and industry-level labor shares. Industries that experienced the most pronounced increases in digitalization, such as Chemical Products and Metals and Metal Products, also tend to exhibit declining or persistently low labor shares. Conversely, industries with relatively slower digitalization growth, such as Textile, Leather, and Shoes, maintained comparatively higher labor shares. While these aggregate trends are merely suggestive and cannot establish causality, they provide compelling descriptive motivation for the econometric analysis that follows, in which we formally examine whether digitalization induces factor-biased technical change that systematically alters the distribution of income between labor and other factors of production.

## 3 Related Literature

This study contributes to three strands of literature: production function estimation, factor-augmenting technical change and labor share dynamics, and the effects of digitalization and AI on productivities.

A substantial and growing body of literature has examined the impact of digitalization and information and communication technologies (ICT) on productivity (Nucci et al., 2013; Cardona et al., 2013; Brynjolfsson & Yang, 1996; Brynjolfsson & Hitt, 2000; Baily, 2002; Dedrick et al., 2003; Melville et al., 2004; Stiroh, 2005; Draca et al., 2008; Holt & Jamison, 2009). Much of these literatures find that digitalization is associated with higher productivity (Nucci et al., 2013; Cardona et al., 2013; Holt & Jamison, 2009). However, the evidence is far from unanimous. Several studies, including Acemoglu et al. (2014) DeStefano et al. (2018), Haller & Lyons (2015), Bertschek et al. (2015), and Colombo et al. (2013), find no significant relationship between digitalization and productivity. Acemoglu et al. (2014) investigate the effect of digital technology intensity on labor productivity in U.S. manufacturing industries and finds no statistically significant effect except in the computer-producing sector.

Among studies that do find positive effects, methodological approaches vary considerably. Nucci et al. (2013) employ difference-in-differences and propensity score matching using Italian manufacturing survey data from 2016–2018. Gal et al. (2019) use a control function approach and similarly report positive effects of digitalization on TFP. Anderton et al. (2023) examine the relationship using a panel dataset from EU countries and confirm a positive association. Cusolito (2020) investigates the impact using firm-level data from 82 developing countries drawn from the World Bank Enterprise Survey.

A common limitation across these studies is that most rely on total factor productivity (TFP) or other aggregate productivity measures that do not distinguish between Hicks-neutral and factor-augmenting components of technological change. At the same time, a parallel strand of literature estimates firm-level markups using production-based methods that require reliable output elasticities, raising concerns when technology operates through multiple dimensions simultaneously.

A further limitation concerns the measurement of digitalization itself. Most studies rely on single

indicators, such as ICT spending or IT capital stock, as proxies for digitalization (Bresnahan et al., 2002; Brynjolfsson & Hitt, 1996; Bertschek & Kaiser, 2004; Hempell, 2005; Baily & Lawrence, 2001; Stiroh, 1998, 2002; Morrison, 1997; Gordon, 2000; Jorgenson & Stiroh, 1999; Oliner & Sichel, 2000; Jorgenson, 2001). This approach is unlikely to capture the multifaceted nature of digital transformation within organizations, a concern echoed by earlier work highlighting the data limitations inherent in measuring digitalization (Black & Lynch, 2001; Greenan & Mairesse, 2000; Loveman, 1994). In contrast, the richness of our dataset enables us to incorporate 14 distinct digitalization variables to construct a comprehensive index. Following Añón Higón & Bonvin (2023), we further decompose this index into four dimensions: IT technological components, digital-related human capital, automation, and interaction with stakeholders. This multidimensional approach provides a more robust characterization of digitalization compared to prior studies and allows us to examine how digitalization affects both neutral and non-neutral productivity as well as the labor share.

A large body of work on firm-level productivity estimation has focused on factor-neutral productivity. Classic contributions include OP, LP, ACF, and GNR. These studies employ control-function approaches to address the endogeneity of unobserved productivity, using investment, materials, or other intermediate inputs as proxies. GNR departs from this convention by using the input share to identify a subset of parameters and relying on timing assumptions about productivity dynamics to identify the remainder.

Empirical work on factor-augmenting productivity is more limited but growing. A key motivation for this line of research is that estimating only factor-neutral productivity, while ignoring the possibility that technical change may be biased toward particular inputs, can distort inference about productivity and its evolution. Much of the existing literature on biased technical change relies on constant elasticity of substitution (CES) structures and often assumes homothetic separability of capital from other inputs. While convenient, this assumption restricts the interactions among inputs in the production process. Studies such as Zhang (2019), Raval (2019), and Demirer (2025) have examined biased technological change, but all rely on CES production technologies. This widespread reliance on CES specifications, without sufficient consideration of more flexible alternatives, represents a notable gap in the empirical literature.

More recent studies have begun to relax some of these restrictions by adopting more flexible functional forms. Malikov et al. (2020) and Doraszelski & Jaumandreu (2019) estimate factor-augmenting productivity using translog production functions, but still impose homothetic separability on the capital input. While preparing this paper, we discovered that Zhao et al. (2024) also estimate factor-augmenting productivity without imposing homothetic separability in a translog framework; however, our approach differs from theirs. This paper contributes to the literature by proposing a method to estimate factor-biased productivity within a translog framework without imposing homothetic separability, accommodating both perfectly and imperfectly competitive product markets.

Acemoglu (2003) examined the determinants of factor-augmenting technical change, modeling the invention of new production technologies as a deliberate action, and argued that long-run technological

change is labor-biased. His model also shows that, as the economy moves away from the balanced growth path, technical change in the production process can be capital-augmenting. He recommends that the reasons why technical change may be labor-augmenting should be further investigated.

The literature on the effect of digitalization on the labor share remains limited. However, there is a growing body of literature on the effects of digitalization on Chinese firms. Liu et al. (2025) examine the effect of digital innovation on the labor share using Chinese firm-level data spanning 2000 to 2021. They define the labor share as the ratio of cash compensation to employees over enterprise value added. Their findings reveal a positive impact of digitalization on the labor share, with the effect being more pronounced among firms characterized by advanced technologies, greater market power, state ownership, and fewer financing constraints. Similarly, Li et al. (2024) investigate the impact of digital transformation on the labor share in China between 2007 and 2020, finding that enterprise digital transformation improves the labor share through two channels: expanding employment opportunities and increasing the share of highly skilled labor. Also Li et al. (2025) found a positive effect of digitalization on the labor share of income

In developed economies, Doraszelski & Jaumandreu (2018) (DJ) examine the bias of technological change using a CES production framework that allows for both factor-neutral and factor-nonneutral productivity, imposing homothetic separability of capital from other inputs. Using Spanish manufacturing data for 1990–2006, they find evidence that technological change is biased toward labor, with labor-augmenting productivity and Hicks-neutral productivity each contributing about 1.5% to annual output growth. Decomposing the labor share into its underlying components, they show that labor-biased technological change is associated with a decline in the labor share over time. Their counterfactual exercises suggest that, absent labor-augmenting technical change, the labor share would have remained roughly stable. Based on these results, they argue that labor-biased technological change is a primary driver of the decline in the aggregate labor share in the Spanish manufacturing industry. We use the same Spanish manufacturing dataset as DJ, but our sample period spans 2000–2019. Our methodology also differs: we estimate a translog production function and do not impose homothetic separability, allowing for richer interactions among inputs.

Oberfield & Raval (2021) develop a model to estimate the elasticity of substitution between capital and labor using plant-level data. They estimate an aggregate elasticity of substitution of approximately 0.7 over the period 1972–2007 and an average plant-level elasticity of about 0.5. They find that biased technological change accounts for most of the downward shift in the labor share in U.S. manufacturing since. In contrast, changes in factor prices alone explain relatively little of the decline.

Kerspien et al. (2026) contend that changes in capital composition have driven the decline in labor's share since 1980. Specifically, they point to a falling capital-output ratio of buildings and a high elasticity of substitution between machinery and labor ($\sigma > 1$), which, coupled with falling machinery prices, shifts income away from labor and toward capital owners. Karabarbounis & Neiman (2014) also document the global decline in labor share since the 1980s and argue that the primary cause is the decline in the

relative price of capital goods, often attributed to advances in information technology, which encouraged firms to shift away from labor toward capital. They estimate that the lower price of investment goods contributed about half of the decline. Their framework relates the labor share of income to markups, capital-augmenting technology, and the rental rate of capital. In contrast, our study relates the labor share of gross output to markups, the output elasticity of capital, and labor-augmenting technology.

By developing a novel approach to estimating factor-nonneutral technology within a flexible translog production function without imposing homothetic separability, we contribute to the growing literature on factor-nonneutral technological change. Within a unified framework, this paper examines the effects of digitalization on Hicks-neutral productivity, factor-augmenting productivity, the labor share, and markups, thereby bridging several strands of the production economics literature that have largely proceeded in isolation.

# 4 Data

This study uses firm-level data from Spanish manufacturing sectors, sourced from the Encuesta Sobre Estrategias Empresariales (ESEE), administered by Spain's Ministry of Industry. Our analysis covers the period from 2000 to 2019. The survey included a random radom sample of SME companies employing between 1 and 200 workers. All firms with 200 or more employees are invited to participate in the survey. To address potential attrition bias, survey administrators regularly include new firms using the same sampling criteria as the baseline year, thereby preserving the sample's representativeness over time. The dataset contains comprehensive information on outputs, inputs, digitalization practices, price variations in inputs and outputs, and other operational activities at the firm level.

Our dataset selects firms with at least 3 years of data, yielding 2,795 firms across 10 industries and 23,252 observations. Table 1 reports the sample size across the 10 industries in our study. In this section, we explain how prices and digitalization variables are constructed. We also remove outliers from the dataset by limiting the observations to firms with at least 10 staff and removing the 1% tail.

Regarding price data, the ESEE reports price variations rather than absolute price levels for both materials and sales. Following the methodology outlined by Jaumandreu & Lin (2018), we construct Paasche price indices for both input and output to address this limitation [2].

Our output variable is measured as the value of goods and services produced, deflated by an output price index constructed using the Paasche index formula. We construct the capital stock using the perpetual inventory method (PIM) with an assumed annual depreciation rate of 15%, consistent with standard practice in the manufacturing productivity literature. We construct capital through $K_{jt+1} = (1-\delta)\frac{P_{it}}{P_{it-1}}K_{jt} + I_{jt}$. Investment $I_{jt}$ is chosen in period $t$ but becomes effective in period $t+1$. We update the value of the past capital stock using the manufacturers' investment price index $P_{it}$. Real-term capital is obtained by deflating capital at current replacement values by the investment price

[2]For details about the price index construction, see Jaumandreu & Lin (2018)

index. $\frac{K_{it}}{P_{it}}$.

The materials input captures total intermediate consumption, comprising raw materials, energy, and purchased services. We deflate nominal intermediate consumption expenditures using an intermediate consumption price index constructed from the price variations of intermediate inputs reported in the ESEE dataset. This approach ensures that our materials variable reflects quantities rather than value changes driven by price fluctuations.

Labor input is measured in two dimensions. The quantity of labor is captured by total hours. In contrast, the price of labor services is proxied by the hourly wage rate, calculated as total labor compensation divided by total hours worked. This decomposition allows us to separately identify the effects of changes in labor quantity and labor quality or efficiency on production outcomes.

While the ESEE dataset originally classifies firms into 20 industrial categories, we aggregate these into 10 broader industry groups following the International Standard Industrial Classification (ISIC) framework. This reclassification enhances sample sizes within each industry, improving the precision of our industry-specific estimates while maintaining meaningful sectoral distinctions that reflect differences in production technology and market structure.

### 4.1 Digitalization Indices

To construct our digitalization index, we employ the same method and underlying variables employed by Calvino et al. (2018) and Añón Higón & Bonvin (2023). The construction of the index, rather than using a single variable, is based on the belief that digitalization is complex and multidimensional, and that it should be represented with multidimensional indices rather than single variables, as most literature does. The sub-indices identified by Calvino et al. (2018) are organized into four thematic sub-indices: information technology (IT) infrastructure, digitalization-related human capital, automation intensity, and digital stakeholder interaction. In addition, we include a set of supplementary digitalization variables that do not neatly fit into any single sub-index but reflect meaningful aspects of a firm's digital engagement. Together, these components constitute the overall digitalization index.

IT infrastructure captures a firm's investment in core information technology. Specifically, it includes investment in computer equipment and the employment of software programmers. These variables proxy for the extent to which the firm has built the foundational digital infrastructure necessary to support broader digitalization efforts. Digitalization-Related Human Capital reflects a firm's commitment to building digital competencies among its workforce. It is measured by the firm's external expenditure on IT-related training. This dimension recognizes that hardware and software investments alone are insufficient; the effective deployment of digital technologies requires a workforce with adequate digital skills.

Automation Intensity captures the degree to which a firm has integrated advanced automation technologies into its production processes. It encompasses the use of industrial robotics, computer

numerical control (CNC) machine tools, computer-aided design (CAD) systems, flexible manufacturing systems, and local area networks (LAN). Collectively, these variables reflect the firm's capacity to leverage programmable and networked technologies to enhance production efficiency.

Digital Stakeholder Interaction measures the extent to which firms employ digital channels in their interactions with external stakeholders. It includes whether the firm owns an internet domain, maintains a corporate website, and conducts online sales to both businesses (B2B) and consumers (B2C). This dimension captures the outward-facing, market-oriented component of a firm's digitalization strategy. Beyond the four sub-indices, we incorporate additional variables that capture other facets of firm-level digitalization. These include purchases from online suppliers and the firm's self-reported assessment of the internet's impact on its sales. While these variables do not map directly onto a single thematic sub-index, they contribute to a more comprehensive characterization of the firm's overall digital engagement. They are therefore included in the construction of the aggregate digitalization index. The table in the appendix compares our digitalization categorization with Calvino et al. (2018).

We follow the procedure proposed by Calvino et al. (2018) and adopted by Añón Higón & Bonvin (2023) to construct our composite digitalization index. The construction proceeds in several steps designed to ensure comparability across variables measured on different scales.

First, monetary variables are converted into capital stocks using the perpetual inventory method and expressed as ratios to their industry-year means. Each observation is then assigned a score based on the decile of the distribution to which it belongs, and the resulting values are rescaled to the [0, 1] interval. Second, categorical variables that are observed only at four-year intervals, namely, the use of robots, computer-aided design (CAD), flexible manufacturing systems, and local area networks (LANs), are extrapolated to annual frequency for the next three years and subsequently normalized to the [0, 1] range. The remaining binary categorical variables require no further transformation.

This procedure yields 14 harmonized variables, each bounded between 0 and 1. To obtain a synthetic digitalization index, we aggregate these variables as an unweighted sum and then normalize it to the [0, 1] interval. Values close to 0 indicate that a firm exhibits a low degree of digitalization in a given period, while values close to 1 reflect a high degree of digital technology adoption.

### 4.2 Descriptive Statistics

Table 1 presents the descriptive statistics of the key variables used in the estimation, disaggregated across ten manufacturing sub-industries in Spain over the period 2000 to 2019. The pooled sample reveals substantial heterogeneity in firm size and input usage across industries. Average real output across all industries is approximately 38.58 million euros, while real capital and real materials average 19.34 million and 29.39 million euros, respectively. The large standard deviations relative to the means across all three variables indicate considerable within-industry dispersion in firm scale, a pattern consistent with the well-documented heterogeneity in firm productivity within narrowly defined manufacturing sectors.

Among the sub-industries, Transport Equipment stands out as the largest in terms of average real output (68.20 million euros), real capital (32.92 million euros), and labor input (538,063 hours), reflecting the capital-intensive and scale-dependent nature of vehicle and equipment manufacturing. Chemical Products ranks second in output and materials usage, with an average real output of 56.55 million euros and a real materials use of 43.52 million euros. At the other end of the spectrum, Textile, Leather, and Shoes and Timber and Furniture represent the smallest sub-industries, with average real output of 11.04 million and 13.75 million euros, respectively. These industries also exhibit the lowest average labor hours and capital stocks, consistent with their reliance on smaller, labor-intensive production processes.

Wage levels display meaningful variation across industries. The highest average wages are observed in Agricultural and Industrial Machinery (22.31 euros per hour) and Chemical Products (22.20 euros per hour), both technology-intensive sectors that typically employ higher-skilled workers. In contrast, Textile, Leather, and Shoes reports the lowest average wage at 13.28 euros per hour, followed by Timber and Furniture at 14.69 euros per hour. The pooled average wage of 18.93 euros per hour with a standard deviation of 7.58 suggests notable cross-firm dispersion in labor compensation, likely driven by differences in skill composition and collective bargaining arrangements.

The output and materials price indices are centered close to unity across all sub-industries, indicating that the deflation procedure has effectively normalized nominal values to real terms. The output price index ranges from 1.009 in Transport Equipment to 1.036 in Textile, Leather, and Shoes, while the materials price index varies between 0.994 in Food, Drink, and Tobacco and 1.005 in Transport Equipment. The relatively modest standard deviations of these indices confirm limited dispersion in firm-level price movements within each industry.

The factor cost shares reveal informative patterns regarding input composition. The average labor share across all industries is 0.260, while the materials share averages 0.666, indicating that materials constitute the dominant cost component in Spanish manufacturing. Food, Drink, and Tobacco exhibits the lowest labor share (0.202) and the highest materials share (0.715), consistent with the raw-material-intensive nature of food processing. Conversely, Metal and Metal Products and Timber and Furniture display relatively higher labor shares at 0.297 and 0.295, respectively, reflecting more labor-intensive production technologies. These cost-share patterns are broadly consistent with stylized facts in the production economics literature and provide an important foundation for the subsequent estimation of factor-augmenting productivity and for labor-share decomposition.

Table 1: Descriptive Statistics by Industry

| Industry | $r_y$ | $K$ | $r_m$ | Labor Hours | Wages | $p_y$ | $p_m$ | $s_L$ | $s_M$ |
|---|---|---|---|---|---|---|---|---|---|
| All Industries | 38,577 | 19,335 | 29,385 | 294,463 | 18.93 | 1.025 | 1.000 | 0.260 | 0.666 |
| | (78,151) | (36,863) | (63,097) | (466,286) | (7.58) | (0.108) | (0.149) | (0.138) | (0.148) |
| Agric. & Ind. Machinery | 28,922 | 13,197 | 20,982 | 268,707 | 22.31 | 1.032 | 1.004 | 0.282 | 0.644 |
| | (46,220) | (20,365) | (36,401) | (384,327) | (6.72) | (0.089) | (0.129) | (0.125) | (0.145) |
| Chemical Products | 56,554 | 26,809 | 43,517 | 344,649 | 22.20 | 1.026 | 0.998 | 0.217 | 0.701 |
| | (96,625) | (45,106) | (79,099) | (465,645) | (8.52) | (0.130) | (0.163) | (0.104) | (0.127) |
| Electrical Goods | 45,101 | 22,497 | 34,096 | 367,501 | 20.46 | 1.017 | 1.002 | 0.287 | 0.654 |
| | (85,836) | (39,787) | (68,743) | (530,100) | (6.81) | (0.113) | (0.148) | (0.134) | (0.147) |
| Food, Drink, & Tobacco | 50,382 | 21,930 | 41,322 | 323,917 | 16.37 | 1.027 | 0.994 | 0.202 | 0.715 |
| | (98,726) | (39,036) | (83,251) | (539,855) | (6.52) | (0.110) | (0.159) | (0.134) | (0.154) |
| Metal & Metal Products | 34,446 | 16,603 | 26,888 | 248,852 | 20.04 | 1.027 | 1.004 | 0.297 | 0.629 |
| | (75,645) | (34,480) | (63,234) | (395,523) | (6.75) | (0.121) | (0.186) | (0.153) | (0.157) |
| Non-Metallic Minerals | 37,276 | 24,652 | 26,039 | 310,833 | 18.90 | 1.021 | 1.001 | 0.265 | 0.650 |
| | (75,757) | (44,925) | (55,470) | (475,695) | (7.34) | (0.111) | (0.120) | (0.138) | (0.138) |
| Paper & Paper Products | 29,198 | 19,623 | 21,153 | 232,497 | 20.34 | 1.023 | 1.001 | 0.271 | 0.632 |
| | (54,011) | (37,090) | (41,235) | (355,769) | (7.38) | (0.101) | (0.134) | (0.127) | (0.141) |
| Textile, Leather, & Shoes | 11,041 | 6,521 | 7,851 | 179,346 | 13.28 | 1.036 | 1.001 | 0.282 | 0.663 |
| | (20,344) | (12,196) | (14,114) | (318,819) | (6.87) | (0.092) | (0.118) | (0.146) | (0.153) |
| Timber & Furniture | 13,751 | 7,659 | 9,938 | 177,971 | 14.69 | 1.028 | 0.996 | 0.295 | 0.653 |
| | (31,087) | (15,058) | (24,281) | (319,904) | (5.10) | (0.084) | (0.115) | (0.129) | (0.131) |
| Transport Equipment | 68,199 | 32,916 | 49,374 | 538,063 | 21.74 | 1.009 | 1.005 | 0.252 | 0.678 |
| | (96,597) | (47,274) | (71,988) | (686,185) | (7.01) | (0.076) | (0.136) | (0.129) | (0.144) |

*Notes:* Standard deviations are reported in parentheses. Real output ($r_y$), real capital ($K$), and real materials ($r_m$) are expressed in thousands of euros. Labor hours are annual total hours. Wages are in euros per hour. $p_y$ and $p_m$ are output and materials price indices, respectively. $s_L$ and $s_M$ denote labor and materials cost shares of revenue.

# 5 Model

The existing literature on factor-biased productivity has predominantly relied on constant elasticity of substitution (CES) production functions. However, the CES specification imposes constant input elasticities and cannot capture potential interactions between factors when estimating the direction and magnitude of productivity shifts. A few recent studies ((Doraszelski & Jaumandreu, 2018; Malikov et al., 2024) have made progress by estimating factor-augmenting productivity using flexible functional forms that generate observation-specific elasticities. Nevertheless, these approaches maintain the assumption of homothetic separability between capital and other inputs, which may be overly restrictive in many production contexts.

This study contributes to the literature by identifying production function parameters using a translog specification that allows for non-homothetic production technology. Importantly, our framework does not impose homothetic separability on capital, permitting richer patterns of input substitution and complementarity. We further relax the assumption of perfect competition by allowing firms to operate in imperfectly competitive output markets, thereby affecting the estimation of the production function and the interpretation of measured productivity changes.

We state our technological function in equation 1.

$$Y_{it} = F\big(K_{it}, L^*_{it}, M_{it}\big)\, e^{\omega_{it}} \tag{1}$$

$$L^*_{it} = L_{it}\, e^{\omega_{L,it}} \tag{2}$$

In equation (1), $Y_{it}$, $L^*_{it}$, and $M_{it}$ are observed output, labor, and materials, respectively, $K_{it}$ is derived from the perpetual investment model then multiply by capacity utilization, $F(.)$ is the technology we want to model, $\omega_{L,it}$ and $\omega_{it}$ are labor and factor neutral productivity, respectively. In our model, the firm has two choice variables available when deciding on the production of goods and services: labor $L_{it}$ and materials $M_{it}$. These two variables enter the firm's profit maximization problem as flexible inputs whose values are determined in the current period. The capital $K_{it}$ and $\omega_{it}$ are the state variables in the model. Let $P_{it} = P(Y_{it}, z_{it})$ be an inverse demand with shifters $z_{it}$. The objective of the firm is to maximize profit

$$\Pi_{it} \;=\; P(Y_{it}, z_{it})\, F(\cdot)\, e^{\omega_{it}} \;-\; W_{L,it} L_{it} \;-\; W_{M,it} M_{it}. \tag{3}$$

in choosing the variable inputs $M$ and $L$. This gives us the following first-order conditions (FOC).

**FOC w.r.t. M**

$$\begin{aligned} P(\cdot)e^{\omega}\frac{\partial F(\cdot)}{\partial M} + e^{\omega}F(\cdot)\frac{\partial P}{\partial M} &= W_M \\ \Rightarrow\ P(\cdot)e^{\omega}\frac{\partial \ln F(\cdot)}{\partial \ln M}\cdot\frac{F(\cdot)}{M} + e^{\omega}F(\cdot)\frac{\partial \ln P(\cdot)}{\partial \ln Y}\cdot\frac{\partial \ln Y}{\partial \ln M}\cdot\frac{P}{M} &= W_M \\ \Rightarrow\ F(\cdot)e^{\omega}P(\cdot)\varepsilon^*_M + F(\cdot)e^{\omega}\varepsilon_P(\cdot)\cdot\varepsilon^*_M &= W_M M \\ \Rightarrow\ \varepsilon^*_M \times (1+\varepsilon_P) &= \frac{W_M M}{PY} \equiv S_M \end{aligned} \tag{4}$$

where

$$\frac{\partial \ln F(\cdot)}{\partial \ln M}\cdot\frac{F(\cdot)}{M} = \frac{\partial \ln Y}{\partial \ln M}\cdot\frac{F(\cdot)}{M} = \varepsilon_M, \qquad \varepsilon_P = \frac{\partial \ln P(\cdot)}{\partial \ln Y}.$$

Similarly, the **FOC w.r.t. L** is:

$$\begin{aligned} P(\cdot)\frac{\partial F(\cdot)}{\partial L}e^{\omega} + F(\cdot)e^{\omega}\frac{\partial P}{\partial L} &= W_L \\ \Rightarrow\ P(\cdot)\frac{\partial \ln F(\cdot)}{\partial \ln L^*}\cdot\frac{\partial \ln L^*}{\partial \ln L}\cdot\frac{F(\cdot)}{L}e^{\omega} + F(\cdot)e^{\omega}\frac{\partial \ln P(\cdot)}{\partial \ln L} &= W_L \\ \Rightarrow\ F(\cdot)e^{\omega}\varepsilon^*_L + F(\cdot)e^{\omega}\varepsilon_P\cdot\varepsilon^*_L &= \frac{W_L L}{P} \\ \Rightarrow\ \varepsilon^*_L \times (1+\varepsilon_P) &= \frac{W_L L}{PY} \equiv S_L \end{aligned} \tag{5}$$

where

$$\frac{\partial \ln F(\cdot)}{\partial \ln L^*}\cdot\frac{F(\cdot)}{L^*} = \frac{\partial \ln Y}{\partial \ln L^*}\cdot\frac{F(\cdot)}{L^*} = \varepsilon^*_L.$$

Since we use panel data, we attach the $i$ and $t$ subscripts for firm and time. Thus, $s_{M,it} \equiv \frac{W_{M,it}M_{it}}{P_{it}Y_{it}}$ and $s_{L,it} \equiv \frac{W_{L,it}L_{it}}{P_{it}Y_{it}}$ are the cost shares of material and labor in output, respectively. Finally, $\varepsilon_{P,it} = \frac{\partial \ln P_{it}}{\partial \ln Y_{it}}$ is the inverse price elasticity of demand.

Using the panel subscripts $i$ and $t$, the FOCs in (4) and (5) are written as

$$s_{M,it} = \big(1+\varepsilon_{P,it}\big)\varepsilon^*_{M,it}, \tag{6}$$

$$s_{L,it} = \big(1+\varepsilon_{P,it}\big)\varepsilon^*_{L,it}. \tag{7}$$

Where $\varepsilon^*_{M,it}$ and $\varepsilon^*_{L,it}$ are the output elasticities of materials and labor that include labor augmenting productivity as part of their components, they are defined in equation (9) and (10) below. The technology is specified as an unrestricted translog, viz.,

$$\begin{aligned} \ln F(K_{it}, L^*_{it}, M_{it}) = \beta_0 &+ \beta_K \ln K_{it} + \beta_L \ln L^*_{it} + \beta_M \ln M_{it} \\ &+ \tfrac{1}{2}\beta_{KK}(\ln K_{it})^2 + \tfrac{1}{2}\beta_{LL}(\ln L^*_{it})^2 + \tfrac{1}{2}\beta_{MM}(\ln M_{it})^2 \\ &+ \beta_{KL}\ln K_{it}\ \ln L^*_{it} + \beta_{KM}\ln K_{it}\ \ln M_{it} + \beta_{ML}\ln M_{it}\ \ln L^*_{it}. \end{aligned} \tag{8}$$

Therefore,

$$\begin{aligned}\varepsilon^*_{M,it} &= \frac{\partial \ln F}{\partial \ln M_{it}} = \beta_M + \beta_{MM}\ln M_{it} + \beta_{KM}\ln K_{it} + \beta_{ML}\ln L^*_{it} \\ &= \big(\beta_M + \beta_{MM}\ln M_{it} + \beta_{KM}\ln K_{it} + \beta_{ML}\ln L_{it}\big) \;+\; \beta_{ML}\,\omega_{L,it}, \qquad (9)\\ \varepsilon^*_{L,it} &= \frac{\partial \ln F}{\partial \ln L^*_{it}} = \beta_L + \beta_{LL}\ln L^*_{it} + \beta_{KL}\ln K_{it} + \beta_{ML}\ln M_{it} \\ &= \big(\beta_L + \beta_{LL}\ln L_{it} + \beta_{KL}\ln K_{it} + \beta_{ML}\ln M_{it}\big) \;+\; \beta_{LL}\,\omega_{L,it}. \qquad (10)\end{aligned}$$

$$\varepsilon_{M,it} = \beta_M + \beta_{MM}\ln M_{it} + \beta_{KM}\ln K_{it} + \beta_{ML}\ln L_{it}, \qquad \varepsilon_{L,it} = \beta_L + \beta_{LL}\ln L_{it} + \beta_{ML}\ln M_{it} + \beta_{KL}\ln K_{it}.$$

The last equalities use $\ln L^*_{it} = \ln L_{it} + \omega_{L,it}$.

From the FOC we let $\theta_{it} \equiv 1 + \varepsilon_{P,it}$. Then (6)–(7) imply

$$s_{M,it} = \theta_{it}\,\varepsilon_{M,it} + \theta_{it}\,\beta_{ML}\,\omega_{L,it}, \qquad \text{(from (9))} \qquad (11)$$

$$s_{L,it} = \theta_{it}\,\varepsilon_{L,it} + \theta_{it}\,\beta_{LL}\,\omega_{L,it}. \qquad \text{(from (10))} \qquad (12)$$

we scaled the share of the inputs to output by $\theta_{it}$, then $s^*_{M,it} \equiv s_{M,it}/\theta_{it}$ and $s^*_{L,it} \equiv s_{L,it}/\theta_{it}$. Then

$$s^*_{M,it} = \varepsilon_{M,it} + \beta_{ML}\,\omega_{L,it}, \qquad (13)$$

$$s^*_{L,it} = \varepsilon_{L,it} + \beta_{LL}\,\omega_{L,it}. \qquad (14)$$

To estimate equations (13) and (14), we assume that labor productivity $\omega_{L,it}$ follows the AR(1) markov process.

$$\omega_{L,it} \;=\; \rho\,\omega_{L,i,t-1} + \alpha_1 D_{i,t-1} + \xi_{it}, \qquad \mathbb{E}[\xi_{it}|\omega_{L,i,t-1}, D_{i,t-1}] = 0. \qquad (15)$$

where $\xi_{it}$ is innovation in labor productivity and $D_{i,t-1}$ is the lag of digitalization.

Quasi-differencing (13)–(14) by $\rho$ yields

$$s^*_{M,it} - \rho\, s^*_{M,i,t-1} = \big(\varepsilon_{M,it} - \rho\,\varepsilon_{M,i,t-1}\big) + (\beta_{ml}\alpha_1)D_{i,t-1} + \nu_{1,it}, \qquad (16)$$

$$s^*_{L,it} - \rho\, s^*_{L,i,t-1} = \big(\varepsilon_{L,it} - \rho\,\varepsilon_{L,i,t-1}\big) + (\beta_{ll}\alpha_1)D_{i,t-1} + \nu_{2,it}, \qquad (17)$$

where $\nu_{1,it} = \beta_{ML}\xi_{it} + v_{mit}$, $\nu_{2,it} = \beta_{LL}\xi_{it} + v_{1it}$. $v_{mit}$ and $v_{lit}$ are misallocations in $M$ and $L$. A system GMM on (16)–(17) identifies the the following coefficients $\rho, \beta_L, \beta_{LL}, \beta_{ML}, \beta_{KL}, \beta_M, \beta_{MM}, \beta_{MK}$.

From (13) and (14), we can express $\omega_{L,it}$ from each equation individually:

$$\omega_{L,it} = \frac{s^*_{M,it} - \varepsilon_{M,it}}{\beta_{ML}}, \tag{18}$$

$$\omega_{L,it} = \frac{s^*_{L,it} - \varepsilon_{L,it}}{\beta_{LL}}. \tag{19}$$

therefore, we obtain $\omega_{L,it}$ as the ratio of equations (13) and (14):

$$\frac{s_{M,it}}{s_{L,it}} = \frac{\varepsilon_{M,it} + \beta_{ML}\,\omega_{L,it}}{\varepsilon_{L,it} + \beta_{LL}\,\omega_{L,it}}. \tag{20}$$

Cross-multiplying and rearranging:

$$\begin{aligned} s_{M,it}\big(\varepsilon_{L,it} + \beta_{LL}\,\omega_{L,it}\big) &= s_{L,it}\big(\varepsilon_{M,it} + \beta_{ML}\,\omega_{L,it}\big), \\ s_{M,it}\varepsilon_{L,it} + s_{M,it}\beta_{LL}\,\omega_{L,it} &= s_{L,it}\varepsilon_{M,it} + s_{L,it}\beta_{ML}\,\omega_{L,it}, \\ \omega_{L,it}\big(s_{M,it}\beta_{LL} - s_{L,it}\beta_{ML}\big) &= s_{L,it}\varepsilon_{M,it} - s_{M,it}\varepsilon_{L,it}. \end{aligned} \tag{21}$$

Therefore,

$$\omega_{L,it} = \frac{s_{L,it}\varepsilon_{M,it} - s_{M,it}\varepsilon_{L,it}}{s_{M,it}\beta_{LL} - s_{L,it}\beta_{ML}} \tag{22}$$

### 5.1 Stage 2: Capital elasticity and Hicks–neutral productivity

$$\widetilde{\ln Y_{it}} = \beta_0 + \beta_K \ln K_{it} + \tfrac{1}{2}\beta_{KK}(\ln K_{it})^2 + H_{it}\big(\widehat{\boldsymbol{\beta}}\big) + \omega_{n,it}, \tag{23}$$

where

$$\begin{aligned} H_{it}(\widehat{\boldsymbol{\beta}}) = \widehat{b}_L \ln L + \frac{1}{2}\widehat{b}_{LL}(\ln L)^2 + \widehat{b}_M \ln M + \frac{1}{2}\widehat{b}_{MM}(\ln M)^2 \\ + \widehat{b}_{ML} \ln M \ln L + \widehat{b}_{KL} \ln K \ln L + \widehat{b}_{MK} \ln M \ln K \end{aligned} \tag{24}$$

$$\omega_{n,it} = \rho_\omega\,\omega_{n,i,t-1} \;+\; \gamma_{\omega 1} D_{i,t-1} \;+\; \eta_{it}, \qquad \mathbb{E}[\eta_{it}] = 0,\ |\rho_\omega| < 1. \tag{25}$$

$$\begin{aligned} \widetilde{\ln Y_{it}} - \rho_\omega \widetilde{\ln Y_{i,t-1}} = (1-\rho_\omega)\beta_0 + \beta_K(\ln K_{it} - \rho_\omega \ln K_{i,t-1}) \\ + \tfrac{1}{2}\beta_{KK}\big[(\ln K_{it})^2 - \rho_\omega(\ln K_{i,t-1})^2\big] + \gamma_{\omega 1} D_{i,t-1} + u_{it}, \end{aligned} \tag{26}$$

where $\widetilde{\ln Y_{it}} := \ln Y_{it} - H_{it}(\widehat{\boldsymbol{\beta}})$.

$$\varepsilon^*_{K,it} = \hat{\beta}_K + \widehat{\beta}_{KK} \ln K_{it} + \widehat{\beta}_{KL} \ln L_{it} + \widehat{\beta}_{KM} \ln M_{it} + \widehat{\beta}_{KL}\, \widehat{\omega}_{L,it}. \tag{27}$$

$$\widehat{\omega}_{n,it} = \left(\widetilde{\ln Y}_{it} - \widehat{\beta}_0 - \widehat{\beta}_K \ln K_{it} - \tfrac{1}{2}\widehat{\beta}_{KK}(\ln K_{it})^2\right) \tag{28}$$

# 6 Identification and Estimation

This section describes how we estimate and identify the parameters of the production function. Our empirical strategy proceeds in three steps. First, we recover the parameter $\theta$, which is required to identify the quasi-differenced share equations (16) and (17). Second, conditional on the estimated inverse elasticity of demand, we estimate the two share equations by stacking the GMM estimates to recover the technology parameters that define labor and material elasticities and the productivity processes.

## 6.1 Step 1: Recovering the theta from demand

We recover $\theta$ from an inverse demand function. Let $\varepsilon_p$ denote the absolute inverse price elasticity of demand. Under the demand-side structure motivating our framework, the theta is a monotone function of $\varepsilon_p$ and can be written as

$$\theta \;=\; 1 + \varepsilon_p. \tag{29}$$

In our empirical implementation, the inverse price elasticity is obtained from the coefficient on log price in the following demand specification:

$$\ln P_{it} = \alpha_0 + \alpha_1 \ln Y_{it} + \alpha_2(t) \ln Y_{it} + \alpha_3\, \mathrm{mktd}_{it} + \alpha_4\, \mathrm{ads}_{it} + \alpha_i + \tau_t + v_{d,it}, \tag{30}$$

where $\ln Y_{it}$ is log of real output, $\ln P_{it}$ is log price index at firm level, $\mathrm{mktd}_{it}$ captures market dynamics, $\mathrm{ads}_{it}$ measures advertising expenditure growth, $\alpha_i$ are firm fixed effects, and $v_{d,it}$ is a demand shock. The coefficients $\alpha_1$ and $\alpha_2(t)$ captures the price elasticity of demand.

$$\hat{\theta} \;=\; 1 + (\hat{\alpha}_1 + \hat{\alpha}_2(t)) \tag{31}$$

A key concern is that output is endogenous in (30), because $Y_{it}$ may respond to the contemporaneous demand shock $v_{d,it}$. We therefore estimate (30) by two-stage least squares (2SLS) with firm fixed effects, and instrumenting $\ln Y_{it}$. We use $\ln Y_{it-2}$ and $\ln Y_{it-2} * t_{-2}$ as instruments under the assumption that the second lag of output is orthogonal to the error in the current demand, once we control for firm fixed effects and observed demand shifters.

### 6.1.1 Step 2: Estimating the share equations

Given $\hat{\theta}$, we substitute the estimated $\hat{\theta}$ into the quasi-differenced share equations (16) and (17) and estimate the resulting system using stacked GMM. This approach is well-suited for our setting for two reasons. First, input choices are potentially endogenous, so valid estimation requires instruments orthogonal to contemporaneous productivity innovations. Second, stacked GMM combines moment conditions from both differenced equations, improving efficiency and reducing finite-sample bias when the variables are persistent.

**Timing assumptions and economic justification.** Our identification strategy relies on timing assumptions standard in the proxy-variable and dynamic input choice literature. We assume that labor ($L_{it}$) and materials ($M_{it}$) are flexible inputs chosen after observing current productivity, while capital ($K_{it}$) is predetermined and evolves more slowly. This timing structure is particularly plausible for Spanish manufacturing. Spain's dual labor market, with a sizable share of temporary contracts alongside highly protected permanent contracts, allows firms to adjust employment at the margin with relatively low short-run frictions Bentolila et al. (2008). Similarly, intermediate inputs which include energy, services, and raw materials, can be adjusted within the production period. These features support the assumption that the first-order conditions for labor and materials bind period-by-period, which is exactly the structure exploited by the quasi-differenced share equations.

**Instrument set.** We construct instruments from predetermined state variables, lagged cost shifters implied by the timing assumptions, the lagged share of labor, the lagged output price, and, in some industries, lagged demand shifters such as lagged market dynamics, lagged advertising, and lagged theta. Also, we include ${}^{2}_{it-1}$ and ${}^{2}_{it-1}$ as instruments. The instrument vector includes

$$\begin{aligned} Z_{it} \in \big\{ & 1,\ \ln K_{it},\ \ln K_{i,t-1},\ (\ln K_{i,t-1})^2,\ \ln W_{i,t-1},\ (\ln W_{i,t-1})^2, \\ & D_{i,t-1},\ \ln P_{i,t-1},\ \ln P^{M}_{i,t-1},\ s^{L}_{i,t-1},\ \text{mktd}_{i,t-1},\ \text{ads}_{i,t-1} \big\}. \end{aligned} \tag{32}$$

The remaining instruments are allowed to vary across industries. For example, in some industries we augment $Z_{it}$ with $\ln P_{it-1}$ , the labor cost share $S_{Lit-1}$, or lagged input-price measures such as $lnPM_{it-1}$. Because we estimate the two share equations, each element of $Z_{it}$ generates moment conditions for each equation, so the total number of moment conditions scales with both the number of instruments and the number of equations in the stacked GMM. We ensure that the number of instruments is sufficient to identify the parameter vector.

The parameters are estimated jointly via two-step GMM using the materials and labor cost-share equations, quasi-differenced to account for the AR(1) Markov process in productivity. Define the parameter vector $\boldsymbol{\theta} = (\beta_m,\ \beta_{mm},\ \beta_{ml},\ \beta_l,\ \beta_{ll},\ \beta_{km},\ \beta_{kl},\ \rho,\ \alpha_1)'$.

**Materials share residual.**

$$
\begin{aligned}
u_{it}^{M} = \big(\tilde{s}_{it}^{M} - \rho\,\tilde{s}_{i,t-1}^{M}\big) - (1-\rho)\,\beta_m - \beta_{mm}\big(\ln M_{it} - \rho\,\ln M_{i,t-1}\big) \\
- \beta_{ml}\big(\ln L_{it} - \rho\,\ln L_{i,t-1}\big) - \beta_{km}\big(\ln K_{it} - \rho\,\ln K_{i,t-1}\big) - \beta_{ml}\,\alpha_1\,lnD_{i,t-1},
\end{aligned}
\tag{33}
$$

**Labor share residual.**

$$
\begin{aligned}
u_{it}^{L} = \big(\tilde{s}_{it}^{L} - \rho\,\tilde{s}_{i,t-1}^{L}\big) - (1-\rho)\,\beta_l - \beta_{ll}\big(\ln L_{it} - \rho\,\ln L_{i,t-1}\big) \\
- \beta_{ml}\big(\ln M_{it} - \rho\,\ln M_{i,t-1}\big) - \beta_{kl}\big(\ln K_{it} - \rho\,\ln K_{i,t-1}\big) - \beta_{ll}\,\alpha_1\,lnD_{i,t-1},
\end{aligned}
\tag{34}
$$

where $\tilde{s}_{it}^{j} \equiv s_{it}^{j}/\mu_{it}$ denotes the cost share deflated by the $\theta$.

**Moment conditions.** The quasi-differencing eliminates the level of $\omega^n$ and isolates the productivity innovation $\xi_{it}$, which is orthogonal to the instrument vector $\mathbf{z}_{it}$ comprising lagged and predetermined variables. The GMM estimator exploits the following moment conditions:

$$
E\left[\mathbf{z}_{it} \otimes \begin{pmatrix} u_{it}^{M} \\ u_{it}^{L} \end{pmatrix}\right] = \mathbf{0}, \tag{35}
$$

The system in (35) is estimated by two-step GMM, where the first step uses an identity weighting matrix and the second step employs the optimal weighting matrix constructed from the first-step residuals.

**Overidentification and specification checks.** We assess instrument validity using the Sargan $J$-test of overidentifying restrictions, which evaluates whether the instruments are collectively orthogonal to the estimated residuals (equivalently, to the innovations in the productivity processes underlying the share system). In specifications with heteroskedasticity-robust weighting, the Hansen $J$-test provides the analogous diagnostic. We interpret these tests jointly with standard instruments and persistence considerations that are especially relevant in dynamic panel settings.

### 6.1.2 Step 3: Identifying the remaining capital-related parameters through Non-Linear Least Square

While stacked GMM applied to (16) and (17) identifies the parameters governing flexible-input elasticities and interaction terms, a subset of capital-related parameters which include the constant and the pure-capital terms $b_0$, $b_k$, $b_{kk}$ in our translog technology, is pinned down in the stage 3 through the markov process of Hicks neutral productivity. We therefore use nonlinear least squares (NLS) to identify these remaining parameters, treating capital as predetermined and exploiting the implication that its current realization is orthogonal to the contemporaneous innovation in Hicks-neutral productivity. Intuitively, since $K_{it}$ is chosen in prior periods, it does not respond one-for-one to productivity innovation within the

period, which makes it suitable for identifying capital terms once flexible-input components have been disciplined by the share system.

**Capital block estimation.** Given the share-equation estimates $\hat{\beta}_m$, $\hat{\beta}_{mm}$, $\hat{\beta}_{ml}$, $\hat{\beta}_l$, $\hat{\beta}_{ll}$, $\hat{\beta}_{km}$, $\hat{\beta}_{kl}$, and the recovered labor-augmenting productivity $\hat{\omega}^L_{it}$, define the labor-augmented labor input as

$$\ln L^*_{it} \equiv \ln L_{it} + \hat{\omega}^L_{it}. \tag{36}$$

The contribution of labor and materials to output is then netted out by constructing

$$\begin{aligned} \ln \tilde{Y}_{it} \equiv\ & \ln Y_{it} - \hat{\beta}_l \ln L^*_{it} - \hat{\beta}_m \ln M_{it} - \hat{\beta}_{kl}\, \ln K_{it}\, \ln L^*_{it} - \hat{\beta}_{km}\, \ln K_{it}\, \ln M_{it} \\ & - \hat{\beta}_{ml}\, \ln L^*_{it}\, \ln M_{it} - \tfrac{1}{2}\, \hat{\beta}_{ll}\, (\ln L^*_{it})^2 - \tfrac{1}{2}\, \hat{\beta}_{mm}\, (\ln M_{it})^2, \end{aligned} \tag{37}$$

so that $\ln \tilde{Y}_{it}$ isolates the capital and Hicks-neutral productivity components of the production function:

$$\ln \tilde{Y}_{it} = \beta_0 + \beta_k \ln K_{it} + \tfrac{1}{2}\, \beta_{kk} (\ln K_{it})^2 + \omega^h_{it} + \varepsilon_{it}. \tag{38}$$

To handle the unobserved Hicks-neutral productivity $\omega^n_{it}$, we impose the AR(1) Markov process $\omega^h_{it} = \rho_K\, \omega^h_{i,t-1} + \gamma_1\, D_{i,t-1} + \xi_{it}$, where $D_{i,t-1}$ is the lagged digitalization index and $\gamma_1$ captures the direct effect of digitalization on Hicks-neutral productivity. Quasi-differencing (38) yields the estimating equation

$$\begin{aligned} \ln \tilde{Y}_{it} = {} & \beta_0 + \beta_k \ln K_{it} + \tfrac{1}{2}\, \beta_{kk} (\ln K_{it})^2 \\ & + \rho_K \Big[ \ln \tilde{Y}_{i,t-1} - \beta_0 - \beta_k \ln K_{i,t-1} - \tfrac{1}{2}\, \beta_{kk} (\ln K_{i,t-1})^2 \Big] + \gamma_1\, D_{i,t-1} + \xi_{it}, \end{aligned} \tag{39}$$

where the term in brackets equals $\hat{\omega}^n_{i,t-1} + \varepsilon_{i,t-1}$, and $\xi_{it}$ is the productivity innovation orthogonal to predetermined variables. The remaining parameter vector $(\beta_0,\, \beta_k,\, \beta_{kk},\, \rho_K,\, \gamma_1)'$ is estimated by nonlinear least squares (NLS) on (39), initialized with OLS estimates from the static regression of $\ln \tilde{Y}_{it}$ on $\ln K_{it}$ and $\frac{1}{2}(\ln K_{it})^2$.

Taken together, this three-step procedure, which include (i) recovering $\theta$ from an demand equation and (ii) estimating the quasi-differenced share equations by stacked GMM and (iii) using NLS to anchor the remaining capital terms, delivers a transparent identification strategy for our model.

## 6.2 Digitalization and Labor Share

In advanced economies, the labor share has been declining for several decades. This decline has predominantly been studied at the aggregate level (Blanchard, 1997; Bentolila & Saint-Paul, 2003; Kerspien et al., 2026). In this section, we examine the effect of digitalization on the labor share using a reduced-form approach at the firm level.

Specifically, we estimate the following panel fixed-effects specification:

$$s_{L,it} = \beta_0 + \beta_1 \text{Dig}_{it-1} + \beta_2 \text{markup}_{it} + \beta_3 \omega_{L,it} + \beta_4 \ln K_{it} + \beta_5 \ln M_{it} + \tau_t + \alpha_i + \nu_{it} \tag{40}$$

where $s_{L,it}$ denotes the labor share of firm $i$ in period $t$, $\text{Dig}_{it-1}$ is the lagged digitalization index, $\text{markup}_{it}$ captures firm-level markups, $\omega_{L,it}$ denotes labor-augmenting productivity, $\ln K_{it}$ and $\ln M_{it}$ are the logarithms of capital and materials, respectively, $\tau_t$ represents time fixed effects, $\alpha_i$ captures firm fixed effects, and $\nu_{it}$ is the idiosyncratic error term.

# 7 Results

This section presents and discusses the estimation results. We begin with the demand estimation, which yields the inverse elasticities of demand and firm-level markups. We then turn to the production function estimates obtained from the GMM share equations and The NLS capital block, examines the output elasticities of materials, labor, and capital across industries. Next, we discuss the recovered productivity components, comprising labor-augmenting productivity and Hicks-neutral productivity, and evaluate the impact of digitalization on each of these channels. We subsequently assess model validity through diagnostic tests, including the Hansen J-test for overidentifying restrictions and the persistence parameters governing the productivity processes. We analyze the Implications of the estimated production structure for the elasticity of substitution between labor and capital, and present the labor share decomposition to quantify the contributions of factor substitution, factor-biased technical change, and digitalization to the evolving labor market share in Spanish manufacturing. Finally, we examine the impact of digitalization on labor share.

Table 2: Demand Estimation Results by Industry (Mean Values)

| Industry | Inv. Elast. ($\bar{\varepsilon}_P$) | Mkt. dynamics ($\hat{\beta}_{mktd}$) | Advertising ($\hat{\beta}_{ads}$) |
|---|---|---|---|
| All Industries | −0.0613 | 0.000203$^{***}$ | 0.001046 |
| Agricultural & Ind. Mach. | −0.0440 | 0.000089 | 0.002050 |
| Chemical Products | −0.1112 | 0.000203 | 0.006357$^{*}$ |
| Electrical Goods | −0.1108 | 0.000637$^{***}$ | −0.013017$^{\cdot}$ |
| Food, Drink & Tobacco | −0.1162 | 0.000330$^{**}$ | 0.002186$^{\cdot}$ |
| Non-Metallic Minerals | −0.0437 | 0.000364$^{*}$ | 0.001567 |
| Paper & Printing Prod. | −0.0463 | 0.000193 | 0.000833 |
| Textile, Leather & Shoes | −0.0372 | 0.000249$^{**}$ | 0.000466 |
| Timber & Furniture | −0.0844 | 0.000005 | −0.004991$^{*}$ |
| Transport Equipment | −0.0263 | 0.000046 | 0.000856 |
| Metal & Metal Products | −0.1043 | 0.000201$^{\cdot}$ | −0.000713 |

*Notes:* Inverse elasticity ($\varepsilon_P$) is the mean across firms and years. $\hat{\beta}_{mktd}$ and $\hat{\beta}_{ads}$ are IV-2SLS coefficient estimates. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 2 presents the results of the demand estimation. Column 2 in Table 2 reports the mean inverse elasticity of demand, $\bar{\varepsilon}_P$, which captures the responsiveness of price to changes in output. Across

all industries, the mean inverse elasticity is $-0.061$, confirming the expected negative relationship between output and price. There is notable heterogeneity across industries. The most price-sensitive group, comprising Chemical Products at $-0.111$, Electrical Goods at $-0.111$, Food, Drink & Tobacco at $-0.116$, and Metal & Metal Products at $-0.104$, exhibits inverse elasticities in the range of $-0.10$ to $-0.12$, implying that a one percent increase in output is associated with roughly a 0.10 to 0.12% decline in price. Timber & Furniture at $-0.084$ falls in an intermediate range. By contrast, Agricultural & Industrial Machinery at $-0.044$, Non-Metallic Minerals at $-0.044$, Paper & Printing Products at $-0.046$, Textile, Leather & Shoes at $-0.037$, and Transport Equipment at $-0.026$ display relatively inelastic demand, with inverse elasticities between $-0.03$ and $-0.05$. This pattern suggests that industries producing more differentiated or essential intermediate goods tend to face less price-sensitive demand.

The effect of market dynamics on price is positive across all industries, indicating that favorable demand conditions, such as market expansion, are associated with higher prices. The estimates are statistically significant for Electrical Goods, Food, Drink & Tobacco, Textile, Leather & Shoes, Non-Metallic Minerals, and the aggregate, while Metal & Metal Products is marginally significant at $p < 0.10$.

The effect of advertising on price is positive for the majority of industries, consistent with the view that advertising enhances perceived product differentiation and supports higher prices. The effect is statistically significant for Chemical Products at $p < 0.05$ and marginally so for Food, Drink & Tobacco at $p < 0.10$. However, three industries, namely Electrical Goods at $-0.013$ with $p < 0.10$, Timber & Furniture at $-0.005$ with $p < 0.05$, and Metal & Metal Products at $-0.001$, exhibit negative advertising coefficients, suggesting that in these sectors advertising may intensify competitive pressure or serve an informative rather than persuasive role, thereby reducing rather than raising prices.

Table 3: Input Elasticities (without $\omega$) by Industry

| | Materials ($E_M$) | | | Labor ($E_L$) | | | Capital ($E_K$) | | |
|---|---|---|---|---|---|---|---|---|---|
| Industry | Q1 | Mean | Q3 | Q1 | Mean | Q3 | Q1 | Mean | Q3 |
| All Industries | 0.640 | 0.767 | 0.891 | 0.017 | 0.203 | 0.397 | 0.027 | 0.049 | 0.072 |
| Agric. & Ind. Mach. | 0.655 | 0.713 | 0.773 | 0.206 | 0.282 | 0.355 | 0.008 | 0.025 | 0.041 |
| Chemical Products | 0.688 | 0.782 | 0.877 | 0.173 | 0.259 | 0.343 | −0.023 | 0.023 | 0.068 |
| Electrical Goods | 0.633 | 0.730 | 0.838 | 0.193 | 0.297 | 0.408 | −0.038 | 0.001 | 0.037 |
| Food, Drink & Tobacco | 0.630 | 0.742 | 0.854 | 0.136 | 0.246 | 0.347 | −0.033 | 0.040 | 0.119 |
| Non-Metallic Minerals | 0.666 | 0.740 | 0.820 | 0.068 | 0.214 | 0.349 | 0.021 | 0.062 | 0.113 |
| Paper & Printing Prod. | 0.570 | 0.647 | 0.726 | 0.249 | 0.332 | 0.415 | 0.035 | 0.045 | 0.055 |
| Textile, Leather & Shoes | 0.646 | 0.751 | 0.858 | 0.152 | 0.255 | 0.355 | 0.008 | 0.016 | 0.022 |
| Timber & Furniture | 0.597 | 0.680 | 0.758 | 0.041 | 0.208 | 0.380 | −0.089 | 0.098 | 0.271 |
| Transport Equipment | 0.610 | 0.684 | 0.762 | 0.218 | 0.282 | 0.343 | 0.040 | 0.069 | 0.103 |
| Metal & Metal Prod. | 0.261 | 0.378 | 0.481 | 0.575 | 0.671 | 0.783 | 0.008 | 0.041 | 0.075 |

*Notes:* Elasticities are computed from GMM estimates of the translog production function (without $\omega_L$ adjustment). Q1 and Q3 denote the 1st and 3rd quartiles, respectively.

Table 4: Labor-Augmenting ($\omega_L$) and Hicks-Neutral ($\omega_h$) Productivity by Industry

| | Labor Productivity ($\omega_L$) | | | Hicks-Neutral Prod. ($\omega_h$) | | |
|---|---|---|---|---|---|---|
| Industry | Q1 | Mean | Q3 | Q1 | Mean | Q3 |
| All Industries | −0.091 | 0.160 | 0.393 | −0.096 | 0.018 | 0.124 |
| Agric. & Ind. Mach. | −0.075 | 0.123 | 0.306 | 0.032 | 0.135 | 0.235 |
| Chemical Products | −0.387 | −0.089 | 0.220 | −0.182 | −0.059 | 0.066 |
| Electrical Goods | −0.102 | 0.089 | 0.289 | −0.010 | 0.089 | 0.194 |
| Food, Drink & Tobacco | −0.423 | −0.171 | 0.077 | −0.102 | −0.001 | 0.095 |
| Non-Metallic Minerals | −0.070 | 0.181 | 0.417 | −0.073 | 0.046 | 0.159 |
| Paper & Printing Prod. | −0.347 | −0.161 | 0.027 | −0.093 | 0.012 | 0.115 |
| Textile, Leather & Shoes | 0.024 | 0.215 | 0.399 | −0.018 | 0.071 | 0.163 |
| Timber & Furniture | −0.110 | 0.343 | 0.772 | −0.033 | 0.102 | 0.300 |
| Transport Equipment | −0.348 | −0.131 | 0.097 | −0.095 | 0.017 | 0.126 |
| Metal & Metal Prod. | −1.838 | −1.606 | −1.383 | −0.067 | 0.042 | 0.161 |

*Notes:* $\omega_L$ is labor-augmenting productivity recovered from the GMM share equations. $\omega_h$ is Hicks-neutral productivity recovered from the capital block (NLS). Q1 and Q3 denote the 1st and 3rd quartiles.

Table 4 shows the distribution of labor-augmenting productivity, $\omega_L$, and Hicks-neutral productivity, $\omega_h$, across industries. The labor-augmenting component captures efficiency gains that operate specifically through the labor input, effectively measuring how technology enhances the productive capacity of each unit of labor. The Hicks-neutral component, recovered from the capital block via nonlinear least squares, captures residual productivity that scales all inputs proportionally without altering relative factor intensities. Together, these two components provide a decomposition of total factor productivity into its factor-specific and neutral constituents.

Across all industries, the mean labor-augmenting productivity is 0.160. Many industries exhibit positive productivity, suggesting that labor-augmenting Technical change has, on average, improved the effective quality of labor in these sectors. Timber & Furniture displays the highest mean $\omega_L$ at 0.343. Textile, Leather & Shoes follows with a mean of 0.215. Non-Metallic Minerals at 0.181, Agricultural & Industrial Machinery at 0.123, and Electrical Goods at 0.089, also show positive mean values, indicating moderate labor-augmenting gains.

In contrast, several industries exhibit negative mean labor-augmenting productivity. Food, Drink & Tobacco at −0.171, Paper & Printing Products at −0.161, and Transport Equipment at −0.131 display negative means. Chemical Products at −0.089 also shows a negative mean, although the third quartile at 0.220 indicates that a meaningful fraction of firms in this industry do benefit from labor-augmenting improvements. Metal & Metal Products also shows a negative mean $\omega_L$ of −1.606.

The Hicks-neutral component shows distribution relative to the labor-augmenting measure. The overall mean across all industries is 0.018, suggesting that hicks neutral productivity is modestly positive on average. Agricultural & Industrial Machinery displays the highest mean Hicks-neutral productivity at 0.135, with the entire interquartile range in positive territory from 0.032 to 0.235, indicating that firms in this sector have benefited from broad-based efficiency improvements that raise output proportionally

across all inputs. Timber & Furniture at 0.102, Electrical Goods at 0.089, and Textile, Leather & Shoes at 0.071 also exhibit positive mean values, suggesting meaningful neutral productivity gains.

At the lower end, Chemical Products shows a negative mean Hicks-neutral productivity of −0.059, while Food, Drink & Tobacco is approximately zero at −0.001, Paper & Printing Products at 0.012, and Transport Equipment at 0.017. Metal & Metal Products shows a mean neutral productivity of 0.042, Industries such as Timber & Furniture and Textile, Leather & Shoes exhibit positive productivity on both dimensions, indicating that these sectors benefit from both factor-specific and neutral technical improvements.

Table 5: Impact of Digitalization on Labor-Augmenting ($\alpha_1$) and Hicks-Neutral ($\gamma_1$) Productivity

| | Labor-Augmenting ($\alpha_1$) | | Hicks-Neutral ($\gamma_1$) | |
|---|---|---|---|---|
| Industry | Estimate | Std. Error | Estimate | Std. Error |
| All Industries | $0.0339^{***}$ | (0.0083) | $0.0294^{***}$ | (0.0078) |
| Agric. & Ind. Mach. | 0.0271 | (0.0362) | $0.0905^{*}$ | (0.0369) |
| Chemical Products | 0.0280 | (0.0389) | −0.0012 | (0.0211) |
| Electrical Goods | 0.0369 | (0.0405) | $0.0547^{\cdot}$ | (0.0299) |
| Food, Drink & Tobacco | $-0.0426^{\cdot}$ | (0.0255) | 0.0210 | (0.0184) |
| Non-Metallic Minerals | 0.0427 | (0.0321) | 0.0366 | (0.0320) |
| Paper & Printing Prod. | −0.0359 | (0.0708) | 0.0194 | (0.0260) |
| Textile, Leather & Shoes | $0.0712^{**}$ | (0.0273) | $0.0461^{\cdot}$ | (0.0261) |
| Timber & Furniture | 0.0867 | (0.0573) | 0.0364 | (0.0469) |
| Transport Equipment | −0.0209 | (0.0406) | 0.0320 | (0.0288) |
| Metal & Metal Prod. | $-0.8915^{***}$ | (0.2315) | $0.0358^{\cdot}$ | (0.0213) |

*Notes:* $\alpha_1$ is the coefficient on lagged digitalization in the GMM share equation (labor-augmenting productivity). $\gamma_1$ is the coefficient on lagged digitalization in the NLS capital block (Hicks-neutral productivity). Standard errors in parentheses. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 5 show the effects of digitalisation on the labor-augmenting productivity, $\alpha_1$, and in the Hicks-neutral productivity, $\gamma_1$. These estimates capture the extent to which prior investments into digital technologies contribute to factor-specific and neutral productivity growth, respectively. The use of lagged digitalization mitigates simultaneity concerns and reflects the plausible temporal lag between digital adoption and its realization in productive efficiency.

At the aggregate level, the coefficient on digitalisation in the labor-augmenting productivity equation remains positive and statistically significant at 0.034 ($p < 0.001$), indicating that digital adoption contributes notably to boosting the effective quality of labor across Spanish manufacturing. At the industry level, the majority sectors exhibit positive point estimates, although the statistical significance varies. Textile, Leather & Shoes displays the largest statistically significant positive effect at 0.071 with $p < 0.01$, suggesting that digitalisation in this sector has been especially effective in augmenting labor productivity, possibly through automation of routine production tasks or improvements in process coordination. Timber & Furniture at 0.087 and Non-Metallic Minerals at 0.043 also show sizable positive estimates, though these do not attain conventional levels of statistical significance given the

relatively large standard errors. Electrical Goods at 0.037, Chemical Products at 0.028, and Agricultural & Industrial Machinery at 0.027 similarly exhibits positive but imprecisely estimated coefficients.

Some industries, however, show a negative relationship. Food, Drink & Tobacco reports a marginally significant negative estimate of $-0.043$ with $p < 0.10$, suggesting that digitalisation in this sector may not translate into labor-augmenting efficiency gains, or that the nature of digital investment in food processing and related activities is directed toward objectives other than enhancing labor productivity, such as quality control or regulatory compliance. Paper & Printing Products at $-0.036$ and Transport Equipment at $-0.021$ also exhibit negative but statistically insignificant estimates. Metal & Metal Products also shows a significant negative coefficient of $-0.892$ with $p < 0.001$. This finding is consistent with the structural attributes of this industry, as shown in Tables 3 and 4, where Metal & Metal Products was identified as highly labor-intensive with negative labor-augmenting productivity.

The aggregate estimate on digitization in the Hicks-neutral productivity equation is significant at 0.029 ($p < 0.001$), indicating that digitalization increases overall productivity in a manner that benefits all inputs proportionally. At the industry level, the Hicks-neutral effects are uniformly positive, with the sole exception of Chemical Products, which exhibits a negligible, statistically insignificant coefficient of $-0.001$. Agricultural & Industrial Machinery displays the largest positive effect at 0.091 with $p < 0.05$, suggesting that digitization in this sector enhances broad-based productive efficiency, consistent with its high Hicks-neutral productivity documented in Table 4. Electrical Goods at 0.055 with $p < 0.10$ and Textile, Leather & Shoes at 0.046 with $p < 0.10$ also show marginally significant positive effects. Metal & Metal Products at 0.036 with $p < 0.10$ exhibits a marginally significant positive Hicks-neutral effect, which stands in strong contrast to its large negative labor-augmenting coefficient, additionally supporting the interpretation that digitalisation in this industry operates through neutral rather than factor-specific channels.

The remaining industries, including Non-Metallic Minerals at 0.037, Timber & Furniture at 0.036, Transport Equipment at 0.032, Food, Drink & Tobacco at 0.021, and Paper & Printing Products at 0.019, all display positive point estimates that do not reach conventional significance levels, suggesting modest but imprecisely estimated Hicks-neutral productivity gains from digitalization.

The findings show an asymmetry in the channels through which digitalization affects productivity throughout Spanish manufacturing. The Hicks-neutral channel is more uniformly operative, with positive coefficients observed in nearly all industries, suggesting that digital technologies generate broad-based efficiency improvements regardless of sector. The labor-augmenting channel, by contrast, shows greater heterogeneity, with four of the ten industries examined showing negative or negligible effects. This pattern suggests that digitalization's capacity to enhance labor-specific productivity is contingent on industry characteristics, including the nature of production processes, the existing skill composition of the workforce, and the extent to which digital technologies augment rather than substitute for labor inputs. Industries where digitalization yields positive effects on both channels, such as Textile, Leather & Shoes, and Electrical Goods, appear best positioned to realize comprehensive productivity gains

from digital adoption. Conversely, industries such as Metal & Metal Products, where digitalization operates exclusively through the neutral channel, may require complementary investments in workforce restructuring or skill upgrading to unlock the labor-augmenting capacity of digital technologies.

Table 6: Model Diagnostics: GMM Estimates, Specification Tests, and Markup by Industry

| | Persistence | | J-Test | | Markup | | |
|---|---|---|---|---|---|---|---|
| Industry | $\hat{\rho}$ (GMM) | $\hat{\rho}_K$ (NLS) | $J$-stat | $p$-value | Q1 | Mean | Q3 |
| All Industries | 0.829 | 0.738 | 13.403 | 0.063 | 1.063 | 1.065 | 1.068 |
| Agric. & Ind. Mach. | 0.812 | 0.667 | 6.529 | 0.480 | 1.046 | 1.046 | 1.046 |
| Chemical Products | 0.870 | 0.833 | 5.821 | 0.324 | 1.116 | 1.125 | 1.133 |
| Electrical Goods | 0.842 | 0.719 | 10.240 | 0.069 | 1.109 | 1.125 | 1.143 |
| Food, Drink & Tobacco | 0.862 | 0.796 | 12.520 | 0.085 | 1.131 | 1.131 | 1.132 |
| Non-Metallic Minerals | 0.836 | 0.769 | 3.198 | 0.670 | 1.028 | 1.046 | 1.063 |
| Paper & Printing Prod. | 0.851 | 0.765 | 18.992 | 0.123 | 1.044 | 1.049 | 1.053 |
| Textile, Leather & Shoes | 0.849 | 0.638 | 24.727 | 0.054 | 1.032 | 1.039 | 1.046 |
| Timber & Furniture | 0.766 | 0.858 | 4.617 | 0.202 | 1.089 | 1.092 | 1.096 |
| Transport Equipment | 0.770 | 0.709 | 2.646 | 0.449 | 1.026 | 1.027 | 1.028 |
| Metal & Metal Prod. | 0.665 | 0.705 | 7.087 | 0.069 | 1.108 | 1.117 | 1.126 |

*Notes:* $\hat{\rho}$ (GMM) is the persistence parameter from the two-step GMM share equation. $\hat{\rho}_K$ (NLS) is from the NLS capital block. The $J$-statistic tests overidentifying restrictions ($H_0$: $E[g] = 0$). Markup is derived from demand estimation. Q1 and Q3 denote the 1st and 3rd quartiles.

Table 6 reports the distribution of firm-level markups derived from demand estimation and model assessments, including the persistence parameters from the GMM and NLS estimations and Hansen's J-test for overidentifying restrictions.

The markup estimates, defined as the ratio of price to marginal cost, provide a measure of the degree of market power exercised by firms across Spanish manufacturing industries. Across all industries, the mean markup is 1.065 with a narrow interquartile range from 1.063 to 1.068, indicating that firm prices are approximately 6.5% above marginal cost. This modest level of market power is consistent with the characterization of manufacturing sectors as operating under imperfect but competitive market structures.

At the industry level, Chemical Products and Electrical Goods exhibit the highest mean markups, both at 1.125, implying that firms in these sectors price roughly 12.5% above marginal cost. Food, Drink & Tobacco follows closely at 1.131, while Metal & Metal Products displays a mean markup of 1.117. These relatively elevated markups may reflect greater product differentiation, higher barriers to entry, or stronger brand effects that afford firms in these industries enhanced pricing power. Notably, Electrical Goods exhibits the widest interquartile range among all industries, spanning from 1.109 to 1.143, indicating considerable within-industry heterogeneity in the degree of market power across firms.

In contrast, Transport Equipment displays the lowest mean markup at 1.027 with a particularly reduced interquartile range from 1.026 to 1.028, suggesting that this sector operates under intensely competitive conditions with minimal pricing power. Non-Metallic Minerals at 1.046, Textile, Leather & Shoes at 1.039, Agricultural & Industrial Machinery at 1.046, and Paper & Printing Products at 1.049

also exhibit relatively low markups, indicating that firms in these sectors face competitive pressures that constrain their ability to set prices substantially above marginal cost. Timber & Furniture occupies an intermediate position with a mean markup of 1.092.

The overall pattern of markups across industries is economically plausible. Sectors characterized by greater product differentiation and higher capital intensity, such as Chemical Products and Electrical Goods tend to show greater markups, while industries producing more homogeneous or standardized goods, such as Transport Equipment and Non-metallic minerals exhibit markups closer to unity. The relatively narrow interquartile Ranges observed in most industries suggest that within-industry variation in market power is limited, with the exceptions of Electrical Goods and Chemical Products, where firm-level Heterogeneity in pricing power is more pronounced.

The persistence parameters capture the degree of serial correlation in the productivity processes and act as indicators of the temporal stability of firm-level efficiency. Our GMM and NLS estimates show that all industries exhibit persistent labor productivity and Hicks-neutral productivity over time. The J-statistic tests the overidentifying restrictions imposed by the GMM estimator, with the null hypothesis that the moment equations are jointly valid. The failure to reject the null supports the validity of the chosen instruments. Across the industry-level estimations, the majority of J-test p-values exceed conventional significance thresholds, indicating that the overidentifying restrictions cannot be rejected. The J-test results give reassurance that the instrument sets employed in the GMM estimation are appropriately specified and that the identifying assumptions underlying the production function estimates are not systematically violated.

Table 7: Allen and Morishima Elasticities of Substitution by Industry

| | Allen ($AES_{KL}$) | | | Morishima ($MES_{KL}$) | | | Morishima ($MES_{LK}$) | | |
|---|---|---|---|---|---|---|---|---|---|
| Industry | Q1 | Mean | Q3 | Q1 | Mean | Q3 | Q1 | Mean | Q3 |
| All Industries | −7.328 | −3.399 | −2.150 | −2.473 | −1.378 | −0.563 | 1.350 | 1.506 | 2.066 |
| Chemical | 9.033 | 11.397 | 13.491 | 3.228 | 3.591 | 3.889 | −0.483 | −0.212 | 0.072 |
| Electrical | −1.560 | 8.783 | 16.629 | −1.037 | 4.505 | 9.347 | −0.755 | −0.182 | −0.018 |
| Food, Drink & Tobacco | 0.609 | 2.177 | 3.933 | −1.682 | 0.316 | 2.786 | −1.702 | −0.786 | −0.157 |
| Metal & Metal Products | 14.270 | 16.860 | 27.050 | 6.297 | 6.374 | 8.778 | −0.435 | 0.155 | 0.443 |
| Non-metallic Minerals | −10.146 | −7.133 | −3.194 | −2.910 | −1.934 | −1.018 | 0.475 | 0.723 | 0.987 |
| Paper & Printing Products | −0.088 | 0.125 | 0.532 | −2.738 | 0.312 | 3.660 | 1.632 | 2.113 | 2.451 |
| Textile, Leather & Shoes | −4.712 | 6.575 | 16.018 | 0.246 | 0.958 | 1.531 | 0.891 | 0.925 | 0.965 |
| Timber & Furniture | −5.006 | −4.395 | −2.823 | −0.213 | −0.038 | 0.136 | −0.409 | −0.290 | −0.154 |
| Transport Equipment | −1.304 | 0.861 | 3.094 | −0.161 | 2.142 | 4.439 | −1.353 | 1.105 | 3.279 |
| Agric. & Ind. Machinery | −5.572 | 1.708 | 11.424 | −5.106 | 1.064 | 8.461 | 0.291 | 0.551 | 0.732 |

*Notes:* $AES_{KL}$ is the Allen elasticity of substitution between capital and labor. $MES_{KL}$ is the Morishima elasticity of substitution, measuring the percentage change in the capital-labor ratio when the price of labor changes, holding output and the price of capital constant. $MES_{LK}$ is the Morishima elasticity of substitution, measuring the percentage change in the labor-capital ratio when the price of capital changes, holding output and the price of labor constant. Q1 = first quartile, Q3 = third quartile. Negative values indicate complementarity, while positive values indicate substitutability.

Table 7 presents the Allen elasticity of substitution between capital and labor ($AES_{KL}$) and the Morishima elasticity of substitution ($MES_{KL}$), which measures the percentage change in the capital to labor ratio in response to a change in the price of labor, holding output and the price of capital constant. The distinction between these two measures is important: while the Allen elasticity is symmetric and provides a global characterization of factor relationships, the Morishima elasticity is asymmetric and captures the direction-specific adjustment of factor ratios, making it the more informative measure for understanding how relative factor demands respond to price changes Blackorby & Russell (1989).

At the aggregate level, the mean $AES_{KL}$ is $-3.399$, indicating that capital and labor are, on average, complements in Spanish manufacturing. The corresponding mean $MES_{KL}$ is $-1.378$, reinforcing the finding of complementarity. The consistently negative values across both measures provide robust evidence that, for the typical Spanish manufacturing firm, capital deepening does not displace labor but rather increases its demand. This aggregate complementarity has direct implications for the labor share: when capital and labor are complements, capital accumulation and technological adoption tend to raise labor demand, thereby supporting the labor share rather than eroding it. The positive aggregate effect of digitalization on the labor share reported in table 8 is consistent with this pattern.

However, industry-level estimates reveal considerable heterogeneity in the capital and labor relationship, with important consequences for the distribution of labor share changes across sectors. Several industries exhibit strong substitutability under both measures. The Metal and Metal Products sector displays the largest mean $AES_{KL}$ of 16.860 and the largest mean $MES_{KL}$ of 6.374, indicating that firms in this sector can readily replace labor with capital when wages rise. Similarly, Chemical Products has a mean $AES_{KL}$ of 11.397 and a mean $MES_{KL}$ of 3.591, while Electrical Goods has a mean $AES_{KL}$ of 8.783 and a mean $MES_{KL}$ of 4.505, though the wide interquartile range in the latter suggests substantial within-industry variation. In sectors where capital and labor are strong substitutes, increases in the relative price of labor or declines in the user cost of capital induce firms to substitute toward capital, placing downward pressure on the labor share. This mechanism is consistent with the theoretical prediction that the labor share declines in response to capital-augmenting technical change or falling capital prices when the elasticity of substitution exceeds unity (Karabarbounis & Neiman, 2014).

In contrast, Non-Metallic Minerals displays strong complementarity with a mean $AES_{KL}$ of $-7.133$ and a mean $MES_{KL}$ of $-1.934$, and Timber and Furniture similarly exhibits complementarity with a mean $AES_{KL}$ of $-4.395$ and a near-zero mean $MES_{KL}$ of $-0.038$. In these sectors, capital accumulation and digitalization are unlikely to erode the labor share; instead, investment in capital reinforces labor demand, providing a stabilizing force against the secular decline observed in other industries.

The asymmetry of the Morishima elasticity provides additional insight into labor share dynamics. The mean $MES_{LK}$, which captures the response of the labor to capital ratio when the price of capital changes, is positive at the aggregate level (1.506), indicating that an increase in the price of capital raises the relative demand for labor. This asymmetry implies that the labor share response depends critically on the source of the price shock: while labor price increases tend to reduce the labor-to-capital

ratio (given the negative $MES_{KL}$), capital price increases tend to raise it. This directional asymmetry highlights the inadequacy of symmetric elasticity measures for understanding labor share movements and underscores the value of the Morishima framework adopted in this study.

Taken together, the sectoral heterogeneity in the elasticities of substitution helps explain the divergent labor share trajectories observed across Spanish manufacturing industries. Industries characterized by high substitutability are more vulnerable to labor share declines in the presence of falling capital costs or capital-augmenting technological change, while industries exhibiting complementarity are more resilient. This pattern underscores the importance of disaggregated analysis, as aggregate estimates may obscure fundamentally different production technologies and factor adjustment mechanisms that drive cross-sectoral changes in labor shares.

### 7.1 Digitalization and Labor Share: Industry Level Results

In this subsection, we examine the effect of digitalization on the labor share. In our model, we showed that the labor share depends on markups, the output elasticities of inputs, and labor-augmenting productivity, where the latter is specified as a function of digitalization. This formulation motivated the development of a theoretical framework for how digitalization affects labor share, which we present in the companion paper to this study. Specifically, Musbaudeen & Kumbhakar (2026) discuss the theoretical foundations and the various channels through which digitalization can affect labor share. We argue that digitalization can cause labor share to rise or fall depending on the elasticities of substitution, task reallocation, markup dynamics, and output expansion. Table 8 reports estimates of the impact of digitalization on the labor share ($s_L$) across all industries and ten disaggregated manufacturing sectors, obtained from two-way fixed effects panel regressions.

Table 8: Effect of Digitalization on Labor Share by Industry

| Industry | Estimate | Std. Error |
|---|---|---|
| All Industries | $0.0267^{***}$ | (0.0041) |
| Agricultural and Industrial Machinery | $-0.0020$ | (0.0153) |
| Chemical Products | $0.0207^{**}$ | (0.0070) |
| Electrical Goods | 0.0033 | (0.0183) |
| Food, Drink and Tobacco | $0.0284^{***}$ | (0.0065) |
| Metal and Metal Products | 0.0120 | (0.0101) |
| Non-Metallic Minerals | $0.0440^{**}$ | (0.0164) |
| Paper and Printing Products | 0.0087 | (0.0111) |
| Textile, Leather and Shoes | $0.0294^{\cdot}$ | (0.0150) |
| Timber and Furniture | $0.0473^{***}$ | (0.0136) |
| Transport Equipment | 0.0209 | (0.0136) |

Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Dependent variable: Labor share ($s_L$). Two-way fixed effects panel models.

Controls: markup, $\omega_L$, $\ln K$, $\ln M$. Standard errors in parentheses.

At the aggregate level, digitalization estimates are positive and highly significant at the 0.1% level, suggesting that, on average, digitalization is associated with an increase in the labor share of income in Spanish manufacturing firms. Specifically, a unit increase in the digitalization index in the prior period is associated with an approximately 2.7 percentage point increase in the labor share, holding all other factors constant. This finding contrasts with the prevalent narrative in the literature that digital technologies inherently displace labor Acemoglu & Restrepo (2019); Autor et al. (2020), and instead lends support to the view that digitalization may complement labor in ways that enhance workers' relative contribution to value added (Bessen, 2019; Li et al., 2025, 2024).

The disaggregated industry-level estimates reveal substantial heterogeneity in the relationship between digitalization and labor share across manufacturing sectors. The Timber and Furniture sector shows that a unit increase in digitalization raises the labor share by approximately 4.7 percentage points, significant at the 0.1% level. Non-Metallic Minerals also show an estimated effect of 4.4 percentage points, significant at the 1% level; Food, Drink and Tobacco with an effect of 2.8 percentage points, significant at the 0.1% level; and Chemical Products with an effect of 2.1 percentage points, significant at the 1% level. The Textile, Leather, and Shoes sector exhibits a marginally significant positive effect of approximately 2.9 percentage points at the 10% level, warranting cautious interpretation.

In contrast, several industries display positive but statistically insignificant coefficients. Metal and Metal Products registers an estimated effect of 1.2 percentage points, Transport Equipment an effect of 2.1 percentage points, Paper and Printing Products an effect of 0.9 percentage points, and Electrical Goods an effect of only 0.3 percentage points. While the point estimates in these sectors are uniformly positive, the lack of statistical significance suggests that the positive effect of digitalization on labor share is not uniformly present across all manufacturing activities. Notably, Agricultural and Industrial Machinery is the only sector exhibiting a small negative coefficient of approximately 0.2 percentage points, which is far from statistically significant, indicating that digitalization has had a negligible effect on the labor share in this sector.

The observed heterogeneity across industries may reflect differences in production processes and the extent to which digital technologies serve as complements or substitutes for labor. Sectors where digitalization significantly raises the labor share, Timber and Furniture, Non-Metallic Minerals, and Food, Drink and Tobacco, tend to be industries where production processes involve a substantial degree of manual and artisanal labor. In these sectors, digital tools may augment worker productivity without displacing labor, thereby increasing the marginal revenue product of labor relative to other inputs. On the other hand, sectors with insignificant effects, such as Electrical Goods and Agricultural and Industrial Machinery, are typically more capital-intensive and may already have undergone significant automation, leaving less scope for digitalization to further alter factor shares.

### 7.2 Summary of Results

The preceding results explain three points: digitalization raises labor-augmenting productivity in most industries, raises Hicks-neutral productivity in nearly all of them, and has a positive net effect on the labor share at the aggregate level. These are not three independent findings. They are connected through our novel method of estimating non-neutral production technology, and this connection is worth spelling out, because the sign of the labor share effect is not obvious from productivity effects alone. It could easily have gone the other way.

Start with the labor-augmenting channel. When digitalization increases labor quality, it reduces the number of raw hours a firm needs to produce a given level of output. A textile firm that adopts digital process coordination, for instance, may achieve the same throughput with fewer but better-supported workers. On its own, this effect reduces labor's share. This is exactly the mechanism that DJ emphasizes in their decomposition of the Spanish labor share from 1990 to 2006, and it operates in our data as well. The labor-augmenting component of technical change, other things equal, is a force against labor's income share.

But other things are not equal, and this is where the elasticities of substitution matter. At the aggregate level, we estimate that capital and labor are complements. The mean Allen elasticity is $-3.40$, and the mean Morishima elasticity is $-1.38$, as reported in Table 8. Under complementarity, an improvement in the effective quality of labor does not lead firms to substitute labor for capital. Instead, the two inputs move together. As labor becomes more productive, the marginal product of capital also rises, firms invest more, and that investment in turn raises labor demand. The labor share rises because labor's revenue-generating capacity grows more rapidly than hours worked decline. This is, admittedly, a somewhat knife-edge argument. It requires that complementarity be strong enough to dominate the hours-reducing effect. In our aggregate estimates, the complementarity is quite strong, and the positive coefficient on digitalization in the labor share regression reported in Table **??** confirms that the net effect is indeed positive.

The Hicks-neutral channel reinforces this, but through a different mechanism. When digitalization raises the efficiency of the entire production process, it expands the output a firm can produce from a given bundle of inputs. This output expansion raises revenue and, if factor markets are reasonably competitive, the additional revenue is shared across inputs roughly in proportion to their output elasticities. Because materials dominate the elasticity structure, with a mean materials elasticity of 0.77 compared to 0.20 for labor and 0.05 for capital, most of the Hicks-neutral gain flows to materials. But labor still benefits, and the near-universal positive sign on $\gamma_1$ across industries as shown in Table **??** means that this channel provides a broad base of support for worker incomes even in industries where the labor-augmenting effect is weak or negative.

The industry-level results sharpen this picture considerably. Non-Metallic Minerals and Timber & Furniture exhibit capital-labor complementarity, with Allen elasticities of $-7.13$ and $-4.40$ respectively,

positive labor-augmenting effects of digitalization, and the two largest positive effects on the labor share at 0.044 and 0.047. Everything lines up, digitalization increases workers' productivity, complementarity ensures that gains are not competed away by substitution into capital, and the labor share rises. The story is similarly coherent, though less dramatic, for Food, Drink, & Tobacco and Chemical Products, where the labor share effects are positive and significant.

Metal & Metal Products presents the opposite case. This industry has the strongest capital-labor substitutability in our sample, with an Allen elasticity of 16.86, a large and significantly negative labor-augmenting coefficient of $-0.892$, and an insignificant effect of digitalization on the labor share. The Hicks-neutral effect is positive and marginally significant, indicating that digitalization improves overall efficiency in this sector. But because capital and labor are strong substitutes, the efficiency gains allow firms to shift their input mix toward capital. Because the labor-augmenting effect is negative, suggesting that digital technologies in this industry may be replacing labor tasks rather than enhancing them, the labor share does not increase.

The chain of reasoning, from digitalization to factor-augmenting productivity to output elasticities and to the labor share, mediated by the elasticity of substitution, is consistent with our estimates, and we find the reasoning compelling. However, our exercises in this study did not estimate a model that simultaneously traces these channels. Instead, we combine estimates from the GMM share equations, the NLS capital block, and the fixed-effects labor share regressions, and link them through production theory. A more demanding test would embed the labor share decomposition directly into the estimation, which we leave to future work [3]. What we can say is that the pattern of results across industries is difficult to rationalize without the interaction between productivity channels and substitution elasticities that we have described. The aggregate positive effect of digitalization on the labor share is not an accident. It reflects a specific configuration of production technology in which the complementarity between capital and labor ensures that, on balance, digital productivity gains accrue to workers.

# 8 Policy Implications and Conclusions

The objective of the paper is to (i) develop a more flexible method for estimating factor-augmenting (neutral and non-neutral) productivity, and (ii) use that method to examine how digitalization shapes production technology and the distribution of income between labor and capital in Spanish manufacturing. On the methodological side, our main contribution is to use a three-stage estimation procedure for a translog production function that does not impose homothetic separability assumption. This matters because separability restrictions constrain interactions among inputs in ways that are at odds with much of the empirical evidence and can distort estimates of both productivity and factor shares. The procedure we propose — combining demand-side 2SLS, stacked GMM on quasi-differenced share equations, and

[3] A companion paper to this study discusses the labor share decomposition and the effects of digitalization through these channels

nonlinear least squares for the capital block — is, we think, reasonably tractable and transparent. It also accommodates both competitive and imperfectly competitive product markets, which is a practical necessity when working with manufacturing data where markups are non-trivial.

The empirical results, drawn from 2,795 firms across 10 manufacturing industries over 2000–2019, yield several findings worth highlighting. First, Spanish manufacturing exhibits substantial heterogeneity in the elasticity of substitution between capital and labor. Two of the ten industries show complementarity; the others display varying degrees of substitutability. This variation has direct implications for how different sectors respond to digitalization and capital-price changes, and it underscores the cost of imposing a common elasticity across sectors as the CES framework requires.

Second, digitalization has a positive and statistically significant effect on both labor-augmenting productivity (3.4%) and Hicks-neutral productivity (2.9%) at the aggregate level. The industry-level picture is more nuanced. The Hicks-neutral channel is broadly operative — positive in nine of ten industries — which suggests that digital technologies tend to generate general efficiency improvements regardless of the production context. The labor-augmenting channel is more uneven: four industries show negative or negligible effects, and Metal and Metal Products shows a large, significant negative coefficient. This pattern suggests that whether digitalization enhances the effective quality of labor — as opposed to substituting for it — depends on sector-specific factors including the composition of the workforce, the nature of production tasks, and the degree to which digital tools can be deployed alongside workers rather than in place of them. Third, and perhaps most directly policy-relevant, digitalization raises the labor share of income by approximately 2.7 percentage points at the aggregate level. This finding runs counter to much of the recent debate, which has tended to treat digital adoption and labor income as in tension. The positive effect is consistent with the capital-labor complementarity we find in the aggregate elasticity estimates: when firms deepen their digital capital in an environment where capital and labor are complements, workers become more productive and their share of revenue tends to rise. That said, we also document a countervailing force. Labor-augmenting technical change — precisely the channel through which digitalization improves worker efficiency — tends, other things equal, to reduce the labor share over time. As fewer hours of labor are needed to produce a given level of output, the revenue accruing to labor can fall even as each remaining worker becomes more productive. The net effect of digitalization on the labor share is positive in our sample, but the mechanism is not simple, and the balance could tip differently in other settings.

These findings have a few implications for policy. The positive aggregate effect on the labor share suggests that policies accelerating digital adoption in manufacturing need not sacrifice labor's income share in exchange for productivity gains. Investment in digital infrastructure — broadband connectivity, cloud platforms, industry-specific digitalization programs — can plausibly support both goals simultaneously. This seems especially relevant for European industrial policy, where concerns about the distributional consequences of automation have often tempered support for technology-promoting initiatives.

At the same time, the heterogeneity in the labor-augmenting effects argues against sector-blind policy. Industries like Textile, Leather and Shoes and Timber and Furniture — where digitalization raises both labor-augmenting productivity and the labor share — appear well-positioned to benefit from targeted digital adoption programs. Industries like Metal and Metal Products, where the neutral channel dominates and the labor-augmenting effect is negative, may need complementary investment in workforce training and skill upgrading before digital technologies can enhance labor productivity rather than simply displacing it. The design of digitalization policy, in other words, probably needs to be sensitive to where in the production technology the relevant effects are operating. The tension between labor-augmenting productivity growth and the labor share also points to a role for active labor market policy. When technology improves worker efficiency and reduces required hours, the gains from that improvement are not automatically distributed broadly. Retraining programs, support for occupational reallocation, and incentives for organizational restructuring that redeploy displaced labor toward new tasks can help ensure that productivity gains translate into broadly shared income growth rather than concentration among capital owners.

Finally, for researchers, our results reinforce the case for flexible production function specifications when the goal is to assess the distributional implications of technological change. The assumption of homothetic separability, which most existing work maintains, is not innocuous: relaxing it yields meaningfully different estimates of factor bias and input interactions. We hope the three-stage procedure developed here proves useful to others working in this area, and we would encourage future work to examine whether similar patterns hold in other countries and sectors, particularly as digitalization continues to evolve and AI-specific effects become more empirically tractable.

## References


Acemoglu, D. (2003). Labor- and capital-augmenting technical change. *Journal of the European Economic Association*, 1(1), 1–37.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review: Papers & Proceedings*, 104(5), 394–399.

Acemoglu, D., Johnson, S., & Autor, D. (2026). Pro-worker AI: Concept and evidence. Working Paper.

Acemoglu, D. & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6), 2411–2451.

Alexopoulos, M. & Cohen, J. (2016). The power of praise: Evidence on the effects of robots. Working Paper.

Anderton, R., Botelho, V., Consolo, A., Dias da Silva, A., Foroni, C., Mohr, M., & Vivian, L. (2023). Digitalisation and productivity. *ECB Occasional Paper*.

Añón Higón, D. & Bonvin, J. (2023). Digitalization in manufacturing: Firm-level evidence from Spain. *Structural Change and Economic Dynamics*, 66, 34–47.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2), 645–709.

Baily, M. N. (2002). IT productivity growth. *Innovation Policy and the Economy*, 2, 1–35.

Baily, M. N. & Lawrence, R. Z. (2001). Information technology and productivity: Where are we now and where are we going? *Journal of Economic Perspectives*, 15(4), 25–44.

Bentolila, S. (2012). Temporary employment in Spain. Working Paper.

Bentolila, S., Dolado, J. J., & Jimeno, J. F. (2008). Two-tier employment protection reforms: The Spanish experience. *CESifo DICE Report*, 6(4), 49–56.

Bentolila, S. & Saint-Paul, G. (2003). An updated estimated of the share of temporary employment. *European Economic Review*, 47(1), 168–189.

Bertschek, I., Briglauer, W., Hüschelrath, K., Kauf, B., & Niebel, T. (2015). Broadband infrastructure and economic growth. *Journal of Economic Surveys*, 29(5), 1042–1065.

Bertschek, I. & Kaiser, U. (2004). What is the voice of your HS? ICT and complementarities in production. *Telecommunications Policy*, 28(3–4), 311–326.

Bessen, J. E. (2019). Automation and jobs: When technology boosts employment. *Economic Policy*, 34(100), 589–626.

Binder, M. & Bound, J. (2019). Artificial intelligence and the labor income share. Working Paper.

Black, S. E. & Lynch, L. M. (2001). How to compete: The impact of workplace practices and information technology on productivity. *Review of Economics and Statistics*, 83(3), 434–445.

Blackorby, C. & Russell, R. R. (1989). Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities). *American Economic Review*, 79(4), 882–888.

Blanchard, O. J. (1997). The medium run. *Brookings Papers on Economic Activity*, 1997(2), 89–158.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1), 339–376.

Brynjolfsson, E. & Hitt, L. M. (1996). Productivity, business profitability, and consumer surplus: Three different measures of information technology value. *MIS Quarterly*, 20(2), 121–142.

Brynjolfsson, E. & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4), 23–48.

Brynjolfsson, E. & Yang, S. (1996). Paradox lost? firm-level evidence on the returns to information systems spending. *Management Science*, 42(4), 541–558.

Calvino, F., Criscuolo, C., Marcolin, L., & Squicciarini, M. (2018). A taxonomy of digital intensive sectors. *OECD Science, Technology and Industry Working Papers*, (2018/14).

Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, 25(3), 109–125.

Colombo, M. G., Croce, A., & Grilli, L. (2013). ICT and productivity: A review of the literature. Working Paper.

Cusolito, A. P. (2020). Firms, technology, and digital transformation. World Bank Working Paper.

Dedrick, J., Gurbaxani, V., & Kraemer, K. L. (2003). Information technology and economic performance: A critical review of the empirical evidence. *ACM Computing Surveys*, 35(1), 1–28.

Demirer, M. (2025). Production function estimation with factor-augmenting technology: An application to markups. Conditionally Accepted, Econometrica.

DeStefano, T., Kneller, R., & Timmis, J. (2018). Broadband and firm performance. Working Paper.

Doraszelski, U. & Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, 126(3), 1027–1084.

Doraszelski, U. & Jaumandreu, J. (2019). Using cost minimization to estimate markups. Working Paper.

Draca, M., Sadun, R., & Van Reenen, J. (2008). ICT, innovation and productivity. Working Paper.

Fu, H. et al. (2021). Internet development and the labor share of income. Working Paper.

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., & Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail—firm-level empirical evidence from EU countries. *OECD Economics Department Working Papers*, (1533).

Gandhi, A., Navarro, S., & Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8), 2973–3016.

Gordon, R. J. (2000). Does the "new economy" measure up to the great inventions of the past? *Journal of Economic Perspectives*, 14(4), 49–74.

Greenan, N. & Mairesse, J. (2000). Computers and productivity in France: Some evidence. *Economics of Innovation and New Technology*, 9(3), 275–315.

Haller, S. A. & Lyons, S. (2015). Broadband adoption and firm productivity: Evidence from Irish manufacturing firms. *Telecommunications Policy*, 39(1), 1–13.

Hempell, T. (2005). Does experience matter? Innovations and the productivity of information and communication technologies in German services. *Economics of Innovation and New Technology*, 14(4), 277–303.

Holt, L. & Jamison, M. (2009). Broadband and contributions to economic growth: Lessons from the US experience. *Telecommunications Policy*, 33(10–11), 575–581.

International Labour Organization (2019). *The Global Labour Income Share and Distribution*. Technical report, ILO.

Jaumandreu, J. & Lin, S. (2018). Accounting for advertising expenditure in the firm production function. Working Paper.

Jorgenson, D. W. (2001). Information technology and the US economy. *American Economic Review*, 91(1), 1–32.

Jorgenson, D. W. & Stiroh, K. J. (1999). Information technology and growth. *American Economic Review*, 89(2), 109–115.

Karabarbounis, L. & Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics*, 129(1), 61–103.

Kerspien, J., Madsen, J. B., & Strulik, H. (2026). Capital composition and the decline of the labor share: Why buildings matter. *European Economic Review*, 184, 105242.

Levinsohn, J. & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2), 317–341.

Li, X., Feng, G.-F., Shum, W. Y., & Chui, K. H. (2024). The impacts of digital transformation on labor income share: Evidence from China. *Emerging Markets Finance and Trade*, 60(6), 1265–1280.

Li, Y., Ding, L., & Wang, H. (2025). Does enterprise digitalization increase labor income share? Evidence from Chinese A-share listed enterprises. *Journal of the Asia Pacific Economy*.

Lin, A. & Parker, K. (2025). *Americans' views on the impact of artificial intelligence*. Technical report, Pew Research Center.

Liu, T., Huang, P., & Wang, Q. (2025). The impact of digital innovation on labor share: Evidence from Chinese firms. *International Review of Economics & Finance*, 99, 104023.

Loveman, G. W. (1994). An assessment of the productivity impact of information technologies. (pp. 84–110).

Malikov, E., Zhao, S., & Kumbhakar, S. C. (2020). Estimation of firm-level productivity in the presence of exports: Evidence from China's manufacturing. *Journal of Applied Econometrics*, 35(4), 457–480.

Malikov, E., Zhao, S., & Zhang, J. (2024). A system approach to structural identification of production functions with multi-dimensional productivity. In C. F. Parmeter, M. G. Tsionas, & H.-J. Wang (Eds.), *Essays in Honor of Subal Kumbhakar*, volume 46 of *Advances in Econometrics* (pp. 211–263). Emerald Group Publishing Limited.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283–322.

Morrison, C. J. (1997). Assessing the productivity of information technology equipment in US manufacturing industries. *Review of Economics and Statistics*, 79(3), 471–481.

Musbaudeen, A. M. & Kumbhakar, S. C. (2026). Digitalization and the labor share: A theoretical framework. Companion Paper.

Nucci, F., Puccioni, C., & Ricchi, O. (2013). Is firm-level digitalization associated with firm productivity? evidence from italian firms. Bank of Italy Working Paper.

Oberfield, E. & Raval, D. (2021). Micro data and macro technology. *Econometrica*, 89(2), 703–732.

Oliner, S. D. & Sichel, D. E. (2000). The resurgence of growth in the late 1990s: Is information technology the story? *Journal of Economic Perspectives*, 14(4), 3–22.

Olley, G. S. & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263–1297.

Raval, D. R. (2019). The micro elasticity of substitution and non-neutral technology. *The RAND Journal of Economics*, 50(1), 147–167.

Stiroh, K. J. (1998). Computers, productivity and input substitution. *Economic Inquiry*, 36(2), 175–191.

Stiroh, K. J. (2002). Information technology and the US productivity revival: What do the industry data say? *American Economic Review*, 92(5), 1559–1576.

Stiroh, K. J. (2005). Reassessing the impact of IT in the production function: A meta-analysis and sensitivity tests. *Annales d'Économie et de Statistique*, (79/80), 529–561.

Zhang, H. (2019). Non-neutral technology, firm heterogeneity, and labor demand. *Journal of Development Economics*, 140, 145–168.

Zhao, S., Malikov, E., & Kumbhakar, S. C. (2024). On the estimation of nonneutral production technologies without homothetic separability. R&R at The RAND Journal of Economics.

## Appendix A: Variable Definitions

- **Investment ($I_{it}$):** The value of current-period investment in equipment goods, excluding buildings, land, and financial assets. Investment made in period $t$ becomes productive in period $t+1$.
- **Capital ($K_{it}$):** The real capital stock, computed using the perpetual inventory method as $K_{it+1} = (1-\delta)\frac{P_t^I}{P_{t-1}^I}K_{it} + I_{it}$, where $\delta = 0.15$ is the annual depreciation rate and $P_t^I$ is the manufacturers' investment price index. Real capital is obtained by deflating capital at current replacement values by the investment price index.
- **Labor ($L_{it}$):** Total effective hours worked by all employees of the firm in year $t$.
- **Materials ($M_{it}$):** The real value of intermediate consumption, comprising raw materials, energy, and purchased services. Nominal intermediate consumption expenditures are deflated by a firm-specific intermediate consumption price index constructed from price variations reported in the ESEE.
- **Output ($Y_{it}$):** The real value of goods and services produced, obtained by deflating nominal production values by a firm-specific output price index constructed using the Paasche index formula.
- **Revenue ($R_{it}$):** The nominal sales value of goods and services sold by the firm in year $t$.
- **Wage ($W_{L,it}$):** The hourly wage rate, defined as total labor compensation divided by total effective hours worked.
- **Output Price Index ($P_{it}^Y$):** A firm-specific Paasche price index constructed from price variations of output sales reported in the ESEE, following the methodology of Jaumandreu and Lin (2018).
- **Materials Price Index ($P_{it}^M$):** A firm-specific Paasche price index constructed from price variations of intermediate consumption reported in the ESEE.
- **Demand Shifters:** Two variables enter the demand specification: (i) market dynamics ($mktd_{it}$), capturing firm-level demand conditions, and (ii) the ratio of advertising expenditure to sales ($ads_{it}$).

- **Labor Share ($s_{L,it}$):** The ratio of total labor compensation to total revenue, $s_{L,it} \equiv W_{L,it}L_{it}/(P_{it}Y_{it})$.
- **Materials Share ($s_{M,it}$):** The ratio of total materials expenditure to total revenue, $s_{M,it} \equiv W_{M,it}M_{it}/(P_{it}Y_{it})$.