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 from 2000 to 2019, we find that digitalization raises both labor-augmenting productivity by 3.4% and Hicks-neutral productivity by 3.0% at the aggregate level, although the labor-augmenting channel is considerably more heterogeneous across industries. Digitalization also increases the labor share by approximately 6.3 percentage points, consistent with the capital–labor complementarity documented 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:

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 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.

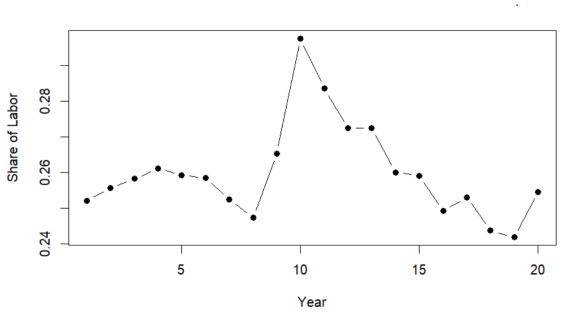


Figure 1: Labor Share (s_L) Over Time

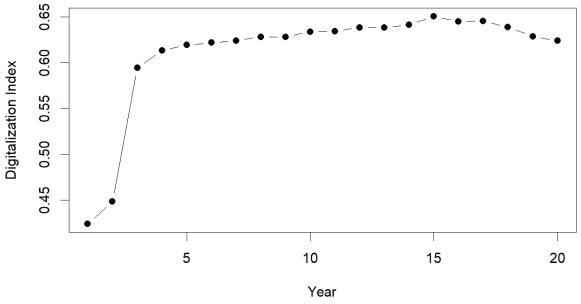


Figure 2: Digitalization Index Over Time

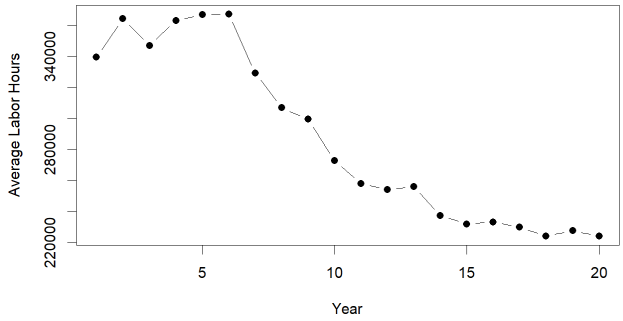


Figure 3: Average Labor Hours Over Time

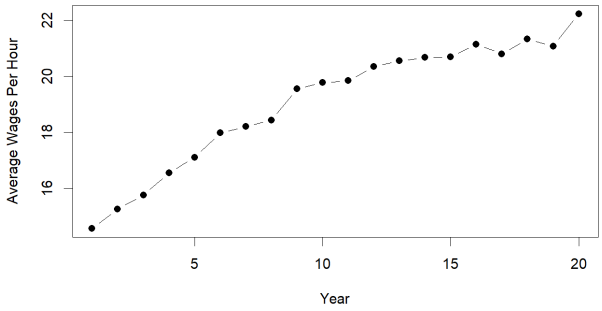


Figure 4: Average Wages Per Hour Over Time

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).

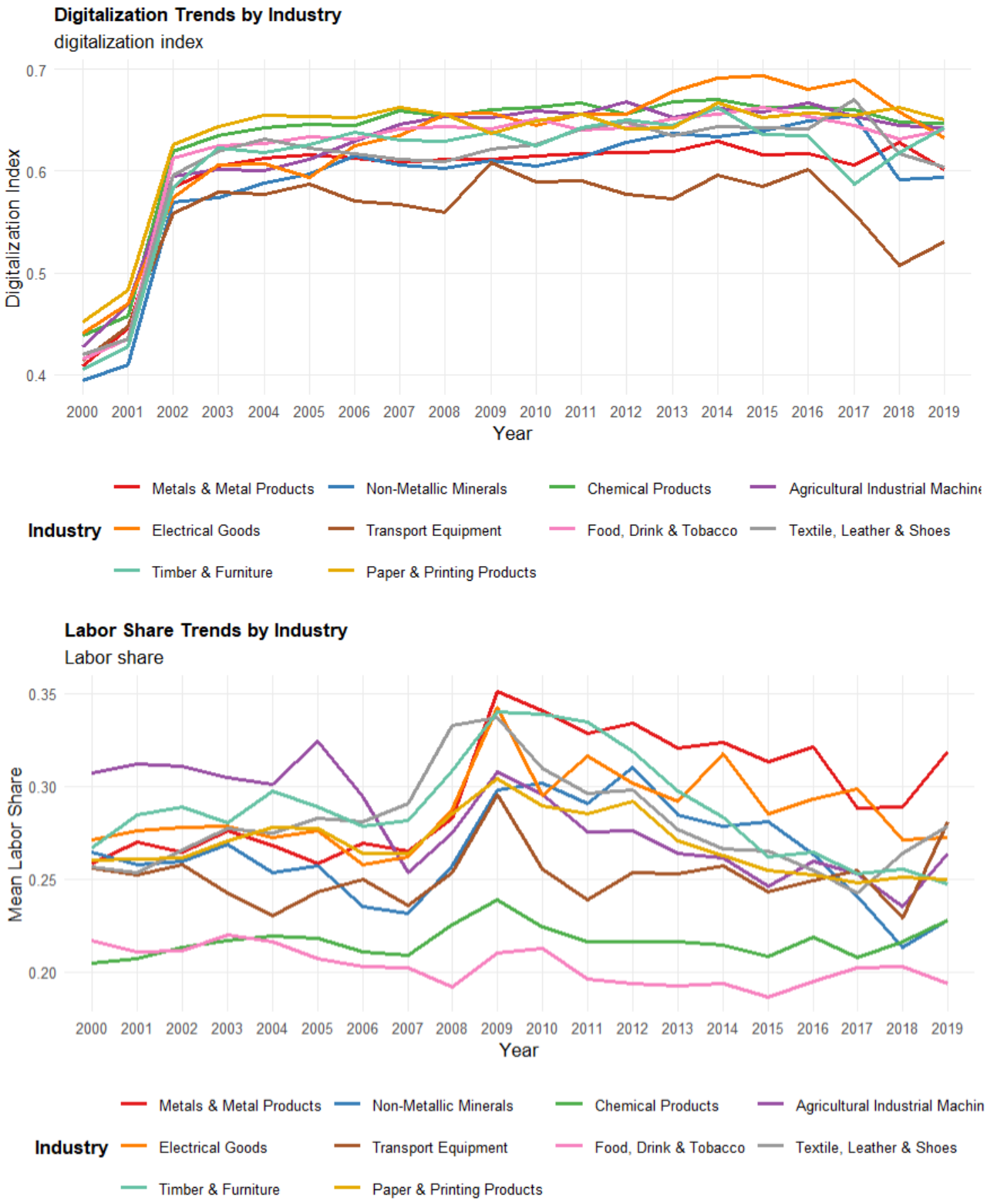


Figure 5: Digitalization and Labor Share Trends (2000–2019). Data sourced from the ESEE manufacturing survey.

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 became aware of a contemporaneous working paper by Zhao et al. (2024) that also attempts to estimate factor-augmenting productivity without imposing homothetic separability in a translog framework. Our approach differs from theirs in several respects. First, we accommodate imperfectly competitive product markets by integrating a demand-side estimation step that recovers markups, whereas their framework assumes perfect competition. Second, we develop a labor share decomposition framework that isolates the contributions of markups, input intensities, and labor-augmenting productivity to changes in the labor share, and further decomposes the productivity

channel into digitalization, persistence, and innovation components; an analytical apparatus that has no counterpart in their paper. Third, our three-stage procedure combines IV-GMM for the quasi-differenced share equations and nonlinear least squares for the capital block, in contrast to their use of 2SLS, which offers efficiency gains under heteroskedasticity through the optimal GMM weighting matrix. Finally, we apply the framework to examine how a multidimensional digitalization index shapes both factor-augmenting and Hicks-neutral productivity and the labor share of income in Spanish manufacturing; empirical questions that lie outside the scope of their analysis.

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 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

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

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 ω_{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 ω_{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 θ_{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 ξ_{it} is innovation in labor productivity and $D_{i,t-1}$ is the lag of digitalization.

Quasi-differencing (13)–(14) by ρ 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

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

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

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

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

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

To estimate inverse demand, we build on the framework of Jaumandreu & Mairesse (2016), while introducing several modifications to better fit our empirical setting. First, unlike Jaumandreu & Mairesse (2016), who model quantity demanded as a function of price, we specify an inverse demand equation in which price is a function of quantity. Second, whereas their model assumes that the unobserved demand component follows a random walk, we assume that it evolves according to an AR(1) Markov process. Third, we allow the latent demand component to depend on observed demand shifters, namely market dynamics and advertising intensity. Formally,

$$\ln P_{it} = f\left(\ln Y_{it}, u^d_{it}\right), \tag{30}$$

$$u^d_{it} = \rho u^d_{i,t-1} + b_1\, \mathrm{mktd}_{it} + b_2\, \mathrm{ads}_{it} + v_{it}. \tag{31}$$

In this specification, $\ln Y_{it}$ is the log of real output, $\ln P_{it}$ is the log of the firm-level price index, mktd_{it} measures market dynamics, ads_{it} is advertising expenditure expressed as a percentage of sales, and v_{it} denotes the innovation in the latent demand component.

Because output may respond to contemporaneous demand shocks, $\ln Y_{it}$ is potentially endogenous. We therefore estimate the model by IV-GMM, using lagged price, lagged output, and their higher-order terms as instruments. For some industries, market dynamics and advertising intensity are also included

in the instrument set under the identifying assumption that they are orthogonal to the innovation in the unobserved demand component.

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 lnK^2_{it-1} and lnW^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 θ.

Moment conditions. The quasi-differencing eliminates the level of ω^n and isolates the productivity innovation ξ_{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 $\hat{\omega}_{it}^L$, define the labor-augmented labor input as

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

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:

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

To handle the unobserved Hicks-neutral productivity ω_{it}^n, we impose the AR(1) Markov process $\omega_{it}^h = \rho_K \, \omega_{i,t-1}^h + \gamma_1 \, D_{i,t-1} + \xi_{it}$, where $D_{i,t-1}$ is the lagged digitalization index and γ_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 $\hat{\omega}_{i,t-1}^n + \varepsilon_{i,t-1}$, and ξ_{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 θ 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 Labor Share Decomposition

In developed economies, the labor share has been declining for several decades while in developing economy the aggregate labor share has been rising. The decline in the aggregate labor share in developed economies has predominantly been studied at the aggregate level (Blanchard, 1997; Bentolila & Saint-Paul,

2003; Kerspien et al., 2026; Doraszelski & Jaumandreu, 2018), whereas the literature on the rise in labor share in developing countries such as China and Brazil has recently grown. We follow Oberfield & Raval (2021) and Doraszelski & Jaumandreu (2018) for the aggregate-level decomposition in our study. But first, we derive a firm-level decomposition of the labor share that isolates the contributions of market power, input intensities, and labor-augmenting productivity, including the digitalization channel embedded in productivity dynamics.

Recall that the labor share of firm i in period t satisfies

$$s_{L,it} \;=\; \theta_{it}\, \varepsilon^{*}_{L,it}, \tag{40}$$

where $\theta_{it} \equiv 1 + \varepsilon_{P,it}$ captures the demand wedge arising from the firm's price elasticity, and

$$\varepsilon^{*}_{L,it} \;=\; \varepsilon_{L,it} + \beta_{LL}\, \omega_{L,it} \tag{41}$$

is an augmented output elasticity of labor. Under the translog production technology, the standard elasticity component is

$$\varepsilon_{L,it} \;=\; \beta_L + \beta_{LL} \ln L_{it} + \beta_{ML} \ln M_{it} + \beta_{KL} \ln K_{it}, \tag{42}$$

so that substituting (42) into (41) gives

$$\varepsilon^{*}_{L,it} \;=\; \beta_L + \beta_{LL} \ln L_{it} + \beta_{ML} \ln M_{it} + \beta_{KL} \ln K_{it} + \beta_{LL}\, \omega_{L,it}, \tag{43}$$

and equation (40) becomes

$$s_{L,it} \;=\; \theta_{it}(\beta_L + \beta_{LL} \ln L_{it} + \beta_{ML} \ln M_{it} + \beta_{KL} \ln K_{it} + \beta_{LL}\, \omega_{L,it})\,. \tag{44}$$

Firm-level change in the labor share. Define first differences $\Delta x_{it} \equiv x_{it} - x_{i,t-1}$ for $x \in \{s_L,\, \theta,\, \varepsilon^{*}_{L}\}$. Because $s_{L,it}$ is the product of θ_{it} and $\varepsilon^{*}_{L,it}$, an exact midpoint decomposition yields

$$\Delta s_{L,it} \;=\; \bar{\varepsilon}^{*}_{L,it}\, \Delta\theta_{it} \;+\; \bar{\theta}_{it}\, \Delta\varepsilon^{*}_{L,it}, \tag{45}$$

where the midpoint averages are

$$\bar{\varepsilon}^{*}_{L,it} \;\equiv\; \frac{\varepsilon^{*}_{L,it} + \varepsilon^{*}_{L,i,t-1}}{2}, \qquad \bar{\theta}_{it} \;\equiv\; \frac{\theta_{it} + \theta_{i,t-1}}{2}. \tag{46}$$

Decomposition (45) is exact—it introduces no approximation error. From (43),

$$\Delta\varepsilon^{*}_{L,it} \;=\; \beta_{LL}\, \Delta \ln L_{it} \;+\; \beta_{ML}\, \Delta \ln M_{it} \;+\; \beta_{KL}\, \Delta \ln K_{it} \;+\; \beta_{LL}\, \Delta\omega_{L,it}. \tag{47}$$

Substituting (47) into (45), the firm-level decomposition of the labor share change is

$$\Delta s_{L,it} \;=\; \bar{\varepsilon}^{*}_{L,it}\,\Delta\theta_{it} \;+\; \bar{\theta}_{it}\,\beta_{LL}\,\Delta\ln L_{it} \;+\; \bar{\theta}_{it}\,\beta_{ML}\,\Delta\ln M_{it} \;+\; \bar{\theta}_{it}\,\beta_{KL}\,\Delta\ln K_{it} \;+\; \bar{\theta}_{it}\,\beta_{LL}\,\Delta\omega_{L,it}. \quad (48)$$

The first term, $\bar{\varepsilon}^{*}_{L,it}\,\Delta\theta_{it}$, captures how changes in the demand wedge θ_{it} redistribute value added between labor and the firm; this is the markup channel. The next three terms reflect how input-intensity changes translate into labor-share movements through the translog cross-elasticities: $\bar{\theta}_{it}\,\beta_{LL}\,\Delta\ln L_{it}$ is the labor-intensity channel, $\bar{\theta}_{it}\,\beta_{ML}\,\Delta\ln M_{it}$ the materials-intensity channel, and $\bar{\theta}_{it}\,\beta_{KL}\,\Delta\ln K_{it}$ the capital-intensity channel. The final term, $\bar{\theta}_{it}\,\beta_{LL}\,\Delta\omega_{L,it}$, transmits labor-augmenting productivity shocks directly into the labor share, and it is this term that we decompose further to isolate the contribution of digitalization.

Productivity dynamics and the digitalization channel. We model labor-augmenting productivity as a first-order Markov process with an exogenous digitalization shifter:

$$\omega_{L,it} \;=\; \rho\,\omega_{L,i,t-1} \;+\; \alpha_1\,D_{i,t-1} \;+\; \xi_{it}, \quad (49)$$

where $D_{i,t-1}$ is the lagged digitalization index and ξ_{it} is an innovation orthogonal to the information set at $t-1$. Taking first differences gives

$$\Delta\omega_{L,it} \;=\; (\rho-1)\,\omega_{L,i,t-1} \;+\; \alpha_1\,D_{i,t-1} \;+\; \xi_{it}. \quad (50)$$

Substituting (50) into the productivity term of (48) expands the decomposition to

$$\begin{aligned}\Delta s_{L,it} \;=\; & \bar{\varepsilon}^{*}_{L,it}\,\Delta\theta_{it} \;+\; \bar{\theta}_{it}\,\beta_{LL}\,\Delta\ln L_{it} \;+\; \bar{\theta}_{it}\,\beta_{ML}\,\Delta\ln M_{it} \;+\; \bar{\theta}_{it}\,\beta_{KL}\,\Delta\ln K_{it} \\ & +\; \bar{\theta}_{it}\,\beta_{LL}\,\alpha_1\,D_{i,t-1} \;+\; \bar{\theta}_{it}\,\beta_{LL}\,(\rho-1)\,\omega_{L,i,t-1} \;+\; \bar{\theta}_{it}\,\beta_{LL}\,\xi_{it}. \quad (51)\end{aligned}$$

The first four terms are as in (48). The three additional terms on the second line arise from substituting the productivity law of motion (49) and each has a distinct economic interpretation. The term $\bar{\theta}_{it}\,\beta_{LL}\,\alpha_1\,D_{i,t-1}$ is the digitalization channel: it measures the contribution of lagged digitalization to the labor share through its effect on labor-augmenting productivity. The term $\bar{\theta}_{it}\,\beta_{LL}\,(\rho-1)\,\omega_{L,i,t-1}$ is the persistence channel: it captures mean reversion in productivity, with $\rho<1$ implying that firms with above-average productivity in $t-1$ experience a partial drag on their labor share going forward. The term $\bar{\theta}_{it}\,\beta_{LL}\,\xi_{it}$ is the innovation channel, reflecting the contribution of unpredictable productivity innovations to labor-share changes. The sign of the digitalization effect is determined jointly by α_1, β_{LL}, and the average demand wedge $\bar{\theta}_{it}$. When $\beta_{LL}<0$—as is typical in translog specifications with diminishing returns to labor—a positive digitalization effect on productivity ($\alpha_1>0$) reduces the labor share, consistent with automation-driven factor substitution.

Aggregate decomposition across continuing firms. Let $\mathcal{S}_t$ denote the set of firms observed in both $t-1$ and t (continuing firms), with renormalized revenue weights

$$\tilde{\lambda}_{it} \;=\; \frac{R_{it}}{\sum_{j\in\mathcal{S}_t} R_{jt}}, \qquad R_{it} \;=\; P_{it}\,Y_{it}. \tag{52}$$

The revenue-weighted aggregate labor share among continuing firms is $SL_t = \sum_{i\in\mathcal{S}_t} \tilde{\lambda}_{it}\, s_{L,it}$, and its change satisfies the exact decomposition

$$\Delta SL_t \;=\; \sum_{i\in\mathcal{S}_t} \tilde{\lambda}_{it}\,\Delta s_{L,it} \;+\; \sum_{i\in\mathcal{S}_t} \left(\tilde{\lambda}_{it} - \tilde{\lambda}_{i,t-1}\right) s_{L,i,t-1}. \tag{53}$$

The first term is the within-firm effect, which aggregates idiosyncratic labor-share changes weighted by current revenue shares. The second term is the between-firm effect, which captures the reallocation of revenue toward high- or low-labor-share firms. Substituting (51) into the within-firm term of (53) yields the aggregate contribution of each channel—markup, input intensities, digitalization, persistence, and innovation—to the evolution of the aggregate labor share.

6.3 Digitalization and Labor Share

In the previous subsection, we showed how digitalization affected labor share through its effects on labor-enhancing productivity. In this subsection, we examine how digitalization directly affects the labor share using a reduced-form approach at the firm level.

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

$$s_{L,it} = \beta_0 + \beta_1 \mathrm{Dig}_{it} + \beta_2 \omega_{L,it} + \beta_3 \ln K_{it} + \beta_4 \ln M_{it} + \tau_t + \alpha_i + \nu_{it} \tag{54}$$

where $s_{L,it}$ denotes the labor share of firm i in period t, Dig_{it-1} is the lagged digitalization index which is used as an instrument for Dig_{it}, digitalization index. The $\omega_{L,it}$ denotes labor-augmenting productivity, $\ln K_{it}$ and $\ln M_{it}$ are the logarithms of capital and materials, respectively, τ_t represents time fixed effects, α_i captures firm fixed effects, and ν_{it} is the idiosyncratic error term. We perform 2SLS to estimate the causal impact of digitalization on labor share.

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: GMM Demand Estimates by Industry

Industry	**Inv. elast.** ($\hat{a}_1$)	$\boldsymbol{\theta}$	**Markup**	**Market dyn.**	**Advertising (%)**
All Industries	−0.016	0.984	1.016	0.000166	0.0505
	(0.005)			(0.000017)	(0.0118)
Food, Drink & Tobacco	−0.005	0.995	1.005	0.000128	0.0327
	(0.006)			(0.000038)	(0.0163)
Textile, Leather & Shoes	−0.149	0.851	1.175	0.000340	0.1656
	(0.040)			(0.000092)	(0.0581)
Timber & Furniture	−0.012	0.988	1.012	0.000157	0.2015
	(0.015)			(0.000049)	(0.0495)
Paper & Printing Products	−0.001	0.999	1.001	0.000226	0.2985
	(0.023)			(0.000053)	(0.2436)
Chemical Products	−0.051	0.949	1.054	0.000193	−0.0350
	(0.026)			(0.000059)	(0.0407)
Non-metallic Minerals	−0.381	0.619	1.616	0.004046	8.8372
	(0.182)			(0.003346)	(5.8522)
Metal & Metal Products	−0.078	0.922	1.085	0.001925	−4.2336
	(0.125)			(0.001279)	(2.3598)
Agri. & Ind. Machinery	−0.030	0.970	1.031	0.000188	−0.0047
	(0.023)			(0.000064)	(0.0400)
Electrical Goods	−0.051	0.949	1.054	0.000247	−0.0543
	(0.043)			(0.000100)	(0.0872)
Transport Equipment	−0.044	0.956	1.046	0.000213	0.0637
	(0.014)			(0.000039)	(0.1105)

Standard errors in parentheses. Inv. elast. = inverse elasticity of demand ($\hat{a}_1$). Here $\theta = 1 + \hat{a}_1$, and markup is defined as $1/\theta$. Market dyn. = coefficient of market dynamics ($\hat{b}_1$). Advertising reports $100 \times \hat{b}_2$, so it is interpreted as the approximate percentage change in price associated with a 1 percentage-point increase in advertising intensity, where advertising intensity is defined as (advertising expenses/sales) $\times 100$. Estimation by two-step GMM (Quadratic Spectral kernel).

The demand estimates reported in Table 2 summarize the inverse demand relationship for the full sample and across industries. Column 2 reports the estimated inverse elasticity of demand, $\hat{a}_1$, column 3 reports $\theta = 1 + \hat{a}_1$, column 4 reports the implied markup, $1/\theta$, and the last two columns report the effects of market dynamics and advertising intensity on demand. Because the specification is written as an inverse demand equation, the coefficient is identified from variation in output rather than from the usual price-based demand elasticity formulation. A negative estimate of $\hat{a}_1$ is therefore consistent with the

expected inverse relationship between price and output: higher output is associated with a lower price.

Overall, the estimated inverse demand elasticities are economically sensible and mostly well behaved. For the sample of all industries, the inverse elasticity is small and negative (-0.016), implying $\theta = 0.984$ and a modest markup of 1.016. This suggests that, on average, firms operate in markets with limited but nonzero market power. Across industries, however, there is substantial heterogeneity. Some sectors, such as Food, Drink & Tobacco, Timber & Furniture, and Paper & Printing Products, exhibit inverse elasticities close to zero, implying θ values close to one and markups only slightly above unity. This pattern is consistent with relatively competitive product markets. In contrast, Textile, Leather & Shoes and especially Non-metallic Minerals display larger negative inverse elasticities, which translate into lower θ and higher implied markups. For example, Non-metallic Minerals has an estimated inverse elasticity of -0.381, implying $\theta = 0.619$ and a markup of 1.616, indicating substantially greater market power in that sector.

The estimated coefficients on market dynamics are positive in all industries, although their magnitudes vary considerably. This suggests that favorable market conditions are generally associated with stronger demand. The advertising coefficients are more heterogeneous. In some industries, such as Textile, Leather & Shoes and Timber & Furniture, advertising appears to be positively associated with demand, while in others the estimates are small or even negative. These mixed results suggest that the effectiveness of advertising is industry specific and may depend on sectoral differences in product differentiation, branding, and consumer responsiveness. At the same time, some of the very large coefficients, such as for Non-metallic Minerals, should be interpreted cautiously given their large standard errors.

Table 3 reports the persistence parameter AR(1), $\hat{\rho}$, and the Sargan J-test of overidentifying restrictions. The estimates of $\hat{\rho}$ are all high, generally lying between 0.91 and 0.98, which indicates substantial persistence in the unobserved component of demand over time. The results of the J-test generally support the validity of the set of instruments, since the null hypothesis of valid overidentifying restrictions is not rejected at conventional significance levels for most industries. However, the evidence is somewhat borderline in a few cases, such as Textile, Leather & Shoes, Agri. & Ind. Machinery, and Electrical Goods, where the p-values are close to 0.05. Thus, while the diagnostic results are broadly reassuring, these industries should be interpreted with somewhat greater caution.

Taken together, the results indicate that the estimated demand system delivers economically plausible inverse demand elasticities, reasonable implied markups, and meaningful variation across industries in both market power and the roles of market dynamics and advertising. The diagnostic tests further suggest that the empirical specification is generally well supported by the data and instrument set.

Table 3: GMM Demand Diagnostics by Industry

Industry	$\hat{\rho}$	J-statistic	J p-value
All Industries	0.945 (0.005)	1.621	0.445
Food, Drink & Tobacco	0.911 (0.012)	1.175	0.556
Textile, Leather & Shoes	0.980 (0.005)	5.429	0.066
Timber & Furniture	0.946 (0.012)	2.331	0.312
Paper & Printing Products	0.940 (0.017)	0.564	0.453
Chemical Products	0.958 (0.016)	0.669	0.716
Non-metallic Minerals	0.928 (0.058)	0.001	0.974
Metal & Metal Products	0.969 (0.022)	0.001	0.980
Agri. & Ind. Machinery	0.968 (0.014)	12.296	0.056
Electrical Goods	0.952 (0.020)	5.347	0.069
Transport Equipment	0.950 (0.017)	3.386	0.184

Standard errors of $\hat{\rho}$ in parentheses. ρ is the AR(1) price persistence parameter. The J-statistic tests overidentifying restrictions; a high p-value indicates instrument validity.

Table 4 shows the estimated output elasticities of capital, labor, and materials across industries when labor-augmenting productivity is not included in the specification. Overall, the estimated elasticities are economically plausible and broadly well behaved. The results indicate that materials make the largest contribution to output across nearly all industries, followed by labor, while capital contributes the least on average.

For all industries, the mean materials elasticity is 0.793, substantially larger than the mean labor elasticity of 0.088 and the mean capital elasticity of 0.092. This pattern suggests that production is driven primarily by intermediate inputs, with smaller average contributions from labor and capital. Although there is some heterogeneity across industries, the dominant role of materials is remarkably consistent. In most sectors, the mean materials elasticity lies well above the corresponding labor and capital elasticities, confirming that materials are the most important input in the production process. There is, however, meaningful cross-industry variation in the relative importance of capital and labor. For example, labor contributes more strongly in industries such as Non-Metallic Minerals, Metal & Metal Products, Textile, Leather & Shoes, and Transport Equipment, whereas capital elasticities are generally modest across sectors.

Table 7 reports the model diagnostics. The Hansen J-test results generally support the validity of the instrument set, as the null hypothesis of valid overidentifying restrictions is not rejected for most industries. An important exception is Metal & Metal Products, where the J-test p-value is 0.000, indicating rejection of the overidentifying restrictions. The estimates for this industry should therefore be interpreted with caution. The pooled sample result is also borderline, with a p-value of 0.050, and should likewise be viewed with some caution.

The estimated persistence parameters, $\hat{\rho}_{\text{GMM}}$ and $\hat{\rho}_{\text{NLS}}$, indicate that both labor-related productivity and Hicks-neutral productivity are persistent over time in most industries. In general, the estimated AR(1) coefficients are positive and often relatively large, suggesting substantial serial dependence in

the underlying productivity processes. While the degree of persistence varies across sectors, the overall pattern supports the presence of dynamic productivity effects in both the stacked GMM cost-share equations and the capital NLS block.

Table 4: Input Elasticities without Labor-Augmenting Productivity by Industry

	Capital Elasticity (E_K)			Labor Elasticity (E_L)			Materials Elasticity (E_M)		
Industry	Q1	Mean	Q3	Q1	Mean	Q3	Q1	Mean	Q3
All Industries	0.053	0.092	0.130	−0.266	0.088	0.457	0.573	0.793	1.006
Food, Drink & Tobacco	0.062	0.138	0.220	0.083	0.193	0.298	0.537	0.642	0.747
Textile, Leather & Shoes	−0.067	0.018	0.103	0.186	0.313	0.445	0.663	0.840	1.002
Timber & Furniture	−0.065	0.112	0.277	0.029	0.188	0.350	0.547	0.630	0.708
Paper & Printing	0.067	0.078	0.088	0.028	0.108	0.185	0.723	0.799	0.876
Chemical Products	0.036	0.077	0.117	0.164	0.245	0.324	0.658	0.743	0.831
Non-Metallic Minerals	−0.622	0.167	0.983	0.105	0.357	0.588	0.536	0.987	1.399
Metal & Metal Products	0.026	0.001	0.029	0.236	0.323	0.421	0.609	0.714	0.808
Agric. & Ind. Machinery	0.020	0.036	0.052	0.203	0.279	0.351	0.644	0.702	0.763
Electrical Goods	0.005	0.025	0.048	0.162	0.271	0.380	0.629	0.719	0.810
Transport Equipment	0.025	0.055	0.088	0.221	0.287	0.349	0.621	0.696	0.776

Notes: E_K is obtained from the capital NLS block; E_L and E_M are obtained from the stacked GMM cost-share equations. Q1 and Q3 denote the first and third quartiles of the estimated cross-sectional distributions.

Table 5 shows the distribution of labor-augmenting productivity, ω_L, and Hicks-neutral productivity, ω_h, across industries. The labor-augmenting component captures productivity gains that operate specifically through labor, reflecting improvements in the efficiency of effective labor input. By contrast, the Hicks-neutral component, recovered from the capital block via nonlinear least squares, captures a neutral productivity term that shifts the production function proportionally without changing the relative intensities of capital, labor, and materials. Taken together, these two components provide a decomposition of productivity into factor-specific and neutral sources of firm performance.

For all the industries, the mean labor-augmenting productivity is 0.181, while the mean Hicks-neutral productivity is 0.010. This pattern suggests that, on average, productivity gains in the sample are driven more strongly by improvements that enhance labor effectiveness than by neutral shifts in overall production efficiency. More generally, the estimates reveal substantial heterogeneity across industries in both the level and the dispersion of the two productivity components.

A number of industries exhibit positive mean labor-augmenting productivity, indicating that labor-enhancing productivity is an important source of firm performance in those sectors. The strongest examples include Paper & Printing, with a mean ω_L of 0.862, and Timber & Furniture, with a mean of 0.349. These results suggest that in such industries, firms benefit relatively more from productivity improvements that raise the effective contribution of labor. Other industries, including Electrical Goods, Agricultural & Industrial Machinery, Textile, Leather & Shoes, and Metal & Metal Products, also display positive average labor-augmenting productivity, although at more moderate levels.

By contrast, a few industries show negative mean labor-augmenting productivity, namely Food, Drink & Tobacco, Chemical Products, Non-Metallic Minerals, and Transport Equipment. These negative

means suggest that, on average, firms in these sectors experience weaker labor-specific productivity performance relative to the normalization used in the model. Among these, Transport Equipment (-0.132) and Chemical Products (-0.104) display the lowest average values.

The Hicks-neutral productivity estimates are generally smaller in magnitude than the labor-augmenting component, which reinforces the view that neutral productivity shifts play a more limited role on average. Several industries show positive mean Hicks-neutral productivity, including Timber & Furniture (0.136), Metal & Metal Products (0.135), Agricultural & Industrial Machinery (0.135), and Electrical Goods (0.085). This suggests that firms in these sectors experience modest positive neutral efficiency shifts that raise output proportionally across inputs. In contrast, Food, Drink & Tobacco, Textile, Leather & Shoes, Chemical Products, and especially Non-Metallic Minerals exhibit negative mean Hicks-neutral productivity. The estimate for Non-Metallic Minerals is particularly notable, with a mean of -1.020 and a very wide interquartile spread, indicating substantial dispersion and potentially pronounced heterogeneity in firm-level neutral productivity within that sector.

Overall, our results showed that labor-augmenting productivity is the more prominent source of productivity differences across firms and industries, while Hicks-neutral productivity plays a smaller but still meaningful role, with considerable heterogeneity across sectors.

Table 5: Labor-Augmenting and Hicks-Neutral Productivity by Industry

	Labor-Augmenting Productivity (ω_L)			Hicks-Neutral Productivity (ω_h)		
Industry	Q1	Mean	Q3	Q1	Mean	Q3
All Industries	−0.116	0.181	0.460	−0.119	0.010	0.128
Food, Drink & Tobacco	−0.404	−0.072	0.257	−0.131	−0.008	0.115
Textile, Leather & Shoes	−0.395	0.148	0.616	−0.304	−0.105	0.074
Timber & Furniture	−0.096	0.349	0.774	−0.036	0.136	0.359
Paper & Printing	0.657	0.862	1.046	−0.090	0.017	0.128
Chemical Products	−0.494	−0.104	0.294	−0.170	−0.047	0.072
Non-Metallic Minerals	−0.257	−0.019	0.333	−0.736	−1.020	0.960
Metal & Metal Products	−0.223	0.056	0.310	−0.081	0.041	0.172
Agric. & Ind. Machinery	−0.079	0.117	0.297	0.030	0.135	0.237
Electrical Goods	−0.073	0.123	0.310	−0.023	0.085	0.191
Transport Equipment	−0.350	−0.132	0.098	−0.092	0.018	0.123

Notes: Entries report Q1, mean, and Q3 of the estimated cross-sectional distributions of firm-level productivity. ω_L is recovered from the stacked GMM cost-share equations; ω_h is recovered from the capital NLS block.

Table 6 shows the estimated effects of digitalization on labor-augmenting productivity, α_1, and Hicks-neutral productivity, γ_1, across industries. These coefficients measure the extent to which lagged digitalization is associated with subsequent productivity gains through factor-specific and neutral channels, respectively.

At the aggregate level, digitalization has a positive and statistically significant effect on both productivity components. The estimated coefficient in the labor-augmenting productivity equation is 0.034 and is significant at the 1% level, while the corresponding coefficient in the Hicks-neutral productivity

equation is 0.030 and is likewise significant at the 1% level. These estimates indicate that, on average, digitalization is associated both with improvements in the effective productivity of labor and with neutral efficiency gains in Spanish manufacturing.

The industry-level estimates reveal substantial heterogeneity in both magnitude and precision. For labor-augmenting productivity, most industries have positive point estimates, suggesting that the labor-augmenting channel may be relevant in a broad range of sectors. However, the estimates are generally imprecise, and in most cases the coefficients are not statistically distinguishable from zero at conventional levels. As such, the industry-specific labor-augmenting effects should be interpreted cautiously. A few industries, including Food, Drink & Tobacco and Transport Equipment, display negative point estimates, but these are also estimated imprecisely and therefore do not provide strong evidence of negative labor-specific productivity effects.

The Hicks-neutral estimates exhibit somewhat stronger evidence in a limited number of sectors. In particular, Agricultural & Industrial Machinery shows a positive and statistically significant coefficient, while Electrical Goods and Food, Drink & Tobacco also display positive coefficients with weaker statistical support. This pattern suggests that, in some industries, digitalization may operate primarily through broad-based efficiency gains that raise productivity proportionally across inputs. By contrast, for several other sectors the Hicks-neutral coefficients are small or estimated with substantial uncertainty, which limits the scope for precise inference. This is particularly true for Non-Metallic Minerals, where the estimated coefficient is large in magnitude but highly imprecise.

Overall, the results provide clear evidence that digitalization is positively associated with both labor-augmenting and Hicks-neutral productivity at the aggregate level. At the industry level, however, the effects are more uneven and often imprecisely estimated. The evidence therefore points to heterogeneous productivity returns to digitalization across sectors, consistent with differences in technological opportunities, organizational complementarities, and market environments.

Table 6: Impact of Digitalization on Labor-Augmenting and Hicks-Neutral Productivity

Industry	**Labor-Augmenting** (α_1)	**Hicks-Neutral** (γ_1)
All Industries	0.034***	0.030***
	(0.009)	(0.008)
Food, Drink & Tobacco	-0.031	0.031*
	(0.029)	(0.018)
Textile, Leather & Shoes	0.204	-0.042
	(0.255)	(0.035)
Timber & Furniture	0.089	0.034
	(0.056)	(0.045)
Paper & Printing	0.230	0.022
	(0.165)	(0.026)
Chemical Products	0.046	0.001
	(0.040)	(0.021)
Non-Metallic Minerals	0.041	-1.697
	(0.035)	(7.208)
Metal & Metal Products	0.026	0.034
	(0.125)	(0.022)
Agric. & Ind. Machinery	0.025	0.090**
	(0.037)	(0.037)
Electrical Goods	0.035	0.056*
	(0.033)	(0.029)
Transport Equipment	-0.021	0.032
	(0.041)	(0.029)

Notes: Standard errors in parentheses. α_1 is estimated from the stacked GMM cost-share equations; γ_1 is estimated from the capital NLS block. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Model Diagnostics by Industry

Industry	$\hat{\rho}_{\text{GMM}}$	$\hat{\rho}_{\text{NLS}}$	J-test	J-test p-value
All Industries	0.838	0.746	7.818	0.050
Food, Drink & Tobacco	0.899	0.833	9.005	0.109
Textile, Leather & Shoes	0.517	0.799	0.163	0.687
Timber & Furniture	0.768	0.895	4.658	0.199
Paper & Printing	0.836	0.776	16.995	0.108
Chemical Products	0.864	0.830	5.268	0.384
Non-Metallic Minerals	0.838	0.080	1.497	0.913
Metal & Metal Products	0.848	0.730	36.996	0.000
Agric. & Ind. Machinery	0.814	0.673	6.192	0.288
Electrical Goods	0.831	0.726	13.421	0.144
Transport Equipment	0.771	0.702	2.708	0.439

Notes: $\hat{\rho}_{\text{GMM}}$ and $\hat{\rho}_{\text{NLS}}$ are the estimated AR(1) persistence parameters from the stacked GMM cost-share equations and the capital NLS block, respectively. The J-statistic and associated p-value are from the Hansen overidentification test applied to the pooled sample. A p-value above 0.05 indicates failure to reject instrument validity.

Table 8 reports the Allen elasticity of substitution between capital and labor, AES_{KL}, and the

Morishima elasticity of substitution, MES_{KL}, by industry. The distinction between the two measures is important. The Allen elasticity is symmetric and provides a local measure of substitution between inputs, whereas the Morishima elasticity is asymmetric and captures the directional response of the capital–labor ratio to a change in the price of labor, holding output and the price of capital constant. For this reason, the Morishima elasticity is often more informative for assessing how firms may adjust factor proportions in response to changes in relative factor prices.

At the aggregate level, both measures suggest complementarity between capital and labor. The mean AES_{KL} is -1.389, while the mean MES_{KL} is -0.536. The negative sign of both elasticities indicates that, on average, capital and labor tend to move together rather than substitute for one another in Spanish manufacturing. This aggregate pattern is consistent with a production structure in which capital deepening need not mechanically displace labor and may instead be associated with complementary use of labor.

The industry-level distributions, however, suggest substantial heterogeneity in the relationship between capital and labor. Some sectors exhibit positive mean elasticities under one or both measures, indicating greater scope for substitution. The clearest examples are Chemical Products, with a mean AES_{KL} of 8.655 and a mean MES_{KL} of 1.537, and Textile, Leather & Shoes, with a mean AES_{KL} of 4.079 and a mean MES_{KL} of 1.125. These patterns suggest that firms in these industries may have greater flexibility to substitute capital for labor when relative labor costs rise. Positive mean elasticities are also observed in Metal & Metal Products, Transport Equipment, and Agricultural & Industrial Machinery, although the wide interquartile ranges in some of these sectors indicate substantial within-industry dispersion.

By contrast, other industries display patterns more consistent with complementarity between capital and labor. Timber & Furniture shows negative mean elasticities under both measures, with a mean AES_{KL} of -4.118 and a mean MES_{KL} of -0.076. Electrical Goods likewise exhibits strong complementarity, with a mean AES_{KL} of -13.535 and a mean MES_{KL} of -6.513. At the same time, the large magnitudes and wide interquartile ranges in some sectors suggest that these relationships vary considerably across firms, so the reported means should be interpreted as broad descriptive summaries rather than uniform technological features within each industry.

A comparison of the Allen and Morishima measures further suggests that conclusions regarding factor substitutability may depend on the elasticity concept employed. In some sectors, the two measures point in the same qualitative direction, as in Chemical Products and Textile, Leather & Shoes, where both indicate substitutability. In other sectors, however, the two measures differ in sign. For example, Non-Metallic Minerals has a positive mean AES_{KL} of 0.323 but a negative mean MES_{KL} of -0.803, while Timber & Furniture has a negative mean AES_{KL} but a Morishima elasticity close to zero. These differences reflect the fact that the Morishima elasticity is directional and therefore may provide a more informative description of how factor ratios respond to changes in relative input prices.

Overall, the results suggest complementarity between capital and labor in the aggregate, alongside

pronounced heterogeneity across industries. Some sectors appear to have greater scope for substitution between capital and labor, whereas others exhibit patterns more consistent with complementarity. This heterogeneity is likely to matter for labor share dynamics, since the effects of capital accumulation, technological change, or digitalization on labor demand may differ depending on the underlying degree of substitutability between capital and labor.

Table 8: Allen and Morishima Elasticities of Substitution by Industry

	Allen (AES_{KL})			Morishima (MES_{KL})		
Industry	Q1	Mean	Q3	Q1	Mean	Q3
All Industries	−1.974	−1.389	−0.671	−0.742	−0.536	−0.265
Chemical	10.481	8.655	14.327	1.151	1.537	2.190
Electrical	−21.433	−13.535	−5.278	−10.541	−6.513	−2.276
Food, Drink & Tobacco	−11.493	−3.272	6.256	−2.291	−0.520	1.531
Metal & Metal Products	−4.720	1.578	8.135	−0.294	2.257	4.913
Non-metallic Minerals	−0.205	0.323	0.947	−1.896	−0.803	−0.263
Paper & Printing Products	−1.185	0.924	2.890	−2.198	0.702	3.555
Textile, Leather & Shoes	3.628	4.079	4.679	0.901	1.125	1.394
Timber & Furniture	−4.610	−4.118	−2.729	−0.254	−0.076	0.098
Transport Equipment	−1.442	1.149	3.431	0.162	2.200	4.421
Agric. & Ind. Machinery	−3.982	2.788	10.307	−4.096	1.822	7.992

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. Q1 = first quartile; Q3 = third quartile. Negative values indicate complementarity; positive values indicate substitutability.

7.1 Digitalization and Labor Share

In this subsection, we decompose labor share into components such as markup, output elasticities of labor, and labor augmenting productivity. In our estimation, we exclude markup because our demand estimation and markup are industry-level, so there is no variability at the firm level. We also 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) discusses 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 11 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.

7.1.1 Labor Share Decomposition

Table 9 reports the average annual decomposition of changes in the labor share across industries. At the top level, the change in the labor share is partitioned into within-firm and between-firm components. The within-firm component is then further decomposed into contributions from labor intensity, capital intensity, materials intensity, labor-augmenting productivity, and a residual term. Since all entries are reported in percentage points, the table provides a direct accounting of the average annual sources of labor share adjustment among continuing firms.

At the aggregate level, the labor share declines by 0.091 percentage points per year. This decline is accounted for primarily by within-firm adjustment, which contributes -0.139 percentage points, whereas the between-firm component is positive but smaller in magnitude at 0.048 percentage points. The aggregate pattern therefore suggests that the decline in the labor share is not mainly driven by reallocation across firms, but rather by changes in input use and productivity occurring within incumbent firms.

The within-firm decomposition indicates that materials intensity is the dominant force behind the aggregate decline in the labor share. The materials channel contributes -1.192 percentage points per year, substantially outweighing the positive contributions of labor intensity (0.635) and capital intensity (0.608). The labor-augmenting productivity channel also contributes negatively, at -0.160 percentage points, while the residual is quantitatively small at -0.030. Taken together, these magnitudes suggest that the aggregate decline in the labor share is closely associated with a rising role for materials in production, with offsetting but incomplete support from changes in labor and capital intensity. This pattern is consistent with firms adjusting production organization in ways that raise the share of intermediate

inputs relative to labor compensation.

The industry-level decomposition reveals substantial heterogeneity in both the sign and composition of labor share changes. In most sectors with declining labor shares—including Agricultural & Industrial Machinery, Chemical Products, Electrical Goods, Food, Drink & Tobacco, Metal & Metal Products, and Transport Equipment—the within-firm component is negative, while the between-firm component is positive. This pattern suggests that labor share decline in these industries is primarily an incumbent-firm phenomenon rather than the result of compositional shifts toward firms with systematically lower labor shares.

At the same time, the internal composition of the within-firm effect differs markedly across industries. In Agricultural & Industrial Machinery, Food, Drink & Tobacco, and Transport Equipment, the negative within-firm contribution is driven mainly by the materials channel, indicating that increased materials intensity is closely associated with a decline in labor share. In Chemical Products, both capital and materials contribute negatively, while labor-augmenting productivity contributes positively, partially offsetting the decline. In Electrical Goods, the negative within-firm effect reflects weaker labor intensity and stronger materials intensity, with positive contributions to capital and productivity only partly counterbalancing these forces. These patterns suggest that similar reductions in the labor share may arise through different combinations of technological change and input reallocation across sectors. A smaller set of industries, Paper & Paper Products, Textile, Leather & Shoes, and Timber & Furniture, show rising labor shares on average. Here too, however, the underlying mechanisms differ.

Table 10 further decomposes the labor-augmenting productivity channel into the components of digitalization, persistence, and innovation. At the aggregate level, the total contribution of labor-augmenting productivity is negative, at -0.160 percentage points, despite a strongly positive digitalization contribution of 2.171 percentage points. This positive contribution is more than offset by negative persistence (-1.748) and innovation (-0.582) components. The aggregate evidence therefore suggests that digitalization supports the labor share through the labor-augmenting productivity channel, but that this support is, on average, offset by adverse dynamic forces associated with mean reversion and innovation shocks.

The industry-level decomposition again indicates pronounced heterogeneity. In some industries, digitalization contributes positively but is offset by unfavorable persistence or innovation terms. Paper & Paper Products is a particularly clear example: digitalization contributes 3.003 percentage points, but this effect is nearly neutralized by a persistence term of -3.100, leaving only a modest positive total contribution. Textile, Leather & Shoes combines positive digitalization and persistence effects with a large negative innovation term, yet still records a strongly positive overall labor-augmenting productivity contribution. By contrast, Timber & Furniture exhibits a positive digitalization effect that is more than outweighed by negative persistence and especially negative innovation, yielding a strongly negative total productivity contribution.

Other sectors show that digitalization need not be the dominant determinant of the labor-augmenting

productivity channel. In Chemical Products, the positive total contribution of $\Delta\omega_L$ is supported by both digitalization and innovation. In Food, Drink & Tobacco, both digitalization and persistence are negative, and these outweigh the positive innovation term, producing a negative total contribution. In Non-Metallic Minerals, digitalization is positive, but a large negative innovation component dominates, resulting in a strongly negative net effect. Transport Equipment still presents a different pattern, with a positive total contribution driven primarily by persistence rather than digitalization.

Overall, the decomposition suggests three main conclusions. First, labor share dynamics are shaped predominantly by within-firm adjustments rather than by between-firm reallocation. Second, the aggregate decline in the labor share is closely associated with increased materials intensity, with labor-augmenting productivity playing a secondary but still important role. Third, the contribution of labor-augmenting productivity is itself the outcome of offsetting digitalization, persistence, and innovation forces, with substantial variation across industries. These findings are consistent with the view that labor share changes reflect firm-level adjustments in production structure and technology adoption, and that the relative importance of these margins differs sharply across sectors.

Table 9: Labor Share Decomposition by Industry: Average Annual Contributions

		Within-firm effect						
Industry	ΔSL_t	Total	Labor	Capital	Materials	$\Delta\omega_L$	Residual	Between
All industries	−0.091	−0.139	0.635	0.608	−1.192	−0.160	−0.030	0.048
Agric. & Ind. Machinery	−0.054	−0.284	0.109	0.064	−0.514	0.001	0.057	0.230
Chemical Products	−0.069	−0.157	0.095	−0.351	−0.369	0.494	−0.027	0.087
Electrical Goods	−0.052	−0.219	−0.188	0.250	−0.262	0.025	−0.044	0.167
Food, Drink & Tobacco	−0.073	−0.126	0.332	0.288	−0.314	−0.259	−0.173	0.054
Metal & Metal Products	−0.138	−0.241	−0.089	−0.004	−0.232	0.039	0.045	0.103
Non-Metallic Minerals	−0.067	−0.010	−0.027	0.975	−0.026	−0.689	−0.244	−0.056
Paper & Paper Products	0.118	0.195	−0.045	0.002	−0.006	0.126	0.118	−0.077
Textile, Leather & Shoes	0.403	0.412	−0.033	−1.139	0.332	0.954	0.298	−0.010
Timber & Furniture	0.089	0.168	−0.062	2.135	0.004	−1.825	−0.083	−0.079
Transport Equipment	−0.155	−0.253	−0.045	0.062	−0.209	0.186	−0.247	0.098

Notes: All entries are multiplied by 10^2 (i.e. reported as percentage points). The decomposition follows equation (53). At the top level, the change in the labor share satisfies

$$\Delta SL_t = \text{Within} + \text{Between}.$$

The within-firm effect is further partitioned into the labor-intensity, capital-intensity, materials-intensity, labor-augmenting productivity ($\Delta\omega_L$), and residual components following equation (48). Thus, the residual is part of the within-firm decomposition rather than a separate top-level component. Averages are computed over the balanced sample of continuing firms (stayers) observed in consecutive years, 2000–2019.

Table 10: Decomposition of the Labor-Augmenting Productivity Channel by Industry

		of which:		
Industry	$\Delta\omega_L$ total	Digitalization	Persistence	Innovation
All industries	−0.160	2.171	−1.748	−0.582
Agric. & Ind. Machinery	0.001	0.318	−0.259	−0.058
Chemical Products	0.494	0.275	−0.130	0.349
Electrical Goods	0.025	0.658	−0.159	−0.475
Food, Drink & Tobacco	−0.259	−0.305	−0.419	0.465
Metal & Metal Products	0.039	0.254	−0.277	0.062
Non-Metallic Minerals	−0.689	0.718	−0.262	−1.145
Paper & Paper Products	0.126	3.003	−3.100	0.223
Textile, Leather & Shoes	0.954	1.573	1.026	−1.645
Timber & Furniture	−1.825	1.907	−1.003	−2.729
Transport Equipment	0.186	−0.166	0.331	0.021

Notes: All entries are multiplied by 10^2 (i.e. reported as percentage points). The $\Delta\omega_L$ total column reproduces the labor-augmenting productivity channel from Table 9. The three sub-components follow equation (51): the digitalization effect is $\bar{\theta}_{it}\beta_{LL}\alpha_1 D_{i,t-1}$, the persistence effect is $\bar{\theta}_{it}\beta_{LL}(\rho-1)\omega_{L,i,t-1}$, and the innovation effect is $\bar{\theta}_{it}\beta_{LL}\xi_{it}$. By construction, the three sub-components sum to the $\Delta\omega_L$ total in each row.

7.1.2 Effect of Digitalization on Labor Share

This subsection presents the estimates of the effect of digitalization on the labor share. To address potential endogeneity of digitalization, we instrument current digitalization with its lagged value and estimate the specification using two-stage least squares with firm and time fixed effects. We exclude markup from the industry-level regressions because, in our empirical setup, it is not estimated with within-industry variation and is therefore not separately identified in these specifications.

Table 11: Effect of Digitalization on Labor Share by Industry

Industry	Estimate	Std. Error
All Industries	0.0625***	(0.0083)
Agricultural and Industrial Machinery	0.0012	(0.0343)
Chemical Products	0.0740**	(0.0132)
Electrical Goods	0.0224	(0.0386)
Food, Drink and Tobacco	0.065***	(0.0065)
Metal and Metal Products	0.0386·	(0.0203)
Non-Metallic Minerals	0.095**	(0.0311)
Paper and Printing Products	0.045*	(0.0111)
Textile, Leather and Shoes	0.098·	(0.0441)
Timber and Furniture	0.0680*	(0.0317)
Transport Equipment	0.0613·	(0.0334)

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: ω_L, $\ln K$, $\ln M$. Standard errors in parentheses.

At the aggregate level, digitalization has a positive and precisely estimated effect on the labor share.

The coefficient of 0.0625, significant at the 0.1% level, indicates that digitalization is associated with a higher labor share in the pooled sample of Spanish manufacturing firms, conditional on labor-augmenting productivity, capital, materials, and two-way fixed effects. This result provides evidence that, on average, digitalization is associated with a reallocation of value added toward labor rather than away from it. In that sense, the aggregate estimate is more consistent with a labor-complementing interpretation of digital adoption than with a purely labor-displacing one.

The industry-level estimates reveal substantial heterogeneity in both magnitude and precision. Several sectors display positive and statistically significant coefficients, indicating that digitalization is positively associated with the labor share in those industries. The largest effects are observed in Non-Metallic Minerals (0.095, significant at the 1% level), Chemical Products (0.074, significant at the 1% level), Timber & Furniture (0.068, significant at the 5% level), Food, Drink & Tobacco (0.065, significant at the 0.1% level), and Paper & Printing Products (0.045, significant at the 5% level). These estimates provide reasonably strong evidence that digitalization raises the labor share in these sectors, holding constant firm fixed effects, time effects, and other covariates.

A second group of industries exhibits positive but less precisely estimated coefficients. Textile, Leather & Shoes (0.098), Transport Equipment (0.0613), and Metal & Metal Products (0.0386) all have positive estimates that are only marginally significant at the 10% level. These coefficients are consistent with a positive relationship between digitalization and the labor share, but the statistical support is weaker, so they should be interpreted as suggestive rather than conclusive. Electrical Goods also has a positive coefficient (0.0224), but it is not statistically distinguishable from zero at conventional levels.

Agricultural & Industrial Machinery stands out as the sector in which the estimated effect is essentially zero (0.0012) and statistically insignificant. For this industry, the regression provides little evidence of a systematic association between digitalization and the labor share. More broadly, the variation across sectors indicates that the labor-share consequences of digitalization are not uniform across manufacturing activities.

This heterogeneity is economically plausible. The labor-share effect of digitalization depends not only on whether digital technologies substitute for or complement labor, but also on how they alter production organization, task allocation, and the demand for intermediate inputs within firms. In industries where digital adoption complements labor-intensive tasks or raises worker productivity in production, coordination, or monitoring, digitalization is more likely to increase labor's share of value added. By contrast, in sectors where digital tools primarily improve process efficiency without materially increasing labor's relative contribution, the estimated effect on the labor share may be smaller or less precisely estimated. Overall, the regression results indicate a positive aggregate relationship between digitalization and the labor share, while also pointing to substantial sectoral heterogeneity in the strength of that relationship.

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 Doraszelski & Jaumandreu (2018) 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 -1.3890, and the mean Morishima elasticity is -0.536, 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 11 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 0.79 compared to 0.09 for labor and 0.09 for capital, most of the Hicks-neutral gain flows to materials. But labor still benefits, and the near-universal positive sign on γ_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 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 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 (3.0%) at the aggregate level. The industry-level picture is more nuanced. The Hicks-neutral channel is broadly operative — positive in eight of ten industries — which suggests that digital technologies tend to generate general efficiency improvements regardless of the production context. Similarly, the labor-augmenting channel shows positive effects in eight of the ten industries. This pattern suggests that whether digitalization enhances the effective

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

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 6.3 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 use of 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 straightforward, and the balance could tip in the opposite direction 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.

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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, $s_{M,it} \equiv W_{M,it}M_{it}/(P_{it}Y_{it})$.