Superstar Firms and Labor Share Decline: The Role of Digitalization in France, Germany, Italy, and Spain[1]

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Abstract

This paper examines how market concentration and firm size interact with labor productivity, wages, and labor share in four European economies – France, Germany, Italy, and Spain – through the lens of the superstar firms hypothesis. Using aggregated firm-level data from CompNet and digitalization indicators derived from EU-KLEMS, the analysis reveals that labor share exhibits a robust negative and non-linear relationship with total factor productivity, consistent with the idea that high-productivity superstar firms allocate a smaller share of value added to labor. At the industry level, a clear positive association emerges between market concentration and both labor productivity and wages, while concentration correlates negatively with labor share. Within industries, firm size is also positively linked to labor productivity and wages but negatively linked to labor share. Although digital capital investments substantially increase productivity and wages among firms in the top size quintiles, these digitalization indicators show no significant moderating or accelerating effect on labor share declines. The findings suggest that the benefits of digitalization tend to accrue disproportionately to larger, frontier firms, while labor share continues to erode alongside rising productivity and concentration.

Keywords: *superstar firms, digitalization, labor productivity, labor share*

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Introduction

The ongoing technological revolution, characterized by digitalization and robotization, interacts with firm size to reshape labor markets. Technological progress is typically associated with increased productivity and a declining labor share due to the reallocation of task production from labor to capital (Acemoglu and Autor, 2011). This has sparked a heated debate on the impact of technological change on labor productivity, wages, and labor share. Furthermore, increasing market concentration in North America and Europe – linked to stagnating labor productivity and a declining labor share in recent decades – has garnered considerable attention in the literature (Brynjolfsson et al., 2020). One explanation for this aggregate labor share decline is the super- star firms hypothesis (Autor et al., 2020), alongside alternatives such as outsourcing (Feenstra and Hanson, 1999) or institutional changes, including deunionization (Fortin and Lemieux, 1997; Lemieux, 2006).

The primary objective of this paper is to empirically test the key predictions of the superstar firms hypothesis, as proposed by Autor et al. (2017; 2020), within the contexts of France, Germany, Spain, and Italy. These countries are selected for their status as advanced economies with established industrial structures and higher levels of market concentration, which likely influence labor market outcomes. This contrasts with smaller, more open economies in the EU, which are predominantly shaped by post-transition shocks and EU integration processes and associated insourcing.

First, I investigate whether firms in the top quintiles of the total factor productivity (TFP) distribution within industries exhibit lower labor shares and whether this relationship is non-linear, as predicted by Autor et al. (2017). Second, I test whether firms in the top quintiles of the size distribution demonstrate significantly higher productivity and wages alongside lower labor shares. Lastly, I explore whether digital technologies moderate or accelerate the relationships between labor share, labor productivity, and wages across the firm-size distribution.

I use aggregated firm-level data from CompNet to measure average labor shares, labor productivity, wages, and capital intensity. These data are complemented by the EU-KLEMS database, which captures industry-level investment and the deepening of digital capital. This approach enables us to examine the effects across the size distribution of firms within European industries.

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The findings can be summarized as follows. I observe a consistent non-linear decline in labor share and TFP toward superstar firms, particularly in non-manufacturing industries in France, Germany, Italy, and Spain. At the industry level, there is a robust positive cross-country association between average industry concentration and both labor productivity and wages, while a negative correlation is observed with labor share-most notably in France. Within industries, there is also a consistent positive link between firm size and labor productivity, wages, and labor share decline.

Additionally, I find that investment and the deepening of digital capital significantly accelerate productivity only in firms operating in the fourth and fifth quintiles of the firm-size distribution. Medium- and small-sized firms, however, do not experience the same benefits from industry-level investments and digital capital deepening.

The contribution of this paper lies in its comprehensive examination of the superstar firms hypothesis within the context of four major European economies – France, Germany, Italy, and Spain. While previous evidence (as discussed below) on the hypothesis has been fragmented and largely country-specific, this paper bridges the gap by providing a cross-country analysis that connects industry concentration, firm size, digital capital investments, and labor market outcomes. By leveraging aggregated firm-level data from CompNet and integrating digitalization indicators from EU-KLEMS, the paper uncovers a robust non-linear relationship between TFP and labor share, highlighting how high-productivity superstar firms allocate a smaller share of value added to labor. Additionally, it sheds light on how digitalization disproportionately benefits larger firms while leaving smaller firms with limited gains, offering a novel perspective on the unequal effects of digitalization across firm size distributions and its connection to labor share declines and productivity gains in an era of rising market concentration and technological advancements.

The remainder of the paper is structured as follows. Section 1 discusses the related literature. Section 2 formulates the theoretical model and hypotheses. Section 3 describes the methods and data. Section 4 presents the main results, and the last section concludes.

1. Related Literature

Extensive empirical research has been conducted to explore the relationship between technology (including digitalization), market concentration, and productivity. In the United States, market concentration has increased by more than 75% over the last 20 years across all industries (Grullon et al., 2019), while in Europe, the increase over the same period is more muted (see Bajgar et al., 2019; Cavalleri et al., 2019). Ciapanna et al. (2022) documented that country-level markups are continuously decreasing in France, Germany, and Italy, though this trend was reversed in 2010 in Spain. Market concentration is positively associated with intangible capital (Affeldt et al., 2021) and investment in robots (Stiebale et al., 2020). Calvino et al. (2018) showed that increasing concentration trends are driven by firms at the top of the digitalization distribution and operating in highly digital-intensive industries.

Focusing on Germany, Ferschli et al. (2021) revealed that while high industrial concentration and a high level of digital intensity may not necessarily overlap, highly concentrated industries tend to exhibit higher productivity. Stiel and Schiersch (2022) found that German firms in the upper part of the TFP distribution indeed pay lower labor shares; moreover, the marginal effects of TFP on labor share decline are non-linear. Their findings also suggest that the primary driver of labor share decline is rising markups rather than reductions in fixed overhead costs. Along similar lines, Calligaris et al. (2018) showed that the average increase in markups is largely driven by top-performing firms, while the markups of firms along the bottom half of the distribution have plateaued over time; notably, markups tend to be higher in digital-intensive industries.

Further supporting these trends, Mertens (2022) analyzed German firm-level data in manufacturing industries and found positive associations between increasing market power, productivity, and wages. While superstar firms do pay higher wages, these wages remain below competitive levels (a situation when wages and marginal revenue products equalize across all firms), and the gap between the marginal revenue of products and wages has widened over time (Mertens, 2022). Lotti et al. (2019) demonstrated that top-decile Italian firms in terms of TFP distribution are more profitable, invest more, and earn higher revenues, although not necessarily employing more workers. They also found that TFP growth at these top-decile firms has accelerated in recent decades, widening the divide between firms at the top and the bottom of the TFP distribution.

Despite these findings, there remains a notable lack of empirical evidence using firm-level data to evaluate the superstar firms hypothesis in France and Spain, highlighting a gap in the existing literature.

2. Superstar Firms Hypothesis

Superstar firms refer to large firms that dominate product market shares (Autor et al., 2020). These firms are the most productive therefore are able to capture the greater market shares, they employ the latest technology (Tambe et al., 2020), charge higher markups (De Loecker et al., 2020), and pay above average wages despite having lower labor share on average (Autor et al., 2020). In particular Autor et al. (2017) assume that total labor (L_i) is the sum of a fixed amount of overhead labor (*F*), equal to each firm, and of a firm-specific about of variable labor that is required in production (V_i). They use Cobb-Douglas production function, with decreasing returns to scale and labor elasticity of substitution α_i. Both labor and capital are purchased in the perfectly competitive factor market for marginal revenue products for wage rate (*w*) and interest rate (*r*), respectively. Autor et al. (2017) assume imperfect competition in the product market, where firms charge non-zero markups μ_i (share of price over marginal costs). In a cost minimizing first order condition Autor et al. (2017) derived the expression for labor share (S_i), representing the proportion of total labor compensation over the nominal value added, as follows:

$$S_i = \left(\frac{wL}{PY}\right)_i = \frac{\alpha_L}{\mu_i} + \frac{wF}{(PY)_i} \tag{1}$$

Autor et al. (2017; 2020) offer two plausible explanations, not necessarily distinct, for the phenomenon of superstar firms exhibiting, on average, lower labor shares: *(i)* they have above-average firm-level markups, and *(ii)* below-average fixed overhead costs. The first view is based on a model of monopolistic competition under which assumptions superstar firms face less elastic demand and choose higher markups, consequently, labor shares are necessarily decreasing as markup increases. The second explanation lies in the fact that superstar firms are able to spread fixed overhead costs over more revenues (value added if we assume no intermediate costs), again resulting in a lower labor share. Assuming that within industry markups are constant ($\mu_i = \mu$) imply that the first term in the Equation 1 must be also constant (Autor et al., 2017), so the labor share declines as value added increases. Since the value-added increases with TFP, the model implicitly assumes a negative relationship between TFP and the labor share of firms (Stiel and Schiersch, 2022). Stiel and Schiersch (2022) showed that the relationship between TFP and labor share must be non-linear with negative marginal effects that decrease as TFP increases and converge to α_L/μ as depicted in Figure 1.

Based on the previous discussion, I formulate and test these hypotheses:

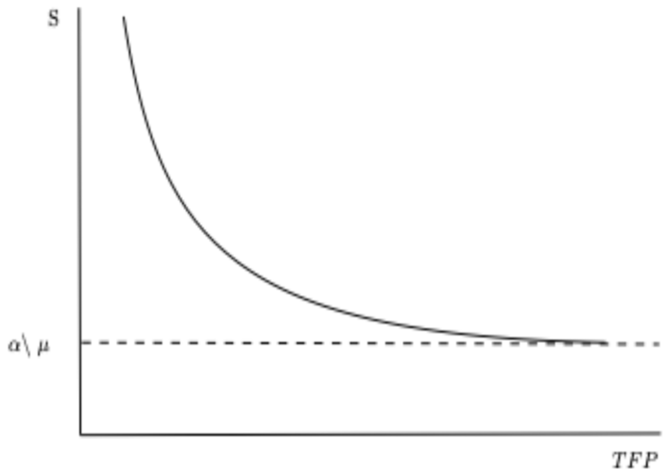
Hypothesis 1. Firms with higher total factor productivity exhibit lower labor shares. This relationship is non-linear, with negative marginal effects that decrease as TFP increases, converging to α_L/μ as the firm's TFP reaches higher levels (Stiel and Schiersch, 2022).

Hypothesis 2. Firms in the top quintiles of the size distribution demonstrate significantly higher productivity and wages alongside lower labor shares. This builds on the idea that superstar firms dominate their markets due to economies of scale and higher TFP, resulting in enhanced productivity and wage levels. However, their labor share declines due to rising markups and the substitution of labor with capital in highly concentrated industries (Calligaris et al., 2018; Mertens, 2022; Stiebale et al., 2020).

Hypothesis 3. Digital technologies moderate or accelerate the relationship between labor share, labor productivity, and wages across the firm-size distribution. Digital intensity is expected to amplify productivity gains and reinforce labor share declines in top-performing firms, as they are better positioned to leverage intangible assets and automation technologies. Conversely, smaller and less productive firms may not benefit equally from digitalization, further widening disparities in productivity, wages, and labor share (Calvino et al., 2018; Ferschli et al., 2021; Stiel and Schiersch, 2022).

F i g u r e 1

Relationship between the Labor Share and Total Factor Productivity in the Superstar Model



Source: Based on Stiel and Schiersch (2022).

3. Data and Methods

To empirically examine the relationships between digital capital, industry concentration (both between and within industries), productivity, wages, and labor share in France, Germany, Italy, and Spain, I use data at the NACE Rev. 2 two-digit industry level from the February 2023 release of EU-KLEMS (Bontadini et al., 2023). This data allows me to measure changes in digital capital between 2005 and 2020. To define and measure changes in digital capital across industries, I adopt the digitization indicators framework from Ferschli et al. (2021), which includes three additive components of digitization: (1) technological intensity, (2) knowledge intensity, and (3) digital capital deepening.

I approximate technological intensity by the investment in information and communication technology (ICT) as a share of gross fixed capital formation in each industry. This measure distinguishes between information technology ('IT share'), communication technology ('CT share'), and software and databases ('Soft share'). Knowledge intensity is approximated by research and development (R&D) investment as a share of gross fixed capital formation ('R&D share'). Additionally, I measure both the flow and stock of digital capital to capture its role in the production process. For digital capital deepening, I include the stock of information technology digital capital ('IT deep') and communication technology digital capital ('CT deep'), both normalized by hours worked in the industry. When constructing consistent and aggregated industry-country group averages of digital capital in the EU-KLEMS database, I use total employment as the weight for disaggregated industries.

I complement the EU-KLEMS data with aggregated firm-level data from the Competitiveness Research Network of the EU System of Central Banks (CompNet) 9th vintage.[2]

CompNet applies a common methodology to analyze firm-level datasets from 22 European countries, providing joint statistical moments at the industry, regional, or country levels while preserving firm-level confidentiality. This dataset enables me to analyze average labor productivity, wages, and labor share across firms' size distributions from 2000 to 2020. Specifically, I use data on inputs aggregated at the level of two-digit industries, constructed as population-weighted statistical moments.[3]

I narrow my analysis to the period from 2005 to 2020 when complementing CompNet data with digitalization indicators from the EU-KLEMS database. Otherwise, I utilize data spanning from 2000 to 2020. Due to the more detailed industry breakdown in the CompNet database compared to EU-KLEMS, I calculate weighted averages of mean labor productivity, wages, and labor share over the quintiles of the total revenue distribution, using total real revenues as weights.

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[2] Both data sources, EU-KLEMS and CompNet, are collected on an annual frequency.

[3] More specifically I use the datasets: jd_inp_industry2d_20e_weighted; op_decomp_industry2d_20e_weighted; unconditional_industry2d_20e_weighted.

To determine the non-linearity in the relationship between labor share and TFP, as implied by the fixed-cost mechanism in Equation 1, I follow Stiel and Schiersch (2022). I estimate the mean labor share function at both the aggregate level and the industry level in the following form:

$$S_{it} = \frac{wL_{it}}{P_{it}Y_{it}} = \gamma_0 + \gamma_1\omega_{it} + \gamma_2\omega_{it}^2 + \tau_t + z_s + u_{it} \tag{2}$$

My primary interest lies in the marginal effects within the 10th, 50th, and 90th percentiles of the TFP distribution for each industry. These marginal effects are defined as $\theta_i = \gamma_1 + 2\gamma_2\omega_{it}$, where ω_{it} represents logged industry TFP, τ_t denotes time, and z_s accounts for country fixed effects. I expect these marginal effects to decline in magnitude as I move toward superstar firms.

I also estimate the effects of digitalization indicators using quintiles of real revenue distributions in the following form:

$$\begin{aligned} Y_{cit} = \beta_0 + \sum\nolimits_{k=1}^{4}\beta_k Q_{k+1ci} + \beta_5 DI_{ci,t-1} + \sum\nolimits_{k=1}^{5}\beta_{k+5}\left(Q_{k+1ci} \times DI_{ci,t-1}\right) + \\ + \beta_{10} Capital\,intensity_{ci,t-1} + \alpha_c + \gamma_i + \rho_t + \varepsilon_{cit} \end{aligned} \tag{3}$$

Here, Y_{cit} represents the mean labor productivity, wage, or labor share in industry *i*, within country *c*, at time *t*. Q_{1ci}, Q_{2ci}, …, Q_{5ci} are dummy variables indicating the quintiles of the real revenue distribution in a given industry and country. $DI_{ci,t-1}$ represents digitalization indicators interacted with the firm size dummy variables in each industry and country. All covariates are lagged by one period to minimize contemporaneous endogeneity. Additionally, I control for capital intensity, defined as the ratio of real capital to labor, using data from the CompNet database. The parameters $\alpha_c + \gamma_i$ and ρ_t represent country-, industry-, and time-fixed effects, respectively. In this analysis, only complete time series data are used, with no missing data imputation.

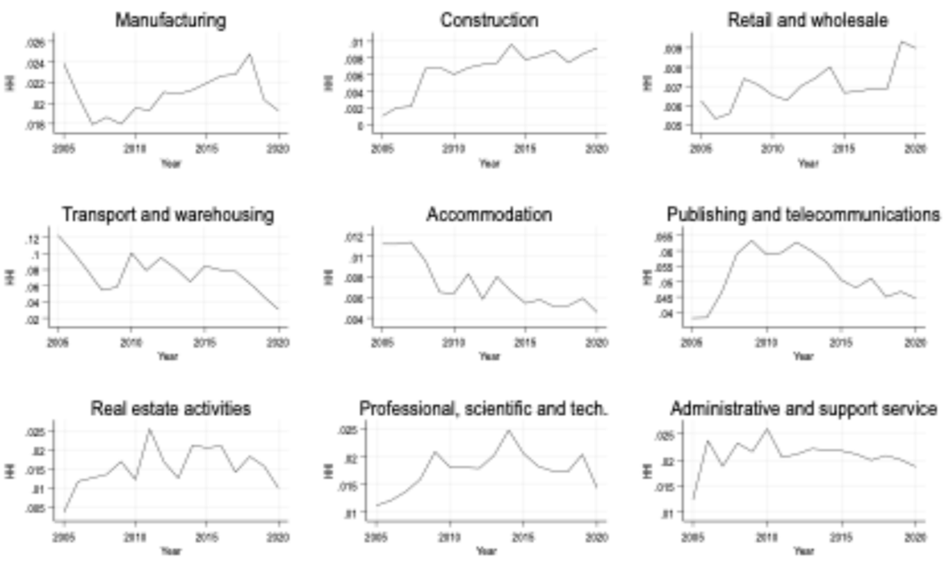
4. Results and Discussion

In this section, I examine the relationship between industry concentration, labor productivity, wages, and labor share in France, Germany, Italy, and Spain. To begin, Figure 2 illustrates industrial concentration, measured by the average Herfindahl-Hirschman Index (HHI), across nine aggregated sectors in these countries.

Sectors such as manufacturing, construction, retail, and wholesale experienced a notable increase in average industry concentration over the observed period. In contrast, transportation and storage, along with publishing and telecommunications, underwent a sustained decline in average industry concentration, despite starting from some of the highest initial levels. For other sectors, the overall trend is less distinct and can generally be described as stable over the observed period.

F i g u r e 2

Average Industrial Concentration across Aggregated Industries in France, Germany, Italy, and Spain, 2005 – 2020



Note: That the y-axis is variable.

Source: CompNet database. Figure displays an evolution of mean industrial concentration measured by HHI from total revenues in France, Germany, Italy, and Spain across nine (aggregated as the weighted average of total employment) obtained from CompNet database.

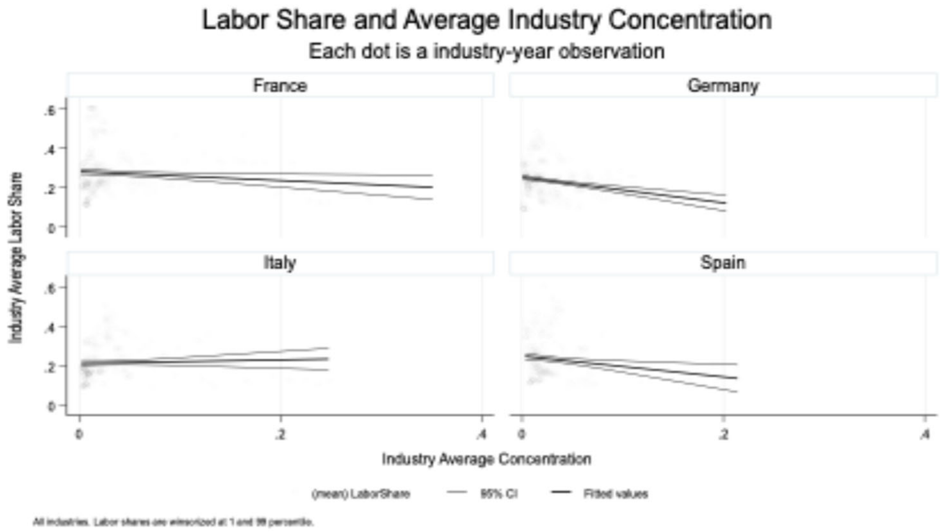
Linking industrial concentration and labor share across time and countries in Figure 3, a negative correlation is observed between higher industrial concentration and labor share in all countries except Italy.

Figures A3 and A4 in the Appendix illustrate the reduced-form relationships between industry concentration and labor productivity and wages at the country level. All four countries exhibit a positive and significant relationship between industry concentration, labor productivity, and wages. France displays the highest observed concentration, while the strongest relationship between industrial concentration and both labor productivity and wages is observed in Spain.

However, the bivariate relationship between wages and industrial concentration is less pronounced compared to the relationship between productivity and industrial concentration.

F i g u r e 3

Average Industrial Concentration and Labor Share across All Industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2000 – 2020



Source: CompNet database. Figure displays a scatter plot of the relationship between average industrial concentrations and labor productivity in France, Germany, Italy, and Spain across twenty-two EU-KLEMS (aggregated as the weighted average of total revenues). Labor share is measured as nominal labor cost over nominal value added. Industrial concentration is proxied by HHI in terms of total revenues (CV07_hhi_rev_pop_2D_tot) directly obtained from CompNet database.

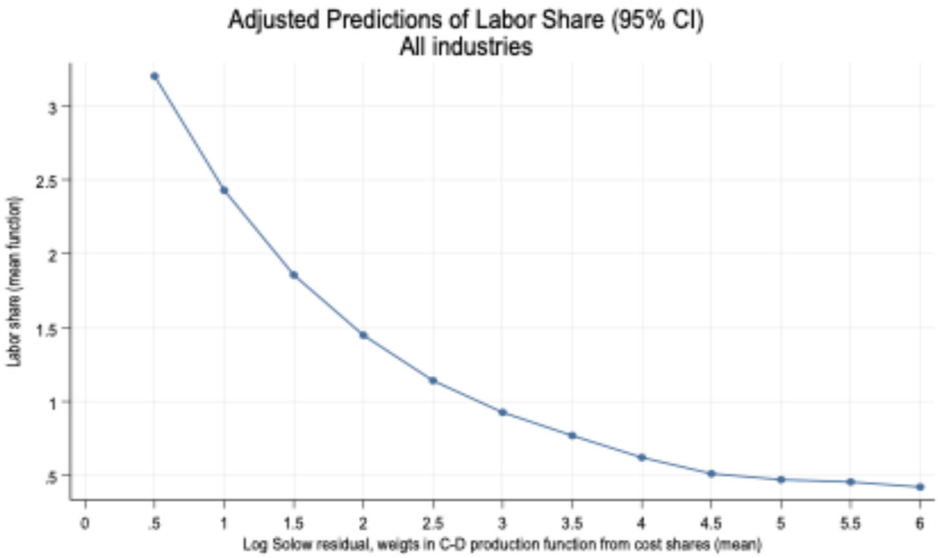
Now, I complement this visual analysis with a more formal approach. As a first step, I estimate a nonparametric local linear regression (NPLLR) to examine the relationship between industry- level labor share and TFP, testing whether the labor share decreases in a nonlinear manner as TFP increases. Equation 1 describes this relationship, assuming that when markups within industries remain constant, the labor share depends solely on firms' productivity. According to the superstar firms hypothesis, increasing firm productivity leads to a nonlinear decline in the labor share as discussed in Section 2.

Figure 4 presents the marginal effects of the estimated bivariate NPLLR model for all industries in 2020. These results remain consistent over time, despite some inconsistencies in the lower tail of the TFP distribution. This figure also supports the prediction that firms spread fixed overheads, particularly fixed labor costs, over higher sales volumes.

Furthermore, the relationship between TFP and labor share is distinctly nonlinear, with negative and diminishing marginal effects across the TFP distribution. These findings are consistent with the results of Stiel and Schiersch (2022) in Germany.

F i g u r e 4

Mean Function of Labor Share and Total Factor Productivity in France, Germany, Italy, and Spain, 2020



Source: CompNet database. All variables are taken from CompNet 9th vintage. Labor share is measured as nominal labor cost over nominal value added (LR01_lc_va_mn). Total factor productivity is log transformed Solow residual from the Cobb-Douglas production function (PV05_lnsr_cs).

As the second step, I do the same exercise as before, but now on the subset of manufacturing and non-manufacturing industries in Figures A1 and A2 in Appendix. The predictions about the function behavior hold since I can observe a systematically predicted lower labor share in manufacturing and steeper (relative and absolute) declines as I move toward frontier TFP firms. It is not surprising that the labor share of firms with the lowest productivity is above one. This pattern has also been observed in firm-level data in Canada (Gouin-Bonenfant, 2022) and the US (Kehrig and Vincent, 2017). Gouin-Bonenfant (2022) claims that since there is a large share of firms with a labor share above one, it cannot simply be attributed to measurement error. This implies that the gross profits of those firms are negative Gouin-Bonenfant (2022).

To strengthen this assertion, I further examine the nonlinear effect by regressing the labor share on TFP at the level of grouped industries using a second-order polynomial, as specified in Equation 2. The results of this analysis are presented in Table 1. The findings indicate that the labor share decreases as the TFP of firms within grouped industries increases, as illustrated in Figure 1.

Table 1

The Relationship between Labor Share and TFP withing the Grouped Industries

Industry group	ω_{it}	ω^2	**Constant**	R^2	**N**
Manufacture of Food, Beverages and Tobacco Products	–0.595*** (0.15)	0.064*** (0.023)	1.738*** (0.238)	0.409	551
Textile, Apparel and Leather Industries	–0.598*** (0.084)	0.042*** (0.012)	2.22*** (0.154)	0.773	797
Wood, Paper and Printing Manufacturing	–0.915*** (0.094)	0.101*** (0.013)	2.471*** (0.174)	0.675	883
Chemicals and Pharmaceuticals	–1.042*** (0.057)	0.115*** (0.008)	2.771*** (0.108)	0.632	2968
Transport Equipment Manufacturing	–0.848*** (0.127)	0.083*** (0.018)	2.584*** (0.227)	0.610	1156
Construction	–0.68*** (0.08)	0.054*** (0.01)	2.398*** (0.168)	0.864	766
Wholesale and Retail Trade	–1.868*** (0.256)	0.206*** (0.034)	4.682*** (0.493)	0.596	675
Transportation and Warehousing	–0.444*** (0.041)	0.037*** (0.005)	1.656*** (0.089)	0.730	1064
Accommodation and Food Services	–1.261*** (0.125)	0.184*** (0.022)	2.584*** (0.184)	0.730	450
Information and Communication Services	–0.701*** (0.05)	0.054*** (0.006)	2.59*** (0.11)	0.532	1528
Professional, Scientific and Technical Services	0.577*** (0.044)	–0.107*** (0.007)	0.244*** (0.082)	0.318	2062
Other Services	–0.399*** (0.058)	0.024*** (0.008)	1.798*** (0.114)	0.415	1770

Note: Robust standard errors in parentheses. p∗ < 0.10, p∗∗ < 0.05, p∗∗∗ < 0.01.

Source: CompNet database.

Based on Equation 2, I compute the marginal effects at the 10th, 50th, and 90th percentiles of the TFP distribution, as shown in Table 2. The results in Table 2 test a crucial assumption of the superstar firms hypothesis. The findings demonstrate that, across all industries, the relationship between TFP and the labor share is negative and decreases in magnitude as it approaches the superstar firms.

Table 2

Marginal Effects Obtained Using Delta Method at 10, 50, 90th Percentile Distribution of TFP

Industry group	**p(10)**	**p(50)**	**p(90)**
Manufacture of Food, Beverages and Tobacco Products	–0.232***	–0.144***	–0.027
Textile, Apparel and Leather Industries	–0.36***	–0.303***	–0.226***
Wood, Paper and Printing Manufacturing	–0.336***	–0.196***	–0.01
Chemicals and Pharmaceuticals	–0.384***	–0.225***	–0.012
Transport Equipment Manufacturing	–0.373***	–0.258***	–0.105***
Construction	–0.373***	–0.299***	–0.199***
Wholesale and Retail Trade	–0.694***	–0.41***	–0.03
Transportation and Warehousing	–0.233***	–0.182***	–0.113***
Accommodation and Food Services	–0.208***	0.046	0.386***
Information and Communication Services	–0.392***	–0.317***	–0.217***
Professional, Scientific and Technical Services	–0.032***	–0.179***	–0.376***
Other Services	–0.26***	–0.226***	–0.182***

Note: Robust standard errors in parentheses. p∗ < 0.10, p∗∗ < 0.05, p∗∗∗ < 0.01.

Source: CompNet database.

It is worth noting that the link between TFP and the labor share in professional, scientific, and technical service industries is substantially weaker compared to all other industries. I attribute this observation to the labor-intensive nature of service industries, where the relative savings on labor costs from fixed overhead labor are less pronounced compared to the rest of the sample. In contrast, in other industries, such as transport equipment manufacturing, the labor share reacts more strongly to changes in TFP. For example, the labor share of firms in this industry decreases by 0.37 percentage points when TFP increases by one percent for firms at the 10th percentile of the TFP distribution, and by 0.11 percentage points for firms at the 90th percentile.

Lastly, I complement the analysis of labor market outcomes, TFP, and income distribution with the interaction of industry-level digital capital indicators, including technological intensity, knowledge intensity, and digital capital deepening. My main objective is to determine whether new digital technologies accelerate or moderate these trends and whether these effects are evenly distributed across the total revenue quintiles within industries.

The superstar firms hypothesis relies predominantly on within-industry variation in firms' size. As discussed in Section 1, a substantial body of empirical evidence suggests that superstar firms are concentrated in highly digital industries and that larger firms benefit more from digital capital than their smaller competitors within the same industry. To investigate this further, I estimate the model for each labor market outcome specified in Equation 3, incorporating both intertemporal and firm size variation. The results, presented in Tables A1 – A2, allow for an analysis of the impacts of digital capital investments and deepening across firms of varying sizes.

Regarding the estimation of labor share changes, presented in Table A1, the predicted negative trend across size quintiles is confirmed. However, digitalization does not appear to play a significant accelerating or moderating role in this relationship. Exceptions include firms in the second quintile, where investments in information technologies correlate with even lower labor shares, and firms in the third quintile, where increased R&D investment is associated with a similar outcome.

Table A2 shows that firms in the upper quintiles exhibit significantly higher labor productivity than those in the lower quintiles. This holds even after controlling for additive digital capital components, capital intensities (columns (1) – (6)), and fixed effects for country, industry, and year. The observed patterns align with those shown in Table A3 for wages and Table A1 for labor share. Notably, the variation in productivity, wages, and labor share changes explained by the linear regression models ranges from 75% for productivity to 50% for labor share.

Consistent with the superstar firms hypothesis and previous literature, positive estimates are observed for the fourth and fifth size quintiles, particularly in relation to investments in information and communication capital and deepening in information technologies. This suggests that the positive effects of digitalization on labor productivity are most pronounced for frontier firms, while middle-sized firms do not experience significant benefits. To illustrate, my model predicts a positive and significant β_9 coefficients ranging from 0.026 (s.e. = 0.003) for information technology to 0.046 (s.e. = 0.007) for software. These results indicate that a 10% increase in investment in information technology or software increases average labor productivity by 0.26% and 0.46%, respectively, for firms in the fifth quintile.

Interestingly, additional investments in software and the deepening of information and communication technologies reduce labor productivity in firms in the first quintile. Investments in R&D, however, do not exhibit significantly different effects across the entire size distribution.

Regarding wages, the findings follow a similar pattern to labor productivity. Additional digitalization is significantly and positively associated with higher wages, but this effect is evident only in firms in the fourth and fifth quintiles. This suggests that workers in superstar firms benefit from above-average wage increases due to digitalization, while no significant effects are observed for the rest of the firms' size distribution. Notably, investments in information and communication technologies (columns (1) and (2)) and their deepening relative to the labor force (columns (5) and (6)) negatively impact the smallest firms in the first quintile. Conversely, R&D investments play an accelerating role in wages exclusively for these smaller firms.

Conclusions

In the context of the rise of superstar firms in Europe and the decline in labor share, I examined key predictions of the superstar firms hypothesis and the role of digitalization in this relationship in France, Germany, Italy, and Spain. Aggregated firm-level data from the period 2005 to 2020 were used to explore whether the mean function of labor share declined in a non-linear manner with increasing TFP as firms approached frontier (superstar) status. My results indicated that this was consistently the case in four major European countries, especially in non-manufacturing industries.

At the industry level, I found a positive association between average industry concentration and both labor productivity and wages, while a negative association was observed between industry concentration and labor share. I also explored within-industry variation in terms of firm size and consistently observed a positive association between firm size and both labor productivity and wages, along with a negative association between firm size and labor share.

Consistent with prior empirical research in the US and OECD countries, I found that increases in digital capital significantly accelerated productivity only in firms operating in the fourth and fifth quintiles of the firm size distribution. More specifically, positive estimates for digitalization indicators were observed in the fifth size quintile, particularly for investments in information and communication technologies and the deepening of information technology capital. The similar findings are for real wages. Interestingly, investments in research and development had a more polarizing effect on labor productivity, rather than an equalizing one. This suggested that the positive impacts of digitalization on labor productivity and real wages were concentrated among superstar firms, while medium and small-sized firms did not experience significant benefits from the digitization process.

In terms of labor share declines, I did not find any significant impact from the digitalization indicators across the distribution of firm sizes.

This paper used data up to 2020, the most recent release of the CompNet database. While the findings are grounded in long-term structural trends, they do not account for significant global disruptions after 2020, such as the COVID-19 pandemic and geopolitical tensions, which may have influenced labor market outcomes and their links to industry concentration. Future research with updated data is essential to examine how these developments might have affected the observed relationships. I hypothesize that these trends could have become even more pronounced following these shocks, as larger firms tend to be more resilient, while smaller, labor-intensive firms may have faced bankruptcy, potentially increasing market concentration further.

Data Availability Statement

The data used to measure the digitization indicators and to support the findings of this paper are publicly available at Luiss Labo of European Economics at <https://euklems-intanprod-llee.luiss.it/download/> from Bontadini et al. (2023). The firm-level data on firm productivity, wages, labor share, wages, TFP across the firm size distribution, and average industrial concentration are not publicly available but can be obtained for research purposes from CompNet by submitting a data request form at <https://www.comp-net.org/data/9th-vintage/>.

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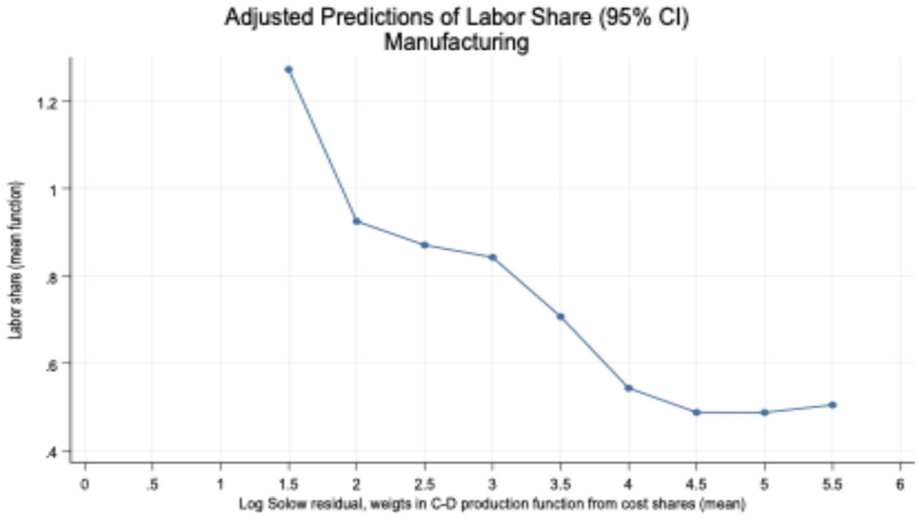
Appendix A

Figure A1

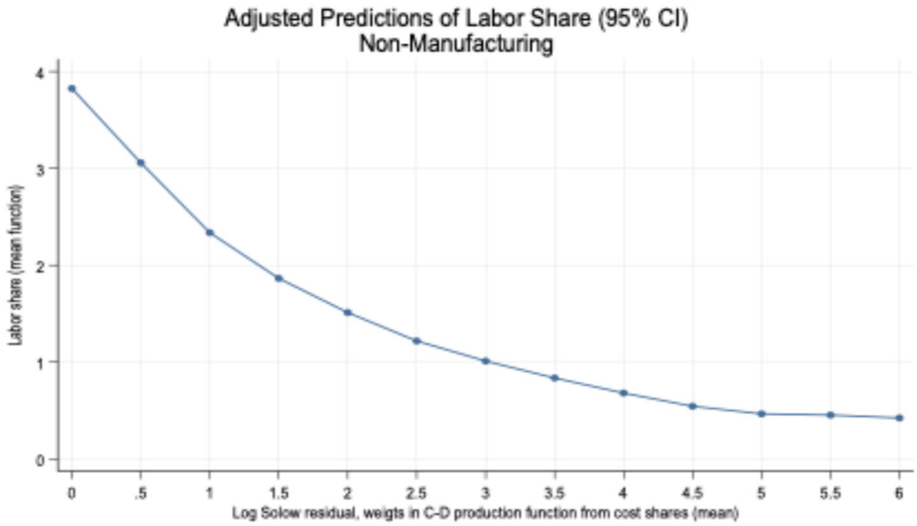
Mean Function of Labor Share and Total Factor Productivity in Manufacturing Industries (C10-C33, NACE Rev. 2) in France, Germany, Italy, and Spain, 2020



Source: CompNet database.

Figure A2

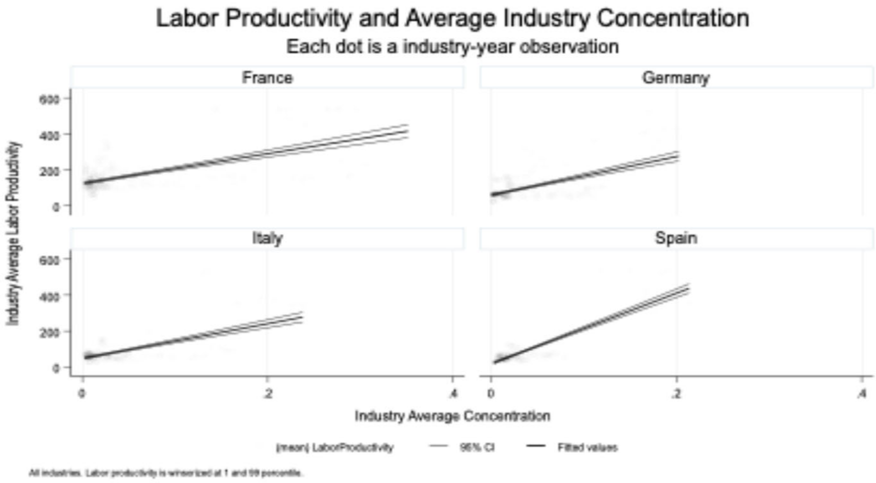
Mean Function of Labor Share and Total Factor Productivity in Non-Manufacturing Industries (F-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2020



Source: CompNet database.

F i g u r e A3

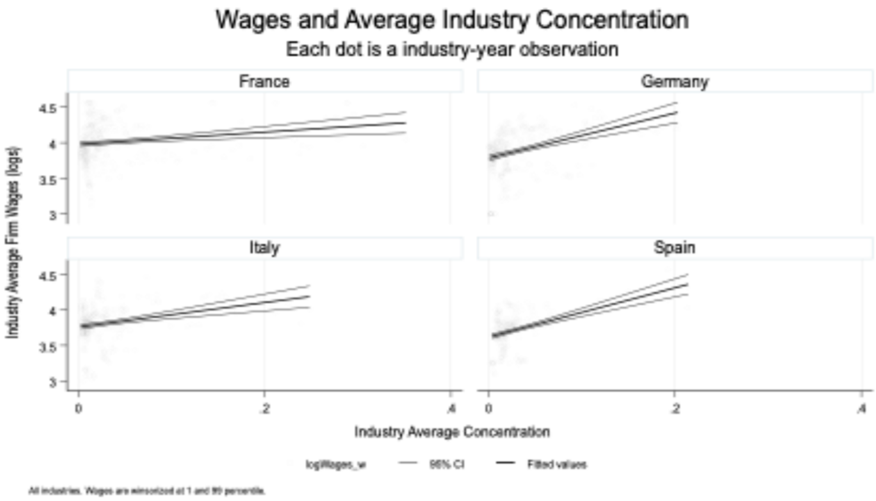
Average Industrial Concentration and Labor Productivity across All Industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2000 – 2020



Source: CompNet database. Figure displays a scatter plot of the relationship between average industrial concentrations and labor productivity in France, Germany, Italy, and Spain across twenty-two EU-KLEMS (aggregated as the weighted average of total revenues). Labor productivity is measured as real value added over the total labor stock. Industrial concentration is proxied by HHI in terms of total revenues (CV07_hhi_rev_pop_2D_tot) directly obtained from CompNet database.

F i g u r e A4

Average Industrial Concentration and Wages across All Industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2000 – 2020



Source: CompNet database. Figure displays a scatter plot of the relationship between average industrial concentrations and labor productivity in France, Germany, Italy, and Spain across twenty-two EU-KLEMS (aggregated as the weighted average of total revenues). Real wages are directly available. Industrial concentration is proxied by HHI in terms of total revenues (CV07_hhi_rev_pop_2D_tot) directly obtained from CompNet database.

T a b l e A1

Relationship between Quintiles of Mean Firm Size (Defined by Quintiles of Mean Firms' Revenues) And Digitalization Indicator in France, Germany, Italy, and Spain, 2005 – 2020

log (Labor share)						
	(1)	(2)	(3)	(4)	(5)	(6)
2. Quintile	–0.115*** (0.012)	–0.132** (0.028)	–0.077** (0.020)	–0.111*** (0.014)	–0.132** (0.033)	–0.124*** (0.013)
3. Quintile	–0.163*** (0.024)	–0.178** (0.039)	–0.114* (0.038)	–0.159** (0.033)	–0.165* (0.069)	–0.183*** (0.031)
4. Quintile	–0.201*** (0.028)	–0.222** (0.050)	–0.146* (0.049)	–0.198** (0.037)	–0.222* (0.080)	–0.219*** (0.032)
5. Quintile	–0.237*** (0.038)	–0.239** (0.049)	–0.162* (0.060)	–0.233** (0.055)	–0.296 (0.128)	–0.278** (0.071)
	IT share $_{t-1}$	*CT share* $_{t-1}$	*Soft share* $_{t-1}$	*R&D share* $_{t-1}$	*IT deep* $_{t-1}$	*CT deep* $_{t-1}$
1. Quintile	–0.010 (0.006)	–0.009 (0.007)	0.025 (0.012)	–0.001 (0.005)	0.001 (0.009)	0.002 (0.003)
2. Quintile	–0.006* (0.002)	–0.002 (0.001)	0.008 (0.008)	–0.004 (0.004)	–0.004 (0.003)	–0.001 (0.003)
3. Quintile	0.002 (0.003)	–0.003 (0.002)	0.002 (0.007)	–0.003** (0.001)	0.000 (0.004)	–0.004 (0.003)
4. Quintile	–0.001 (0.002)	–0.001 (0.004)	–0.000 (0.010)	–0.002 (0.002)	–0.005 (0.007)	–0.004 (0.002)
5. Quintile	–0.005 (0.006)	–0.008 (0.007)	–0.010 (0.009)	–0.002 (0.005)	–0.015 (0.016)	–0.011 (0.011)
Capital intensity	–0.000** (0.000)	–0.000* (0.000)	–0.000** (0.000)	–0.000** (0.000)	–0.000** (0.000)	–0.000** (0.000)
Constant	0.560*** (0.015)	0.592*** (0.015)	0.514*** (0.031)	0.581*** (0.017)	0.561*** (0.038)	0.575*** (0.019)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.534	0.533	0.536	0.515	0.534	0.533
N	13820	13839	13795	13275	13869	13869

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: All variables are taken as means from CompNet 9th vintage database and aggregated to EU-KLEMS 2-digit industries as a weighted average by total real revenues. Quintiles distribution is taken from real revenue variable distribution (FV17_rrev). Labor share is measured as nominal labor cost over nominal value added (LR01_lc_va_mn), and capital intensity is measured as real capital over labor (FR30_rk_l). All variables are log-transformed. Digitalization measures follow the description in the Section 3 and are computed from EU-KLEMS data. All covariates are log-transformed. Fixed effects are defined as twenty-two EU-KLEMS (C – N, NACE rev. 2) and country combinations. Standard errors are clustered at the country level.

T a b l e A2

Relationship between Quintiles of Firm Size (Defined by Mean Firms' Revenues) Labor Productivity and Digitalization Indicator in France, Germany, Italy, and Spain, 2005 – 2020

log (Labor productivity)						
	(1)	(2)	(3)	(4)	(5)	(6)
2. Quintile	0.346*** (0.031)	0.335*** (0.056)	0.296*** (0.033)	0.351*** (0.031)	0.443*** (0.017)	0.417*** (0.024)
3. Quintile	0.518*** (0.054)	0.477** (0.089)	0.424*** (0.055)	0.525*** (0.060)	0.616*** (0.038)	0.632*** (0.050)
4. Quintile	0.662*** (0.075)	0.563*** (0.094)	0.501*** (0.060)	0.662*** (0.084)	0.790*** (0.072)	0.827*** (0.096)
5. Quintile	0.849*** (0.084)	0.721*** (0.085)	0.657*** (0.057)	0.822*** (0.101)	1.035*** (0.113)	1.035*** (0.108)
	IT share $_{t-1}$	*CT share* $_{t-1}$	*Soft share* $_{t-1}$	*R&D share* $_{t-1}$	*IT deep* $_{t-1}$	*CT deep* $_{t-1}$
1. Quintile	0.008* (0.003)	–0.010 (0.011)	–0.044* (0.015)	0.015 (0.010)	–0.019* (0.007)	–0.030** (0.007)
2. Quintile	0.006 (0.005)	–0.006 (0.013)	–0.020*** (0.003)	0.008 (0.009)	0.006 (0.003)	–0.008 (0.010)
3. Quintile	0.003 (0.008)	0.005 (0.015)	–0.000 (0.006)	0.003 (0.005)	0.006 (0.006)	0.006 (0.007)
4. Quintile	0.013 (0.007)	0.027* (0.010)	0.031* (0.013)	0.002 (0.005)	0.014 (0.006)	0.022** (0.004)
5. Quantile	0.026*** (0.003)	0.038*** (0.006)	0.046*** (0.007)	0.006 (0.011)	0.028 (0.014)	0.028** (0.009)
Capital intensity	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.002*** (0.000)	0.001** (0.000)	0.001** (0.000)
Constant	4.022*** (0.039)	4.021*** (0.018)	4.093*** (0.050)	3.864*** (0.075)	3.945*** (0.035)	3.912*** (0.056)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.785	0.786	0.788	0.799	0.785	0.786
N	13820	13839	13795	13275	13869	13869

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: All variables are taken as means from CompNet 9th vintage database and aggregated to EU-KLEMS 2-digit industries as a weighted average by total real revenues. Quintiles distribution is taken from real revenue variable distribution (FV17_rrev). Labor productivity is measured as mean real value added over labor stock (PV03_lnlprod_va), and capital intensity is measured as real capital over labor (FR30_rk_l). Digitalization measures follow the description in the Section 3 and are computed from EU-KLEMS data. All variables are log-transformed. Fixed effects are defined as twenty-two EU-KLEMS (C – N, NACE rev. 2) and country combinations. Standard errors are clustered at the country level.

T a b l e A3

Relationship between Quintiles of Firm Size (Defined by Mean Firms' Revenues) Real Wages and Digitalization Indicator in France, Germany, Italy, and Spain, 2005 – 2020

log (Real Wages)						
	(1)	(2)	(3)	(4)	(5)	(6)
2. Quintile	0.206*** (0.014)	0.183*** (0.022)	0.201*** (0.028)	0.224*** (0.019)	0.333*** (0.009)	0.244*** (0.033)
3. Quintile	0.304*** (0.021)	0.276*** (0.040)	0.293*** (0.043)	0.329*** (0.027)	0.470*** (0.010)	0.351*** (0.038)
4. Quintile	0.391*** (0.023)	0.321*** (0.025)	0.344*** (0.041)	0.412*** (0.030)	0.617*** (0.036)	0.481*** (0.033)
5. Quintile	0.522*** (0.026)	0.438*** (0.006)	0.476*** (0.037)	0.527*** (0.038)	0.805*** (0.053)	0.619*** (0.041)
	IT share $_{t-1}$	*CT share* $_{t-1}$	*Soft share* $_{t-1}$	*R&D share* $_{t-1}$	*IT deep* $_{t-1}$	*CT deep* $_{t-1}$
1. Quintile	–0.022* (0.007)	–0.013* (0.005)	–0.008 (0.011)	0.014** (0.004)	–0.041*** (0.003)	–0.016** (0.003)
2. Quintile	–0.006 (0.005)	–0.004 (0.007)	–0.004 (0.004)	0.003 (0.003)	–0.009 (0.005)	–0.004 (0.007)
3. Quintile	–0.000 (0.006)	–0.001 (0.011)	–0.001 (0.002)	–0.002 (0.004)	0.001 (0.005)	–0.002 (0.009)
4. Quintile	0.013** (0.003)	0.014 (0.002)	0.016*** (0.006)	–0.002 (0.004)	0.016** (0.006)	0.011 (0.005)
5. Quintile	0.027** (0.008)	0.020* (0.003)	0.017** (0.008)	0.002 (0.003)	0.030** (0.010)	0.013 (0.006)
Capital intensity	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001** (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	3.289*** (0.037)	3.320*** (0.033)	3.303*** (0.055)	3.199*** (0.043)	3.128*** (0.045)	3.242*** (0.030)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.710	0.708	0.707	0.732	0.713	0.708
N	13820	13839	13795	13275	13869	13869

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: All variables are taken as means from CompNet 9th vintage database and aggregated to EU-KLEMS 2-digit industries as a weighted average by total real revenues. Quintiles distribution is taken from real revenue variable distribution (FV17_rrev). Real wages are directly available (LV24_rwage), and capital intensity is measured as real capital over labor (FR30_rk_l). All variables are log-transformed. Digitalization measures follow the description in the Section 3 and are computed from EU-KLEMS data. All variables are log-transformed. Fixed effects are defined as twenty-two EU-KLEMS (C – N, NACE rev. 2) and country combinations. Standard errors are clustered at the country level.