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Digitalization, Industry Concentration, and Labor Dynamics: Evidence from CEE Countries

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Abstract

This paper examines the relationship between industry concentration, digitalization, and labor outcomes in Central and Eastern European countries using aggregated firm-level data from CompNet and EU-KLEMS for the period 2005 to 2020. Our analysis reveals a strong correlation between higher industry concentration and improved labor productivity and wages, while simultaneously observing a decline in the labor share, consistent with the superstar firm hypothesis. However, the diverse labor market dynamics in the CEE region underscore the complexity of these relationships. Furthermore, we examine the significant role of digitalization in positively accelerating labor productivity, especially in more concentrated industries. Our results suggest that increased digital investment does not mitigate but rather accelerates the negative impact of increasing concentration on labor share, suggesting a potentially dominant labor-saving effect of these technologies.

1. Introduction

The ongoing technological revolution, driven by digitalization and robotization, is transforming global labor markets. Technological progress is generally associated with increased productivity and a declining labor share, as tasks shift from labor to

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capital (Acemoglu & Autor, 2011). Given that technological advances are typically labor-saving and linked to rising productivity, assessing the impact of digitalization on productivity is crucial for understanding the broader implications of this technological shift.

These trends are closely related to rising industry concentration, particularly in the United States. In Europe, the increase in industry concentration has been more modest (Bajgar, Berlingieri, Calligaris, Criscuolo, & Timmis, 2019); however, evidence indicates similar secular trends, such as stagnating labor productivity and declining labor share (Da Silva, Di Casola, Gomez-Salvador, & Mohr, 2024; Van Ark, O'Mahony, & Timmer, 2008). Recent literature has focused on these trends (Brynjolfsson, Benzell, & Rock, 2020). While Brynjolfsson and McAfee (2014) envision digitalization as a potential catalyst for a significant and prolonged productivity revival, addressing these challenges, others argue that the labor-saving effects of digitalization could accelerate the adverse shift against labor (Acemoglu & Restrepo, 2018a; Restrepo, 2023). This is especially true when the productivity effects of these new technologies are modest. One influential explanation for the decline in labor share is the superstar firms hypothesis, introduced by Autor, Dorn, Katz, Patterson, and Reenen (2017) and elaborated upon in the following section.

This paper investigates these trends in the Central and Eastern European (CEE) region to broaden the empirical scope of the aforementioned ideas. Among the six CEE countries analyzed in this paper, four exhibit significant declines in aggregate labor shares over the past two decades (see Figure 17 in Kónya, Krekó, and Oblath (2020)), with the notable exceptions of Czechia and Slovakia. As reported by Karabarbounis and Neiman (2014), labor shares in CEE countries have consistently declined, ranging from approximately 2% per decade in the Czechia to as much as 25% in Poland.

More specifically, this paper aims to empirically investigate the role of superstar firms as potentially one of the main drivers of an increasing industry concentration within the context of CEE countries (Croatia, Czechia, Hungary, Poland, Slovakia, and Slovenia). This region is particularly compelling due to its lower labor shares compared to other European nations, both at the aggregate and sectoral levels (Kónya et al., 2020). Furthermore, a significant portion of Europe's manufacturing production has been nearshored to this region (Majzlíková, 2024), potentially leading to observed increases in industry concentration (Weche & Wambach, 2021), productivity gains, and wage growth, while further depressing labor shares.

To address these trends, we pursue three key objectives: (1) to examine whether industries experiencing larger increases in concentration also see greater declines in labor share; (2) to assess whether industries with higher concentration exhibit faster productivity growth, particularly through digitalization; and (3) to explore whether digital technologies moderate or accelerate the relationships between industry concentration and labor productivity, wages, or labor share.

We employ aggregated firm-level data from CompNet, supplemented by EU-KLEMS data, to measure investment and digital capital deepening across industries between 2005 and 2020. Our analysis uses an unbalanced panel of twenty-eight industries. We estimate a fixed-effects model to examine labor productivity, wages, and labor share. These variables are conditioned on the average industry concentration, various investments in digital capital, and capital intensity. Our findings confirm a positive correlation between industry concentration and both labor productivity and wages. Our analysis suggests a positive correlation between industry concentration and both labor productivity and wages. However, the relationship between investments into digital capital and labor market outcomes is more complex, with mixed effects on wages and labor share. Digitalization frequently depresses the labor share, as technological innovations can automate or replace certain workers' tasks, thereby reducing the demand for labor. Consequently, average wages exhibit a negative or insignificant associations with increases in industry-level investments into digital capital.

The rest of the paper is structured as follows. Section 2 provides the related literature. Section 3 describes the methods and data used in the paper. Sections 4 discusses the main results, and Section 5 concludes.

2. Superstar Firms Hypothesis

Superstar firms are defined as large firms that dominate product market shares (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020). They employ the latest technologies (Tambe, Hitt, Rock, & Brynjolfsson, 2020), charge higher markups (De Loecker, Eeckhout, & Unger, 2020), and pay above-average wages, despite having a lower average labor share (Autor et al., 2017). Specifically, Autor et al. (2017) model total labor (L_i) as the sum of a fixed amount of overhead labor (F) shared by all firms and a firm-specific amount of variable labor required for production (V_i). They employ a Cobb-Douglas production function with decreasing returns to scale and a labor elasticity of substitution α_L. Both labor and capital are acquired in a perfectly competitive factor market for marginal revenue products at 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 (the ratio of price to marginal costs). They derive the expression for labor share (S_i), representing the proportion of total labor compensation to nominal value added, as follows:

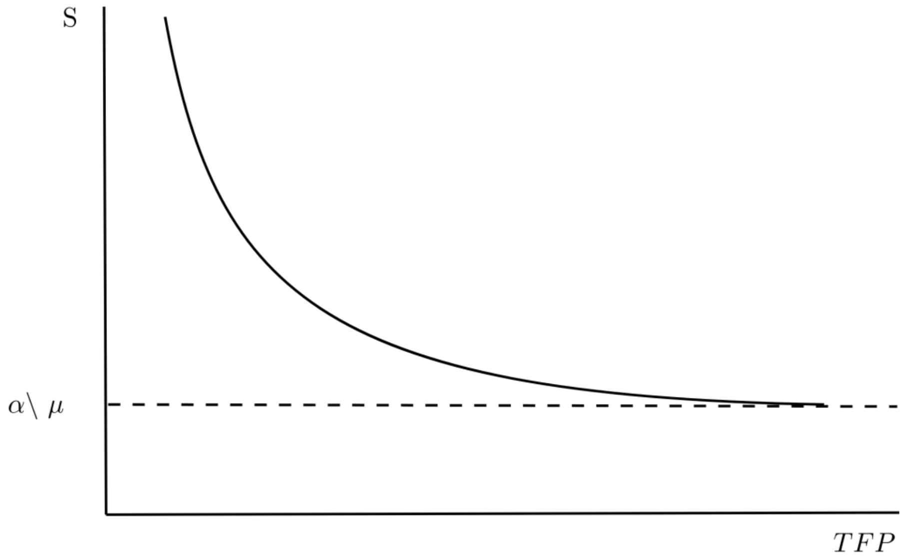
$$S_i = \left(\frac{wL}{PY}\right)_i = \frac{\alpha_L}{\mu_i} + \frac{wF}{(PY)_i} \quad \#(1)$$

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 explanation for the below-average labor share paid by superstar firms is based on a model of monopolistic competition. Under its assumptions, superstar firms face less elastic demand relative to other firms in the market and choose higher markups (μ_i), so that their labor shares (S_i) necessarily decline as the markup increases. The second explanation lies in the fact that superstar firms can spread fixed overhead costs ($(PY)_i$) over more sales (or value added if we assume no intermediate costs), again resulting in a below-average labor share paid by superstar firms. Assuming that within industry markups are constant ($\mu_i = \mu$) implies that the first term in the Equation 1 must be also constant (Autor et al., 2017), so the labor share declines as the firms' value added increases.

Since the value added increases with total factor productivity (TFP), the model implicitly assumes a negative relationship between TFP and the labor share of firms

(Stiel & 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.

Figure 1 Relationship between the Labor Share and Total Factor Productivity in the Superstar Model Based on Stiel and Schiersch (2022).



Hence the rise of superstar firms correlates with their higher productivity and market share capture, the aggregate labor share must also decline as concentration increases (for more detail see also Shim, Chung, and Ryu (2018)). Extensive empirical research has explored the relationship between technology, industry concentration, and productivity. In the U.S., industry concentration has risen by more than 75% across all industries over the last 20 years (Grullon, Larkin, & Michaely, 2019), while in Europe, this increase has been more muted (see Bajgar et al. (2019); Cavalleri et al. (2019)). Ciapanna, Formai, Linarello, and Rovigatti (2022) found that country-level markups in France, Germany, and Italy are continuously decreasing, although this trend reversed in Spain around 2010. Industry concentration is positively associated with intangible capital (Affeldt, Duso, Gugler, & Piechucka, 2021) and investment in robots (Stiebale, Suedekum, & Woessner, 2020). Calvino, Criscuolo, Marcolin, and Squicciarini (2018) indicate that increasing concentration trends are driven by firms at the top of the TFP distribution, particularly in highly digital-intensive sectors. Furthermore, Ferschli, Rehm, Schnetzer, and Zilian (2021) studied industry concentration and productivity in Germany, revealing that while high industry concentration and high digital intensity may not necessarily coincide, there is evidence supporting the notion that highly concentrated industries tend to exhibit higher productivity.

Stiel and Schiersch (2022) found that German firms operating in the upper segment of the TFP distribution indeed have a lower labor share, with non-linear marginal effects of TFP, as predicted in Figure 1. Their findings indicate that substantial markups, rather than reductions in fixed overhead costs, primarily drive the decline in labor share. Calligaris, Criscuolo, and Marcolin (2018) show that the average increase in markups is largely driven by top firms in the markup distribution, while markups for firms in the lower half plateaued over time. Additionally, their findings indicate that markups are higher in digital-intensive sectors. Using German firm-level data in manufacturing industries, Mertens (2022) documented positive associations between increasing market power, productivity, and wages. They found that superstar firms pay higher wages, although these wages remain below competitive levels. Over time, the gap between the marginal revenue of products and wages paid by these firms has widened (Mertens, 2022). Lastly, Lotti, Sette, et al. (2019) found that top-decile Italian firms in terms of TFP distribution are more profitable, invest more, and are larger in revenue, though not in employee count. They also noted that TFP growth among top-decile firms has intensified over recent decades, further widening the divide between firms at the top and bottom of the TFP distribution.

Despite extensive research on industry concentration and labor share in the U.S. and Western Europe, limited empirical evidence exists for CEE countries. Growiec (2012); Curuk and Rozendaal (2022); Weche and Wambach (2021) provide some indirect evidence on the relationship between industry concentration and decreasing labor share in Poland and other European countries. However, no study has yet tested these three aspects of superstar firms hypothesis directly in CEE countries, making this paper a contribution to the literature and addressing an important research gap.

3. Data and Methods

To empirically examine the relationships between digitalization, industry concentration, productivity, wages, and labor share in CEE countries, we combine data at the NACE 2-digit industry level from EU-KLEMS by (Bontadini, Corrado, Haskel, Iommi, & Jona-Lasinio, 2023) with aggregated firm-level data from CompNet 9th vintage. This allowed us to analyze industry concentration, average labor productivity, wages, and labor share for the period 2005 to 2020 (for the precise definition and selection of variables from the CompNet database, see the description in Table 2 and in the Appendix).

Labor productivity is defined as the ratio of real value added to total labor. Wages are measured as the ratio of total labor costs to total labor. Labor share is measured as the ratio of total labor costs to value added, all based on CompNet data. Due to the more detailed industry breakdown in the CompNet database compared to the EU-KLEMS data, we calculate weighted averages of mean labor productivity, wages, and labor share at the industry level using total CompNet industries revenues as the weighting factor.

Due to the lack of data on digital capital investments and stocks, we omitted Poland and Croatia from the panel data set in order to examine more additive aspect of digitalization constructed from the EU-KLEMS data and to pool the remaining three countries. However, we include a full set of CEE countries when examining the relationship between industry concentration and labor market outcomes, as data for these countries are reported for the period 2005 to 2020 in the CompNet data. We rely on the sample that covers firms with 20 or more employees, as Slovakia does not cover all firms in the CompNet database in this period. We obtain an unbalanced panel due to missing values in the digital capital measure in some industries and estimate the model in the form:

$$\log y_{c,i,t} = \beta_0 + \beta_1 \log \mathrm{HHI}_{c,i,t-1} + \sum_{k=1}^{6} \beta_{k+1} \log \mathcal{DI}_{c,i,t-1} +$$
$$\beta_8 \log \text{Capital intensity}_{c,i,t-1} + \alpha_c + \gamma_i + \rho_t + \varepsilon_{c,i,t} \ \#\{2)$$
#

The outcome $\log y_{c,i,t}$ is the average labor productivity, wage, or labor share across countries, industries and time. All covariates included in the models are lagged by one period, to minimize the contemporaneous endogeneity between covariates and labor market outcomes. To measure average industry concentration we make use of the Hirschman-Herfindahl Index (HHI) measured from total firms' revenues. To investigate the role of digitalization in CEE countries, we use EU-KLEMS data and borrow the definition of digitalization indicators ($\mathcal{DI}$) constructed as in Ferschli et al. (2021) to measure three additive aspects of digitalization: (1) technological intensity, (2) knowledge intensity, and (3) digital capital deepening. We approximate, technological intensity by investment in information and communication technology (ICT) as a share of gross fixed capital formation. We distinguish between information technology ('IT share'), communication technology ('CT share'), and software and databases ('Soft share'). Knowledge intensity is approximated by research and development investment as a share of gross fixed capital formation ('R&D share'). In addition, we measure not only the flows but also the relative importance of digital capital deepening in the production process. We measure the stock of information technology digital capital ('IT deep') and communication digital capital ('CT deep'), both relative to hours worked. All the digitalization indicators are used iteratively, for β_{k+1}. In addition, we control for different capital intensities, defined as the ratio of real capital to labor, obtained from the CompNet database. Finally, the parameters $\alpha_c, \gamma_i, \rho_t$ stand for country, industry and time fixed effects, respectively.

As a robustness check we explore different effects of each digitalization indicator across industries that have a higher concentration, we included interaction terms between the digitalization indicators and capital intensity with HHI in the form:

$$\log y_{c,i,t} = \beta_0 + \beta_1 \log \mathrm{HHI}_{c,i,t-1} + \sum_{k=1}^{6} \beta_{k+1} \log \mathcal{DI}_{c,i,t-1} + \sum_{k=1}^{6} \beta_{k+7} \log \mathcal{DI}_{c,i,t-1}$$
$$\times \log \mathrm{HHI}_{c,i,t-1} + \beta_{14} \log \text{Capital intensity}_{c,i,t-1}$$
$$+ \beta_{15} \log \text{Capital intensity}_{c,i,t-1} \times \log \mathrm{HHI}_{c,i,t-1}$$

$$+\alpha_c + \gamma_i + \rho_t + \varepsilon_{c,i,t} \#(3)$$

To exclude the possibility that our results of models specified in Equation (2), and (3) are driven by outliers, we winsorized all variables at 1 and 99 percentile.

The combination of these two data sources yields an unbalanced panel at the industry level, with summary statistics across all CEE countries presented in Table 1 below.

Table 1 Summary Statistics of the Variables Used, in Levels, 2005-2020. Source: EU-KLEMS and CompNet (2023) Databases.

Variable	*N*	*Mean*	*SD*	*25th Pct.*	*50th Pct.*	*75th Pct.*
Labor Productivity	2427	37.97	33.63	20.87	29.32	41.17
Wages	2417	18.04	7.26	12.75	16.67	22.10
Labor Share	2419	0.54	0.18	0.41	0.56	0.67
Herfindahl-Hirschman Index	2436	0.07	0.08	0.02	0.04	0.09
Intangible Capital Ratio	2432	0.12	1.44	0.02	0.04	0.08
Capital Intensity	2434	41.94	38.40	20.22	31.33	48.79
IT share	1152	4.36	7.47	1.11	2.09	4.74
CT share	1152	12.55	21.86	1.60	3.80	14.14
SOFT share	1600	6.31	10.22	1.54	3.14	5.83
RD share	1600	7.16	11.00	0.05	1.34	10.36
IT deepening	1152	1.34	5.85	0.01	0.04	0.55
CT deepening	1152	0.51	2.04	0.00	0.01	0.20

Table 1 shows that wages and labor productivity are right-skewed, suggesting that a few high-performing industries drive the averages upward. Industry concentration, measured by the HHI, is relatively low, indicating competitive markets, but its highly right-skewed distribution points to a few industries dominated by a small number of firms. Capital intensity is notably high, while labor share is left-skewed, reflecting lower labor cost shares in revenue for many industries. The digitalization indicators, such as IT and CT shares, exhibit significant variation, with some industries relatively heavily investing in digital capital while others lag behind.

4. Results and Discussion

In this section, we explore the associations between industry concentration, labor productivity, wages, and labor share across CEE countries. Figures 3 - 5 present the reduced-form relationships between industry concentration and both labor productivity and wages, focusing on country-specific patterns. The results reveal that Croatia has the highest average industry concentration across the entire period, followed by Slovakia, Slovenia, Hungary, Czechia, and Poland.

In Figure 3, all CEE countries exhibit higher labor productivity in more concentrated industries, especially in Poland, Czechia, and Hungary. Slovakia, however, shows no significant correlation between industry concentration and labor productivity. There is also a strong and significant relationship between wages and labor productivity across all countries (not shown here). As a result, the association between wages and industry concentration (Figure 4) mirrors the pattern seen for labor productivity, albeit with a weaker effect. In Slovenia, this relationship is particularly muted compared to the other countries.

When considering the relationship between labor share and industry concentration (Figure 5), we consistently observe a negative association, as outlined in Section 2 in most of the CEE countries. Slovakia, however, exhibits no significant relationship, with labor share increasing over the past two decades, a trend similarly observed in Czechia, as observed in aggregate level analysis by Kónya et al. (2020). Interestingly, while one might expect a similar insignificant relationship in Czechia, market concentration still appears to have strong explanatory power in this context, revealing a nuanced trend that was not highlighted in Kónya et al. (2020)'s aggregate level of analysis that warrants further exploration.

Table 3 explores the relationship between market concentration, measured by the HHI, and key labor market outcomes—namely labor productivity, wages, and labor share—across pooled CEE countries from 2005 to 2020. This analysis accounts for the ratio of intangible capital to capital investments, capital intensity relative to labor, and incorporates fixed effects for country, industry, and time. The table is structured into three panels: (1) All Industries, (2) Manufacturing Industries, and (3) Non-Manufacturing Industries. All independent variables—including HHI, capital intensity, and the intangible capital ratio—are log-transformed. This transformation allows us to interpret coefficients as elasticities.

Results for all industries reveal two key patterns. First, industries with higher concentration exhibit increased labor productivity and wages, while also showing a decreased labor share relative to capital. These findings support the superstar firms hypothesis, though they appear predominantly driven by manufacturing industries, as the same conditional correlation does not hold for wages and labor share in a subset of non-manufacturing industries. Second, the higher investments to intangible capital are significantly correlated with higher wages, not with productivity across all industries as well as across their subsets.

Specifically, across all industries, our models predict that a 10% increase in the lagged HHI is associated with a 0.9% increase in labor productivity, a 0.32% increase in wages, and a 0.33% decrease in labor share while holding all other variables constant, all significant at the 1% level. This suggests that higher concentration correlates with more efficient production processes, albeit at the expense of labor's income share, as discussed in Section 2. The effects are more pronounced in the subset of manufacturing industries, where a 10% increase in lagged HHI results in a 1.25% increase in labor productivity, a 0.36% increase in wages, and a 0.85% decrease in labor share, indicating that the benefits of concentration in these industries are greater, alongside a more severe negative impact on labor share. In contrast, the relationship between HHI and labor outcomes is weaker in non-manufacturing industries. A 10% increase in lagged HHI leads to only a 0.045% increase in labor productivity, marginally significant at the 10% level, with no significant effects on wages or labor share. This suggests a limited role for market concentration in shaping labor outcomes in non-manufacturing sectors.

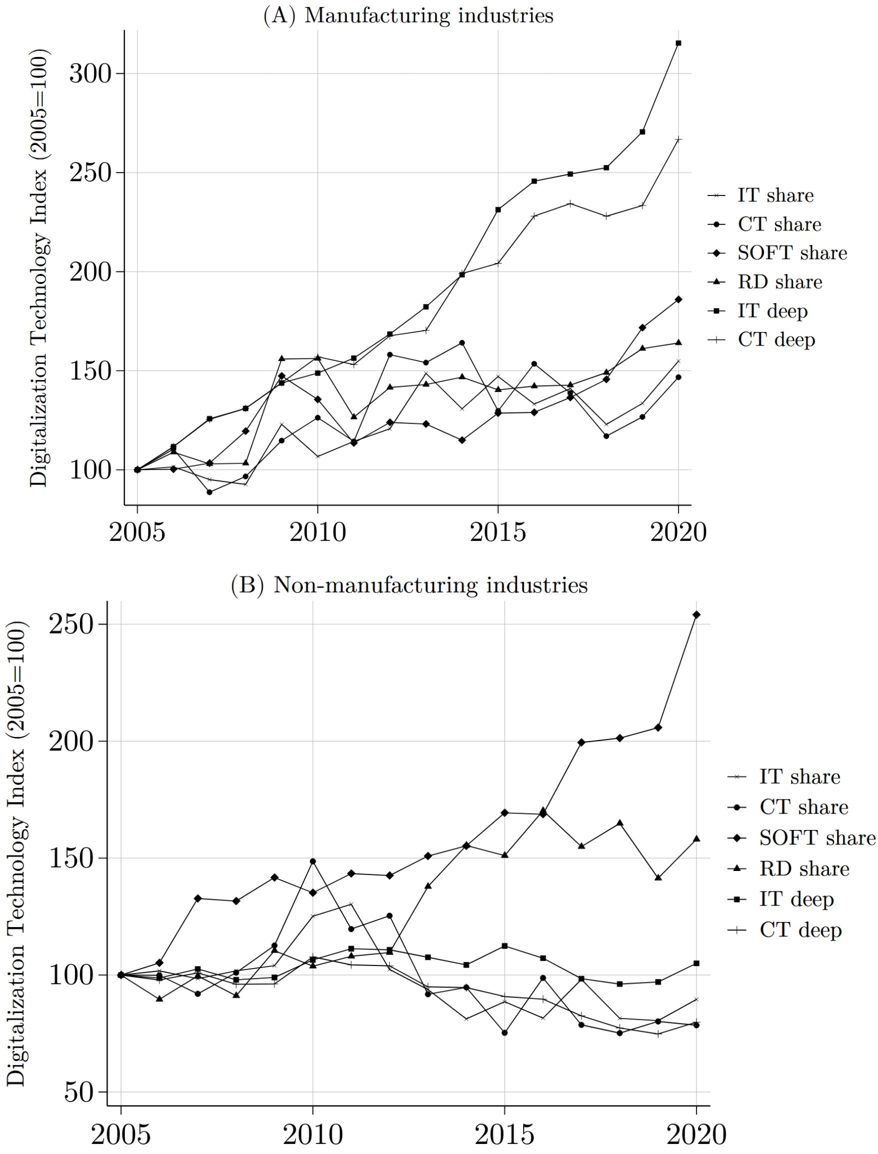
Across all industries, our model predicts that a 10% increase in intangible capital is associated with a 0.54% increase in wages, indicating that industries investing in intangibles tend to offer higher wages, probably due to the complementarity between intangible capital and high-skilled labor. However, the effects on labor productivity and labor share are not statistically significant, suggesting that intangible capital's influence on productivity and income distribution may be indirect or long-term. In manufacturing industries, a 10% increase in the intangible capital ratio results in a 0.31% increase in wages, while the effects on labor productivity and labor share are not significant. This suggests that intangible capital may not be fully leveraged to enhance productivity in manufacturing industries, or that its benefits are concentrated in wage premiums for specific worker categories. Conversely, in non-manufacturing industries, the intangible capital ratio has a more substantial impact, leading to a 0.64% increase in wages and a 0.55% increase in labor share for a 10% rise in the intangible capital ratio, both statistically significant. This indicates that in non-manufacturing sectors, investments in intangible capital not only elevate wages but also enhance labor's income share, contrasting with the findings for market concentration. The positive relationship between intangible capital and labor share suggests that such investments may foster more inclusive growth in non-manufacturing sectors, potentially mitigating some inequality effects associated with rising industry concentration. These results for labor productivity and labor share are robust when standard errors are clustered at the industry level; however, the coefficient for wages in the manufacturing industries loses its significance.

Country-level estimates for all industries, presented in Table 4, reveal substantially mixed results. The significance of labor productivity, wages, and the lagged HHI shows a statistically significant and positive conditional correlation only in two countries—Poland and Czechia—where the strongest unconditional relationships were previously observed. This is likely due to the low number of observations. Interestingly, in Slovenia, the lagged HHI is not statistically significant in relation to labor productivity, but more concentrated industries appear to pay higher wages, holding all other variables constant.

Regarding labor share, the lagged HHI does not exhibit statistical significance at the country level, except for a weak significance observed in Hungary. The results for investments in intangible capital are similarly mixed. Although no clear pattern emerged in the pooled sample, we observe a positive association between investments in intangible capital and labor productivity in Croatia, Czechia, Poland, and Hungary. In smaller subset of countries (Czechia, Poland, Slovenia), this relationship extends to wages as well. However, in Slovakia, the findings are the opposite: more concentrated industries tend to have lower productivity and pay lower wages as investments in intangible capital increase.

In our previous analysis, we examined intangible capital using CompNet data, which aggregates investments in software and databases, patents, and research and development across industries. To gain a more comprehensive understanding of the relationship between (intangible) digital capital and labor market outcomes, we complement this data with a more granular accounting of digital capital from the EU-KLEMS data. This allows us to construct detailed measures of technological intensity, knowledge intensity, and digital capital deepening, as outlined in Section 3. Figure 2 illustrates the evolution of flows and stocks of 'digital capital' across four CEE countries: Czechia, Hungary, Slovakia, and Slovenia.

Figure 2 Digitalization Technologies Indexes Over four CEE Countries, 2005-2020.



Notes: Figure shows the evolution of the digitalization indices based on (Ferschli et al., 2021) and the KLEMS database. Investment in information technology ('IT share'), investment in communication technology ('CT share'), investment in research and development ('RD share'), and software and databases ('SOFT share'), all measured as a share of non-residential gross fixed capital formation. The stock of IT capital ('IT deep') and the stock of software and databases ('SOFT deep') are both relative to hours worked. Weighted averages by industry employment of digitalization technologies are taken for four countries and all industries for which data on the above-mentioned flows and stocks of 'digital capital' are available. All 2-digit manufacturing industries are imputed by the 1-digit manufacturing sector in Slovenia, as the data for 2-digit industries are not available.

Process of digitalization in this period was much more intensive in manufacturing industries (top panel of Figure 2), contrasting with the relatively stagnant levels observed in most digitalization capital investment intensities within non-manufacturing sectors (bottom panel of Figure 2). To illustrate, the average share of investment in communication and information technologies (IT) relative to gross investment surged by 50% in 2020 compared to 2005 levels. Additionally, both IT capital deepening and IT's share of total investments soared by over 150% in 2020 when compared to the base year. Notably, within non-manufacturing industries, several digitalization capital indices exhibited negligible or even negative growth. However, exceptions were found in investments related to research and development (R&D) and IT capital deepening, which witnessed increases of nearly 50% and 150%, respectively, in 2020 relative to the start-of-the period.

In Table 5 and 6 we estimate the models specified in Section 3 for labor productivity and in Table 9, and 10 for labor share and the more granular indicators of digitalization at the industry level. The empirical findings presented in these tables more consistently align with three key aspects of the superstar firms hypothesis: (i) the more concentrated industries tend to have higher labor productivity, (ii) higher wages, and (iii) lower labor share, controlling for industry, country, year fixed effects and capital intensity.

First, we find a positive relationship between increases of an average industry concentration and labor productivity in Table 5. This relationship remains robust even after controlling for various additive components of digital capital and capital intensities among firms. Although we find a positive association between the lagged HHI and productivity—indicating that more concentrated industries tend to have higher productivity on average, when holding all other factors constant—only half of the digitalization measures show a positive relationship with statistical significance. Interestingly, we identify a negative effect of higher investments in software technologies. As a robustness check, we estimated the interaction between the HHI and the digitalization indicators in Table 6. Notably, the main effect for the lagged HHI loses its significance in all columns where we account for digitalization as a share on total investments both slope and the interaction terms of technological intensity, knowledge intensity, and digital capital deepening significantly improve productivity across all industries, but in more concentrated industries which are even more digitized and more productive as well. For the digitalization indicators, both the main and interaction terms are consistently positive and statistically significant, except for the main effect of software share, which does not achieve significance. This suggests that more concentrated industries benefit from digitalization even more than averagely concentrated industries. The signs and magnitudes of these results are comparable to those reported by Ferschli et al. (2021) for the German economy.

In our previous analysis, we observed similar effects in both the signs and magnitudes of industry concentration and intangible capital ratios on labor productivity and wages. Given this connection, it is intriguing to explore the additive effects of digitalization on wages, similar to how we analyzed its impact on labor productivity. Table 7 presents estimates indicating that a higher HHI is associated with higher wages, consistent with our prior analysis. However, our measures for technological intensity and knowledge intensity did not significantly accelerate nor moderate wages paid at the industry level. In Table 8, we introduced interaction terms between digitalization indicators and the HHI. Our analysis reveals that both the main and interaction terms are generally non-significant, and when significant, they are negative. Our models predict that for the same industry, year, industry concentration, and capital intensity, only digital capital deepening is significantly associated with higher wages. This suggests a noteworthy conclusion: digitalization may be negatively associated with wages, at least in the short term. This may indicate that the negative labor-saving effect (discussed below) may dominate over the positive labor-productivity effect (discussed above) as also documented in Lábaj and Vitáloš (2024). Therefore, we observe a decline in average wages across industries where digitalization is increasing. Moreover, the interaction term between investments in digital capital and stocks is negative, implying that while investments in digital capital in more concentrated industries may enhance productivity, these improvements do not necessarily translate into increased wages. Interpreting this cautiously, it raises the possibility that industries with a large presence of superstar firms may not offer competitive wage levels or may be utilizing digital capital to substitute rather than complement labor. This notion is indirectly supported by Mertens (2022)'s findings in Germany. However, it is crucial to note that this conclusion is not consistent with findings based solely on CompNet data in Table 3.

The third and most crucial aspect of the superstar firms hypothesis—an expected negative relationship between industry concentration and labor share—is well-established empirical observation across the pool of CEE industries. As evidenced in Tables 9 and 10, higher industry concentration is consistently linked to a lower labor share. This suggests that large, dominant firms can spread fixed overhead costs across a larger output, leading to a decline in the share of labor compensation relative to total value added. Alternatively, increasing industry markups could also explain this observed phenomenon, as outlined in Section 2. However, at this level of analysis, we cannot disentangle which mechanism is driving our results. To examine whether digitalization technologies are employed in a labor-saving manner, we focused on the additive effects of digital investments: technological intensity, knowledge intensity, and digital capital deepening. Our baseline model in Table 9 indicates that all digital investment measures are correlated with a rapid decline in labor share in the short term. However, a notable exception is knowledge intensity. Research and development (R&D) appears to mitigate this trend in this baseline model, potentially due to complementarities between skilled labor and technological advancements. When we interacted the digitalization indicators in Table 10 with the HHI, both the main and the interaction terms showed an even more negative effect on labor share decline. This suggests that these technologies may also have a large labor-saving effect (Acemoglu & Restrepo, 2018b), which is even accelerated in the more concentrated industries, but accompanied by the productivity effect discussed above.

5. Conclusions

This paper examined three central predictions of the superstar firm hypothesis in the context of industries in CEE countries. First, we examined the relationship between industry concentration, productivity growth, and the role of digitalization in this process. Our analysis revealed that increasing industry concentration is correlated with higher labor productivity and wage levels across industries. Moreover, our results indicated that increased investment in digital capital significantly accelerates labor productivity, although the effect on wages remains muted. Specifically, we found that a 10% increase in the lagged HHI is associated with a 0.9% increase in labor productivity and a one-third increase in wages, while leading to a 0.33% decrease in the labor share on average across the pooled sample of countries. Regarding the impact of digitalization, our results are mixed when we use more granular data on investments in digital capital. We documented that the intensive digitization processes in the manufacturing sector during the period under review contrasted sharply with the largely stagnant levels of most digitization indicators in non-manufacturing industries. While investment in digital capital can increase productivity, its impact on wages and labor share is more complex. We find that digitalization can contribute to higher wages, but this effect is not always significant. Moreover, digital investment tends to be associated with declining labor shares, suggesting potential labor-saving effects of new digital technologies. However, the impact of digitalization on labor market outcomes depends on the specific type of digital investment and the industry context. In particular, investments in communication and information technologies increased significantly. Additionally, we found that higher industry concentration is correlated with higher productivity, but this relationship does not uniformly extend to wages. While concentrated industries tend to offer higher wages, the relationship is not statistically significant, suggesting that digitalization does not necessarily translate into wage increases. These results are similar to those obtained by Ferschli et al. (2021) in the German economy.

Our analysis revealed some surprising results, particularly the adverse effect of digitalization on wages, which was more pronounced in highly concentrated industries. Further investigation is required to determine whether digitalization enhances productivity in these concentrated industries and to understand why it does not translate into wage increases. This finding also raises important questions about the competitive dynamics of superstar firms. It may suggest that the labor-saving effect of digitalization dominates the labor-productivity effect, as argued by Acemoglu and Restrepo (2018a). A similar observation was made by Mertens (2022) in Germany. Additionally, our results show a consistent negative relationship between industry concentration and labor share. This suggests that larger firms tend to distribute fixed costs across greater value added or increase their markups. While we could not disentangle which mechanism is driving these results at this level of analysis, further exploration of these dynamics is an interesting area for future research. To gain deeper insights into firm heterogeneity and labor market outcomes, future researchers should rely on more granular firm-level or sub-industry data. Moreover, access to data on the distributions of digitalization capital investments, along with the key variables used in this analysis, could enable future research to capture more effective within-industry variation. By applying quantile regression, researchers could, for example, analyze variations across the TFP distribution. This approach would allow them to move beyond relying solely on between-industry variation.

Our findings, when considered alongside these limitations, allow us to propose several policy recommendations to address the challenges posed by industry concentration and digitalization in the CEE region. Our findings clearly show that investments in most digitalization technologies increase the polarization between labor and capital even further. Our paper makes it clear that there is a need for policy interventions that are nuanced and promote the equitable distribution of the shared prosperity of digitalization, particularly in targeted highly concentrated industries. The relationship between digitalization, industry concentration, and labor market outcomes is complex. There is no doubt that increasing market concentration has a significant impact on the labor market, particularly in terms of reducing the labor share, leading to labor and capital polarization and potentially leading to increase of income inequalities in the long run. Therefore, policymakers must carefully examine whether the negative effects of rising market concentration result from increasing markups or rising labor productivity, as this distinction is challenging to disentangle in our analysis. Rising concentration undoubtedly improves productivity and wages, but its overall impact on welfare is unclear. Furthermore, encouraging digital investment across all industries and supporting digitalization initiatives—particularly in concentrated sectors—is essential for fostering innovation and productivity. However, this policy approach has the potential to further depress a labor share, emphasizing the necessity for policies that ensure a more equitable distribution of the benefits of digitalization.

APPENDIX

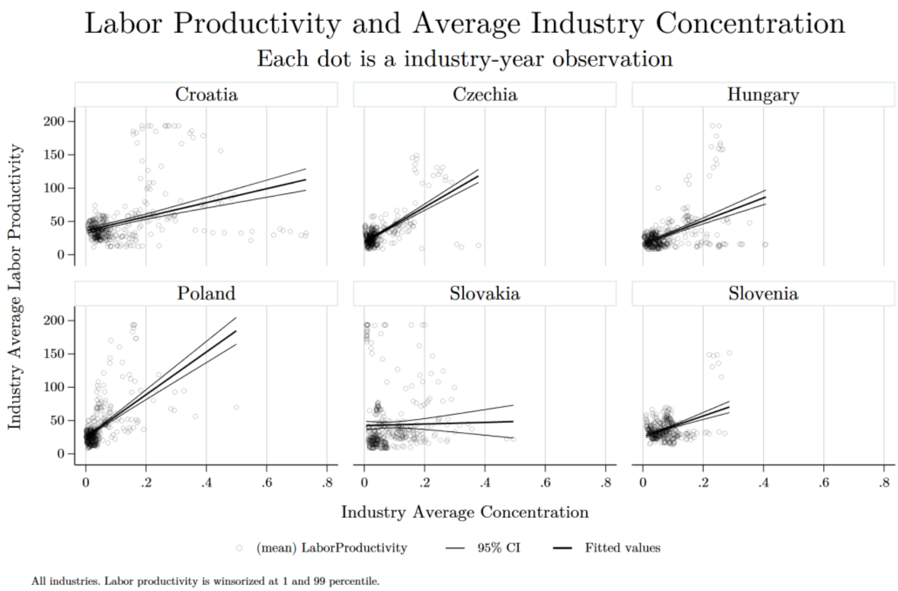
Table 2 Definition of Used Variables

Variable	Definition
Labor Productivity	[Real value-added, computed as deflated nominal value added (mean)]/[Labor: number of employees in headcounts (mean)× Summed weight (=population number of firms)]; CompNet
Wages	[Nominal labor costs (mean) × Summed weight (=population number of firms)]/[Labor: number of employees in headcounts (mean)× Summed weight (=population number of firms)]; CompNet
Labor Share	[Nominal labor costs (mean) × Summed weight (=population number of firms)] / [Nominal value- added (mean) × Summed weight (=population number of firms)]; CompNet
HHI	Hirschman-Herfindahl Index, nominal revenue shares, industry, population number of firms shares, industry, population number of firms (mean); CompNet
Intangible Capital Ratio	Ratio: Nominal intangible fixed assets/Nominal capital (mean); CompNet
Capital Intensity	Ratio: Real capital/Labor (mean); CompNet
IT share	IT - Computer hardware investment/Gross fixed capital formation; EU-KLEMS
CT share	CT - Telecommunications equipment/Gross fixed capital formation; EU-KLEMS
SOFT share	SOFT - Computer software and databases /Gross fixed capital formation; EU-KLEMS
RD share	RD - Research and development/Gross fixed capital formation; EU-KLEMS
IT deep	IT - Computer hardware investment/Hours worked; EU-KLEMS
CT deep	CT - Telecommunications equipment/Hours worked; EU-KLEMS

Notes: Ratio Indicated a Value Directly Obtained from a Dataset

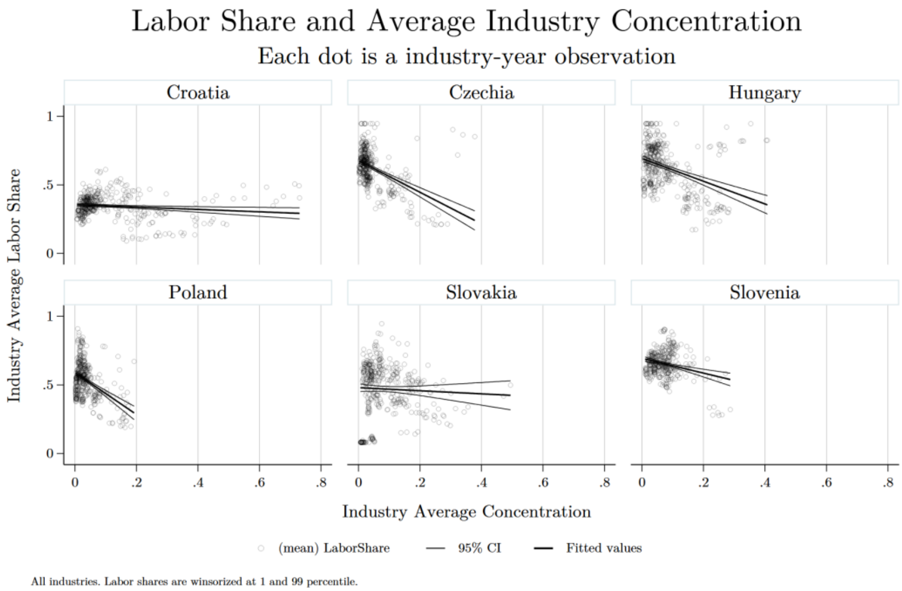
Source: EU-KLEMS and CompNet 9th vintage databases.

Figure 3 Average Industry Concentration and Labor Productivity across All Industries in CEE Countries, 2005-2020



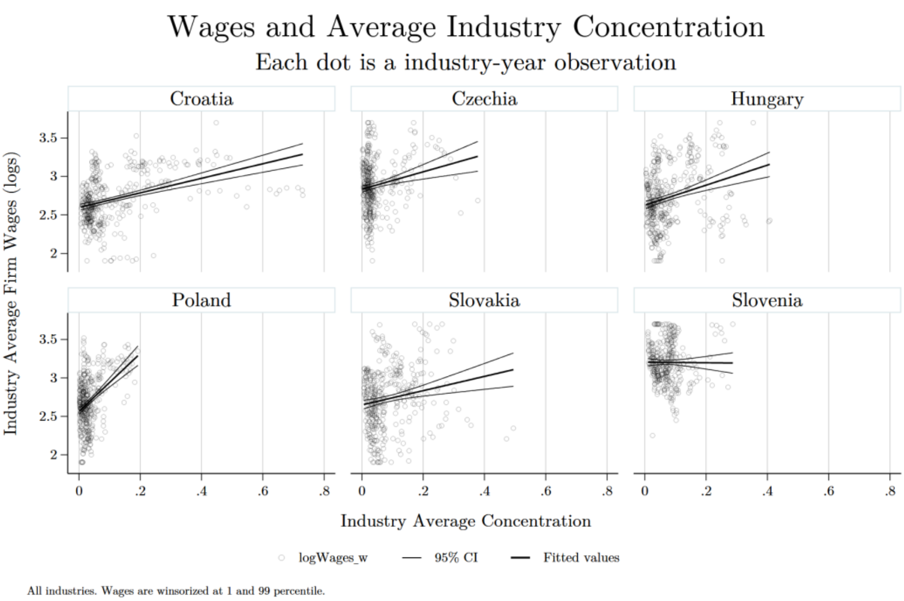
Source: CompNet (2023)

Figure 4 Average Industry Concentration and Wages across All Industries in CEE Countries, 2005-2020.



Source: CompNet (2023)

Figure 5 Average Industry Concentration and Labor Shares across All Industries in CEE Countries, 2005-2020.



Source: CompNet (2023)

Table 3 Relationship between Labor Productivity and Digitalization in CEE countries, 2005-2020

	log(Labor Productivity) (1)	*log(Wages)* (2)	*log(Labor Share)* (3)
	All industries		
HHI_{t-1}	0.090***	0.032***	-0.033***
	(0.015)	(0.006)	(0.011)
Intangible Capital $Ratio_{t-1}$	-0.014	0.054***	0.018
	(0.018)	(0.007)	(0.014)
Capital $Intensity_{t-1}$	0.318***	0.146***	-0.132***
	(0.017)	(0.009)	(0.014)
Constant	2.560***	2.604***	-0.272***
	(0.083)	(0.040)	(0.064)
R2	0.688	0.890	0.618
N	2271	2261	2262
Manufacturing industries			
HHI_{t-1}	0.125***	0.036***	-0.085***
	(0.026)	(0.008)	(0.013)
Intangible Capital $Ratio_{t-1}$	-0.047	0.031**	-0.016
	(0.028)	(0.012)	(0.019)
Capital $Intensity_{t-1}$	0.478***	0.289***	-0.213***
	(0.050)	(0.024)	(0.028)
Contant	1.958***	1.982***	-0.247*
	(0.204)	(0.105)	(0.120)
R2	0.648	0.874	0.728
N	1057	1057	1057
Non-manufacturing industries			
HHI_{t-1}	0.045***	0.012	0.019
	(0.018)	(0.009)	(0.015)
Intangible Capital $Ratio_{t-1}$	0.006	0.064***	0.055**
	(0.023)	(0.009)	(0.019)
Capital $Intensity_{t-1}$	0.296***	0.117***	-0.115***
	(0.019)	(0.010)	(0.017)
Contant	2.580***	2.719***	-0.068
	(0.086)	(0.044)	(0.073)
R2	0.755	0.904	0.657
N	1214	1204	1205
Industry, Country, Year FE	Yes	Yes	Yes

Notes: All variables are winsorized at 1st and 99th percentile. Robust standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Source: CompNet (2023)

Table 4 Country-Level Relationships between Labor Productivity, Wages, Labor Share, and Industry Concentration in CEE Countries from 2000 to 2020.

	log(Labor Productivity)	*log(Wages)*	*log(Labor Share)*	*log(Labor Productivity)*	*log(Wages)*	*log(Labor Share)*
		Croatia			***Poland***	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	-0.072	-0.087	-0.023	0.105***	0.019*	-0.004
	(0.092)	(0.059)	(0.024)	(0.033)	(0.011)	(0.024)
Intangible Capital $Ratio_{t-1}$	0.096***	0.042***	-0.058**	0.108**	0.002	-0.096*
	(0.035)	(0.016)	(0.028)	(0.055)	(0.018)	(0.058)
Capital $Intensity_{t-1}$	-0.059	-0.047	-0.151***	0.089	0.065***	0.070
	(0.076)	(0.042)	(0.052)	(0.071)	(0.025)	(0.052)
Constant	3.990***	2.771***	-0.813***	3.907***	2.594***	-1.205***
	(0.242)	(0.096)	(0.175)	(0.296)	(0.095)	(0.218)
R^2	0.921	0.946	0.862	0.923	0.981	0.901
N	384	384	384	399	390	390
		Czechia			***Slovakia***	
HHI_{t-1}	0.101***	0.028**	-0.025	-0.066	-0.002	0.032
	(0.032)	(0.013)	(0.023)	(0.050)	(0.015)	(0.031)
Intangible Capital $Ratio_{t-1}$	-0.008	-0.033**	0.017	-0.097***	-0.041***	0.028*
	(0.032)	(0.014)	(0.019)	(0.024)	(0.009)	(0.015)
Capital $Intensity_{t-1}$	0.135***	0.077***	-0.132***	0.340***	0.050	-0.083
	(0.049)	(0.025)	(0.033)	(0.099)	(0.032)	(0.053)
Constant	3.207***	2.667***	-0.123	1.746***	2.465***	-0.422*
	(0.191)	(0.088)	(0.139)	(0.418)	(0.124)	(0.222)
R^2	0.949	0.978	0.900	0.864	0.959	0.958
N	378	378	379	373	373	373
		Hungary			***Slovenia***	
HHI_{t-1}	0.065	-0.016	-0.053*	0.022	0.039**	-0.017
	(0.041)	(0.012)	(0.028)	(0.027)	(0.017)	(0.025)
Intangible Capital $Ratio_{t-1}$	0.095**	-0.014	-0.048	-0.024	-0.005	0.007
	(0.038)	(0.018)	(0.041)	(0.029)	(0.014)	(0.015)
Capital $Intensity_{t-1}$	0.038	0.097**	-0.059	0.073*	0.057**	-0.067**
	(0.100)	(0.038)	(0.065)	(0.041)	(0.027)	(0.027)
Constant	3.555***	2.269***	-0.616**	3.261***	3.111***	-0.222
	(0.384)	(0.149)	(0.310)	(0.184)	(0.114)	(0.142)
R^2	0.896	0.960	0.798	0.945	0.958	0.871
N	391	391	391	346	345	345
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All variables are winsorized at the 1st and 99th percentiles.

Source: CompNet (2023).

Table 5 Relationship between Labor Productivity, Industry Concentration and Digitalization in CEE Countries, 2005-2020

	log(Labor Productivity)						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
HHI_{t-1}	0.088***	0.109***	0.052**	0.043*	0.082***	0.096***	0.088***
	(0.028)	(0.028)	(0.024)	(0.026)	(0.027)	(0.028)	(0.032)
IT $share_{t-1}$	0.044**						0.072**
	(0.019)						(0.033)
CT $share_{t-1}$		-0.011					-0.057**
		(0.014)					(0.029)
SOFT $share_{t-1}$			-0.070***				-0.090***
			(0.020)				(0.031)
RD $share_{t-1}$				-0.004			0.007
				(0.012)			(0.016)
IT $deep_{t-1}$					0.065***		0.014
					(0.019)		(0.034)
CT $deep_{t-1}$						0.008	0.021
						(0.015)	(0.031)
Capital $Intensity_{t-1}$	0.246***	0.221***	0.281***	0.272***	0.230***	0.237***	0.191***
	(0.029)	(0.032)	(0.022)	(0.023)	(0.028)	(0.029)	(0.038)
Constant	2.556***	2.828***	2.544***	2.357***	2.657***	2.687***	2.934***
	(0.193)	(0.195)	(0.149)	(0.151)	(0.184)	(0.191)	(0.221)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.682	0.687	0.682	0.676	0.686	0.682	0.693
N	953	910	1344	1204	955	954	783

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Relationship between Labor Productivity, Industry Concentration and Digitalization in CEE Countries, 2005-2020.

	log(Labor Productivity)						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
HHI_{t-1}	0.058*	0.039	0.014	0.018	0.179***	0.254***	0.230
	(0.030)	(0.032)	(0.027)	(0.026)	(0.034)	(0.040)	(0.151)
IT share$_{t-1}$	0.155***						-0.015
	(0.047)						(0.136)
IT share ×HHI_{t-1}	0.039***						-0.025
	(0.014)						(0.041)
CT share$_{t-1}$		0.113***					-0.079
		(0.036)					(0.090)
CT share ×HHI_{t-1}		0.045***					-0.000
		(0.012)					(0.030)
SOFT share$_{t-1}$			0.060				0.129
			(0.046)				(0.087)
SOFT share ×HHI_{t-1}			0.044***				0.062***
			(0.014)				(0.023)
RD share$_{t-1}$				0.076**			-0.070*
				(0.030)			(0.037)
RD share ×HHI_{t-1}				0.024***			-0.024**
				(0.009)			(0.011)
IT deep$_{t-1}$					0.184***		-0.064
					(0.029)		(0.100)
IT deep ×HHI_{t-1}					0.045***		-0.027
					(0.007)		(0.031)
CT deep$_{t-1}$						0.139***	0.230**
						(0.026)	(0.098)
CT deep ×HHI_{t-1}						0.048***	0.074**
						(0.007)	(0.030)
Capital Intensity×HHI_{t-1}							0.003
							(0.039)
Capital Intensity$_{t-1}$	0.249***	0.220***	0.288***	0.260***	0.241***	0.252***	0.200
	(0.029)	(0.032)	(0.023)	(0.023)	(0.028)	(0.029)	(0.125)
Constant	2.472***	2.687***	2.441***	2.303***	2.930***	3.114***	3.392***
	(0.195)	(0.197)	(0.150)	(0.149)	(0.194)	(0.209)	(0.495)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.685	0.694	0.685	0.680	0.703	0.701	0.720
N	953	910	1344	1204	955	954	783

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 7 Relationship between Wages, Industry Concentration and Digitalization in CEE Countries, 2005-2020

	log(Wages)						
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***
HHI_{t-1}	0.021**	0.017**	0.008	0.008	0.017**	0.020**	0.017**
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
IT $share_{t-1}$	-0.001						-0.002
	(0.005)						(0.010)
CT $share_{t-1}$		0.003					-0.003
		(0.005)					(0.007)
SOFT $share_{t-1}$			-0.002				0.016**
			(0.006)				(0.006)
RD $share_{t-1}$				0.002			0.001
				(0.003)			(0.004)
IT $deep_{t-1}$					0.011**		0.001
					(0.004)		(0.009)
CT $deep_{t-1}$						0.013**	0.019*
						(0.005)	(0.010)
Capital Intensity	0.078***	0.077***	0.140***	0.144***	0.077***	0.081***	0.086***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.011)	(0.011)	(0.013)
Constant	2.090***	2.081***	1.946***	1.951***	2.071***	2.093***	2.097***
	(0.060)	(0.064)	(0.059)	(0.061)	(0.057)	(0.057)	(0.072)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.933	0.931	0.899	0.908	0.933	0.933	0.947
N	953	910	1344	1204	955	954	783

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Relationship between Wages, Industry Concentration and Digitalization in CEE Countries, 2005-2020.

	log(Wages)						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
HHI_{t-1}	0.027***	0.018*	0.022**	0.009	0.001	0.001	-0.185***
	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.047)
IT $share_{t-1}$	-0.023*						0.033
	(0.013)						(0.037)
IT share×HHI_{t-1}	-0.008**						0.009
	(0.004)						(0.011)
CT $share_{t-1}$		0.001					0.010
		(0.010)					(0.022)
CT share×HHI_{t-1}		-0.001					0.007
		(0.003)					(0.008)
SOFT $share_{t-1}$			-0.049***				0.024
			(0.018)				(0.020)
SOFT share×HHI_{t-1}			-0.016***				0.006
			(0.005)				(0.005)
RD $share_{t-1}$				-0.001			-0.008
				(0.010)			(0.010)
RD $share_{t-1}$×HHI_{t-1}				-0.001			-0.004
				(0.003)			(0.003)
IT $deep_{t-1}$					-0.009		-0.056
					(0.007)		(0.038)
IT deep×HHI_{t-1}					-0.008***		-0.021*
					(0.002)		(0.012)
CT $deep_{t-1}$						-0.003	0.047
						(0.007)	(0.038)
CT deep×HHI_{t-1}						-0.006***	0.011
						(0.002)	(0.012)
Capital Intensity×HHI_{t-1}							0.055***
							(0.012)
Capital $Intensity_{t-1}$	0.078***	0.077***	0.137***	0.145***	0.075***	0.079***	0.238***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.011)	(0.011)	(0.037)
Constant	2.107***	2.084***	1.983***	1.953***	2.026***	2.042***	1.564***
	(0.063)	(0.066)	(0.063)	(0.061)	(0.057)	(0.057)	(0.143)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.934	0.931	0.900	0.908	0.934	0.934	0.951
N	953	910	1344	1204	955	954	783

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 9 Relationship between Labor Share, Industry Concentration and Digitalization in CEE Countries, 2005-2020.

	log(Labor Share)						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
HHI_{t-1}	-0.034* (0.019)	-0.040** (0.020)	-0.073*** (0.018)	-0.076*** (0.017)	-0.017 (0.019)	-0.036* (0.019)	-0.014 (0.023)
$IT\ share_{t-1}$	-0.084*** (0.015)						-0.035 (0.027)
$CT\ share_{t-1}$		-0.025** (0.010)					-0.009 (0.023)
$SOFT\ share_{t-1}$			0.024 (0.017)				0.045** (0.023)
$RD\ share_{t-1}$				0.032*** (0.009)			0.015 (0.014)
$IT\ deep_{t-1}$					-0.105*** (0.014)		-0.091*** (0.028)
$CT\ deep_{t-1}$						-0.019* (0.011)	0.056* (0.029)
$CT\ deep{\times}HHI_{t-1}$	-0.110*** (0.022)	-0.102*** (0.022)	-0.128*** (0.017)	-0.113*** (0.016)	-0.076*** (0.022)	-0.096*** (0.020)	-0.048 (0.030)
Constant	-0.241** (0.118)	-0.415*** (0.118)	-0.470*** (0.104)	-0.619*** (0.096)	-0.380*** (0.114)	-0.430*** (0.105)	-0.491*** (0.160)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.655	0.648	0.576	0.580	0.664	0.639	0.651
N	915	873	1279	1146	917	914	750

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 10 Relationship between Labor Share, Industry Concentration and Digitalization in CEE Countries, 2005-2020.

	log(Labor Share)						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
HHI_{t-1}	-0.017	0.033	-0.015	-0.057^{***}	-0.122^{***}	-0.255^{***}	-0.507^{***}
	(0.022)	(0.027)	(0.021)	(0.017)	(0.027)	(0.034)	(0.164)
$IT\ share_{t-1}$	-0.148^{***}						0.135
	(0.040)						(0.095)
$IT\ share{\times}HHI_{t-1}$	-0.022						0.043
	(0.014)						(0.034)
$CT\ share_{t-1}$		-0.157^{***}					0.129^{*}
		(0.030)					(0.072)
$CT\ share{\times}HHI_{t-1}$		-0.047^{***}					0.044
		(0.011)					(0.029)
$SOFT\ share_{t-1}$			-0.177^{***}				-0.320^{***}
			(0.038)				(0.066)
$SOFT\ share{\times}HHI_{t-1}$			-0.067^{***}				-0.110^{***}
			(0.013)				(0.022)
$RD\ share_{t-1}$				-0.044^{**}			0.061^{**}
				(0.020)			(0.029)
$RD\ share{\times}HHI_{t-1}$				-0.023^{***}			0.014
				(0.007)			(0.009)
$IT\ deep_{t-1}$					-0.235^{***}		0.061
					(0.024)		(0.106)
$IT\ deep{\times}HHI_{t-1}$					-0.050^{***}		0.049
					(0.007)		(0.037)
$CT\ deep_{t-1}$						-0.205^{***}	-0.316^{***}
						(0.023)	(0.113)
$CT\ deep{\times}HHI_{t-1}$						-0.066^{***}	-0.122^{***}
						(0.007)	(0.039)
$Capital\ Intensity{\times}HHI_{t-1}$							0.071^{**}
							(0.034)
$CT\ deep{\times}HHI_{t-1}$	-0.115^{***}	-0.111^{***}	-0.140^{***}	-0.101^{***}	-0.096^{***}	-0.121^{***}	0.148
	(0.022)	(0.022)	(0.017)	(0.017)	(0.023)	(0.023)	(0.099)
Constant	-0.173	-0.209^{*}	-0.276^{**}	-0.598^{***}	-0.621^{***}	-0.996^{***}	-1.931^{***}
	(0.124)	(0.121)	(0.107)	(0.093)	(0.135)	(0.139)	(0.439)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.657	0.658	0.588	0.588	0.694	0.691	0.741
N	915	873	1279	1146	917	914	750

Notes: All variables are log-transformed. Dependent variable is winsorized at 1st and 99th percentile. Fixed effects are defined as twenty-eight EU-KLEMS (C - N NACE rev. 2) industry categories and four CEE countries (Czechia, Hungary, Slovakia, and Slovenia). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

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