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Digitalization, Industry Concentration, and Productivity in Germany

https://doi.org/10.1515/jbnst-2020-0058
Received October 29, 2020; accepted June 9, 2021

Abstract: This paper investigates the links of digitalization and industry concentration with labor productivity at the sectoral level in Germany. Combining data for digitalization and labor productivity from the EU KLEMS database with firm-level data from the CompNet and Orbis Bureau Van Dijk databases to construct industry concentration measures between 2000 and 2015, we show that (1) the German economy appears to have digitized since 2000, and (2) there is no clear-cut relationship between digitalization and market concentration at the industry level. Using a time and sector fixed effects model and controlling for capital intensity, however, we find evidence for (3) a positive effect of both lagged industry concentration and lagged digitalization on productivity at the sectoral level in Germany. This finding is robust to alternative measures of digitalization and industry concentration as well as to their interaction but sensitive to the sector sample and to scale effects from the capital intensity. We, therefore, cautiously conclude that recent technological change appears to have been labor-saving and that productivity-enhancing aspect of a partial "superstar firm" effect may be identified in the German economy, in particular in its manufacturing sector.

Keywords: digitalization, market concentration, labor-productivity, productivity, paradox, superstar firms

JEL Classifications: D24, D42, L16, O14, O33, L12, O47

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1 Introduction

Modern economies may well be in the midst of a technological revolution, driven by digitalization, computerization, and robotization, whose economic impact is still unfolding. Since technological progress is typically defined as labor-saving, i.e. linked to rising (labor) productivity, the question of how digitalization has affected productivity is at the heart of assessing the consequences of this most recent technological revolution. At the same time, stagnating profits may force companies to restore margins through means such as mergers and acquisitions, leading to market concentration (Autor et al. 2020; Perez 2010). These two factors – digitalization and monopolization – could thus be expected to raise productivity. That measured labor productivity has been stagnating over the past decades – the so-called empirical productivity "paradox" – has consequently garnered attention in the literature (Brynjolfsson et al. 2019; Goldin et al. 2019, 2020; Gordon 2015, 2016; OECD 2019). Whether these trends, documented most extensively for the United States (US) and forming the basis for a "superstar firm hypothesis" (Autor et al. 2020), are also relevant for Germany with its strong manufacturing sector and its paucity of large platform-based firms; and specifically, whether digitalization and market (or rather industry) concentration[1] explain labor productivity in Germany at the sectoral level, is the focus of this paper.

Germany is a particularly interesting case due to its strong industrial base (Fuchs 2018), its knowledge-intensive economy (Godin 2006; Kouli et al. 2020), as well as its export-oriented and corporatist model (Alexis 1983; Racy et al. 2019; Wiarda 1996). Germany is also one of the most advanced countries in terms of digitalization (Arntz et al. 2016), while its market concentration appears to be moderate compared to other countries, in particular, the US (Weche and Wagner 2020; Weche and Wambach 2018).

Concretely, we first investigate digitalization trends with EU KLEMS data from 2000 to 2015 and then compare more recent cross-sector concentration trends with the digital intensity taxonomy developed by the OECD and concentration indices based on firm-level data from Orbis for 2013 to 2015. The descriptive evidence based on EU KLEMS data shows that the German economy has digitalized from 2000 to 2015, especially with regard to digital capital deepening and knowledge intensity. However, the cross-sectoral comparison based on the OECD digital intensity taxonomy shows that there is no clear-cut relationship between digitalization and industry concentration: While the German economy contains both

1 We use industry concentration as a proxy for market concentration. As Heidorn and Weche (2020) argue, available industry data can be used to approximate market concentration, but they do not fully meet the economic definition of markets.

highly concentrated and highly digitalized sectors, these two characteristics do not necessarily coincide. Second, we use a balanced panel comprising data for 15 two-digit NACE sectors, mainly in manufacturing, construction, information and communication, and professional and administrative services to estimate a fixed-effects model of productivity using lagged industry concentration and digitalization indicators and controlling for capital intensity. The panel data from 2000 to 2015 includes EU KLEMS data on digitalization and labor productivity and concentration measures from CompNet (2000–2010) and Orbis (2011–2015). The results show a positive link between the level of digitalization and labor productivity for these 15 sectors, indicating the labor-saving character of digitalization. These findings are corroborated by extensive robustness checks. However, they do not speak to the effect of digitalization on unemployment, as labor-saving technologies may also increase output when holding labor input constant. Moreover, we find a slightly more tenuous correlation between industry concentration and productivity in particular in the manufacturing of transport equipment and telecommunications, cautiously suggesting evidence for the presence of what may be called productive "Deutsche superstar firms".

The rest of the paper is structured as follows. Section 2 reviews the theoretical hypotheses and the empirical literature on digitalization, market concentration, and productivity nexus. Section 3 describes the data and provides summary statistics. Section 4 shows descriptive evidence on digitalization and industry concentration for recent years 2013–2015, and Section 5 contains the multivariate estimations of the relationship between digitalization and industry concentration with productivity with a balanced sample from 2000 to 2015. Section 6 checks the robustness of our results, and Section 7 concludes.

2 The Digitalization-Concentration-Productivity Nexus

Economic development can be characterized through historical phases of technological revolutions (Ab Rahman et al. 2017; Coleman 1956; Landes 1969; McCraw 1998). Perez (2010), for example, identifies five subsequent techno-economic paradigms initiated by "big bang-technologies" up to the present: the industrial revolution, the steam age, the age of steel, the age of oil, and/or mass production, and the age of information. This latest stage has also been described as "digitalization" (Beernaert and Fribourg-Blanc 2017; Hislop et al. 2017; Kieselbach and Lehmann-Waffenschmidt 2019), and it is associated with concepts such as artificial intelligence (Brynjolfsson and McAfee 2014) and Industry 4.0 (Brödner 2015;

Schwab 2016). At the same time, the literature observes rising market concentration and the emergence of superstar firms both in the US (Autor et al. 2020) and in Europe (Cavalleri et al. 2019). There is evidence that these trends are particularly present in sectors with high degrees of digitalization which leads to the observation that concentration is positively associated with increased productivity at the sector level (Bighelli et al. 2020). For the US, these links have been synthesized into the so-called "superstar firm hypothesis" (Autor et al. 2020), which claims that digitalization affects productivity, which in turn leads to higher market concentration and redistribution from labor to capital. The original proposition of "superstar firms" was formulated as an/the explanation for falling wage shares in the US (Autor et al. 2020). Highly innovative firms, mostly in IT, have become disproportionately productive, allowing them to accrue rising market power. Since labor represents a relatively small part of the value added of these companies, this puts a drag on the wage share. The hypothesis thus suggests a positive relationship between productivity and market concentration, a positive relationship between digitalization and productivity, and a negative relationship between market concentration and wage share. Although the "superstar firms" hypothesis was formulated for the US, it has also received some empirical support for Germany, especially for the service sector (Ponattu et al. 2018).

In this paper, we are interested in the links between the new technological era of digitalization, the dynamics of industry concentration, and (labor) productivity at the sector level. Figure 1 shows key causal relationships between digitalization, market concentration, and productivity based on theoretical considerations developed in the economic literature, which we discuss individually below. We concentrate first on the relationships of interest for this paper, running from digitalization and market concentration to productivity (solid lines), before discussing possible confounding effects from productivity on digitalization and market concentration, as well as between our explanatory variables, digitalization, and market concentration (dashed lines).

First, digitalization is positively linked to productivity in most economic theories (edge (1) of Figure 1). Traditional economic growth models, for example, establish technological change as a contemporaneous cause of labor productivity (Solow 1956). Exogenous technological progress, such as the introduction of new technologies, saves labor and thus increases labor productivity, leading to higher growth and output. Modern growth theory endogenizes technological progress through human capital accumulation (Rebelo, 1991; Romer 1986), based on the same productivity function of technology. Evolutionary economics, while sharing the general idea, distinguishes between incremental innovations of products and processes, mostly driven by engineers with experience in the production process, and radical innovations which emerge in discontinuity and can often be traced to

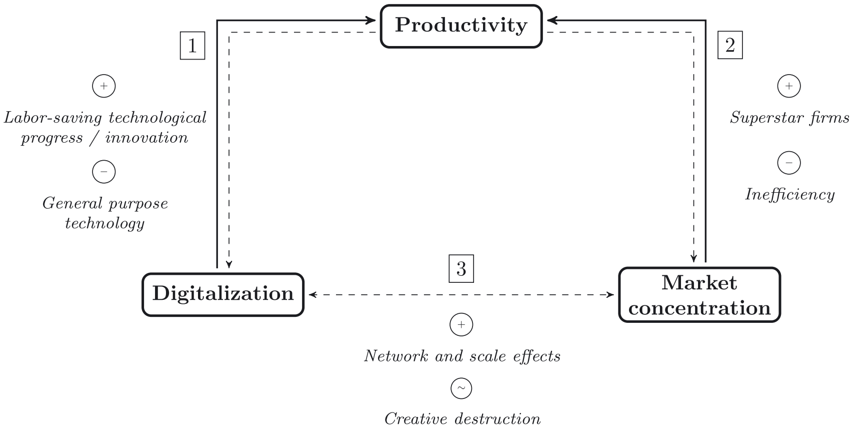


Figure 1: Directed acyclic graph of the digitalization, market concentration, and productivity nexus.
Source: own elaboration.

efforts by companies, universities, and research facilities (Kemp et al. 2001). The more applied understanding of innovation in evolutionary theory also suggests a delay between innovations and their effective implementation in the productive process, rather than a contemporaneous effect. The theory thus suggests a positive link between digitalization (or technological change more generally) and productivity growth.

Empirically, however, a slowdown in productivity growth in most industrial countries is evident in recent decades, despite the progress in digitalization (Gordon, 2015, 2016; OECD 2019; Schmalensee 2018). This new productivity paradox (Brynjolfsson et al. 2019; Goldin et al. 2019, 2020) is well documented for digitalization and robotization, while empirical studies finding that digitalization and robotization increase labor productivity are the exceptions (Dauth et al. 2018). At this stage, the main disagreement in the empirical literature is whether the empirically observed productivity slowdown will be temporary (Crafts 2017), or whether digitalization simply holds less potential for future productivity growth compared to previous technological revolutions (Gordon 2015).

Several hypotheses for a negative link between digitalization and productivity growth have been put forward. Most notably, if digitalization has similar characteristics as a “general-purpose technology” (Brynjolfsson and McAfee 2014) in the sense that it triggers broad socioeconomic change and leads to a technological revolution, then technological innovation may take more time to dissipate before productivity gains are realized (Perez 2010). That is because both universal adoption and discovering the most efficient deployment of these innovations (e.g. in reducing shirking, improving market access, etc.) may take time (Brynjolfsson et al. 2019). The theory thus suggests a lagged effect of digitalization on labor productivity.

Regarding the relationship between market concentration and labor productivity (edge (2) in Figure 1), standard microeconomic theory suggests a negative link. Non-competitive markets are inefficient in their allocation of production factors (Varian 2017), so markets controlled by monopolies have lower productivity growth than perfectly competitive markets. Macroeconomically, high market concentration and monopolization are in turn expected to lead to economic stagnation (Baran and Sweezy 1966; Steindl 1952). The theoretical argument is microeconomic: Once firms achieve a monopolistic position, the incentives for innovating – and thus raising productivity – lessen. More recent macroeconomic stagnation hypotheses focus on the dampening effects of rent-seeking associated with monopolization, particularly by big tech companies, on productivity growth (Stiglitz 2014, 2016; Summers 2013). A focus on shareholder value may also reorient firms toward short-term financial goals, away from long-term investment in R&D and innovation (Ferschli et al. 2019a,b; Spencer 2017; Spencer and Slater 2020). Such a slowdown in investment despite sustained profitability is also documented by the literature on financialization (Orhangazi 2008; Stockhammer 2006).

Alternatively, market concentration might be positively associated with productivity, as shown by the edge (2) in Figure 1. For instance, monopolies may be able to drive technological progress if they invest their monopoly rents paid by consumers, which are not available to firms under more competitive pressure, into research and development. This could conceivably lead to higher innovation and thus productivity for more monopolized markets. Monopolists could also choose to invest their rents in higher wages – or be forced to do so by a better organizable labor force – which might improve productivity through an efficienct wage channel. The high and increasing productivity of digital superstar firms may thus be due to their ability to attract highly skilled and productive workers in global labor markets (Autor et al. 2020; Stiebale et al. 2020). This strand of the literature emphasizes the self-perpetuating effect of high market shares of highly productive firms and digitalization. Finally, real competition might force firms to invest in innovation independently of the level of market concentration, since they are always under the threat of market capture by competitors (Shaikh 2016). Time lags may play a role in all of these theoretical approaches – microeconomic, macroeconomic, financial, institutional, political economy –, so that a delayed effect of market concentration on productivity is possible.

The empirical literature documents rising market concentration in the US in recent decades (Autor et al. 2020) – which some attribute to increased profit margins rather than productivity gains (Grullon et al. 2018) –, but is inconclusive whether Europe followed this trend. While e.g. Döttling et al. (2017), De Loecker and Eckhout (2017), and Valetti (2017) find market concentration only in the US, Barkai (2016), Bourguignon (2017), Weche and Wambach (2018), and Stiebale et al. (2020) also show rising market concentration for European countries. Bighelli et al. (2020) find rising market concentration in Europe and conclude that it is the more productive firms that are able to increase their market shares. Moreover, the authors suggest a positive relationship between market concentration and productivity at a sectoral level, with Germany as the main driver of their results for Europe. For Germany, a sectoral study between 2008 and 2016 finds that rising market concentration in the service sector is associated with increasing productivity, while there is a negative but statistically insignificant relationship for the manufacturing sectors (Ponattu et al. 2018). Finally, Weche and Wagner (2020) do not find an overall increase in market power and concentration in the German manufacturing sector between 2005 and 2013. However, they find both increasing markups as well as concentration for many individual industries.

The dashed lines in Figure 1 indicate possible confounding relationships for the research question of this paper. Productivity may affect digitalization if high-productivity firms are better able to invest in new technologies. That is, the causality of edge (1) in Figure 1 may run in the opposite direction. Similarly, higher productivity may lead to higher market concentration if high-productivity firms manage to increase their market share (edge (2) in Figure 1). Indeed, this is the prediction of the superstar firm hypothesis, if higher productivity is driven by digitalization.

Furthermore, digitalization and market concentration may directly influence each other, without recourse to productivity (edge (3) in Figure 1). The theoretical literature is inconclusive whether this nexus is positive or negative (Moen et al. 2018). On the one hand, in the Schumpeterian notion of creative destruction (Schumpeter 1987 [1942]), the recurring process of innovation, imitation, and diffusion driven by innovative entrepreneurs in their self-motivated quest for technological superiority and associated transient monopoly profits, results in high business dynamism with small, agile, and highly innovative digital start-ups capturing market shares and thus reducing market concentration. On the other hand, large players tend to acquire small start-ups (Makridakis 2017) and network and scale effects can lead to a winner-take-all market structure due to negligible marginal costs. Both aspects link digitalization and rising market concentration (Allen 2017; Furman and Seamans 2019; Krämer 2018). The empirical literature tends to find a positive relationship between digitalization and market concentration, especially for the US (CEA 2016). The largest technological firms have the highest revenues, in particular in relation to their employees (Rosoff 2016), the highest margins, and absolute profits (Chen 2015). Rising market concentration is more prevalent not only in dynamic industries that exhibit faster technological progress (Autor et al. 2020) but also in European countries (Stiebale et al. 2020). However, Weche and Wagner (2020) find that digitalization and market power are not complementary phenomena in the German manufacturing sector.

It is thus not possible to discard reverse causation and confounding effects in our research question *a priori*. Nonetheless, since our research question focuses on the role of digitalization and market concentration for changes in productivity, we will attempt to investigate these issues empirically. As data availability is restricted to the industry level, we use industry concentration as a proxy for market concentration. The next sections, therefore, aim to answer the questions (1) whether our data show that the German economy has digitalized and (2) whether digitalization and industry concentration explain labor productivity in Germany at the sectoral level.

3 Data

We empirically investigate these questions – how digitalization and industry concentration relate to productivity in Germany – by combining sectoral data at the NACE two-digit level from EU KLEMS for productivity and digitalization, and firm-level data from CompNet and Orbis for industry concentration for the time period 2000 to 2015. Due to data limitations, especially with regard to industry concentration measures prior to 2011, the balanced panel used in the regression analysis comprises 15 sectors mainly in manufacturing, construction, information and communication, and professional and administrative services. For descriptive analysis of recent trends, however, we are able to include more sectors and alternative data sources.

The variables are defined as follows: Labor productivity is calculated using EU KLEMS data as value added per hours worked[2] (Jäger 2018). To assess the degree of digitalization, we use EU KLEMS to measure three additive aspects: (1) *technological intensity*, (2) *knowledge intensity*, and (3) *digital capital deepening*.

(1) Technological intensity is approximated by investment in information and communications technology (ICT) as a share of nonresidential gross fixed capital formation, analogous to Calvino et al. (2018). ICT includes computer and network hardware as well as software products and databases. The share of ICT investments in gross fixed capital formation thus shows the extent to which firms at the industry level are able to process and use information, for

2 Hours worked as a measure of labor input is preferable to the headcount number of employed people since the latter may be affected by changes in the former, such as increasing part-time work.

example, market or customer data. We distinguish between information technology ("IT share"), communication technology ("CT share"), and software and databases ("Soft share") – all measured as a share of nonresidential gross fixed capital formation – to capture the increasing relevance of intangible capital as digitalization progresses.

(2) Knowledge intensity is approximated by research and development (R&D) investments, which cover an important aspect of intangible capital, i.e. knowledge. According to national accounts, R&D investment includes both internally generated and purchased (including imported) R&D services but does not include R&D intended for sale. We use R&D investment as a share of gross fixed capital formation ("RD share") as an indicator of the R&D or knowledge intensity of the production process within a sector (Unger et al. 2017). Since a key feature of digitalization is the change (and improvement) of production processes, this indicator can also be interpreted as the extent to which industries are equipped with the prerequisites for digitalization.

(3) Finally, digital capital deepening is an indicator used in the McKinsey Industry Digitization Index (2015) to show the extent to which different sectors rely on digital capital compared to labor as factors of production. We distinguish between tangible digital capital measured as the stock of IT capital ("IT deep") and intangible digital capital measured as stock of software and databases ("Soft deep"), both relative to hours worked. Note that these measures may run into issues of multicollinearity with our dependent variable labor productivity; we, therefore, exclude digital capital deepening from our preferred estimates in Section 4.

In addition, we use the OECD taxonomy of digital intensive sectors developed by Calvino et al. (2018) for cross-sectoral comparisons of digitalization, descriptive analysis of recent years, and robustness checks. This indicator ranks sectors by their degree of digitalization into four categories (low, medium–low, medium–high, and high). This taxonomy is based on ICT investment, robot use, and ICT specialists, among others. However, this data is only available for the years 2013–2015.

For industry concentration, we combine the firm-level data of CompNet for the period 2000 to 2010 with Orbis data for 2011–2015. CompNet contains both the revenue share of the 10 largest firms (c10) and the Herfindahl-Hirschman index (HHI)[3] at the sectoral level. However, these data are only available for Germany until 2012, and large firms appear to be overrepresented. We, therefore, use Orbis

3 The HHI is defined as the sum of the squared market shares α of the N firms in a sector. The higher the corresponding value, the higher the share of individual firms i in the overall production: H := i = 1Ni2. The normalized HHI ranges from 0 to 1: HHI_n := (H-1N)1-1N for $N > 1$ and HHI_n := 1 for $N = 1$.

data for the 5000 largest individual firms in each sector to calculate the market share of the largest three firms (c3), as well as c10, and the (normalized) HHI. Due to missing observations in previous years, we use Orbis data starting only in 2011 with linear interpolation of missing observations. To avoid double counting, we consolidate parent and subsidiary companies.

Finally, we control for capital intensity in order to mitigate potential omitted variable bias, since larger capital requirements might affect market concentration via scale effects and barriers to entry. We use data for capital intensity from EU KLEMS, measured as the real fixed capital stock of all assets at 2010 prices, divided by value added.

These data yield a balanced panel of 240 observations, which reduce to 225 due to the lag structure in the regression. Table 1 provides summary statistics of our variables of interest. Since we use two different datasets for the concentration measures, we present them individually for CompNet and Orbis data. The data

Table 1: Summary statistics.

Variable	*N*	Mean	St. Dev.	Min	25th pctl	Median	75th pctl	Max
Concentration measures (CompNet): 2000–2010								
c10	219	0.439	0.249	0.098	0.250	0.389	0.623	0.998
HHI (norm.)	219	0.081	0.138	0.002	0.011	0.025	0.084	0.809
Concentration measures (Orbis): 2011–2015								
HHI	145	1409.7	2063.7	66.6	168.8	792.2	1525.2	9770.3
HHI (norm.)	145	0.141	0.206	0.007	0.017	0.079	0.153	0.977
c3	145	0.411	0.261	0.071	0.166	0.418	0.535	0.994
c10	145	0.542	0.242	0.204	0.334	0.559	0.675	0.997
EU KLEMS technology and labor productivity indicators: 2000–2015								
CT share	240	0.032	0.068	0.004	0.007	0.011	0.021	0.355
IT share	240	0.027	0.028	0.004	0.010	0.015	0.036	0.158
RD share	240	0.230	0.176	0.007	0.098	0.165	0.395	0.594
Soft share	240	0.083	0.092	0.009	0.026	0.056	0.079	0.432
Soft deep	240	0.002	0.004	0.0001	0.0003	0.001	0.003	0.020
IT deep	240	0.001	0.001	0.0001	0.0003	0.0005	0.001	0.009
Lab. Prod.	240	0.054	0.024	0.026	0.038	0.047	0.063	0.143
Cap. Int.	240	1.183	0.435	0.395	0.850	1.156	1.434	2.579

The table shows summary statistics of yearly and sectoral data at the NACE for the revenue share of the 10 (3) largest firms per sector (c10/c3); the Herfindahl-Hirschman index (HHI); the share of information technology ("IT share"), communication technology ("CT share"), R&D investment ("RD share"), and software and databases ("Soft share"), all measured as a share of nonresidential gross fixed capital formation; the stock of IT capital ("IT deep") and the stock of software and databases ("Soft deep"), both relative to hours worked; labor productivity ("Lab. Prod."), value added per hours worked by employees; and capital intensity ("Cap. Int."), real net capital stock as a share of value added.
Source: own calculations; Data: EU KLEMS (2018), CompNet (2019), Orbis (2019).

show that German sectors on average are characterized by very low concentration according to the normalized HHI. This is true even at the 75th percentile; however, the maximum values are close to one, especially for Orbis data, implying that there is at least one sector that is dominated by a single firm. Similarly, the concentration ratios c3 and c10 show that, on average, concentration is low; again, some sectors with high concentration are the exception. Furthermore, concentration in the CompNet data is on average lower than concentration measures derived with Orbis data. For example, in the CompNet database covering the period from 2000 to 2010, the average share of revenues going to the 10 largest firms is 44% compared to 54% when using Orbis data for the years 2011 until 2015. Unfortunately, our data do not permit us to distinguish measurement issues from underlying changes in industry concentration over time.

The summary statistics for the digitalization indicators from EU KLEMS show that on average the R&D investment share is highest, followed by the software investment share. Furthermore, the sectors of the German economy seem to differ little with regard to digital capital deepening, while the investment shares, especially for R&D, are more dispersed[4].

4 Digitalization and Concentration at the Sector Level in Germany: Descriptive Evidence

Figure 2 indicates that the German economy as a whole appears to have digitized since 2000, at least as measured by some indices. In particular, not only digital capital deepening (that is, the stock variables of software and IT deepening) but also knowledge intensity (the R&D investment share) have increased. Technological intensity shows a less clear picture, with the investment share in software and databases rising, but IT and communication technology declining. The latter may be due to falling costs, increasing the longevity of equipment, or saturation in the technical infrastructure. Figures 4A and 5A in the Appendix differentiate these developments by sector at the NACE two-digit level. It shows that some sectors have become highly knowledge-intensive over the period of observation; the broad picture at the sectoral level confirms the development of the German economy as a whole as one of digitalization, especially with regard to the deepening of IT capital intensity.

4 We graph these variables for the different sectors in the Appendix: Figures 4A and 5A present the changes in the digitalization indicators, Figures 6A, 7A and 8A, 9A show the changes in the concentration measures from CompNet and Orbis, respectively, and Figures 10A and 11A illustrate shifts in labor productivity.

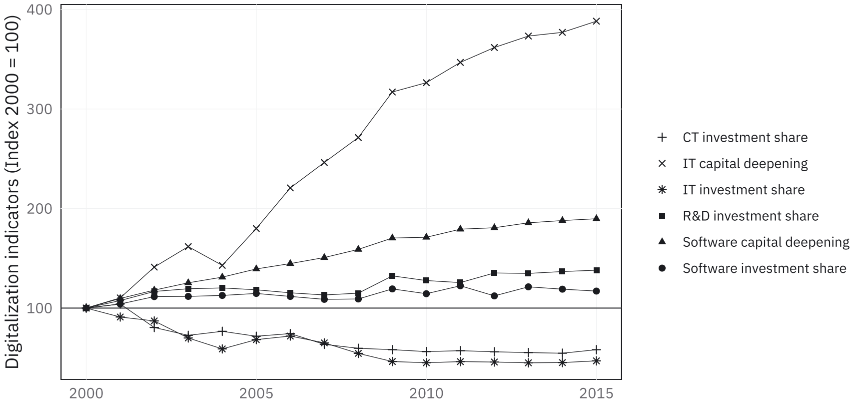


Figure 2: Digitalization in Germany.
Source: own calculations; data: EU KLEMS (2018).

Next, we compare sectors ranked by their digital intensity according to the OECD taxonomy (Table 2). Since the Calvino et al. (2018) taxonomy is based on data between 2013 and 2015, we use simple means of the concentration measures for the same period. A three-level grayscale indicates sectoral concentration, with cut-off points for the HHI following the EU (2004) guidelines for the assessment of horizontal mergers: below 1,000 signifies low concentration (light gray), between 1000 and 2000 corresponds to medium concentration (medium gray), and values greater than 2000 signal highly concentrated markets (dark gray). The thresholds for concentration ratios are set to a c3 above 0.7 indicating a highly concentrated market (dark gray), and a c3 below 0.45 showing low concentration (light gray). Finally, for c10, we use the thresholds of 0.5 and 0.9.

Table 2 documents that our data show no clear-cut relationship between digitalization and concentration in the German economy. The majority of sectors are competitive with HHI values below 1000, and there is no particularly clear association of industry concentration with any one of the four categories of digital intensity. Four sectors are highly concentrated with HHI values greater than 2000: Mining (B05–09), coke and refined petroleum production (C19), manufacturing of transportation equipment (C29–30), and telecommunications (J61). In these sectors, revenue shares of the three largest enterprises amount to more than 70%, in telecommunications even to 90%. Two of these four highly concentrated industries (telecommunications and manufacturing of transport equipment) are also highly digitalized, but the other two fall into the low (mining) and medium-low (coke and refined petroleum production) categories. Finally, six out of nine digital intensive sectors have a low concentration index with HHI values below 1000.

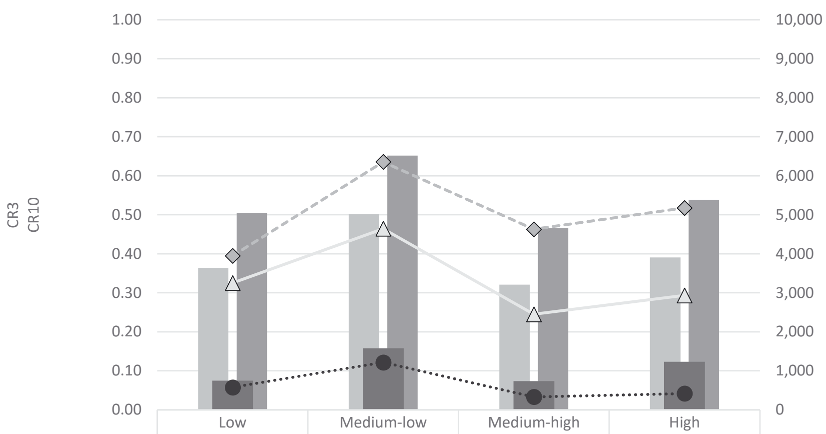
Table 2: Concentration measures by the digital intensity of sectors (2013–2015).

Sectors	NACE1	NACE2	Quartile of digital intensity 2013–15	av.HHI	av.c3	av.c10
Agriculture	A	01–03	Low	834.19	0.46	0.58
Mining	B	05–09	Low	2116.50	0.71	0.88
Food and beverages	C	10–12	Low	184.13	0.17	0.34
Electricity and gas	D	35	Low	1443.51	0.58	0.81
Water and sewerage	E	36–39	Low	226.45	0.21	0.39
Construction	F	41–43	Low	574.56	0.32	0.39
Transportation and storage	H	49–53	Low	1099.79	0.55	0.68
Hotels and restaurants	I	55–56	Low	82.51	0.12	0.22
Real estate	L	68	Low	152.25	0.15	0.25
Textiles and apparel	C	13–15	Medium–low	265.85	0.22	0.36
Coke and ref. petroleum	C	19	Medium–low	4000.30	0.85	0.96
Chemicals	C	20	Medium–low	1380.40	0.50	0.74
Pharmaceuticals	C	21	Medium–low	1983.10	0.60	0.80
Rubber and plastics	C	22–23	Medium–low	1049.40	0.43	0.52
Metal products	C	24–25	Medium–low	767.72	0.41	0.53
Wood and paper prod.	C	16–18	Medium–high	154.36	0.18	0.30
Computer and electronics	C	26	Medium–high	402.79	0.27	0.51
Electrical equipment	C	27	Medium–high	255.59	0.22	0.42
Machinery and equipment	C	28	Medium–high	1171.72	0.52	0.60
Furniture and other	C	31–33	Medium–high	1775.51	0.49	0.58
Wholesale and retail	G	45–47	Medium–high	124.83	0.16	0.27
Media	J	58–60	Medium–high	1786.15	0.52	0.68
Arts and entertainment	R	90–93	Medium-high	218.23	0.21	0.38
Transport equipment	C	29–30	High	3029.46	0.86	0.93
Telecommunications	J	61	High	5244.12	0.90	0.96
IT services	J	62–63	High	168.55	0.17	0.35
Finance	K	64–66	High	591.46	0.36	0.58
Legal and accounting	M	69–71	High	106.58	0.12	0.26
Scientific R&D	M	72	High	416.40	0.29	0.52
Marketing and other	N	73–75	High	1028.73	0.40	0.58
Administrative services	N	77–82	High	319.65	0.26	0.35
Other services	S	94–96	High	154.20	0.16	0.32

Source: own calculations; Data: Calvino et al. (2018), Orbis (2019).

We, therefore, find no clear evidence for a relationship between higher digital intensity and industry concentration when comparing the (unweighted) means and medians of concentration measures from 2013 to 2015 by the relative digital intensity of industries. Figure 3 presents the mean and median industry concentration measures by digital intensity. On average, sectors in the second quartile of the digital intensity taxonomy (medium-low) are the most highly concentrated, followed by the top quartile (high). The lowest and the third quartile show similar patterns of industry concentration.

In conclusion, based on the cross-sectoral descriptive analysis, we cannot identify a clear-cut relationship between digital intensity and market concentration, as would have been predicted by the superstar firm hypothesis developed for the US. Instead, the results indicate that there are large variations in terms of concentration between sectors. Although two out of the four highly concentrated industries are also among the most highly digitalized, the overall picture shows that the German economy contains both sectors that are characterized by high concentration and other sectors that are marked by high digital intensity. However, these two characteristics do not necessarily coincide in the same sectors in our data. Whether they are related to productivity individually is the question we try to answer in the next section.



	Low	Medium-low	Medium-high	High
Cr3	0.36	0.50	0.32	0.39
Cr10	0.50	0.65	0.47	0.54
HHI	745.99	1574.46	736.15	1228.79
C3 Median	0.32	0.46	0.24	0.29
C10 Median	0.39	0.64	0.46	0.52
HHI Median	574.56	1214.90	329.19	416.40

DIGITAL INTENSITY

Figure 3: Mean and median of concentration by the digital intensity of sectors (2013–2015). Source: own calculations; Data: Calvino et al. (2018), Orbis (2019).

5 Labor Productivity, Market Concentration, and Digitalization: Multivariate Analysis

In this section, we address the relationship of labor productivity with industry concentration and digitalization over time. As discussed above, theoretical explanations for both the productivity-concentration nexus and the impact of digitalization on productivity are ambiguous, while our descriptive data suggest, if anything, individual relationships of concentration and digitalization with productivity. We, therefore, try to shed light on the multivariate relationship between labor productivity and concentration on the one hand, and various technology indicators capturing different aspects of the process of digitalization on the other hand.

To identify the effects of industry concentration and digitalization on labor productivity in Germany, we use a panel over 16 years and 15 sectors, covering those sectors for which we have complete time series data for our variables of interest.[5] We use a fixed-effects estimation approach with both time fixed effects (v_t) and sector fixed effects (u_i) to account for aggregate time trends affecting all variables and unobservable sector-specific characteristics that are constant across time but vary between sectors. We lag our control variables of interest by one period to mitigate potential endogeneity. As long as neither digitalization nor industry concentration of the previous period is affected by the current period's labor productivity, this approach provides evidence for predictive causality. Finally, we control for overall capital intensity to capture scale effects:

$$LP_{it} = \alpha_i + \beta_1 HHI_{it-1} + \beta_2 IT_{it-1} + \beta_3 SOFT_{it-1} + \beta_4 CT_{it-1} + \beta_5 RD_{it-1} + \beta_6 K_{it} + v_t + u_i + \epsilon_{it}, \tag{1}$$

where the dependent variable is labor productivity (LP_{it}) for each time period t and sector i, calculated as value added per hours worked. Our explanatory variables of interest are the normalized HHI_{it-1} to measure industry concentration, and the three digitalization indicators (IT_{it-1}, $SOFT_{it-1}$, and CT_{it-1}) and RD_{it-1} for knowledge intensity. Capital intensity is denoted by K_{it}.

The fixed effects estimators are obtained by demeaning all variables which then leads to a reduced form:

$$\widetilde{LP}_{it} = \beta_1 \widetilde{HHI}_{it-1} + \beta_2 \widetilde{IT}_{it-1} + \beta_3 \widetilde{SOFT}_{it-1} + \beta_4 \widetilde{CT}_{it-1} + \beta_5 \widetilde{RD}_{it-1} + \beta_6 \tilde{K}_{it} + \theta_{it}, \tag{2}$$

where all variables x are adjusted for the mean of each sector over time, and for the mean of all sectors over time, $\tilde{x}_{it} = x_{it} - \overline{x_i} - \overline{x_t}$. The estimated model now only

5 For an overview of the sample, see Appendix.

contains the transformed stochastic error term θ_{it}, which is assumed to be exogenous with zero expected mean. To deal with heteroskedasticity, autocorrelation, and serial correlation, which are all present in our empirical setting, we use the Driscoll-Kraay standard error correction (Driscoll and Kraay 1998).

Table 3 shows the regression results for six specifications with labor productivity as the dependent variable. Column (1) regresses the one-period lagged standardized HHI on labor productivity, and columns (2) to (5) regress each of the one-period lagged digitalization indicators individually on labor productivity while controlling for capital intensity.[6] Both the standardized HHI and the digitalization indicators are statistically significant at the 1%-level, except for the CT investment share, which is statistically significant at the 5%-level. Column (1) shows a positive correlation between higher industry concentration and labor productivity, while the results displayed in columns (2) to (5) show that the effects of IT, software, and R&D investment shares are positive and the effect of the CT investment share is negative. However, in the full model presented in column (6), the CT investment share turns statistically insignificant while all other explanatory variables retain their statistical significance. Capital intensity is negatively related to productivity, as expected, and statistically significant in all model specifications.

We thus find empirical support for two aspects of a potential "superstar firm" effect: (1) a positive relationship between industry concentration and productivity and (2) a positive relationship between digitalization and productivity. The finding that digitalization and concentration are positively related to productivity, suggests that larger and more "technologized" firms are also more productive. The third element of the "superstar firms" hypothesis, which is a negative relationship between market concentration and the wage-share in Germany is not part of our analysis but has been tested in other studies (Ponattu et al. 2018). Our results should be interpreted with caution. First, we do not establish a clear-cut relationship between concentration and digitalization. There are highly digitalized sectors, and highly concentrated sectors in Germany, which do not necessarily overlap. They do so, however, in individual industries like the manufacturing of transport equipment. While Ponattu et al. (2018) suggest a "superstar firm" effect for the German service sector, we find evidence for "Deutsche superstar firms" in manufacturing industries such as automotive manufacturing. Crucially, however, such a view abstracts from the central role of the "hidden champions" of small and medium-sized enterprises (SME) in German manufacturing. We thus suggest that the German economy with its

6 See Table 9A in the Appendix for specifications with the digitalization indicators and the HHI lagged by three periods. The results are qualitatively similar; however, the IT investment share becomes insignificant, and the statistical significance of the software investment share increases with each time lag. This suggests that the productivity gains from software investment may take longer to materialize than productivity gains from other types of digital investment.

Table 3: Regression results.

	Dependent variable: labor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
HHI ($t-1$)	0.039***					0.028**
	(0.008)					(0.012)
IT investment share ($t-1$)		0.092***				0.115**
		(0.017)				(0.046)
Software investment share ($t-1$)			0.081***			0.062**
			(0.013)			(0.029)
CT investment share ($t-1$)				−0.082**		−0.038
				(0.039)		(0.034)
R&D investment share ($t-1$)					0.043***	0.030**
					(0.014)	(0.012)
Capital intensity	−0.008***	−0.007***	−0.011***	−0.009***	−0.008***	−0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Industry FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.:	225	225	225	225	225	225
R-squared	0.259	0.095	0.155	0.109	0.096	0.342
Adj. *R*-squared	0.144	−0.044	0.025	−0.029	−0.044	0.224

FE-estimations with Driscoll and Kraay standard errors. Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Source: own calculations; Data: EU KLEMS (2018), CompNet (2019), Orbis (2019), sector sample as in Table 6A.

strong industrial base might be experiencing a different process than the US: Although the German economy is digitalizing, this does not take necessarily place in the same sectors that are highly concentrated (such as pharmaceuticals, transport equipment, electricity, and telecommunications). This likely leads to more nuanced predictions with regard to the interaction of these processes, as well as to their redistributive effects. Since our results also show that the digitalization indices (IT intensity and software intensity) are positively correlated with labor productivity, the results from the estimated full model also indicate support for the hypothesis that digitalization is leading to labor-saving technological innovations in Germany – although it should be noted that this does not automatically imply rising unemployment, since labor-saving technologies may also increase output when holding labor input constant.

Although they square well with the literature, our results should of course still be interpreted with caution for a number of reasons. First, our empirical analysis is limited by data availability since we combine datasets of varying granularity and covering different time periods. The main results are thus based on 15 aggregated NACE sectors, which may not adequately describe all aspects of the relationship between digitalization, industry concentration, and labor productivity in Germany and in particular do not capture dynamics at a lower level of aggregation. However, since the available data comprises key sectors for the German economy, our results shed light on prevalent general trends. Second, while we attempt to address issues of endogeneity by using lagged independent variables, it is of course possible that this approach is not able to capture all feedback effects from labor productivity on digitalization and industry concentration. Finally, as discussed in Section 2, digitalization and industry concentration may be linked, and scale effects and/or entry barriers might play a role. We investigate these issues, as well as potential measurement errors, in the robustness checks section below.

6 Robustness Checks

We conduct three robustness checks to investigate whether our findings are affected by measurement error and joint effects of our independent variables. We first re-estimate the relationship between labor productivity, digitalization, and industry concentration using alternative datasets (1) for digitalization, namely the OECD digital intensity taxonomy proposed by Calvino et al. (2018), and (2) for industry concentration, with the data used in Weche and Wambach (2018). We (3) then introduce an interaction term between digitalization and concentration.

For our first robustness check, we use the OECD taxonomy of digital intensive sectors, which is based on a broad set of indicators. These include not only the technology indicators in our main results but also human capital variables, robot use, and online sales. These are summarized into an overall indicator with four categories (see Calvino et al. 2018, p. 31) This digital intensity indicator aims to measure the degree to which sectors have been subject to a digital transformation.

We then estimate an OLS model:

$$\log(LP_{it}) = \beta_0 + \beta_1 \log(HHI_{it}) + \beta_2 D_i + \beta_3 X_t + \epsilon_{it} \tag{3}$$

using logs of labor productivity and the HHI, and including year dummies (X_t). To measure the digital intensity of our sectors, we use the ordinal variable digital intensity D_i with the category "low" as the base category. The digital intensity variable is available for two periods, 2001–2003 and 2013–2015. We use them separately in the regression since the categorization changed only for few sectors. The estimated effects confirm our main results (see Table 10A in the Appendix): for sectors with higher digital intensity, digitalization is associated with higher labor productivity in both periods. Furthermore, there is a positive relationship between higher industry concentration and labor productivity. The coefficients for digital intensity are robust to the inclusion of concentration and digital intensity remains statistically significant at the 1%-level.

For our second robustness check, we re-run our regressions with the HHI provided by the German monopoly commission also used in Weche and Wambach (2018). While this dataset is available at a highly disaggregated level (4-digit NACE), for consistency with the OECD taxonomy we aggregate it at the two-digit NACE level.[7] Since these data cover every second year starting in 2007, we use the HHI from CompNet for the years 2000–2006, and the biannual HHI data of Weche and Wambach (2018) from 2007 to 2015. As a consequence, the sector sample differs between the two time periods.[8] Our findings are robust – higher digital intensity and industry concentration are both statistically significantly and positively related to productivity – when using a balanced panel, i.e. including only those sectors for which concentration data is available for the entire period (see Tables 11A and 13A in the Appendix).[9]

Our third robustness check estimates a regression model with interaction terms in order to take possible joint effects of industry concentration and digitalization into account:

$$\begin{aligned}\widetilde{LP}_{it} &= \beta_1\widetilde{\mathrm{HHI}}_{it-1} + \beta_2\widetilde{IT}_{it-1} + \beta_3\widetilde{\mathrm{SOFT}}_{it-1} + \beta_4\widetilde{\mathrm{CT}}_{it-1} + \beta_5\widetilde{\mathrm{RD}}_{it-1} \\ &\quad + \beta_j\left(\widetilde{\mathrm{HHI}}_{it-1} \times \widetilde{\mathrm{DIGI}}_{it-1}\right) + \beta_{11}\left(\widetilde{\mathrm{HHI}}_{it-1} \times \tilde{K}_{it}\right) + \beta_{12}\tilde{K}_{it} + \theta_{it} \qquad (4)\end{aligned}$$

where the variables are defined analogously to the model of Eq. (2) and β_j are the coefficients of the interactions between the concentration index $\tilde{\mathrm{HHI}}_{it-1}$ and the vector of digitalization indices, which comprises $\tilde{\mathrm{IT}}_{it-1}$, $\tilde{\mathrm{SOFT}}_{it-1}$, $\tilde{\mathrm{CT}}_{it-1}$, and $\tilde{\mathrm{RD}}_{it-1}$. β_{11} gives the effect of the interaction of industry concentration with capital intensity. As in Table 3, we first regress labor productivity on concentration with each digitalization indicator individually, before estimating the full model. The results in Table 4 show that in models (1)–(5), the effects of concentration, the software investment share, the communication technology share, the R&D investment share, and capital intensity on labor productivity are robust to the inclusion of interaction terms. The interaction terms of industry concentration with the IT and the software investment share are negative, which suggests an inverted u-shaped function: At low levels of concentration, software investment is more strongly productivity-enhancing than at high levels of concentration; more precisely, the positive effect of software

7 We use the median value to reduce the influence of outliers.

8 The sector samples for these robustness checks are listed in Tables 6A to 8A in the Appendix.

9 These results are robust to linearly interpolating the biannually missing data, in order to obtain the same number of observations as in our main results.

Table 4: Regression results with interaction effects.

	Dependent variable: labor productivity					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
HHI(t – 1)	0.039***	0.059***	0.049***	0.039***	0.024***	−0.038**
	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.018)
IT investment share (t – 1)		0.149				0.240***
		(0.092)				(0.071)
HHI (t – 1) × IT investment share (t –1)		−0.798***				−0.321
		(0.301)				(0.259)
Software investment share (t – 1)			0.089***			0.069***
			(0.021)			(0.022)
HHI (t – 1) × Software investment share (t – 1)			−0.095***			−0.049
			(0.031)			(0.031)
CT investment share (t – 1)				−0.059*		−0.079**
				(0.032)		(0.038)
HHI (t – 1) × CT investment share (t – 1)				−0.012		0.083
				(0.038)		(0.086)
R & D investment share (t – 1)					0.040***	0.028**
					(0.013)	(0.012)
HHI (t – 1) × R & D investment share (t – 1)					0.079***	0.082
					(0.016)	(0.051)
Capital intensity	−0.008***	−0.008***	−0.010***	−0.008***	−0.006**	−0.008***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)
HHI (t – 1) × capital intensity						0.040***
						(0.015)
Industry FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.:	225	225	225	225	225	225
R-squared	0.259	0.307	0.323	0.28	0.317	0.463
Adj. R-squared	0.144	0.192	0.21	0.16	0.203	0.349

FE-estimations with Driscoll and Kraay standard errors. Standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.
Source: own calculations; Data: EU KLEMS (2018), CompNet (2019), Orbis (2019), sector sample as in Table 6A.

investment on productivity decreases with rising industry concentration. This effect appears to be inverse for the R&D investment share.

However, we would caution against a confident interpretation of these findings, given that the full model (6) shows that our main results are largely robust to the inclusion of interaction terms. In our preferred full specification, all variables of the main result presented in the previous section are statistically significant, and both the direction of their effect on productivity and the order of magnitude are the same. The notable exception is industry concentration, which switches signs. All interaction terms of concentration and digitalization indicators cannot be statistically significantly distinguished from zero in the full specification. This tallies with the descriptive evidence presented in Section 3, which showed that digitalization and industry concentration do not appear to be high in the same sectors in Germany. In contrast, the interaction of concentration and capital intensity is positive and statistically significant in the full specification. This strengthens the evidence for capital intensity to be associated with scale effects and/or entry barriers at the sectoral level in Germany.

These results cautiously suggest that our results are robust with respect to using different digitalization indicators, with respect to using concentration measures from different databases, and with respect to including interaction terms for industry concentration and digitalization indices. However, the link between concentration and productivity may be sensitive to industry selection, and we find some evidence for a possible interaction between concentration and capital intensity.

7 Conclusion

This paper investigates the effect of digitalization and industry concentration on labor productivity at the sectoral level in Germany. Using a balanced panel with EU KLEMS data for digitalization and labor productivity, as well as combining firm-level data from CompNet and Orbis for industry concentration from 2000 to 2015, we estimate a fixed-effects model of productivity with concentration and digitalization, controlling for capital intensity.

This produces three notable results. First, we find evidence for digitalization trends in the German economy as a whole, especially not only with regard to capital deepening (that is, software and IT deepening) but also for knowledge intensity (i.e. the R&D share). Technological intensity shows a more nuanced picture, with the investment share in software and databases rising, but IT and communication technology declining. These general patterns are differentiated further when we zoom in to the sector level.

Second, descriptive evidence does not suggest a link between digitalization and concentration at the industry level. Neither distributional analysis neither using a heat map nor aggregation over digital intensity yield a clear-cut relationship between our digitalization indices and industry concentration, as measured by the HHI and the concentration ratios c3 and c10. The German economy contains both highly concentrated and highly digitalized sectors, but these two characteristics do not appear to coincide in the same sectors. This would suggest that a key element of the standard US version of the "superstar firm hypothesis" – digitalization leading to higher productivity and thus industry concentration – is not supported by our data for Germany.

Third, we estimate a fixed-effects model explaining labor productivity with the HHI and the digitalization indices – capturing technological and knowledge intensity – as lagged independent variables, and controlling for capital intensity. In our full specification, we find both industry concentration and technological intensity positively affecting productivity individually. These results are robust to alternative specifications as well as using different measures of digitalization and concentration. Specifically, we reproduce our main results with the OECD digital intensity taxonomy proposed by Calvino et al. (2018) and industry concentration measures for German sectors based on Weche and Wambach (2018). We also control for joint effects of industry concentration and digitalization; the insignificant interaction terms support our descriptive evidence that digitalization and concentration do not necessarily coincide.

Our findings thus cautiously suggest that (a) recent technological change has likely been labor-saving, and (b) that some aspects of a "superstar firm" effect may be identified in Germany, albeit of a different nature than the "superstar firm" effect for the US. It should be noted that our extensive robustness checks caution against an overconfident interpretation of this positive link between industry concentration and productivity, since it may be sensitive to industry selection and to scale effects and/or entry barriers resulting from the capital intensity. In addition, due to the combination of different datasets, our main results are based on a subsample of 15 aggregated NACE sectors. Furthermore, while using lagged explanatory variables allows us to address potential endogeneity problems, we might not fully capture all feedback effects from labor productivity on digitalization and industry concentration. However, provided that the current period's labor productivity neither affects digitalization nor the concentration of the previous period, the lagged-variables approach provides evidence for predictive (Granger) causality. In conclusion, while our findings may provide interesting first insights, additional analysis would thus be required for investigating such a "Deutsche superstar firm", which would, in particular, take into account the role of SME's in German manufacturing and the fact that positive effects of concentration and technological intensity on productivity only exist for selected industries.

These results have direct policy implications, as digitalization and market concentration will remain on the agenda in the near future (Rehm and Schnetzer 2018). Digitalization ranks as a major challenge for today's labor markets since many tasks are prone to restructuring or obsolescence. This creates policy challenges for education with a focus on digital skills, in order to prepare future generations for a diversified job market. Adapting curricula of schools, universities, and vocational training is as crucial as harnessing social security systems in dealing with the foreseeable differential unemployment impacts of digitalization.

Concerning market concentration and inequality, rising market power entails unfavorable consequences for the economic order as competition is fundamental for a well-functioning market economy. Less competition might increase income inequalities and macroeconomic vulnerability (Weche and Wambach, 2018). Since inequality is likely to remain highly relevant in the future (Ederer et al. 2020; Mokre and Rehm 2020), our findings point to Germany as an interesting research area, given their potentially more nuanced predictions with regard to the effects of digitalization on distribution, such as the development of the labor share. In addition, market power – like inequality – may be associated with political power (Rehm and Schnetzer 2015), which could reinforce the negative effects of high market concentration. Thus, policymakers should closely monitor the market dominance of single corporate agents and curb the political influence of large corporations that could undermine democratic decision-making.

There are a number of interesting avenues for future research. First, improved time series data for market or industry concentration at the firm level might yield additional insights into monopolization over time in Germany. Delving more deeply into individual sectors with more granular data, for instance disaggregating at higher-digit NACE levels or focusing on small subsectors, would likely lead to less generalizable but more detailed information on channels and developments. Third, internationally comparable data could provide valuable insights into country-specific developments of digitalization and market concentration. While the US is a standard case study for highly concentrated digital markets, our findings for Germany show slightly different results at a sectoral level. Thus, detailed cross-country studies could shed light on the different degrees of these processes and put our results in an international perspective. Finally, exploring the more nuanced implications of our "Deutsche superstar firms" hypothesis for distributional issues both theoretically and empirically would be highly worthwhile.

Acknowledgments: The authors thank participants at the Re:Publica and the Digital Capitalism conferences 2019, two anonymous reviewers, and the editor for comments and suggestions. Naturally, all remaining errors are our own.

Appendix

Technology indicators at two-digit NACE level

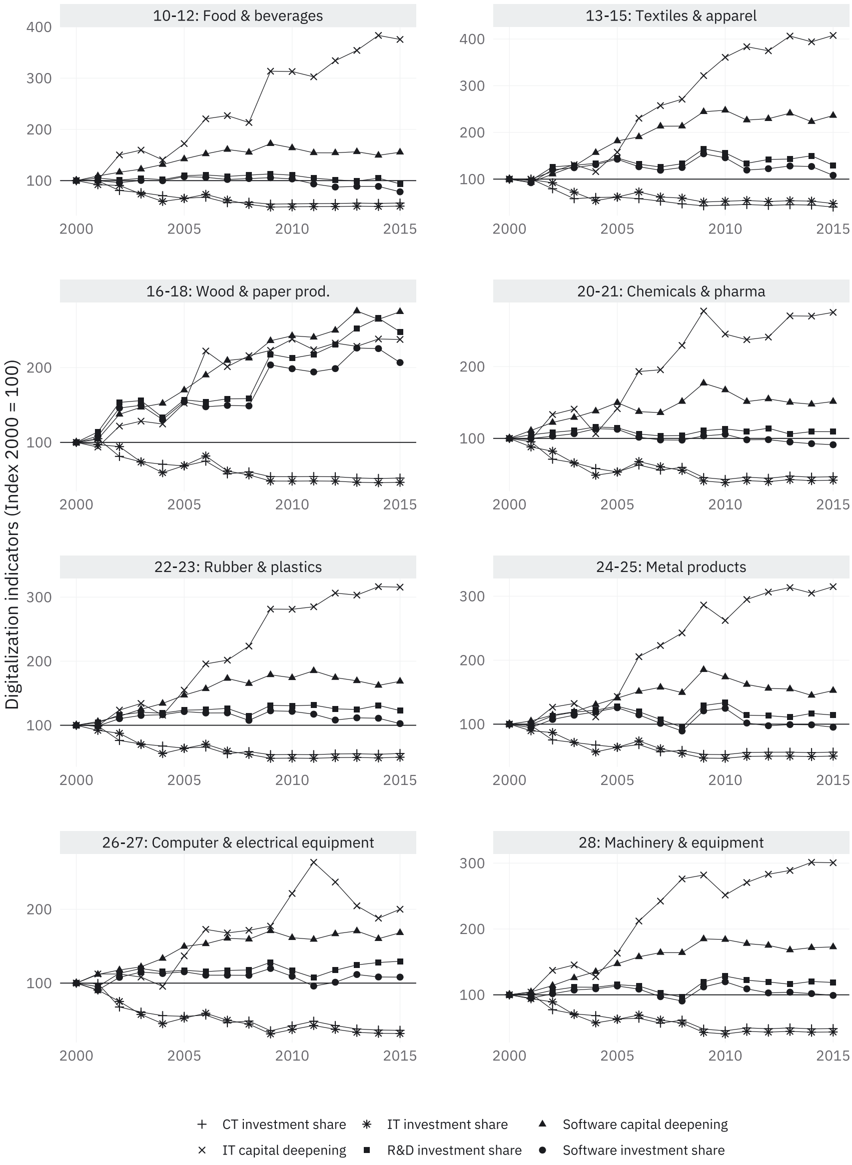


Figure 4A: Development of digitalization indicators for NACE sectors 10–28.
Source: own calculations; data: EU KLEMS (2018).

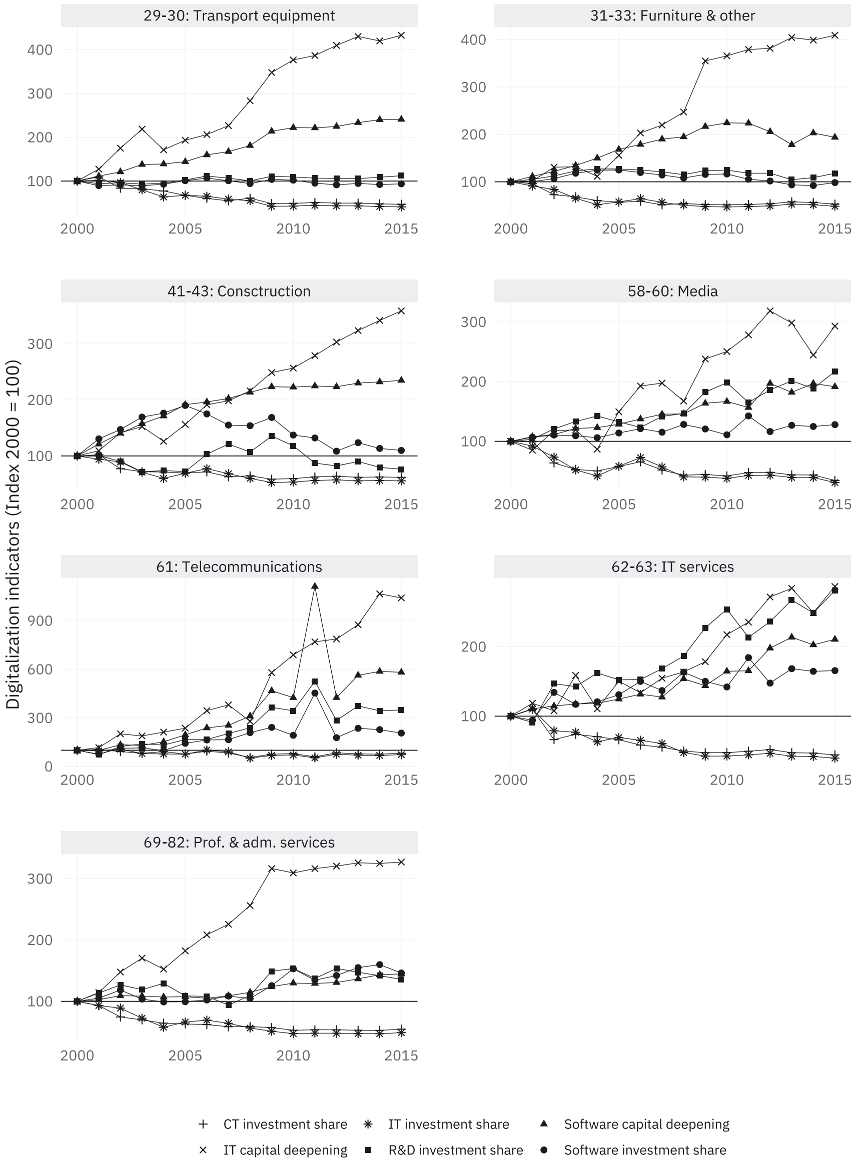


Figure 5A: Development of digitalization indicators for NACE sectors 29–82. Source: own calculations; data: EU KLEMS (2018).

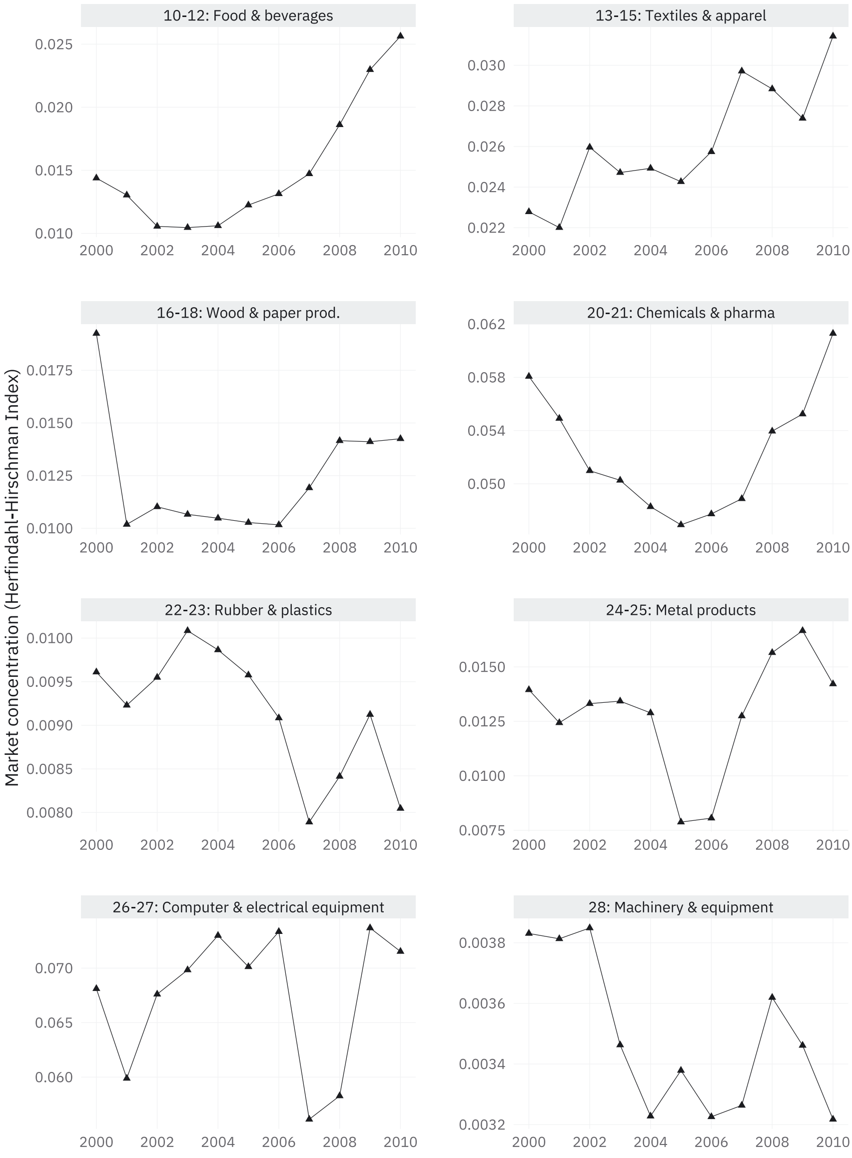


Figure 6A: Development of CompNet market concentration for NACE sector 10-28.
Source: own calculations; data: CompNet (2019).

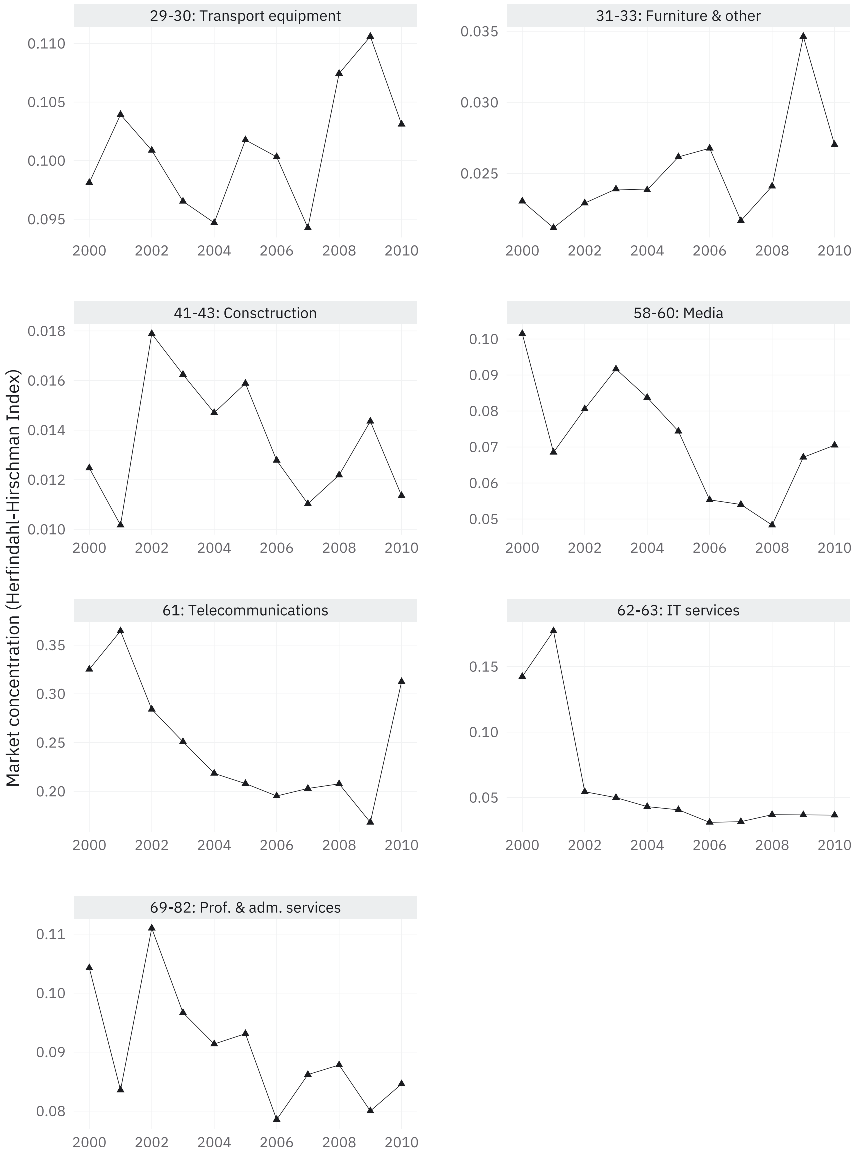


Figure 7A: Development of CompNet market concentration for NACE sectors 29-82.
Source: own calculations; data: CompNet (2019).

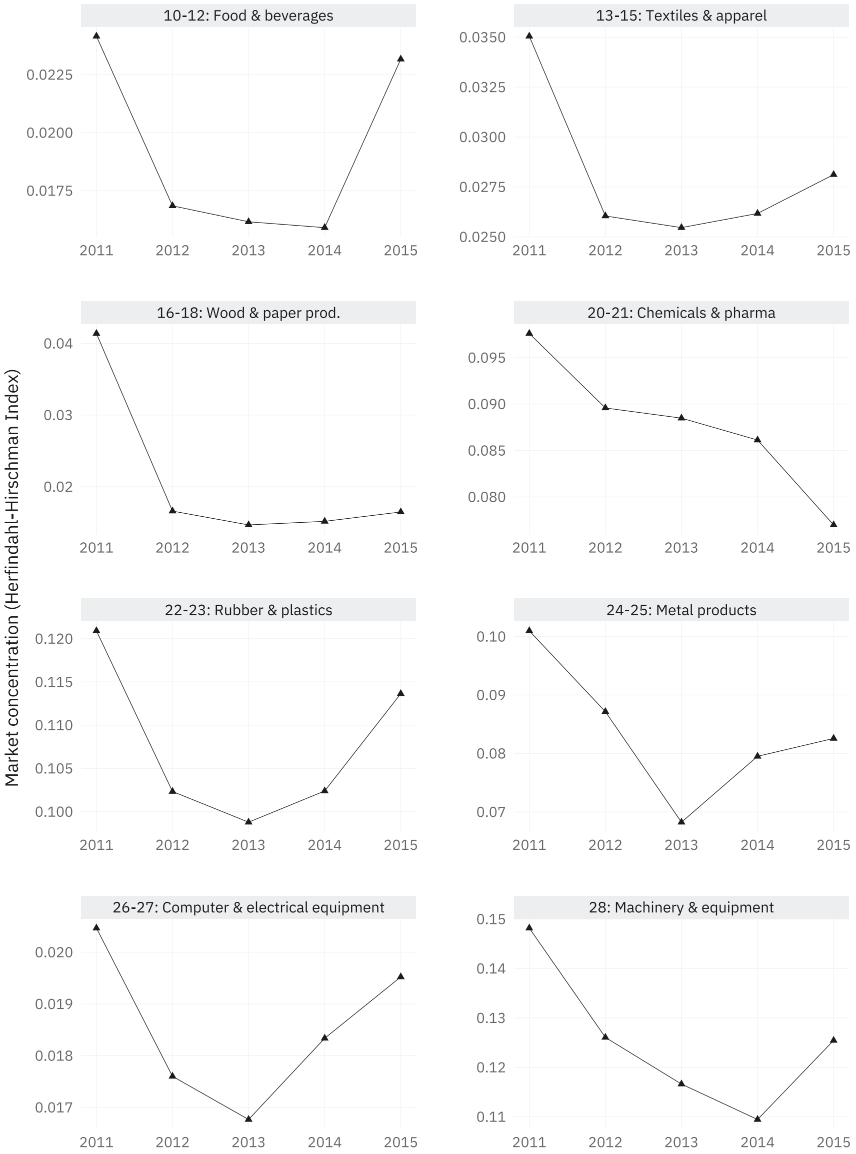


Figure 8A: Development of Orbis market concentration for NACE sector 10–28.
Source: own calculations; data: Orbis (2019).

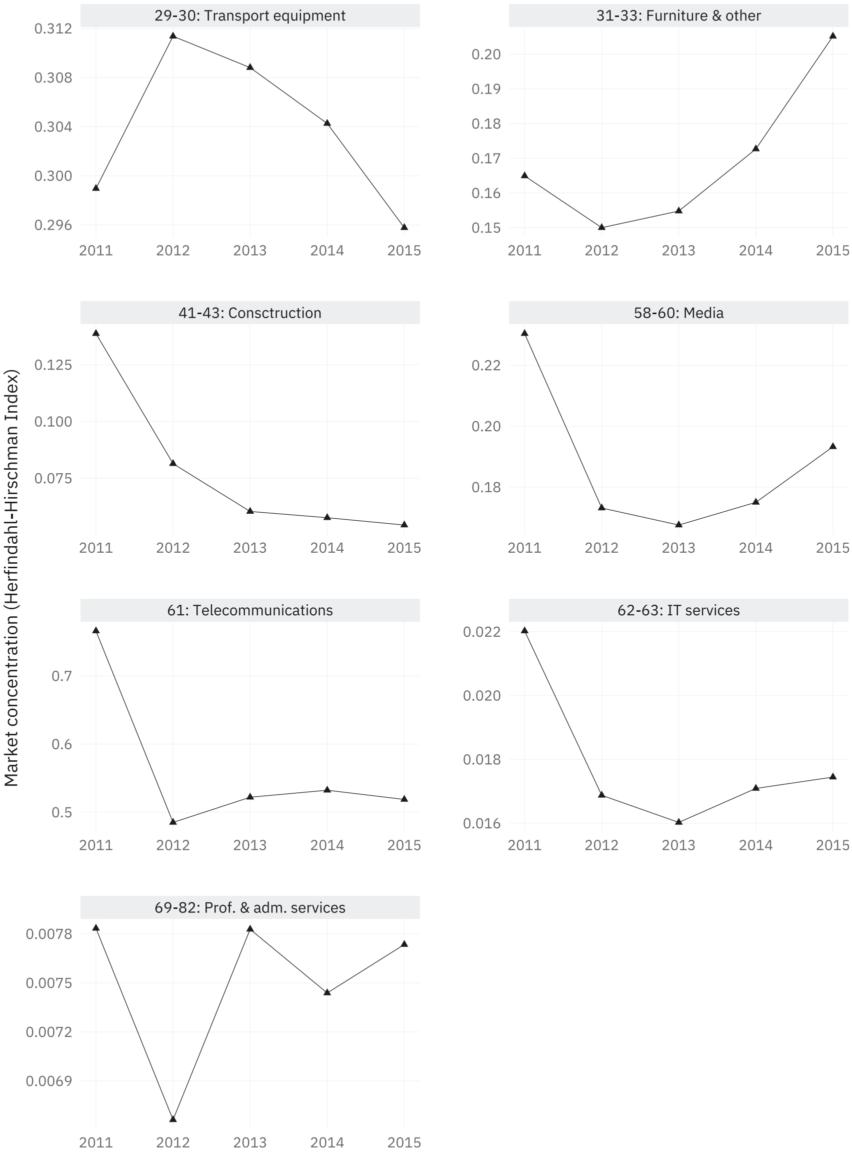


Figure 9A: Development of Orbis market concentration for NACE sector 29–82.
Source: own calculations; data: Orbis (2019).

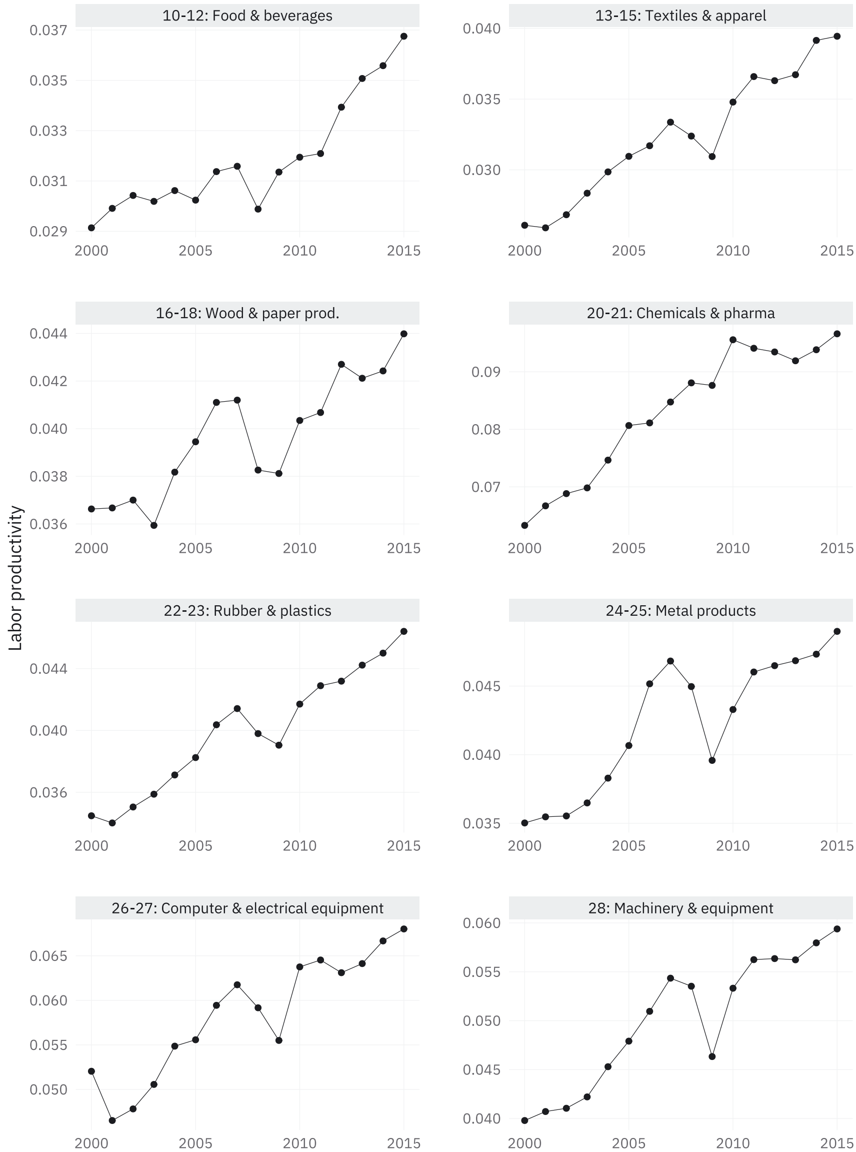


Figure 10A: Development of labor productivity for NACE sector 10–28.
Source: own calculations; data: EU KLEMS (2018).

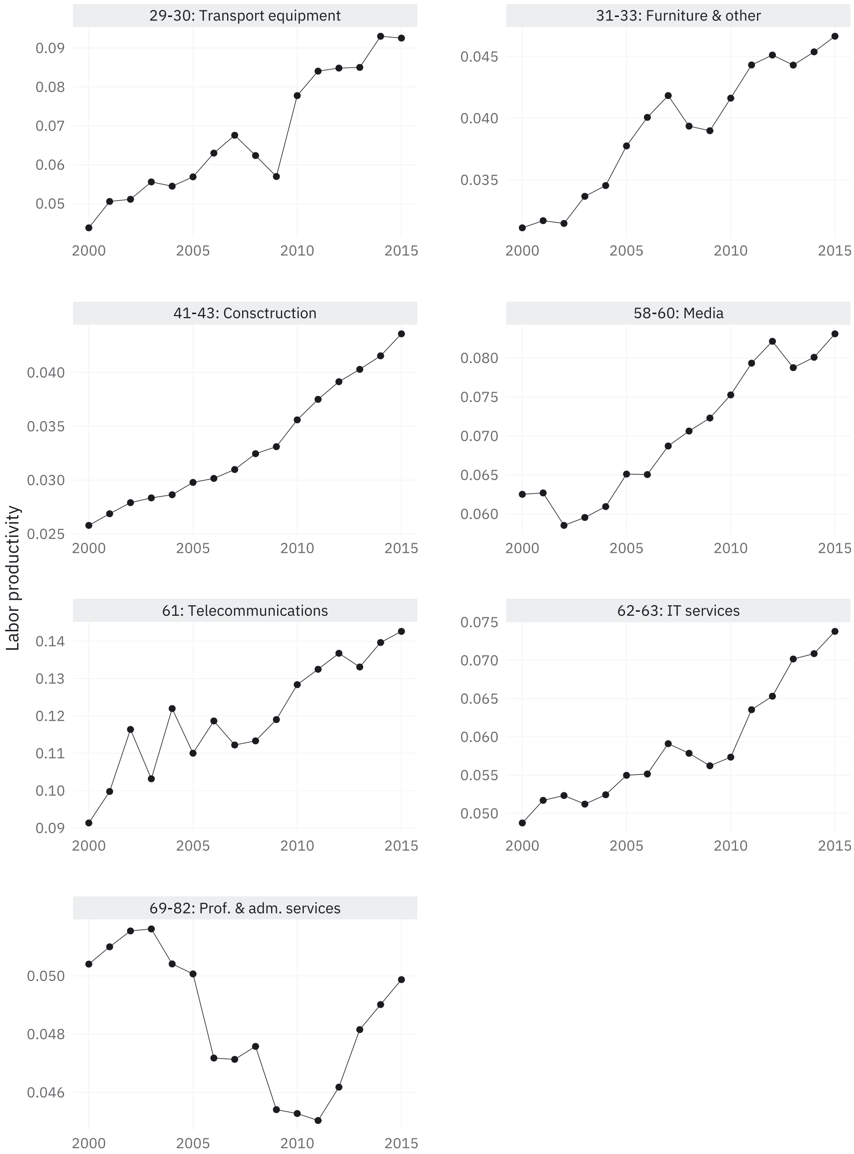


Figure 11A: Development of labor productivity for NACE sectors 29–82.
Source: own calculations; data: EU KLEMS (2018).

Table 5A: Market concentration and digital intensity 2013–2015 using Weche and Wambach (2018) data.

Sectors	NACE1	NACE2	Quartile of digital intensity 2013–2015	av.HHI	av.c6
Mining	B	05–09	Low	1348.0	61.5
Food and beverages	C	10–12	Low	953.6	63.0
Electricity and gas	D	35	Low	1228.4	68.7
Water and sewerage	E	36–39	Low	355.5	37.8
Construction	F	41–43	Low	59.8	24.2
Transportation and storage	H	49–53	Low	1931.7	61.9
Hotels and restaurants	G	55–56	Low	47.0	27.8
Real estate	L	68	Low	31.2	
Textiles and apparel	C	13–15	Medium–low	644.6	52.2
Coke and ref. petroleum	C	19	Medium–low	3776.7	89.1
Chemicals	C	20	Medium–low	1332.5	67.5
Pharmaceuticals	C	21	Medium–low	683.1	55.5
Rubber and plastics	C	22–23	Medium–low	1031.6	61.8
Metal products	C	24–25	Medium–low	623.6	53.7
Wood and paper prod.	C	16–18	Medium–high	545.3	48.1
Computer and electronics	C	26	Medium–high	1367.6	58.0
Electrical equipment	C	27	Medium–high	1287.1	61.0
Machinery and equipment	C	28	Medium–high	477.6	48.3
Furniture and other	C	31–33	Medium–high	392.6	43.6
Wholesale and retail	G	45–47	Medium–high	222.5	34.1
Media	J	58–60	Medium–high	458.8	51.3
Transport equipment	C	29–30	High	1809.8	72.8
Telecommunications	J	61	High	3071.4	86.3
IT services	J	62–63	High	366.2	35.6
Finance	K	64–66	High	621.1	56.1
Legal and accounting		69–71	High	79.0	21.7
Scientific R&D	M	72	High	216.3	32.0
Marketing and other	M	73–75	High	96.9	27.6
Administrative services		77–82	High	380.9	39.5

Source: own calculations; Data: Calvino et al. (2018), Orbis (2019), Weche and Wambach (2018).

Industry Samples Included in Regressions

Table 6A: Sample for regressions with EU KLEMS technology indicators, CompNet, and Orbis data.

Sector	NACE 1	NACE 2	Coverage	*N*
Food and beverages	C	10–12	2000–2015	16
Textiles and apparel	C	13–15	2000–2015	16
Wood and paper prod.	C	16–18	2000–2015	16
Chemicals and pharma	C	20–21	2000–2015	16
Rubber and plastics	C	22–23	2000–2015	16
Metal products	C	24–25	2000–2015	16
Computer, electrical and optical equipment	C	26–27	2000–2015	16
Machinery and equipment	C	28	2000–2015	16
Transport equipment	C	29–30	2000–2015	16
Furniture and other	C	31–33	2000–2015	16
Construction	F	41–43	2000–2015	16
Media	J	58–60	2000–2015	16
Telecommunications	J	61	2000–2015	16
IT	J	62–63	2000–2015	16
Professional, scientific, technical, administrative services	M-N	69–82	2000–2015	16
			Total *N*	*240*

Source: own calculations; Data: EU KLEMS (2018), CompNet (2019), Orbis (2019).

Table 7A: Sample for regressions with OECD taxonomy, CompNet, and Orbis data.

Sectors	NACE 1	NACE 2	Coverage	*N*
Agriculture	A	01–03	2011–2015	5
Mining	B	05–09	2011–2015	5
Food and beverages	C	10–12	2000–2015	16
Textiles and apparel	C	13–15	2000–2015	16
Wood and paper prod.	C	16–18	2000–2015	16
Coke and ref. petroleum	C	19	2011–2015	5
Rubber and plastics	C	22–23	2000–2015	16
Metal products	C	24–25	2000–2015	16
Machinery and equipment	C	28	2000–2015	16
Transport equipment	C	29–30	2000–2015	16
Furniture and other	C	31–33	2000–2015	16
Construction	F	41–43	2000–2015	16
Wholesale and retail	G	45–47	2000–2015	16
Transportation and storage	H	49–53	2000–2015	16
Hotels and restaurants	I	55–56	2000–2015	5
Media	J	58–60	2000–2015	16

Table 7A: (continued)

Sectors	NACE 1	NACE 2	Coverage	*N*
Telecommunications	J	61	2011–2015	16
IT	J	62–63	2000–2015	16
Finance	K	64–66	2011–2015	5
Real estate	L	68	2011–2015	5
			Total *N*:	*254*

Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), Orbis (2019).

Table 8A: Sample for regressions with Weche-data.

Sectors	NACE 1	NACE 2	Coverage	*N*
Mining	B	05–09	2007, 2009, 2011, 2013, 2015	5
Food and beverages	C	10–12	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Textiles and apparel	C	13–15	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Wood and paper prod.	C	16–18	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Coke and ref. petroleum	C	19	2007, 2009, 2011, 2013, 2015	5
Rubber and plastics	C	22–23	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Metal products	C	24–25	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Machinery and equipment	C	28	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Transport equipment	C	29–30	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Furniture and other	C	31–33	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Construction	F	41–43	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Wholesale and retail	G	45–47	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Transportation and storage	H	49–53	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Hotels and restaurants	I	55–56	2007, 2009, 2011, 2013, 2015	5
Media	J	58–60	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Telecommunications	J	61	2000–2006, 2007, 2009, 2011, 2013, 2015	12
IT	J	62–63	2000–2006, 2007, 2009, 2011, 2013, 2015	12
Finance	K	64–66	2000, 2009, 2011, 2013, 2015	5
Real estate	L	68	2000, 2009, 2011, 2013, 2015	5
			Total *N*:	*193*

Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), Orbis (2019), Weche and Wambach (2018).

Robustness Checks: Regression Results

Table 9A: Regression results with cumulated time lags.

	Dependent variable: labor productivity					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
HHI (*t* – 1)	0.037***					0.031***
	(0.008)					(0.010)
HHI (*t* – 2)	−0.002					−0.015
	(0.006)					(0.010)
HHI (*t* – 3)	0.007**					0.018**
	(0.003)					(0.008)
IT investment share (*t* – 1)		−0.024				0.080
		(0.128)				(0.111)
IT investment share (*t* – 2)		0.094				0.177
		(0.082)				(0.113)
IT investment share (*t* – 3)		0.011				−0.116
		(0.073)				(0.099)
Software investment share (*t* – 1)			0.037**			0.008
			(0.015)			(0.019)
Software investment share (*t* – 2)			0.054***			0.062**
			(0.010)			(0.026)
Software investment share (*t* – 3)			0.055***			0.036**
			(0.008)			(0.016)
CT investment share (*t* – 1)				−0.079*		−0.034
				(0.044)		(0.042)
CT investment share (*t* – 2)				−0.055**		−0.075***
				(0.023)		(0.028)
CT investment share (*t* – 3)				−0.061*		0.033
				(0.035)		(0.048)
R & D investment share (*t* – 1)					0.036***	0.002
					(0.011)	(0.011)
R & D investment share (*t* – 2)					0.008	0.022
					(0.016)	(0.019)
R & D investment share (*t* – 3)					0.043***	0.017
					(0.016)	(0.014)
Capital intensity	−0.006**	−0.004	−0.011***	−0.007*	−0.006**	−0.009**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Industry FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.:	195	195	195	195	195	195

Table 9A: (continued)

	Dependent variable: labor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
R-squared	0.27	0.053	0.205	0.133	0.091	0.432
Adj. *R*-squared	0.136	−0.12	0.06	−0.025	−0.075	0.275

FE-estimations with Driscoll and Kraay standard errors. Standard errors in parentheses. **p* < 0.1; ***p* < 0.05; ****p* < 0.01. Source: own calculations; Data: EU KLEMS (2018), CompNet (2019), Orbis (2019), sector sample as in Table 6A.

Table 10A: Regression results with digital intensity indicator as an explanatory variable: HHI from CompNet and Orbis.

	Dependent variable: labor productivity (log)			
	(1)	(2)	(3)	(4)
log(HHI)		0.116***		0.100***
		(0.015)		(0.017)
Digital intensity 2001–2003				
Q2 in 2001/03: Medium–low	0.370***	0.408***		
	(0.067)	(0.057)		
Q3 in 2001/03: Medium–high	0.415***	0.472***		
	(0.065)	(0.055)		
Q4 in 2001/03: High	0.794***	0.749***		
	(0.062)	(0.054)		
Digital intensity 2013–2015			0.381***	0.404***
Q2 in 2013/15: Medium–low			(0.062)	(0.058)
Wenn				
			0.460***	0.507***
Q3 in 2013/15: Medium–high			(0.057)	(0.054)
			0.894***	0.787***
Q4 in 2013/15: High			(0.061)	(0.060)
Capital intensity	0.187***	0.177***	0.176***	0.177***
	(0.011)	(0.009)	(0.010)	(0.009)
Constant	−3.714***	−3.549***	−3.952***	−3.603***
	(0.054)	(0.104)	(0.097)	(0.107)
Time FE	✓	✓	✓	✓
Obs.:	254	254	254	254
R-squared	0.616	0.741	0.695	0.736
Adj. *R*-squared	0.61	0.719	0.67	0.713

Reference category for digital intensity is the lowest quartile (Q1). Standard errors in parentheses. **p* < 0.1; ***p* < 0.05; ****p* < 0.01. Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), CompNet (2019), Orbis (2019), sector sample as in Table 7A.

Table 11A: Regression results with digital intensity indicator as an explanatory variable: HHI from CompNet and Weche and Wambach (2018).

	Dependent variable: labor productivity (log)			
	(1)	**(2)**	**(3)**	**(4)**
log(HHI)		0.099***		0.080***
		(0.019)		(0.020)
Digital intensity 2001–2003				
Q2 in 2001/03: Medium–low	0.393***	0.409***		
	(0.075)	(0.064)		
Q3 in 2001/03: Medium–high	0.414***	0.459***		
	(0.073)	(0.063)		
Q4 in 2001/03: High	0.770***	0.723***		
	(0.070)	(0.061)		
Digital intensity 2013–2015				
Q2 in 2013/15: Medium–low			0.403***	0.408***
			(0.067)	(0.064)
Q3 in 2013/15: Medium–high			0.456***	0.484***
			(0.062)	(0.060)
Q4 in 2013/15: High			0.864***	0.773***
			(0.066)	(0.068)
Capital intensity	0.206***	0.209***	0.198***	0.207***
	(0.011)	(0.010)	(0.010)	(0.010)
Constant	−3.753***	−3.640***	−3.978***	−3.703***
	(0.059)	(0.111)	(0.095)	(0.114)
Time FE	✓	✓	✓	✓
Obs.:	193	193	193	193
R-squared	0.686	0.783	0.763	0.783
Adj. *R*-squared	0.68	0.763	0.743	0.763

Reference category for digital intensity is the lowest quartile (Q1). Standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), CompNet (2019), Weche and Wambach (2018), sector sample as in Table 8A.

Table 12A: Regression results with digital intensity indicator as an explanatory variable and matched sector sample: HHI from CompNet and Orbis.

	Dependent Variable: Labor productivity (log)			
	(1)	**(2)**	**(3)**	**(4)**
log(HHI)		0.149***		0.119***
		(0.012)		(0.014)
Digital intensity 2001–2003				
Q2 in 2001/03: Medium–low	0.141**	0.161***		
	(0.058)	(0.041)		
Q3 in 2001/03: Medium–high	0.300***	0.281***		

Table 12A: (continued)

	Dependent Variable: Labor productivity (log)			
	(1)	**(2)**	**(3)**	**(4)**
	(0.056)	(0.039)		
Q4 in 2001/03: High	0.721***	0.620***		
	(0.052)	(0.038)		
Digital intensity 2013–2015				
Q2 in 2013/15: Medium–low			0.142***	0.157***
			(0.050)	(0.043)
Q3 in 2013/15: Medium–high			0.323***	0.333***
			(0.046)	(0.039)
Q4 in 2013/15: High			0.823***	0.679***
			(0.047)	(0.044)
Capital intensity	0.077***	−0.036	0.078***	−0.012
	(0.028)	(0.023)	(0.024)	(0.023)
Constant	−3.498***	−3.004***	−3.705***	−3.146***
	(0.061)	(0.090)	(0.081)	(0.096)
Time FE	✓	✓	✓	✓
Obs.:	224	224	224	224
R-squared	0.517	0.778	0.673	0.758
Adj. R-squared	0.508	0.756	0.642	0.735

Balanced sample including sectors C10-12, C13-15, C16-18, C22-23, C24-25, C28, C29-30, C31-33, F41-43, G45-47, H49-53, J58-60, J61, J62-63. Reference category for digital intensity is the lowest quartile (Q1). Standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), CompNet (2019), Weche and Wambach (2018).

Table 13A: Regression results with digital intensity indicator as an explanatory variable and matched sector sample: HHI from CompNet and Weche and Wambach (2018).

	Dependent Variable: Labor productivity (log)			
	(1)	**(2)**	**(3)**	**(4)**
log(HHI)		0.148***		0.108***
		(0.018)		(0.019)
Digital intensity 2001–2003				
Q2 in 2001/03: Medium–low	0.141**	0.109**		
	(0.058)	(0.047)		
Q3 in 2001/03: Medium–high	0.300***	0.253***		
	(0.056)	(0.045)		
Q4 in 2001/03: High	0.721***	0.612***		
	(0.052)	(0.044)		

Table 13A: (continued)

	Dependent Variable: Labor productivity (log)			
	(1)	**(2)**	**(3)**	**(4)**
Digital intensity 2013–2015				
Q2 in 2013/15: Medium–low			0.142***	0.115**
			(0.050)	(0.046)
Q3 in 2013/15: Medium–high			0.323***	0.301***
			(0.046)	(0.043)
Q4 in 2013/15: High			0.823***	0.704***
			(0.047)	(0.049)
Capital intensity	0.077***	−0.033	0.078***	−0.007
	(0.028)	(0.027)	(0.024)	(0.027)
Constant	−3.498***	−2.988***	−3.705***	−3.177***
	(0.061)	(0.117)	(0.081)	(0.119)
Time FE	✓	✓	✓	✓
Obs.:	224	224	224	224
R-squared	0.517	0.716	0.673	0.718
Adj. *R*-squared	0.508	0.688	0.642	0.69

Balanced sample including sectors C10-12, C13-15, C16-18, C22-23, C24-25, C28, C29-30, C31-33, F41-43, G45-47, H49-53, J58-60, J61, J62-63. Reference category for digital intensity is the lowest quartile (Q1). Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Source: own calculations; Data: EU KLEMS (2018), Calvino et al. (2018), CompNet (2019), Weche and Wambach (2018).

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Article Note: This article is part of the special issue "Market Power and Concentration and Developments: Evidence and Implications for Germany and Europe" published in the Journal of Economics and Statistics. Access to further articles of this special issue can be obtained at www.degruyter.com/jbnst.