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Labor-Saving Technological Change? Sectoral Evidence for Germany

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Abstract

This paper investigates the links between digitalization, market concentration, and 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 market concentration measures between 2000 to 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 sectoral and descriptive level. Using a time and sector fixed effects model, however, we find evidence for (3) a positive relationship of productivity to both market concentration and digitalization at the sectoral level in Germany. This finding is robust to alternative measures of digitalization and market concentration, but sensitive to the sector sample. We therefore cautiously conclude that recent technological change appears to have been labor-saving, and that productivity-enhancing "superstar firm" effects seem to exist in Germany.

1. Introduction

The German economy 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. rising (labor) productivity, the question how digitalization has affected productivity is at the heart of assessing the consequences of this most recent technological revolution. An empirical "productivity paradox" – that is, the stagnation of measured labor productivity over the past decades – has therefore garnered attention in the literature (Gordon, 2015, 2016; Brynjolfsson et al., 2019; OECD, 2019; Goldin et al., 2019/2020). At the same time, the relevant technologies are omnipresent and core industries face saturated markets when technological revolutions reach their mature stage, so stagnating profits may force companies to extend market shares through means such as mergers and acquisitions, leading to market concentration (Perez, 2010).

This paper thus investigates the nexus of digitalization, market concentration, and productivity at the sectoral level in Germany. 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 (Wiarda, 1999; Alexis, 2007; Racy et al., 2019). 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 United States (Weche and Wambach, 2018).

Concretely, we use data from EU KLEMS for digitalization and labor productivity, combine it with firm-level data from CompNet and Orbis for market concentration from 2000 to 2015, and estimate a fixed effects model of productivity with market concentration and digitalization. The results show a positive link between the level of digitalization and labor productivity for sectors, indicating the labor-saving character of digitalization. Moreover, we find a slightly more tenuous correlation between market concentration and productivity, cautiously suggesting the presence of productive superstar firms.

The rest of the paper is structured as follows. Section 2 reviews the theoretical hypotheses and the empirical literature on the digitalization, market concentration, and productivity nexus. Section 3 describes the data and provides summary statistics. Section 4 shows descriptive evidence on digitalization and market concentration, and Section 5 contains the multivariate estimations of the relationship between digitalization and market concentration with productivity. Section 6 checks the robustness of our results, and section 7 concludes.

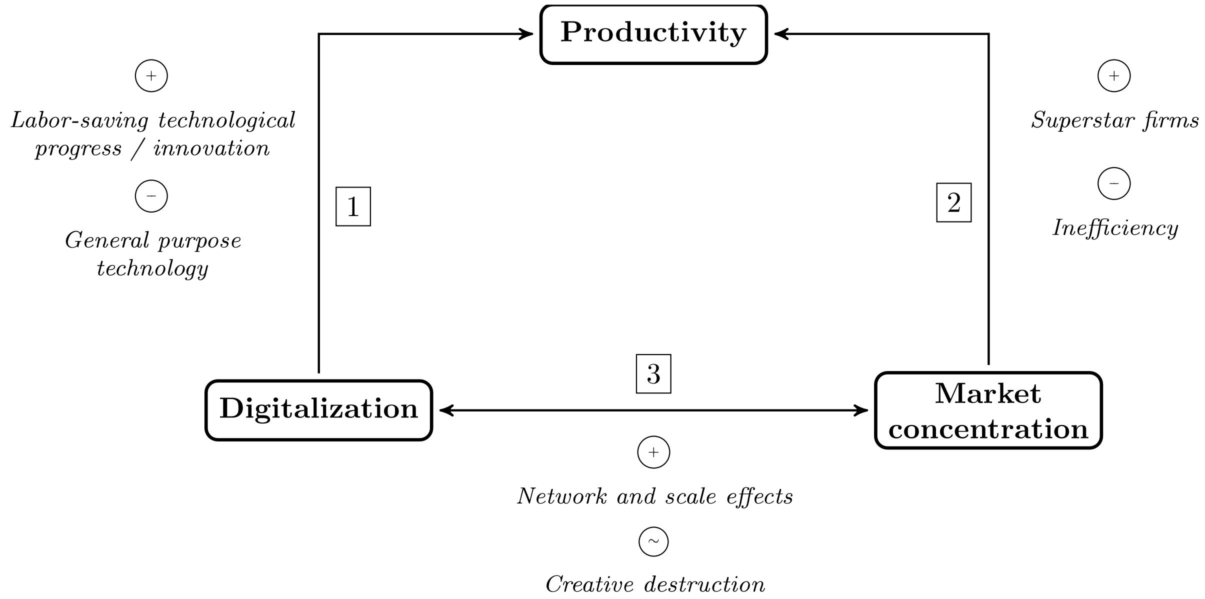
2. The digitalization-concentration-productivity nexus

Economic development can be characterized through historical phases of technological revolutions (Coleman, 1956; Landes, 1969; McCraw, 1998; Perez, 2010; Ab Rahman et al. 2017). 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” (Hislop et al. 2017; Beernaert und Fribourg-Blanc, 2017; Kiselbach und 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).

We are interested in how this new technological era of digitalization is linked to dynamics of market concentration, and how both in turn may affect (labor) productivity. Figure Figure *1* shows key contemporaneous causal relationships between digitalization, market concentration, and productivity based on theoretical considerations developed in the economic literature, which we discuss individually below.

First, digitalization is positively linked to productivity in most economic theories (edge (1) of Figure 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 (Romer, 1986; Rebelo, 1991), 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 efforts by companies, universities, and research facilities (Kemp et al., 2001). Theory thus suggests a positive link between digitalization (or technological change more generally) and productivity growth.

Figure 1: Directed acyclic graph of the digitalization, market concentration, and productivity nexus



Empirically, however, a slowdown in productivity growth in most industrial countries is evident in recent decades, despite the progress in digitalization (Gordon, 2015; 2016; Schmalensee, 2018; OECD, 2019). This new productivity paradox (Brynjolfsson et al. 2019; Goldin et al., 2019/2020) is well documented for digitalization and robotization, while empirical studies which find that digitalization and robotization increase labor productivity are the exception (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 (edge (1) of Figure Figure *1*). 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). Other issues like mismeasurement of productivity or sectoral change towards less productive services may have outweighed and thus masked productivity gains from digitalization in the manufacturing sector (Brynjolfsson et al., 2019).

Regarding the relationship between market concentration and labor productivity (edge (2) in Figure Figure *1*), standard microeconomic theory suggests a negative link. Noncompetitive 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 (Steindl, 1952; Baran and Sweezy, 1966). 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 (Summers, 2013; Stiglitz, 2014; Stiglitz, 2016). A focus on shareholder value may also reorient firms towards short term financial goals, away from long term investment in R&D and innovation (Spencer, 2017; Ferschli et al. 2019a; Ferschli et al. 2019b; Spencer and Slater, 2020). Such a slowdown in investment despite sustained profitability is also documented by the literature on financialization (Stockhammer, 2006; Orhangazi, 2008).

Alternatively, market concentration might be positively associated with productivity, as shown by edge (2) in Figure 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 efficiency 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 into innovation independently of the level of market concentration, since they are always under the threat of market capture by competitors (Shaikh, 2016).

The empirical literature documents rising market concentration in the United States 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), DeLoecker 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 manufacturing sectors (Ponattu et al., 2018).

Regarding the link between digitalization and market concentration (edge (3) in Figure Figure *1*), the literature is inconclusive whether the nexus is positive or negative (Øystein et al., 2018). One aspect is captured by the Schumpeterian notion of creative destruction (Schumpeter, 1987 [1942]). Innovation of entrepreneurs is driven by a self-motivated quest for technological superiority, rewarded by transient monopoly profits. According to Schumpeter, the major incentive to innovate is thus to escape competition and to obtain monopolistic power. However, new innovations recurrently disrupt the prevailing market order resulting in competition for monopoly. Startups in the digital economy fit the bill almost perfectly, with small, agile, and highly innovative firms developing new technologies and capturing shares of the digital market. Notably, Aghion et al. (2005) suggest a non-linear relationship and find an inverted U-shape link, where innovation is low at both the highest and lowest levels of competition, and high in between.

The recent competitive structure of mature digitalized markets indicates that large players tend to acquire small start-ups (Makridakis, 2017), providing one of several possible theoretical bases for a positive relationship between digitalization and market concentration. More importantly, network and scale effects play a key role in linking digitalization and market concentration (Allen, 2017; Krämer, 2018). Network effects occur when the value of a commodity increases with the number of users (Shapiro and Varian, 1999), which leads to the winner-take-all market structure of digital platforms such as search engines, social media or operating systems (Allen, 2017). These are driven by scale effects because marginal costs of software, databases, and patents are negligible (Furman and Seamans, 2019).

The empirical literature tends to find a positive link between digitalization and market concentration, especially for the United States (CEA, 2016). The largest technological firms have the highest revenues, in particular in relation to their employees (Rosoff, 2016). They thus have the highest margins and absolute profits (Chen, 2015), which may be mediated by risk premiums (Guellec and Paunov, 2017). In particular, rising market concentration is more prevalent in dynamic industries that exhibit faster technological progress in the United States (Autor et al., 2020). Stiebale et al. (2020) document a similar relationship for six European countries: already highly productive firms benefitted most from industrial robotization in terms of higher productivity and increased markups, a measure of market concentration. Finally, technological superstar firms have displayed an aggressive acquisition policy: Google, Apple Amazon and Facebook acquired more than 400 companies until 2016 (Makridakis, 2017).

3. Data

We empirically investigate these questions – how digitalization and market 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 market concentration for the time period 2000 to 2015. Labor productivity is calculated using EU KLEMS data as value added per hours worked[1] (Jäger 2018). To assess the degree of digitalization, we also use EU KLEMS data to measure three additive aspects of digitalization: (1) *technological intensity*, (2) *knowledge intensity*, and (3) *digital capital deepening*.

(1) Technological intensity is approximated by ICT investment as a share of non-residential 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 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 non-residential gross fixed capital formation – to capture the increasing relevance of intangible capital as digitalization progresses.
(2) Knowledge intensity is approximated by 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 the digital capital compared to

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

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 taxonomy of digital intensive sectors developed by Calvino et al. (2018) for cross-sectoral comparisons of digitalization. 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.

For 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 ten largest firms ("c10") and the Herfindahl-Hirschman index ("HHI")[2] 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 data for the 5,000 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 in 2011 with linear interpolation of missing observations. To avoid double counting, we consolidate parent and subsidiary companies.

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 show that German sectors on average are characterized by very low market 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, market concentration is low; again, some sectors with high concentration are the exception. Furthermore, concentration in the CompNet data is on average lower than market 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 ten 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 market 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.

[2] 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: $H := \sum_{i=1}^{N} \alpha_i^2$. The normalized HHI ranges from 0 to 1: $HHI\_n := {(H - 1/N)}\Big/{1 - 1/N}$ for $N > 1$ and $HHI\_n := 1$ for $N = 1$.

Table 1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	25th pctl	Median	75th pctl	Max
Summary statistics concentration measures (CompNet): 2000-2010								
c10	219	0.439	0.249	0.098	0.250	0.389	0.623	0.998
HHI_n	219	0.081	0.138	0.002	0.011	0.025	0.084	0.809
Summary statistics concentration measures (Orbis): 2011-2015								
HHI	145	1,409.7	2,063.7	66.6	168.8	792.2	1,525.2	9,770.3
HHI_n	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
Summary statistics EU KLEMS technology and labor productivity indicators: 2000-2015								
CT share	600	0.031	0.047	0.003	0.010	0.018	0.030	0.355
IT share	600	0.033	0.028	0.004	0.013	0.022	0.042	0.186
RD share	600	0.131	0.158	0.000	0.014	0.067	0.171	0.594
Soft share	600	0.072	0.073	0.003	0.025	0.048	0.094	0.432
Soft deep	540	0.002	0.003	0.000	0.0004	0.001	0.002	0.020
IT deep	540	0.001	0.001	0.000	0.0004	0.001	0.001	0.009
Lab.Prod.	540	0.067	0.093	0.012	0.036	0.045	0.062	0.673

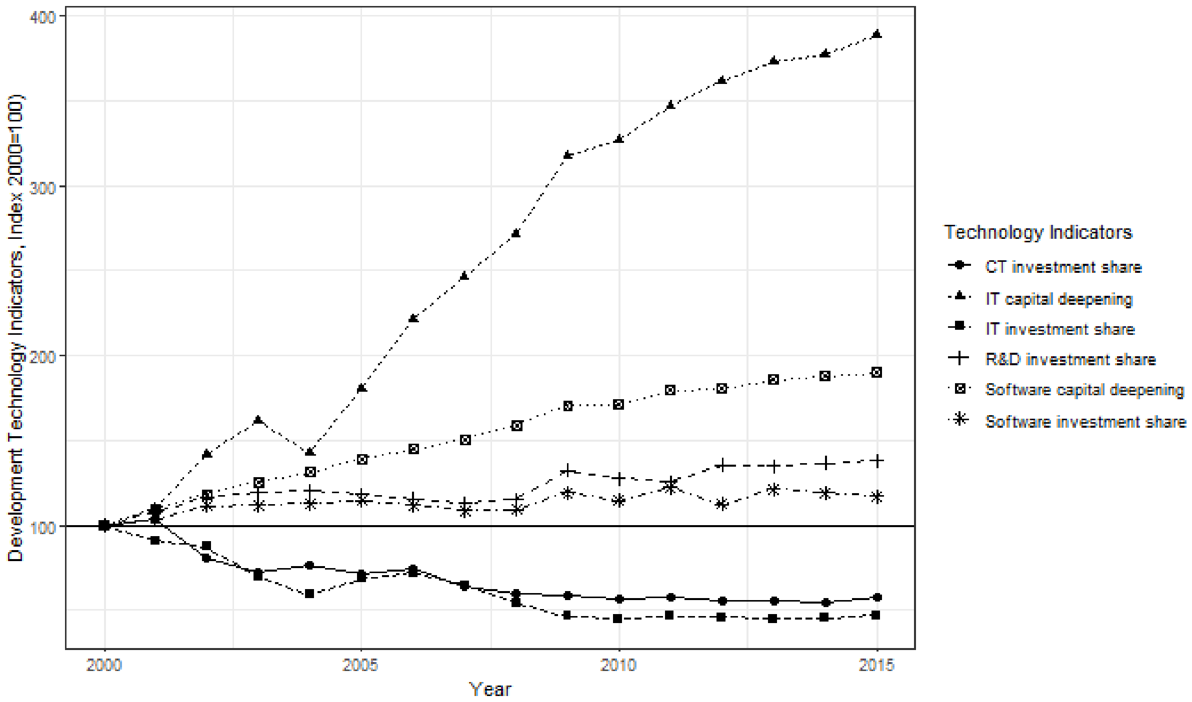
Note: This table shows summary statistics of yearly and sectoral data at the NACE for the revenue share of the 10 (3) largest firms per sector (c10/c3); the Herfindahl-Hirschman index (HHI); the share of information technology (“IT share”), communication technology (“CT share”), R&D investment (“RD share”), and software and databases (“Soft share”), all measured as a share of non-residential 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; and labor productivity (“Lab. Prod.”), value added per hours worked by employees.

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

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, digital capital deepening (that is, the stock variables of software and IT deepening), but also knowledge intensity (the R&D 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 longevity of equipment, or saturation in the technical infrastructure. Figure Figure *3*A in the Appendix differentiates 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.

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 grey scale 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 grey), between 1,000 and 2,000 corresponds to medium concentration (medium grey), and values greater than 2,000 signal highly concentrated markets (dark grey). The thresholds for concentration ratios are set to a c3 above 0.7 indicating a highly concentrated market (dark grey), and a c3 below 0.45 showing low concentration (light grey). Finally, for c10, we use the thresholds of 0.5 and 0.9.

Table *2* shows that there is no clear-cut relationship between digitalization and concentration. The majority of sectors are competitive with HHI values below 1,000, and there is no particularly clear association of market concentration with any one of the four categories of digital intensity. Four sectors are highly concentrated with HHI values greater than 2,000: 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) category. Finally, six out of nine digital intensive sectors have a low concentration index with HHI values below 1,000.

Table 2: Concentration measures by digital intensity of sectors (2013-2015)

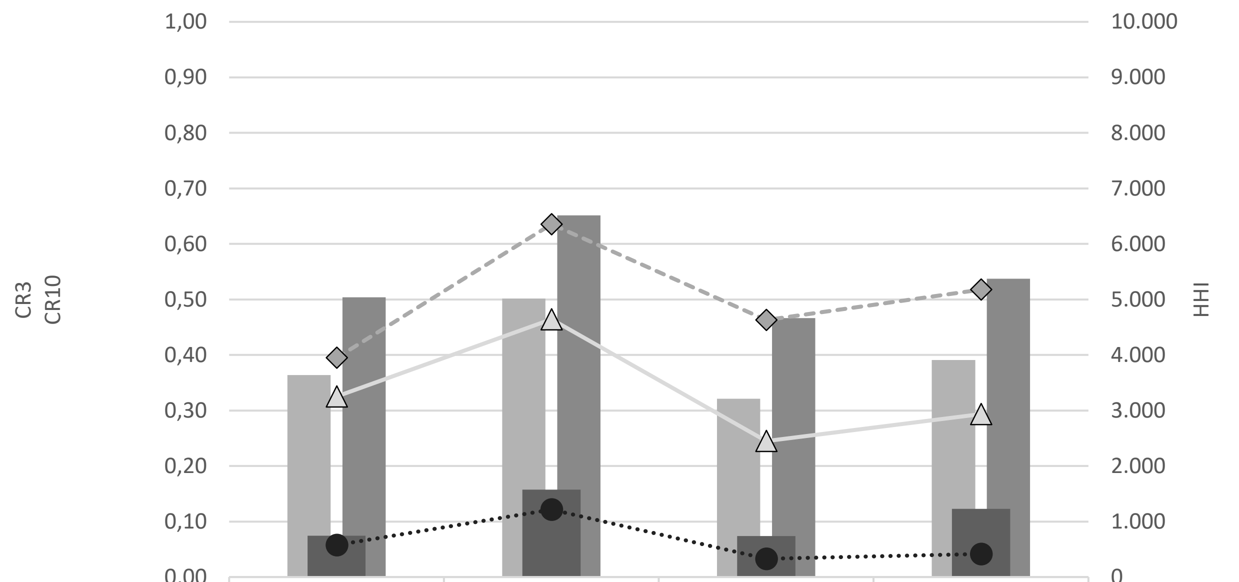
Sectors	NACE 1	NACE2	Quartile of digital intensity 2013-15	av.HHI	av.c3	av.c10
Agriculture	A	01-03	Low	834.19	0.46	0.58
Mining	B	05-09	Low	2116.50	0.71	0.88
Food & beverages	C	10-12	Low	184.13	0.17	0.34
Electricity & gas	D	35	Low	1443.51	0.58	0.81
Water & sewerage	E	36-39	Low	226.45	0.21	0.39
Construction	F	41-43	Low	574.56	0.32	0.39
Transportation & storage	H	49-53	Low	1099.79	0.55	0.68
Hotels & restaurants	I	55-56	Low	82.51	0.12	0.22
Real estate	L	68	Low	152.25	0.15	0.25
Textiles & apparel	C	13-15	Medium-low	265.85	0.22	0.36
Coke & 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 & 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 & paper prod.	C	16-18	Medium-high	154.36	0.18	0.30
Computer & 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 & other	C	31-33	Medium-high	1775.51	0.49	0.58
Wholesale & 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 & 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 & accounting	M	69-71	High	106.58	0.12	0.26
Scientific R&D	M	72	High	416.40	0.29	0.52
Marketing & 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 market concentration when comparing the (unweighted) means and medians of concentration measures by relative digital intensity of industries. Figure 2 presents the mean and median market 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 market concentration.

In conclusion, based on the cross-sectoral descriptive analysis, we cannot identify a clear-cut relationship between digital intensity and market concentration. However, the data indicate that there are large variations in terms of market 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 market concentration, and other sectors that are marked by high digital intensity. However, these two characteristics do not necessarily coincide in the same sectors.

Figure 2: Mean and median of concentration by digital intensity of sectors (2013-2015)



	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

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 between labor productivity, market concentration and digitalization over time. As discussed in the literature review, theoretical explanations as well as the empirical evidence for both the productivity-concentration nexus and the impact of digitalization on productivity is ambiguous. 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 market concentration and digitalization on labor productivity in Germany, we use a panel over 15 years and 16 sectors, covering those sectors for which we have complete time series data for our variables of interest.[3] Concretely, 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:

$$LP_{it} = \alpha_i + \beta_1 HHI_{it} + \beta_2 IT_{it} + \beta_3 SOFT_{it} + \beta_4 CT_{it} + \beta_5 RD_{it} + v_t + u_i + \epsilon_{it}, \quad (1)$$

where the dependent variable is labor productivity (LP_{it}) for each time period t and sector i, calculated as value added per hours worked. As explanatory variables, we use the normalized Herfindahl-Hirschmann Index (HHI_{it}) to measure market concentration, the three digitalization indicators (IT_{it}, $SOFT_{it}$ and CT_{it}), and RD_{it} for knowledge intensity.[4]

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

$$\widetilde{LP}_{it} = \beta_1 \widetilde{HHI}_{it} + \beta_2 \widetilde{IT}_{it} + \beta_3 \widetilde{SOFT}_{it} + \beta_4 \widetilde{CT}_{it} + \beta_5 \widetilde{RD}_{it} + \theta_{it}, \quad (2)$$

Where all variables x are adjusted for the mean of each sector over time, and for the mean of all sectors over time, $\tilde{x}_{it} = x_{it} - \bar{x}_i - \bar{x}_t$. The estimated model now only 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.[5]

Table 3 shows the regression results for six specifications with labor productivity as the dependent variable. Column (1) regresses the standardized HHI on labor productivity, and columns (2) to (5) regress each of the digitalization indicators individually on labor productivity. While the standardized HHI is statistically significant at the 1%-level, the digitalization indicators are statistically significant at the 10%-level, except for the R&D investment share. Column (1) shows a positive correlation between higher market concentration and labor productivity, while the results displayed in columns (2) to (4) show that the effects of IT and software investment shares are positive and the effect of the CT investment share is negative. However, in the full model presented in column (6), the statistical significance of the IT investment share and the software investment share increases while CT turns statistically insignificant.

The effect of the HHI is therefore robust with respect to the inclusion of all technology indicators. This suggests that higher market concentration correlates positively with labor productivity in our data when we control for digitalization. Since most of the sectors in our data are characterized by competitive market structures, this result could be interpreted as a possible “superstar firm” effect. This finding is in line with recent research on concentration in Europe (CompNet, 2020) and Germany (Ponattu et al. 2018). Since our results also show that the digitalization indices (IT intensity and

[3] For a list of sectors, see the Appendix.

[4] We do not include the digital capital intensity variables as they are calculated relative to total hours worked, which would lead to multicollinearity problems with our dependent variable.

[5] All calculations were conducted in R using the *plm* and *lmtest* package for the regressions and regression diagnostics. The standard error correction proposed by Driscoll and Kraay (1998) is implemented in the *plm*-package.

software intensity) are positively correlated with labor productivity, the results from the estimated full model also indicates support for the hypothesis that digitalization is leading to labor-saving technological innovations in Germany.

Table 3: Regression results

	Dependent Variable: Labor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	0.042***					0.030***
	(0.012)					(0.006)
IT investment share		0.160*				0.162***
		(0.089)				(0.044)
Software investment share			0.049*			0.058**
			(0.025)			(0.023)
CT investment share				-0.044*		-0.016
				(0.026)		(0.032)
R&D investment share					0.029	0.021
					(0.031)	(0.017)
Industry FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs.:	240	240	240	240	240	240
R-squared	0.203	0.074	0.029	0.009	0.011	0.267
Adj. R-squared	0.089	-0.059	-0.11	-0.133	-0.131	0.146

Note: 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).

6. Robustness checks

As robustness checks, we re-estimate the relationship between labor productivity, digitalization, and market concentration using alternative measures for digitalization and for market concentration, namely the OECD digital intensity taxonomy proposed by Calvino et al. (2018), and concentration data used in Weche and Wambach (2018), respectively.

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 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 Table Table 4A in the Appendix). 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:

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

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 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 Table 8A in the Appendix): for sectors with high digital intensity (and only those), digitalization is associated with higher labor productivity in both periods. Furthermore, there is a positive, albeit weaker, relationship between higher market concentration and labor productivity. The coefficients for digital intensity are robust to the inclusion of market concentration; in addition, when controlling for market concentration medium-high digitally intensive sectors are also statistically significantly related to labor productivity at the 10% 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 2-digit NACE level.[6] 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.[7] Our findings are robust – high digital intensity and market 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 Table Table *10*A and Table *11*A in the Appendix.[8] However, with an unbalanced panel only high digital intensity remains statistically significant, while market concentration does not (Table 9a in the Appendix). This leads us to cautiously conclude that our results are robust with respect to using different digitalization indicators and with respect to using concentration measures from different databases; however, the link between market concentration and productivity may be sensitive to industry selection.

7. Conclusion

This paper investigates the links between digitalization, market concentration, and labor productivity at the sectoral level in Germany. Using data from EU KLEMS for digitalization and labor productivity, as well as combining firm-level data from CompNet and Orbis for market concentration from 2000 to 2015, we estimate a fixed effects model of productivity with market concentration and digitalization.

We find evidence of digitalization for the German economy as a whole, especially 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, the descriptive evidence for a link between digitalization and market concentration is inconclusive at the sector level. Neither distributional analysis using a heat map nor aggregating over digital intensity yield a clear-cut relationship between our digitalization indices and market concentration, as measured by the Herfindahl-Hirschman index and the concentration ratios c3 and

[6] We use the median value to reduce the influence of outliers.

[7] The sector samples for these robustness checks are listed in Tables 5A to 7A in the Appendix.

[8] 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.

c10. The German economy contains both highly concentrated and highly digitalized sectors, but these two characteristics do not necessarily coincide in the same sectors.

Third, we estimate a fixed effects model explaining labor productivity with the HHI and our digitalization indices capturing technological and knowledge intensity. In our full specification, we find a positive link between both market concentration and technological intensity with productivity. These results are robust to alternative specifications as well as using alternative measures of digitalization and market concentration, specifically our results are reproducible with the OECD digital intensity taxonomy proposed by Calvino et al. (2018) and market concentration measures for German sectors based on Weche and Wambach (2018). However, one specification using an unbalanced panel cautions against an overconfident interpretation of our multivariate finding for the positive link between market concentration and productivity, since it may be sensitive to industry selection.

In summary, we show for Germany at the sector level that digitalization is positively related to labor productivity and that higher market concentration may be, too. This suggests that (a) recent technological change has likely been labor-saving, and (b) that positive superstar firm effects potentially exist in Germany.

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 of vocational training is as crucial as harnessing social security systems in order to deal with the foreseeable differential unemployment impacts of digitalization.

Concerning market concentration, rising market power entails unfavorable consequences for the economic order as competition is fundamental for the market economy. Less competition might increase income inequalities and macroeconomic vulnerability (Weche and Wambach, 2018). In addition, market power is often associated with political power which could reinforce the negative effects of high market concentration. Thus, policy makers 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 concentration at the firm level might yield additional insights into monopolization over time in Germany. Delving more deeply into individual sectors, 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. Finally, internationally comparable data could provide valuable insights in country-specific developments of digitalization and market concentration. While the United States often rank as case study for highly concentrated digital markets, our findings for Germany show a similar but attenuated trend. Thus, detailed cross-country studies could shed light on the different degrees of these processes and put our results in an international perspective.

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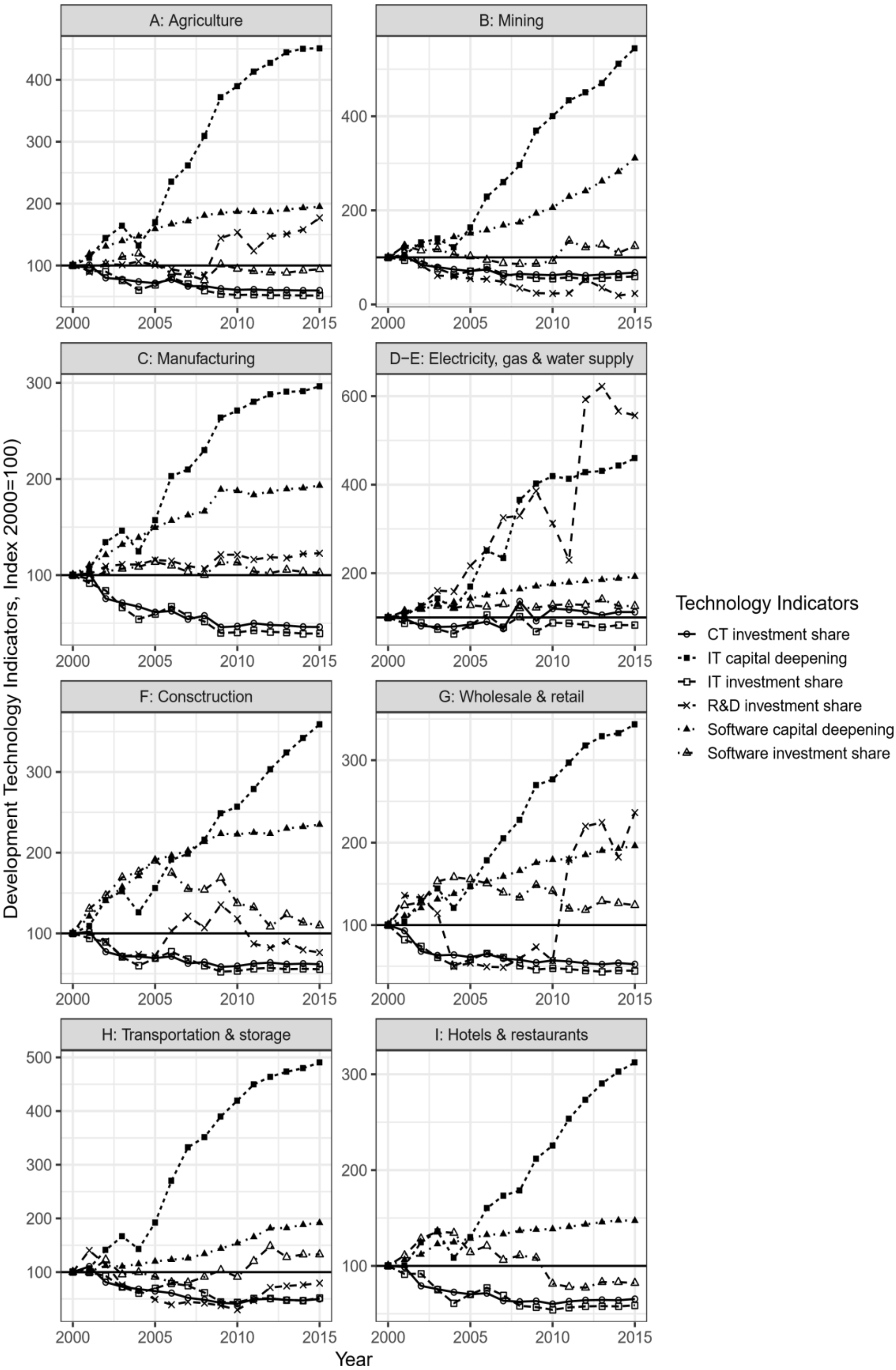
9. Appendix

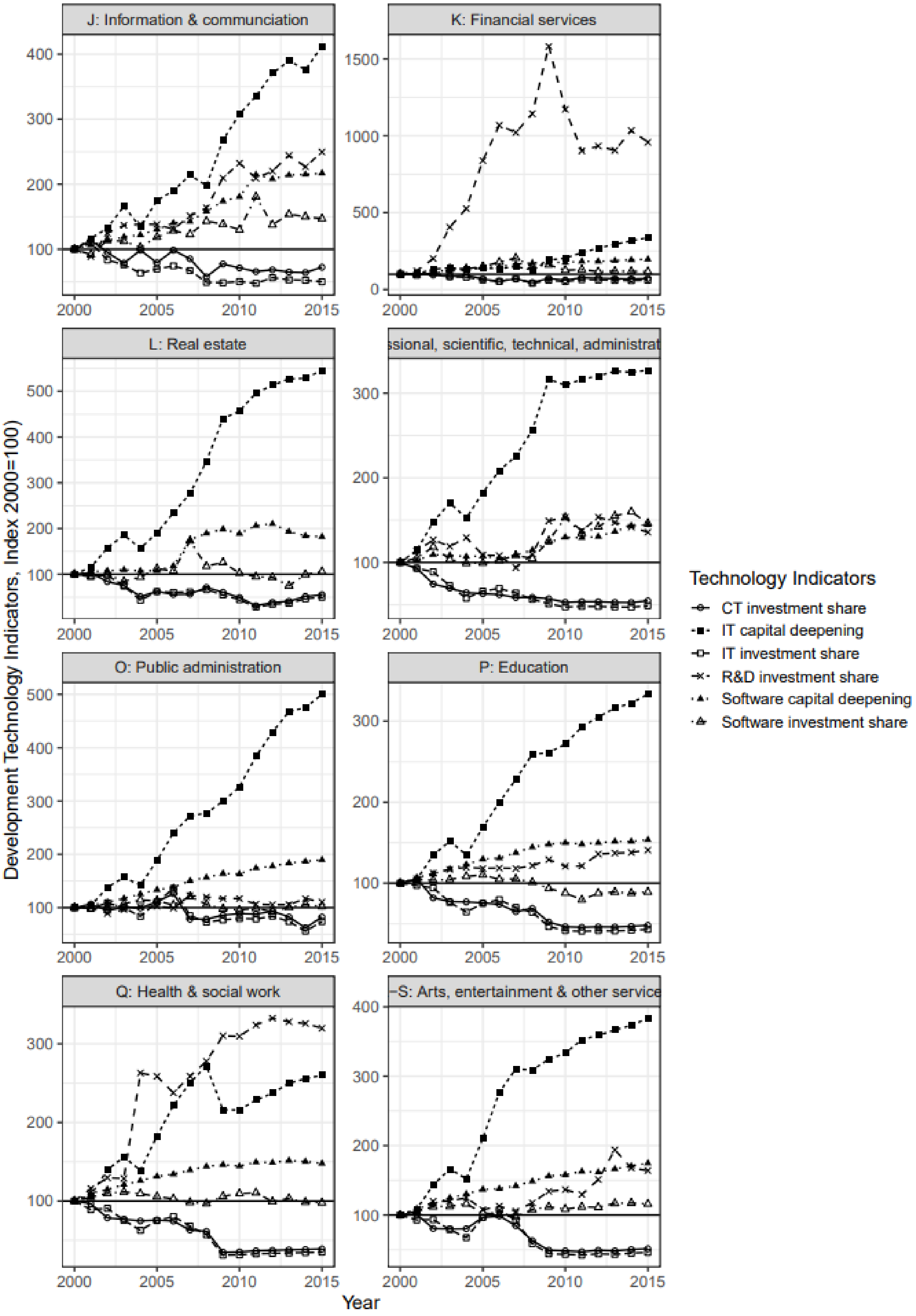
9.1 Technology indicators at 1-digit NACE level

Figure 3A: Development of technology indicators for sectors A to I



Source: own calculations; Data: EU KLEMS (2018).

Figure 4A Development of technology indicators for sectors J to S



Source: own calculations; Data: EU KLEMS (2018).

Table 4A: Market concentration and digital intensity 2013-2015 using Weche and Wambach (2018) data

Sectors	NACE1	NACE2	Quartile of digital intensity 2013-15	av.HHI	av.c6
Mining	B	05-09	Low	1348.0	61.5
Food & beverages	C	10-12	Low	953.6	63.0
Electricity & gas	D	35	Low	1228.4	68.7
Water & sewerage	E	36-39	Low	355.5	37.8
Construction	F	41-43	Low	59.8	24.2
Transportation & storage	H	49-53	Low	1931.7	61.9
Hotels & restaurants	G	55-56	Low	47.0	27.8
Real estate	L	68	Low	31.2	
Textiles & apparel	C	13-15	Medium-low	644.6	52.2
Coke & 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 & plastics	C	22-23	Medium-low	1031.6	61.8
Metal products	C	24-25	Medium-low	623.6	53.7
Wood & paper prod.	C	16-18	Medium-high	545.3	48.1
Computer & 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 & other	C	31-33	Medium-high	392.6	43.6
Wholesale & 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 & accounting		69-71	High	79.0	21.7
Scientific R&D	M	72	High	216.3	32.0
Marketing & 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).

9.2 Industry samples included in regressions

Table 5A: Sample for regressions with EU KLEMS technology indicators, CompNet and Orbis data

Sector	NACE 1	NACE 2	Coverage	N
Food & beverages	C	10-12	2000-2015	16
Textiles & apparel	C	13-15	2000-2015	16
Wood & paper prod.	C	16-18	2000-2015	16
Chemicals & pharma	C	20-21	2000-2015	16
Rubber & plastics	C	22-23	2000-2015	16
Metal products	C	24-25	2000-2015	16
Computer, electrical & 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 & 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 6A: 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 & beverages	C	10-12	2000-2015	16
Textiles & apparel	C	13-15	2000-2015	16
Wood & paper prod.	C	16-18	2000-2015	16
Coke & ref. petroleum	C	19	2011-2015	5
Rubber & 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 & other	C	31-33	2000-2015	16
Construction	F	41-43	2000-2015	16
Wholesale & retail	G	45-47	2000-2015	16
Transportation & storage	H	49-53	2000-2015	16
Hotels & restaurants	I	55-56	2000-2015	5
Media	J	58-60	2000-2015	16
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 7A: Sample for regressions with Weche-Data

Sectors	**NACE 1**	**NACE 2**	**Coverage**	**N**
Mining	B	05-09	2007, 2009, 2011, 2013, 2015	5
Food & beverages	C	10-12	2000-2006, 2007, 2009, 2011, 2013, 2015	12
Textiles & apparel	C	13-15	2000-2006, 2007, 2009, 2011, 2013, 2015	12
Wood & paper prod.	C	16-18	2000-2006, 2007, 2009, 2011, 2013, 2015	12
Coke & ref. petroleum	C	19	2007, 2009, 2011, 2013, 2015	5
Rubber & 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 & 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 & retail	G	45-47	2000-2006, 2007, 2009, 2011, 2013, 2015	12
Transportation & storage	H	49-53	2000-2006, 2007, 2009, 2011, 2013, 2015	12
Hotels & 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).

9.3 Robustness checks: Regression results

Table 8A: Regression results with digital intensity indicator as explanatory variable: HHI from CompNet and Orbis

	Dependent Variable: Labor productivity (log)			
	(1)	(2)	(3)	(4)
log(HHI)		0.118***		0.096***
		(0.025)		(0.027)
Digital intensity 2001-2003				
Q2 in 2001/03: Medium-Low	-0.019	0.059		
	(0.095)	(0.088)		
Q3 in 2001/03: Medium-High	-0.002	0.105		
	(0.091)	(0.084)		
Q4 in 2001/03: High	0.454***	0.447***		
	(0.089)	(0.083)		
Digital intensity 2013-2015				
Q2 in 2013/15: Medium-Low			0.033	0.054
			(0.090)	(0.088)
Q3 in 2013/15: Medium-High			0.098	0.142*
			(0.082)	(0.080)
Q4 in 2013/15: High			0.606***	0.502***
			(0.090)	(0.092)
Constant	-3.124***	-3.039***	-3.450***	-3.112***
	(0.063)	(0.163)	(0.142)	(0.167)
Time FE	✓	✓	✓	✓
Obs.:	254	254	254	254
R-squared	0.136	0.325	0.283	0.321
Adj. R-squared	0.126	0.27	0.228	0.266

Note: 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).

Table 9A: Regression results with digital intensity indicator as explanatory variable: HHI from CompNet and Weche and Wambach (2018)

	Dependent Variable: Labour productivity (log)			
	(1)	(2)	(3)	(4)
log(HHI)		0.020		-0.017
		(0.035)		(0.037)
Digital intensity 2001-2003				
Q2 in 2001/03: Medium-Low	-0.018	0.016		
	(0.121)	(0.117)		
Q3 in 2001/03: Medium-High	-0.044	0.020		
	(0.116)	(0.113)		
Q4 in 2001/03: High	0.402***	0.429***		
	(0.113)	(0.113)		
Digital intensity 2013-2015				
Q2 in 2013/15: Medium-Low			0.019	0.022
			(0.115)	(0.116)
Q3 in 2013/15: Medium-High			0.042	0.040
			(0.105)	(0.106)
Q4 in 2013/15: High			0.537***	0.559***
			(0.115)	(0.125)
Constant	-3.106***	-3.339***	-3.413***	-3.475***
	(0.081)	(0.210)	(0.163)	(0.214)
Time FE	✓	✓	✓	✓
Obs.:	193	193	193	193
R-squared	0.1	0.21	0.229	0.229
Adj. R-squared	0.085	0.143	0.168	0.164
Notes:	***Significant at the 1 percent level.			
	**Significant at the 5 percent level.			
	*Significant at the 10 percent level.			

Note: 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 10A: Regression results with digital intensity indicator as explanatory variable and matched sector sample: HHI from CompNet and Orbis

	Dependent Variable: Labor productivity (log)			
	(1)	(2)	(3)	(4)
log(HHI)		0.140***		0.116***
		(0.011)		(0.013)
Digital intensity 2001-2003				
Q2 in 2001/03: Medium-Low	0.090	0.179***		
	(0.056)	(0.040)		
Q3 in 2001/03: Medium-High	0.241***	0.304***		
	(0.052)	(0.037)		
Q4 in 2001/03: High	0.693***	0.636***		
	(0.052)	(0.037)		
Digital intensity 2013-2015				
Q2 in 2013/15: Medium-Low			0.090*	0.163***
			(0.048)	(0.041)
Q3 in 2013/15: Medium-High			0.266***	0.340***
			(0.043)	(0.037)
Q4 in 2013/15: High			0.803***	0.686***
			(0.048)	(0.042)
Constant	-3.367***	-3.098***	-3.565***	-3.179***
	(0.039)	(0.067)	(0.070)	(0.072)
Time FE	✓	✓	✓	✓
Obs.:	224	224	224	224
R-squared	0.501	0.775	0.656	0.758
Adj. R-squared	0.494	0.754	0.626	0.736

Note: 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 11A: Regression results with digital intensity indicator as 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)		0.136***		0.105***
		(0.015)		(0.016)
Digital intensity 2001-2003				
Q2 in 2001/03: Medium-Low	0.090	0.127***		
	(0.056)	(0.044)		
Q3 in 2001/03: Medium-High	0.241***	0.276***		
	(0.052)	(0.041)		
Q4 in 2001/03: High	0.693***	0.630***		
	(0.052)	(0.042)		
Digital intensity 2013-2015				
Q2 in 2013/15: Medium-Low			0.090*	0.119***
			(0.048)	(0.044)
Q3 in 2013/15: Medium-High			0.266***	0.305***
			(0.043)	(0.039)
Q4 in 2013/15: High			0.803***	0.708***
			(0.048)	(0.046)
Constant	-3.367***	-3.090***	-3.565***	-3.198***
	(0.039)	(0.082)	(0.070)	(0.084)
Time FE	✓	✓	✓	✓
Obs.:	224	224	224	224
R-squared	0.501	0.714	0.656	0.718
Adj. R-squared	0.494	0.687	0.626	0.692

Note: 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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