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DISCUSSION PAPER

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Unleashing Productivity Growth in the Age of Digitalisation – Evidence From German SMEs

Unleashing Productivity Growth in the Age of Digitalisation - Evidence from German SMEs*

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Abstract

Recent literature has increasingly focused on deciphering the modern *productivity puzzle*, with particular attention given to the link between digital technologies and firm-level productivity. So far, much of this research has primarily focused on large and publicly listed firms. Leveraging a panel dataset covering German small- and medium-sized enterprises (SMEs) over the period 2016 to 2021, we investigate whether digitalisation can help revive the sluggish productivity growth and narrow the gap between productivity frontrunners and laggards. We measure digitalisation through firms' digital capital stocks (DK) that we derive from a broad measure of digitalisation expenditures. Building on an augmented Cobb-Douglas production function, we examine the relationship between DK and labour productivity (LP). Our findings show that higher DK is positively associated with higher LP levels, with the effect being even stronger for firms that are already more digitally advanced. Moreover, higher digitalisation expenditures appear to be related to narrowing the productivity gap between laggards and the frontier.

Keywords: Heterogeneity of Digitalisation, Productivity, Firm-level Data

JEL Classification: L25, O14, O33

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1 Introduction

Digital technologies are widely recognised as General Purpose Technologies (GPT), characterised by dynamic technological development and broad applicability across industries (Anderton et al., 2020). Moreover, GPTs are widely expected to foster innovation and increase productivity (Bresnahan, 2010; Bresnahan and Trajtenberg, 1995). Yet, despite the increasing diffusion and transformative potential of digital technologies, aggregate productivity growth has slowed down in most industrialised countries over the recent decades (van Ark and Pilat, 2024). This trend, however, masks significant heterogeneity of firm-level productivity within industries. Andrews et al. (2019) document a growing divide between the most productive firms, referred to as the productivity frontier, as opposed to all other firms. This divergence appears to be driven by a decreasing catch-up dynamic among non-frontier firms[1] and less market selection below the frontier, further amplifying the productivity gap (Andrews et al., 2019; Mattsson and Reshid, 2023). As past research primarily focused on large or publicly listed firms (see Brynjolfsson and Hitt, 2003; Eller et al., 2020; Wu et al., 2019a), research on the progress of digitalisation among small- and medium-sized enterprises (SMEs) (Bouncken et al., 2025) and the corresponding implications for their productivity development remains scarce – despite the fact that SMEs account for 99 percent[2] of all European enterprises. This highlights a lack of evidence on the interdependence of SMEs' digitalisation activities and performance metrics such as productivity to derive sound recommendations for managers and policy makers alike.

This paper provides empirical evidence on the link between digitalisation and both productivity and the productivity gap (i.a. Anderton et al., 2023), with a specific focus on SMEs in Germany. It investigates the extent to which digitalisation can serve not only as a remedy to spur productivity growth but also as a means for low-performing firms to catch up with the productivity frontier. Using data on firms belonging to the "German Mittelstand"[3], we shed light on the implications of digitalisation for micro, small- and medium-sized companies that account for the vast majority of firms in Germany. In particular, we use the KfW[4] SME Panel covering the years 2016 to 2021 to investigate the link between digitalisation expenditures and labour productivity (LP) of the "German Mittelstand", encompassing primarily SMEs. The KfW SME Panel is an annual survey of firms across various industries, with a strong focus on innovation and digitalisation activities. We leverage information on digitalisation expenditures covering a wide range of digitalisation activities to construct firm-level digital capital stocks. This digitalisation measure captures not only investments in digital hardware and software but also encompasses expenditures on cloud services and big data activities, employee training, and the uptake

[1] If not stated differently, we use the terms *laggards*, *non-frontier firms* and *firms below the productivity frontier* interchangeably.

[2] `https://www.europarl.europa.eu/factsheets/en/sheet/63/small-and-medium-sized-enterprises`.

[3] The "German Mittelstand" is subject to a broader definition than SMEs. Although no universal understanding of the term exists, the unity of management and ownership represents a central characteristic (Pahnke, 2023). Our panel dataset encompasses firms with at least one employee and a maximum turnover of up to €500 million. If not stated differently, we use the terms SMEs and "German Mittelstand" synonymously in the course of this paper.

[4] Formerly known as German Bank for Reconstruction (German: *Kreditanstalt für Wiederaufbau*). It is a German state-owned investment and development bank located in Frankfurt.

of IT consultancy services. The resulting comprehensive and multifaceted measure accounts for a wide range of aspects of a firm's digitalisation efforts, thereby, accommodating the complexity of digitalisation that can hardly be depicted by one single indicator (Añón Higón et al., 2026). A broad measure of digitalisation accommodates the fact that firms differ significantly in the efficiency with which they leverage specific digital technologies (Brand et al., 2024).

Estimating an augmented Cobb-Douglas production function, we find digital capital stocks of German SMEs to be positively related to the level of labour productivity, measured as real sales per full-time equivalent (FTE). Firms that already have a relatively high level of digital capital stock per FTE show a stronger relationship between digitalisation and labour productivity. This result points to learning effects related to firms' past digitalisation efforts. Finally, we also show that higher digital capital stocks are related to narrowing the productivity gap between laggards and firms at the productivity frontier within industries. These results suggest that firms investing in digital capital are able to increase their productivity and to catch up with productivity frontrunners in their respective industry. Again, we observe this relationship to be stronger for firms with a higher initial digital capital endowment, pointing towards potential learning effects. In summary, our findings show important implications for the economy as a whole by highlighting the potential of digitalisation to stimulate economic growth.

Our study contributes to the literature in various ways: First, we provide evidence on the productivity implications of digitalisation expenditures for micro, small- and medium-sized firms. In particular, we focus on firms belonging to the "German Mittelstand", which are often regarded as the backbone of the German economy. Second, in contrast to much of the existing literature, we employ a comprehensive measure of digitalisation. Third, we move beyond average productivity effects of digital capital and show that productivity gains depend on firms' initial level of digitalisation. Finally, we present evidence suggesting that digitalisation has the potential to narrow the productivity gap within industries.

The rest of the paper is structured as follows. Section 2 provides an overview of the recent literature on digitalisation and productivity. Section 3 describes the KfW SME Panel in greater detail and presents summary statistics of the variables used for the empirical analysis. Section 4 introduces the empirical framework, while results are presented in Section 5. Section 6 concludes and discusses managerial and policy implications.

2 Related Literature

The recent literature largely reports a positive relationship between the use of digital technologies and firm-level performance measured as innovation output and productivity. This development is of particular importance as we observe not only a slowdown in labour productivity growth in most developed countries (van Ark and Pilat, 2024) but at the same time a growing divide with respect to labour productivity between the top-performing frontier firms and the rest (Andrews et al., 2019). The growing divergence seems to go along with a decreasing catch-up of non-frontier firms and less market selection among firms below the productivity frontier, which further contributes to a widening of the gap (Andrews et al., 2019; Mattsson and Reshid, 2023). At the same time, it is a priori not clear to what extent digitalisation and digital technologies may affect productivity growth and the productivity gap. Mattsson and Reshid (2023) find increases in productivity differences to be greater in digital-intensive sectors and sectors with a higher share of intangibles. Anderton et al. (2023) show that firms that are more heavily invested in digital technologies show faster total factor productivity (TFP) growth, despite not all firms and sectors benefitting equally from digitalisation. Moreover, they find no differences in the impact of digitalisation efforts on the productivity growth of frontier firms compared to other firms.

Positive effects of digitalisation may be owed to digital technologies reducing not only transportation costs but also the costs that arise in the context of information gathering and comparison, allowing firms to generate productivity gains (Goldfarb and Tucker, 2019). While the literature on the productivity implications of digitalisation reveals a positive impact for some digital technologies, such as cloud computing (Alexandre et al., 2026; DeStefano et al., 2025; Duso and Schiersch, 2025) and robots (Koch et al., 2021), evidence is less clear for others, such as broadband (Bertschek et al., 2015; Duso et al., 2025). Besides, there is also evidence of a positive association between technologies that require firms to handle large amounts of data, such as artificial intelligence (AI) (Aldasoro et al., 2026; Calvino and Fontanelli, 2023, 2024; Czarnitzki et al., 2023; Rammer et al., 2022)[5], data-driven decision making (DDD) (Brynjolfsson and McElheran, 2019) and big data analytics (Alexandre et al., 2026; Andres et al., 2025; Niebel et al., 2019; Wu et al., 2019b), and performance metrics such as innovation and productivity. At the same time, advanced digital technologies increase firms' demand for skills (Acemoglu et al., 2023; Calvino and Fontanelli, 2024). Moreover, literature shows that intangible assets like software and R&D positively affect the productivity growth implications of general purpose technologies, such as certain ICTs (Aldasoro et al., 2026; Brynjolfsson et al., 2021b; van Ark, 2016). Other complements that enable digital technologies like AI to unfold their productivity impact include digital infrastructure investments in, amongst others, fast broadband connections (Calvino and Fontanelli, 2024). Brynjolfsson et al. (2021a) highlight the necessity of workplace complements in the form of IT capital, educated workers or appropriate workplace designs to crucially affect the productivity impact of predictive analytics. Bloom et al. (2012) point out the necessity of well-aligned people management practices to optimally leverage information technologies. Calvino et al. (2026) further emphasise the importance of technological and human capital in the process advanced technology adoption, but also mention that these factors themselves already act productivity-enhancing. Overall, research shows that the entire productivity benefits of GPTs, such as AI and other digital technologies, do not necessarily materialise in the short-term but require some time (Brynjolfsson et al., 2021b; David, 1990). However, this time lag as well as the technology-associated gains related to GPTs may not be evenly distributed across industries and firm characteristics (McElheran et al., 2025) but rather be highly heterogeneous.

Digitalisation also bears the potential to increase countries' and firms' resilience in times of crisis. Han et al. (2025) find that firms using AI exhibit a higher resilience in the face of natural disasters. They highlight an even larger beneficial potential for firms underperforming in terms of productivity. However, these firms often lack the necessary complementary organisational designs to fully reap the benefits of

[5] In an international survey by Yotzov et al. (2026), the majority of firms stated that they have not noticed any impact of AI on productivity or employment yet, but expect it to materialise in the near future.

digital technologies. In the context of the COVID-19 pandemic, Bertschek et al. (2023) show that the emergency-aid program by the German federal government benefitted self-employed, whose businesses were highly digitalised, much more than those with less digitalised businesses. Additionally, firms with a high level of digitalisation were hit less in terms of productivity loss during the global financial crisis in 2008 and 2009 than firms with a low level of digitalisation (Bertschek et al., 2019). On the aggregate level, European countries with higher levels of ICT intensity were less affected by output losses with respect to cyclical GDP during the COVID-19 pandemic (Papaioannou, 2023).

Digitalisation has the potential to provide new ways to enhance performance, generate innovation and, finally, improve firm-level productivity not only for large firms but also for SMEs. This, in turn, may allow the latter to increase their competitiveness, enabling them to keep up with larger firms (OECD, 2021). Despite the upside potential that digitalisation offers, SMEs often lack the financial and human resources as well as technology-related skills and knowledge, which prevents them from adopting new digital technologies. Consequently, they fail to catch up with larger firms' pace in the digital transformation race. Hence, gaps in digital uptake intensify, adversely affecting overall productivity and increasing inequalities (OECD, 2021). Additionally, Aldasoro et al. (2026) show that conditional on AI adoption, SMEs show poorer productivity outcomes.

Evidence for the US shows that prior to the COVID-19 pandemic the average firm-level adoption of AI technologies weighted by employment amounted to only 18 percent. SMEs exhibit not only considerably lower adoption rates but also lower intensity of use compared to large companies (McElheran et al., 2024). During the COVID-19 pandemic, the majority of firms in advanced economies intensified their use of digital technologies. However, most of these new adopters were larger firms. In contrast, the uptake of digital technologies by SMEs corresponds only to half of that observed by larger firms (OECD, 2021). In the case of AI, current data from 2024 shows that large companies in the European Union (> 250 employees) are using this technology much more intensively than medium-sized (50-249 employees) and small (10-49 employees) companies (41% vs. 21% vs. 11%).[6] However, a recent survey among AI-using firms in the Group of Seven (G7) countries suggests that the average number of AI applications per firm does not significantly differ across size classes (OECD/BCG/INSEAD, 2025).

[6]Data retrieved from Eurostat, Artificial intelligence by size class of enterprise, `https://ec.europa.eu/eurostat/databrowser/bookmark/0f3b956c-b35f-457a-bef2-4f33c25bc597?lang=en&createdAt=2025-11-05T13:22:24Z` (accessed on 23 December 2025).

3 Data & Measurement

3.1 The KfW SME Panel

Our empirical analysis builds on the KfW SME Panel[7] (*KfW-Mittelstandspanel*), which is collected on a yearly basis since 2003.[8] It includes firms corresponding to the so-called "German Mittelstand", which is subject to a broader definition than SMEs. While the latter refers to firms with a staff headcount of less than 250 employees and less than €50 million turnover[9], the KfW SME Panel encompasses firms with at least one employee and a maximum turnover of up to €500 million. In the 2017-wave of the panel, which refers to the year 2016, questions on digitalisation projects and digitalisation expenditures were introduced to the questionnaire. Our observation period covers the years 2016 to 2021 (corresponding to the panel waves 2017 to 2022) and our final sample encompasses 21,821 firm-year observations.[10] The panel contains data on the sum of firms' yearly ICT investments and other digitalisation expenditures. In addition, the panel provides detailed information on firms' general investment and innovation activities as well as on various firm characteristics (i.a. number of employees, sales, share of high-skilled employees, industry, firm age). To ensure consistency and comparability of our analyses, we restrict our sample to firms that were already contained in the first wave under observation. This may raise concerns that our results could be spuriously driven by a survival bias. We conduct various tests to address these concerns. Amongst others, we run the main regressions on a balanced panel and our results are robust to this alternative specification.

Our main focus lies on the question asking for expenditures on digitalisation projects. Thereby, digitalisation projects encompass measures to renew the IT structure or to use new digital applications, to digitalise products (incl. services), customer and supplier relations as well as measures to build up knowledge, to reorganise workflows in connection with digitalisation or to develop and introduce new digital marketing/sales concepts. The questionnaire explicitly asks the interviewee to sum up total expenditures for all digitalisation projects. This digital expenditure measure comprises the sum for i.a. the acquisition of new IT hardware and software, the introduction of new forms of computer and storage capacity (e.g. cloud-computing), the analysis of large amounts of data (big data), the linking of IT between business processes and areas, the introduction of new IT security concepts and applications, the use of IT consulting and further training measures (with regard to digitalisation).[11]

[7]For further information on the KfW SME Panel, see `https://www.kfw.de/About-KfW/KfW-Research/KfW-Mittelstandspanel.html`.Data from the KfW SME Panel are proprietary and not publicly available. Access requires permission from KfW.

[8]The KfW SME Panel has been widely used for studies on innovation topics (e.g. Baumann and Kritikos, 2016; Thomä and Zimmermann, 2020).

[9]For further details on the definition by the EU Commission, see `https://single-market-economy.ec.europa.eu/smes/sme-fundamentals/sme-definition_en`.

[10]For a detailed overview of the number of observations by industry over time, see Table A.1 in the Appendix.

[11]Appendix A.1 shows the respective part of the questionnaire translated into English language.

3.2 Measurement of Digitalisation

We leverage the information on digitalisation expenditures to calculate digital capital stocks which serve as our main independent variable of interest. For the calculation of real digital capital stocks (Equation 1) and real capital stocks (Equation 2), we follow the perpetual inventory method (PIM) (see e.g. Dhyne et al., 2021). Besides, we use data from the 2025 release of the EUKLEMS & INTANProd capital and national accounts including information on deflators and depreciation rates at the two-digit industry level (Bontadini et al., 2023).

Each period's digital capital stock $DK_{i,t}$ is calculated by taking the previous period's digital capital stock $DK_{i,t-1}$, depreciate it with the corresponding depreciation rate δ^{ICT}, which is 31.5 percent, and then adding the current period's digitalisation expenditures $d_{i,t}$.

$$\mathrm{DK}_{i,t} = \mathrm{DK}_{i,t-1} * (1 - \delta^{ICT}) + \mathrm{d}_{i,t} \tag{1}$$

In line with the digital capital stock calculation, the capital stock variable is generated following the same approach. Instead of digitalisation expenditures, we use current period's investments $i_{i,t}$ and the previous period's capital stocks $K_{i,t}$ get depreciated with the corresponding discount rate for all assets δ^K.

$$\mathrm{K}_{i,t} = \mathrm{K}_{i,t-1} * (1 - \delta^{K}) + \mathrm{i}_{i,t} \tag{2}$$

Using total digitalisation expenditures instead of just ICT investment figures comes with a number of implications: On the one hand, expenditures on hardware and software but also on ICT-related services and employee training allow us to employ a more comprehensive measure of total ICT-related activities compared to former digitalisation measures (see Brynjolfsson and McElheran, 2019). Earlier papers relied, for instance, on more basic measures such as the proportion of employees working with a computer or on simply counting the number of technologies applied within the company or the share of firms in an industry using a certain technology (Gal et al., 2019; Greenana and Mairesse, 2000) – regardless of the extent of actual use. On the other hand, in our data, digitalisation expenditures cannot be attributed to single projects but are only available as a sum. Therefore, and since investment expenditures are also asked for as a separate variable in the questionnaire, we cannot fully rule out double counting in the digitalisation measure as digitalisation expenditures may also show up to some extent in the total investment figures.[12]

[12] We acknowledge the risk of potential double counting as the expenditures for digitalisation projects could in part also be accounted for by the total capital stock measure k_{it}. Yet, we do not consider this to be a major issue since the share that ICT capital accounts for in total capital stock is comparably small. In addition, our digitalisation measure is calculated from all digitalisation related expenditures and not only from ICT investments. Only the latter would increase the total capital stock. Hence, deducting the potentially overlapping part of our digital capital stock measure from our measure of total capital stock may hardly have an impact.

3.3 Summary Statistics

Summary statistics shown in Table 3.1 indicate that across the observation period, firms exhibit an average real digital capital stock DK of around €40,000. Interestingly, the median value lies at only €277 and the value for the 10^{th} percentile hardly above zero. This right-skewed distribution indicates that many firms in the sample either only built up a negligible digital capital stock or have a digital capital stock that got already largely depreciated in the period of observation. Moreover, the average value for real labour productivity LP, our dependent variable, lies around €198,000 and has a median value slightly below €127,000. It is calculated as real sales per FTE[13]. Looking at the value of LP at different points of the LP distribution, we observe a widening of the productivity gap between the productivity frontier and the rest of the firms for our sample at hand (see Figure 3.1). The sample primarily encompasses German SMEs, the so-called "German Mittelstand", in the years 2016 to 2021. This trend resembles findings in the literature referred to in Section 2 (Andrews et al., 2019; Mattsson and Reshid, 2023). In particular, we observe a stagnation in average labour productivity for firms below the productivity frontier since the beginning of our observation period while the frontier itself is constantly growing since 2017 (top panel of Figure 3.1).[14] The average number of full-time equivalents (FTE) amounts to 34, with the median being roughly one third of this value (12). Most firm-age observations (93 percent) lie above the 7-year threshold[15]. This dummy differentiates between recently established young firms on the one side and more mature firms on the other side. This is necessary as firms in different stages of their lifecycle exhibit very different characteristics regarding i.a. investment behaviour, growth, and financial constraints. Roughly 70 percent of our sample received financial support by KfW at some point in time. We explicitly account for this fact by adding a corresponding binary variable in all regression models, as firms that benefitted from this kind of support are oversampled in the data.

[13] We drop the top and bottom 0.5 percent of each industry's LP distribution to account for outliers.

[14] The bottom panel of Figure 3.1 shows the evolution of the labour productivity index over time for frontier and non-frontier firms with the value being set to 100 in 2016.

[15] To a large extent this seemingly high value is an artefact of our sample construction, which requires firms to be part of the survey in the first year of observation (2016). Hence, over time no "young" firms enter the sample while, at the same time, the included firms get older.

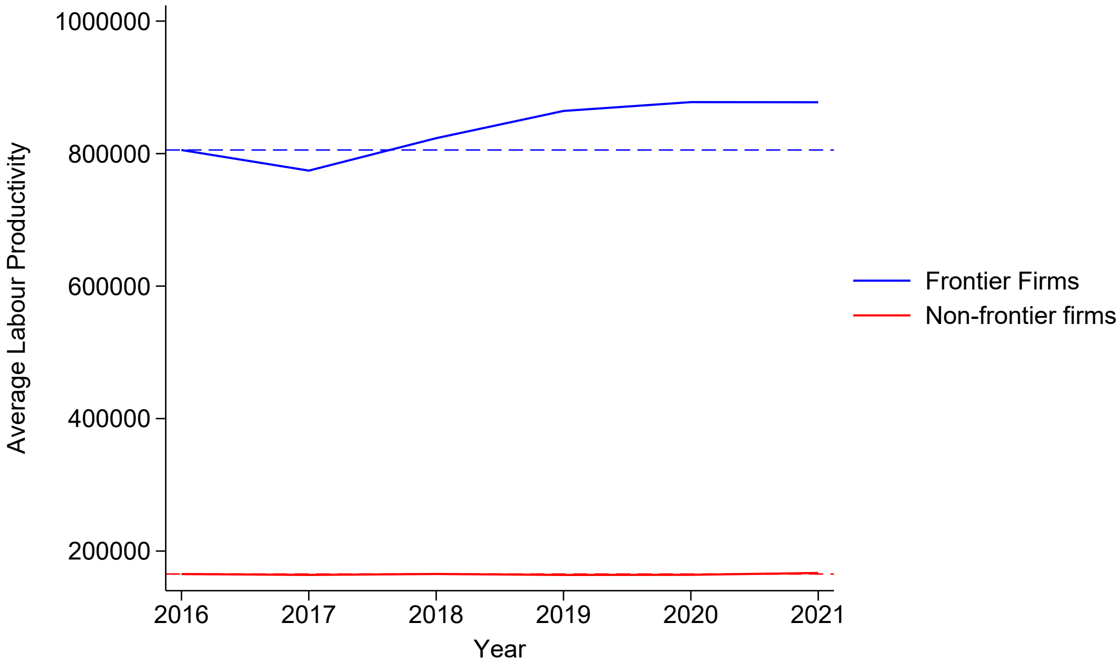
Table 3.1: Summary Statistics Estimation Sample

	N	Mean	Median	SD	p5	p95
Real labour productivity (sales per FTE)	21,788	197,906	126,569	252,204	41,630	577,949
Δ Labour productivity	14,817	0.055	-0.0077	0.52	-0.37	0.55
Real digital expenditure (gross)	21,542	17,703	0.99	121,972	0.65	74,471
Digital capital stock	21,788	40,404	277	347,259	1	154,832
Δ Digital capital stock	16,411	0.56	0.18	1.6	-0.31	3.7
Digital capital stock per FTE	21,788	1,006	25	6,166	0.037	4,501
Δ Digital capital stock per FTE	14,809	0.63	0.17	1.8	-0.39	4.2
Digitalisation projects (binary)	21,735	0.35	0	0.48	0	1
Real investment (gross)	21,604	361,930	18,854	2,015,998	0.96	1,462,994
Capital stock	21,788	1,131,795	92,007	5,309,665	1.9	4,744,812
Δ Capital stock	16,307	0.41	0.19	0.8	-0.13	1.9
Capital stock per FTE	21,788	31,715	7,959	131,224	0.23	100,225
Innovation (binary)	21,629	0.34	0	0.47	0	1
Product innovation (binary)	18,407	0.28	0	0.45	0	1
Process innovation (binary)	21,489	0.26	0	0.44	0	1
FTE	21,788	34	12	78	1	135
Share of high-skilled employees	21,788	0.13	0	0.25	0	0.8
Firm age	21,788	40	27	38	6	118
Age > 7 years	21,788	0.93	1	0.26	0	1
Received KfW financial support	21,788	0.7	1	0.46	0	1

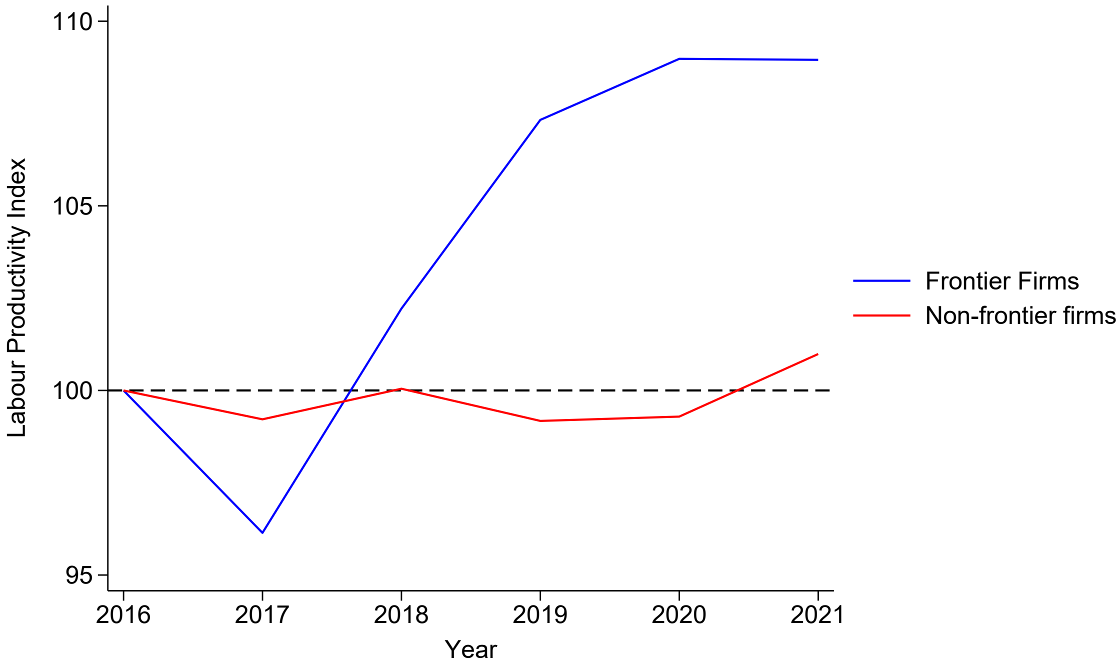
NOTES: Summary statistics of selected variables in the estimation sample.

Figure 3.1: Evolution of Real Labour Productivity of Frontier vs. Laggard Firms

Average Real Labour Productivity over Time by Frontier Status (in t)



Real Labour Productivity Index over Time by Frontier Status (2016 = 100)



Notes: The top figure depicts the yearly evolution of real labour productivity for the productivity frontier (blue) versus the rest of the firms (red). The dashed lines refer to the initial values of real labour productivity for each of the two groups in 2016. The bottom figure shows the evolution of the index of labour productivity for the productivity frontier (blue) versus the rest of firms (red). The index is set to 100 in the starting year 2016 which is indicated by the dashed black line. The productivity frontier refers to the top 5 percent of firms in their industry-specific productivity distribution by year.

4 Analytical Framework

For our econometric analysis, we use an augmented Cobb-Douglas production function in logarithmic terms. Log labour productivity $lp_{i,t}$ of firm i in year t as dependent variable is measured as real sales per FTE. Log digital capital stock $dk_{i,t}$ is the main explanatory variable of interest. We further include traditional production factor inputs like log real capital stock $k_{i,t}$ and log labour $l_{i,t}$, measured in FTE. Moreover, we assume variable returns to scale (VRS) as this is supposed to be less restrictive than constant returns to scale (CRS).[16] We control for additional covariates $\mathbf{X_{i,t}}$, including the share of high-skilled employees in a company, firm age and whether the firm has received any financial support by KfW. Besides, we include industry- and year-fixed effects (FE), λ_j and δ_t (Equation 3). We expect the production elasticity of digital capital represented by coefficient β_{dk} to be positive and statistically significant.

Labour Productivity as Dependent Variable

We estimate our baseline regressions using ordinary least squares (OLS) with variables expressed in logarithmic terms to target different aspects of how the digital capital stock dk may be related to labour productivity lp:

$$lp_{i,t} = \beta_{dk} * dk_{i,t} + \beta_k * k_{i,t} + \beta_l * l_{i,t} + \beta_{\mathbf{X}} * \mathbf{X}_{i,t} + \delta_t + \lambda_j + \epsilon_{i,t} \tag{3}$$

In addition to these baseline regressions in levels, we also estimate specifications in first differences to eliminate unobserved firm-specific factors:[17]

$$\Delta\ lp_{i,t} = \beta_{dk} * \Delta\ dk_{i,t} + \beta_k * \Delta\ k_{i,t} + \beta_l * \Delta\ l_{i,t} + \beta_{\mathbf{X}} * \mathbf{X}_{i,t} + \delta_t + \gamma_j + \epsilon_{i,t} \tag{4}$$

Moreover, firms might benefit from previous investments in digital capital, for instance, through accumulated experience and learning effects as well as from first-mover advantages. Therefore, in the next step, we account for effect heterogeneity of the digital capital stock (dk), conditional on the firm's initial level of digitalisation. We categorise firms in the first year of observation, 2016, into quartiles $dq_{i,s,2016}$[18] by industry (j) depending on their dk per FTE. This can be regarded as firms' relative initial digital endowment. Afterwards, we include an interaction term between firms' dk and their initial position in the digitalisation distribution in our regression (Equation 5). With this specification, we aim to investigate how an increase in digital capital is related to the firms' labour productivity depending on their initial position within the digitalisation distribution in their respective industry.

$$lp_{i,t} = \beta_{dk} * dk_{i,t} + \beta_{dq} * dq_{i,2016} + \beta_{dk*dq} * dk_{i,t} * dq_{i,2016} + \beta_k * k_{i,t} + \beta_l * l_{i,t} + \beta_{\mathbf{X}} * \mathbf{X}_{i,t} + \delta_t + \lambda_j + \epsilon_{i,t} \tag{5}$$

[16] See e.g. Duso and Schiersch (2025) for a more extensive discussion.
[17] See e.g. Dobbelaere and Mairesse (2013) and Stiroh (2005).
[18] In the following, we drop the indices for year and sector for better readability.

In addition, we run several robustness checks. These checks encompass, i.a. the use of fixed effects panel regression methods and the application of translog production functions as opposed to Cobb-Douglas production functions. Translog production functions allow for greater flexibility, i.a. not imposing constant elasticities of substitution, and provide a better fit to the data. Additionally, we also include an innovation variable separately to avoid that our digitalisation variable is spuriously driven by the effect of innovation. Finally, we run an alternative specification where we introduce a digitalisation dummy instead of the digital capital stock.

Labour Productivity Gap as Dependent Variable

Modifying the original setting and going beyond the pure question of whether the (growth of the) digital capital stock can act as a means to enhance labour productivity (growth), we focus in Section 5.3 on how dk affects the productivity gap. More precisely, we refer to the distance in lp of firm i to firms belonging to the same industry's productivity frontier in the respective year (Equation 6):

$$gap_{i,t} = \beta_{dk} * dk_{i,t} + \beta_k * k_{i,t} + \beta_l * l_{i,t} + \beta_{\mathbf{X}} * \mathbf{X}_{i,t} + \delta_t + \lambda_j + \epsilon_{i,t} \tag{6}$$

As before, we investigate effect heterogeneity according to firms' initial position in the digitalisation distribution of their respective industry (Equation 7):

$$gap_{i,t} = \beta_{dk} * dk_{i,t} + \beta_{dq} * dq_{i,2016} + \beta_{dk*dq} * dk_{i,t} * dq_{i,2016} + \beta_k * k_{i,t} + \beta_l * l_{i,t} + \beta_{\mathbf{X}} * \mathbf{X}_{i,t} + \delta_t + \lambda_j + \epsilon_{i,t} \tag{7}$$

5 Results

5.1 Baseline Results

OLS regression results for the specifications 3, 4, and 5 of the augmented Cobb-Douglas production function described in Section 4 are contained in Table 5.1. Column (1) shows the results when regressing log labour productivity lp on log digital capital stock dk, log capital stock k, and log labour l while controlling for the share of high-skilled employees within the firm, firm age, industry- and year-fixed effects as well as for having received KfW support in the past (Equation 3). We find a positive and highly statistically significant association between dk and lp. Results suggest an increase in lp by roughly 0.159 percent if dk is increased by 10 percent. Our results imply that if a median company doubled its digital capital stock, corresponding to a €277 increase, this would be associated, on average, with a 1.59 percent increase in labour productivity. In column (2) we run the same regression as in column (1) but on the same sample of firms that we use in column (4) where we look at how growth in the independent variables affects lp growth (Equation 4). This makes the results more comparable by ensuring that changes in the outcomes are not the result of mere changes in the sample composition. Reassuringly, results resemble those obtained in the first column both in size and statistical significance.

In column (4), we estimate the same specification as in column (2) but using first differences instead of levels. Results show a positive and statistically significant correlation between the growth of dk at the firm level and lp growth. Increasing dk growth by 1 percentage point is associated with a 0.0113 percentage point increase in lp growth.

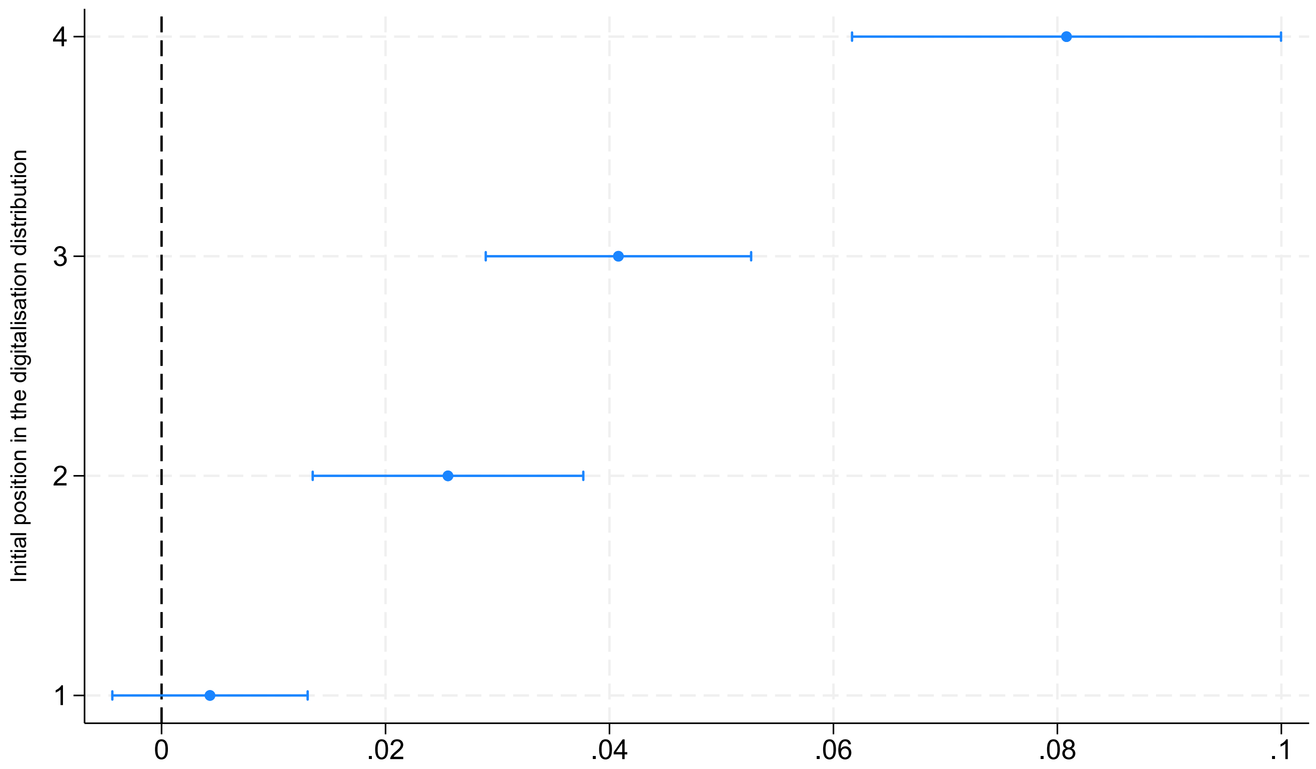
5.2 Effect Heterogeneity

To account for differences in firms' experience with and endowment of digital technologies, we classify them into quartiles based on their position in the digitalisation distribution within their industry in 2016, the first year of observation. The digitalisation distribution is based on firms' digital capital dk per FTE.

Interaction Effects

In Table 5.1, column (3) sheds light on how firms' relative position in the digitalisation distribution within an industry affects the association between dk and lp. In particular, we augment the regression described in Equation (3) by adding an interaction term between the initial position in the digitalisation distribution dq_{2016} and the current digital capital stock dk (Equation 5).

Figure 5.1: Marginal Effect of Log Digital Capital Stock on Labour Productivity by Initial Position in the Digitalisation Distribution



NOTES: Marginal effect of $dk_{i,t}$ on $lp_{i,t}$ after including an interaction term between $dk_{i,t}$ and $dq_{i,2016}$ in the baseline specification (Equation 5).

Table 5.1: OLS Baseline Regressions

	Log Labour Productivity			Δ Log LP
	(1)	(2)	(3)	(4)
Log digital capital stock	0.0159***	0.0147***	0.0043	
	(0.002)	(0.003)	(0.005)	
Δ Log digital capital stock				0.0113**
				(0.005)
2^{nd} Digitalisation quartile in t = 0 (2016)			-0.1997***	
			(0.035)	
3^{rd} Digitalisation quartile in t = 0 (2016)			-0.3836***	
			(0.064)	
4^{th} Digitalisation quartile in t = 0 (2016)			-0.6786***	
			(0.122)	
2^{nd} Digitalisation quartile in t = 0 (2016)			0.0213**	
x Log digital capital stock			(0.009)	
3^{rd} Digitalisation quartile in t = 0 (2016)			0.0365***	
x Log digital capital stock			(0.009)	
4^{th} Digitalisation quartile in t = 0 (2016)			0.0765***	
x Log digital capital stock			(0.012)	
Log capital stock	0.0225***	0.0241***	0.0210***	
	(0.002)	(0.003)	(0.002)	
Δ Log capital stock				0.0300***
				(0.007)
Log labour	0.0563***	0.0584***	0.0099	
	(0.009)	(0.010)	(0.012)	
Δ Log labour				-0.6595***
				(0.040)
Constant	10.6997***	10.6705***	10.9600***	0.0373*
	(0.086)	(0.096)	(0.092)	(0.021)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE (2-digit)	Yes	Yes	Yes	Yes
Observations	21788	13880	21788	13880
Adjusted R-squared	0.262	0.258	0.274	0.266

NOTES: Dependent Variable: ln(labour productivity) in (1)-(3) and Δ ln(labour productivity) in (4). Column (2) shows the results for the same regression used in (1) but with the sample of (4). Digitalisation quartiles are constructed by industry in 2016. The coefficients of the interaction terms have to be interpreted relative to the base group, which is the first digitalisation quartile. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Results show that firms that already built up a digital capital stock that is comparably large within their respective industry at the beginning of the observation period exhibit a stronger link between their current *dk* and *lp*. The higher firms rank in their industry digitalisation distribution the higher the coefficient of the interaction term between *dk* and dq_{2016}. Our results imply that for a company located in the fourth digitalisation quartile in 2016 a 10 percent increase in *dk* is associated with 0.765 percentage points higher increase in *lp* as compared to a company that used to be located in the first quartile. Figure 5.1 depicts the marginal effect of *dk* on *lp* growth when including an interaction term between *dk* and dq_{2016} in the baseline specification (Equation 5). It indicates that the positive association between digital capital and labour productivity is even more pronounced for firms that were already more digitally advanced at the beginning of our sample in 2016, while it is not statistically significant for the initially least digitalised firms. This result suggests some kind of learning process or compounding returns to digital capital.

Subsample Estimations

The results of Table 5.1 get confirmed if, instead of interacting *dk* with dq_{2016}, we run separate fixed effects regressions for each digitalisation quartile as depicted in Table 5.2. Although the coefficients of *dk* for the first and second quartile are not statistically significant, we observe a substantial increase in the absolute size of the *dk* coefficients from the first and second to the third and fourth quartile, with the latter two being highly statistically significant. Also, the size of the coefficients is between almost 4 and 7 times higher for the top two quartiles, affirming the conjecture of an ongoing learning process or some form of compounding returns to digital capital.

5.3 Link Between Digitalisation and the Productivity Gap

A major issue in the productivity literature is the growing divide in the evolution of firm-level productivity between firms. The so-called labour productivity gap measures the distance between a firm's labour productivity and the average labour productivity of the top 5 percent of firms in the labour productivity distribution in the corresponding industry in a given year. In Table 5.3, we present regression results following Equations (6) and (7).[19] Controlling for the same firm characteristics as in the previous specification, we regress the productivity gap on *dk*, *k*, *l*. Column (1) shows the results from estimating Equation (6) on our sample. We find that a higher *dk* is associated with firms catching up with their respective productivity frontier, thereby contributing to closing the productivity gap.[20] Results in column (1) of Table 5.3 suggest that a 10 percent increase in *dk* is on average associated with a 0.139 percent decrease in the labour productivity gap. Column (2) shows the results for the same regression

[19] To account for the fact that the productivity-related association between *dk* and *lp* gap may only become visible with a time lag, we re-run the regressions shown in Table 5.3 lagging the independent variables by 1 year. The results are depicted in Table A.2 in the Appendix and largely confirm those relying on contemporary data. Similar to Figure 5.2, Figure A.2 shows the corresponding marginal effects.

[20] Excluding firms at the productivity frontier, our estimation strategy identifies the association between digitalisation and the gap to the productivity frontier among laggard firms, conditional on not reaching the frontier. Hence, our regression results provide a conservative (i.e., lower-bound) estimate of the coefficient of log digital capital stocks.

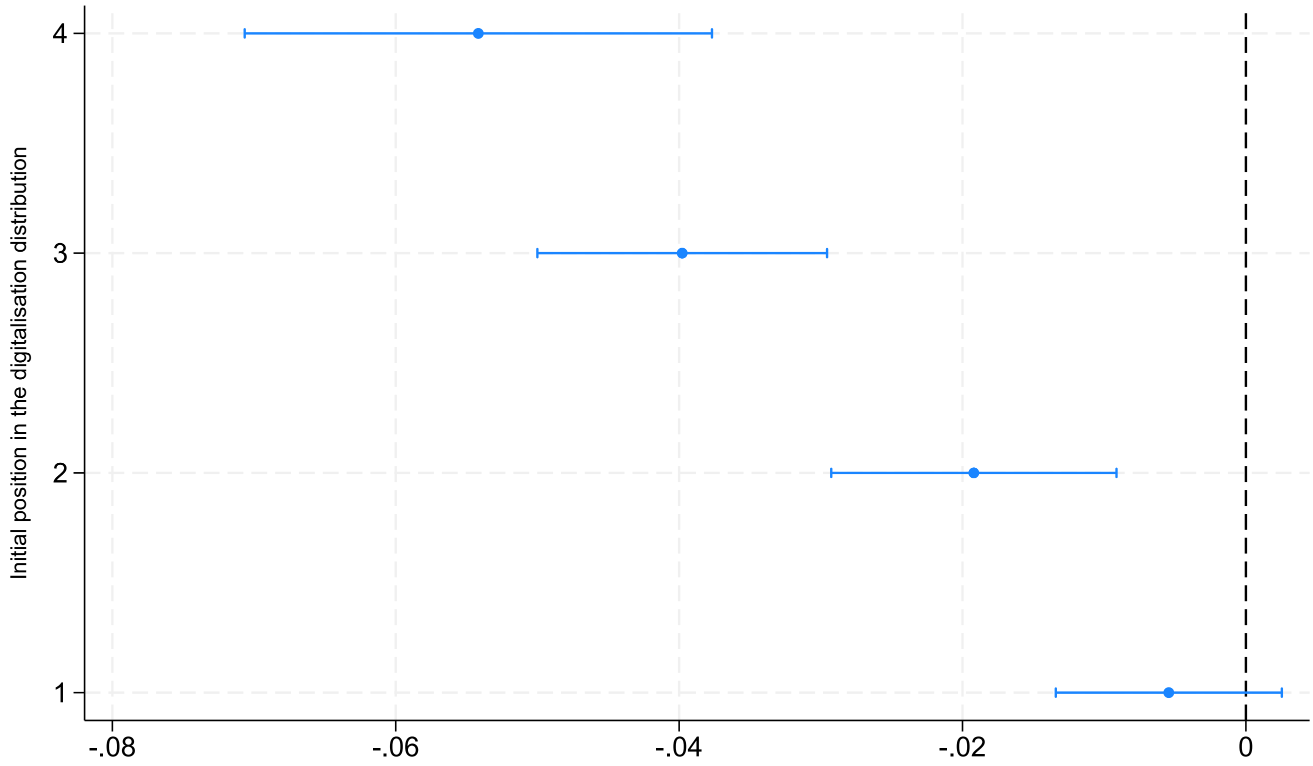
Table 5.2: Fixed-Effects Subsample Regressions by Digitalisation Quartile

	Log Labour Productivity			
	(1)	(2)	(3)	(4)
	$1^{st} Quartile$	$2^{nd} Quartile$	$3^{rd} Quartile$	$4^{th} Quartile$
Log digital capital stock	0.0031	0.0037	0.0149***	0.0228***
	(0.003)	(0.005)	(0.005)	(0.007)
Log capital stock	0.0133***	0.0112*	0.0017	0.0206**
	(0.004)	(0.006)	(0.005)	(0.009)
Log labour	-0.5689***	-0.5607***	-0.5955***	-0.3642***
	(0.065)	(0.045)	(0.036)	(0.079)
Constant	13.3959***	12.2224***	13.1761***	12.4449***
	(0.215)	(0.092)	(0.127)	(0.260)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5384	5199	5648	5557
Adjusted R-squared	0.232	0.190	0.229	0.105

NOTES: Dependent Variable: ln(labour productivity). Digitalisation quartiles are constructed by industry in 2016. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

after additionally accounting for the growth of the productivity frontier Δ $Log\ frontier\ LP$. This barely affects the results regarding the relation between dk and lp. In column (3), we introduce an interaction term between dk and dq_{2016} (Equation 7). As in Section 5.1, we find statistically significant coefficients on the interaction terms with the absolute coefficient size being larger the higher the firm initially ranks in the digitalisation distribution. The negative sign of the coefficients of the interaction terms points towards initially more digitalised companies being seemingly better at leveraging dk to catch up with the most productive firms in their respective industry. This result is robust to adding productivity growth of the frontier as another explanatory variable (column 4). Figure 5.2 illustrates the marginal effect of dk on lp, which increases in absolute terms along the digitalisation distribution.

Figure 5.2: Marginal Effect of Log Digital Capital Stock on the LP Gap to the Frontier by Initial Position in the Digitalisation Distribution



NOTES: Marginal effect of $dk_{i,t}$ on $gap_{i,t}$ after including an interaction term between $dk_{i,t}$ and $dq_{i,2016}$ in Equation (6) (Equation 7).

5.4 Robustness Checks

We run several robustness checks to verify our findings. This includes running fixed-effects panel regressions, using a translog-production function[21] instead of the Cobb-Douglas production function, and

[21] Translog production functions can be regarded as an extension to standard Cobb-Douglas production functions as they are more flexible and allow for variable elasticities of substitution between inputs. Thereby, they account for potentially complex

Table 5.3: OLS Regressions with Productivity Gap as Dependent Variable & Interaction with Initial Position in the Digitalisation Distribution

	Gap to the Frontier			
	(1)	(2)	(3)	(4)
Log digital capital stock	-0.0139***	-0.0129***	-0.0054	0.0025
	(0.002)	(0.002)	(0.005)	(0.008)
2^{nd} Digitalisation quartile in t = 0 (2016)			0.1537***	0.1728***
			(0.029)	(0.035)
3^{rd} Digitalisation quartile in t = 0 (2016)			0.3481***	0.4040***
			(0.055)	(0.064)
4^{th} Digitalisation quartile in t = 0 (2016)			0.4248***	0.5010***
			(0.105)	(0.121)
2^{nd} Digitalisation quartile in t = 0 (2016)			-0.0138*	-0.0245**
x Log digital capital stock			(0.007)	(0.011)
3^{rd} Digitalisation quartile in t = 0 (2016)			-0.0343***	-0.0452***
x Log digital capital stock			(0.007)	(0.010)
4^{th} Digitalisation quartile in t = 0 (2016)			-0.0487***	-0.0621***
x Log digital capital stock			(0.011)	(0.013)
Log capital stock	-0.0195***	-0.0203***	-0.0184***	-0.0191***
	(0.002)	(0.002)	(0.002)	(0.002)
Log labour	-0.0647***	-0.0666***	-0.0278***	-0.0254**
	(0.008)	(0.009)	(0.011)	(0.012)
Δ Log frontier LP		0.5048***		0.5037***
		(0.038)		(0.037)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE (2-digit)	Yes	Yes	Yes	Yes
Observations	20700	13166	20700	13166
Adjusted R-squared	0.287	0.289	0.296	0.300

NOTES: Dependent Variable: ln(gap to the productivity frontier). Digitalisation quartiles are constructed by industry. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

separately controlling for innovation to account for potential risk of *dk* simply capturing the effect of innovation as well as replacing *dk* with a binary digitalisation project measure.

Fixed-Effects Regressions

Table 5.4: Fixed-Effects Baseline Regressions

	Log Labour Productivity		Δ Log LP
	(1)	(2)	(3)
Log digital capital stock	0.0053***	0.0033	
	(0.002)	(0.002)	
Δ Log digital capital stock			0.0086
			(0.005)
2^{nd} Digitalisation quartile in t = 0 (2016)		-0.0045	
x Log digital capital stock		(0.005)	
3^{rd} Digitalisation quartile in t = 0 (2016)		0.0054	
x Log digital capital stock		(0.005)	
4^{th} Digitalisation quartile in t = 0 (2016)		0.0302***	
x Log digital capital stock		(0.007)	
Log capital stock	0.0118***	0.0112***	
	(0.003)	(0.003)	
Δ Log capital stock			0.0222**
			(0.009)
Log labour	-0.5063***	-0.5101***	
	(0.033)	(0.033)	
Δ Log labour			-0.7269***
			(0.051)
Controls	Yes	Yes	Yes
Year DVs	Yes	Yes	Yes
Observations	21788	21788	13880
Adjusted R-squared	0.175	0.177	0.299

NOTES: Dependent Variable: ln(labour productivity) in (1)-(2) and Δ ln(labour productivity) in (3). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5.4 shows the results for running the baseline regressions presented in Table 5.1 using panel

interrelations among different input factors.

Results suggest a positive marginal effect of the average firm of *dk* on *lp*. We also look at how the marginal effect varies along the distribution of central covariates. Interestingly, the marginal effect seems to be more pronounced for observations with comparably low levels of the major covariates (10^{th} percentile), meaning with comparably lower levels of capital k, labour l, and the *share of high-skilled workers*. It even becomes negative and statistically significant for firms with comparably high levels of the covariates (90^{th} percentile).

estimation techniques accounting for firm-fixed effects. For the specification focusing on the relation between *dk* and *lp* in levels, the estimated coefficient for *dk* remains highly statistically significant and positive (column 1) though considerably smaller in magnitude compared to the OLS estimates. Column (2) compares to column (3) in the baseline results. We observe a statistically insignificant interaction term for the second and the third digitalisation quartile. However, for the interaction of *dk* with the fourth quartile, the coefficient remains statistically significant but decreases in magnitude compared to the baseline. In column (3) that compares to column (4) in Table 5.1, the coefficient decreases by roughly one fourth in size as compared to the OLS estimates and turns statistically insignificant. Moreover, the coefficients on *k* and *l* remain highly statistically significant and are mostly of similar magnitude as in the comparable OLS estimates.

Controlling for Innovation and Fluctuating Digitalisation expenditures

There may be concerns that the digitalisation variable *dk* rather captures the relation between innovation and *lp* than the association between *dk* and *lp*. To dispel such doubts, we run further robustness checks in Table 5.5. Column (1.1) corresponds to column (1) in Table 5.1. In column (1.2), we add a dummy variable capturing whether the corresponding firm introduced any product innovation during the previous three years.[22] We find that the coefficient of our digitalisation measure *dk* remains positive and highly statistically significant. It even slightly increases in size. Hence, we are confident that our findings in Section 5.1 are not driven by *dk* reflecting the mere influence of innovation activities. Moreover, we run a regression for Equation (3) using an alternative measure of digitalisation (column 1.3). More precisely, we replace *dk* by a dummy variable indicating whether firms completed any digitalisation project in the course of the previous three years.[23] This robustness check is supposed to account for the potential concern that digitalisation investments in SMEs often happen on an irregular basis and can occasionally be hard for firms to report with full accuracy on a yearly basis. Also, we are unable to capture digitalisation expenditures happening prior to 2016, the first year in which digitalisation questions were asked in the KfW SME Panel. Hence, the digitalisation project dummy, with its three-year retrospective perspective going back to 2014, more broadly captures digitalisation activities and also helps to account for those activities already undertaken just before the start of the sample period in our analysis. The digitalisation dummy's coefficient is also highly statistically significant, further supporting the positive association between digitalisation and firm-level *lp*. Column (3.1) refers to column (3) in Table 5.1, where we include an interaction term between *dk* and dq_{2016} (Equation 5). After including the product innovation dummy in column (3.2), the results for the interactions terms remain positive and statistically significant and of comparable magnitude to those in column (3.1). In contrast to the results in Section 5.1, even the coefficient of *dk* remains statistically significant further strengthening the positive association between *dk* and *lp*. In column (3.3) where we replace *dk* with the binary digitalisation project variable, the coefficients

[22] Since we only observe the actual years in which firms indicate the completion of product innovations within a 3-year period, we lose observations as opposed to the regressions where we only include the (digital) capital stock measures.

[23] Again, we lose some observations as opposed to column (1.1). While digitalisation capital stocks get accumulated and depreciated over time, allowing to span years where no active digitalisation expenditures take place, the completion of digitalisation projects is a one-time occurrence.

of the interaction terms remain positive but turn statistically insignificant. This may be owed to the fact that the dummy variable does not contain information on the intensive margin of digitalisation activities as dk does. Lastly, column (4.1) refers to column (4) in Table 5.1. Adding the binary innovation variable in column (4.2) hardly affects the Δ dk coefficient. Also, the digitalisation project dummy in column (4.3) is positive and highly statistically significant.

Table 5.5: Robustness Checks – OLS Baseline Regressions

	Log Labour Productivity			Log Labour Productivity			Δ Log LP		
		(1)			(3)			(4)	
	(1.1)	(1.2)	(1.3)	(3.1)	(3.2)	(3.3)	(4.1)	(4.2)	(4.3)
Log digital capital stock	0.0159***	0.0182***		0.0043	0.0186**				
	(0.002)	(0.002)		(0.005)	(0.008)				
Δ Log digital capital stock							0.0113**	0.0097**	
							(0.005)	(0.005)	
Digitalisation project(s)			0.0623***			-0.0346			0.0221***
(binary)			(0.015)			(0.039)			(0.004)
2nd Digitalisation quartile				-0.1997***	-0.2117***	-0.0766**			
in t=0 (2016)				(0.035)	(0.035)	(0.030)			
3rd Digitalisation quartile				-0.3836***	-0.4007***	-0.0617**			
in t=0 (2016)				(0.064)	(0.063)	(0.029)			
4th Digitalisation quartile				-0.6786***	-0.8021***	0.1663***			
in t=0 (2016)				(0.122)	(0.127)	(0.033)			
2nd Digitalisation quartile				0.0213**	0.0157				
× Log digital capital stock				(0.009)	(0.011)				
3rd Digitalisation quartile				0.0365***	0.0274***				
× Log digital capital stock				(0.009)	(0.010)				
4th Digitalisation quartile				0.0765***	0.0767***				
× Log digital capital stock				(0.012)	(0.014)				
2nd Digitalisation quartile						0.0243			
× Digitalisation project(s)						(0.055)			
3rd Digitalisation quartile						0.0492			
× Digitalisation project(s)						(0.045)			
4th Digitalisation quartile						0.0098			
× Digitalisation project(s)						(0.046)			
Product innovation (binary)		-0.0314*			-0.0474***			0.0199***	
		(0.018)			(0.018)			(0.007)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21788	18407	21735	21788	18407	21735	13880	11249	13841
Adjusted R-squared	0.262	0.264	0.257	0.274	0.277	0.267	0.266	0.272	0.264

NOTES: Dependent Variable: ln(labour productivity) in (1.1)–(3.3) and Δ ln(labour productivity) in (4.1)–(4.3). Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

6 Conclusion and Policy Implications

Based on a large panel of firms belonging to the "German Mittelstand", we analyse the association between SMEs' digitalisation activities and their labour productivity. Our dataset provides firm-level information on digitalisation expenditures from 2016 to 2021, which we use to construct digital capital stocks. In our analysis, we focus on the association between these digital capital stocks and firms' labour productivity. In addition, we analyse heterogeneity of productivity gains from digital capital by assessing whether they vary with firms' initial level of digitalisation. Finally, we examine how firms' ability to catch up with their respective industry-specific productivity frontier relates to their digital capital stock.

Our results show a positive and statistically significant link between the digital capital stock of companies in the "German Mittelstand" and their labour productivity. Further, we find that comparably more digitalised firms are likely to profit more strongly from higher digital capital stocks. This means that firms with an initially higher degree of digitalisation as compared to their industry peers seem to be able to better leverage the productivity-enhancing properties of additional digitalisation expenditures. Moreover, our findings show a positive association between firm-level digitalisation and the ability to catch up with the respective industry's productivity frontier, reducing inequality among firms.

Overall, our findings highlight the need for continuous digitalisation expenditures to enhance productivity. However, small enterprises often find it difficult to continuously invest in digitalisation as they are constrained by a lack of financial and human resources. This frequently hinders the successful implementation of new digital solutions, impedes further digitalisation efforts and increases dependencies on – often expensive – external expertise. Our results imply that policy makers should raise awareness for the benefits of digitalisation. This can include offering targeted incentives to foster SMEs' investment efforts in digitalisation. Following the literature, the success of investments into digitalisation critically depends on accompanying investment into complementary assets like R&D as well as the provision of appropriate organisational designs and management practices. Moreover, current research highlights the need for skills and well-educated employees, which necessitates adequate alignment of curricula in schools, vocational training and academic education. Improving digital and data literacy among the current and future workforce enables firms to better leverage the potential of digital technologies.

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A Appendix

A.1 Questionnaire

Figure A.1: Definition of Digitalisation Project (Expenditures) in the KfW SME Panel 2021

IV. Digitalisation

Digitalisation projects are projects and measures to **renew the IT structure** or to **use new digital applications**, to digitalise **products** (incl. services), customer and supplier **relations** as well as **measures to build up knowledge, to reorganise workflows** in connection with digitalisation or to develop and introduce **new digital marketing/sales concepts.**

This includes, for example, the acquisition of new IT hardware and software for your company (including programming), the introduction of new forms of computer and storage capacity (e.g. cloud computing), the analysis of large amounts of data (big data), the linking of IT between business processes and areas, the introduction of new IT security concepts and applications, the use of IT consulting and further training measures (with regard to digitalisation).

29. Have you completed digitalisation projects in your company in the years 2018 - 2020?

- ☐ Yes
- ☐ No

30. What kind of digitalisation projects did you complete during this period? (multiple answers possible)

- ☐ Digitalisation of products and services (e.g. products and services with chips/sensors, product-related digital applications)
- ☐ Modernisation of IT structures and use of new digital technologies (e.g. use of big data)
- ☐ Digitalisation of contact with customers and suppliers
- ☐ Linking IT between functional areas
- ☐ Development of know-how (e.g. use of IT consulting, further training)
- ☐ Reorganisation of the workflow due to digitalisation
- ☐ Introduction of new digital marketing/sales concepts
- ☐ Other, namely:

31. How much was your company's total expenditure on digitalisation projects in 2020 (including personnel costs and investments)?

ca. € ______ ☐ **No** expenditure on digitalisation

NOTES: Translation of the original German language questionnaire into English. Source: KfW SME Panel.

A.2 Further Tables

Table A.1: Number of firms by industry over time (Updated)

Nace Rev. 2 code	2016	2017	2018	2019	2020	2021	Total
A	111	95	77	54	46	41	424
C10-C12	169	153	119	103	83	68	695
C13-C15	35	31	25	21	17	13	142
C16-C18	126	110	96	75	68	29	504
C20-C21	31	31	24	21	19	19	145
C22-C23	122	109	85	78	57	54	505
C24-C25	388	334	299	233	177	154	1585
C26	60	52	44	31	24	20	231
C27	47	46	36	26	21	20	196
C29-C30	30	28	17	18	15	14	122
C31-C33	209	182	156	138	104	82	871
F	1058	965	824	689	552	461	4549
G45	246	199	179	147	110	91	972
G46	523	451	387	298	249	200	2108
G47	736	653	541	427	324	261	2942
H	236	216	161	136	106	92	947
J	87	84	67	49	41	38	366
K	28	26	22	17	13	15	121
M	731	640	523	431	344	292	2961
N	379	335	256	186	143	103	1402
Total	5352	4740	3938	3178	2513	2067	21788

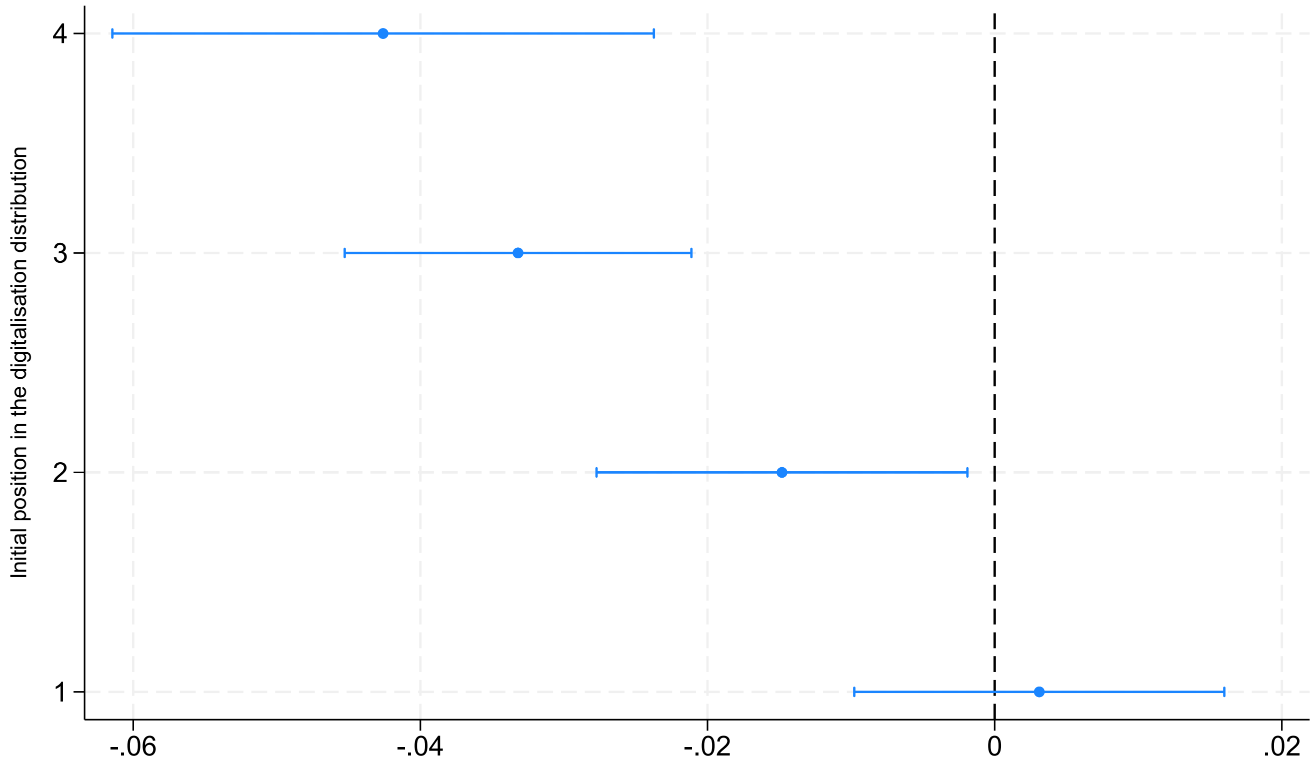
Table A.2: OLS Regressions with Productivity Gap as Dependent Variable & Interaction with Initial Position in the Digitalisation Distribution

	Gap to the Frontier			
	(1)	(2)	(3)	(4)
Lag log digital capital stock	-0.0123***	-0.0122***	0.0031	0.0027
	(0.002)	(0.002)	(0.008)	(0.008)
2^{nd} Digitalisation quartile in t = 0 (2016)			0.1203***	0.1205***
			(0.034)	(0.034)
3^{rd} Digitalisation quartile in t = 0 (2016)			0.3033***	0.3034***
			(0.064)	(0.064)
4^{th} Digitalisation quartile in t = 0 (2016)			0.3082***	0.3092***
			(0.119)	(0.119)
2^{nd} Digitalisation quartile in t = 0 (2016)			-0.0179*	-0.0185*
x Lag log digital capital stock			(0.011)	(0.011)
3^{rd} Digitalisation quartile in t = 0			-0.0363***	-0.0358***
x Lag log digital capital stock			(0.010)	(0.010)
4^{th} Digitalisation quartile in t = 0 (2016)			-0.0457***	-0.0453***
x Lag log digital capital stock			(0.013)	(0.013)
Lag log capital stock	-0.0185***	-0.0187***	-0.0175***	-0.0176***
	(0.002)	(0.002)	(0.002)	(0.002)
Lagged log FTE	-0.0802***	-0.0805***	-0.0526***	-0.0528***
	(0.009)	(0.009)	(0.012)	(0.012)
Δ Log frontier LP		0.5054***		0.5043***
		(0.037)		(0.037)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE (2-digit)	Yes	Yes	Yes	Yes
Observations	13166	13166	13166	13166
Adjusted R-squared	0.288	0.293	0.296	0.301

NOTES: Dependent Variable: ln(gap to the productivity frontier). Digitalisation quartiles are constructed by industry. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

A.3 Further Graphs

Figure A.2: Marginal Effect of Lagged Log Digital Capital Stock on the LP Gap to the Frontier by Initial Position in the Digitalisation Distribution



Notes: Marginal effect of $l.dk_{i,t}$ on $gap_{i,t}$ after including an interaction term between $l.dk_{i,t}$ and $dk_{i,2016}$ in Equation (6) (see Equation 7).

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