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Climate Protection Potentials of Digitalized Production Processes: Microeconometric Evidence?

Climate Protection Potentials of Digitalized Production Processes: Microeconometric Evidence?

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Abstract

Although information and communication technologies (ICT) consume energy themselves, they are considered to have the potential to reduce overall energy intensity within economic sectors. While previous empirical evidence is based on aggregated data, this is the first large-scale empirical study on the relationship between ICT and energy intensity at the firm level. For this purpose, we employ administrative panel data on 28,600 manufacturing firms from German Statistical Offices collected between 2009 and 2017. Our results confirm a statistically significant and robust negative link between software capital as an indicator for the firm-level degree of digitalization and energy intensity, but the effect size is rather small. Hence, we conclude that energy intensity reductions related to the use of digital technologies are lower than expected.

Keywords: ICT, Firm-level panel data, Energy intensity improvements.

JEL Codes: D22, D24, L60, O12, O14, O33, Q40.

1. Introduction

To limit global warming, it is essential to cut down carbon emissions (IPCC, 2018). Those related to energy use, however, are still at alarmingly high levels (IEA, 2021). Especially many production processes are very energy-intensive. In 2018, the industrial sector was responsible for 37 percent of global energy use and for 24 percent of total carbon emissions (IEA, 2020*b*). One way to improve the environmental impact of industrial processes while remaining competitive is to decouple greenhouse gas emissions from economic growth, as stated in the European Green Deal (European Commission, 2019), for example by reducing energy intensity.

In addition to a growing need for environmental improvements, the use of digital technologies has increased strongly in recent decades. For example, new markets emerged, such as online platforms, and new channels to communicate developed, such as messaging services and digital video conferencing systems. Furthermore, "ICTs [...] heavily affected the opportunities and efficiency of how firms produce and provide goods and services" (Cardona et al., 2013, p.13). Accordingly, digital technologies – most likely – also affected energy use patterns of (manufacturing) firms and will continue to do so in the future.

However, how ICT influence environmental outcomes is ambiguous ex ante. On the one hand, digital technologies may increase firm-level energy intensity, as they consume

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energy themselves. On the other hand, even though they do, they may reduce overall firm-level energy intensity due to energy efficiency improvements as well as the dematerialization of products (Berkhout and Hertin, 2004). For instance, digital technologies improve the quantity and quality of information. This allows for an improved prevention of excess production and a reduction of error rates. To put this in a nutshell, two simultaneous trends exist. Parallel to a strong need for energy intensity improvements and overall energy savings, digital technologies lead to large changes within firms. As this concurrence may contribute to or conflict with the achievement of climate targets set out in the Paris Agreement (2015), it is essential to assess how both, energy consumption and the use of digital technologies, relate to each other.

Especially grey literature assigns high climate protection potentials to digital technologies.[1] Also, previous econometric studies employing aggregated data confirm at the sectoral level that ICT can be linked to significant environmental improvements in manufacturing sectors (Schulte et al., 2016; Bernstein and Madlener, 2010). However, the use of aggregated data has several drawbacks. For instance, it does not allow for the disentanglement of dynamics within industries. Hence, it remains unobserved if actual improvements within firms exists or whether merely the composition of firms changes. Accordingly, results of studies based on aggregated data may be misleading for policy makers.

Despite the need for further research, most manufacturing countries launched programs promoting smart manufacturing such as the German “Industrie 4.0” as well as the US initiative "Smart Manufacturing Leadership Coalition" (SMLC) (Thoben et al., 2017) and emphasize its potentials for a more sustainable production.[2] Also the “Masterplan for a Competitive Transformation of EU Energy-intensive Industries Enabling a Climate-neutral, Circular Economy by 2050” launched by the European Commission states that “digital technologies will [...] act as crosscutting enablers for industrial transformation” (European Union, 2019, p.8). Considering the number of already initiated measures, it is highly relevant from a policy perspective to correctly understand the relationship between digital technologies and energy use.

To the best of our knowledge, no large-scale microeconometric study exists yet that analyzes climate protection potentials of digitalized production processes at the firm-level, which may provide new and more detailed insights into how the growing use of digital technologies relates to energy savings. Accordingly, this study sheds light into this relationship by employing microeconometric methods. The analysis is based on administrative panel data on 28,600 German manufacturing firms (AFiD)[3] collected between 2009 and 2017 and provided by the Research Data Centres of the Statistical Offices of the Federation and the Federal States (RDC). AFiD data are of particular high quality, as reporting to the statistical offices is obligatory and the data is thoroughly checked.

Furthermore, we analyze whether firm-level software capital, as an indicator for ICT usage, affects energy intensity. The descriptive statistics already show a strong increase in software capital intensity over time, while energy intensity decreases. To ensure comparability to previous findings at the sector level, we apply a translog cost function approach for the econometric analysis. Results confirm a statistically significant link between software usage and energy intensity improvements at the firm level. However, the relationship is considerably smaller than in previous findings at the industry level.

[1] For instance, see GeSI & Accenture (2015).

[2] The use of sensors, computing platforms, communication technology, control and simulation methods, data intensive modelling and predictive engineering within production processes is summarized as smart manufacturing (Kusiak, 2018).

[3] Amtliche Firmendaten für Deutschland.

We find that a 1 percent increase in software capital relates to an average decrease in energy intensity between 0.007 percent and 0.011 percent, depending on the approach how to calculate this elasticity. Results are robust to different sample restrictions as well as software capital stock modifications and the link appears to be more pronounced for energy-intensive firms and industries. Moreover, we find larger differences between than within firms. Hence, firms which have a high software capital stock on average appear to be less energy intensive on average, but when the software capital stock changes within a firm, effects have much smaller magnitude. To further analyze the robustness of our results, we conduct a reduced-form estimate with a selection of variables based on a CES production function. Respective results lead to the same conclusion, which is that the use of digital technologies is only to a small extent associated with energy intensity improvements at the firm level. As the relationship is very inelastic, we conclude that digital technologies relate to energy intensity improvements to some extent, but the effect size is not large enough to attribute substantial environmental improvements.

The remainder of this paper is structured as follows: Section 2 summarizes related literature and Section 3 presents our theoretical framework. Section 4 describes the data and provides descriptive statistics. Section 5 presents econometric specifications. Results are reported in Section 6 and discussed in Section 7. Section 8 concludes.

2. Related Literature

The European Union has declared energy efficiency improvements as a key dimension of its climate action policy (European Parliament and the Council of the European Union, 2018). “Energy efficiency is a generic term” and “refers to using less energy to produce the same amount [of output]” (Patterson, 1996, p.377). For example, a more energy efficient production process uses less energy with respect to a comparable one. A commonly-used indicator for energy efficiency is energy intensity, which is the actual amount of energy used to generate one unit of output, not necessarily considering differences in prevailing conditions, e.g., the type of product or local weather (cf. IEA, 2020*a*).

The digital transformation may influence overall energy use and intensity in various ways. Berkhout and Hertin (2004), Hilty et al. (2006) and Lange et al. (2020) develop frameworks that structure potential impact mechanisms. Based on these frameworks, the net effect on the environment consists of three different channels:

(I) Direct (Berkhout and Hertin, 2004; Lange et al., 2020) or first-order effects (Hilty et al., 2006) relate to the energy and resources consumption during the production, usage and disposal of ICT. Accordingly, direct effects have a negative environmental impact and increase energy and resource use.[4]

(II) Energy efficiency improvements (Lange et al., 2020), indirect (Berkhout and Hertin, 2004) or second-order effects (Hilty et al., 2006) refer to changes in consumption due to the application of digital technologies. Through improvements in energy efficiency as well as a substitution by dematerialized solutions, digital technologies have the potential to decrease energy intensity in different sectors.[5] For example, Big Data allows for an improved prediction of demand and may prevent excess production, it also helps to reduce error rates. Simulation methods as well as 3D printing may drastically reduce resource and energy use associated with the design and development of new products

[4]For examples of findings on the energy consumption of YouTube see Preist et al. (2019), for the cryptocurrency Bitcoin see Stoll et al. (2019) and Corbet et al. (2021), and for data centers see Masanet et al. (2020).

[5]Fur instance, see Zhang et al. (2019), Ghobakhloo and Fathi (2021) or Friedrich et al. (2021) for studies that qualitatively discuss ICT-enabled energy savings in manufacturing.

(OECD, 2017; IEA, 2018). Hence, even though digital technologies consume energy, they can have a positive net effect on the environment.

(III) Structural and behavioral impacts (Berkhout and Hertin, 2004) or third-order effects (Hilty et al., 2006) describe fundamental changes associated with the use of digital technologies. For instance, a decrease in overall energy use due to energy efficiency improvements is only possible when these are not largely dampened by rebound effects (Lange et al., 2020) and digital systems are a substitute rather for than a complement to existing solutions (Berkhout and Hertin, 2004). Moreover, structural and behavioral impacts have no clear direction of impact. Therefore, Lange et al. (2020) focus on two main mechanisms with less ambiguous directions of impact: Economic growth and tertiarization. Additional consumption resulting from ICT-induced economic growth may lead to an increased energy and resource consumption. Sectoral shifts to less energy-intensive goods and services may contribute to environmental improvements.

These frameworks illustrate the complexity of the relationship between digital technologies and environmental impacts. Accordingly, determining and measuring the net impact of ICT on energy usage is not trivial. Not without reason do studies on overall trends come to different conclusions. The academic discussion presumably starts with Walker (1985), who predicts that due to productivity improvements and structural changes, the importance of electric energy will increase and overall energy efficiency will enhance. More recently, GeSI & Accenture (2015, p.8) predict based on twelve use cases that "ICT can enable a 20 percent reduction of global carbon emissions by 2030" and a large share of this reduction is attributed to the manufacturing sector. In contrast, Ferreboeuf et al. (2019) state that every year the direct energy footprint of ICT increases by 9 percent and growth could be limited to 1.5 percent, if measures to reduce the environmental impact of ICT were introduced. Also, Belkhir and Elmeligi (2018) claim that worldwide ICT-related carbon emissions could increase from approximately 3 percent in 2017 to 14 percent by 2040. Van Heddeghem et al. (2014), Andrae and Edler (2015) and Malmodin and Lundén (2018) are further studies analyzing overall trends.[6] Most of these general studies rely on strong assumptions and not all of them are peer-reviewed. In this regard, Santarius et al. (2020) highlight the need for further research on overall trends.

To determine the net environmental impact of digital technologies it is crucial to accurately measure the size of actual energy intensity improvements. Using aggregated data to measure energy efficiency improvements within manufacturing and service industries studies come to mixed results, but tend to support the hypothesis that digital technologies are associated with a decrease in energy intensity. Using a CES production function, Collard et al. (2005) investigate the relationship between ICT and energy use in the French service sector. The authors find that electric energy intensity decreased with the diffusion of communication devices, while it increased with the use of computers and software. Applying the same approach, Bernstein and Madlener (2010) analyze the impact of ICT capital on electricity intensity in five manufacturing industries and eight EU countries from 1991 to 2005. Even though the effect seems to depend on the sector-specific production processes, the authors conclude that the diffusion of ICT is generally linked to electric efficiency improvements.

Analyzing 27 industries of ten OECD countries between 1995 and 2007 and using a translog cost function approach, Schulte et al. (2016) come to a similar conclusion. They

[6]For an overview of different (historical) studies at the sectoral or country level see Chimbo et al. (2020). For instance, applying a logistic smooth transition regression model, Lahouel et al. (2021) confirm an improved carbon efficiency related to ICT usage in Tunisia from 1970-2018 at the country level.

find that an increase in ICT capital of 1 percent is linked to a decrease in energy intensity of 0.235 percent at the sectoral level. Additionally, a sample split into manufacturing and service industries shows only significant effects for the manufacturing sector.

Unfortunately, sector-level data does not enable the analysis of dynamics within industries. It remains unknown how many energy inefficient firms drop out of the market and new, potentially ICT-intensive firms appear. This phenomenon may explain changes at the sectoral level. Furthermore, effects could only be valid for certain types of firms, e.g., larger firms that have different energy use patterns may tend to invest more in ICT. This and other issues can cause noise or misleading results as emphasized in Draca et al. (2007). Crépon and Heckel (2002) show that different methods to derive sector-level ICT capital stocks can lead to non-trivial differences in the share of ICT capital in value added. Furthermore, research that analyzes the relationship between overall capital intensity and energy use comes to different conclusions for sectoral and firm-level data (Haller and Hyland, 2014).

Comprehensive information at the firm level in manufacturing is scarce. Previous literature reviews are emphasizing the difficulty of finding objective or non-speculative studies (Ghobakhloo and Fathi, 2021; Chen et al., 2020). Exceptions are some questionnaire-based surveys with non-technical self-assessments of firms. For instance, in a survey conducted in 2020, 1700 German manufacturing and services firms were asked about measures in the areas of energy efficiency and digitalization (Bertschek et al., 2020). Energy savings were the least frequently named reason for conducting ICT projects. Moreover, most manufacturing firms stated that their absolute and relative ICT-related energy use remained constant during the last three years. A survey among 65 Italian manufacturers shows that firms seldom see benefits in Industry 4.0 for environmental sustainability (Brozzi et al., 2020). The largest study in this regard was conducted on behalf of the European Commission in 2021 (European Union, 2021). For this purpose, 10,006 firms were interviewed. In this survey, firms also stated that improving the environmental footprint is not the dominant motivation for implementing digital technologies. Nonetheless, 70 percent of all firms reported energy savings due to their use.

To the best of our knowledge, there is only one study at the firm-level to date that focuses on quantifiable environmental impacts. Wen et al. (2021) analyze environmental pollution measured by chemical oxygen demand (COD) and sulfur dioxide emissions (SO_2). The authors find that an increase in ICT investments and services at the provincial-city level relates to significant reductions thereof at the firm level.

No large-scale firm-level econometric study exists yet that analyzes the impact of ICT on energy use patterns or carbon emissions. However, this might reveal new insights as "using micro data rather than industry data allows the well-documented firm level heterogeneity in productivity and investment patterns to be taken into account [...]" (Draca et al., 2007, p.113).

3. Theoretical Framework

To analyze the relationship between ICT use and energy intensity at the firm-level, we apply the same theoretical model as Schulte et al. (2016). This study is the most comprehensive at the sectoral level with results not only limited to electricity use but to general energy use and therefore best suited for a direct comparison.

The model is built on a dual translog cost function approach based on the seminal work of Christensen et al. (1973), Berndt and Wood (1975), Brown and Christensen (1980) and Berndt and Hesse (1986). We assume that the translog cost function is twice differentiable, linearly homogeneous and concave in factor prices. Different forms of capital are considered as quasi-fixed factors and materials as weakly separable. Applying

Shephard's lemma, assuming homogeneity of degree one and imposing symmetry allows estimating the following equation, in which the share of energy costs in variable costs is a function of the energy price relative to the labor price, time, output as well as ICT and non-ICT capital.[7]

$$\begin{aligned} S_E =& \beta_E + \beta_{EE} ln\left(\frac{P_E}{P_L}\right) + \beta_{EK_{ICT}} ln\left(\frac{K_{ICT}}{Y}\right) + \beta_{EK_N} ln\left(\frac{K_N}{Y}\right) \\ &+ \beta^*_{EY} lnY + \delta_{ET} t \end{aligned} \tag{1}$$

S_E captures the share of energy costs in variable costs (VC), which is the sum of labor and energy costs. E indicates energy, L labor and P respective prices. K_{ICT} relates to ICT capital and K_N to tangible (non-ICT) capital. Y measures total output[8] and t the analyzed time period, which also controls for time-dependent disembodied technological progress.

The effect size of ICT on energy intensity[9] is captured by a demand elasticity, which can be decomposed into two different effects: The first term of Equation (2) captures the effect of ICT on the share of energy costs in variable costs and the second term captures the effect of ICT on total variable costs.

$$\epsilon_{EK_{ICT}} = \frac{\partial \ln S_E}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} = \frac{\partial \ln E}{\partial \ln K_{ICT}} \tag{2}$$

Assuming that $\partial VC/\partial K_{ICT}$[10] equals the shadow price of ICT and rearranging Equation (2) allows measuring the demand elasticity by Equation (3) following Schulte et al. (2016). $S_{K_{ICT}}$ captures the ratio of ICT capital costs to variable costs.

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} - S_{K_{ICT}} \tag{3}$$

In contrast, Foster-McGregor et al. (2013) and Hijzen et al. (2005) assume that the reduction in variable costs is negligible ($\partial VC/\partial K_{ICT} = 0$). Accordingly, the demand elasticity for energy intensity following these authors is calculated as:

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} \tag{4}$$

Both elasticities are reported in the later analysis.

4. Data

Our analysis focuses on firm-level data on the German manufacturing sector (AFiD) collected between 2009 and 2017 and provided by the Research Data Centres of the Statistical Offices of the Federation and the Federal States (RDC). Within our data, firms are assigned to the manufacturing sector if they have the highest value added in associated industries. In 2019, for instance, the manufacturing sector was responsible

[7] For a detailed description of the derivation of the model and demand elasticities see Appendix C.

[8] $\beta^*_{EY} = \beta_{EY} + \beta_{EK_N} + \beta_{EK_{ICT}}$; Schulte et al. (2016) scale capital by output to be consistent with literature that measures effects of ICT on labor and output. Consequently, β_{EY} has to be modified to β^*_{EY}.

[9] It is energy intensity and not energy demand as it is controlled for output (Y).

[10] $\partial VC/\partial K_{ICT}$ in $\partial lnVC/\partial lnK_{ICT} = (\partial VC/\partial K_{ICT})(K_{ICT}/VC)$.

for 28 percent of energy demand in Germany. Approximately two-thirds were used for process heat. Mechanical energy, e.g., for operating motors or machines, represented roughly a quarter, while heating of rooms accounted only for a small share of total energy consumption (German Environment Agency, 2021). Besides, the manufacturing sector is considered as the backbone of the German economy and it is known for its efficiency.

4.1. Data Sources

We combine two AFiD datasets merged by internal identifiers from the RDC:

(A) The AFiD-Panel Industrial Units[11], which contains two sub-datasets that are relevant for our analysis.

(A.1) The Census on Investment is used – including information about investments in tangible and intangible assets. It is a full census covering all German firms in the manufacturing sector with 20 employees or more. From this survey, we retrieve our indicator for the firm-level degree of digitalization, which is software usage. Information on software investments is available since 2009. We include information on investments in property, plant and equipment from 2003 onward. This allows considering investments in tangible assets before the observation period and improves calculations of respective capital stocks. Software investments have a very high depreciation rate. Therefore, not observing such investments before the observation period is not a substantive issue, which is confirmed by a robustness check.

(A.2) The second applied sub-dataset is the Cost Structure Survey. It contains comprehensive annual information at the firm level about produced output as well as inputs such as energy costs, labor costs and the number of employees. The Cost Structure Survey is a stratified (partly) rotating panel. Firms with 500 employees or more are fully included in the survey, whereas firms with fewer employees are generally observed for at least four consecutive years if they are surveyed. Accordingly, our entire observation period can be divided into three sequences (2009-2011, 2012-2015, 2016-2017).

(B) The AFiD-Module Use of Energy[12] (at the plant level) is the second applied AFiD dataset. It entails detailed information about the use of different energy sources at the plant-level. The dataset is also a full census including all German manufacturing plants with 20 employees or more. For information on firm-level energy use, we aggregate plant-level information for each firm. One minor drawback is that we do not observe the units of firms that are assigned to the service sector. Hence, when we observe software investments, it may be that they were made in a service sector facility and we cannot observe corresponding changes in energy use in that facility. However, establishments in the service sector consume a much smaller fraction of energy compared to plants in the manufacturing sector. We also do not expect to see large differences in the degree of digitalization between units within firms, as digitalization projects are most likely implemented company wide.

Additionally, we add information from several data sources. We combine AFiD with gross value added deflators from Eurostat at the two-digit industry level (NACE Rev.

[11] DOI: 10.21242/42221.2017.00.01.1.1.0
[12] DOI: 10.21242/43531.2017.00.03.1.1.0

2 classification) to calculate real output. Annual software deflators are also taken from Eurostat. This allows us to consider real software investments and thus quality improvements in software to be taken into account. EU KLEMS data is added (also at the two-digit industry level) to receive information about capital growth rates, depreciation rates as well as tangible capital deflators. The yearly producer price index provided by the German Federal Statistical Office (Destatis) is complemented, as well as information on prices of different energy carriers. We add yearly information for national (industry) prices for the following energy sources: Electricity, natural gas, coal, heating oil, district heat, liquid gas and biomass. For a detailed overview of additionally added data, see Table A.5 in the Appendix. Sources for prices of different energy carriers are also listed here.

4.2. Variable Description

Employing the raw data described in Section 4.1, we conduct the following additional calculations to generate our model variables. The AFiD module Use of Energy entails information (in kWh) about electricity consumption as well as energetic and non-energetic use of different energy carriers, which we summarize by the following categories: Biomass, natural gas, coal, heating oil, district heat, liquid gas, and other energy sources.[13] We define overall firm-level energy use (E) as the sum of energetic use of different energy carriers plus electricity use. Additionally, we subtract self-generated electricity by means of the listed energy carriers from electricity use to avoid double counting.

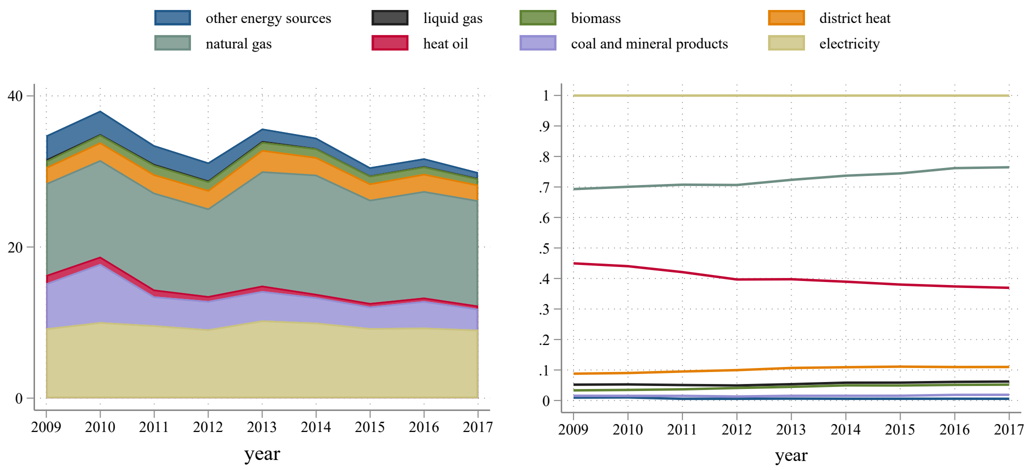

Figure 1: Mean use in GWh (left) and share of firms that use (right) different energy sources per year.

Mean use of different energy sources per year for our sample is displayed in Figure 1 (left panel). The mean fluctuates above 30 GWh and we find a small decrease in mean energy use over time. The descriptive statistics in Table 2 show that the median fluctuates around 2 GWh. Hence, the distribution of energy use is highly skewed, some firms consume far more energy than the large body of firms. To illustrate numbers, the mean firm-level energy use is more than 1900 times higher than the mean energy use of private

[13]See B.6 in the Appendix for a detailed overview of which energy carriers are included in each category.

households in 2017; the median is approximately 115 times higher.[14] Figure 1 (right panel) additionally shows the share of firms that use different energy sources. All firms consume electricity. Also, more than three-quarters consume natural gas and this number is slightly increasing. Both, electricity and natural gas, also make up a large part of the mean energy use. Consequently, they can be considered as the most dominant energy sources. It should also be noted here that heating oil, which is declining, is used by more than a quarter of firms, but it accounts for only a small proportion of mean energy use. The opposite holds for coal and mineral products. They account for the third largest fraction of mean energy use, but are used by only a small amount of firms.

Energy costs ($P_E E$) can be directly retrieved from the Cost Structure Survey. Furthermore, the analysis requires information on energy prices, which are not directly available in AFiD. Following Haller and Hyland (2014), we divide energy costs by energy use (E) to receive information on the energy price for each firm (P_E; in €/kWh). This approach is prone to issues resulting from misreporting. If a firm reports, for example, too low energy use, we observe too high prices. To control for outliers, we exclude the highest and lowest percentile with respect to the energy price from our analysis. The resulting price distribution is displayed in Figure F.6 in the Appendix. The energy price of most firms is between 0.02 and 0.20 €/kWh. Values are plausible considering industry prices for different energy sources. However, prices are endogenous as they depend, for instance, on the chosen quantity. To solve this issue, we calculate a second price variable using external energy prices (P_E [external]). We use prices of different energy sources (if available) from official statistics and weight them by the firm-level use of the respective energy source.[15] Figure F.8 in the Appendix compares internal and approximated external energy prices and confirms a statistical relationship between both.[16] The distribution of external prices is displayed in Figure F.7 in the Appendix, which is similar to internal energy prices, but the distribution is less skewed to the right.

Gross wages and salaries, statutory and other social costs are summarized to receive information on labor costs ($P_L L$). The amount of full-time equivalents (L) is measured by the total number of employees adjusted for part-time employees. In the analyzed time frame, firms employ slightly more than 270 full-time equivalents on average. The yearly wage is derived by dividing labor costs by full-time equivalents. For hourly wages, we adjust values by the average yearly hours worked in 2016 in German manufacturing.[17] The average hourly labor price (P_L) is 29 €.[18]

Variable costs (VC) are calculated based on the sum of energy and labor costs. S_E measures the share of energy costs in variable costs, S_L the share of labor costs. The average share of energy costs in variable costs is around 0.09, which is comparable to the average sector-level share derived by Schulte et al. (2016).

Output (Y) is measured by real value added based on information specified in the Cost Structure Survey. We do not subtract energy costs to calculate value added, as we consider capital, energy and labor in our production function (KLE), but we assume materials to be weakly separable and subtract them. Output is deflated using Eurostat data on a two-digit industry level.

[14] Mean energy use of private households was 17,376 kWh in 2017, see website link (accessed 12. Nov 2021).

[15] See Table A.5 in the Appendix.

[16] Due to a strict anonymization policy, we are not able to publish a scatter plot, as this would show individual observations.

[17] See website link (accessed 13. Nov 2021).

[18] The value is a slightly higher in statistics adjusted for the overall population (website link, accessed 14. Nov 2021).

Software capital (K_{SW}) approximates the degree of firm-level digitalization and tangible capital (property, plant and equipment) represents the non-software capital stock (K_N).[19] It has to be noted here that we only account for purchased software capital and firms may also use software that is free of charge. Software and non-software capital stocks are based on investments reported in the Census on Investments. We deflate them based on Eurostat (software) and EU KLEMS data (non-software). Furthermore, the perpetual inventory method (PIM) is applied to estimate capital stocks (Griliches, 1980; Berlemann and Wesselhöft, 2014; Lutz, 2016; Dhyne et al., 2018; Löschel et al., 2019). If calculated correctly, PIM allows measuring the total productivity-relevant capital by considering next to current investments previous investments and depreciation rates. The depreciation rate of software capital in our preferred specification is 31.5 percent, as in EU KLEMS. We also calculate an average depreciation rate for non-software capital based on EU KLEMS data. Moreover, PIM requires assumptions about initial capital stocks, which are calculated based on average investments in the first three observation periods as well as depreciation and capital growth rates. Consequently, we only consider observations that are observed at least three years in a row. For a detailed description of PIM see Appendix D. Our calculated capital stocks confirm findings of Kaus et al. (2020), who analyze tangible and intangible capital within the German manufacturing sector. Software capital (as a form of intangible capital) is growing faster in comparison to tangible capital. Furthermore, both distributions of respective investments are heavily skewed and lumpy, but software investments show these characteristics to a greater extent. For instance, we find approximately 25 percent of firms without any software investments in the analyzed period. Accordingly, we add 1 € to every software capital stock, as this allows for taking the logarithm when software capital stocks are zero. We will discuss this issue further in subsequent sections.

To evaluate the plausibility of estimated software capital stocks and to analyze whether they are a sufficient proxy for the firm-level degree of digitalization, we conduct the following comparisons. Firstly, we compare our results with the Survey on the Use of Information and Communication Technologies in Companies (ICT survey, 2012 - 2017), which is a stratified random sample and entails more detailed information on ICT usage.[20] We are able to match 16,813 observations from our sample with the ICT survey. Unfortunately, different questions are asked every year and a large share of missing values exists, so the number of observations is much lower for each survey item. Figure 2 shows mean software capital intensity, i.e., the amount of software capital used to generate one unit of output, for firms in which at least 20 percent of employees use a personal computer (PC) and for firms in which less 20 percent use a PC. Firms have a much higher software capital intensity when at least every fifth employee uses a PC. Figure 3 illustrates software capital intensity by the firm-level maximum data transmission rate. The figure depicts that the higher the Mbit/s range (the faster the internet speed), the higher also the mean software capital intensity. Consequently, we see a clear relationship between software capital and the use of other digital technologies.

Secondly, we analyze whether sectoral and regional differences with respect to software usage are plausible. Figure 4 shows average software capital intensity for different industries. Manufactures of wearing apparel (Division 14) and basic pharmaceutical products (Division 21) show the highest average software capital intensity. The pharmaceutical industry (combined with the chemical industry) was the most digital German

[19]Leasing capital is excluded.

[20]The ICT survey is additionally provided by the RDC. Doi: 10.21242/52911.2012.00.00.1.1.0 - Doi: 10.21242/52911.2017.00.00.1.1.0

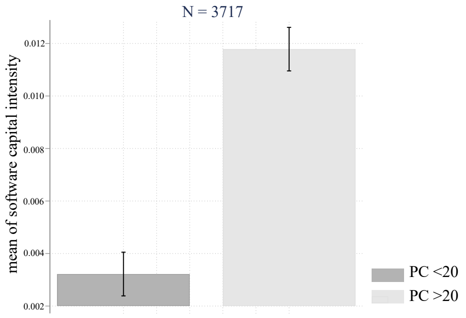

Figure 2: Software capital intensity by firms' PC usage.

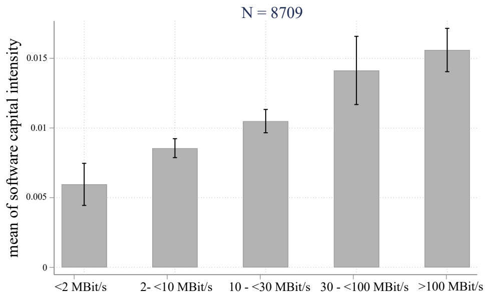

Figure 3: Software capital intensity by maximum data transmission rate.

manufacturing industry in 2018 according to Weber et al. (2018). The high software capital intensity of the wearing apparel industry can be explained by the fact that it is a market with highly interconnected supply chains and fast changing trends. Besides, digitalization allows for an increased individualization of products, which is especially important for this industry. Furthermore, it is also intuitive that the computer industry (Division 26) uses more software than most other industries. Manufacturers of other transport equipment (Division 30) may have a comparatively high software capital intensity because related industries such as aircraft and spacecraft construction are highly innovative.

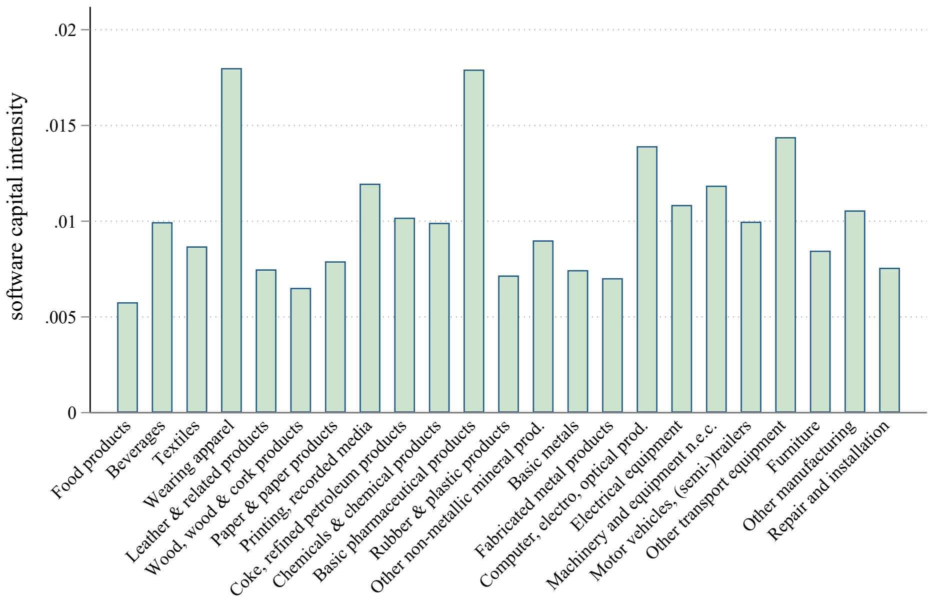

Figure 4: Average software capital intensity by industry between 2009 and 2017. The tobacco industry is excluded because of too few observations.

The geographic distribution of software capital intensity is displayed in Figure F.9 in the Appendix. The darker the blue color of the respective area, the higher the average software capital intensity. The white area in between marks regions for which we either observe no or less than three enterprises.[21] We find that areas with a very high software capital intensity coincide with major German cities. For example, Berlin, Munich, Dresden, Stuttgart and Hanover show very high values. As digital enterprises usually concentrate in larger cities, we consider this as a further indicator that software capital is suitable for measuring the firm-level degree of digitalization.

Additionally, the following control variables (C) are included in the analysis. We add federal state dummies as well as industry dummies on a two-digit level, dummies capturing different size classes, measured by the number of employees,[22] and a dummy indicating whether a firm has multiple establishments. By means of the electric energy consumption and the ratio of electric energy costs to value added, we approximate whether firms receive a full or a partial exemption from the EEG levy. Accordingly, we include two dummies relating either to a full or partial exemption. Moreover, a dummy that controls whether a firm produces energy is included, as this may affect energy costs, as well. Last but not least, we include a dummy which is one if a firm has trading commodities.

Although AFiD data are the corner stone of many official German governmental statistics and several plausibility checks are conducted by Destatis, we find small shares of implausibly small or high values. To address this, we trim our sample by the internal labor and energy price at the 1^{th} and 99^{th} percentile, and winsorize all growth rates included in Equation (1) at the 0.1^{th} and the 99.9^{th} percentile. We also exclude firms with zero labor, energy or non-software capital use, as well as firms with a negative output. Additionally, we exploit the panel structure to identify outliers and exclude firms for which the standard deviation relative to the median of input-output ratios as well as labor and energy prices is higher than 100.

4.3. Additional Descriptive Statistics

After the described prepossessing steps our sample includes 123,362 observations, 28,600 firms in total, and on average about 13,700 firms per year (Table 1). Around 13 percent of these firms are multi-unit establishments. We point out that the last panel sequence includes slightly fewer observations than the first two. Moreover, we apply the first-difference estimator in the subsequent statistical analysis. This reduces our main estimation sample to 89,653 observations.

	Year									
Panel sequence		1			2			3		
Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**Total**
% multi-unit firms	13.5%	13.8%	11.3%	11.3%	13.5%	13.8%	13.8%	13.9%	13.9%	13.2%
Total	13,886	14,196	13,671	13,672	14,139	13,931	13,581	13,306	12,980	123,362

Table 1: Number of observations per year.

An overview of mean, median, and standard deviation of selected variables can be found in Table 2. Values are also presented for annual change rates ($100 \times \Delta\, ln$).

[21] As the RDC is not allowed to provide information at this granular level due to German data protection laws.

[22] Size classes: 20 to 49 employees, 50 to 99 employees, 100 to 249 employees, 250 to 499 employees, 500 to 999 employees, 1000 and more.

	(1)			(2)		
	sample statistics in levels			**100 × Δln***		
	mean	median	sd	mean	median	sd
E	33 331 227.84	2 021 331.63	405 383 675.97	2.23	1.76	25.28
$P_E E$	1 848 518.09	245 000.00	14 004 206.33	3.81	2.93	29.79
L	273.15	88.50	1 957.65	1.28	0.86	11.88
$P_L L$	16 269 208.85	3 778 850.00	158 115 569.30	3.80	3.75	11.46
P_E	0.13	0.11	0.09	1.57	1.32	35.98
P_L	28.74	27.99	9.17	2.52	2.46	11.24
K_{SW}	258 458.48	13 389.11	2 703 507.41	18.05	0.00	133.26
K_N	20 110 799.14	3 011 534.63	204 487 549.41	2.11	−1.50	18.06
Y	22 929 312.43	5 060 662.00	213 216 121.19	3.82	3.31	27.48
Y/L	65 881.09	57 474.03	42 847.85	2.54	1.94	29.16
E/Y	1.07	0.38	3.86	−1.59	−1.70	36.24
K_{SW}/Y	0.01	0.0024	0.06	14.37	−9.56	136.68
K_N/Y	0.93	0.54	4.50	−1.64	−3.33	33.02
VC	18 117 726.95	4 190 796.00	165 630 044.11	3.71	3.62	11.35
S_L	0.91	0.94	0.10	0.05	0.02	2.24
S_E	0.09	0.06	0.10	−0.05	−0.02	2.14
N	123 362.00			89 653.00		

All monetary variables in €; Energy is measured in kWh. *Please note that S_E and S_L are not logarithmized.

Table 2: Summary statistics of selected variables.

Column group (1) displays the sample statistics in levels. In an average manufacturing firm an employee generates approximately 65,881 € output and for approximately one euro of output 1.07 kWh is used. However, half of the firms only consume 0.38 kWh or less per euro of output. Moreover, mean software capital intensity is only 0.01 and median software capital intensity is only 0.024. In comparison mean tangible capital intensity is 0.93 and median tangible capital intensity is 0.54.[23]

Column group (2) shows descriptive statistics for growth rates. Mean growth rates for energy use, labor use, tangible capital and software capital are positive. Hence, the absolute use of input factors grows over time at the firm-level. Moreover, the growth rate for output is also positive. Looking at intensities, we see that output increases more strongly than most inputs. Consequently, labor, energy and capital intensity decrease over time. In contrast, software capital intensity strongly increases. It has an average growth rate of 14 percent. With 18 percent, unscaled software capital is rising even more sharply. As a clear relationship between software usage and the use other digital technologies exists, we can assume that overall ICT capital also grew strongly within the analyzed time frame. Furthermore, the descriptive statistics of growth rates point to an issue. Median software capital growth is zero and median software capital intensity growth is actually negative. Also, tangible capital (intensity) shows a negative median growth rate, which can be explained by the fact that we generally observe a highly skewed distribution of investments, a similar issue applies to software capital intensity. Moreover, zero software capital stock growth rates exist because we allow for firms with no software investments at all. Related software capital stocks remain constant at one obligatory euro. Thus, they cannot shrink and their growth rate is zero. These observations are potentially problematic for the econometric analysis. Therefore, a considerable fraction of robustness checks will address this issue. It should also be noted here that standard deviations for all logarithmized growth rates are larger than those of aggregated sector-level data.

Figure F.10 in the Appendix shows time trends of mean software and non-software capital as well as mean labor and energy capital divided by output relative to 2009. All

[23]Ratios are comparable to aggregated EU KLEMS data.

variables decrease until 2011, which can be explained by an increase in output due to recovery after the economic crisis in 2009. Software capital intensity increases after 2011 and exceeds at the end of the observation period its level from 2009, whereas the other variables decrease in total. Moreover, the change of mean software capital should not be mistaken with the mean change of software capital.

5. Econometric Specifications

For the econometric analysis, we take first differences of Equation (1) to remove firm-specific fixed effects. Accordingly, Δu_{it} captures the time-specific firm-level deviation of firm i. To capture disembodied technological change at time t, we add a dummy variable for every year. Even though there is an unambiguous relationship between software capital intensity and the use of other digital technologies, we change ICT capital (K_{ICT}) to software capital (K_{SW}) to be accurate. Nevertheless, we assume that an increase in software capital is proportional to an overall increase in the use of digital technologies. Accordingly, percentage growth between software and other ICT capital should be comparable.

Except for the basic specification, we also add $d \in D$ control dummy variables (C). In all our specifications, we allow for clustering of observations at the firm-level when calculating the standard errors of estimates. Accordingly, Equation (1) is transformed to Equation (5).

$$\begin{aligned}\Delta S_{Eit} =& \beta_{EE} \Delta ln \left(\frac{P_E}{P_L}\right)_{it} + \beta_{EK_{SW}} \Delta ln \left(\frac{K_{SW}}{Y}\right)_{it} + \beta_{EK_N} \Delta ln \left(\frac{K_N}{Y}\right)_{it} \\ &+ \beta^*_{EY} \Delta ln Y_{it} + \sum_{t=2010}^{T} \delta_{Et} t_{it} + \sum_{c=d}^{D} \gamma_c C_{cit} + \Delta u_{it}\end{aligned} \tag{5}$$

We do not control for any further characteristics in our first specification (FD basic). However, in our second specification (FD all), which is our preferred specification, we do control for industry-specific fixed effects on a two-digit level and for firms with multiple establishments. We also add federal-state fixed effects to account for differences in wage growth as well as other differences between German federal states. Size-class dummies are included, since the cost structure may depend on the size of the firm, which is approximated by the number of employees. We additionally control for firms that may receive a full or a partial exemption from the EEG levy and for firms that produce energy by themselves. We also include a dummy indicating whether a firm has trading commodities, to control for different trends with respect to firms that outsource parts of their production due to new digital communication channels. The listed control variables will be used in all following steps.

Moreover, initial capital stocks may be unstable and investments need to be considered for a couple of periods to calculate solid capital stocks. To shed light into this issue, we will run a regression with firms observed in their third period or later in a third step ($t > 3$).

Additionally, we may observe a misleading correlation. If firms do not invest, their capital stock is depreciated. Hence, it decreases automatically. If especially those firms, which do not invest, increase their relative energy use, we would also measure negative capital intensity coefficients. However, this result would be deceptive. To analyze whether this is an issue with respect to software usage, we re-estimate Equation (5) and only consider observations for which the software capital stock is increasing ($\Delta ln K_{SW}(\uparrow)$).

Furthermore, endogeneity issues are a common problem in empirical studies at the firm level. We address this issue by removing time-invariant firm-specific fixed effects from the estimation. Therefore, endogeneity issues due to omitted variables are considerably reduced. For endogeneity issues caused by measurement errors of our main variable of interest, we provide various robustness checks with respect to different modifications in the calculation of software capital stocks and respective growth rates. For instance, we analyze how results change if we calculate software capital stocks assuming depreciation rates of 25, 33 and 50 percent. Also, different period lengths are employed to calculate initial capital stocks: We estimate initial software capital stocks based on two, four, and six observation periods if available.

Still, software capital stocks may be imprecisely estimated. One reason could be that a large share of firms do not report any software investments. As we impute these capital stocks in every period by an obligatory euro, they can neither rise nor shrink. However, it is not clear whether this is accurate, since firms could very well have invested in software before the observation period and their software capital stock would actually decrease in the observed time frame. Another problem may occur for firms that do not invest in periods used to calculate initial capital stocks, but start to invest afterwards. We observe then huge percentage increases in software capital stocks, since change rates from "zero" to large natural numbers are large by construction.[24]

We conduct the following robustness checks to analyze issues with respect to "zero" software capital stocks. Firstly, we exclude all observations that have "zero" software capital stocks as well as those observations that have a software capital stock that increases from "zero" and re-estimate our model. This allows us measuring to what extent results differ when potentially problematic observations are excluded. Secondly, we look closer at observations which have "zero" software capital stocks. Hence, their software capital growth rate is zero. We do not know whether firms actually have acquired no software capital or whether they invested before the observation period and their software capital stock decreases due to depreciation. To analyze whether this makes a difference, we impute "zero" growth rates. We replace them by the logarithmic change rate that we would have observed in a firm that has software capital, but does not invest in the current period. Hence, in a further re-estimation, software capital decreases by the depreciation rate for all observations that do not invest. Thirdly, we deal with the issue that some software capital stocks increase from "zero". This may result in implausibly large growth rates. Therefore, we censor very large values that increase from "zero". We consider increases more than 5-fold as implausible, limit them at this threshold and re-estimate the model.

Moreover, we conduct a robustness check with respect to the economic crisis and exclude observations before 2011. We also estimate our model only with single-unit firms to analyze to what extent results may be biased due to inaccurately matched information in multi-unit firms. Additionally, we test whether the inclusion of tangible capital may lead to multicollinearity issues, as software investments are often complementary to them. Further, we substitute changes in software capital intensity for changes in the previous period to examine whether there are time lags in effects. In an additional specification, we include fixed effects at the sector-year level.

Furthermore, we analyze different outcomes with respect to the econometric model. Accordingly, we estimate the translog model by applying a pooled OLS and a fixed-effects estimator. Moreover, we additionally employ a hybrid Mundlak model (Mundlak, 1978; Allison, 2009). This estimator allows for the analysis of differences within and between

[24]In fact they actually rise from 1 € as zero values are imputed.

firms. It is a random effects estimator in which variables are decomposed into firm-level averages (between effect) as well as their distance to the firm-level average (within effect).[25] Including group averages allows to relax assumptions of the random-effects estimator.

Analyses with respect to different effects regarding the sector assignment, observational period, size class and energy intensity as well as software intensity levels are displayed in Section 6.2. To further tackle endogeneity issues we aimed at conducting IV estimates, which are described in Section 6.3. In Section 6.4, we estimate a reduced form of a CES production function in order to investigate to what extent results depend on the econometric specification.

6. Estimation Results

6.1. Main Results

Table 3 shows results for the first four specifications conducted as described in the previous section. The energy intensity elasticity is calculated by both, Equation (3) [Schulte] and Equation (4) [Foster]. In addition, it is displayed for the average elasticity and the elasticity at averages of the energy cost share (S_E) and software capital cost share (S_{SW}). Details on respective distributions are provided by Table F.7 in the Appendix.[26] The first column shows results for the baseline specification. The second column entails results for our preferred specification including a wide range of fixed effects. Both columns show similar results. All coefficients point in the same direction as in previous estimates using sector-level data. The relative energy price is positively linked to the energy cost share and the coefficient size is about the same magnitude. The coefficient for software capital intensity is negative and significant at a high threshold, but its effect size is much smaller than in previous sector-level estimates. According to the demand elasticity calculated by Equation (3), the relationship is highly inelastic. An increase in software capital of 1 percent is only associated with a 0.011 percent decrease in energy intensity. Employing Equation (4), the elasticity is only 0.007 percent. Consequently, the relationship is much smaller considering microeconometric data. In their study, Schulte et al. (2016) display Equation (3) at averages. Comparing results illustrates how large differences are between different observational levels. Applying AFiD, a 1 percent increase in software capital intensity relates to a decrease in energy intensity of 0.007 percent at firm-level averages of S_E and $S_{K_{ICT}}$, while the mentioned authors measure a decrease of 0.235 percent. One reason why we measure a smaller elasticity is the fact that we only subtract the ratio of software capital costs to variable costs and not the ratio of ICT capital cost to variable costs, which is higher by definition. However, this only explains a deviation of approximately 0.05 percentage points, thus, only a small fraction of differences. Besides, we also observe that the tangible capital and the output coefficient point into familiar directions, but have lower magnitudes than in estimates based on aggregated data. However, differences are much smaller.

The following robustness checks address issues with respect to software capital stocks. The third column displays results only including firms observed in their third period or later. Except that the output coefficient becomes insignificant, we cannot identify any notable difference to our preferred specification. The fourth column shows results only for

[25] In the case of one independent variable, a hybrid Mundlak model would be $y_{it} = \beta_0 + \beta_W(x_{it} - \bar{x}_i) + \beta_B(\bar{x}_i) + \varepsilon_{it}$

[26] The capital compensation or shadow price to approximate $S_{K_{SW}}$ is derived by the user costs of capital calculated with EU KLEMS data and it is assumed to be 0.4 €.

Table 3: First-difference estimation results of Equation (5).

	(1)	(2)	(3)	(4)
	FD Basic	FD ALL	$t > 3$	$\Delta lnK_{SW}(\uparrow)$
	$\Delta\ S_E$	$\Delta\ S_E$	$\Delta\ S_E$	$\Delta\ S_E$
$\triangle\ln(\frac{P_E}{P_L})$	0.0285***	0.0284***	0.0295***	0.0251***
	(62.02)	(169.56)	(51.02)	(35.08)
$\triangle\ln(\frac{K_{SW}}{Y})$	-0.000245***	-0.000238***	-0.000206***	-0.000214***
	(-5.20)	(-5.19)	(-4.47)	(-4.11)
$\triangle\ln(\frac{K_N}{Y})$	-0.0013***	-0.0015***	-0.0013**	-0.0011
	(-3.43)	(-4.42)	(-3.27)	(-1.31)
$\triangle\ln(Y)$	0.0017**	0.0013***	0.0010	0.0014
	(3.21)	(3.32)	(1.48)	(1.43)
Year	x	x	x	x
Economic sector		x	x	x
Multi-unit		x	x	x
Federal state		x	x	x
Size class		x	x	x
EEG exemption		x	x	x
Producer		x	x	x
$\bar{\epsilon}_{EK_{SW}}$ (Schulte)	-0.0111	-0.0110	-0.0102	-0.0137
$\epsilon_{EK_{SW}}$ at $\overline{S}_{E,K_{SW}}$ (Schulte)	-0.0068	-0.0068	-0.0066	-0.0098
$\bar{\epsilon}_{EK_{SW}}$ (Foster)	-0.0069	-0.0067	-0.0059	-0.0062
$\epsilon_{EK_{SW}}$ at $\overline{S}_{E,K_{SW}}$ (Foster)	-0.0026	-0.0026	-0.0022	-0.0024
Observations	89653	89653	59405	25715
Adjusted R^2	0.267	0.271	0.290	0.250

t statistics in parentheses. First-difference estimation. Clustered standard errors.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. $\bar{\epsilon}_{EK_{SW}}$ displays the average demand elasticity for energy intensity for equation (3) and for equation (4). $\epsilon_{EK_{SW}}$ at $\overline{S}_{E,K_{SW}}$ displays the demand elasticity for energy intensity at averages of S_E and $S_{K_{SW}}$.

increasing software capital stocks. The software capital coefficient is again significant at a high threshold and the effect size is comparable to our preferred specification. However, non-software capital and output are insignificant. Both Equation (3) elasticities are slightly larger. This deviation is due to a higher average ratio of software capital costs to variable costs for the subsample used in this estimation. Also, note that slight differences in Columns (3) and (4) might stem from dramatically reduced sample sizes as well as from a selective consideration of observations.

Estimates employing different depreciation rates for the software capital stock can be found in Table G.8 in the Appendix. Results show that changes in the depreciation rate of the software capital stock only lead to marginal differences between coefficients. Hence, results appear to be robust in this regard. Results for different maximum lengths of observation periods considered for the initial capital stock calculation are displayed in Table G.9 in the Appendix. We find slight differences for initial software capital stocks that include two as well as up to six periods. For initial stocks based on two periods, we find effects that are marginally smaller. For initial stocks based on up to six periods, the effect size is slightly larger and the software capital coefficient becomes −0.0003. However, we do not consider this deviation to be large enough to have an effect on the economic interpretation of results, which would be that a 1 percent increase in software capital intensity relates only to marginal energy intensity improvements within firms.

Result with respect to issues related to "zero" software capital stocks can be found in Table G.10 in the Appendix. In the first column, we exclude observations that have "zero" software capital stocks as well as observations that have a software capital stock that increases from "zero". The effect size of the software capital coefficient is comparable to our preferred specification, however, it is only significant at the 10%-level. Consequently, even though the exclusion of potentially problematic observations does only marginally alter the coefficient size, we have to acknowledge that the relationship is now significant at a lower threshold. The second column displays results for imputed depreciation rates for "zero" software capital stocks that would occur if a firm had invested in previous periods. We find that this modification does not notably affect results and the coefficient of interest is comparable to baseline results. Hence, is does not make a difference whether we depreciate "zero" software capital stocks or not. The last two columns relate to estimates in which increases from "zero" software capital stocks are limited to a threshold. In Column (3), "zero" software capital stocks are included and in Column (4) excluded. Results of both columns are comparable and the coefficient slightly increases, but not substantially. To sum up, different treatments of growth rates related to "zero" software capital stocks only marginally affect results, i.e. they can hardly be the reason why we find smaller effects in comparison to aggregated estimates.

Table G.11 in the Appendix shows effects for single-unit firms (Column 1) and estimation results, in which only observations after 2011 are considered (Column 2). The restricted estimates are consistent with our baseline results. Both software coefficients point into a negative direction and are significant, but software coefficients are slightly smaller for both restricted samples. Moreover, our results are also robust with respect to the exclusion of tangible capital (Column 3). We additionally estimate the influence of lagged software capital and do not find any effect of an increase in the software capital stock in the previous period on current changes in the share of energy costs in variables costs (Column 4). Including sector-year level fixed effects does not affect baseline results notably (Column 5).[27]

Table G.12 shows results with respect to different econometric models. Column (1) displays results for the pooled OLS estimator. The software capital coefficient becomes nearly seven times larger, but also other coefficients change. Column (2) provides results for the fixed-effects estimator. The coefficients of the fixed effects model are comparable to coefficients in Table 3. The coefficients point in the same direction and have more or less the same magnitude – except tangible capital, which is insignificant. The consistency of both models supports the validity of both approaches. Differences between the pooled OLS estimator and the first-difference or the fixed-effects estimator indicate a large omitted variable bias if individual-specific effects remain unconsidered. Column (3) shows results for the hybrid Mundlak model, in which the overall effect is decomposed into a between and within effect. The significance of the coefficient for average software capital confirms that individual-specific effects are correlated with the dependent variable in this regard. Results also illustrate that between effects – differences between firms – are much larger than within effects – changes within a firm. In other words, firms which

[27]Besides, we also performed an estimation in which we replaced software capital intensity with software investment and measured a comparable relationship. The results are available from the authors upon request.

have on average a higher software capital intensity tend to have lower relative energy costs on average. However, a 1 percent increase in software capital intensity within a firm only relates to a marginal reduction of relative energy costs or energy intensity.

To summarize results, an increase in software capital intensity is associated with a decrease in relative energy demand, but the relationship has a much smaller magnitude than previous industry-level estimates suggests. Effect sizes at the firm-level are robust with respect to various econometric specifications.

6.2. Robustness with Respect to Firm-level Characteristics

In this section, we shed light into the robustness of estimates with respect to different manufacturing industries, energy and software-capital-intensity levels, CSS waves as well as size classes.

6.2.1. Industries

To analyze to what extent results differ for certain types of firms, we first split our sample based on sector affiliations. Accordingly, we individually fit Equation (5) for different industries at the two-digit level (NACE classification). Estimation coefficients for software capital intensity by industry are displayed in Figure 5. The colored dots mark respective estimation coefficients and the corresponding lines represent confidence intervals at the 95%-level. If estimated independently, the software coefficient is negative but insignificant for most industries. However, it has significant negative effects for manufacturers of paper and paper products (Division 17), chemicals and chemical products (Division 20), other non-metallic products – including the cement industry – (Division 23), basic metals – including iron and steel industry – (Division 24), electrical equipment (Division 27) as well as for the repair and installation industry (Division 33). Most of these sectors show a very high energy intensity.[28] Consequently, a reduction in the share of energy costs in variable costs may be driven by sectors that are highly energy intensive, such as the non-metallic products and the basic metals industry. Hence, although their magnitude is small, effects at least appear to be more pronounced in industries with potentials to save larger amounts of energy.

6.2.2. Energy and Software Capital Intensity

To shed more light into the extent to which results diverge for different energy and software capital intensity levels, we split our sample into quartiles with respect to firm-level averages of both variables respectively. Moreover, we estimate the translog model by employing a fixed-effects estimator. We do this because the fixed-effects estimator considers divergences from means. This allows for the analysis of effect differences regarding the distance to different average intensity levels.[29] Results are displayed in Figure H.11. The blue bars correspond to quartiles of firms with the lowest average energy or software capital intensity.

The left panel relates to different levels of average energy intensity. For the two quartiles with the lowest average energy intensity levels, the point estimates of the software capital coefficient ($\beta_{EK_{SW}}$) do barely differ from zero. For the two quartiles with the highest energy intensity, however, the magnitude of the coefficient increases and the relationship is significantly negative. Hence, the higher the average energy intensity level, the more pronounced reductions in the share of energy costs in variable costs.

[28] See website link (accessed 13. Oct 2021).

[29] Please note here that this is particularly relevant for different levels of average software capital intensity.

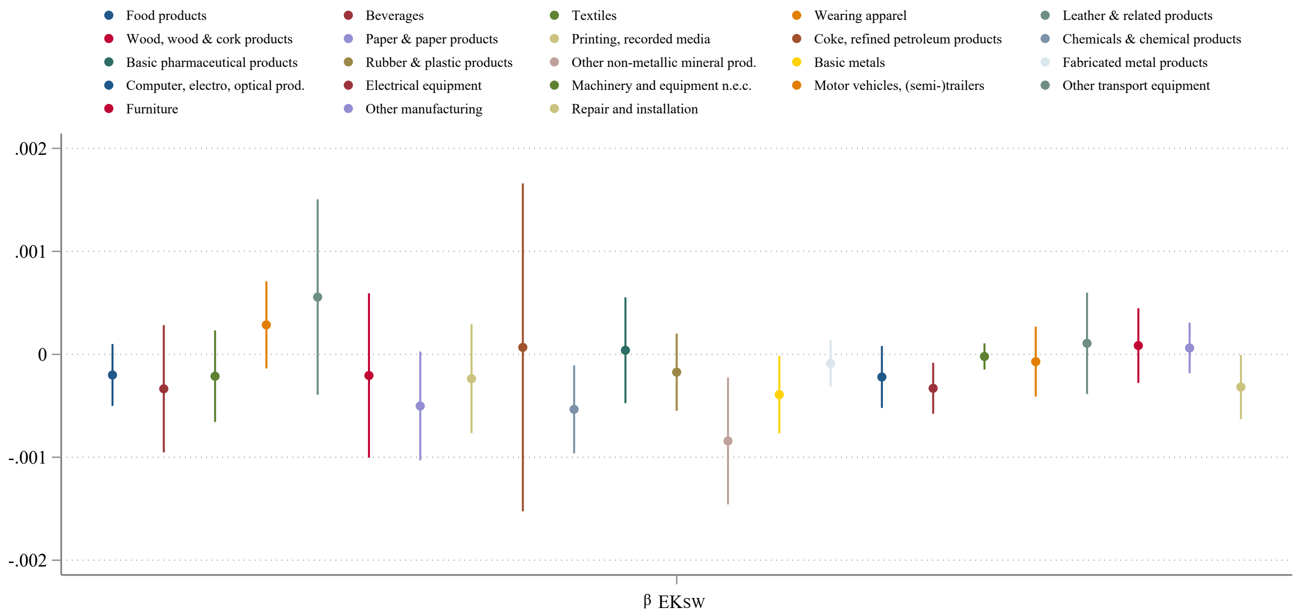

Figure 5: Heterogeneous effects - Sector level estimations (two-digit NACE level). Tobacco industry excluded because of too few observations.

The right panel relates to different levels of average software capital intensity. The quartile with the lowest average software capital intensity has a very large confidence interval. This can be explained by the fact that we observe a large share of "zero" software capital stocks, which are included here. Moreover, we do not observe a clear trend with respect to higher levels of software capital intensity. Effects of the third and the fourth quarter appear to be more pronounced, but differences are not substantial.

6.2.3. Time

Moreover, the relationship between software usage and energy intensity improvements may generally change over time. For instance, new energy-efficient technologies may appear or energy-saving potentials of already existing technologies may become exhausted. Also, effects may differ by CSS samples, as it is a rotating panel, in which a considerable share of firms is only observed for four consecutive years. Hence, the composition of firms partly changes every four years. We investigate differences with respect to the observed time frame by always estimating our model for a time frame of four years, but rotating forward by one year for each estimation. Results are displayed in Figure H.12. Software capital coefficients are always negative and significantly different from zero. Moreover, the magnitude slightly declines between the first two samples including the earliest observations and then continuously rises. However, the increase is very small. As a consequence, the difference between early and later observed samples is only marginal and we cannot find any substantial differences with respect to time.

6.2.4. Size Classes

We also estimate the translog model individually for different size classes with respect to the number of employees.[30] Results are presented in Figure H.13. We cannot find a linear pattern for different size classes. The software capital coefficient is relatively small and insignificant for small firms between 20 and 49 employees as well as for larger mid-sized firms between 100 and 249 employees. Effects are more pronounced and significant for smaller mid-sized firms between 50 and 99 employees as well as for large firms with 250 employees or more.

6.3. IV estimates

Even though we account for a large share of endogeneity issues by removing time-invariant firm-specific effects from the estimation, we still may observe biased coefficients. For instance, software capital intensity could be endogenous due to a simultaneous relationship or a still not detected measurement error. To analyze this issue, we include information on household broadband availability (HBA) at the municipality level and use different levels of maximum available data transmission rates as instruments for software usage. A similar approach has been conducted for example by Bertschek et al. (2013). Unfortunately, HBA instruments are weak and yield unreliable estimates. Therefore, we abstained from including results in the analysis.[31]

Moreover, endogenous control variables do not lead to biased coefficients when uncorrelated with the variable of interest, but they do if they relate to each other (Frisch and Waugh, 1933). In particular, the relationship between output and software capital could potentially bias results, because both variables may highly depend on each other. A

[30] We use four size classes instead of six to ensure that the number of observations in every subsample is comparable.

[31] Results are available from the authors upon request.

similar problem may exist with respect to the energy-labor-price ratio, as the use of software usually requires skills that are in high demand. To test whether these issues affect results, we conduct the following IV estimates as further robustness checks. Respective results are displayed in Table G.13.

For the analysis of endogeneity problems related to our output indicator, a problem arises because the variable is included in the model and also both capital stocks are scaled by output. However, from an econometric perspective it is not necessary to scale capital stocks by output since we already control for it.[32] Accordingly, we rearrange Equation (1) and do not scale both capital stocks by output anymore. Hence, we now estimate β_{EY} instead of β^*_{EY} (see Section 3 or Appendix C). The translog model is re-estimated and displayed in Column (1). It is straightforward to see that this modification barely affects software and tangible capital coefficients. In a second step, we instrument output by a firm's market share in terms of sales. Market shares are calculated using four-digit and two-digit industry levels and employing the Census on Investments, accordingly two different instruments are used. Additionally, we calculate market shares only if at least three observations per industry are available. Hence, we exclude a small share of observations from the estimation. Results are displayed in Column (2). The output coefficient gently increases, but the software capital coefficient is barely affected. In a last step, we instrument the energy-labor-price ratio by an exogenous energy price variable. To calculate the exogenous energy price, we use prices of different energy sources (if available) from official statistics and weight them by the individual use of the respective energy source.[33] Results are displayed in Column (3), in Column (4) output is instrumented as well. The effect size of the price coefficient decreases and it is now significant at lower threshold, but the software capital coefficient is not affected and comparable to the baseline specification. Besides, test statistics of tests for underidentification and weak identification as well as the Sargan–Hansen test indicate that the exogenous energy price and market shares are appropriate instruments.

6.4. Estimate of a reduced CES production function

To test the robustness of results derived by the translog model, we estimate a second model in which we use energy intensity directly as a dependent variable. For this purpose, we apply a nested CES production function approach with 3-inputs (K,L; E). This approach has also been used previously in studies at the sectoral level (Bernstein and Madlener, 2010; Collard et al., 2005). Here, energy intensity is modelled as a function of the energy-related level of technology (A), the energy price relative to a general input price level (P_E/P_{PPI}), an elasticity (σ) as well as a constant (ω) (Collard et al., 2005; Van der Werf, 2008; Lagomarsino, 2020; Bernstein and Madlener, 2010).

$$ln\left(\frac{E}{Y}\right)_{it} = \sigma ln(\omega) - \sigma ln\left(\frac{P_E}{P_{PPI}}\right)_{it} + (1-\sigma) lnA_{it} \tag{6}$$

Following Collard et al. (2005), we assume that the energy-related level of technology evolves as:

$$lnA_{it} = \theta_0 + \theta_{ICT} ln\left(\frac{K_{ICT}}{K_N}\right)_{it} + \theta_t t_{it} \tag{7}$$

[32] We scale software capital by output in our preferred specification to be consistent with Schulte et al. (2016).

[33] See Table A.5 in the Appendix for more details on data sources. The distribution of the exogenous price variable and its relationship to the potentially endogenous energy price variable is displayed in Appendix Appendix F.1.

To analyze whether effects differ between production function approaches, we plug Equation (7) in Equation (6), take first differences and estimate a reduced form as illustrated in Equation (8). The general input price level is measured by the producer price index[34], which is retrieved at a two-digit industry level from Destatis. Technological progress t is measured by time dummies.

$$\begin{aligned} \Delta ln\left(\frac{E}{Y}\right)_{it} =& \Delta\beta_{\frac{P_E}{P_{PPI}}} ln\left(\frac{P_E}{P_{PPI}}\right)_{it} + \Delta\beta_{\frac{K_{ICT}}{K_N}} ln\left(\frac{K_{ICT}}{K_N}\right)_{it} \\ &+ \sum_{t=2010}^{T} \delta_{Et} t_{it} + \sum_{c=d}^{D} \gamma_c C_{it} + \Delta u_{it} \end{aligned} \tag{8}$$

Results are presented in Table 4. Three specifications are estimated. In the first column, the specification is equivalent to our preferred specification in Table 3.

Table 4: First-difference results of Equation (8).

	(1) FD ALL	(2) Excluding problematic observations	(3) $K_{SW}(\uparrow)$
	$\Delta\ ln\ E/Y$	$\Delta\ ln\ E/Y$	$\Delta\ ln\ E/Y$
$\triangle\ \ln(\frac{P_E}{P_{PPI}})$	-0.446***	-0.462***	-0.481***
	(-58.43)	(-50.21)	(-34.27)
$\triangle\ \ln(\frac{K_{SW}}{K_N})$	-0.00289***	-0.00456*	-0.00239**
	(-3.71)	(-2.31)	(-2.68)
Year	x	x	x
Economic sector	x	x	x
Multi-unit	x	x	x
Federal state	x	x	x
Size class	x	x	x
EEG exemption	x	x	x
Producer	x	x	x
Observations	89267	64991	25609
Adjusted R^2	0.228	0.231	0.252

t statistics in parentheses; First-difference estimation; Clustered standard errors; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The adjusted R^2 value is now 0.23, which is slightly smaller than that of the translog model. The price ratio is negative and significant at a high threshold. As expected, an increase in the relative energy price relates to a decrease in energy intensity.[35] The software coefficient also shows a highly significant negative relationship. If the ratio between software and non-software capital increases by 1 percent, energy intensity decreases by 0.003 percent. Consequently, this effect size is slightly smaller but comparable to average elasticities derived with the translog model and is very similar to the Equation (4) elasticity at averages of S_E and S_{SW}. It should be emphasized here that the coefficient could be slightly biased since we assume a linear relationship. Moreover, we now measure the

[34] We lose a small fraction of observations here as the producer price index is not available for the repair and installation industry (Division 33) for 2009.

[35] Please note here that this relationship is not strictly exogenous.

effect of software capital relative to tangible capital and no longer the effect of software capital relative to output. In a second specification, we re-estimate the model but exclude potentially problematic observations with respect to "zero" software capital stocks. The software capital coefficient is now only significant at a 95%-level. We observe a similar phenomenon for the translog model. Furthermore, the magnitude of the effect increases, but this increase is not substantial. Therefore, we still consider the effect size as inelastic. In the third column, we only consider increasing software capital stocks. The coefficient of software capital relative to tangible capital is comparable to the first specification, however, it is only significant at a 99%-threshold. Moreover, the adjusted R^2 slightly increases. To sum up, results based on a reduced form of a CES-production function are robust to different econometric specifications and comparable to those derived with the translog model.

7. Discussion

Previous studies on manufacturing industries point out that the ongoing digital transformation may have synergies with climate targets. A higher amount of data and an improved exploitation of information increases efficiency within production processes and may decrease relative energy use, despite the fact that ICT consume energy themselves.

To the best of our knowledge, this is the first empirical study that uses firm-level data to analyze the validity of this claim. Using software capital intensity as a proxy for the firm-level degree of digitalization, we find that an increase thereof relates to a decrease in relative energy use, however, to a much smaller magnitude than previous sector-level estimates state. Consequently, the relationship is highly inelastic. Nevertheless, we would like to emphasize that we cannot fully rule out that estimated coefficients are small because they are downward biased due to a measurement error in software capital. However, the estimated software capital coefficient is robust to several sample restrictions and different modifications of software capital stocks. This consistency may provide some confidence.

It is not unusual that effects are smaller when microeconometric data is employed. In a meta analysis on the relationship between IT and productivity, Stiroh (2005) observes a similar phenomenon. The respective elasticity tends to be larger at the industry level and including firm-level fixed effects decreases the magnitude of the relationship. Also, Kaus et al. (2020) find lower effects of intangibles on output at the firm level than Niebel et al. (2017) at the aggregated level.

Furthermore, we analyze the robustness of results with respect to different firm-level characteristics. For instance, for most industries we find that the effect size is not significant, but software-related reductions in energy costs are significant and tend to be more pronounced for exactly those firms and industries that are comparatively energy intensive. Thus, there is some ray of hope.

Moreover, although the relationship is small, it does not necessarily mean that it is not relevant as software capital grew strongly in our sample in the observed time frame. Hence, software capital may still relate to considerable energy intensity improvements due to its large growth rate. To analyze this, we perform the following back-of-the-envelope calculation. We multiply the demand elasticity by the average annual growth rate of software capital intensity, which is 18.05 percent. Using the translog model, this translates into an annual decrease in energy intensity between 0.12 and 0.20 percent, depending on the approach used to calculate the elasticity. Over ten years this would result in energy intensity improvements of roughly 1.5 percent, assuming that software capital would continue to grow at such a high rate. This shows that software investments do relate to energy intensity improvements to some extent, but are not a key driver for achieving climate targets.

A further question is whether it would be economically rational to invest in software to save energy. To shed light into economic considerations, we approximate average savings in energy costs per euro invested in software. We use the average energy intensity elasticity derived by Equation (3) in Column (1) of Table 3 to calculate energy cost savings per euro invested in software. In Appendix E, our approach is described in detail. We measure that 1 € invested in software saved on average approximately 0.03 € of energy costs in the analyzed time frame. This calculation illustrates that conducting software investments to save energy (costs) does generally not appear to be economical from a firm perspective. This confirms a rational already observed in questionnaire-based surveys, in which firms were asked for non-technical self-assessments: Savings in energy consumption due to the use of digital technologies are rather a welcome side effect and do not appear to be substantial enough to be the main motivation for conducting digitalization projects.

What does our result imply for the net impact of ICT on total energy consumption? As the level of output is considered in both econometric models, the measured relationship indicates not necessarily a decrease in absolute energy consumption. By means of the translog model, we analyze the relationship between software capital intensity and the ratio between energy and labor costs. By estimating a reduced form of a CES production function approach, we consider the relationship between software usage and the ratio between energy use and output. Many economic studies show a clear link between labor and ICT (e.g., Van Reenen 2011, Michaels et al. 2014 and Atasoy et al. 2016) as well as productivity and ICT (Stiroh, 2005; Cardona et al., 2013). In other words, the observed relationship may be exclusively driven by positive effects of software capital on labor and output. Accordingly, there is not necessarily a decrease in absolute energy use within firms. It may be just less affected by software usage. Therefore, we abstain to make conclusions on absolute energy consumption. Besides, we want to emphasize that even if output or labor increases due to software usage and energy consumption remains constant or grows to a lower extent, energy intensity improvements still occur, as energy is used relatively less. Moreover, to be precise, we solely measure energy intensity improvements inside firms. For instance, we cannot make conclusions about additional energy that is consumed in external data centers due to an increase in the use of Could Computing. However, Cloud Computing has been not used very frequently in the observed time frame and its use has only picked up in more recent years.[36] An analysis with more recent data would probably run into greater difficulties here.

One issue of this study may be that energy efficiency improvements may be accompanied by rebound effects (Amjadi et al., 2018). For example, potential energy savings may not be fully realized because improvements in energy efficiency increase the attractiveness of using energy as an input factor. How the use of ICT relates to this issue could be worth looking into in further research.

Furthermore, effects may be small because software capital is insufficient to approximate the degree of digitalization. Unlike other digitalization indicators, e.g., the amount of employees working with a computer, software capital has the advantage that it is measured in monetary values. In addition, almost all hardware requires software. Especially technologies that optimize production by analyzing large amounts of data and thus potentially improve energy efficiency, heavily rely on software. We show a clear relationship between software usage and the use of other digital technologies in Section

[36]See website link (accessed 12. Dec 2021).

4.2. Consequently, another advantage in using software capital is that it is very general in comparison to other technologies such as Cloud Computing or 3D printing. Considering all possible indicators, we believe that for the purpose of this study, software capital is the most suitable indicator. Nonetheless, further analyses using different types of digital technologies may be useful, as heterogeneous effects with respect to different types of digital technologies could exist. Moreover, we have to acknowledge the issue that we do not consider the use of software that is free of charge. However, as we only look at relative percentage changes and it is likely that for most firms both, the use of free of charge and paid software, are proportional to each other, we assume that this does not have a large effect on our results.

Besides, we want to mention that AFiD data provide information on the use of different energy sources. Hence, it is also possible to analyze the influence of software capital on the energy mix, which may be affected by digital technologies, as well. However, a respective analysis would also require information on energy costs and prices for different sources. Unfortunately, the matched price data is often not sufficiently accurate, and different specifications of cost shares for each energy source yielded unreliable estimates. Therefore, we abstained from the analysis. This does not affect our main findings, as information on overall energy costs are surveyed by Destatis.

8. Conclusion and Outlook

Climate change and the emergence of digital technologies are considered as current megatrends. Consequently, to analyze how both relate to each other is of great importance. In particular, it is assumed that digital technologies may relate to a decrease in carbon emissions through energy intensity improvements especially in manufacturing industries, as they are considered to have very high potentials in this regard.

This is the first large-scale empirical study that analyzes the relationship between the usage of digital technologies and energy intensity improvements at the firm level. For this purpose, we employ administrative panel data on 28,600 firms in the German manufacturing sector collected between 2009 and 2017. Furthermore, we use software capital intensity as an indicator for the firm-level degree of digitalization and apply a translog cost function approach. Results show a statistically significant link between software capital and energy intensity improvements, but the effect size is much smaller than expected. Our findings are robust to several sample restrictions as well as to modifications of the software capital stock. Thus, we conclude that an increase in the firm-level software capital stock cannot be associated with substantial energy intensity improvements within firms. However, there is some ray of hope, as we find that effects are more pronounced in firms and industries that are very energy intensive.

Our results may be relevant for policy makers, consultants and firms that aim to improve energy intensity within establishments and may overestimate synergies between digital technologies and energy savings.

Moreover, effects are small for software usage, but they may be different for specific digital technologies. Future research that analyzes how different digital technologies relate to effect heterogeneity would be a further important contribution, for which the application of firm-level data has great potential. External factors such as carbon prices or market concentration may also incentivize the use of digital technologies to improve energy intensity and thus potentially influence effect heterogeneity. An analysis in this regard may be very useful for designing appropriate policies dealing with climate protection potentials of digital technologies. Last but not least, the analysis of ICT-related rebound effects as well as the inclusion of an appropriate instrumental variable that allows measuring whether the relationship is truly causal would be of great value.

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Appendix A. Additional Data

For our analysis, we add, inter alia, information on prices of different energy sources, gross value added deflators to calculate real value added and growth and depreciation rates as well as investment deflators to calculate capital stocks. All data sources are listed in Table A.5. The identifier denotes the variable that is used to merge the dataset with AFiD.

Table A.5: Description of additional data sources.

Information	Data source	Comments	Identifier
Price for energy source (electricity, natural gas, heating oil, coal)	Gesamtausgabe der Energiedaten, Federal Ministry for Economic Affairs and Energy (BMWi), status: 31.03.2020, link to website (Retrieved on: 01.04.2020)	Prices for hard coal (import prices), heavy heating oil (industry prices, VAT excluded), light heating oil (light, industry prices, VAT excluded), electricity and natural gas prices independent from the consumption level. are retrieved. The respective units have all been converted to €/kWh.	Year
Price for energy source (district heat)	Fernwärme – Preisübersicht, AGFW | Der Energieeffizienzverband für Wärme, Kälte und KWK e. V., status: 01.10.2017, link to website (Retrieved on: 14.08.2019)	Absolute price development from 2009-2017 for the connected loads of 160 kW (p.8) are used. Values are converted from €/MWh to €/kWh. Prices are retrieved without VAT.	Year
Price for energy source (biomass)	Brennstoffkostenentwicklung von Gas, Öl und Pellets, Deutsches Pelletinstitut GmbH (DEPI), status: 2019, link to website (Retrieved on: 13.09.2019)	Pellet price for 2015 is taken, value converted from cent/kWh to €/kWh (VAT excluded).	Year
Price for energy source (biomass)	Index der Erzeugerpreise gewerblicher Produkte (5.10 Holzprodukte - GP09-1629 14 908 Pellets, Briketts, Scheiten o.ä. Formen aus Sägespänen u.a. Sägenebenprodukt), from: Daten zur Energiepreisentwicklung - Lange Reihen von Januar 2005 bis Mai 2020, Statistisches Bundesamt (Destatis), status: 26.06.2020, link to data (Retrieved on: 16.07.2020)	The base year of the Destatis index is 2015. Therefore, the DEPI-price is taken from the year 2015 and multiplied by the index for each year to receive information about the change in the price for biomass.	Year
Price for energy source (liquid gas)	IEA Energy Prices and Taxes Statistics, International Energy Agency, status: 1.Quarter 2019, link to website (Retrieved on: 04.09.2019)	Prices (VAT excluded) from 2009-2017 for liquid gas are retrieved. Values are converted from €/l to €/kWh.	Year
Producer price index (PPI)	Index der Erzeugerpreise gewerblicher Produkte (Inlandsabsatz) nach dem Güterverzeichnis für Produktionsstatistiken Ausgabe 2009 (GP 2009) - Lange Reihen der Fachserie 17, Reihe 2 von Januar 2005 bis September 2020, Statistisches Bundesamt (Destatis), status: 20.10.2020, link to data (Retrieved on: 12.11.2020)	Index on the yearly average change is retrieved.	Year, economic sectors (two-digit NACE code)
Gross value added deflators	National accounts aggregates by industry, Eurostat, status: 24.03.2020, Eurostat bookmark (Retrieved on: 01.04.2020)	Price index (implicit deflator), base year 2010, national currency.	Year
Capital stock	Cross-classification of gross fixed capital formation by industry and by asset (flows) - Computer software and databases (gross), Eurostat, status: 30.03.2020, Eurostat bookmark (Retrieved on: 01.04.2020)	Table PD10_NAC, price index (implicit deflator), base year 2010, national currency. Software deflators are retrieved. See Appendix D for detailed information on how we calculate software as well as non-software capital stocks.	Year

Information	Data source	Comments	Identifier
Capital stock	EU KLEMS database - 2019 release, Germany capital input data, see Stehrer, R., A. Bykova, K. Jäger, O. Reiter and M. Schwarzhappel (2019): Industry level growth and productivity data with special focus on intangible assets, wiiw Statistical Report No. 8. link to data (Retrieved on: 18.04.2020)	Real gross fixed capital formation (in prices from 2010) to calculate growth rates, depreciation rates as well as investment deflators (except software deflators) are taken from the EU KLEMS database for the years 2003-2017. See Appendix D for detailed information on how we calculate software as well as non-software capital stocks	Year, economic sectors (two-digit NACE code)
Household broadband availability	Breitbandatlas des Bundes (German Broadband Atlas) - Release 2/2021 (Retrieved on: 9.04.2021). Data is restricted in usage. Access can be requested at atene KOM GmbH (link to website)	Not integrated in the analysis	municipality level (AGS)

Appendix B. Categorization of Different Energy Carriers

Category	Summarized energy carriers
Biomass	Solid biogenic substances, liquid biogenic substances, biogas, sewage gas, landfill gas, sewage sludge
Natural gas	Natural gas, petroleum gas
Coal	Hard coals, hard coal coke, raw lignites, lignite briquettes, hard coal briquettes, other hard coals, lignite cokes, fluidized bed coals, pulverized and dry coals, other lignite
Heating oil	Light and heavy heating oil
District heat	District heat
Liquid gas	Liquid gas
Other energy sources	Mine gas, coke oven gas, blast furnace gas, converter gas, other gases, waste (household waste, industrial waste), other energy carriers (waste heat, etc.)

Table B.6: Categorization of different energy carriers.

Appendix C. Derivation of Schulte et al.'s (2016) Dual Cost Function Model

Variable costs are defined by energy (E) and labor (L) use and the corresponding energy (P_E) and labor prices (P_L).

$$VC = P_E E + P_L L \tag{C.1}$$

Moreover, the restricted variable cost function depends on the following parameters, which are defined in Section 3.

$$VC = f(P_E, P_L, K_{ICT}, K_N, Y, t) \tag{C.2}$$

This relationship is approximated by a translog cost function:

$$\begin{aligned}
lnVC =&\beta_0 + \beta_E lnP_E + \beta_L lnP_L + \beta_{K_{ICT}} lnK_{ICT} + \beta_{K_N} lnK_N + \beta_Y lnY + \beta_T t \\
&+ \frac{1}{2}\beta_{EE} ln(P_E)^2 + \frac{1}{2}\beta_{LL} ln(P_L)^2 + \frac{1}{2}\beta_{K_{ICT}K_{ICT}} ln(K_{ICT})^2 \\
&+ \frac{1}{2}\beta_{K_N K_N} ln(K_N)^2 + \frac{1}{2}\beta_{YY} ln(Y)^2 + \frac{1}{2}\beta_{TT}(t)^2 \\
&+ \frac{1}{2}\beta_{EL} lnP_E lnP_L + \beta_{EK_{ICT}} lnP_E lnK_{ICT} + \beta_{EK_N} lnP_E lnK_N \\
&+ \beta_{EY} lnP_E lnY + \delta_{ET} lnP_E t \\
&+ \frac{1}{2}\beta_{LE} lnP_L lnP_E + \beta_{LK_{ICT}} lnP_L lnK_{ICT} + \beta_{LK_N} lnP_L lnK_N \\
&+ \beta_{LY} lnP_L lnY + +\delta_{LT} lnP_L t \\
&+ \frac{1}{2}\beta_{K_{ICT}K_N} lnK_{ICT} lnK_N + \beta_{K_{ICT}Y} lnK_{ICT} lnY + \delta_{K_{ICT}T} lnK_{ICT} t \\
&+ \frac{1}{2}\beta_{K_N K_{ICT}} lnK_N lnK_{ICT} + \beta_{K_{NY}} lnK_N lnY + \delta_{K_N T} lnK_N t \\
&+ \delta_{YT} lnY t
\end{aligned} \tag{C.3}$$

Applying logarithmic differentiation with respect to the energy price and Shephard's lemma, leads to Equation (C.4).

$$\begin{aligned}
\frac{\partial lnVC}{\partial lnP_E} = \frac{P_E E}{VC} = S_E =&\beta_E + \frac{1}{2}\beta_{EL} lnP_L + \frac{1}{2}\beta_{LE} lnP_L + \beta_{EE} lnP_E \\
&+ \beta_{EK_N} lnK_N + \beta_{EK_{ICT}} lnK_{ICT} + \beta_{EY} lnY + \delta_{ET} t
\end{aligned} \tag{C.4}$$

Assuming symmetry ($\beta_{EL} = \beta_{LE}$) and homogeneity of degree one ($\beta_{EL} = -\beta_{EE}$) (see Christensen et al. 1973 and Berndt and Wood 1975) enables the transformation to the estimation equation $S_E = \beta_E + \beta_{EE} lnP_E/P_L + \beta_{EK_N} lnK_N + \beta_{EK_{ICT}} lnK_{ICT} + \beta^*_{EY} lnY + \delta_{ET} t$.[37]

The demand elasticity is derived following Kratena (2007). The demand elasticity of a good j can be defined as the change in $lnj \in \{E, L\}$ with respect to lnK_{ICT}. Expressing j as $S_j VC/P_j$ allows decomposing the demand elasticity into three different effects. The effect of ICT on the share of energy costs in variable, the effect of ICT on total variable costs and the effect of ICT on prices.

[37] With $\beta^*_{EY} = \beta_{EY} + \beta_{EK_N} + \beta_{EK_{ICT}}$

$$\epsilon_{jK_{ICT}} = \frac{\partial \ln j}{\partial \ln K_{ICT}} = \frac{\partial \ln \frac{S_j VC}{P_j}}{\partial \ln K_{ICT}} = \frac{\partial \ln S_j}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} - \frac{\partial \ln P_j}{\partial \ln K_{ICT}} \tag{C.5}$$

Assuming exogenous prices implies $\partial \ln P_j / \partial \ln K_{ICT} = 0$, which leads to Equation (C.6).

$$\epsilon_{jK_{ICT}} = \frac{\partial \ln S_j}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} \tag{C.6}$$

Which can be also expressed as:

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} + \frac{\partial VC}{\partial K_{ICT}} \frac{K_{ICT}}{VC} \tag{C.7}$$

Assuming that $\partial VC / \partial K_{ICT}$ is a shadow price for capital allows writing Equation (C.8).

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} - \frac{R_{K_{ICT}} K_{ICT}}{VC} \tag{C.8}$$

Furthermore, according to Schulte et al. (2016) $(R_{K_{ICT}} K_{ICT})/VC$ can be approximated by the share of ICT capital cost to variable costs ($S_{K_{ICT}}$). We assume a shadow price of software capital of 0.4 €.

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} - S_{K_{ICT}} \tag{C.9}$$

Appendix D. Perpetual Inventory Method (PIM)

In the spirit of Griliches (1980), Berlemann and Wesselhöft (2014), Lutz (2016), Dhyne et al. (2018) and Löschel et al. (2019) capital stocks are calculated for software capital and non-software capital by means of the perpetual inventory method (PIM).

Given geometric constant depreciation, the capital stock K_t at period t can be written as a function of previous period's capital stock K_{t-1}, gross investments I_t, and the consumption of fixed capital at rate δ. Hence, capital stocks except initial ones can be calculated by the following equation.

$$K_t = (1-\delta)K_{t-1} + I_t \tag{D.1}$$

To calculate initial capital stocks, one can express annual percentage increase in capital as the amount of investments minus the capital depreciated in the previous period.

$$\frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \delta \tag{D.2}$$

Assuming that capital grows at a constant rate ($g_K = (K_t - K_{t-1})/K_{t-1}$), one can obtain the following expression.

$$K_{t-1} = \frac{I_t}{g_K + \delta} \tag{D.3}$$

Setting $t = 1$ allows to calculate the initial capital stock.

$$K_0 = \frac{I_1}{g_K + \delta} \tag{D.4}$$

For the calculation of firm-level initial capital stocks, it is recommended to use average investments of the first three years within the observation period because investments highly fluctuate over time.[38]

$$\hat{I}_1 = \frac{\sum_{t=1}^{3} I_t}{n} \tag{D.5}$$

Accordingly, in this study we calculate initial capital stocks by applying Equation (D.4) and (D.5), subsequent capital stocks are calculated by Equation (D.1).

PIM requires information on capital growth rates. These are estimated by calculating the compound annual growth rate at industry level using real gross fixed capital formation at prices from 2010. Information on gross fixed capital formation volume of software and total capital is retrieved from the EU KLEMS database. Depreciation rates and deflators for non-software capital are also taken from the EU KLEMS database. Software capital deflators are retrieved from Eurostat (see Table A.5).

[38]Please note here that we do robustness checks with respect to different period lengths to calculate initial capital stocks.

Appendix E. Calculation of Energy Cost Savings per Software Investment

By Equation (E.1), we initially calculate relative improvements in energy intensity per year related to software usage ($relative\,savings$). To do this, we multiply the energy intensity elasticity ($\epsilon_{EK_{SW}}$) by the relative change in software capital (ΔlnK_{ICT}) for each firm i in year t.

$$relative\ savings_{it} = \epsilon_{EK_{SW_{it}}} \times \Delta lnK_{SW_{it}} \tag{E.1}$$

To calculate savings in energy consumption, we assume that output is constant and calculate how much energy consumed in the previous period has been saved in the current period with respect to changes in the software capital stock (Equation E.2). Savings in energy costs are then approximated by multiplying savings in energy consumption by the firm-specific energy price.

$$cost\ savings_{it} = relative\ savings_{it} \times E_{i,t-1} \times P_E \tag{E.2}$$

In order to estimate the average savings in energy costs per euro invested in software, we sum up firm-level energy cost savings over all periods for which we have information and divide them by the sum of all software investments that have taken place in the same time period (Equation E.3).

$$savings\ per\ investment = \frac{\sum_{t=2010}^{2017} absolute\ savings_{it}}{\sum_{t=2010}^{2017} software\ investments_{it}} \tag{E.3}$$

Appendix F. Additional Descriptive Statistics

Appendix F.1. Distribution of Energy Prices

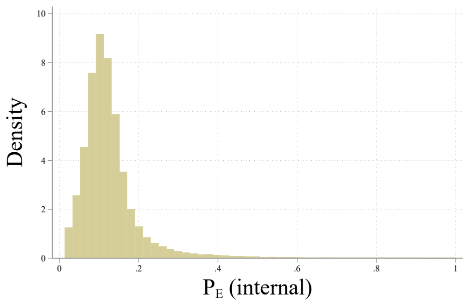

Figure F.6: Distribution of P_E.

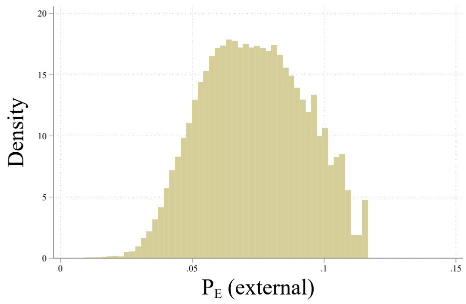

Figure F.7: Distribution of P_E [external].

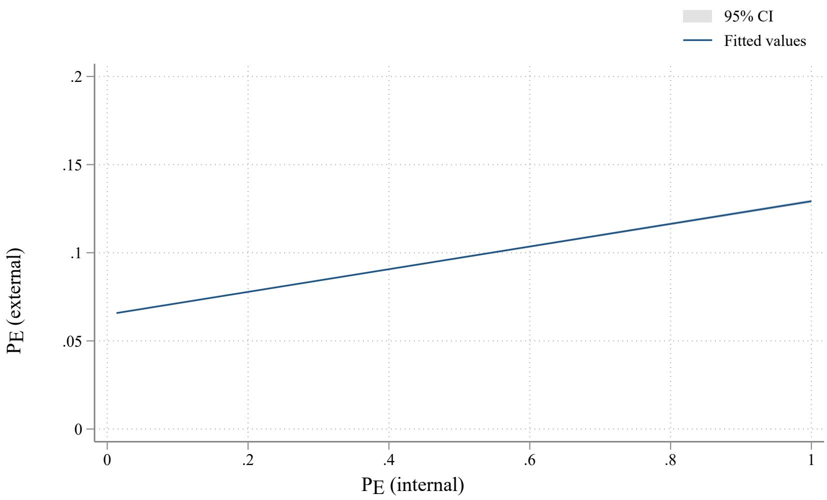

Figure F.8: Relationship between both energy prices.

Appendix F.2. Average Software Capital Intensity by Region

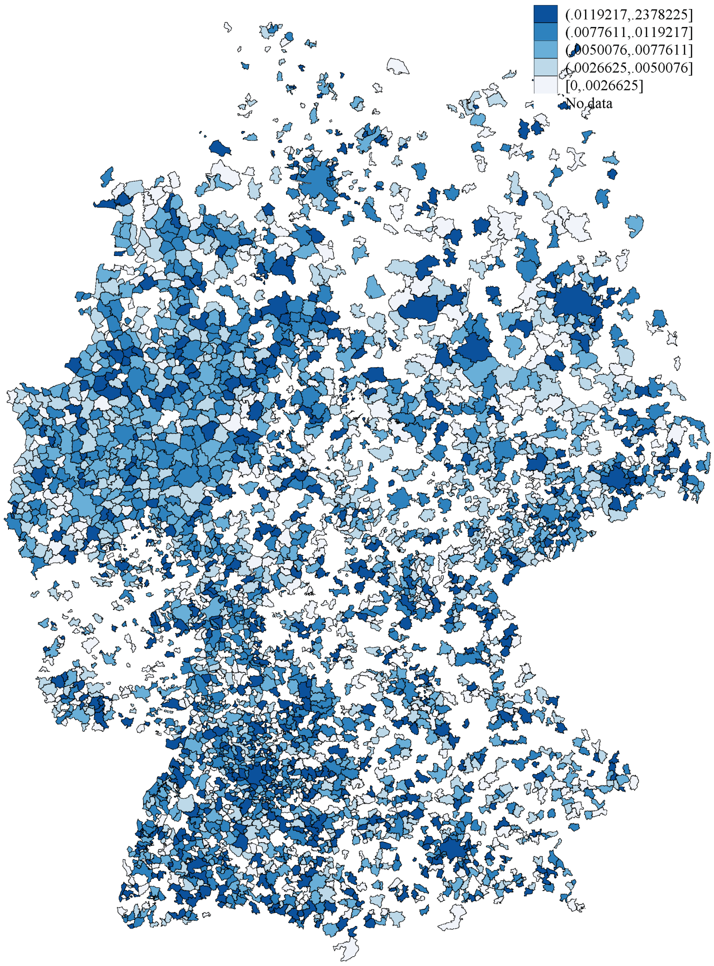

Figure F.9: Average software capital intensity by region between 2009–2017. The dark blue regions represent those with the highest average software capital intensity. Regions with less than three observations per year or with no observations are not displayed.

Appendix F.3. Percentage change of mean (non-) software capital, labor and energy use divided by output (base year 2009)

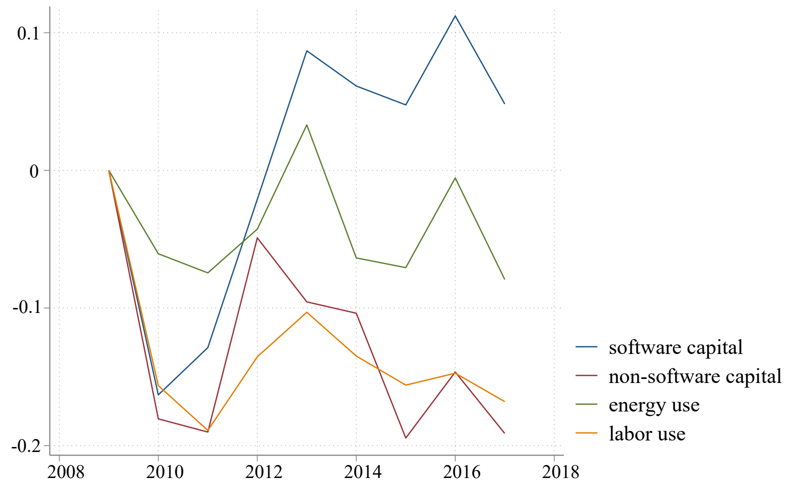

Figure F.10: Change of mean (non-) software capital, labor and energy use divided by output (base year 2009).

Appendix F.4. Details on the Distribution of S_{SW} and S_E

	mean	sd	p5	p50	p95
$S_{K_{SW}}$	0.004	0.010	0.000	0.001	0.017
S_E	0.090	0.102	0.012	0.055	0.292
Observations	123362				

Table F.7: Detailed descriptive statistics on the distribution of S_{SW} and S_E.

Appendix G. Further Estimation Results

	(1)	(2)	(3)
		depreciation rates	
	25 percent	33 percent	50 percent
	ΔS_E	ΔS_E	ΔS_E
$\triangle \ln(\frac{P_E}{P_L})$	0.0284***	0.0284***	0.0284***
	(61.74)	(61.74)	(61.74)
$\triangle \ln(\frac{K_{SW}}{Y})$	-0.000219***	-0.000237***	-0.000242***
	(-5.13)	(-5.18)	(-5.16)
$\triangle \ln(\frac{K_N}{Y})$	-0.0015***	-0.0015***	-0.0015***
	(-3.76)	(-3.77)	(-3.78)
$\triangle \ln(Y)$	0.0014*	0.0013*	0.0013*
	(2.56)	(2.51)	(2.49)
Year	x	x	x
Economic sector	x	x	x
Multi-unit	x	x	x
Federal state	x	x	x
Size class	x	x	x
EEG exemption	x	x	x
Producer	x	x	x
Observations	89653	89653	89653
Adjusted R^2	0.271	0.271	0.271

t statistics in parentheses. First-difference estimation. Clustered standard errors. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.8: Equation (5) with software capital stocks modified by different depreciation rates.

	(1)	(2)	(3)
	number of periods maximal included for initial software capital calculation		
	2	4	6
	ΔS_E	$\Delta\ S_E$	$\Delta\ S_E$
$\triangle \ln(\frac{P_E}{P_L})$	0.0284***	0.0284***	0.0284***
	(61.74)	(61.74)	(61.74)
$\triangle \ln(\frac{K_{SW}}{Y})$	-0.000167***	-0.000212***	-0.000325***
	(-4.68)	(-4.25)	(-4.69)
$\triangle \ln(\frac{K_N}{Y})$	-0.0015***	-0.0015***	-0.0015***
	(-3.83)	(-3.82)	(-3.82)
$\triangle \ln(Y)$	0.0014**	0.0013*	0.0012*
	(2.61)	(2.52)	(2.29)
Year	x	x	x
Economic sector	x	x	x
Multi-unit	x	x	x
Federal state	x	x	x
Size class	x	x	x
EEG exemption	x	x	x
Producer	x	x	x
Observations	89653	89653	89653
Adjusted R^2	0.271	0.271	0.271

t statistics in parentheses. First-difference estimation. Clustered standard errors. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.9: Equation (5) with software capital stocks modified by different lengths of periods considered for the initial capital stock calculation.

	(1)	(2)	(3)	(4)
	excluding potentially problematic observations	"zero" growth rates imputed	growth rates starting from "zero" imputed (I)	growth rates starting from "zero" imputed (II)
	ΔS_E	$\Delta\ S_E$	$\Delta\ S_E$	$\Delta\ S_E$
$\triangle \ln(\frac{P_E}{P_L})$	0.0270***	0.0284***	0.0270***	0.0284***
	(50.15)	(61.74)	(51.13)	(61.74)
$\triangle \ln(\frac{K_{SW}}{Y})$	-0.000225+	-0.000238***	-0.000356***	-0.000350***
	(-1.87)	(-5.14)	(-4.86)	(-4.77)
$\triangle \ln(\frac{K_N}{Y})$	-0.0017***	-0.0015***	-0.0015**	-0.0015***
	(-3.42)	(-3.78)	(-3.17)	(-3.76)
$\triangle \ln(Y)$	0.0011+	0.0013*	0.0011+	0.0012*
	(1.70)	(2.52)	(1.69)	(2.32)
Year	x	x	x	x
Economic sector	x	x	x	x
Multi-unit	x	x	x	x
Federal state	x	x	x	x
Size class	x	x	x	x
EEG exemption	x	x	x	x
Producer	x	x	x	x
N	65226	89653	66841	89653
adj. R^2	0.258	0.271	0.260	0.271

t statistics in parentheses. First-difference estimation. Clustered standard errors. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.10: Robustness checks with respect to "zero" software capital stocks.

	(1) after 2011	(2) single-unit firms	(3) no tangible capital	(4) lagged K_{SW}	(5) sector-year fixed effects
	ΔS_E	$\Delta\ S_E$	ΔS_E	$\Delta\ S_E$	$\Delta\ S_E$
$\triangle\ \ln(\frac{P_E}{P_L})$	0.0292***	0.0290***	0.0284***	0.0277***	0.0284***
	(52.32)	(59.68)	(61.74)	(45.84)	(61.80)
$\triangle\ \ln(\frac{K_{SW}}{Y})$	-0.000209***	-0.000177***	-0.000249***		-0.000228***
	(-4.52)	(-3.78)	(-5.37)		(-4.95)
$\triangle\ \ln(\frac{K_N}{Y})$	-0.0013***	-0.0015***		-0.0015**	-0.0014***
	(-3.30)	(-3.81)		(-3.13)	(-3.60)
$\triangle\ \ln(Y)$	0.00087	0.0015**	0.0028***	0.0000	0.0018***
	(1.39)	(2.71)	(7.43)	(0.14)	(3.37)
$\triangle\ \ln(\frac{K_{SW}}{Y})_{t-1}$				0.0000562	
				(0.94)	
Year	x	x	x	x	x
Economic sector	x	x	x	x	x
Multi-unit	x	x	x	x	x
Federal state	x	x	x	x	x
Size class	x	x	x	x	x
EEG exemption	x	x	x	x	x
Producer	x	x	x	x	x
Economic sector $\times$ Year					x
Observations	62821	77029	89653	59650	89653
adj. R^2	0.285	0.284	0.271	0.255	0.281

t statistics in parentheses. First-difference estimation. Clustered standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.11: Further robustness checks (Equation (5)).

	(1)	(2)	(3)
	OLS	FE	Mundlack
	S_E	S_E	S_E
$ln(\frac{P_E}{P_L})$	-0.0038***	0.0316***	
	(-8.73)	(57.23)	
$\triangle ln(\frac{P_E}{P_L})$			0.0316***
			(160.60)
$\mu(ln(\frac{P_E}{P_L}))$			-0.0054***
			(-8.06)
$ln(\frac{K_{SW}}{Y})$	-0.00165***	-0.000213***	
	(-32.95)	(-3.48)	
$\triangle ln(\frac{K_{SW}}{Y})$			-0.000212***
			(-5.77)
$\mu(ln(\frac{K_{SW}}{Y}))$			-0.00151***
			(-17.63)
$ln(\frac{K_N}{Y})$	0.0061***	-0.0001	
	(30.85)	(-0.26)	
$\triangle ln(\frac{K_N}{Y})$			-0.0001
			(-0.37)
$\mu(ln(\frac{K_N}{Y}))$			0.0040***
			(16.42)
$ln(Y)$	0.0397***	0.0040***	
	(69.70)	(6.18)	
$\triangle ln(Y)$			0.0040***
			(11.96)
$\mu(ln(Y))$			0.0359***
			(48.22)
Year	x	x	x
Economic sector	x	x	x
Multi-unit	x	x	x
Federal state	x	x	x
Size class	x	x	x
EEG exemption	x	x	x
Producer	x	x	x
Observations 123362	123362	123362	
R^2	0.577	0.268	0.266

t statistics in parentheses. First difference estimation. Clustered standard errors except for Mundlak specification. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.12: Pooled OLS, fixed effects as well as Mundlak

	(1)	(2)	(3)	(4)
	capital not scaled by output	Y instrumented	$\frac{P_E}{P_L}$ instrumented	Y, $\frac{P_E}{P_L}$ instrumented
	$\Delta\ S_E$	$\Delta\ S_E$	$\Delta\ S_E$	$\Delta\ S_E$
$\triangle \ln(\frac{P_E}{P_L})$	0.0284***	0.0283***	0.0023*	0.0018+
	(0.000)	(0.000)	(0.019)	(0.068)
$\triangle \ln(K_{SW})$	-0.000242***	-0.000260***	-0.000245***	-0.000265***
	(0.000)	(0.000)	(0.000)	(0.000)
$\triangle \ln(K_N)$	-0.0016***	-0.0019***	-0.0012**	-0.0015**
	(0.000)	(0.000)	(0.006)	(0.002)
$\triangle \ln(Y)$	0.0031***	0.011***	0.0036***	0.0108**
	(0.000)	(0.001)	(0.000)	(0.001)
Year	x	x	x	x
Economic sector	x	x	x	x
Multi-unit	x	x	x	x
Federal state	x	x	x	x
Size class	x	x	x	x
EEG exemption	x	x	x	x
Producer	x	x	x	x
Observations	89653	89017	89653	89017
Underidentification		64.16	816.0	63.83
Weak identification		42.61	1139.2	27.93
P-value Hansen J statistic		0.864		0.909

p-values in parentheses. First-difference estimation. Clustered standard errors.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Underidentification test displays the Kleibergen-Paap LM statistic and the weak identification test displays the Kleibergen-Paap Wald F-statistic.

Table G.13: IV estimates

Appendix H. Results – Firm-level Characteristics

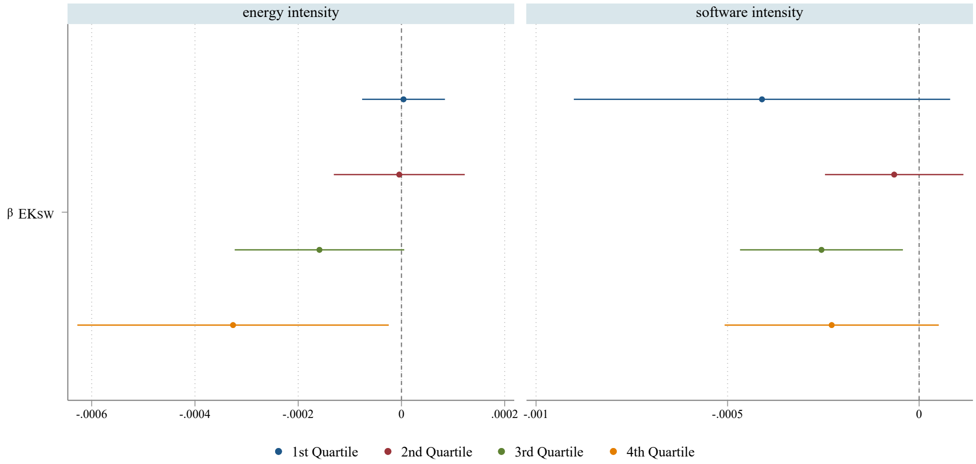

Figure H.11: Heterogeneous effects - Energy and software capital intensity (1st Quartile: Lowest level of average energy or software capital intensity)

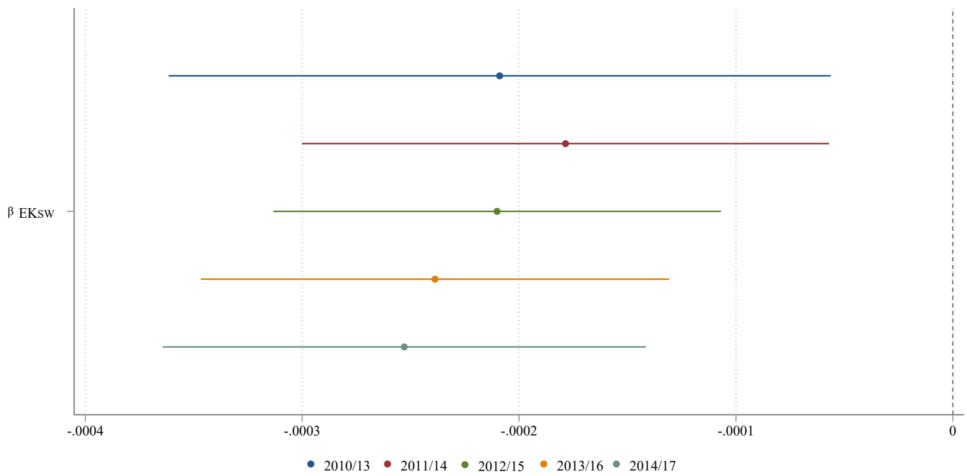

Figure H.12: Heterogeneous effects - Time differences

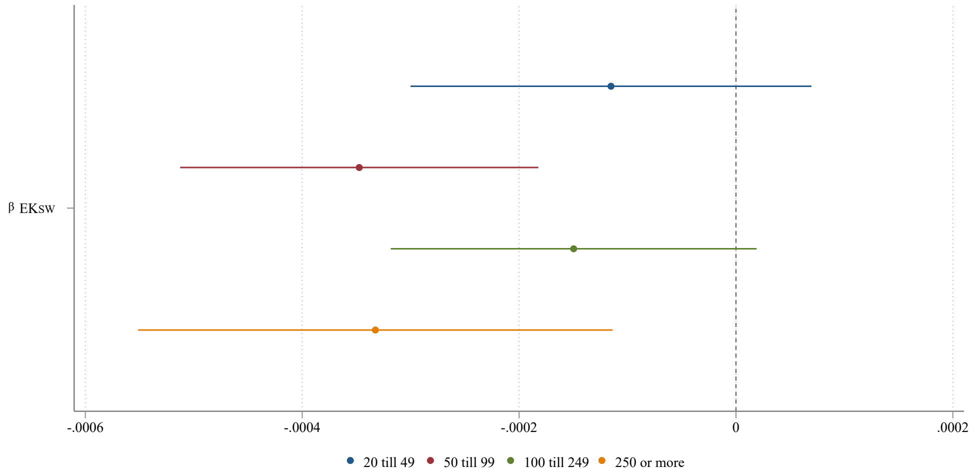

Figure H.13: Heterogeneous effects - Size class differences by number of employees

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