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 improve overall energy efficiency 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 efficiency at the firm level. For this purpose, we employ administrative panel data on 28,734 manufacturing firms from German Statistical Offices of the Federation and the Federal States collected between 2009 and 2017. Using software capital intensity as an indicator for the firm-level degree of digitalization, we analyze whether an increase thereof relates to energy efficiency improvements. Results confirm the statistically significant negative link between software capital and energy use. However, the relationship is highly inelastic and does not suggest economic relevance. Therefore, we conclude that effects of ICT on energy use are not large enough to substantially improve energy efficiency.

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1 Introduction

Climate change has become increasingly severe in recent decades (IPCC, 2014). Effects of global warming, such as droughts and rising sea levels, are becoming more and more visible. To limit global temperature rise, it is highly important to cut down carbon emissions (IPCC, 2018), those related to energy use, however, are still increasing and are on a historic high (IEA, 2019). Therefore, one goal of the European Union is to improve energy efficiency substantially (European Commission, 2020; PE/54/2018/REV/1).

Within the last few decades, economic as well as social structures also changed tremendously due to the diffusion of digital technologies. For example, new markets like the mobile app market emerged and new ways to communicate appeared, 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). Considering the comprehensive process of the digital transformation as well as the on-going climate crisis, effects of ICT on energy use patterns are essential to assess. However, whether digital technologies increase or decrease emissions in total is still controversial. For instance, Belkhir and Elmeligi (2018) state that if not mitigated, ICT-related emissions will increase dramatically. On the contrary, GeSI & Accenture (2015) claim that ICT will reduce carbon emissions in the future by 20%.

Many production processes are very energy-intensive. In 2018, the industry sector was responsible for 37% of global energy use and for 25% of total carbon emissions (IEA, 2020). However, digital technologies such as smart manufacturing have the potential to improve energy efficiency within this part of the economy: The fact that ICT improve the quantity and quality of information, which can increase efficiency within production processes and may reduce energy consumption is one reason for this claim. In addition, ICT consume mostly electric energy but may reduce, in particular, non-electric energy consumption. Consequently, digitalization may also change the energy mix as non-electric and potentially fossil-intensive energy use may decline.

Previous literature provides evidence at the sectoral level that ICT are linked to a reduction in energy demand within industries (Schulte et al., 2016; Bernstein and Madlener, 2010; Collard et al., 2005).[1] Furthermore, Schulte et al. (2016) confirm that there is a more pronounced link between ICT and a reduction in non-electric energy use than in electric energy use. However, to the best of our knowledge, no large-scale study exists yet that analyzes climate protection potentials of digitalized production processes at the firm-level. Microeconomic data allows to control for firm-specific effects and to analyze whether

[1] Bernstein and Madlener (2010) and Collard et al. (2005) only consider the effect of ICT on electricity intensity.

effects diverge for different types of firms. This may provide new insights into how ICT relate to energy efficiency improvements as well as to changes in the energy mix.

Our study is the first empirical analysis that focuses on the microeconomic level. It is based on administrative panel data on 28,734 German manufacturing firms (AFiD)[2] collected between 2009 and 2017 and provided by Research Data Centres of the Statistical Offices of the Federation and the Federal States (RDC). AFiD data is of particular high quality, as reporting to the statistical offices is obligatory and the data is thoroughly checked.

In particular, we analyze whether firm-level software capital intensity, as an indicator for total ICT usage, affects energy efficiency. The descriptive statistics show a strong increase in mean and median software capital over time, while energy intensity fluctuates much less. Consistent with previous literature, we apply a translog cost function approach. Results confirm a statistically significant link between ICT and energy efficiency improvements at the firm level. However, effects are much smaller than in previous estimates using aggregated data. According to the translog model, a 1% increase in software capital relates to an average decrease in energy intensity between 0.007% and 0.011%. Results are robust to different sample restrictions and software capital stock modifications. To further check for robustness, we conduct a reduced-form estimate with a selection of variables based on a CES production function. Results lead qualitatively to the same conclusion. Digitalization is only to a small extent associated with energy efficiency improvements. As the relationship between software capital and energy efficiency is very inelastic, we conclude that the digitalization of the German manufacturing sector is only related to minor efficiency increases in the analyzed period. Accordingly, the firm-level degree of digitalization appears neither as a means to substantially increase energy efficiency nor does it worsen it.

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

2 Previous Literature

The digital transformation may influence resource and energy consumption in various ways. The academic discussion presumably starts with Walker (1985), who assesses the potential impact of digital technologies on energy use in advanced economies. He predicts that due to productivity improvements and structural

[2] Amtliche Firmendaten für Deutschland

changes the importance of electricity will increase and energy efficiency will enhance.

More recent studies deal, inter alia, with the overall effect of digitalization on energy use. Most of them focus on future scenarios and can have pessimistic as well as optimistic viewpoints. For instance, Ferreboeuf et al. (2019) state that every year the direct energy footprint of ICT increases by 9% and growth could be limited to 1.5%, if measures were introduced that reduce the environmental impact of ICT. Belkhir and Elmeligi (2018) claim that worldwide ICT-related carbon emissions could increase from approximately 3% in 2017 to 14% by 2040. In contrast, GeSI & Accenture (2015, p.8) predict that "ICT can enable a 20% reduction of global carbon emissions by 2030". Both studies consider emission levels at the mid-2010s. Van Heddeghem et al. (2014), Andrae and Edler (2015), Malmodin and Lundén (2018) are further studies analyzing overall trends. Moreover, most of these general studies rely on strong assumptions and not all are peer-reviewed. Lange et al. (2020) develop a theoretical framework to structure potential impact channels. The effect of ICT on energy consumption is split into four different areas: I) Energy consumption within the ICT sector, II) ICT's impact on overall economic growth, III) effects on energy efficiency, and IV) ICT's influence on the sectoral composition within the economy. The authors draw conclusions about the overall effect of ICT by analyzing previous studies focusing on one of these areas. They find that the first two effects increased energy use in the past, whereas the last two effects may reduce energy consumption, although one still has to consider that energy efficiency improvements are often accompanied by rebound effects.

Moreover, studies exist that only cover specific aspects of the relationship between ICT and energy use, which can be either a single or a group of digital technologies as well as a particular unit of observation. For example, the following studies solely analyze particular technologies. Preist et al. (2019) focus on the streaming platform YouTube. They calculate that its energy consumption is comparable to that of cities like Glasgow or Frankfurt. A similar study shows that the annual energy consumption of the cryptocurrency Bitcoin is between the amount of Jordan and Sri Lanka (Stoll et al., 2019). The study of Masanet et al. (2020) states that in 2018 data centers accounted for 1% of global energy consumption. Moreover, in a meta analysis of 31 studies focusing on the substitution of material products with electronic equivalents, Court and Sorrell (2020) find higher energy saving potentials for e-publications, e-news and e-music, and less potential for e-business and e-videos and e-games. However, the authors emphasize that different assumptions for, e.g., product lifetime lead to opposite results. Matthews et al. (2001), Weber et al. (2010), Fehske et al. (2011), Tahara et al. (2018), are also examples for studies focusing on particular technology fields. Findings that focus on a particular technology rely less on strong assumptions, however, it is usually difficult to generalize results.

Studies that concentrate on a particular unit of observation are those that focus on households, firms, economic sectors or countries. Moreover, studies may consider either total or relative energy use (e.g., energy efficiency). For an overview of different studies at the sectoral or country level see Chimbo et al. (2020). Research that focuses on economic sectors mostly claims that digital technologies have huge potentials to improve energy efficiency within industries (IEA, 2018). 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). Most manufacturing countries launched programs promoting smart manufacturing like 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. For example, Big Data potentially allows better predicting demand and may prevent excess production. Simulation methods as well as 3D printing may drastically reduce resource and energy use related to new product design and engineering (OECD, 2017).

Using aggregated data to measure effects within industries, studies tend to indicate that digital technologies are associated with an increase in energy efficiency. Using a CES production function, Collard et al. (2005) investigate the relationship between ICT and energy use in the French service sector. Analyzing a time frame from 1986 to 1998, the authors find that electric energy intensity increased with the use computers and software, while it decreased with the diffusion of communication devices.

Applying the same approach, Bernstein and Madlener (2010) analyze the impact of ICT capital on electricity intensity in five 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. The authors define energy efficiency as the share of energy costs in variables costs. They find that an increase in ICT capital of 1% is linked to a decrease in energy intensity of 0.235% at the sectoral level. In addition to an increase in energy efficiency, they show that the use of ICT within production processes is associated with changes in the energy mix. In fact, only the share of non-electric energy costs, which is potentially related to higher carbon emissions, decreases significantly with ICT capital. Additionally, a sample split into manufacturing and service industries shows only significant effects for the manufacturing sector. Selected results are presented in Table 2.1.

Table 2.1: Results of Schulte et al. (2016); preferred specification presented in Table 3 & 5 (pp.133).

Dependent variable: Respective share in variable costs	△ Energy (Table 3)	△ Electric energy (Table 5)	△ Non-electric energy (Table 5)
△ ICT capital scaled on output	-0.016*** (-6.01)	0.001 (0.90)	-0.014*** (-5.21)
$\epsilon_{EK_{ICT}}$	-0.235***	-0.028	-0.319***
Observations	2,889	2,889	2,889
Adjusted R^2	0.35	0.41	0.39

t values in parentheses.

Unfortunately, sector-level data does not enable the analysis of dynamics within industries. It remains unknown how many firms drop out of the market if aggregated data is applied: Energy inefficient firms may leave the market and new ICT-intensive ones may appear. This phenomenon may explain changes at the sectoral level. Furthermore, effects could only be valid for certain kinds 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. Also studies that analyze the relationship between overall capital intensity and energy use show different results at the sectoral and firm-level (Haller and Hyland, 2014). Accordingly, applying aggregated data may be misleading for policy makers and promoting ICT intensity within firms may not necessarily increase their energy efficiency. Manufacturing firms are related to one quarter of global carbon emissions (IEA, 2020). Hence, it is especially important to promote energy efficiency within this part of the economy.

Detailed firm-level information on energy use, digital technology diffusion and investment decisions is scarce. One exception is a small questionnaire-based survey conducted by the ZEW Mannheim in 2020 (Bertschek et al., 2020). In this survey, 1700 German firms are asked about measures applied in the last three years to increase energy efficiency. More than 30% of manufacturing firms answered that improvements in energy efficiency are one reason why they implemented digital technologies. Nonetheless, the use of ICT is the least frequently named reason. Moreover, 65% of all manufacturing firms stated that their absolute and relative ICT-related energy use remained constant during the last three years, 22% said it decreased and 13% stated that their absolute energy use increased.

To the best of our knowledge, no large-scale econometric study exists yet at the firm-level. Hence, we firstly aim to provide statistical evidence regarding the effect on energy efficiency at the microeconomic level. As stated in Draca et al.(2007, p.113), "Using micro data rather than industry data allows the welldocumented firm level heterogeneity in productivity and investment patterns to be taken into account [...]."

3 Theoretical Framework

To analyze the relationship between ICT use and energy efficiency at the firm-level, we apply the same theoretical model used by Schulte et al. (2016) and measure energy efficiency by the share of energy costs in variable costs. It is the first model applied at the sectoral level with results not only limited to electric energy intensity but to energy efficiency overall. Therefore, it is best suited to compare results at different levels of observation.

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 (1981) 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, where the share of energy costs in variable costs is a function of the energy price relative to the labor price, output as well as software and non-software capital.[3]

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

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 software capital and K_N to non-software capital. Y measures total output[4] and t the analyzed time period, which also controls for time-dependent technological progress.

To analyze whether diverging effects for electric and non-electric energy efficiency exist, the model is modified to equation (2). $Elec$ relates to electric energy and $NElec$ to non-electric energy ($j \in \{Elec, NElec\}$).

$$\begin{aligned} S_j = \beta_{j\,Elec} \ln\left(\frac{P_{Elec}}{P_L}\right) + \beta_{jNElec} \ln\left(\frac{P_{NElec}}{P_L}\right) \\ + \beta_{jK_{ICT}} \ln\left(\frac{K_{ICT}}{Y}\right) + \beta_{jK_N} \ln\left(\frac{K_N}{Y}\right) + \beta_{jY} \ln Y + \delta_{jT} t \end{aligned} \tag{2}$$

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

[4] $\beta^*_{EY} = \beta_{EY} + \beta_{EK_N} + \beta_{EK_{ICT}}$; Schulte et al. (2016) scale capital on 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} to transform the model.

The effect size of ICT on energy demand and intensity is captured by a demand elasticity, which can be decomposed into two different effects: The first term of equation (3) captures the effect of ICT on the share of $j \in E, Elec, NElec$ in variable costs and the second term captures the effect of ICT on total variable costs.

$$\epsilon_{jK_{ICT}} = \frac{\partial \ln S_j}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} = \frac{\partial \ln j}{\partial \ln K_{ICT}} \tag{3}$$

Rearranging equation (3) and assuming that $\partial VC/\partial K_{ICT}$ in $\frac{\partial lnVC}{\partial lnK_{ICT}} = \frac{\partial VC}{\partial K_{ICT}} \frac{K_{ICT}}{VC}$ equals the shadow price of ICT allows measuring the demand elasticity by equation (4) (Berndt and Hesse, 1986; Schulte et al., 2016).

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

4 Data

Our analysis focuses on firm-level data on the German manufacturing sector (AFiD) collected between 2009 and 2017 and provided by the RDC. The manufacturing sector is responsible for 30% of energy demand as well as for 40% of electric energy demand in Germany (German Environment Agency, 2020). Moreover, it is considered as the backbone of the German economy. Therefore, we consider it as especially important to analyze how ICT relates to energy use patterns within the manufacturing sector. Within our data, firms are assigned to the manufacturing sector if they have the highest value added in associated industries.

4.1 Data Sources

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

(A) The AFiD-Panel Industrial Units, which contains two data subsets that are relevant for our analysis.

(A.1) The Census on Investment is used as it includes information about investments in tangible and intangible assets. It is a full census including all German firms in the manufacturing sector with 20 or more employees. Information on software investments is available since 2009. Moreover, we have information on investments in property, plant and equipment since 2003. 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 problem, which is confirmed by several robustness checks.

(A.2) The second applied subset of the AFiD-Panel Industrial Units 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 rotating panel with 18,000 firms surveyed each year. The same firms are observed for four consecutive years. Hence, our observation period can be divided in three sequences with consecutive observations (2009-2011, 2012-2015, 2016-2017).

(B) The AFiD-Module Use of Energy (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 or more employees. For information on firm-level energy use, we aggregate plant-level information for each firm. One minor drawback is the fact that we do not observe the units of firms that are originated in the service sector. We control for that by adding a multi-unit dummy. On average, we observe 13% of multi-unit firms every year.

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. 2 classification) to calculate real output. Yearly software deflators are taken from Eurostat, as well. 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. Yearly consumer and producer price indices provided by the German Federal Statistical Office (Destatis) are 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 an detailed overview of additional added data, see Table A.1 in the Appendix.

4.2 Variable Description

Starting from the raw data described in Section 4.1, we perform the following additional calculations. The AFiD module Use of Energy entails information (in kWh) about purchased, self-generated and soled electricity 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.[5] We define overall firm-level energy use (E) as the sum of energetic use of different energy carriers (E_{NElec}) plus electricity use (E_{Elec}). To calculate electricity consumption, we subtract purchased electricity as well as self-generated electricity (excluding wind, hydro or solar), as the latter is already included in the total use of energy carriers.[6]

Mean and median energetic use of different energy sources per year for our sample is displayed in Figure 4.1. The mean fluctuates above 30 GWh. The median use fluctuates around 1 GWh. Hence, a comparison of both sub-figures reveals that 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 1800 times higher than the average energy use of private households in 2017; the median is approximately 60 times higher.[7] Besides, we find in our sample a small decrease in mean energy use over time, but a slight increase in median energy use. The figure also reveals that firms mostly consume electricity and natural gas, as the median of all other energy sources is zero. Moreover, there is a strong decline in the use of coal and mineral products and an increase in natural gas, whereas the use of electricity remains constant over the years.

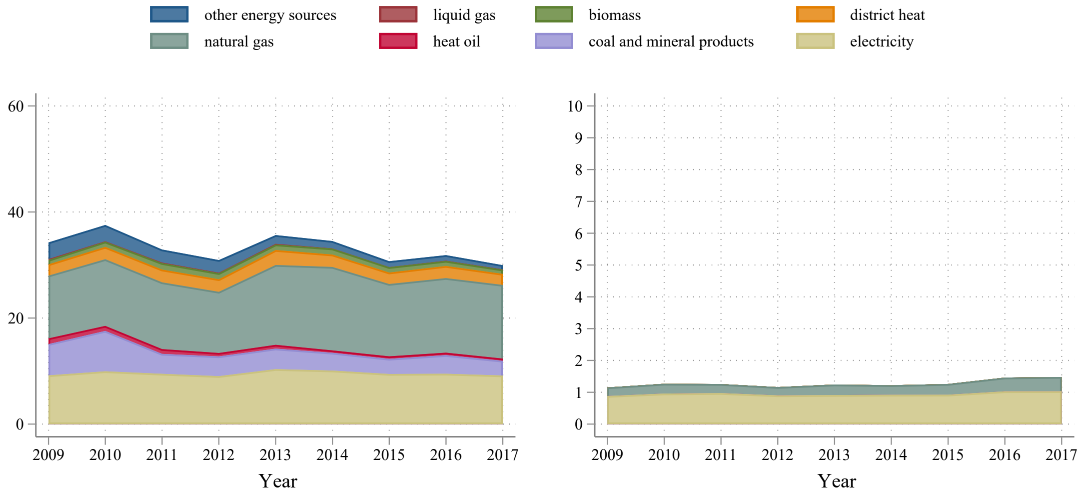

Figure 4.1: Mean (left) & median (right) use of different energy sources per year.

Furthermore, the analysis requires information on energy prices, which are not directly available in AFiD. However, information on energy use and energy costs is accessible. Following Haller and Hyland (2014), we divide energy costs ($P_E E$) from AFiD[8] by the calculated energy use (E) to receive information on the energy price for each firm (P_E; in €$/kWh$).

[5] See B.1 for a detailed overview on which energy carriers are included in each category.
[6] We will address in a robustness check the issue that electricity self-produced by fossil fuels can be either accounted as electric or non-electric energy use.
[7] https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Umwelt/Materialfluesse-Energiefluesse/_inhalt.html
[8] Available in the Cost Structure Survey.

This approach is prone to issues resulting from misreporting. If a firm reports, for example, too low energy use, we observe too high prices. As stated in Section 4.1, 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 4.2. 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 on the chosen quantity, i.e., the firm-level decision-making process. 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.[9] Figure 4.3 compares internal and approximated external energy prices and confirms a statistical relationship between both.[10] The distribution of external prices is displayed in Figure 4.4. The range is similar to internal energy prices, but the distribution is less skewed to the right.

Unlike energy use, we observe energy costs at the firm level as this information is included in the Cost Structure survey. Hence, if a firm is a multi-unit firm, values may be reported by different entities and mismatched information is possible. To address this, we control for multi-unit firms in our estimates and analyze to what extent results differ when only considering single-unit firms.

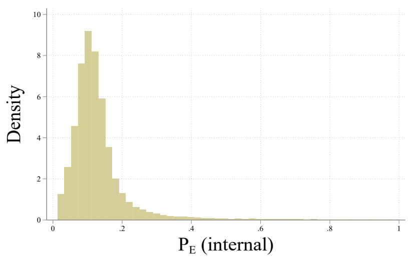

Figure 4.2: Distribution of internal energy prices.

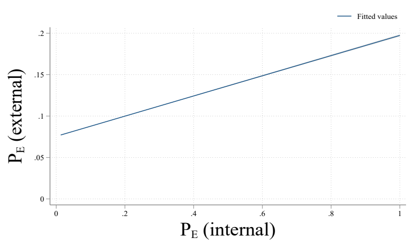

Figure 4.3: Relationship between internal and external energy prices.

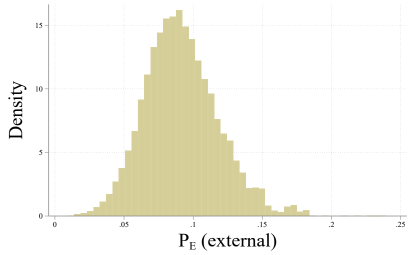

Figure 4.4: Distribution of external energy prices.

P_{Elec} captures the price for electric energy. We use external prices from Eurostat to approximate the firm-level electricity price. Eurostat reports industry prices for different levels of electricity use. Electricity costs are calculated by multiplying the external price times the use of electricity ($P_{Elec}E_{Elec}$). The costs of non-electric energy ($P_{NElec}E_{NElec}$) are calculated by subtracting the costs for electric energy from total energy costs. Non-electric energy costs are then divided by non-electric energy use (E_{NElec}) to receive information about the price for non-electric energy (P_{NElec}). We prefer this approach because prices

[9] We use electricity and natural gas prices for different amounts of use. We assume that firms have only a constrained flexibility to react to price changes and only reduce (increase) consumption to a limited amount and not to the extent that they would face another price level.

[10] Due to the German data protection law, we are not able to publish a scatter plot, as this would show individual observations.

are not available for every non-electric energy source. One resulting issue is, however, that electricity prices reported by Eurostat need to exactly match the firm-level electricity prices to calculate non-electric energy costs accurately. Although, we assume that resulting deviations are random, we restrict our sample to plausible values and exclude non-electric energy prices lower than 0.01 €$/kWh$ and larger than 0.75 €$/kWh$ from our analysis of the energy mix. Accordingly, the energy mix sample is slightly smaller than the one for the analysis of total energy use. Distributions of electric and non-electric energy prices can be found in the Appendix D in Figures D.1 and D.2. The average price for electric energy is 0.14 €$/kWh$ and the average for non-electric energy is 0.13 €$/kWh$.

Gross wages and salaries, statutory and other social costs (also reported in the Cost Structure Survey) 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 persons employed 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. The average labor price (P_L) is 29 €.[11] Additionally, we calculate exogenous hourly wages based on the average wage for each two-digit industry with respect to each region and size level. The firm for which the exogenous price is calculated for is excluded.

Variable costs (VC) are calculated based on the sum of energy and labor costs. S_E indicates the level of energy efficiency and measures the share of energy costs in variable costs. S_{Elec} and S_{NElec} capture shares of electric and non-electric energy costs and S_L the share of labor costs. Figure 4.5 shows average cost shares over time. The average share of energy costs in variable costs is around 0.09 and decreases over time. The electric energy and non-electric energy cost shares are about the same size. Furthermore, it can be observed that electric and non-electric energy cost shares cross over time – presumably a consequence of the of the yearly increasing EEG levy, which only affects electric energy costs. Besides, values are comparable to sector-level shares derived by Schulte et al. (2016).

[11] The value is a slightly higher in official statistics (https://www.destatis.de/DE/Themen/Arbeit/Arbeitskosten-Lohnnebenkosten/_inhalt.html#sprg233842).

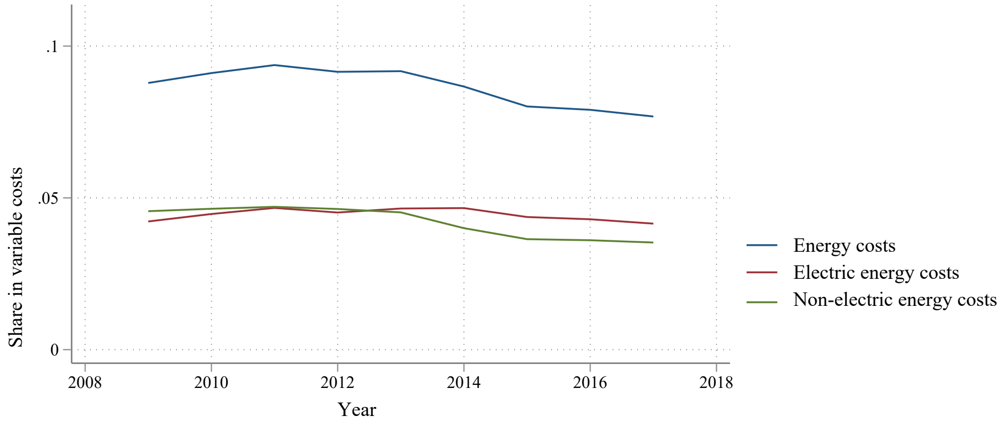

Figure 4.5: Average share of total, electric and non-electric energy costs per year.

Output (Y) is measured by real value added based on information specified in the Cost Structure Survey.[12] We deflate output using Eurostat data on a two-digit industry level.

Software capital approximates the degree of firm-level digitalization and tangible capital (property, plant and equipment) represents the non-software capital stock.[13] It has to be acknowledged here that we only account for purchased software capital and firms may also use open source software. Both, 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 (non-software) data. Furthermore, the perpetual inventory method (PIM) is applied to estimate capital stocks (Griliches, 1980; Harberger, 1988; Berlemann and Wesselhöft, 2014; Lutz, 2016; Vanormelingen 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%. 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 E. Our data confirms 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 are heavily skewed and lumpy, but software capital shows these characteristics to a greater extent. For instance, we find approximately 20% of firms without any software investments in the analyzed period. We add 1 € to every software capital stock. This enables

[12]We do not subtract energy costs to calculate value added, as we consider capital, energy and labor in our production function (KLE). We assume materials to be weakly separable and subtract them.

[13]Leasing capital is excluded.

us to logarithmize and calculate growth rates when software capital stocks are zero.

Figure 4.6 shows average software capital divided by output for different industries. Values fluctuate around 1%. The industries "wearing apparel" and "basic pharmaceutical products" show the highest software capital intensity. This distribution seems plausible. The pharmaceutical industry (combined with the chemical industry) was the most digital German manufacturing industry in 2018 according to Weber et al. (2018). That the "wearing apparel" industry shows a high software capital intensity can be explained by the fact that it is a market with highly interconnected supply chains and fast changing trends. Besides, digitalization allows to increase individualization, which is especially important for this industry. Furthermore, it is also intuitive that the computer industry uses more software than most other industries.

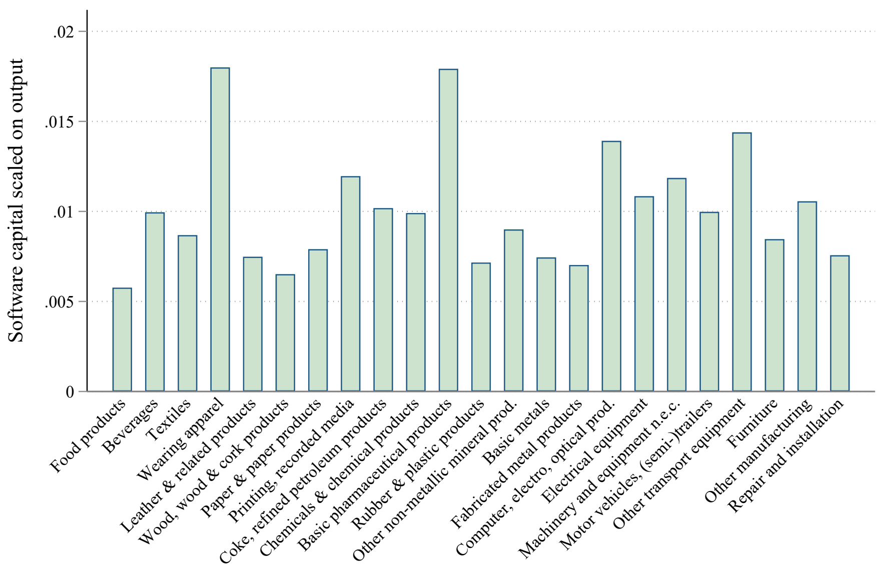

Figure 4.6: Average software capital intensity by industry between 2009 and 2017. The tobacco industry is excluded because of too few observations.

The geographic distribution of software capital intensity is displayed in Figure F.1. The darker the blue color of the respective area the higher the average software intensity. The grey area marks regions for which we either observe no or less than three enterprises.[14] 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. Next to the industry distribution, this is a further indicator that software capital is a suitable proxy for digitalization, as digital enterprises usually concentrate in larger cities.

Additionally, the following control variables are included in the analysis. We add federal state dummies

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

as well as industry dummies on a two-digit level, dummies capturing effects for different size classes[15] and a dummy capturing whether a firm has a single or multiple establishments. By means of the electric energy consumption and the ratio of electric energy costs to value added, we estimate whether firms receive a full or a partial exemption from the EEG levy. Moreover, a dummy that controls whether a firm generates energy is included as this may affect energy costs as well.

Although AFiD is 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. We also exclude firms with zero labor, energy or non-software capital use, as well as firms with a negative output. In our main specification, we have abstained from excluding firms with zero software capital because it is possible that firms do not use any software at all or use open source software. Additionally, we exploit the panel structure to identify outliers and exclude observations 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 124,057 observations based on 28,734 firms in total and on average about 13,800 firms per year (Table 4.1). We point out that in 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 sample to 90,179 observations, as we observe a large share of observations only for four years.[16]

	Year									
Panel sequence	1			2				3		
Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**Total**
% multi-unit firms	13.3%	13.6%	11.1%	11.2%	13.4%	13.7%	13.7%	13.9%	13.9%	13.1%
Total	14,042	14,381	13,874	13,749	14,192	13,950	13,582	13,314	12,973	124,057

Table 4.1: Number of observations per year.

An overview of mean, median, and standard deviation of selected variables can be found in Table 4.2. Values are presented for the main sample as well as for the sub-sample employed in the analysis of the energy mix. Comparing both samples shows notable statistical differences in average energy use, intensity and cost share. This is an issue that we aim to address in a more advanced version of our analysis.

[15] 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.

[16] This is because of the Cost Structure Survey, which rotates every four years.

The descriptive statistics also reveal relationships between variables. For instance, in an average (mean) manufacturing firm one employee generates approximately 65,710 € output and for approximately 1 € of output 1.6 kWh is used. However, half of the firms only consume 0.38 kWh or less per 1 € of output. Moreover, software capital constitutes only 1% of what non-software capital amounts to.[17] Also, the ratios between non-software capital and other variables, such as output or variable costs, are much higher than those for software capital. The same applies to respective variances.

Table 4.2: Summary statistics.

	Main sample			**Energy mix sample**		
	mean	median	s.d.	mean	median	s.d.
Relevant variables						
E	33,121,000	2,003,000	404,220,000	25,743,000	2,101,000	384,120,000
L	272	88	1,952	279	92	1,932
P_E (internal)	0.1309	0.1123	0.0940	0.1222	0.1125	0.0584
P_E (external)	0.0915	0.0896	0.0266	0.0883	0.0873	0.0233
P_L	28.69	27.95	9.16	28.78	28.13	9.15
K_{ICT}	257,000	13,00	2,696,000	261,000	14,000	2,557,000
K_N	20,594,000	3,154,000	206,990,000	20,197,000	3,243,000	197,200,000
$\frac{K_{ICT}}{K_N}$	0.0218	0.0035	0.1269	0.0222	0.0038	0.1324
Y	22,791,000	5,026,000	212,600,000	22,925,000	5,219,000	205,470,000
$\frac{Y}{L}$	65,710	57,327	42,814	65,1143	57,367	40,397
$\frac{E}{Y}$	1.0619	0.3815	3.7242	0.9609	0.3816	3.4132
$\frac{K_{ICT}}{Y}$	0.0093	0.0024	0.0637	0.0090	0.0025	0.0293
$\frac{K_N}{Y}$	0.9446	0.5857	4.5565	0.9150	0.5780	4.0443
S_L	0.9098	0.9448	0.1016	0.9133	0.9453	0.0951
S_E	0.0902	0.0552	0.1016	0.0867	0.0547	0.0951
$S_{K_{ICT}}$	0.0041	0.0011	0.0096	0.0041	0.0012	0.0091
S_{K_N}	1.0743	0.6985	1.4423	1.0504	0.6899	1.3994
Only included in the energy mix analysis						
P_{Elec}				0.1378	0.1348	0.0248
P_{NElec}				0.1304	0.0907	0.1192
S_{Elec}				0.0445	0.0287	0.0487
S_{NElec}				0.0422	0.0215	0.0612
Observations	124057			106347		

All monetary variables in €; Energy is measured in kWh. Values have been rounded where necessary to improve clarity.

Figure 4.7 (mean) and Figure 4.8 (median) show time trends of software and non-software capital as well as labor and energy capital divided by output relative to 2009. All 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 strongly after 2011 and the median increases more sharply than the mean. The mean only increases by roughly 6% in the observation period, whereas the median nearly doubles. Hence, the median software capital intensity in 2017 is almost twice as high as in 2009. Besides,

[17] This ratio is comparable to aggregated EU KLEMS data.

labor and non-software capital use do not change notably after 2011, but mean energy use increases whereas the median roughly stays constant.

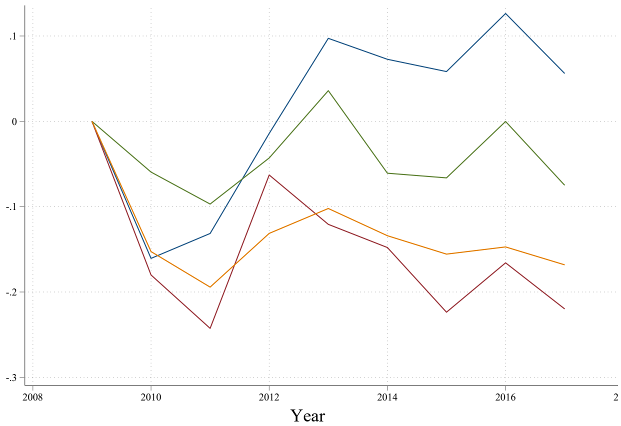

Figure 4.7: Percentage change of mean (non-) software capital, labor and energy use divided by output (base year 2009).

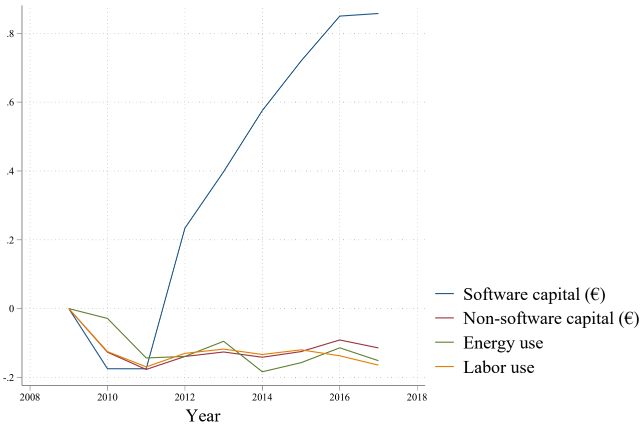

Figure 4.8: Percentage change of median (non-) software capital, labor and energy use divided by output (base year 2009).

5 Econometric Specifications

For the econometrical analysis, we take first differences of equation (1) to remove firm-specific fixed effects and add a firm-specific stochastic error term. Accordingly, Δu_{it} captures the firm-specific deviation of firm i at time t. To capture disembodied technological change t, we add a dummy variable for every year. Depending on the econometric specification D, we also add $c \in C_D$ control dummy variables. Accordingly, equation (1) is transformed to equation (5). The same transformation applies to the analysis of the energy mix. In addition, in all our specifications we allow for clustering of observations at the firm-level.

$$\begin{aligned}\Delta S_{Eit} =& \beta_{EE}\Delta ln(\frac{P_E}{P_L})_{it} + \beta_{EK_{ICT}}\Delta ln(\frac{K_{ICT}}{Y})_{it} + \beta_{EK_N}\Delta ln(\frac{K_N}{Y})_{it} + \beta^*_{EY}\Delta lnY_{it} \\ &+ \sum_{d=2010}^{T}\delta_{Et}t_{it} + \sum_{d=c}^{D}\gamma_d C_{dit} + \Delta u_{it}\end{aligned} \quad (5)$$

In our first specification (D_{basic}), we control for industry-specific fixed effects on a two-digit level and for firms with multiple establishments. In our second specification (D_{CS}), we add federal state dummies to account for wage differences between German regions. Other aspects of the firm-level cost structure (CS) may also differ between federal states. Size class dummies are included as well, since wages and the cost structure depend on the size of the firm, which is approximated by the number of employees. In a further specification (D_{all}), we additionally control for firms that may receive a full or partial exemptions from the EEG levy and for firms that self-generate energy. D_{all} is our preferred control variable set and it will be used in all following steps.

Software capital stocks may be biased as we observe a large share of firms without any software investments. This may become especially a problem if firms start to investment. We observe huge percentage increases in this situation, as change rates starting from "zero" to large natural numbers are large by construction. To analyse the severeness of this issue, we estimate our model only with observations that have non-zero software capital stocks.

To further test the robustness of our capital stocks, we measure how estimations change if we modify the calculation of software capital stocks. We estimate models with software capital depreciation rates of 25, 33 and 50%. Also, different maximum period lengths are used to recalculate initial capital stocks: We estimate initial software capital stocks based on the first five and seven observation periods if available.

Furthermore, initial capital stocks may be unstable and investments need to be considered for a couple of periods to calculate solid capital stocks. Accordingly, we will run a regression with firms observed for the third time or later in our sample.

Endogeneity issues are a common problem in empirical studies at the firm level. We address this issue by removing time-invariant firm-specific effects from the estimation. Therefore, endogeneity issues due to omitted variables are considerably reduced. Furthermore, for endogeneity issues caused by measurement errors of our main variable of interest, we provide various robustness checks, for instance, different modifications of the calculation of initial capital stocks. Moreover, endogenous control variables do not lead to biased coefficients when uncorrelated with the variable of interest. However, they do if a relationship exists (Frisch and Waugh, 1933). This could especially be the case between labor price and software capital, as the use of software usually requires skills that are in high demand. To test whether the effect of software capital on energy use is biased by endogenous prices, we replace price variables with exogenous price variables calculated as described in Section 4.2.

To further test for robustness, we also run the translog model only with single-unit firms as multi-unit firms are more prone to inaccurate information due to different respondents. An estimation excluding observations before 2011 is conducted because these observations may be affected by the economic crisis and its aftermaths.

Finally, we analyze effects of ICT on the energy mix. We run two different estimations for electric and non-electric cost shares. Firstly, we plug in the variables as described in Section 4.2 in equation (2). The use of energy carriers to generate electricity can be either assigned to non-electric or to electric energy use. Secondly, to test for robustness we re-estimate the two cost shares with self-generated electricity assigned to the electric energy cost share.

6 Estimation Results

6.1 Main Results

Table 6.1 shows estimation results for the total energy model formalized in equation (5). The first three columns represent our baseline results with different control dummy variable specifications. All coefficients point in the same direction as in the previous macroeconomic approach by Schulte et al. (2016): 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 is negative and highly significant, but its size is much smaller than in previous industry-level estimates. According to the demand elasticity calculated by equation (4) and displayed in Table 6.2, a 1% increase in software capital is only associated with a 0.007% decrease in energy demand (or energy intensity as output is held constant).[18] We also observe that the non-software capital coefficient points into the familiar direction, but has a lower magnitude than in the estimate with aggregated data. This relationship is, however, often insignificant in the Schulte et al. (2016) model and the difference is not as large. Therefore, it is difficult to make a judgment in this regard.

As stated before, one reason for lower estimation coefficients could be that we underestimate initial software capital stocks and therefore overestimate the average increase in software capital, especially if software capital stocks rise from "zero".[19] To see whether the source of small estimation coefficients are growth rates starting from wrongly calculated initial values, we exclude observations with "zero" software capital. The fourth column of Table 6.1 shows results. The magnitude of the software coefficient is now larger as in the baseline specification, but the demand elasticity does not change considerably as it decreases by merely 0.004 percentage points and is now -0.011%. The fifth column of Table 6.1 displays results only including firms observed in their third period or later. No notable difference to our main specification can be identified here. The sixth column shows estimation results with exogenous prices. We highlight that the price variable is not significant on a 5% level anymore and the adjusted R^2 drops very sharply. Hence, a large share of explained variation results from internal prices. Nonetheless, the ICT coefficient does not seem to be influenced by this issue and remains at its usual height.

[18] The capital compensation or shadow price for ICT is derived by the user costs of capital calculated with EU KLEMS data and it is assumed to be 0.4 €.

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

Estimation results with different depreciation rates can be found in Table G.1 and results for different maximum lengths of observation periods for initial capital stocks in Table G respectively. Assuming a 50% depreciation rate of software capital, decreases the coefficient for software capital to -0.004. Nonetheless, we consider this change not large enough to have an effect on the qualitative interpretation of results. The same applies to modifications of initial capital stocks. The estimation with initial capital stocks ranging over up to seven years shows the largest coefficient for software capital, but the effect size is still much lower than the effect size derived at the sectoral level.

Table 6.1: First-difference estimation results of the total energy model.

	(1) D_{basic}	(2) D_{CS}	(3) D_{all}	(4) No "zero" capital stocks	(5) No early capital stocks	(6) Exogenous prices
$\triangle S_E$						
$\triangle \ln(\frac{P_E}{P_L})$	0.0289***	0.0290***	0.0289***	0.0273***	0.0302***	
	(50.05)	(50.07)	(49.89)	(38.73)	(38.78)	
$\triangle \ln(\frac{P_E}{P_L})$ *ext.*						0.000580
						(1.38)
$\triangle \ln(\frac{K_{ICT}}{Y})$	-0.000247***	-0.000251***	-0.000246***	-0.000429**	-0.000209***	-0.000251***
	(-5.29)	(-5.38)	(-5.33)	(-2.70)	(-4.56)	(-4.82)
$\triangle \ln(\frac{K_N}{Y})$	-0.00107**	-0.00116***	-0.00120***	-0.00156**	-0.00100*	-0.000662
	(-3.09)	(-3.35)	(-3.47)	(-3.20)	(-2.15)	(-1.69)
$\triangle \ln(Y)$	0.00255***	0.00226***	0.00199***	0.00193*	0.00185*	0.00307***
	(4.44)	(3.89)	(3.44)	(2.56)	(2.21)	(4.59)
Year	x	x	x	x	x	x
Economic sector	x	x	x	x	x	x
Multi-unit	x	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
Producer			x	x	x	x
Observations	90179	90179	90179	63663	59594	90179
Adjusted R^2	0.258	0.260	0.262	0.247	0.286	0.035

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

Table G.3 in the Appendix shows effects for single-unit firms and estimation results for observations after 2011. The restricted estimates are consistent with our baseline results. Both software coefficients point into a negative direction and are highly significant. Software capital coefficients are slightly smaller for both samples than for the entire sample. This difference, however, does not affect the economic interpretation of results.

To summarize results of our total energy model, software capital coefficients are consistently small.

Hence, effect sizes are robust with respect to various econometric specifications and 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.

Table 6.2: Factor demand elasticities.

Specification	Total energy use	Electric vs non-electric energy use	
	$\epsilon_{EK_{ICT}}$	$\epsilon_{ElecK_{ICT}}$	$\epsilon_{NElecK_{ICT}}$
D_{all}	-0.007***	-0.004	-0.008***
No zero capital stocks	-0.011***	[-]	[-]

6.2 Energy Mix

Table 6.3: First-difference estimation results for cost shares of electric and non-electric energy.

	(1)	(2)	(1)	(2)
	self-generated to $NElec$	self-generated to $Elec$	self-generated to $NElec$	self-generated to $Elec$
$\triangle S_{Elec}$			$\triangle S_{NElec}$	
$\triangle \ln(\frac{P_{Elec}}{P_L})$	0.0141***		-0.00254***	
	(24.93)		(-3.51)	
$\triangle \ln(\frac{P_{NElec}}{P_L})$	-0.00367***		0.0166***	
	(-29.67)		(61.39)	
$\triangle \ln(\frac{P_{Elec}}{P_L})$ *prod.*		0.0139***		-0.00212**
		(24.40)		(-2.92)
$\triangle \ln(\frac{P_{NElec}}{P_L})$ *prod.*		-0.00347***		0.0164***
		(-28.18)		(61.22)
$\triangle \ln(\frac{K_{ICT}}{Y})$	-0.00000171	-0.00000198	-0.000154***	-0.000154***
	(-0.06)	(-0.07)	(-3.35)	(-3.37)
$\triangle \ln(\frac{K_N}{Y})$	-0.000416*	-0.000422*	-0.000937***	-0.000926***
	(-2.41)	(-2.44)	(-3.39)	(-3.35)
$\triangle \ln(Y)$	0.0000509	0.0000304	0.000652	0.000674
	(0.20)	(0.12)	(1.09)	(1.14)
D_{all}	x	x	x	x
Observations	73993	73993	73993	73993
Adjusted R^2	0.126	0.122	0.271	0.268

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

Table 6.3 shows results with respect to the energy mix. The first two columns present results for the electric energy cost share. The use of energy carriers to generate electricity is attributed to non-electric energy in column (1) and to electric energy in column (2). The values in both columns lead to the same conclusion: Relative energy prices do not notably differ from sector-level estimates. Coefficients point in the same directions as before and are all highly significant. In both specifications, the non-software capital coefficients show significant negative effects and their magnitudes are slightly lower than in the total energy model. The software capital coefficients, however, are not significant. Hence, no conclusions can be made regarding the relationship between digitalization and the demand for electric energy. Furthermore, the adjusted R^2 is between 12% and 13%. Columns (3) and (4) show results for non-electric energy. Coefficients for relative energy prices point into opposite directions now, which is consistent with previous literature. Furthermore, both capital coefficients are significant and negative, but smaller than in the total energy model. Nonetheless, the demand elasticity is slightly larger than in the main specification: According to column (3), a 1% increase in software capital intensity is related to a decrease in non-electric energy use by 0.008%. The adjusted R^2 is between 27% and 28%, which is much larger than for the electric energy cost share model. Therefore, it should be considered when comparing both models that the latter model can be in general explained better. Still, we conclude that the analysis of the energy mix is in line with previous findings considering the direction of coefficients and significance levels, but not regarding the magnitude of effects.

6.3 Energy Intensity

To test the robustness of our total energy model, we estimate a second model with another measure of energy efficiency: Energy intensity, which captures energy use scaled on output. Applying a nested CES production function approach with 3-inputs (KL; E), energy intensity can be explained as a function of the energy-related level of technology (A), the relative energy price with respect to the general 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).

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

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

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

To analyze whether effects differ between production function approaches, we plug equation (7) in equation (6), take first differences and estimate a reduced form of equation (8). The general price level is measured by the producer price index, which is retrieved at a 2-digit industry level from Destatis. Technological progress t is measured by time dummy variables.

$$\Delta ln(\frac{E}{Y})_{it} = \Delta\beta_{\frac{P_E}{P_{PPI}}} ln(\frac{P_E}{P_{PPI}})_{it} + \Delta\beta_{\frac{K_{ICT}}{K_N}} ln(\frac{K_{ICT}}{K_N})_{it} + \sum_{d=2010}^{T} \delta_{Et} t_{it} + \sum_{d=c}^{D} \gamma_d C_{dit} + \Delta u_{it} \tag{8}$$

Results are presented in Table 6.4. Two specifications are estimated, one with self-calculated prices and another with exogenous prices. Both price coefficients are statistically significant. The adjusted R^2 values are 0.23% and 0.16%. Hence, in comparison to the translog model it drops less when applying exogenous prices. Furthermore, if the ratio between software and non-software capital increases by 1%, energy intensity decreases by 0.003%. Compared to the translog model, the size of the effect is even smaller and leads qualitatively to the same conclusion. The relationship between the firm-level degree of digitalization and energy efficiency does not suggest economic relevance. Moreover, it is not model-specific nor does it depend on the indicator of relative energy use that the relationship is comparatively small.

Table 6.4: First-difference results of equation 8.

	(1)	(2)
	D_{all}	Exogenous prices
$\triangle ln \frac{E}{Y}$		
$\triangle$ ln($\frac{P_E}{P_{PPI}}$)	-0.447***	
	(-57.66)	
$\triangle$ ln($\frac{P_E}{P_{PPI}}$) *ext.*		-1.181***
	(-47.46)	
$\triangle$ ln($\frac{K_{ICT}}{K_N}$)	-0.00273***	-0.00265***
	(-3.63)	(-3.22)
D_{all}	x	x
Observations	89790	89790
Adjusted R^2	0.226	0.157

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

7 Discussion

As previous studies point out, the on-going digital transformation may have synergies with climate protection policies. 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 microeconomic 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 studies state. We find that a 1% increase in software capital is associated with a decrease in energy demand of 0.011% at maximum. This result is robust to several sample restrictions and different modifications of software capital stocks.

We want to discuss the economic relevance of this result. Although the relationship is inelastic, software capital grows strongly. The median software capital nearly doubled in the observation period. Hence, software capital may still have an effect as it offsets its small impact with a large increase. However, a 100% increase, which may be a reasonable number within a decade, would only translate into a decrease between 0.7% and 1.1% in energy use within the same period and this only if output is held constant. Hence, considering microeconomic data, software capital does not appear to have large synergies with energy efficiency improvements. Nonetheless, software capital did not show negative effects either and efficiency improvements at least offset the energy they consume. Therefore, our results neither support the assumption that ICT will lead to large reductions of global carbon emissions as argued by GeSI & Accenture (2015) nor that it relates to large increases in carbon emissions as stated by Ferreboeuf et al. (2019) and Belkhir and Elmeligi (2018).

Furthermore, it is not unusual that effects are smaller when microeconomic 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.

Besides, controlling for other intangibles, Kaus et al. (2020) find that a 1% increase in software capital is associated with a 0.008% increase in gross output and a 0.026% increase in value added. Comparing these values to our results indicates that the positive effect of software capital on output has a larger magnitude than the effect of software capital on relative energy intensity. Hence, as output is held constant in our estimates, there is not necessarily a link to a decrease in absolute energy consumption. The translog model measures the relationship between ICT and the ratio between energy and labor costs. 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). In other words, effects may be exclusively driven by positive effects of software capital on output and labor and there is no decrease in absolute energy use, it may just be less affected. It is noteworthy here that there would still be an effect on energy efficiency as energy is used relatively less.

One could argue that effects are 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 and analyze large amounts of data, which potentially improves energy efficiency, heavily rely on software. Another advantage that we see in software capital is that it is quite general in comparison to other technologies like Cloud Computing or 3D printing. Therefore, considering all available indicators, we believe that for the purpose of this study software capital is the best digitalization indicator at the firm level. Nonetheless, the analyzed relationship might be heterogeneous with respect to different forms of digital technologies. To analyze whether different effects on energy use patterns exist, we aim to include different digital technologies in our future research.

8 Conclusion and Future Research

This study is the first empirical analysis on the relationship between digitalization and energy efficiency at the firm level. For this purpose, we use administrative panel data on 28,734 firms from the German manufacturing sector collected between 2009 and 2017. Software capital intensity is used as an indicator for the firm-level degree of digitalization. Furthermore, we apply a translog cost function approach for our statistical analysis as it has been used previously at the industry level.

Results show a statistically significant link between software capital intensity and energy efficiency improvements. Separating between electric and non-electric energy use also confirms that energy efficiency improvements are only significantly related to non-electric energy and not to electric energy. Furthermore, effects point into the same direction as in previous studies, but are not as large. According to the translog model, a 1% increase in software capital intensity is related to a decrease in energy use between 0.007% and 0.011%, depending on the applied econometric specification. Results are robust to several sample restrictions as well as to modifications of the software capital stock. We conclude that digital technologies cannot be associated with economically significant energy efficiency improvements at the firm level. This result may be relevant for policy makers, consultants and firms that aim to improve energy efficiency within establishments and may overestimate synergies between digitalization and energy efficiency.

In our future research, we aim to identify heterogeneous effects with respect to specific digital technologies and firm characteristics. Even though effects are small on average, they might be larger or change directions for certain types of technologies or firms. In our opinion, an investigation that analyzes diverging effects would be another important contribution to this study's research field, for which the application of firm-level data has great potential. Moreover, the inclusion of an appropriate instrumental variable that allows to investigate whether the relationship is truly causal would be of great value.

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Appendices

A Additional Data

For our analysis use 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.1:

Table A.1: Description of additional data sources.

Information	Data source	Comments	Identifier
Price for energy source	Gesamtausgabe der Energiedaten, Federal Ministry for Economic Affairs and Energy (BMWi), status: 31.03.2020, https://www.bmwi.de/Redaktion/DE/Artikel/Energie/energiedaten-gesamtausgabe.html (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) are retrieved. The respective units have all been converted to €/kWH.	Year
Price for energy source	Fernwärme – Preisübersicht, AGFW | Der Energieeffizienzverband für Wärme, Kälte und KWK e. V., status: 01.10.2017, https://www.agfw.de/energiewirtschaft-recht-politik/wirtschaft-und-markt/markt-preise/preisanpassung/ (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	Brennstoffkostenentwicklung von Gas, Öl und Pellets, Deutsches Pelletinstitut GmbH (DEPI), status: 2019, https://depi.de/de/pelletpreis-wirtschaftlichkeit#dau2v (Retrieved on: 13.09.2019)	Pellet price for 2015 is taken, value converted from cent/kWh to €/kWh (VAT excluded).	Year

Information	Data source	Comments	Identifier
Price for energy source	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, https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Publikationen/Energiepreise/energiepreisentwicklung-pdf-5619001.pdf?__blob=publicationFile (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	Electricity prices for non-household consumers - bi-annual data (from 2007 onwards) [nrg_pc_205], Eurostat, status: 08.04.2019, Eurostat bookmark (Retrieved on: 15.07.2020)	Average price per year is calculated, prices are retrieved excluding VAT and other recoverable taxes and levies.	Year, electricity use
Price for energy source	Gas prices for non-household consumers - bi-annual data (from 2007 onwards) [nrg_pc_203], Eurostat, status: 10.02.2020, Eurostat bookmark (Retrieved on: 15.07.2020)	Average price per year is calculated, prices are retrieved excluding VAT and other recoverable taxes and levies. Natural gas use is converted from GJ to kWH.	Year, natural gas use
Price for energy source	IEA Energy Prices and Taxes Statistics, International Energy Agency, status: 1.Quarter 2019, https://www.oecd-ilibrary.org/energy/data/iea-energy-prices-and-taxes-statistics_eneprice-data-en (Retrieved on: 04.09.2019)	Prices excluding taxes from 2009-2017 for liquid gas are retrieved. Values are converted from €/l to €/kWh.	Year

Information	Data source	Comments	Identifier
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, https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Erzeugerpreisindex-gewerbliche-Produkte/Publikationen/Downloads-Erzeugerpreise/erzeugerpreise-lange-reihen-pdf-5612401.html (Retrieved on: 12.11.2020)	Index on the yearly average change is retrieved.	Year, economic sectors (2-digit NACE codel)
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 E for detailed information on how we calculate software as well as non-software capital stocks.	Year
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. https://euklems.eu/excel/DE_Capital_SDB_2019.xlsx (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 E for detailed information on how we calculate software as well as non-software capital stocks	Year, economic sectors (2-digit NACE code)

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.1: Categorization of different energy carriers.

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).

$$VC = P_E E + P_L L \tag{9}$$

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

$$VC = f(P_E, P_L, K_{ICT}, K_N, Y, t) \tag{10}$$

This relationship is approximated by a translog cost function:

$$\begin{aligned} lnVC =& \beta_0 + \beta_Y lnY + \frac{1}{2}\beta_{YY} ln(Y)^2 + \beta_T t + \frac{1}{2}\beta_{TT} t^2 + \beta_L lnP_L + \beta_E lnP_E + \beta_{K_{ICT}} lnK_{ICT} \\ & + \beta_{K_N} lnK_N + \frac{1}{2}\beta_{EL} lnP_E lnP_L + \frac{1}{2}\beta_{LE} lnP_L lnP_E + + \frac{1}{2}\beta_{EE} lnP_E^2 + \frac{1}{2}\beta_{LL} lnP_L^2 \\ & + \beta_{EK_N} lnP_E lnK_N + \beta_{LK_{ICT}} lnP_L lnK_{ICT} + \beta_{EK_{ICT}} lnP_E lnK_{ICT} \\ & + \beta_{LK_N} lnP_L lnK_N + \beta_{EY} lnP_E lnY \\ & + \beta_{LY} lnP_L lnY + \frac{1}{2}\beta_{K_{ICT}K_N} lnK_{ICT} lnK_N + \frac{1}{2}\beta_{K_N K_{ICT}} lnK_N lnK_{ICT} \\ & + \frac{1}{2}\beta_{K_N K_N} lnK_N^2 + \frac{1}{2}\beta_{K_{ICT}K_{ICT}} lnK_{ICT}^2 \\ & + \beta_{K_{ICT}Y} lnK_{ICT} lnY + \beta_{K_N Y} lnK_N lnY + \delta_{ET} lnP_E t + \delta_{LT} lnP_L t \\ & + \delta_{K_{ICT}T} lnK_{ICT} t + \delta_{K_N T} lnK_N t + \delta_{YT} lnY t \end{aligned} \tag{11}$$

Applying logarithmic differentiation with respect to the energy price (Shephard's lemma), leads to equation (12).

$$\frac{\partial lnVC}{\partial lnP_E} = \frac{P_E E}{VC} = S_E = \beta_E + \frac{1}{2}\beta_{EL}lnP_L + \frac{1}{2}\beta_{LE}lnP_L + \beta_{EE}lnP_E \\ + \beta_{EK_N}lnK_N + \beta_{EK_{ICT}}lnK_{ICT} + \beta_{EY}lnY + \delta_{ET}t \tag{12}$$

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 $S_E = \beta_E + \beta_{EE}ln\frac{P_E}{P_L} + \beta_{EK_N}lnK_N + \beta_{EK_{ICT}}lnK_{ICT} + \beta^*_{EY}lnY + \delta_{ET}t$ with $\beta^*_{EY} = \beta_{EY} + \beta_{EK_N} + \beta_{EK_{ICT}}$.

Following Kratena (2007) and Christensen et al. (1973), having three different variable cost factors and assuming of homogeneity of degree one ($\beta_{ElecL} = -\beta_{ElecElec} - \beta_{ElecNElec}$) allows writing in the electric versus non-electric energy efficiency model.

The demand elasticity is derived by following Kratena (2007), as well. 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 $\frac{S_j VC}{P_j}$ 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.

$$\epsilon_{jK_{ICT}} = \frac{\partial \ln j}{\partial \ln K_{ICT}} = \frac{\partial \ln \frac{S_j VC}{P_j}}{\partial \ln K_{ICT}} = \frac{\partial \ln S_j}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} - \frac{\partial \ln P_j}{\partial \ln K_{ICT}} \tag{13}$$

Assuming exogenous prices implies $\frac{\partial \ln P_j}{\partial \ln K_{ICT}} = 0$, which leads to equation 14.

$$\epsilon_{jK_{ICT}} = \frac{\partial \ln S_j}{\partial \ln K_{ICT}} + \frac{\partial \ln VC}{\partial \ln K_{ICT}} \tag{14}$$

Which can be also expressed as:

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} + \frac{\partial VC}{\partial K_{ICT}}\frac{K_{ICT}}{VC} \tag{15}$$

Assuming that $\frac{\partial VC}{\partial K_{ICT}}$ is a shadow price for capital allows writing equation (16).

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} - \frac{R_{K_{ICT}}K_{ICT}}{VC} \tag{16}$$

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

$$\epsilon_{jK_{ICT}} = \frac{\beta_{jK_{ICT}}}{S_j} - S_{K_{ICT}} \tag{17}$$

D Distribution of Electric and Non-electric Energy Prices

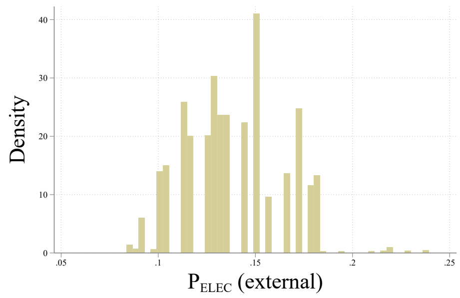

Figure D.1: Distribution of electric energy prices.

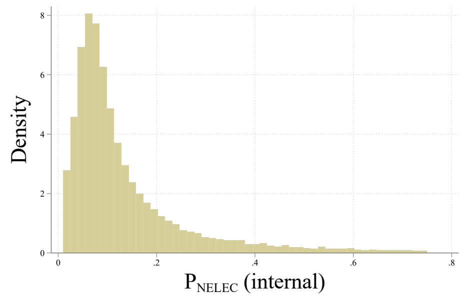

Figure D.2: Distribution of non-electric energy prices.

E Perpetual Inventory Method (PIM)

In the spirit of Griliches (1980), Harberger (1988), Berlemann and Wesselhöft (2014), Lutz (2016), Vanormelingen 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.

$$K_t = (1-\delta)K_{t-1} + I_t \tag{18}$$

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.

$$\frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \delta \tag{19}$$

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

$$K_{t-1} = \frac{I_t}{g_K + \delta} \tag{20}$$

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

$$K_0 = \frac{I_1}{g_K + \delta} \tag{21}$$

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.

$$\hat{I}_1 = \frac{\sum_{t=1}^{3} I_t}{n} \tag{22}$$

Accordingly, in this study we calculate initial capital stocks by applying equation (21) and (22), subsequent capital stocks are calculated by equation (18).

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.

F Average Software Capital Intensity by Region

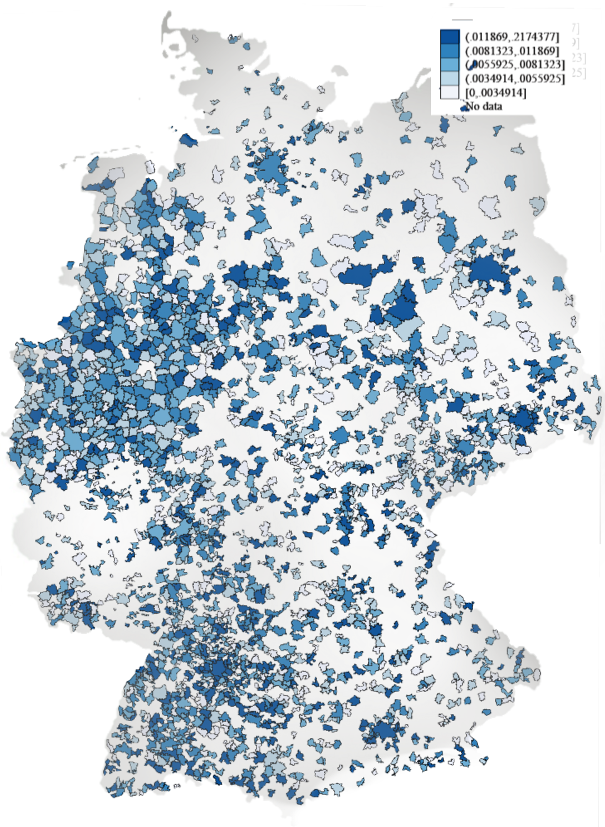

Figure F.1: Average software capital scaled on output by region between 2009–2017. The dark blue regions represent those with the highest software capital. Regions with less than three observations per year or with no observation are marked in grey.

G Further Estimation Results

Table G.1: Equation (5) with software capital stocks modified by different depreciation rates.

	(1)	(2)	(3)
	Depreciation rates		
	25 percent	33 percent	50 percent
$\triangle S_E$			
$\triangle \ln(\frac{P_E}{P_L})$	0.0289***	0.0289***	0.0289***
	(49.89)	(49.89)	(49.89)
$\triangle \ln(\frac{K_{ICT}}{Y})$	-0.000297***	-0.000366***	-0.000387***
	(-4.56)	(-4.33)	(-4.08)
$\triangle \ln(\frac{K_N}{Y})$	-0.00121***	-0.00121***	-0.00122***
	(-1.11)	(-1.19)	(-1.16)
$\triangle \ln(Y)$	0.00194***	0.00186**	0.00183**
	(3.33)	(3.18)	(3.12)
D_{all}	x	x	x
Observations	90179	90179	90179
Adjusted R^2	0.262	0.262	0.262

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

Table G.2: Equation (5) with software capital stocks modified by different lengths of periods considered for the initial capital stock calculation.

	(1)	(2)
	Number of periods maximal included in initial software capital stocks	
	5	7
$\triangle S_E$		
$\triangle \ln(\frac{P_E}{P_L})$	0.0289***	0.0289***
	(49.89)	(49.89)
$\triangle \ln(\frac{K_{ICT}}{Y})$	-0.000269***	-0.000371***
	(-4.65)	(-4.28)
$\triangle \ln(\frac{K_N}{Y})$	-0.00121***	-0.00122***
	(-3.48)	(-3.50)
$\triangle \ln(Y)$	0.00196***	0.00185**
	(3.38)	(3.16)
D_{all}	x	x
Observations	90179	90179
Adjusted R^2	0.262	0.262

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

Table G.3: Equation (5) with further sample restrictions.

	(1) After 2011	(2) Only single-unit firms
$\triangle S_E$		
$\triangle \ln(\frac{P_E}{P_L})$	0.0289***	0.0289***
	(40.43)	(47.13)
$\triangle \ln(\frac{K_{ICT}}{Y})$	-0.000211***	-0.000185***
	(-4.60)	(-3.94)
$\triangle \ln(\frac{K_N}{Y})$	-0.00105*	-0.00132***
	(-2.26)	(-3.90)
$\triangle \ln(Y)$	0.00166*	0.00217**
	(2.07)	(3.53)
D_{all}	x	x
Observations	63017	77583
Adjusted R^2	0.282	0.273

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