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# The Diffusion of Technological Progress in ICT

## Abstract

We study whether technology gains in sectors related to Information and Communications Technology (ICT) increase productivity in the rest of the economy. To separate exogenous gains in ICT from other technological progress, we use the relative price of ICT goods and services in a structural VAR with medium-run restrictions. Using local projections to estimate the effect of ICT-related technology gains on sectoral technology (TFP), we find two sets of results. First, since the mid-2000s there have been positive and persistent technology spillovers to sectors intensively using ICT. Second, neglecting leasing activity leads to an overestimation of the TFP response for all sectors except the leasing sector, where it is strongly underestimated.

JEL-Codes: C320, D240, E220, E240, O330, O470, O520.

Keywords: digitization, information and communications technology, technology shocks, local projections, structural VARs, medium-run restrictions, growth accounting.

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# 1. Introduction

Since the mid-1990s the digital revolution has gone hand in hand with rapid technological progress in Information and Communications Technology (ICT). However, a long-standing question that remains is whether the technological innovations in the ICT-producing sectors have also induced further technological advances in other sectors. Standard neoclassical growth theory suggests that progress in ICT-related technology lowers the relative price of ICT goods and services. This leads to capital deepening via higher ICT investments throughout the economy. Yet, there are no technology gains outside the ICT-producing sectors (see, e.g., Basu and Fernald, 2007).

Looking beyond the predictions of neoclassical growth theory, progress in ICT-related technology may accelerate technological advancements outside ICT-producing sectors. When ICT is a general-purpose technology, ICT-related technological progress fundamentally changes the production process of non-ICT producers (see, e.g., Helpman and Trajtenberg, 1998). This is because the adoption of these new technologies could initiate complementary innovations, resulting in an improvement of total factor productivity (TFP) in other parts of the economy. Examples are easier forms of collaboration with other firms to create new knowledge, faster information processing, lower administrative and search costs, better supply chain management, and new forms of distribution and inventory systems.[1] However, empirical evidence concerning the existence of such spillovers over the past 25 years has been somewhat inconclusive.[2]

This paper examines whether technological progress in the ICT-producing sectors initiates productivity gains in other sectors. We propose a novel approach for identifying exogenous ICT-related technological changes (ICT-shocks) by combining a structural vector autoregressive (VAR) model with medium-run restrictions and the relative price of ICT goods and services. To estimate the spillover effects of these ICT-shocks, we extract sector-specific TFP data from EU KLEMS for Germany. To account for the growing proportion of rented investments, we augment this data set with unique data on leasing activity from the Ifo Investment Database (IIDB). Subsequently, we use local projections to analyze the dynamics of spillover effects.

We provide two sets of results: First, since the mid-2000s there have been positive and persistent TFP spillovers to sectors that intensively use ICT goods and services.[3] These spillovers occur in the year of the ICT-shock and the two subsequent years. However, we do not find significant technology spillovers before the mid-2000s. These results may be due

[1] See, e.g., Forman and van Zeebroeck (2012); Hempell (2005); Laursen and Foss (2003); Antonioli *et al.* (2010).

[2] Studies that find an effect include Brynjolfsson and Hitt (2003); Basu and Fernald (2007); Marsh *et al.* (2017); Pieri *et al.* (2018), while no evidence for spillovers is found by Stiroh (2002a); Inklaar *et al.* (2008); Acharya (2016).

[3] We distinguish between ICT-producing and non-ICT-producing sectors, the latter can be further broken down to sectors that intensively use ICT and those that do not.

to a slow adoption and dissemination of digital expertise, the rigid German labor market until the mid-2000s, and additional ICT-shocks between 2006 and 2010 (Brynjolfsson and Hitt, 2003; Cette *et al.*, 2014; Gust and Marquez, 2004; Cette and Lopez, 2012). Second, our results indicate that neglecting leasing activity results in overestimating the response of TFP for all sectors aside from the leasing sector, where it is strongly underestimated. Therefore, using data only from growth accounting databases such as KLEMS leads to an upward bias for almost all TFP responses.

Our paper addresses several strands of the productivity literature. From a methodological perspective, we propose a method to identify ICT-shocks. Thus far, the literature has relied on either growth accounting approaches or the estimation of production functions to analyze ICT spillover effects (for an overview, see Cardona *et al.*, 2013). To circumvent potential endogeneity issues, some papers use lagged values for ICT, instrument the endogenous variable with its own lagged values or with the OECD index of regulating the telecommunication service industry (Basu and Fernald, 2007; Brynjolfsson and Hitt, 2003; Marsh *et al.*, 2017). Lagged values of the independent variable can suffer from weak instrument problems or harm the exclusion restriction. Addressing these concerns, our approach complements the existing literature by establishing a system of equations that is solved by an identifying assumption derived from economic theory.

We identify ICT-shocks using the relative price of ICT goods and services in a structural VAR model with medium-run restrictions. The relative price is crucial to separate technology gains that are solely related to ICT from changes that drive non-ICT technology.[4] To disentangle technology from non-technology shocks we rely on medium-run restrictions (Uhlig, 2004) instead of the widely-used approach with long-run restrictions (see, e.g., Galí, 1999; Fisher, 2006; Altig *et al.*, 2011). In our view, assumptions imposed by long-run restrictions are too strict since they imply that only technology shocks have long-run effects on labor productivity.[5]

A second methodological contribution lies in the improved measurement of sectoral TFP. To construct these series, we integrate data from the IIDB into the commonly used EU KLEMS database (O'Mahony and Timmer, 2009). The major advantage of the IIDB is that it contains additional information about investment based on both the owner and user concept. Measuring investment according to the two concepts can greatly differ when investment goods are leased instead of bought (Strobel *et al.*, 2013; Strobel, 2016). According to the owner concept all investments related to leasing are assigned to the sector 'Professional and Business Service Providers', while the user concept attributes it to the sectors actually operating with these investments. Therefore, TFP may be overstated in sectors intensively leasing investment goods.

[4] This is in the spirit of Fisher (2006) and Altig *et al.* (2011), who use the price of investment relative to consumption goods to distinguish between neutral and investment-specific technology changes.

[5] The long-run restriction approach has been criticized by, among others, Uhlig (2004); Erceg *et al.* (2005); Chari *et al.* (2008).

Since most official accounts lack information about sectoral leasing activity, statistical offices across countries only provide figures based on the owner concept. Hence, EU KLEMS only has investment data based on this concept. We demonstrate that, unconditionally, cumulative TFP deviations amount to 2 percent to 7 percent between the two concepts, and the conditional responses of TFP following an ICT-shock are biased. Therefore, an accurate measurement of TFP spillovers needs to take leasing activity into account.

We use Jordà's (2005) local projection method to assess the spillover effects of ICT-shocks. Local projections reveal potential lags between technological progress in the ICT-producing sectors and its adoption in other sectors. These time lags may arise due to the fact that adopting new technologies requires time if it entails changes in business processes and organizational structures (Brynjolfsson and Hitt, 2003; Bloom *et al.*, 2012). To account for these dynamics, previous empirical studies regress productivity on the lagged values of different types of ICT capital variables (Brynjolfsson and Hitt, 2003; Basu and Fernald, 2007; Marsh *et al.*, 2017). Our approach estimates a sequence of regressions of a variable of interest, e.g., TFP, on exogenous ICT-related technological changes for different prediction horizons. We derive impulse responses from these estimates to which we can attribute a causal interpretation.

The remainder of this paper is structured as follows. The next section describes the identification of the ICT-shocks using a structural VAR model. In Section 3 we present the data and construction of the TFP series. In Section 4 we introduce the local projection model and present the estimated effects of ICT technology shocks. The last section concludes.

# 2. Identification of ICT-Shocks

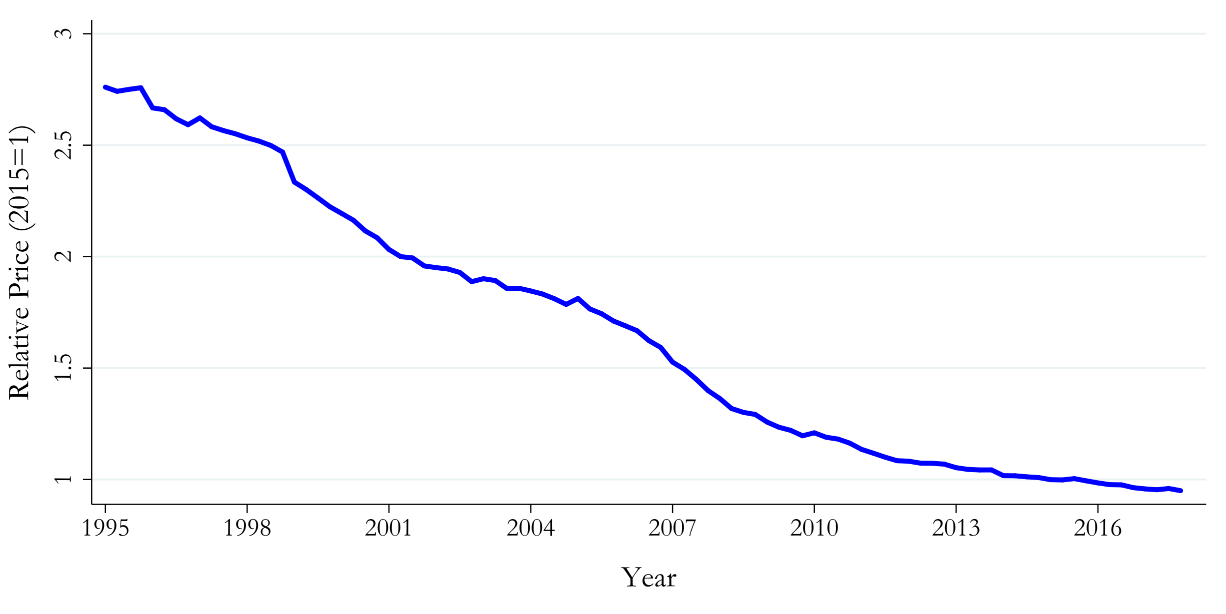
## 2.1. Investment-Specific Technology Shocks and Relative Prices

We are interested in a particular type of investment-specific technology shock, namely those that originate from producers of ICT goods and services. Therefore, our goal is to separate these ICT-shocks from other technological progress which are called neutral technology shocks. To do so, we rely on the relative price of ICT goods and services, motivated by Fisher (2006) and Altig *et al.* (2011).[6] Compared to other prices in the economy, prices of ICT goods and services have been steadily declining over the years (see Figure 1). These relative declines in prices are due to the high level of technological progress in the ICT-producing sectors, which include the sectors 'Manufacturing of Computer, Electronic and

[6] This price measure was suggested by Elstner *et al.* (2018) who apply a combination of long- and short-run restrictions in a VAR model to identify ICT-shocks. They assume that ICT-shocks have a contemporaneous effect on the relative ICT price, while non-ICT technology shocks have only a lagged impact. This approach implies that the forecast error variance of labor productivity is solely explained by technology shocks in the long run. We relax this stringent assumption by using medium-run restrictions. In our framework, both types of shocks may have a contemporaneous impact on the relative price.

Optical Products', 'Telecommunications', and 'IT and Other Information Services'.[7] Even in the presence of price rigidities, quality improvements map into reductions in the ICT deflator due to hedonic price measurement.[8] We therefore use the diverging development of ICT and non-ICT prices to isolate the ICT-shocks from neutral technology shocks.

**Figure 1:** Relative Price of Gross Value Added in the ICT-Producing Sectors




*Notes*: The figure shows the relative price of gross value added (2015=1) for the ICT-producing sectors compared to all non-ICT-producing sectors in Germany, constructed from National Accounts data as described in the Appendix.

Our identification approach is inspired by Fisher (2006) who incorporates investment-specific technology shocks in a neoclassical growth model to obtain two identifying restrictions for a structural VAR model. First, both the neutral and the investment-specific technology shock influence labor productivity in the long run, which lies in contrast to Galí (1999). He argues that only neutral technology shocks have long lasting effects on labor productivity. Second, the model suggests that only investment-specific technology shocks have a long-run effect on the real price of investment goods. In contrast, neutral technology shocks do not affect the relative price between both types of goods. In sum, this theoretical framework places the relative price at the center of the identification procedure to distinguish between different types of technology shocks.

[7]Here, we follow the definition of the Federal Statistical Office and the OECD. Due to data limitations, our measure for the ICT-producing sectors does not include ICT wholesale trade, software publishing and repair of computers and communication equipment. Our measure explains about 70 percent of total sales of the ICT-producing sectors according to the definition of the Federal Statistical Office in 2015. The remaining 30 percent are almost entirely due to the missing ICT wholesale trade sector. Regarding investment expenditures, our sectoral definition encompasses more than 97 percent of the total ICT-producing sectors.

[8]The Federal Statistical Office conducts a hedonic price adjustment only for ICT goods and used cars (Ademmer *et al.*, 2017).

## 2.2. Empirical Approach

We identify ICT-shocks, $\varepsilon_t^{\text{ICT}}$, according to the identification scheme illustrated in Figure 2. The identification proceeds in two steps. In step 1 we use medium-run restrictions to separate all types of technology shocks (so-called auxiliary shocks) from non-technology factors. Step 2 divides these auxiliary shocks into ICT-shocks and neutral technology shocks.

**Step 1.** Our VAR model includes eight variables: labor productivity in the ICT-producing sectors, $\text{LP}_t^{\text{ICT}}$, labor productivity of all non-ICT-producing sectors, $\text{LP}_t^{\overline{\text{ICT}}}$, relative price between ICT-producing and non-ICT-producing gross value added, $\widehat{P}_t = \text{Price}_t^{\text{ICT}} / \text{Price}_t^{\overline{\text{ICT}}}$, hours worked per employer, private consumption per capita, equipment investment per capita, the terms of trade defined as the ratio of the export and the import deflator, and the real interest rate. To calculate per capita, the respective variable is divided by the labor force. The real interest rate is calculated as the difference between the EONIA rate and the CPI annual inflation rate. After 2004 we replace the EONIA rate by the shadow rate constructed by Krippner (2013) to consider the zero lower bound episode. All other data have been retrieved from the Federal Statistical Office.

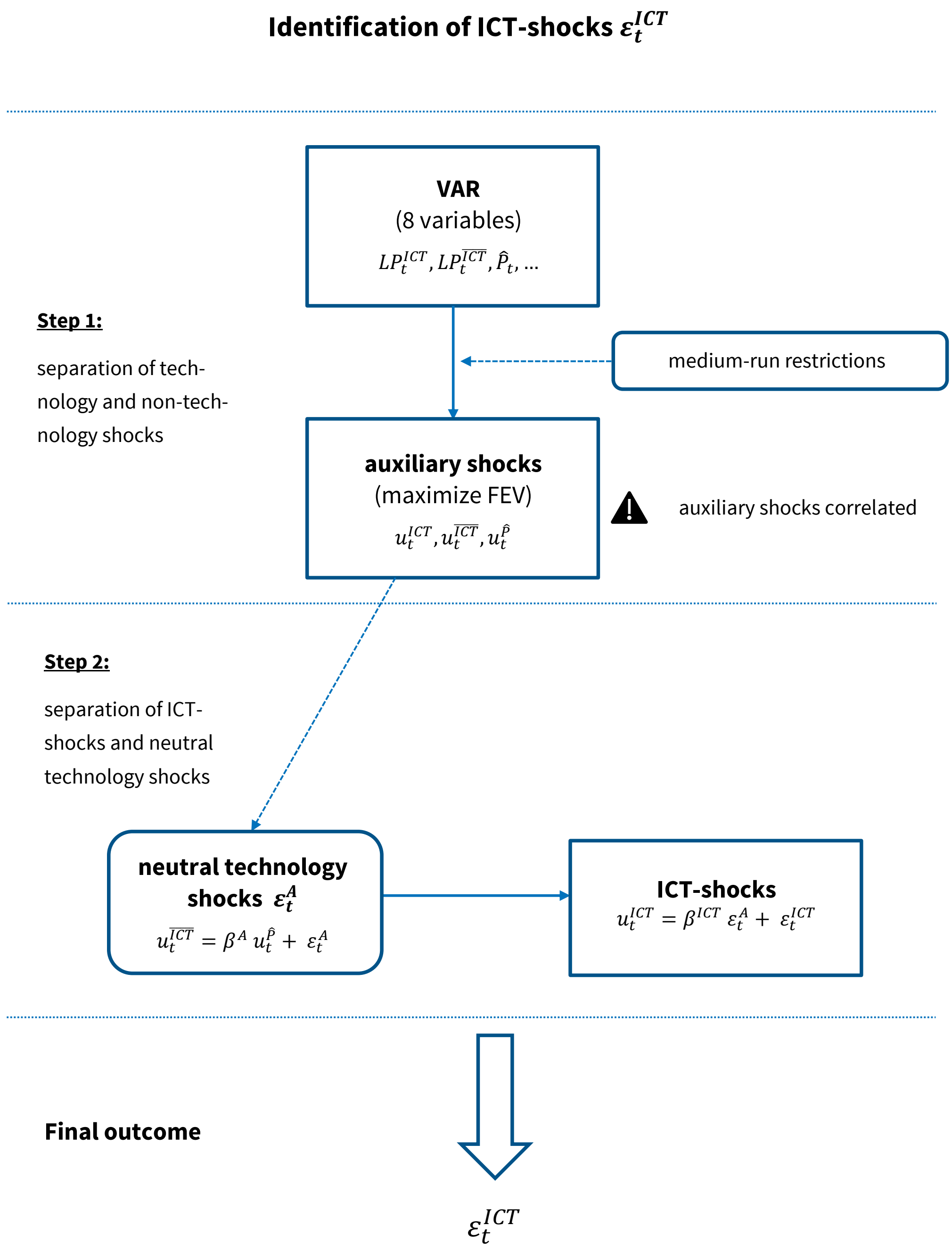
The model includes four lags and is estimated at a quarterly frequency for the period from 1993:Q4 to 2017:Q4. This enables us to extract productivity shocks for the period from 1995 to 2017. The sample is confined to this period due to data availability in the EU KLEMS database, which we rely on for the construction of TFP as described in Section 3. We also use this starting point owing to structural changes in the German economy following the German reunification.

As some relevant variables are only available at an annual frequency, we apply the temporal disaggregation approach proposed by Chow and Lin (1971).[9] All variables from German National Accounts are seasonally and, if necessary, calendar-adjusted and transformed into log-differences beforehand. That does not apply to the interest rate which enters in differences. We estimate the VAR in log-differences, since all our per-capita variables demonstrate a trending behavior that does not persist over time. Especially labor market outcomes such as total hours worked are highly influenced by the German labor market reforms (Hartz reforms), with a reversed trending behavior after 2005. We, therefore, refrain from modeling such structural changes in log-levels and apply log-differences instead.

Based on the VAR, we extract all shocks related to technology, that is, the auxiliary shocks. To do this, we apply the medium-run identification procedure proposed by Uhlig (2004). The idea of this approach is to find the shock that maximizes the forecast error variance (FEV) of the target variable over the forecast horizon $h \in \left[\underline{h}, \overline{h}\right]$, with $\underline{h}$ and $\overline{h}$ as the lower and upper bound of the maximization horizon. The auxiliary shock series is the dominant, but not the exclusive source of target variable fluctuations in our approach.

[9] For details on the data sources and the temporal disaggregation procedure, see Appendix A.

**Figure 2:** Overview of the Identification Scheme




*Notes*: The scheme outlines the identification of ICT-shocks $\epsilon_t^{ICT}$ as described in Section 2. Step 1 estimates a VAR model, which includes, among other variables, labor productivity in all non-ICT-producing sectors, $\text{LP}_t^{\overline{\text{ICT}}}$, labor productivity in the ICT-producing sectors, $\text{LP}_t^{\text{ICT}}$, and the ratio of gross value added deflators of the ICT-producing and the remaining sectors of the economy, $\widehat{P}_t$. Since the corresponding auxiliary shocks $u_t^{\overline{\text{ICT}}}$, $u_t^{\text{ICT}}$, and $u_t^{\widehat{P}}$ are still correlated with one another, step 2 deals with their orthogonalization.

We extract three auxiliary shocks $u_t^{\overline{\text{ICT}}}$, $u_t^{\text{ICT}}$, and $u_t^{\widehat{P}}$ that maximize the FEV of $\text{LP}_t^{\overline{\text{ICT}}}$, $\text{LP}_t^{\text{ICT}}$, and $\widehat{P}_t$, respectively, up to a specific forecast horizon. In the baseline, we choose the medium-run horizon to be between 0 and 40 quarters, which is in line with Barsky and Sims (2011) and Kurmann and Otrok (2013).

**Step 2.** All three auxiliary shocks are still correlated with each other due to the partial identification nature of medium-run restrictions. The second step deals with the orthogonalization to isolate the ICT-shocks. Intuitively, we proceed in two sub-steps. First, we regress $u_t^{\text{ICT}}$ on $u_t^{\widehat{P}}$ to obtain neutral technology shocks, $\varepsilon_t^A$, which are, by construction, not the main driver of fluctuations in the relative price. Second, we regress $u_t^{\text{ICT}}$ on the neutral technology shocks $\varepsilon_t^A$. The residuals from this regression, $\varepsilon_t^{\text{ICT}}$, are uncorrelated with neutral technology shocks and, therefore, represent our estimate for exogenous ICT-related changes in the technology level of the ICT-producing sectors.

**Technical Implementation.** From a technical point of view, we consolidate step 1 and 2 as in Cascaldi-Garcia and Galvão (2020) and Belke *et al.* (2020). Equivalent to the two regressions, we apply two QR-decompositions to the three eigenvectors that define the auxiliary shocks from step 1. The first QR-decomposition is calculated from the eigenvectors that define the shocks to the relative price and to the productivity of the non-ICT-producing sectors. Ordering the eigenvector related to the relative price first, and the vector related to productivity of the non-ICT-producing sectors second, the first eigenvector remains unchanged. The resulting second vector is obtained by subtracting its projection over the first one, which is equivalent to the first regression in step 2.

The second QR-decomposition is calculated from the second column of the orthogonal 'Q part' of the first QR-decomposition and the eigenvectors that define the shocks to productivity of the ICT-producing sectors. Ordering this 'Q part' first and the ICT-vector second, the QR-decomposition is equivalent to the second regression in step 2. The second column from the 'Q part' of the second QR-decomposition defines the restriction to calculate the ICT-shocks.

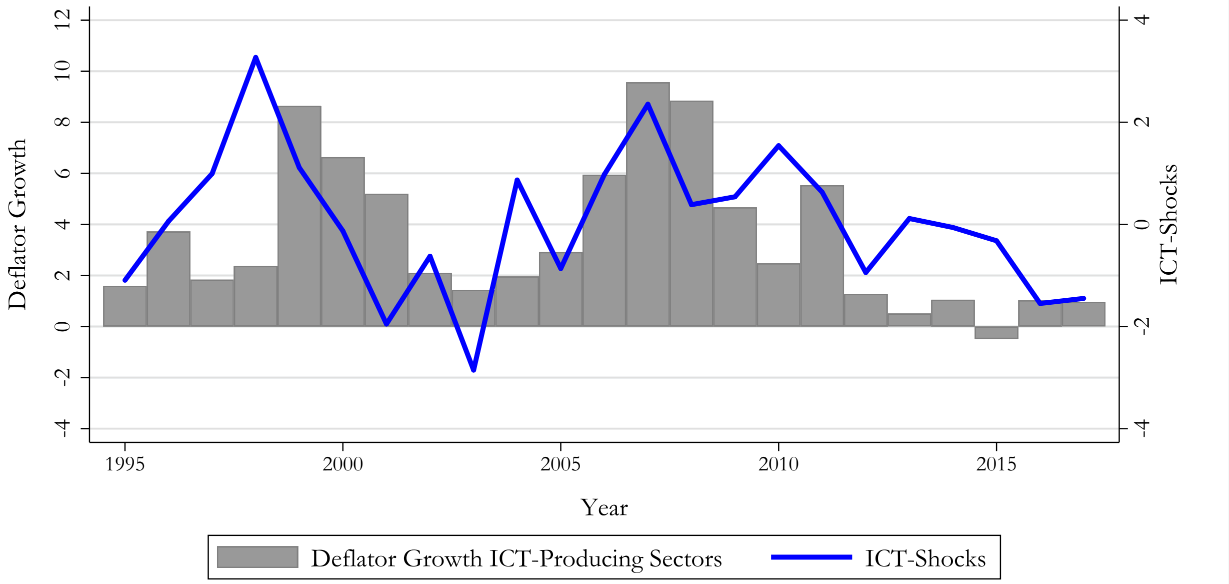
## 2.3. Discussion and Sensitivity

Figure 3 plots the ICT-shocks, depicted as blue lines, together with the growth rate of the deflator of the ICT-producing sectors (Panel (a)) and labor productivity growth in the ICT-producing sectors (Panel (b)). The shocks have been annualized by calculating the yearly sum of the quarterly shock series. The deflator is multiplied by -1 to facilitate a comparison with the shocks. ICT-shocks are associated with price declines of ICT goods and services in most cases. In particular, the large positive shocks between 1997 and 1998 and between 2006 and 2007 are linked to strong price decreases. The correlation between ICT-shocks and the deflator is 0.39.

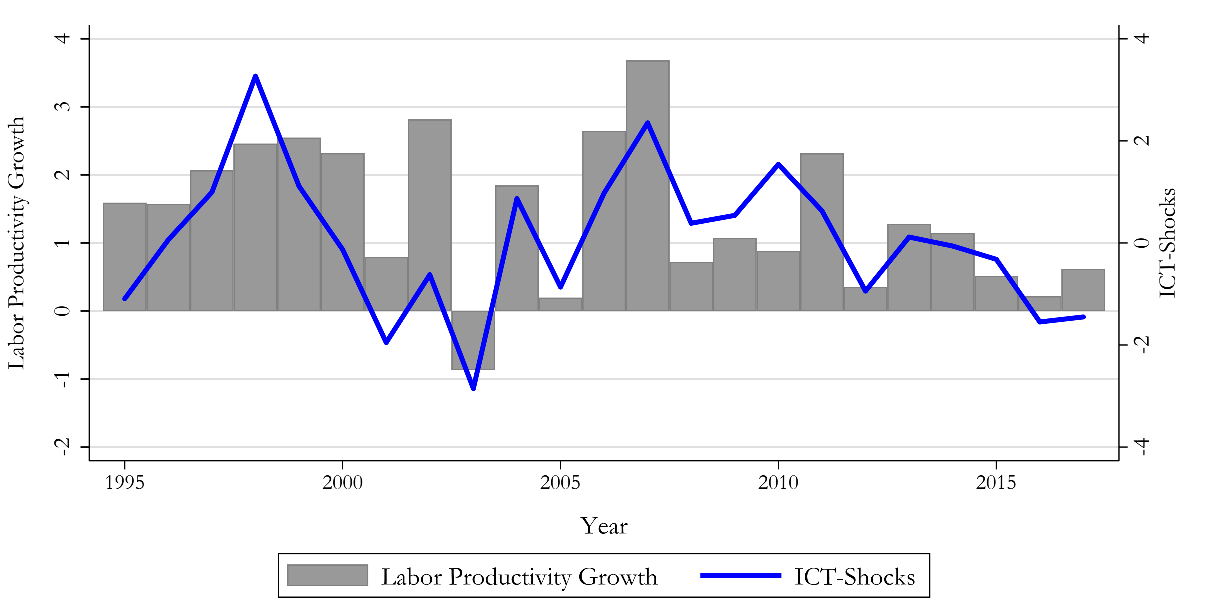
ICT-shocks are also associated with changes in labor productivity in the ICT-producing sectors. The rise and fall of labor productivity growth between 1995 and 2003 is closely related to ICT-shocks. The comovement between the ICT-shocks and labor productivity is supported by the high correlation coefficient of 0.51.

**Figure 3:** ICT-shocks and Deflator and Labor Productivity of ICT-Producing Sectors

(a) ICT-shocks and Deflator of ICT-Producing Sectors




(b) ICT-shocks and Labour Productivity Growth of ICT-Producing Sectors




*Notes*: The figure plots the ICT-shocks together with the growth rates of the deflator (multiplied by minus 1; upper panel) and labor productivity in the ICT-producing sectors (lower panel).

Table 1 displays the fraction of the forecast error variance of $\mathrm{LP}^{\overline{\mathrm{ICT}}}$, $\mathrm{LP}^{\mathrm{ICT}}$, and $\widehat{P}$ that can be attributed to ICT-shocks. They account for a large fraction of the variance of labor productivity in the ICT-producing sectors and the relative price. At a 40 quarters horizon, ICT-shocks account for 54 (51) percent of the variance of labor productivity (the relative price) in the ICT-producing sectors. In contrast, these shocks only explain 11 percent of the variance of productivity in the non-ICT-producing sectors.

**Table 1:** Variation Explained by ICT-Shocks

| Horizon (Quarters) | 5 | 10 | 20 | 40 | 60 | 80 |
|---|---|---|---|---|---|---|
| Variable | Variation Explained by $\varepsilon^{\mathrm{ICT}}$ | | | | | |
| Non-ICT Labor Productivity | 0.01 | 0.03 | 0.09 | 0.11 | 0.11 | 0.12 |
| ICT Labor Productivity | 0.59 | 0.57 | 0.55 | 0.54 | 0.54 | 0.53 |
| Relative Price | 0.42 | 0.49 | 0.51 | 0.51 | 0.51 | 0.51 |

*Notes*: The table shows the fraction of the total forecast error variance of the two labor productivity and the relative price variables, respectively, due to the ICT-shocks.

Finally, we evaluate the sensitivity of the ICT-shocks to changes in the identification procedure and the variable selection. First, we use alternative medium-run restrictions by varying the horizon for which the FEV share is maximized. Compared to the baseline specification with 0-40 quarters, we consider horizons of 0-16 quarters and 40-40 quarters; the former is the choice by Uhlig (2004), the latter is used by Francis *et al.* (2014). Table 2 displays correlations of the alternative shocks with the baseline shocks. The results show that our baseline estimate for ICT-shocks is robust to the use of other plausible medium-run horizons.

Second, we substitute some of the variables used in the SVAR model. We replace the shadow rate from Krippner (2013) with the one constructed by Wu and Xia (2017). Furthermore, we alter the model by dividing consumption and investment by either the gross domestic product or the total population in lieu of the labor force. The correlations with the baseline shocks indicate that the model is fairly robust to these changes. Overall, this analysis lends credibility to the robustness of our ICT-shocks with respect to alternative specifications and variables.

**Table 2:** Alternative Specifications of the VAR-Model

| | | Correlation of ICT-Shocks | |
|---|---|---|---|
| Model | Description | Quarterly | Annual |
| 1 | Baseline: 0-40 Quarters | 1.00 | 1.00 |
| 2 | 0-16 Quarters | 1.00 | 1.00 |
| 3 | 40-40 Quarters | 1.00 | 1.00 |
| 4 | Shadow Rate by Wu and Xia (2017) | 0.96 | 0.98 |
| 5 | Consumption/GDP, Investment/GDP | 0.97 | 0.99 |
| 6 | Consumption/Population, Investment/Population | 0.96 | 0.99 |

*Notes*: The table summarizes the modification of the VAR model used for identifying the ICT-shocks. The column "Description" contains a brief description of the modifications compared to the baseline specification described in Section 2.3. "Baseline": Productivity and relative price: 0-40 Quarters, Shadow Rate by Krippner (2013), Consumption/Labor Force, Investment/Labor Force. "Quarters" refers to the horizon over which the FEV share for the productivity and relative price shocks is maximized. The table also shows the correlation of the alternative shock series to the baseline shocks, at both quarterly and annual frequency.

# 3. Construction of the TFP Data

## 3.1. Growth Accounting Framework

The sectoral TFP series are constructed using the growth accounting framework proposed by Jorgenson *et al.* (1987, 2005). In year $t$, sector $j$ uses capital services $K_{jt}$ and labor service $L_{jt}$ to produce output $Y_{jt}$. Total factor productivity $\text{TFP}_{jt}$ shifts the production function. We follow the EU KLEMS framework insofar as we apply gross value added $V_{jt}$ instead of output $Y_{jt}$. We assume a Cobb-Douglas production function with constant returns to scale. Using a translog transformation, TFP growth can be extracted as follows:

$$\Delta\ln \text{TFP}_{jt} \;=\; \Delta\ln V_{jt} - \alpha\, \Delta\ln K_{jt} - (1-\alpha)\, \Delta\ln L_{jt}\;, \tag{1}$$

where $\alpha$ describes the output elasticity of capital.

Capital services of each sector $j$ in year $t$ depend on the capital stocks, $S_{jkt}$, of various asset types $k$ (for example, information technology, expenditure for research and development or intangible assets). Thus, growth of sector-specific capital services is:

$$\Delta\ln K_{jt} \;=\; \sum_k \overline{v}_{jkt}\; \Delta\ln S_{jkt}\;, \tag{2}$$

where $\overline{v}_{jkt}$ denotes the two-year average weight of each asset type. This aggregation assumes that aggregate services are a translog function of the individual assets' services (see, e.g., O'Mahony and Timmer, 2009). To derive the capital stocks, $S_{jkt}$, we apply the usual capital accumulation equation:

$$S_{jkt} = \left(1 - \delta^S_{jkt}\right)\; S_{jkt-1} + I_{jkt}\;, \tag{3}$$

where $\delta^S_{jkt}$ denotes the depreciation rate and $I_{jkt}$ is investment in asset type $k$. The weights for the individual capital stocks are defined as:

$$v_{jkt} \;=\; \frac{p^K_{jkt}\, S_{jkt}}{\sum_k p^K_{jkt}\, S_{jkt}}\;, \tag{4}$$

which is the ratio between the capital costs of asset $k$ and the total capital costs in sector $j$.

The price of capital, $p^K_{jkt}$, is determined by a no-arbitrage condition (Jorgenson *et al.*, 2005). For a certain price of investment, $p^I_{jkt}$, a firm either buys a financial asset with the nominal interest rate $i_{jt}$, or it invests in a real capital good and receives the price of the real capital good corrected for depreciation during the next year. In equilibrium, the firm must be indifferent between these two options, which yields the cost of capital equation:

$$p^K_{jkt} \;=\; \left(i_{jt} - \pi^I_{jkt}\right)\, p^I_{jkt-1} \;+\; \delta^I_{jk}\, p^I_{jkt}\;, \tag{5}$$

where $\pi^I_{jkt}$ denotes the inflation rate of the investment in asset type $k$. Intuitively, $p^K_{jkt}$ increases in the real sector-specific interest rate and in the depreciation rate as both factors make investment in asset type $k$ relatively more expensive. In line with the literature, we calculate the nominal interest rate as the sector-specific internal rate of return (see, e.g., O'Mahony and Timmer, 2009).

Equation (5) underscores the importance of having heterogeneous deflators across sectors $j$. Since the price of capital influences the weights $v_{jkt}$ through Equation (4), some asset types have a substantial impact on capital services, despite only accounting for a small share in investment, see, e.g., ICT assets.

## 3.2. Data Sources

We use three data sources for constructing TFP: (i) the Federal Statistical Office; (ii) EU KLEMS; and (iii) the IIDB (IIDB, 2016). The Federal Statistical Office provides sectoral data on nominal and real gross value added, $V_{jt}$, as well as data on labor compensation. Furthermore, we take the series on labor services from EU KLEMS since they are based on detailed micro data incorporating labor quality growth.

We combine data from EU KLEMS and the IIDB to benefit from the advantages afforded by both data sources. The IIDB offers more details on the capital side of the economy, especially on the cost of capital. Table 3 presents the similarities and differences of both data sets.

**Table 3:** Characteristics of EU KLEMS and the IIDB

| Characteristic | EU KLEMS | IIDB |
|---|---|---|
| Labor services $L_{jt}$ | ✓ | |
| Deep sectoral disaggregation $j$ | ✓ | ✓ |
| Long time series | ✓ | ✓ |
| Various investment asset types $k$ | ✓ | ✓ |
| Investment deflators for divisions $p^I_{jkt}$ | | ✓ |
| ICT investment data after 2009 | | ✓ |
| Owner vs. user concept | | ✓ |

*Notes*: Own compilation based on O'Mahony and Timmer (2009) and Strobel *et al.* (2013).

The EU KLEMS and the IIDB data provide sectorally disaggregated and long time series for various investment activities. While EU KLEMS includes annual investment data for 10 investment asset types and 33 sectors, the IIDB contains data for 12 asset types and 51 sectors (see Strobel *et al.*, 2013). Using both data sets, we aggregate the investment matrix to $j = 33$ sectors and define $k = 6$ common asset types. These asset types are: 'Information Technology' such as computers, 'Communications Technology' such as satellite communication, 'Transportation Equipment' such as automobiles, 'Other Machinery' such as machines, 'Construction' such as buildings, and 'Other Assets' such as software and expenditure for research and development. This is the highest common level of disaggregation. Tables C1 and C2 in the Appendix provide an overview of this matching process.

We classify our 33 sectors into the following three groups: (i) sectors producing ICT goods and services (ICT-producers), (ii) sectors presenting a relatively high share of ICT capital, but not producing these goods by themselves (ICT-intensive), and (iii) sectors not intensively using ICT goods or services (non-ICT-intensive). ICT-intensive and non-ICT-intensive sectors are separated from each other following Stiroh (2002b): ICT-intensive sectors are those whose share of ICT capital in their total capital stock lies above the median share. This median share is calculated across all sectors that do not produce ICT goods and services, and the share may vary over time. Table C3 in the Appendix shows the taxonomy of the sectors.

**Capital Services.** The IIDB offers three main advantages regarding the investment or capital side, especially in the calculation of capital costs. First, the IIDB provides more information for the investment deflators, $p^I_{jkt}$, across sectors compared to EU KLEMS. Until recently, EU KLEMS reported identical deflators across all sectors, whereas now—from the EU KLEMS vintage of 2019 onward—the deflators vary at the 1-digit sector level. However, in contrast to the IIDB, the deflators are still constant within these 1-digit sectors. Clearly, sectors such as 'Manufacturing' and 'Information and Communication Services' are far from homogeneous. Figure B1 in the Appendix shows that there is considerable cross-sectional variation within the 1-digit sectors.

Second, since 2010 the Federal Statistical Office has been publishing investment series for the asset types 'Information Technology' (IT) and 'Communications Technology' (CT) only as an aggregate together with 'Machinery and Equipment Excluding Transport'. In the EU KLEMS database, the capital series for the ICT-producing sectors for the period 2010-2017 is calculated by disaggregating the aggregate series using 2009 Divisa shares (see Jäger, 2017). By contrast, the IIDB builds on the actual investment data and enables a differentiation between the investments in these three asset types. Figure B2 in the Appendix demonstrates that the variation in the shares are quite large between 2010 and 2017, especially for sectors that do not intensively use ICT.

**Owner vs. User Concept.** Finally, the IIDB has additional information about investment data both according to the owner and the user concept, which is the third and major advantage of this data source. According to the owner concept all investments related to leasing are assigned to the sector that originally purchased the goods.[10] This concerns the service sectors since leasing firms belong to the sector 'Professional and Business Service Providers'

[10] Note that when looking at the sectoral aggregates, i.e. the sum over all asset types by sector, the IIDB according to the owner concept is very similar to EU KLEMS.

(see code M-N in Table C2 in the Appendix). Instead, the user concept attributes these investments to the sectors that use them, which are mainly the manufacturing sectors.

Relying solely on the owner concept in a standard growth accounting framework may lead to biased growth contributions of capital services and TFP across sectors. Compared to the user concept, the owner concept understates a manufacturing firm's capital stock, which leases parts of its goods, and overstates its TFP. The opposite is true for the service provider. Consequently, the estimates for sector-specific TFP may be biased with potential repercussions for the correct measurement of TFP spillovers.

Due to a lack of information about sectoral leasing in most official accounts, statistical offices across countries only provide figures based on the owner concept. With the IIDB, we have detailed information on annual leasing data across sectors and by sub-assets from the Ifo Investment Survey Leasing. The Ifo Institute annually surveys all German leasing companies in collaboration with the Federation of German Leasing Companies. The survey includes several firm-specific leasing statistics, such as the amount of leasing investment, the share of leasing investment to total investment, and leasing by products and sectors.[11]

We now demonstrate that having information on leasing activity changes the size of investment that can be attributed to a sector by a relatively large amount. Using the additional information from the IIDB, panel (a) of Figure 4 plots the percentage deviation of non-ICT investment according to the owner concept from non-ICT investment based on the user concept. We observe strong differences between the two concepts both in terms of the magnitude of the deviation, and the development over time. For sectors intensively using ICT, investment based on the user concept is smaller than when measured by the owner concept. The reason for this is that leasing firms are assigned to the ICT-intensive sectors. By contrast, in the ICT-producing sectors, the relation is reversed and the user concept attributes higher investment than is owned by these sectors. Albeit less pronounced, the last finding is also observed for the non-ICT-intensive sectors. Panel (b) of Figure 4 shows similar patterns for ICT investment for which the deviations magnify, especially in the non-ICT-intensive sectors.

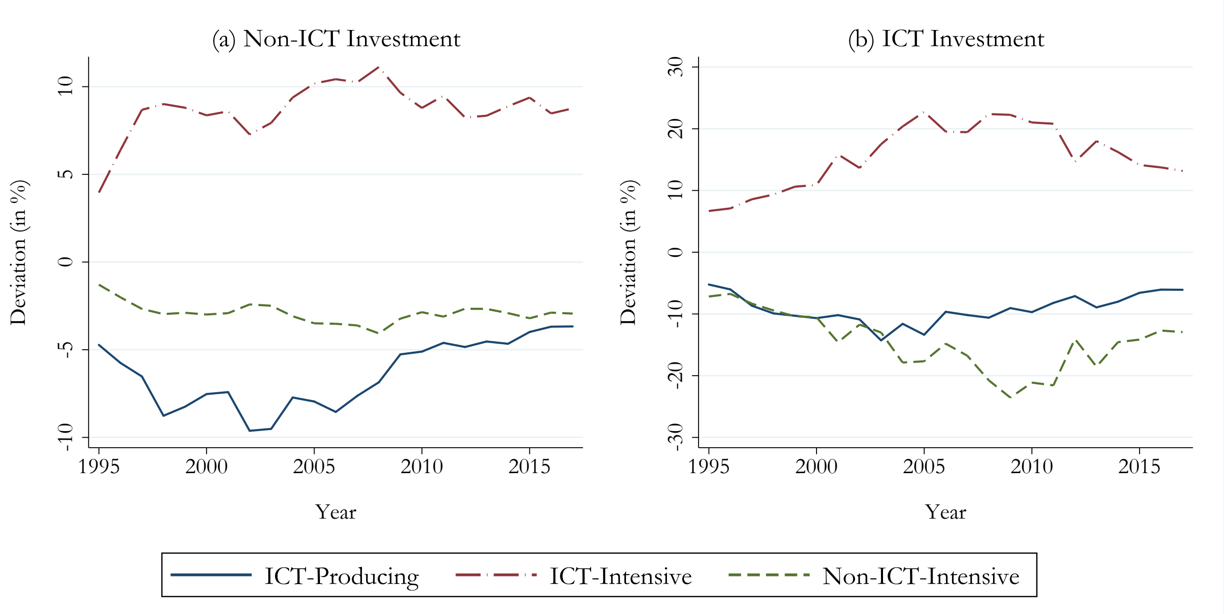
## 3.3. TFP Extraction

The construction of TFP proceeds in four steps. First, we derive the depreciation rates for the capital stocks, $\delta^S_{jkt}$, using capital stock and investment data from EU KLEMS.[12] We use the same depreciation rates $\delta^S_{jkt}$ for the user and owner concept, since an asset's economic

[11] For details, we refer to Goldrian (2007).

[12] Our depreciation rates for the capital stocks do not equal the rates published by EU KLEMS. The main reason is a methodological change: In past vintages, EU KLEMS calculated capital stocks based on its officially published depreciation rates. However, starting from vintage 2016, EU KLEMS has used the capital stock figures provided by Eurostat, which are not consistent with these depreciation rates. Due to their high volatility, we smooth several series with a centered three-year moving average: the implicit depreciation rates for construction assets and value added in the sector 'Coke and Petroleum', and the IT-Deflator in the sector 'Mining and Quarrying'.

**Figure 4:** Deviations of the Owner from the User Concept




*Notes*: Both plots are in percentage deviations of the values according to the owner concept from the values according to the user concept, i.e. $(I_i^{x,\text{owner}} - I_i^{x,\text{user}})/I_i^{x,\text{user}}$, where $x \in \{\text{ICT}, \overline{\text{ICT}}\}$ and the index $i$ refers either to the ICT-producing, ICT-intensive or the non-ICT-intensive sectors. Panels (a) and (b) show the evolution of the percentage deviation for non-ICT investment as well as investment in ICT for the three groups of sectors.

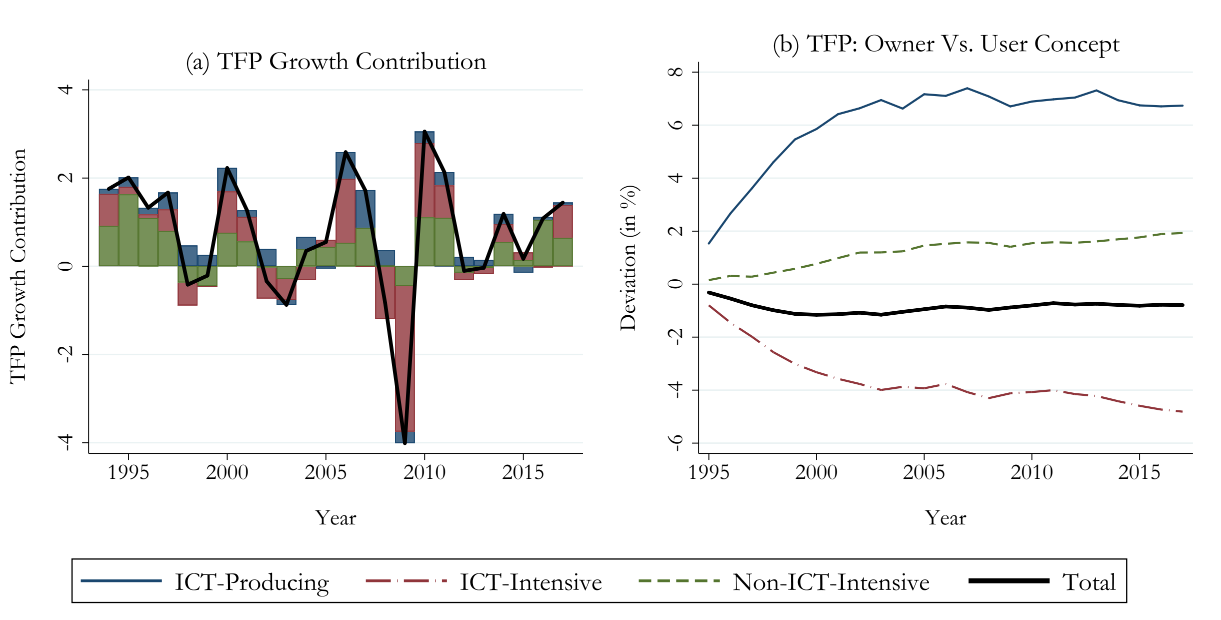
depreciation rate should not differ depending on its owner. Second, we set our nominal sectoral capital stock estimates in 1995 equal to the corresponding values from EU KLEMS: $S_{jkt_0}^{\text{IIDB}} = S_{jk1995}^{\text{KLEMS}}$. Starting from this value, we use Equation (3) to calculate capital stocks according to the owner and the user concept for all other years based on the IIDB. The assumption of equal capital stocks in 1995 is reasonable due to the low importance of leasing in the mid-1990s. Moreover, the starting value of capital stocks is of minor importance as our analysis primarily hinges on changes in capital stocks. Third, we construct capital services growth for each sector as a weighted sum of the capital stock growth rates of individual asset types using Equation (2).

Fourth, the growth rate of annual, sector-specific total factor productivity, $\Delta \ln \text{TFP}_{jt}$, is calculated from Equation (1). The output elasticity of labor services, $1-\alpha$, is determined as the two-year average aggregate of wages over gross value added, according to the procedure described by O'Mahony and Timmer (2009).

In the end, we have TFP series for the period from 1995 to 2017 and for $j = 33$ individual sectors. We present the TFP series in Figure 5. Panel (a) shows the growth contribution of TFP to value added for the three groups of sectors and the total economy. ICT-producing sectors show almost exclusively positive but small contributions to value added. In contrast, most variation in the total contribution stems from ICT-intensive sectors. Fluctuations in the non-ICT-intensive sectors are also large.

Panel (b) displays the corresponding differences in TFP based on the owner and user concept, expressed in percentage deviations. The total deviation is small, with up to 1 percent in 2003. Yet, TFP for the ICT-intensive sectors is on average by up to 5 percent smaller

**Figure 5:** TFP Derived from IIDB and EU KLEMS




*Notes*: Panel (a) shows the growth contributions of TFP to gross value added for the three groups of sectors and the total economy. Panel (b) depicts the difference between the owner and the user concept TFP, expressed in percentage deviations: $d_{jt}^{\text{TFP}} = (\text{TFP}_{jt}^{I,\text{owner}} - \text{TFP}_{jt}^{I,\text{user}})/\text{TFP}_{jt}^{I,\text{user}}$, where $\text{TFP}_{jt}^{I}$ is a TFP-index with base year 1994. The group-specific values have been obtained as weighted averages: $\sum_i d_{jt}^{\text{TFP}} V_{jt}$, where $V_{jt}$ denotes gross value added and the index $i$ refers either to the ICT-producing, ICT-intensive or the non-ICT-intensive sectors.

when estimated according to the owner concept, while it is up to 7 percent (2 percent) larger for the ICT-producing (non-ICT-intensive) sectors. Therefore, the owner concept underestimates actual productivity in the ICT-intensive sectors and overestimates TFP in the ICT-producing and the non-ICT-intensive sectors.

# 4. Spillover Effects of ICT-Shocks

## 4.1. Empirical Model

To assess how the ICT-shocks, identified in Section 2, spill over to the rest of the economy, we use the local projection method proposed by Jordà (2005). Impulse responses are obtained by estimating the following panel regression for each horizon $h$ and dependent variable $Y_{i,t}$:

$$\begin{aligned} \Delta Y_{i,t+h} = \alpha_{i,h} \; &+ \; \left[D_i^{\text{ICT}} \times \varepsilon_t^{\text{ICT}}\right] \beta_h^{\text{ICT}} \; + \; \left[D_i^{\text{INT}} \times \varepsilon_t^{\text{ICT}}\right] \beta_h^{\text{INT}} \\ &+ \; \left[\left(1 - D_i^{\text{ICT}} - D_i^{\text{INT}}\right) \times \varepsilon_t^{\text{ICT}}\right] \beta_h^{\text{NON}} \; + \; u_{i,t+h} \,, \end{aligned} \tag{6}$$

where $\Delta Y_{i,t+h}$ is the growth rate of our variables of interest for sector $i$ between year $t-1$ and $t+h$. We introduce two dummy variables that assign observations to either the ICT-producing ($D^{\text{ICT}}$) or the ICT-intensive sectors ($D^{\text{INT}}$). $u_{i,t+h}$ refers to the error term. $\alpha_i$ are sector-level fixed effects.

$\varepsilon_t^{\text{ICT}}$ denotes the ICT-shocks identified in Section 2. The ICT-shocks are annualized for the local projection.[13] To allow for a quantitative interpretation of our results, the ICT-shocks are standardized to have mean zero and a standard deviation of one.

The coefficient $\beta_h^{\text{ICT}}$ gives the response of the ICT-producing sectors at time $t+h$ to an ICT-shock at time $t$. Similarly, the coefficients $\beta_h^{\text{INT}}$ and $\beta_h^{\text{NON}}$ describe the responses of the ICT-intensive and the non-ICT-intensive sectors, respectively. Impulse responses for each of the three sectors are calculated from the sequence of $\beta_h^j$, where $j = (\text{ICT}, \text{INT}, \text{NON})$ and $h = 0, 1, ..., 4$. The coefficients are estimated using OLS for the period from 1995 to 2017. In line with Ramey and Zubairy (2018), we use the Newey-West correction for standard errors to account for serial correlation in the error terms arising from the successive leading of the dependent variable (see Newey and West, 1987). Following the recommendation by Stock and Watson (2018), the Newey-West corrected standard errors are calculated with $h+1$ lags.

To ensure the validity of the OLS estimates in the absence of further control variables, our shocks $\varepsilon_t^{\text{ICT}}$ have to meet the following three criteria: The shocks should (i) satisfy the contemporaneous exogeneity condition, (ii) fulfill the lag exogeneity condition, and (iii) be uncorrelated with the other shocks identified in our VAR model (Stock and Watson, 2018). In our case, all three requirements are met. First, the contemporaneous exogeneity condition holds by construction. Second, we test for lag exogeneity by regressing the lags of our variables of interest, $\Delta Y_{i,t-l}$ with $l = 1, ..., 5$, on the shock, $\varepsilon_t^{\text{ICT}}$. The estimated coefficients are close to zero and insignificant, implying that the shocks cannot be explained by past developments in the outcome variables. Finally, our shocks are not associated with the other VAR shocks: The cross-correlations between our ICT-shocks and the non-ICT-shocks are small in magnitude and insignificant. In sum, these checks suggest that our coefficient estimates are unbiased despite the parsimonious specification.

Our empirical model requires the groups to be constant over time. Therefore, we assign each sector to the group where it is mostly allocated in our sample. Table C4 in the Appendix shows that 12 out of 33 sectors switch between the ICT-intensive and the non-ICT-intensive sectors over time. However, these switches rarely occur except for the sector 'Textiles, Wearing Apparel, Leather and Related Products'. For at least 70 percent of all observations, all switching sectors belong to either the ICT-intensive or the non-ICT-intensive sectors.[14]

## 4.2. Aggregate Results

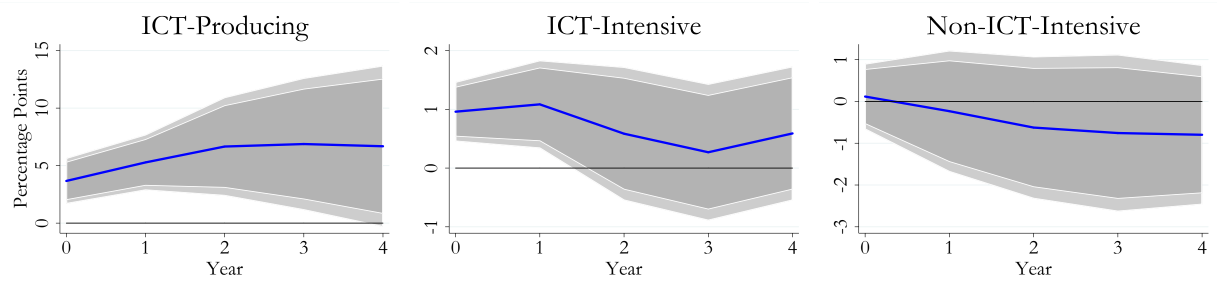
Figure 6 presents the responses of value added to an exogenous, one standard deviation increase in technology in the ICT-producing sectors. In the ICT-producing sectors, we observe a strongly positive response that lasts at least three years after the shock. While

[13] Specifically, the quarterly shocks are transformed to a quarterly index series. Then, we take yearly averages and calculate the annual percentage changes.

[14] We have also experimented with two other schemes to distinguish between sectors that intensively use ICT from those that do not, namely ICT capital services per worker and ICT capital per unit of output (see Robinson *et al.*, 2014). The results remain qualitatively unchanged.

the response of value added for the intensive users of ICT is small and short-lived, we do not detect any effects for the non-ICT-intensive sectors.

**Figure 6:** Effect on Gross Value Added

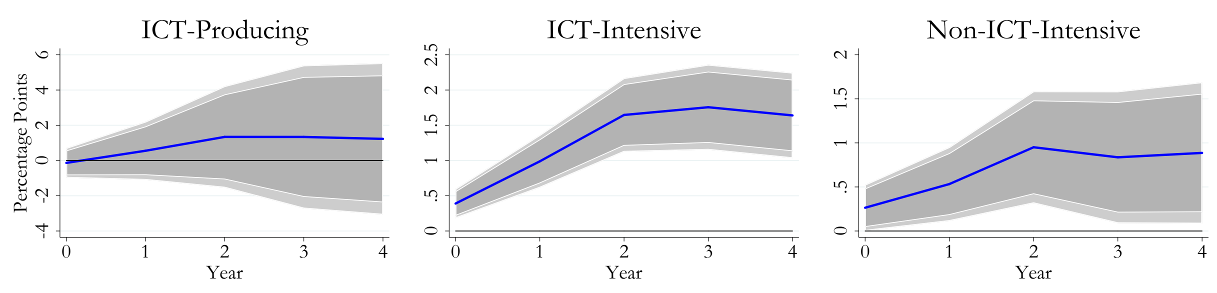



*Notes*: The graph displays the results of a local projection for gross value added as described in Section 4.1. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

The different responses of value added may arise due to several factors. Within the framework outlined in Section 3.1, we consider employment, ICT investment and TFP as potential transmission channels for the ICT-shocks.[15]

First, we look at the responses of sectoral employment. If TFP remains constant, we may expect an increase in labor demand due to the higher marginal product of labor. This is supported by Figure 7. In all three groups of sectors, employment increases steadily until two years after the shock. Subsequently, employment remains persistently higher at levels between one and two percentage points. Both the shape and magnitude of responses are highly similar across the groups of sectors, notwithstanding the insignificant estimates for ICT-producers arising from the small sample size. These findings are consistent with other studies that document a positive conditional correlation between investment-specific productivity shocks and hours worked. As argued by Fisher (2006) and Altig *et al.* (2011), the correlation is driven by the shock's impact on the intertemporal substitution between current and future consumption.

**Figure 7:** Effect on Employment

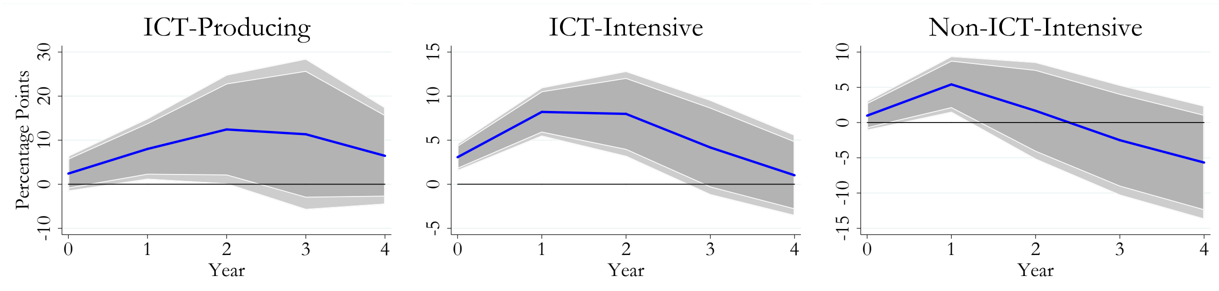



*Notes*: The graph displays the results of a local projection for employment as described in Section 4.1. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

[15] We obtain very similar results when using labor productivity instead of TFP.

Second, we analyze the importance of the capital side for transmitting ICT-shocks.[16] Figure 8 shows the responses of ICT investment for the three groups of sectors. The ICT-producing sectors invest about 2.4 percentage points more in ICT in the year of the shock. One to two years later, the increase in investment growth becomes significant and accumulates to 8.0 and 12.4 percentage points, respectively. Afterward, the level of investment stabilizes. The response for the ICT-intensive sectors is similar. Investment increases contemporaneously by 3.1 percentage points, rising to more than 8 percentage points during the following two years. Then, the response reverts and becomes insignificant. The non-ICT-intensive sectors increase their investment in ICT by one percentage point in the period of the shock, which is barely significant. One year later, the effect becomes strongly significant and increases to 5.4 percentage points and reverts afterwards.[17]

**Figure 8:** Effect on ICT-Investment




*Notes*: The graph displays the results of a local projection for real ICT investment as described in Section 4.1. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

Thus, the evidence suggests that ICT investments of all three groups respond to ICT-shocks, especially with a lag of one or two years.[18] Overall, ICT-shocks, which lower the relative price of ICT goods and services, results in an accelerated growth in ICT investment across all groups of sectors. Therefore, ICT is used more strongly throughout the economy in response to the shock.

Finally, Figure 9 presents the effects of the ICT-shock on TFP growth. In the ICT-producing sectors, the exogenous ICT-related technological progress increases the technology

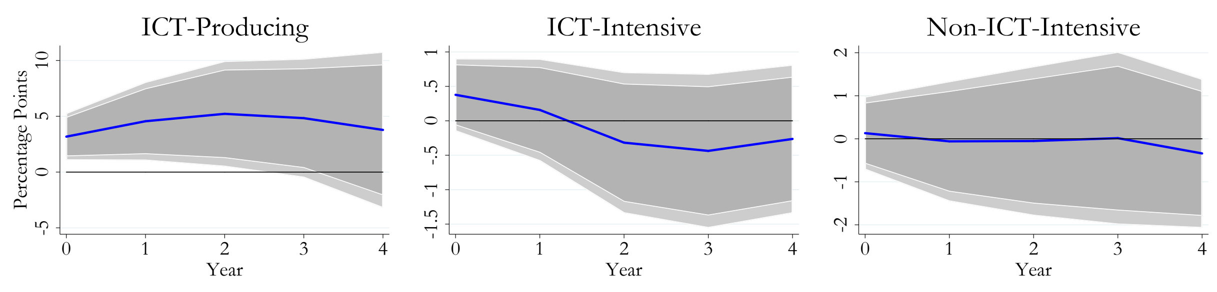
[16] We focus on ICT investment instead of ICT capital stocks. The reason for this is that capital stocks depend both on contemporaneous investment decisions and past non-depreciated capital stocks (see Equation 3). This implies that the ICT-shocks exert their impact on capital stocks exclusively through contemporaneous and future variations in investment activity, since capital stocks in previous periods are determined by past decisions.

[17] This pattern in the magnitude of responses is partly due to the fact that the classification is based on the share of ICT capital stock. As this share depends on the history of past investments, the taxonomy amounts to an endogenous selection according to the outcome variable. Nevertheless, we present the responses for ICT investment for three reasons: First, this taxonomy makes our results comparable to existing studies. Second, we are particularly interested in the dynamics of the adjustment process, which exhibits non-trivial differences across the three groups. Third, we obtain similar results when controlling for the selection by holding the pre-sample shares constant.

[18] The results for investment in other, non-ICT assets are similar, albeit smaller in magnitude (see Figure B3 in the Appendix). This does not only imply spillover effects across sectors, but also potential complementarities between ICT and non-ICT assets.

level in the subsequent two years. The maximum effect occurs two years later, showing an increase of 5.2 percentage points. This is a strong increase in light of the fact that the unconditional dispersion of one-year TFP growth is 7.1 percent for the ICT-producing sectors.[19]

**Figure 9:** TFP Spillover




*Notes*: The graph displays the results of a local projection for TFP as described in Section 4.1. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

We do not find any TFP spillovers to the rest of the economy. In the ICT-intensive sectors, the shock leads to a spillover of 0.4 percentage points on impact. While the contemporaneous response is economically sizeable compared to the average annual growth rate of these sectors' TFP (4.8 percent), it is still insignificant. Similarly, nor do we find evidence for TFP spillovers to the non-ICT-intensive sectors.

In sum, an ICT-shock leads to persistent increases in TFP in the ICT-producing sectors. However, we do not find significant evidence for spillovers to the other sectors for the whole period under investigation, which is in line with Stiroh (2002a), Inklaar *et al.* (2008), and Acharya (2016). However, in contrast to these studies, our approach allows statements to be made regarding causality.

## 4.3. Heterogeneity over Time

So far, we have estimated the effects using the whole data sample. However, it is possible that the spillover effects vary over time. On the one hand, spillovers could have materialized particularly in recent years. While the year 1995 marks the initial appearance of the web browser, it took a long time until it was integrated into most businesses. What is more, business reorganization towards online platforms and communication and collaboration through the internet did not occur immediately. Innovations in communication technology associated with smartphones and social networks appeared only after the mid-2000s. On the other hand, several studies argue that these ICT-shocks only led to a temporary boost in techno-

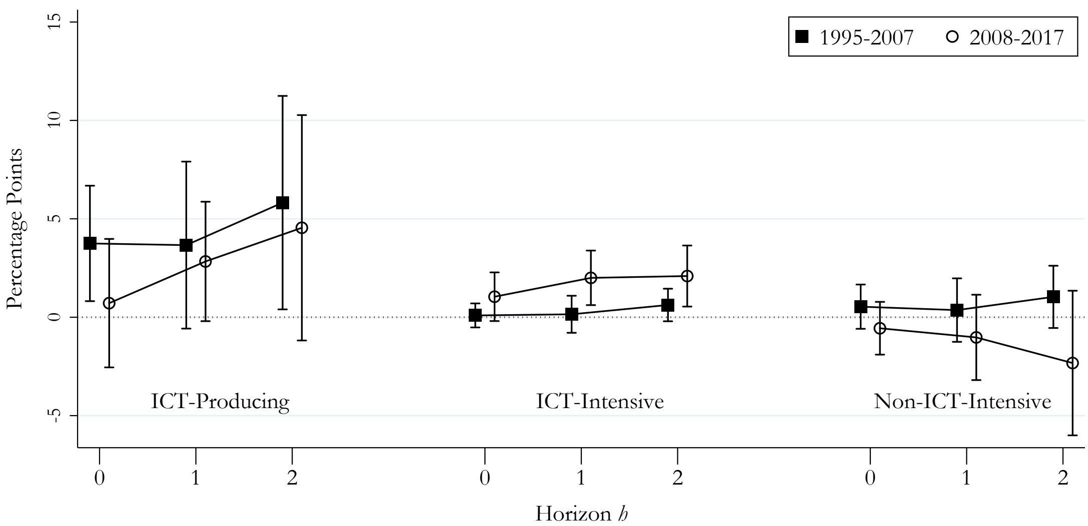
[19]The unconditional dispersion is calculated as follows: first, we calculate the standard deviation of the one-year TFP growth for each sector over time. Then, we calculate the average over the sectoral standard deviations.

logical growth which subsided by the mid-2000s (Gordon and Sayed, 2020; Fernald, 2015; Cette *et al.*, 2016).

Motivated by these considerations, Figure 10 displays the responses of TFP to ICT-shocks for the three groups of sectors and two sub-periods, with the first ranging from 1995 to 2007 and the second one from 2008 to 2017.[20] To ensure the comparability of the results across estimations, we fix the taxonomy, described in Section 3.1, across the two sub-periods. Due to sample limitations, the figure only plots the contemporaneous responses ($h = 0$) and effects occurring during the first two years following the shock ($h = 1, 2$). Note that due to the smaller sample for 2008 to 2017, the standard errors are larger for this sub-sample.

For the ICT-producing sectors, differences between the two samples mainly occur in the period of the shock: TFP increases contemporaneously by 3.7 percentage points for the period up to 2007, while there is no significant contemporaneous response for the period since 2008. During the two years following the initial shock, the responses of TFP are positive and similar in magnitude across the two time periods. Overall, technological gains in the ICT-producing sectors are positive and persistent, independent of the period considered.

**Figure 10:** TFP Spillover by Sub-Period




*Notes*: The graph plots the results of a local projection for TFP as described in Section 4.1 for $h = 0, 1, 2$. The results are obtained from two separate sets of regressions based on a split sample: the first sample ranges from 1995 to 2007 and the second from 2008 to 2017. The confidence bands indicate 95 percent confidence intervals, based on Newey-West-corrected standard errors with $h + 1$ lags.

For the ICT-intensive sectors, there is a positive and significant effect on the technological level for the period after 2007. While the contemporaneous coefficient is only marginally

[20] The timing of the sample split is motivated by large-scale reforms to the German labor market in the mid-2000s (*Hartz reforms*) and the associated transition process that developed in its wake. According to Klinger and Rothe (2012), unemployment dropped sharply between 2006 and 2008 following the introduction of the final phase of reforms in January 2005. In a search and matching model with heterogeneous skills, Krause and Uhlig (2012) find that the German labor market's transition process lasted from 2005 to the end of 2007. However, our results remain robust to moving the threshold forward or backward (see Figure B4 in the Appendix for the ICT-intensive sectors).

significant, responses in the following two years become strongly significant; they are also larger compared to the contemporaneous effect. The latter supports the finding of a lagged response of TFP (Brynjolfsson and Hitt, 2003; Basu and Fernald, 2007; Marsh *et al.*, 2017). Turning to the non-ICT-intensive sectors, the estimation does not reveal any significant ICT spillovers.

Overall, we find a positive TFP spillover after the mid-2000s for the sectors that intensively use ICT goods and services. One reason could be the slow diffusion of broadband internet in Germany. Introduced in July 1999, its prices were rather high and its availability confined to larger cities. According to the Federal Network Agency, 1.9 million people were covered by broadband internet in 2001, 5 years later there were 15 million broadband subscribers, and in 2008 almost 23 million users. Comparing the broadband penetration rates—that is, broadband subscribers per 100 inhabitants—across the OECD-countries, Germany was ranked in the midfield in 2008 (Czernich *et al.*, 2011). Therefore, the digitization process was still ongoing by the beginning of the 2000s, but only about to gain momentum.

Since the diffusion of broadband internet was slow at the beginning, it is likely that business models relying on E-commerce only became profitable during the 2000s. Furthermore, firms that intensively used computers only slowly reorganized their production processes. This reorganization was accompanied by the creation of new, successful managerial ideas (Bloom *et al.*, 2012). Supply chain management was improved through a higher interconnectedness across different production steps or within the firm. Firms started to use factor inputs more efficiently within the production process (Brynjolfsson and Hitt, 2000; Castiglione, 2012). The creation of new organizational knowledge slowly transferred to other firms, creating positive externalities for other firms over time (Brynjolfsson and Hitt, 2003). This dissemination was facilitated by improved business-to-business communication. Thus, the full potential of the digitization of economic activities only seems to have materialized after the mid-2000s.

A second reason could be the labor market reforms in Germany in the mid-2000s, which have reduced labor market rigidities. An effective adoption and diffusion of ICT often requires the possibility to reorganize firms. This can be prohibited by strict labor market regulations (see, e.g., Cette *et al.*, 2014; Gust and Marquez, 2004; Cette and Lopez, 2012). Therefore, the reforms in the mid-2000s may have helped enable TFP spillovers to the ICT-intensive sectors.

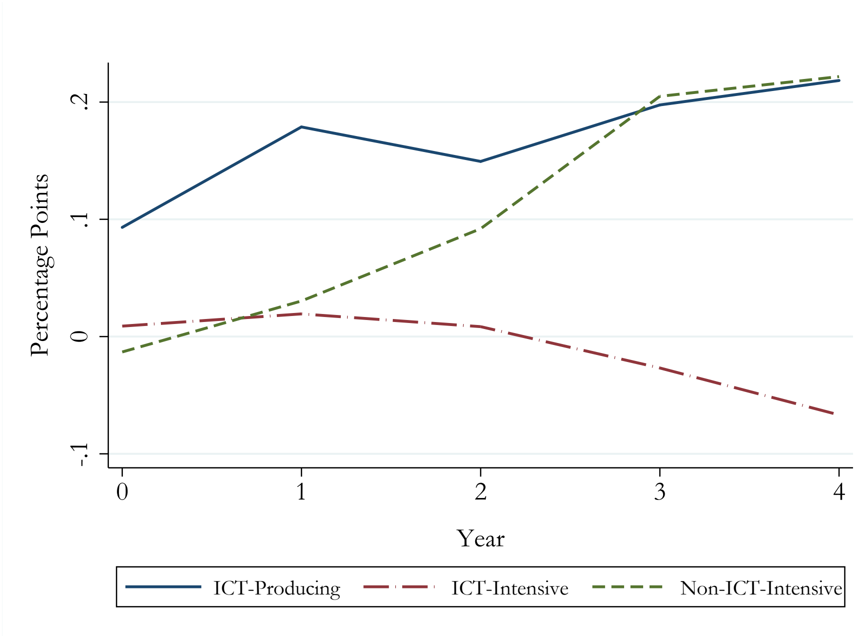
A third reason may be the size of the ICT-shocks themselves. Returning to Figure 3, there were large positive ICT-shocks between 2006 and 2007 and in 2010 which may be a further cause for the spillover effects after the mid-2000s.

## 4.4. Owner vs. User Concept

In Section 3, we showed that TFP differs substantially between the owner and the user concept (see Figures 4 and 5). We check whether these unconditional differences also translate into heterogeneous responses of TFP conditional on ICT-shocks. To do so, we compare the point estimates of Figure 9 with the point estimates of the responses derived from the respective owner-concept data. Figure 11 demonstrates these differences for TFP and the three groups of sectors.

Overall, the responses differ by up to 0.2 percentage points. For the ICT-producing and the non-ICT-intensive sectors, the owner concept overestimates the actual response of TFP. Therefore, some of the reaction of these sectors to ICT-shocks entail an increased leasing of investment goods, which, when not taken into account, would overstate the estimates for TFP. Overall, the differences of the conditional responses of the ICT-producing and the non-ICT-intensive sectors resemble the unconditional differences.

**Figure 11:** TFP Spillover: Owner vs. User Concept

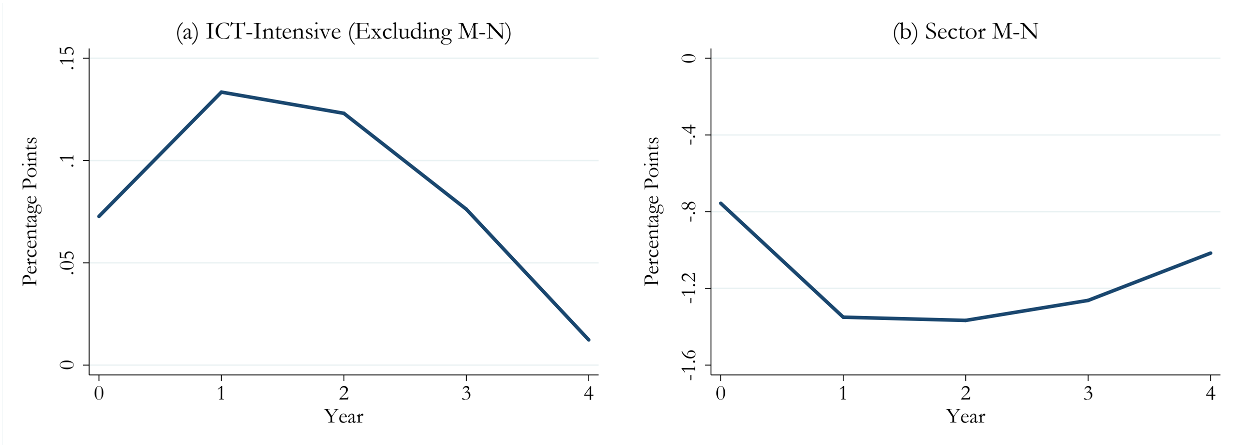



*Notes*: The plot displays the differences in the point estimates of owner-concept TFP from user-concept TFP. The point estimates are obtained from local projections as described in Section 4.1.

For the ICT-intensive sectors, the results are less clear-cut upon first glance: The TFP response is underestimated by the owner concept at longer horizons, but slightly overestimated at shorter horizons. This may be because the leasing companies form part of the sector 'Professional and Business Service Providers' (M-N) which belongs to the ICT-intensive sectors. Therefore, we now analyze to what extent the leasing sector drives the responses of the ICT-intensive sectors.

The left panel in Figure 12 shows the difference of conditional responses of TFP among the ICT-intensive sectors without the leasing sector, and the right panel the corresponding difference of the leasing sector. Similar to the ICT-producing and non-ICT-intensive sectors, the owner concept overestimates the TFP response of the ICT-intensive sectors without the leasing sector. Thus, ICT-shocks increase the amount of leasing here as well. In contrast, the change in TFP of the leasing sector is strongly underestimated by the owner concept. Since all other sectors increase the amount of leasing in response to ICT-shocks, leasing companies strongly increase their purchases of investment goods. Since these assets continue to be the property of the leasing companies but are used in other sectors, the capital stock is upward biased by conventional investment data and, subsequently, the dynamic response of TFP is downward biased.

**Figure 12:** TFP Spillover for ICT-Intensive Sectors: Owner vs. User Concept




*Notes*: The plot displays the differences in the point estimates of owner-concept TFP from user-concept TFP. The point estimates are obtained from local projections as described in Section 4.1. Panel (a) shows the values for the ICT-intensive sectors without the leasing sector (M-N), while Panel (b) shows the respective values for the leasing sector (M-N).

The exercise in this section provides evidence that both the unconditional TFP series and the conditional responses of TFP are biased when leasing activity is not considered. Thus far, the literature relies on investment data derived from the owner concept. This suggests that previous findings on TFP spillovers could be overestimated for most sectors.

# 5. Conclusions and Outlook

This paper revisits the question as to whether the push in digitization that started in the mid-1990s has led to increases in TFP outside the ICT-producing sectors in Germany. To identify exogenous variation in technological progress in the ICT-producing sectors, we use a structural VAR model with medium-run restrictions. In this approach, exploiting the relative price of ICT goods and services enables us to separate ICT-shocks from neutral technology shocks. Moreover, to derive sector-specific TFP series, we combine information from EU KLEMS and the IIDB to consider the increasing importance of leasing of investment goods. Finally, we link the ICT-shocks to sectoral TFP using local projections.

Our results suggest that since the mid-2000s ICT-shocks cause positive and persistent TFP spillovers to sectors intensively using ICT. However, we find no evidence for such spillovers between the mid-1990s and the mid-2000s. These results appear to be due to a combination of slowly adopting ICT knowledge, labor market reforms, and further ICT-shocks in the second half of the 2000s. Furthermore, we find that traditional growth accounting databases such as EU KLEMS may lead to biased results. This is because the level of TFP for all sectors except the leasing sector is overestimated when leasing is neglected.

Can our results give us guidance for current events? Even though our data ends in 2017, the empirical results from this paper allow us to gauge potential effects of the current Corona crisis on developments in productivity. On the one hand, the pandemic may force firms to adopt ICT goods and services that were developed prior to the crisis. As a result, the accelerated rate of ICT adoption could raise TFP. While the Corona crisis will likely induce several additional innovations in the ICT-producing sectors, on the other.

As for the adoption of ICT technologies, since the outbreak of the pandemic the digital transformation has gained momentum. According to the Randstad-Ifo-Survey among human resources managers in Germany, 54 percent of polled firms state that their internal operating processes have become increasingly digitized due to the Corona crisis (Randstad, 2020). This push has been galvanized by the increase in E-commerce and more teleworking, among others factors. The surge in online-shopping during the pandemic has required the optimization of logistic processes, which is why many firms have ramped up their use of new technologies for delivery, such as autonomous vehicles and drones (Li *et al.*, 2020; Okyere *et al.*, 2020).

At the same time, further investments in ICT have been made to enable working from home, shielding employees from layoffs or short-term labor schemes (Brynjolfsson *et al.*, 2020; Alipour *et al.*, 2020). The dramatic increase in teleworking has allowed firms to lower costs by reducing expenditure on office space and travelling. In addition, evidence suggests that teleworking increases productivity and job satisfaction (Bloom *et al.*, 2015; Barrero *et al.*, 2020), thereby reducing job attrition rates.

Overall, the pandemic seems to accelerate the adoption of innovations developed by the ICT-producing sectors in the past. Given our result that ICT-shocks lead to TFP spillovers in the subsequent years, these spillovers may already be taking place or with a delay in the next years.

Besides the use of pre-existing innovations, the digitization push due to the pandemic is likely to boost R&D related to ICT. One reason is that the crisis has increased demand for ICT products and services. That, in turn, reduces interpersonal contact and thus virus transmission. The pandemic has also led to a surge in innovations that facilitate working from home (Bloom *et al.*, 2020). Furthermore, demographic developments in many advanced economies make a labor-saving technological change increasingly necessary, and the Corona crisis may act as a catalyst speeding up the introduction of such new technologies.

In light of the positive externality arising from ICT-shocks, our results suggest a crucial role for government policies to stimulate innovations and facilitate ICT investment. In terms of financial resources, investments in intangible assets, such as R&D, are hard to collateralise in the context of bank loans (Brown *et al.*, 2012; Czarnitzki and Hottenrott, 2011). Therefore, financing these crucial investments could be facilitated by granting sufficient access to venture capital (Schnitzer and Watzinger, 2020). Furthermore, policy measures could include R&D tax credits to create incentives for R&D activity (Bloom *et al.*, 2002). Finally, governments could introduce measures that support working from home, such as tax deductions for related expenses and for vocational training to acquire ICT skills (Falck *et al.*, 2020). All these instruments, coupled with investment in digital infrastructures (Czernich *et al.*, 2011), may help exploit the full potential of ICT-shocks and lead to pronounced TFP spillovers in the aftermath of the Corona crisis.

## References


Acharya, R. C. (2016). ICT use and total factor productivity growth: intangible capital or productive externalities? *Oxford Economic Papers*, **68** (1), 16–39.

Ademmer, M., Bickenbach, F., Bode, E., Boysen-Hogrefe, J., Fiedler, S., Gern, K.-J., Görg, H., Groll, D., Hornok, C., Jannsen, N., Kooths, S. and Krieger-Boden, C. (2017). *Produktivität in Deutschland – Messbarkeit und Entwicklung.* Kieler Beiträge zur Wirtschaftspolitik No. 12, Kiel Institute for the World Economy, Kiel.

Alipour, J.-V., Fadinger, H. and Schymik, J. (2020). My Home Is my Castle – The Benefits of Working from Home During a Pandemic Crisis: Evidence from Germany. ifo Working Paper No. 329.

Altig, D., Christiano, L. J., Eichenbaum, M. and Lindé, J. (2011). Firm-specific capital, nominal rigidities and the business cycle. *Review of Economic Dynamics*, **14** (2), 225–247.

Antonioli, D., Mazzanti, M. and Pini, P. (2010). Productivity, innovation strategies and industrial relations in SMEs. Empirical evidence for a local production system in northern Italy. *International Review of Applied Economics*, **24** (4), 453–482.

Barrero, J. M., Bloom, N. and Davis, S. J. (2020). Why Working From Home Will Stick. BFI Working Paper No. 2020-174.

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of Monetary Economics*, **58** (3), 273–289.

Basu, S. and Fernald, J. (2007). Information and Communications Technology as a General-Purpose Technology: Evidence from US Industry Data. *German Economic Review*, **8** (2), 146–173.

Belke, A., Elstner, S. and Rujin, S. (2020). Growth Prospects and the Trade Balance in Advanced Economies. Ruhr Economic Papers No. 827.

Bloom, N., Davis, S. J. and Zhestkova, Y. (2020). COVID-19 Shifted Patent Applications toward Technologies that Support Working from Home. BFI Working Paper No. 2020-133.

—, Griffith, R. and Van Reenen, J. (2002). Do R&D tax credits work? Evidence from a panel of countries 1979–1997. *Journal of Public Economics*, **85** (1), 1–31.

—, Liang, J., Roberts, J. and Ying, Z. J. (2015). Does Working from Home Work? Evidence from a Chinese Experiment. *The Quarterly Journal of Economics*, **130** (1), 165–218.

—, Sadun, R. and Van Reenen, J. (2012). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review*, **102** (1), 167–201.

Brown, J. R., Martinsson, G. and Petersen, B. C. (2012). Do financing constraints matter for R&D? *European Economic Review*, **56** (8), 1512–1529.

Brynjolfsson, E. and Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives*, **14** (4), 23–48.

— and — (2003). Computing Productivity: Firm-Level Evidence. *Review of Economics and Statistics*, **85** (4), 793–808.

—, Horton, J. J., Ozimek, A., Rock, D., Sharma, G. and TuYe, H.-Y. (2020). COVID-19 and Remote Work: An Early Look at US Data. NBER Working Papers 27344.

Cardona, M., Kretschmer, T. and Strobel, T. (2013). ICT and productivity: conclusions from the empirical literature. *Information Economics and Policy*, **25** (3), 109–125.

Cascaldi-Garcia, D. and Galvão, A. B. (2020). News and Uncertainty Shocks. *Journal of Money, Credit and Banking*, **forthcoming**.

Castiglione, C. (2012). Technical efficiency and ICT investment in Italian manufacturing firms. *Applied Economics*, **44** (14), 1749–1763.

Cette, G., Fernald, J. and Mojon, B. (2016). The pre-Great Recession slowdown in productivity. *European Economic Review*, **88**, 3–20.

— and Lopez, J. (2012). ICT demand behaviour: an international comparison. *Economics of Innovation and New Technology*, **21** (4), 397–410.

—, — and Mairesse, J. (2014). Product and labor market regulations, production prices, wages and productivity. NBER Workig Papers 20563.

Chari, V. V., Kehoe, P. J. and McGrattan, E. R. (2008). Are structural VARs with long-run restrictions useful in developing business cycle theory? *Journal of Monetary Economics*, **55** (8), 1337–1352.

Chow, G. C. and Lin, A.-I. (1971). Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series. *Review of Economics and Statistics*, **53** (4), 372–375.

Czarnitzki, D. and Hottenrott, H. (2011). R&D investment and financing constraints of small and medium-sized firms. *Small Business Economics*, **36** (1), 65–83.

Czernich, N., Falck, O., Kretschmer, T. and Woessmann, L. (2011). Broadband Infrastructure and Economic Growth. *The Economic Journal*, **121** (552), 505–532.

Elstner, S., Feld, L. P. and Schmidt, C. M. (2018). The German Productivity Paradoxon – Facts and Explanations. CESifo Working Paper No. 7231.

Erceg, C. J., Guerrieri, L. and Gust, C. (2005). Can Long-Run Restrictions Identify Technology Shocks? *Journal of the European Economic Association*, **3** (6), 1237–1278.

Falck, O., Heimisch-Roecker, A. and Wiederhold, S. (2020). Returns to ICT skills. *Research Policy*, **forthcoming**.

Fernald, J. G. (2015). Productivity and Potential Output before, during, and after the Great Recession. *NBER Macroeconomics Annual*, **29** (2014), 1–51.

Fisher, J. D. M. (2006). The Dynamic Effects of Neutral and Investment-Specific Technology Shocks. *Journal of Political Economy*, **114** (3), 413–451.

Forman, C. and van Zeebroeck, N. (2012). From Wires to Partners: How the Internet has Fostered R&D Collaborations Within Firms. *Management Science*, **58** (8), 1549–1568.

Francis, N., Owyang, M. T., Roush, J. E. and DiCecio, R. (2014). A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks. *Review of Economics and Statistics*, **96** (4), 638–647.

Galí, J. (1999). Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *American Economic Review*, **89** (1), 249–271.

Goldrian, G. (2007). *Handbook of survey-based business cycle analysis*. Edward Elgar Publishing, Cheltenham.

Gordon, R. J. and Sayed, H. (2020). Transatlantic Technologies: The Role of ICT in the Evolution of U.S. and European Productivity Growth. NBER Working Papers 27425.

Gust, C. and Marquez, J. (2004). International comparisons of productivity growth: the role of information technology and regulatory practices. *Labour Economics*, **11** (1), 33–58.

Helpman, E. and Trajtenberg, M. (1998). Diffusion of General Purpose Technologies. In E. Helpman (ed.), *General Purpose Technologies and Economic Growth*, *4*, Cambridge, MA: The MIT Press, pp. 85–119.

Hempell, T. (2005). What's spurious, what's real? Measuring the productivity impacts of ICT at the firm-level. *Empirical Economics*, **30** (2), 427–464.

IIDB (2016). ifo Investment Database, LMU-ifo Economics & Business Data Center, Munich, doi: 10.7805/ebdc-iidb-2016.

Inklaar, R., Timmer, M. P. and van Ark, B. (2008). Market services productivity across Europe and the US. *Economic Policy*, **23** (53), 140–194.

Jäger, K. (2017). EU KLEMS Growth and Productivity Accounts 2017 Release, Statistical Module, Country Notes for Germany.

Jordà, O. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, **95** (1), 161–182.

Jorgenson, D. W., Gollop, F. M. and Fraumeni, B. M. (1987). *Productivity and U.S. Economic Growth*. North-Holland, Amsterdam.

—, Ho, M. S. and Stiroh, K. J. (2005). *Productivity, Volume 3: Information Technology and the American Growth Resurgence*. The MIT Press.

Klinger, S. and Rothe, T. (2012). The Impact of Labour Market Reforms and Economic Performance on the Matching of the Short-term and the Long-term Unemployed. *Scottish Journal of Political Economy*, **59** (1), 90–114.

Krause, M. U. and Uhlig, H. (2012). Transitions in the German labor market: Structure and crisis. *Journal of Monetary Economics*, **59** (1), 64–79.

Krippner, L. (2013). A Tractable Framework for Zero-Lower-Bound Gaussian Term Structure Models. CAMA Working Paper No. 49/2013.

Kurmann, A. and Otrok, C. (2013). News Shocks and the Slope of the Term Structure of Interest Rates. *American Economic Review*, **103** (6), 2612–2632.

Laursen, K. and Foss, N. J. (2003). New human resource management practices, complementarities and the impact on innovation performance. *Cambridge Journal of Economics*, **27** (2), 243–263.

Li, K., Kim, D. J., Lang, K. R., Kauffman, R. J. and Naldi, M. (2020). How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electronic Commerce Research and Applications*, **44**, 101004.

Marsh, I. W., Rincon-Aznar, A., Vecchi, M. and Venturini, F. (2017). We see ICT spillovers everywhere but in the econometric evidence: a reassessment. *Industrial and Corporate Change*, **26** (6), 1067–1088.

Newey, W. K. and West, K. D. (1987). Hypothesis Testing with Efficient Method of Moments Estimation. *International Economic Review*, **28** (3), 777–787.

Okyere, M. A., Forson, R. and Essel-Gaisey, F. (2020). Positive externalities of an epidemic: The case of the coronavirus (COVID–19) in China. *Journal of Medical Virology*, **92** (9), 1376–1379.

O'Mahony, M. and Timmer, M. P. (2009). Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database. *The Economic Journal*, **119** (538), 374–403.

Pieri, F., Vecchi, M. and Venturini, F. (2018). Modelling the joint impact of R&D and ICT on productivity: A frontier analysis approach. *Research Policy*, **47** (9), 1842–1852.

Ramey, V. A. and Zubairy, S. (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of Political Economy*, **126** (2), 850–901.

Randstad (2020). Randstad-ifo-Personalleiterbefragung, Ergebnisse: 2. Quartal 2020.

Robinson, C., Stokes, L., Stuivenwold, E. and van Ark, B. (2014). Industry Structures and Taxonomies. In M. O'Mahony and B. van Ark (eds.), *EU productivity and competitiveness: An industry perspective. Can Europe resume the catching-up process?*, *2*, European Commission, pp. 37–72.

Schnitzer, M. and Watzinger, M. (2020). Measuring the Spillovers of Venture Capital. *Review of Economics and Statistics*, **forthcoming**.

Stiroh, K. J. (2002a). Are ICT Spillovers Driving the New Economy? *Review of Income and Wealth*, **48** (1), 33–57.

— (2002b). Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? *American Economic Review*, **92** (5), 1559–1576.

Stock, J. H. and Watson, M. W. (2018). Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments. *The Economic Journal*, **128** (610), 917–948.

Strobel, T. (2016). ICT intermediates and productivity spillovers – Evidence from German and US manufacturing sectors. *Structural Change and Economic Dynamics*, **37**, 147–163.

—, Sauer, S. and Wohlrabe, K. (2013). The ifo Investment Database. *Journal of Contextual Economics – Schmollers Jahrbuch*, **133** (3), 449–460.

Uhlig, H. (2004). Do Technology Shocks Lead to a Fall in Total Hours Worked? *Journal of the European Economic Association*, **2** (2-3), 361–371.

Wu, J. C. and Xia, F. D. (2017). Time Varying Lower Bound of Interest Rates in Europe. Chicago Booth Research Paper No. 17-06.

# Appendix

## A. Data Sources and Preparation for the VAR

The data needed for estimating the VAR model is obtained from German National Accounts and described in detail in Table A1. For most sectors, information on sectoral gross value added (GVA), total hours worked, and price deflators is readily available on a quarterly basis. However, the Federal Statistical Office only publishes annual data for the ICT-producing sectors, which is defined as the aggregate of (i) 'Manufacturing of Computer, Electronic, and Optical Products', (ii) 'Telecommunications', and (iii) 'IT services' (see the codes C26, J61, and J62-J63 in Table C2).

Quarterly GVA data for the ICT-producing sectors are obtained by applying the temporal disaggregation approach by Chow and Lin (1971). This procedure requires higher frequency indicators that are strongly correlated with the annual series. For the ICT-producing manufacturing sectors, we proxy (i) real GVA by the sector-specific industrial production, (ii) the price deflator by the sector-specific producer price index, and (iii) hours worked by the total number of hours in manufacturing. Data availability for the ICT-producing service sectors in terms of high-frequent indicators fares worse when compared to manufacturing sectors. We proxy the two series for ICT-producing service sectors by variables from the National Accounts aggregate 'Information and Communication Services'. These are (iv) real GVA, (v) the GVA deflator, defined as the ratio between real and nominal GVA, and (vi) total hours worked. Besides telecommunications and IT services, the National Accounts aggregate 'Information and Communication Services' also contains publishing activities, motion picture, video and television program production, sound recording, music publishing activities as well as programming and broadcasting activities.

Comparing the annual series of interest with the quarterly indicators described in the previous paragraph, Figure A1 shows a close co-movement for all series with their specific indicators. Pairwise correlation coefficients are all 0.7 or higher; in manufacturing we find correlation coefficients of even 0.9 and higher. Based on these high correlations, we apply the Chow-Lin procedure to the three series of interest for each of the three ICT-producing sectors. The individual quarterly series are aggregated to the total ICT-producing sectors afterward, by considering the chaining of real gross value added. Then, we calculate $\mathrm{LP}_t^{\mathrm{ICT}}$ and the numerator of $\widehat{P}_t$. Finally, we derive $\mathrm{LP}_t^{\overline{\mathrm{ICT}}}$ and the denominator of $\widehat{P}_t$ by subtracting the respective quarterly time series for the total ICT-producing sectors from the corresponding quarterly series for the total economy.

**Table A1:** Variables used in the SVAR: Description and Sources

| Variable | Description | Source |
|---|---|---|
| Gross value added ICT manufacturing | Quarterly data series: constructed using the real production index for the manufacture of computer, electronic and optical products (c.e.o. products), Chow-Lin procedure, annual correlation between both time series: 0.89; constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Deflator ICT manufacturing | Nominal gross value added divided by real gross value added; annual time series for ICT manufacturing: converted into a quarterly series using the producer price index of c.e.o. products, Chow-Lin procedure, annual correlation between both time series: 0.72; seasonally adjusted | Federal Statistical Office |
| Hours worked ICT manufacturing | Quarterly data series: constructed using the hours worked series for the total manufacturing, Chow-Lin procedure, annual correlation between both time series: 0.95; seasonally adjusted | Federal Statistical Office |
| Employment ICT manufacturing | Quarterly data series: constructed using the employment series for the total manufacturing, Chow-Lin procedure, annual correlation between both time series: 0.95; seasonally and working day adjusted | Federal Statistical Office |
| Gross value added ICT services | Quarterly data series for the two ICT-producing sub-sectors: constructed using the real gross value added time series for the total IC sector, Chow-Lin procedure, annual correlation between both time series: 0.81 (Telecommunications) and 0.83 (IT services); constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Nominal gross value added ICT services | Quarterly data series: constructed using the nominal gross value added time series for the total IC sector, Chow-Lin procedure, correlation between these time series: 0.79 (Telecommunications) and 0.75 (IT services); constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Hours worked ICT services | Quarterly data series: constructed using the hours worked series for the total IC sector, Chow-Lin procedure, annual correlation between these time series: 0.70 (Telecommunications) and 0.75 (IT services); constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Employment ICT services | Quarterly data series: constructed using the employment series for the total IC sector, Chow-Lin procedure, annual correlation between these time series: 0.53 (Telecommunications) and 0.85 (IT services); constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Gross value added total ICT sectors | Sum of the weighted quarterly growth rates of real gross value added of the ICT-producing manufacturing and the ICT-producing service sectors, corresponding weights: proportions in nominal gross value added of all three ICT-producing sectors of the previous quarter | Federal Statistical Office |

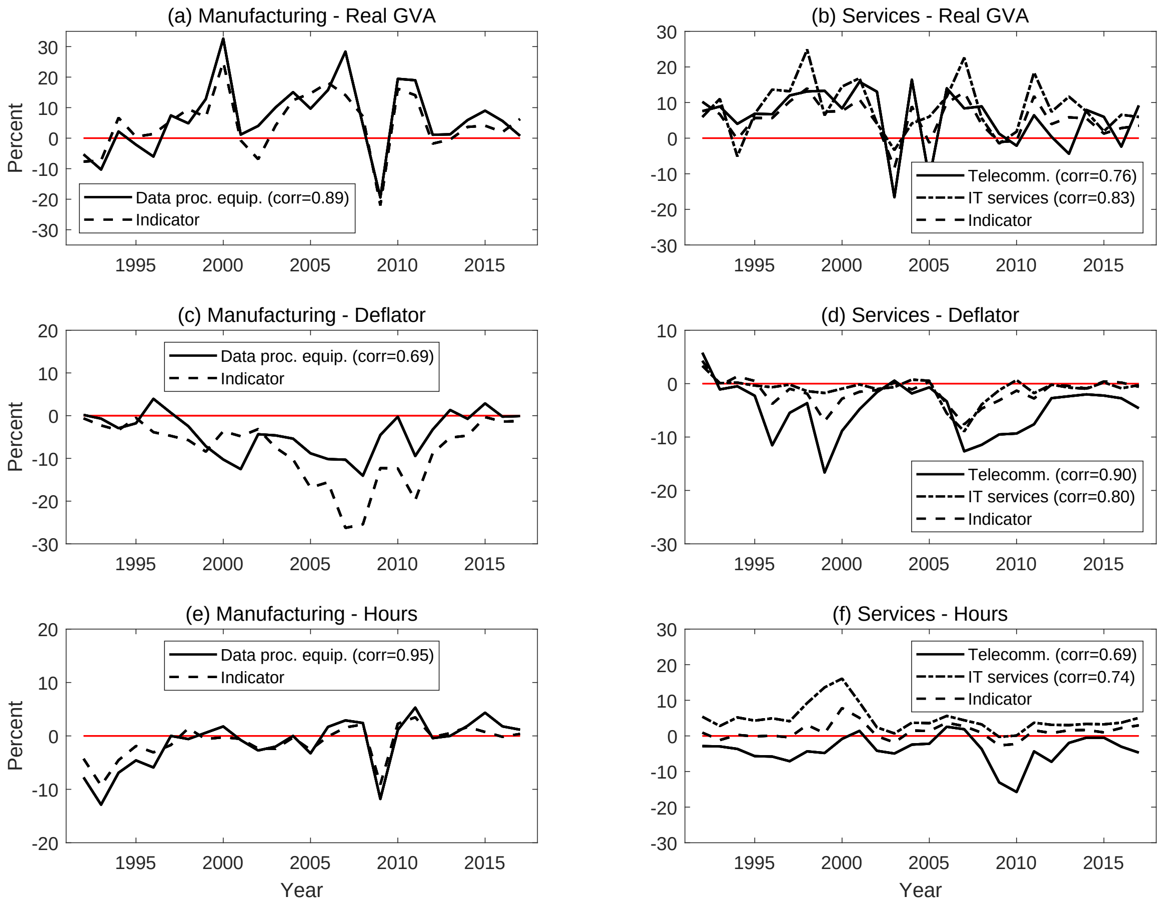
*Continued on next page...*

**Table A1:** Variables used in the SVAR: Description and Sources (cont.)

| **Variable** | **Description** | **Source** |
|---|---|---|
| Private consumption | Final consumption expenditures of households; constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Equipment investment | Gross fixed capital formation: machinery and equipment; constant prices; seasonally and working day adjusted | Federal Statistical Office |
| Terms of trade | Ratio between export and import deflator; seasonally and working day adjusted | Federal Statistical Office |
| Real interest rate | Difference between EONIA rate and CPI inflation, after 2004 EONIA is replaced by the shadow rate | Deutsche Bundesbank; European Banking Federation; Wu and Xia (2017); Krippner (2013) |

*Notes*: ICT manufacturing corresponds to *Manufacture of computer, electronic and optical products*. ICT services include the two service sectors 'Telecommunications' and 'IT services' (computer programming, consultancy and related activities).

**Figure A1:** Comparison Between the Series of Interest and the Indicator, ICT-Producing Sectors

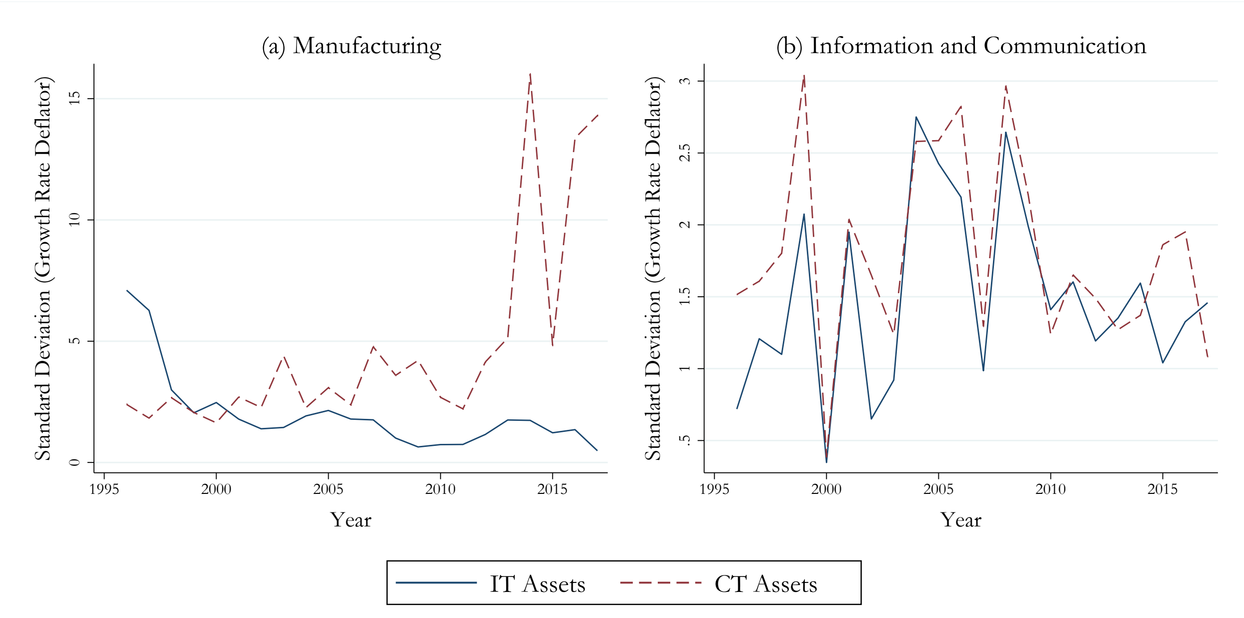



*Notes*: The figure compares our annual series of interest with the indicators that are available at a higher frequency. We consider annual growth rates for the time 1992 to 2017; for this figure the quarterly indicators are transformed into annual values. "Data proc. equip.": manufacture of computer, electronic and optical products. "IT services": computer programming, consultancy and related activities. The data is from the Federal Statistical Office.

# B. Figures

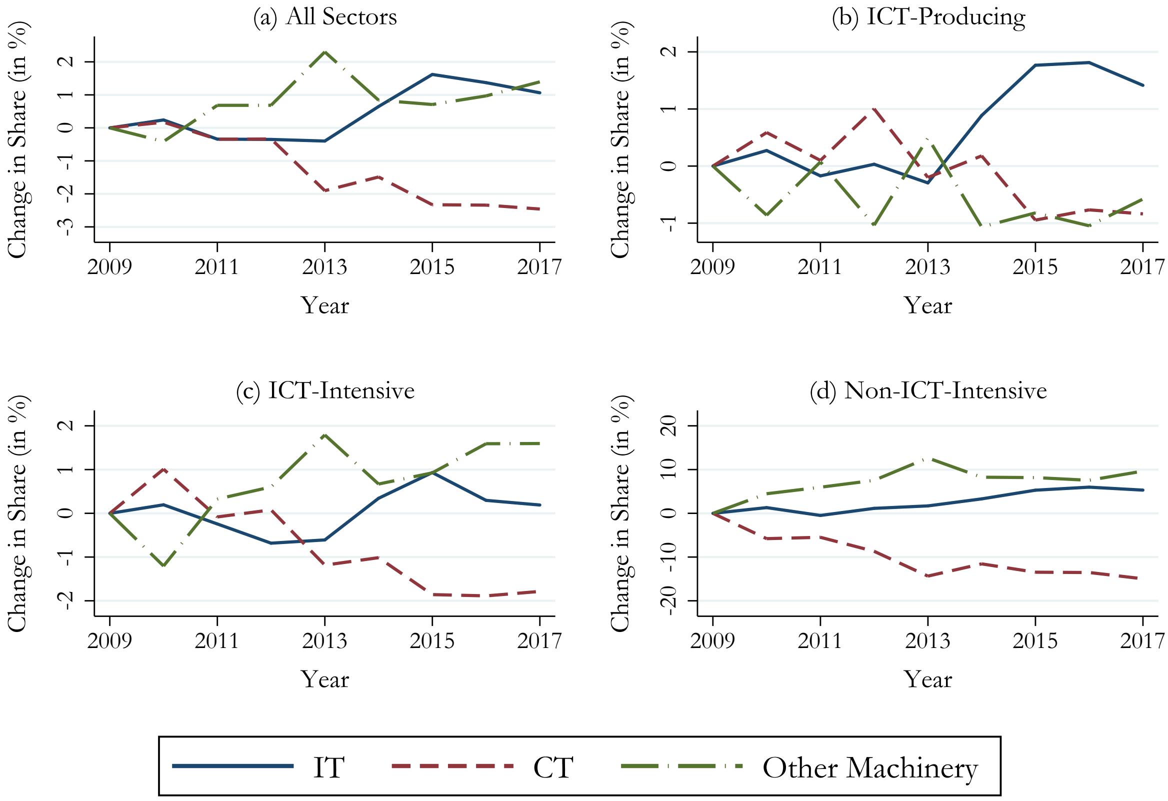
Figure B1 plots the annual dispersion of growth rates for selected investment deflators within these sectors. Since we are particularly interested in the fluctuations of ICT investment, we present the respective data for ICT assets. There is considerable cross-sectional variation within the 1-digit sectors, and the dispersion changes substantially over time. Overall, this heterogeneity underscores the importance of using sector-specific deflators from the IIDB, $p^{I,\mathrm{IIDB}}_{jkt}$. Using these deflators also results in a more precise measurement of the price of capital, $p^{K}_{jkt}$, the internal rate of return, $i_{jt}$, as well as the weights for the capital stocks, $v_{jkt}$.

**Figure B1:** Dispersion of Selected Ifo Deflator Growth Rates



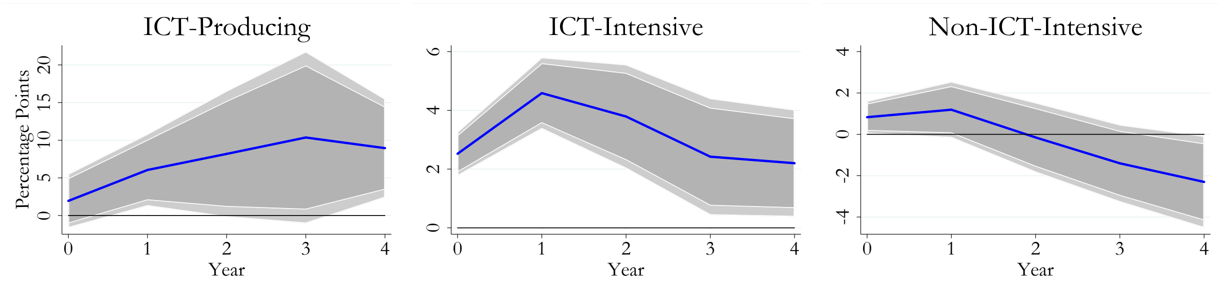

*Notes*: The plots show the standard deviation of the annual growth rates of the deflators for information technology (IT) and communications technology (CT) assets, respectively, within the 1-digit sectors 'Manufacturing' (panel (a)) and 'Information and Communication Services' (panel (b)).

**Figure B2:** Change in Investment Shares of Key Asset Types in the IIDB Data



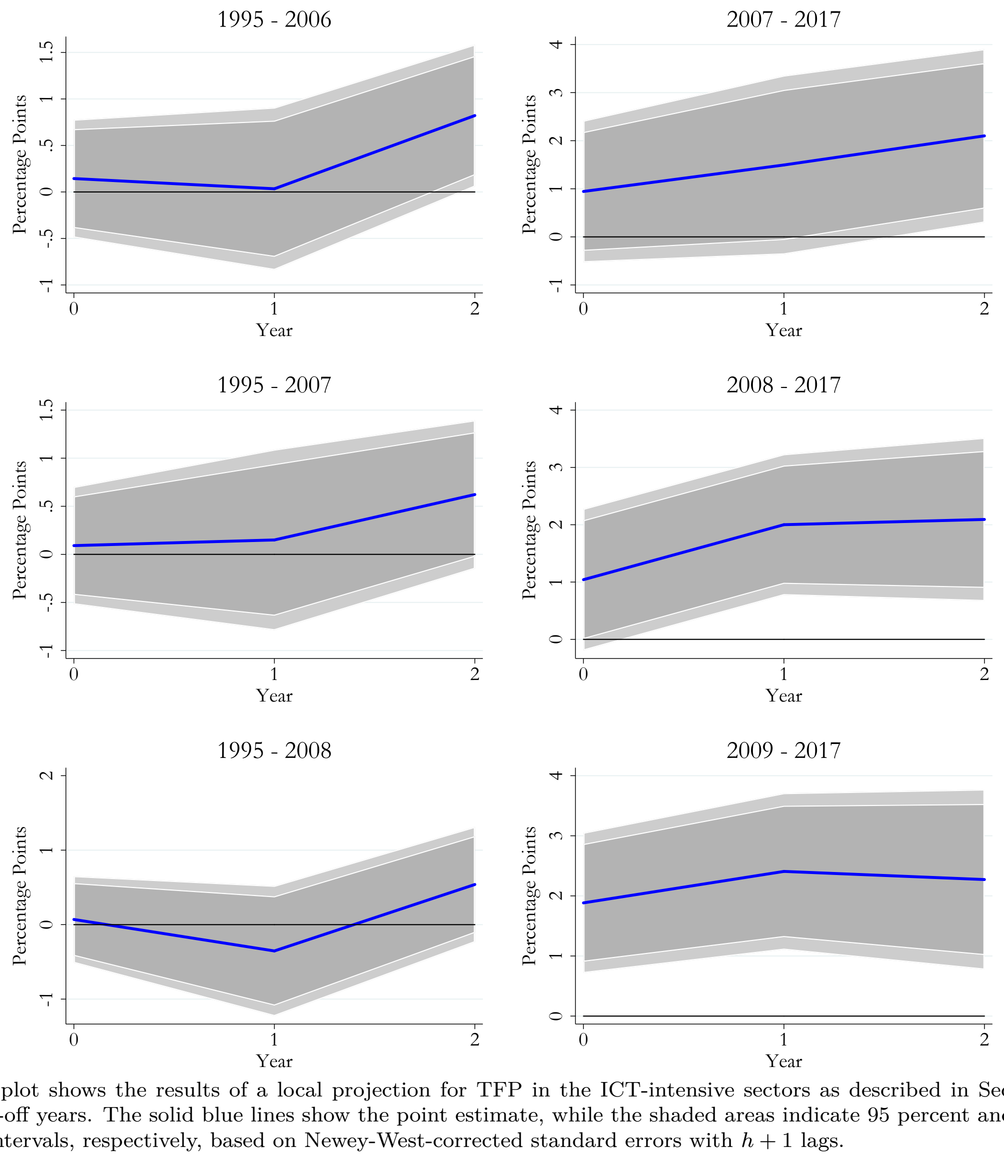

*Notes*: The figure shows the change of the investment shares of Information Technology (IT) and Communications Technology (CT) along with those of Other Machinery (OMach) compared to 2009 (owner concept). The shares of IT, CT, and OMach are computed with respect to the aggregate IT+CT+OMach.

**Figure B3:** Effect on Non-ICT-Investment




*Notes*: The graph displays the results of a local projection for real non-ICT investment as described in Section 4.1. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

**Figure B4:** TFP Spillover by Sub-Period, Robustness to Cut-Off Year, ICT-Intensive Sectors




*Notes*: The plot shows the results of a local projection for TFP in the ICT-intensive sectors as described in Section 4.1 for different cut-off years. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

# C. Tables

**Table C1:** Asset types: EU KLEMS and IIDB

| IIDB/EU KLEMS | IIDB | EU KLEMS |
|---|---|---|
| Information Technology | Computers and Office Equipment | Information Technology |
| Communications Technology | Communications Equipment | Communications Technology |
| Transportation Equipment | Automobiles<br>Other Vehicles | Transportation Equipment |
| Other Machinery | Metal Products<br>Machinery<br>Electrical Generation and Distribution<br>Instruments, Optics and Watches<br>Furniture, Music and Sports | Other Machinery |
| Construction | Structures and Buildings | Residential Structures<br>Other Construction |
| Other Assets | Intangible Assets | R&D<br>Other Intellectual Property Products<br>Software<br>Cultivated Assets |

*Notes*: Summary of the matching process of the assets in the Ifo Investment Database (IIDB) and EU KLEMS.

**Table C2:** Sectoral Classification: EU KLEMS and IIDB

| Sort Nr. | EU KLEMS code | EU KLEMS Description | IIDB Description |
|---|---|---|---|
| 4 | A | Agriculture, forestry and fishing | Agriculture, Forestry, Fishing |
| 5 | B | Mining and quarrying | Mining and Quarrying |
| 7 | C10-C12 | Food products, beverages and tobacco | Food and Tobacco |
| 8 | C13-C15 | Textiles, wearing apparel, leather and related products | Textiles and Apparel |
| 9 | C16-C18 | Wood and paper products; printing and reproduction of recorded media | Wood Products |
| | | | Paper, Pulp |
| | | | Printing |
| 10 | C19 | Coke and refined petroleum products | Coke, Petroleum |
| 11 | C20 | Chemicals and chemical products | Chemicals |
| 12 | C21 | Basic pharmaceutical products and pharmaceutical preparations | Pharmaceuticals |
| 13 | C22-C23 | Rubber and plastics products, and other non-metallic mineral products | Rubber, Plastic |
| | | | Non-Metallic Mineral Products |
| 14 | C24-C25 | Basic metals and fabricated metal products, except machinery and equipment | Basic Metals |
| | | | Fabricated Metal Products |
| 15 | C26 | Computer, electronic and optical products | Computers, Electronics, Optics |
| 16 | C27 | Electrical equipment | Electrical Equipment |
| 17 | C28 | Machinery and equipment n.e.c. | Machinery |
| 18 | C29-C30 | Transport equipment | Motor Vehicles |
| | | | Other Transport Equipment |
| 19 | C31-C33 | Other manufacturing; repair and installation of machinery and equipment | Furniture and Manufacturing n.e.c. |
| | | | Rep. and Install. of Machinery and Equip. |
| 20 | D | Electricity, gas, steam and air conditioning supply | Electricity, Gas |
| 21 | E | Water supply; sewerage; waste management and remediation activities | Water Supply |
| | | | Sewerage, Waste, Material Recovery |
| 22 | F | Construction | Construction |
| 23 | G | Wholesale and retail trade; repair of motor vehicles and motorcycles | Trade |
| 27 | H | Transportation and storage | Transportation and Storage |
| 33 | I | Accommodation and food service activities | Accommodation and Food Service Activities |
| 35 | J58-J60 | Publishing, audio-visual and broadcasting activities | Publishing, Radio, TV |
| 36 | J61 | Telecommunications | Communications |
| 37 | J62-J63 | IT and other information services | Information Services |
| 38 | K | Financial and insurance activities | Financial and Insurance Activities |
| 39 | L | Real estate activities | Real Estate (incl. Leasing) |
| 40 | M-N | Professional, scientific, technical, administrative and support service activities | Professional, Scientific and Technical Activities |
| | | | Administrative and Support Service Activities (incl. Leasing) |
| 42 | O | Public administration and defence; compulsory social security | Public administration and defence; compulsory social security |
| 43 | P | Education | Education |
| 44 | Q | Health and social work | Human Health and Social Work |
| 46 | R | Arts, entertainment and recreation | Arts, Entertainment, Recreation |
| 47 | S | Other service activities | Membership Organizations |
| | | | Repair of Computers and Personal Goods |
| | | | Other Private Services |
| 48 | T | Activities of households as employers, etc | Household Employers |

*Notes*: The table shows the sectors used for the calculation of TFP, taken at the lowest level of disaggregation possible.

**Table C3:** ICT Taxonomy

| Sector | EU KLEMS code | EU KLEMS Description |
|---|---|---|
| **ICT-Producing** | C26 | Computer, electronic and optical products |
| | J61 | Telecommunications |
| | J62J63 | IT and other information services |
| **ICT-Intensive** | C10-C12 | Food products, beverages and tobacco |
| | C16-C18 | Wood and paper products; printing and reproduction of recorded media |
| | C20 | Chemicals and chemical products |
| | C22-C23 | Rubber and plastics products, and other non-metallic mineral products |
| | C27 | Electrical equipment |
| | C28 | Machinery and equipment n.e.c. |
| | C31-C33 | Other manufacturing; repair and installation of machinery and equipment |
| | F | Construction |
| | G | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| | J58-J60 | Publishing, audio-visual and broadcasting activities |
| | K | Financial and insurance activities |
| | M-N | Professional, scientific, technical, administrative and support service activities |
| | S | Other service activities |
| **non-ICT-intensive** | A | Agriculture, forestry and fishing |
| | B | Mining and quarrying |
| | C13-C15 | Textiles, wearing apparel, leather and related products |
| | C19 | Coke and refined petroleum products |
| | C21 | Basic pharmaceutical products and pharmaceutical preparations |
| | C24-C25 | Basic metals and fabricated metal products, except machinery and equipment |
| | C29-C30 | Transport equipment |
| | D | Electricity, gas, steam and air conditioning supply |
| | E | Water supply; sewerage; waste management and remediation activities |
| | H | Transportation and storage |
| | I | Accommodation and food service activities |
| | L | Real estate activities |
| | O | Public administration and defence; compulsory social security |
| | P | Education |
| | Q | Health and social work |
| | R | Arts, entertainment and recreation |
| | T | Activities of households as employers; undifferentiated goods- and services |

**Table C4:** Sectors Switching Between the Groups

| Sector | Frac. Years>Median |
|---|---|
| ICT-intensive sectors | |
| Publishing, audio-visual and broadcasting activities | 0.96 |
| Other manufacturing; repair and installation of machinery and equipment | 0.96 |
| Food products, beverages and tobacco | 0.87 |
| Rubber and plastics products, and other non-metallic mineral products | 0.83 |
| Chemicals and chemical products | 0.70 |
| Non-ICT-intensive sectors | |
| Textiles, wearing apparel, leather and related products | 0.35 |
| Coke and refined petroleum products | 0.26 |
| Accommodation and food service activities | 0.13 |
| Transport equipment | 0.13 |
| Arts, entertainment and recreation | 0.13 |
| Health and social work | 0.09 |
| Mining and quarrying | 0.04 |

*Notes*: The table presents all sectors that switch between the ICT-intensive and the non-ICT-intensive sectors over time and the fraction of years in the sample in which their ICT share is above the median share. The median share is computed across all sectors for each year. All sectors with ICT shares above (below) 0.5 are assigned to the ICT-intensive (non-ICT-intensive) sectors.