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The diffusion of technological progress in ICT

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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.

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 additional 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 increased 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

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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 on the labor productivity of the ICT-producing sectors and the relative price of ICT goods and services. To estimate the spillover effects of these ICT-shocks (technological diffusion), 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 information 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 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 a significant upward bias for almost all TFP responses.

Our paper addresses several strands of the productivity literature. From a methodological perspective, we develop a new 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 regulation in the telecommunication service sector (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.

To identify ICT-shocks, we rely on medium-run fluctuations in labor productivity in the ICT-producing sectors and the relative price of ICT goods and services. Using the joint co-movement of these two variables reflecting ICT-related technological progress assures that our identified shocks are less prone to measurement errors. In particular, the relative price is crucial to separate technology gains that are solely related to ICT from innovations that drive non-ICT technology.[4] To disentangle technology from non-technology shocks, we use medium-run restrictions (Uhlig, 2004; Drechsel, 2022) 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.

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 significantly 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 because 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-shocks. The last section concludes.

[1] See, for example, Forman and van Zeebroeck (2012), Hempell (2005), Laursen and Foss (2003) and Antonioli et al. (2010).

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

[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) and Chari et al. (2008).

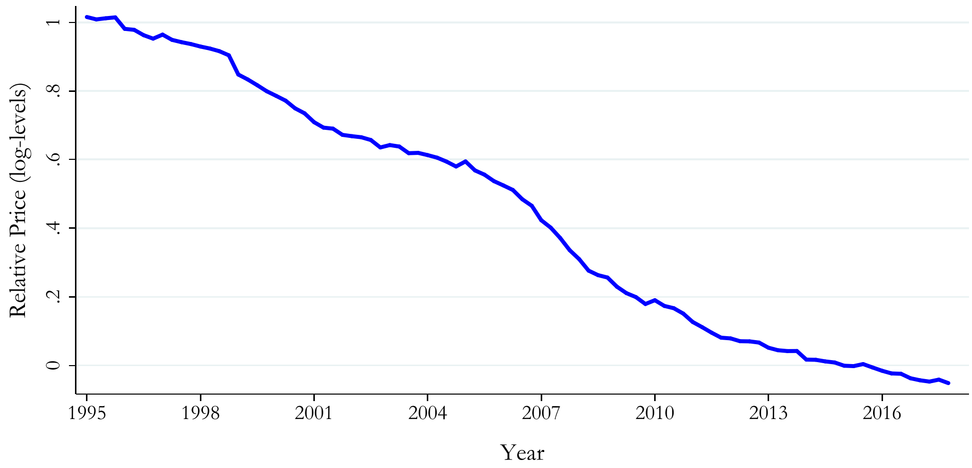

Fig. 1. Relative price of gross value added in the ICT-producing sectors.
Notes: The figure shows the relative price of gross value added for the ICT-producing sectors compared to all non-ICT-producing sectors in Germany (in log-levels), constructed from National Accounts data as described in Section A of the Supplementary Material. The original series are indexed to the base year 2015 = 100.

2. Identification of ICT-shocks

2.1. Motivation

We define ICT-shocks as technological progress originating from innovations in the ICT-producing sectors ‘Manufacturing of Computer, Electronic and Optical Products’, ‘Telecommunications’, and ‘IT and Other Information Services’.[6] The ICT-producing sectors typically display an extraordinarily high productivity growth. Due to these large gains in productivity, the price level (deflator of gross value added) of the ICT-producing sectors has been continuously declining over the years. Even in the presence of price rigidities, quality improvements map into reductions in the ICT deflator due to hedonic price measurement.[7] As a consequence, the relative price of the ICT-producing sectors compared to other sectors has been steadily declining as well (see Fig. 1).

For our analysis, it is crucial to separate ICT-shocks from technological progress stemming from the rest of the economy, which we, henceforth, call neutral technology shocks. Motivated by the falling relative price of ICT goods and services, we consider ICT-shocks as a subgroup of investment-specific technology shocks. Fisher (2006) uses a SVAR framework based on long-run restrictions to identify investment-specific technology shocks. He derives two identifying assumptions. First, both the neutral and the investment-specific technology shocks affect labor productivity in the long run. Second, only investment-specific technology shocks have a long-run effect on the price of investment goods relative to consumption goods. Fisher (2006) therefore places the relative price at the center of his identification procedure.

Chen and Wemy (2015) and Drechsel (2022) use a similar approach. They apply a medium-run restriction framework and define investment-specific technology shocks as those innovations which explain most of the variation in the relative price within a specific time horizon. Their approach solely relies on the price of investment goods relative to consumption goods and needs no further assumptions regarding labor productivity developments. Overall, both the medium- and the long-run approach yield very similar results when using the same VAR specification together with the relative price of investment goods and are, henceforth, labeled as the “Fisher model”.

The identification restrictions of the Fisher model, however, rests on several theoretical assumptions, for example, identical production functions for the investment and consumption goods sectors, free sectoral factor reallocation and perfectly competitive sectors.[8] Moreover, there are additional issues which can complicate the correct identification of technological progress when relying exclusively on the relative price of investment goods. On the one hand, there is an ongoing controversy regarding the correct basket of investment goods, as one could either consider total gross private investments of gross private investments plus consumption expenditures on durables or only investment in equipment and software. On the other hand, it is plausible that quality adjustments in the price measurement of investment goods do not perfectly reflect the technological progress in areas such as equipment

[6] We follow the Federal Statistical Office and the OECD for our definition of ICT-producing sectors. 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.

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

[8] Ben Zeev (2018), Ben Zeev and Khan (2015) and Justiniano et al. (2011) provide a discussion.

and software (Gordon, 1990). All these problems potentially impede the model's capacity to correctly identify investment-specific technology shocks or, in our case, ICT-shocks.

We, therefore, propose an alternative approach for identifying ICT-shocks, which does not solely rely on medium-run variation in the relative price. In contrast to the Fisher model, we incorporate two labor productivity measures in our VAR analysis, one for the ICT-producing sectors and one for the rest of the economy. To identify ICT-shocks, we focus on medium-run productivity developments in the ICT-producing sectors. To separate ICT-shocks from neutral technology shocks, we use the relative price of ICT goods and services. In this framework ICT-shocks are allowed to be the dominant factor for the medium-run fluctuations in the relative price, while this does not hold for neutral technology shocks.

2.2. Empirical approach

To identify ICT-shocks, $\varepsilon_t^{\mathrm{ICT}}$, we proceed in the following two steps. In step 1 we use medium-run restrictions in a VAR setup to separate technological factors, captured by so-called *auxiliary shocks*, from non-technology factors. Since these auxiliary shocks are still correlated with each other, step 2 orthogonalizes and divides them into ICT-shocks and neutral technology shocks.

Step 1. Our VAR model includes eight variables: labor productivity (here and henceforth measured as gross value added per hours worked) in the ICT-producing sectors, $\mathrm{LP}_t^{\mathrm{ICT}}$, labor productivity of all non-ICT-producing sectors, $\mathrm{LP}_t^{\overline{\mathrm{ICT}}}$, relative price between ICT-producing and non-ICT-producing gross value added, $\widehat{P}_t = \mathrm{Price}_t^{\mathrm{ICT}} / \mathrm{Price}_t^{\overline{\mathrm{ICT}}}$, hours worked per employee, 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 terms, 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 are 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 end is due to data availability in the EU KLEMS database, which we rely on for the construction of TFP as described in Section 3. We exclude earlier periods 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 quarterly variables from German National Accounts are seasonally- and, if necessary, calendar-adjusted and transformed into log-differences beforehand. This 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 non-stable trending behavior. Especially labor market outcomes such as total hours worked are highly influenced by the German labor market reforms (Hartz reforms), resulting in different trends before and after 2005. We, therefore, refrain from modeling such structural changes in log-levels and apply log-differences instead. This issue, however, is discussed in the robustness section.

Based on the VAR, we extract the auxiliary shocks using 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 fluctuations in our target variable. Due to the partial identification nature of medium-run restrictions, the auxiliary shocks are still correlated with each other.

In our application, we extract three auxiliary shocks, $u_t^{\overline{\mathrm{ICT}}}$, u_t^{ICT}, and $u_t^{\widehat{P}}$, from the VAR that maximize the FEV of $\mathrm{LP}_t^{\overline{\mathrm{ICT}}}$, $\mathrm{LP}_t^{\mathrm{ICT}}$, 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. Since the three auxiliary shocks are still correlated with each other, the second step deals with the orthogonalization to isolate the ICT-shocks. Our proposed identification strategy employs the vector of auxiliary shocks $u_t = \left(u_t^{\widehat{P}}, u_t^{\overline{\mathrm{ICT}}}, u_t^{\mathrm{ICT}}\right)'$ to obtain the vector of structural shocks $\varepsilon_t = \left(\varepsilon_t^{\widehat{P}}, \varepsilon_t^{A}, \varepsilon_t^{\mathrm{ICT}}\right)'$ using the system $Au_t = B\varepsilon_t$. Specifically, we link the auxiliary shocks to the structural shocks in the following way:

$$\begin{pmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} u_t^{\widehat{P}} \\ u_t^{\overline{\mathrm{ICT}}} \\ u_t^{\mathrm{ICT}} \end{pmatrix} = \begin{pmatrix} b_{11} & 0 & b_{13} \\ 0 & b_{22} & 0 \\ 0 & b_{32} & b_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{\widehat{P}} \\ \varepsilon_t^{A} \\ \varepsilon_t^{\mathrm{ICT}} \end{pmatrix} . \tag{1}$$

Multiplying out yields the following system of three equations:

$$\begin{aligned} u_t^{\widehat{P}} &= b_{11}\varepsilon_t^{\widehat{P}} + b_{13}\varepsilon_t^{\mathrm{ICT}} , \\ u_t^{\overline{\mathrm{ICT}}} &= - a_{21}u_t^{\widehat{P}} + b_{22}\varepsilon_t^{A} , \\ u_t^{\mathrm{ICT}} &= b_{32}\varepsilon_t^{A} + b_{33}\varepsilon_t^{\mathrm{ICT}} . \end{aligned} \tag{2}$$

[9] For details on the data sources and the temporal disaggregation procedure, see Table A1 and Figure A1 in the Supplementary Material.

To identify our final ICT-shocks, $\varepsilon_t^{\mathrm{ICT}}$, we intuitively proceed in two sub-steps. First, we isolate the neutral technology shock, ε_t^A, by regressing $u_t^{\overline{\mathrm{ICT}}}$ on $u_t^{\hat{P}}$.[10] This regression assumes that the dominant factors moving the relative price in the medium-run are not associated with ε_t^A. Moreover, by imposing the restrictions $a_{12} = b_{12} = 0$ in Eq. (1) we rule out that ε_t^A is one of the main drivers of medium-run fluctuations in the relative price. Second, we regress u_t^{ICT} on ε_t^A. The residuals from this regression, $\varepsilon_t^{\mathrm{ICT}}$, are by construction uncorrelated with ε_t^A and, therefore, represent our final ICT-shocks.

Note that $\varepsilon_t^{\mathrm{ICT}}$ is allowed to be a dominant force for the medium-run fluctuations of the relative price, but not vice versa. Put differently, all co-movement between $u_t^{\hat{P}}$ and u_t^{ICT} is allocated to $\varepsilon_t^{\mathrm{ICT}}$. In contrast, all co-movement between $u_t^{\overline{\mathrm{ICT}}}$ and u_t^{ICT} that is independent from $u_t^{\hat{P}}$ is assigned to ε_t^A.

It is instructive to compare our ICT-shocks with those obtained using the Fisher model. In the Fisher model, the ICT-shocks explain most of the variation in the relative price for a specific medium-run horizon and are already identified in step 1. We find a high but not perfect positive correlation between both candidates for ICT-shocks of 0.72.

Technical implementation. From a technical point of view, we consolidate steps 1 and 2 as in Cascaldi-Garcia and Galvão (2021) and Belke et al. (2022). Equivalent to the former 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

In the following, we provide a descriptive discussion of our ICT-shocks. We start by investigating to what extent our ICT-shocks are correlated with other prominent shock series from the literature. Thereafter, we study if our ICT-shock contains more news or surprise elements of ICT innovations. This analysis enables us to interpret our shock series more structurally. We close with some remarks on the connection of our ICT-shock to the variables used in the VAR identification.

Correlation with other shocks. Our ICT-shock should not meaningfully be correlated with other prominent shocks from the literature and thus picking up movements that are unrelated to ICT innovations. Table 1 presents the correlation coefficients of our ICT-shock with 10 other German or international shocks on a quarterly basis. The highest correlation coefficient in absolute terms is 0.20. All other correlations are smaller in magnitude or even zero. None of the correlation coefficients is significant at the 5 percent level. Based on these figures, we conclude that our ICT-shocks are unlikely to be driven by other macroeconomic influences.

News and surprise shocks. In the following we analyze the surprise and news content of our ICT-shocks. As our baseline identification framework is less suited to provide candidates for a news and surprise ICT-shock, we rely on two prominent approaches. The first one is motivated by Barsky and Sims (2011) who identify neutral technology news shocks. Specifically, they identify news as the shock that is orthogonal to the contemporaneous innovation in Fernald's (2014) purified TFP (PTFP) measure and that best explains its future changes. We use the medium-run identification of the Barsky and Sims (2011) approach, but in contrast to them we focus on the relative price of ICT goods and services instead of PTFP. Strictly speaking, we obtain the surprise and news components of our ICT-shocks based on the Fisher model. The VAR specification is the same as outlined in Section 2.2.

The disentanglement according to Barsky and Sims (2011) revealed that our ICT-shock is more strongly connected to the news component and less so to the surprise component. The correlation to the news shock is at 0.62 and at 0.45 to the surprise component. Qualitatively, the resulting impulse responses from the news shock are much more in line with our baseline results presented afterwards (also see Figures E15 and E16 in the Supplementary Material).

The second approach is motivated by Ben Zeev and Khan (2015). They identify investment-specific news shocks as the innovation that is orthogonal to contemporaneous innovations in PTFP as well as the relative price and that best explains future fluctuations in the relative price over a finite horizon. Their approach is therefore an extension of Barsky and Sims (2011). To transfer the approach of Ben Zeev and Khan (2015) to our setup, we replace both labor productivity measures of the ICT and non-ICT sector by an aggregate PTFP measure provided by Christofzik et al. (2021).

According to the disentanglement by Ben Zeev and Khan (2015), our ICT-shock is equally correlated to both the news and surprise component. The corresponding correlation coefficients are 0.45 and 0.44, respectively. However, the impulse responses resulting from the news shock are much more in line with our baseline compared to the surprise component (also see Figures E17 and E18 in the Supplementary Material).

Given the previous correlations, our ICT-shock seems to be a combination of both components. However, as the impulse responses of the news shocks are much in line with our baseline results, we give our ICT-shocks a structural interpretation of rather picking up the news component in ICT innovations.

[10] To be precise, we only identify ε_t^A up to the scaling factor b_{22}. As this does not affect our ICT-shock of interest, $\varepsilon_t^{\mathrm{ICT}}$, we omit this factor for ease of notation.

Table 1
Correlation of our ICT-shock with other shocks.

Shock	Description	Source	Corr
Purified TFP	change in utilization-adjusted TFP based on survey data	Christofzik et al. (2021)	−0.03 [-0.24 0.17]
Tax reforms	legislated tax changes for budget consolidation or structural reasons	Hayo and Uhl (2014)	0.19 [-0.01 0.38]
Revenues social security	exogenous legislative changes to revenues of the social security system	Gechert et al. (2021)	−0.20 [-0.39 0.01]
Expenditures social security	exogenous legislative changes to expenditures of the social security system	Gechert et al. (2021)	−0.03 [-0.24 0.17]
Monetary policy	shock from a sign restricted SVAR defined as an increase in interest rate and a decrease of stock prices	Jarociński and Karadi (2020)	0.07 [-0.16 0.29]
Central bank information	shock from a sign restricted SVAR defined as an increase in both the interest rate and stock prices	Jarociński and Karadi (2020)	0.20 [-0.02 0.41]
Macroeconomic uncertainty	shocks from a SVAR including a macroeconomic uncertainty index	Meinen and Roehe (2017)	−0.14 [-0.35 0.10]
Oil supply	shock from a sign restricted BVAR including oil production, real activity and the real oil price	Baumeister and Hamilton (2019)	−0.05 [-0.26 0.15]
Oil demand	shock from a sign restricted BVAR including oil production, real activity and the real oil price	Baumeister and Hamilton (2019)	−0.01 [-0.22 0.19]
Economic activity	shock from a sign restricted BVAR including oil production, real activity and the real oil price	Baumeister and Hamilton (2019)	0.17 [-0.03 0.36]

Notes: The table shows the correlation coefficients (Corr) of various shocks with our baseline ICT-shock (version 1) on a quarterly basis. The figures in brackets limit the 95 percent confidence interval.

Table 2
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.

Connection to the VAR variables. Fig. 2 plots the ICT-shocks, depicted as blue lines, together with the growth rate of the deflator of the ICT-producing sectors in panel (a) and labor productivity growth in the ICT-producing sectors in panel (b). The ICT-shocks have been annualized by calculating the yearly sum of the quarterly shock series. The deflator is multiplied by minus 1 to facilitate a comparison with the ICT-shocks. These 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 annual correlation between ICT-shocks and deflator growth is −0.34.

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 co-movement between the ICT-shocks and labor productivity growth is supported by the high correlation coefficient of 0.71.

Table 2 displays the fraction of the forecast error variance of $\mathrm{LP}^{\overline{\mathrm{ICT}}}$, $\mathrm{LP}^{\mathrm{ICT}}$, and $\hat{P}$ 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.

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 services L_{jt} to produce output Y_{jt}. Total factor productivity 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; we discuss this assumption in the robustness section. Using a translog transformation, TFP growth can be extracted as follows:

$$\Delta \ln \mathrm{TFP}_{jt} \;=\; \Delta \ln V_{jt} - \alpha_{jt}\, \Delta \ln K_{jt} - (1-\alpha_{jt})\, \Delta \ln L_{jt} \;, \tag{3}$$

where α_{jt} describes the sector-year-specific output elasticity of capital. Note that both K_{jt} and L_{jt} take changes in input quality and quantity into account.

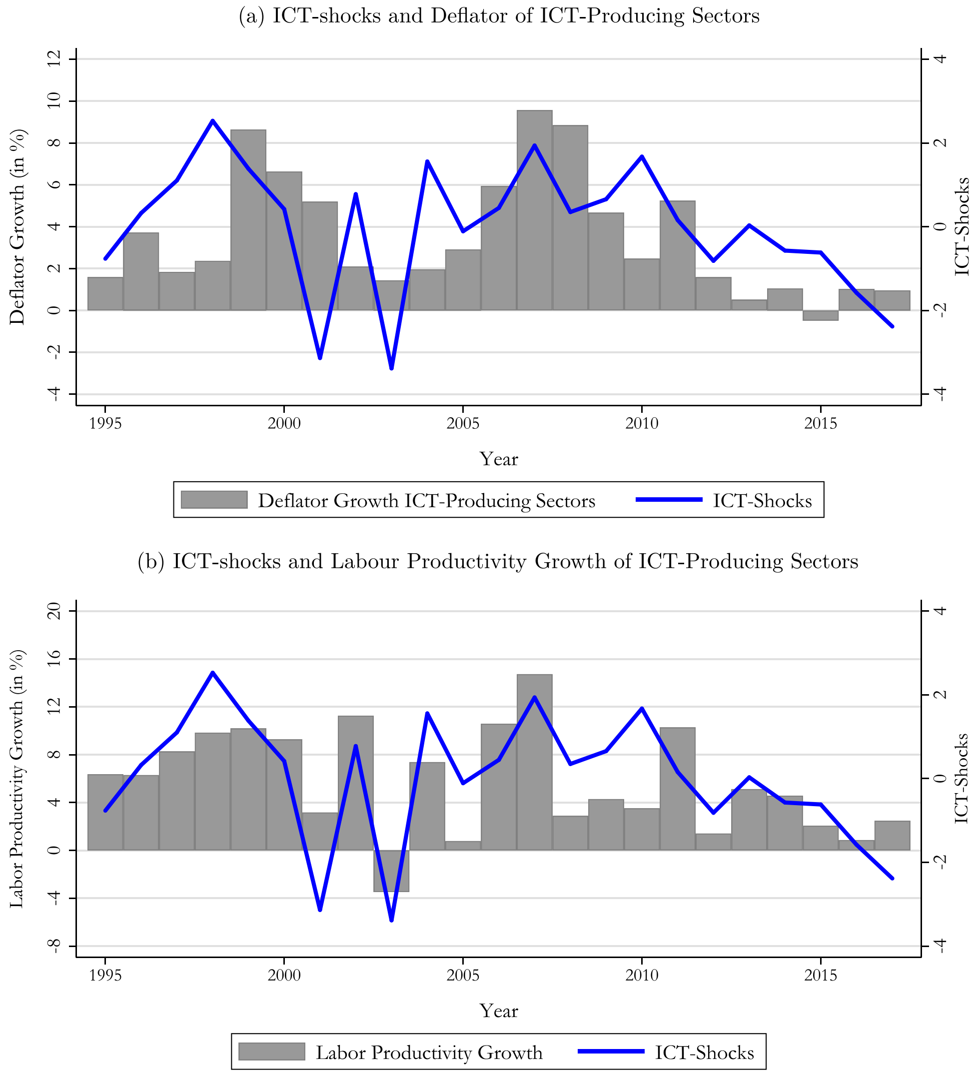

Fig. 2. ICT-shocks and deflator and labor productivity of ICT-producing sectors.
Notes: The figure plots the ICT-shocks together with the growth rates of the deflator (multiplied by minus 1; upper panel) and labor productivity in the ICT-producing sectors (lower panel).

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:

$$\Delta \ln K_{jt} \;=\; \sum_k \bar{v}_{jkt}\, \Delta \ln S_{jkt} \;, \tag{4}$$

where $\bar{v}_{jkt}$ 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:

$$S_{jkt} = \left(1 - \delta^S_{jkt}\right)\, S_{jkt-1} + I_{jkt} \;, \tag{5}$$

where δ^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:

$$v_{jkt} \;=\; \frac{p^K_{jkt}\, S_{jkt}}{\sum_k p^K_{jkt}\, S_{jkt}} \;, \tag{6}$$

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

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 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:

$$p^K_{jkt} = \left(i_{jt} - \pi^I_{jkt}\right) p^I_{jkt-1} + \delta^I_{jk}\, p^I_{jkt} , \tag{7}$$

where π^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).

Eq. (7) underscores the importance of having heterogeneous deflators across sectors j. Since the price of capital influences the weights v_{jkt} through Eq. (6), some asset types have a substantial impact on capital services, despite only accounting for a small share in investment, see, for example, 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 ifo Investment Database (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 of 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.

The EU KLEMS and the IIDB data provide sectoral 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 $|K| = 6$ 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 C3 in the Supplementary Material 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-producing sectors), (ii) sectors presenting a relatively high share of ICT capital, but not producing these goods by themselves (ICT-intensive sectors), and (iii) sectors not intensively using ICT goods or services (non-ICT-intensive sectors). 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 C4 in the Supplementary Material 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' are far from homogeneous. Figure B1 in the Supplementary Material shows that there is considerable cross-sectional variation within 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 Supplementary Material demonstrates that the variation in the shares are quite large between 2010 and 2017, especially for sectors that do not intensively use ICT.

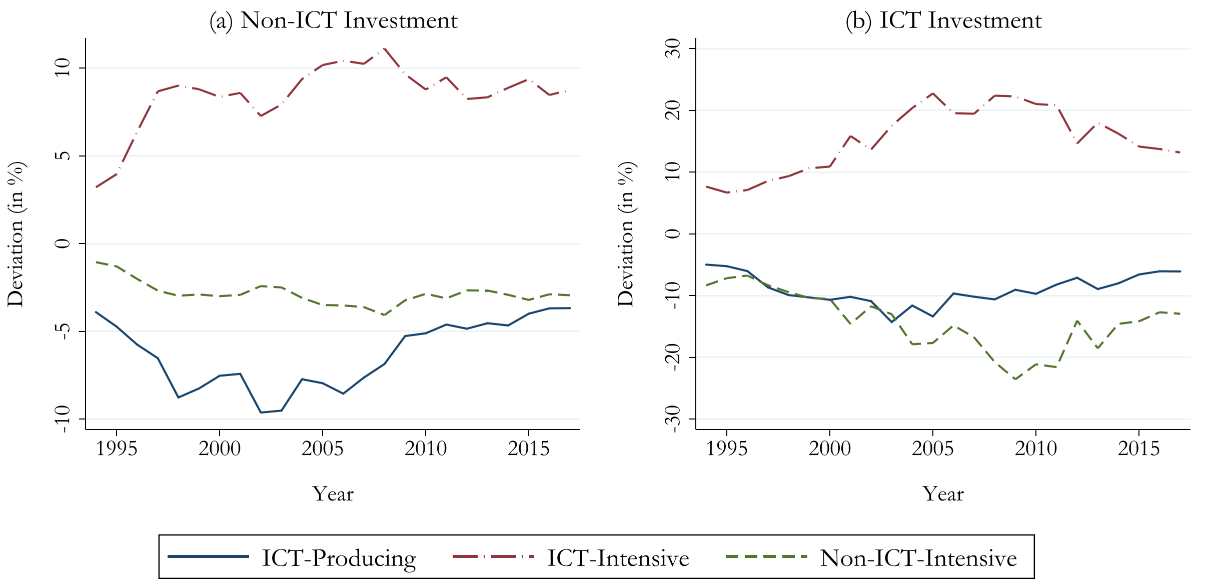

Fig. 3. Deviations of the owner from the user concept.
Notes: Both plots are in percentage deviations of the values according to the owner concept from the values according to the user concept, i.e. $(I_i^{x,\text{owner}} - I_i^{x,\text{user}})/I_i^{x,\text{user}}$, where $x \in \{\text{ICT}, \overline{\text{ICT}}\}$ 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.

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.[11] This concerns the service sectors since leasing firms belong to the sector 'Professional and Business Service Providers' (see code M-N in Table C3 in the Supplementary Material). 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 (see Goldrian, 2007, for more details on the survey).

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 Fig. 3 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 Fig. 3 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, δ_{jkt}^S, using capital stock and investment data from EU KLEMS.[12] We use the same depreciation rates δ_{jkt}^S for the user and owner concept, since an asset's

[11] 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.

[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

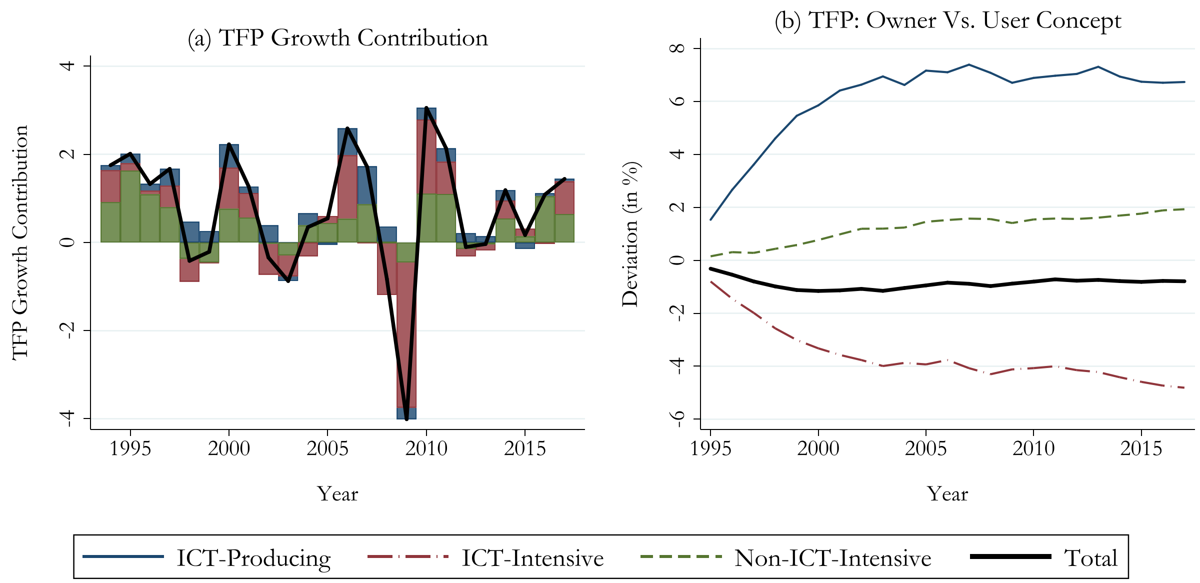

Fig. 4. TFP derived from IIDB and EU KLEMS.
Notes: Panel (a) shows the growth contributions of TFP to gross value added for the three groups of sectors and the total economy. Panel (b) depicts the difference between the owner and the user concept TFP, expressed in percentage deviations: $d^{\text{TFP}}_{jt} = (\text{TFP}^{I,\text{owner}}_{jt} - \text{TFP}^{I,\text{user}}_{jt})/\text{TFP}^{I,\text{user}}_{jt}$, where TFP^{I}_{jt} is a TFP-index with base year 1994. The group-specific values have been obtained as weighted averages: $\sum_i d^{\text{TFP}}_{jt} V_{jt}$, 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.

economic 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: $S^{\text{IIDB}}_{jkt_0} = S^{\text{KLEMS}}_{jk1995}$. Starting from this value, we use Eq. (5) 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 Eq. (4). Fourth, the growth rate of annual, sector-specific total factor productivity, $\Delta \ln \text{TFP}_{jt}$, is calculated from Eq. (3). The output elasticity of labor services, $1 - \alpha_{jt}$, 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 Fig. 4. 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 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.

In the existing literature, there is an ongoing debate on TFP (mis-)measurement. For example, Comin et al. (2020) introduce a new measure for purified TFP (PTFP) that augments TFP estimates by capacity utilization measures from business surveys. In our baseline, we do not consider PTFP, but examine this source of (mis-)measurement in the robustness section.

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 regression for each horizon h and dependent

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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'.

variable $Y_{i,t}$:

$$\Delta Y_{i,t+h} = \alpha_{i,h} + \beta_h^i \varepsilon_t^{\mathrm{ICT}} + \eta_{i,t+h} \ , \tag{8}$$

where $\Delta Y_{i,t+h}$ is the growth rate of our variables of interest for sector $i = (\mathrm{ICT}, \mathrm{INT}, \mathrm{NON})$ between year $t-1$ and $t+h$. $\alpha_{i,h}$ are sector-horizon-specific constants and $\eta_{i,t+h}$ refers to the usual error term.[13]

$\varepsilon_t^{\mathrm{ICT}}$ denotes the ICT-shocks identified in Section 2. The ICT-shocks are annualized for the local projection.[14] 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 $\beta_h^{i=\mathrm{ICT}}$ gives the response of the ICT-producing sectors at time $t+h$ to an ICT-shock at time t. Similarly, the coefficients $\beta_h^{i=\mathrm{INT}}$ and $\beta_h^{i=\mathrm{NON}}$ describe the responses of the ICT-intensive and the non-ICT-intensive sectors, respectively.[15] Impulse responses for each of the three sectors are calculated from the sequence of β_h^i, where $h = 0, 1, \ldots, 4$. 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).[16] 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 $\varepsilon_t^{\mathrm{ICT}}$ 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 $l = 1, \ldots, 5$, on the shock, $\varepsilon_t^{\mathrm{ICT}}$. 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 C2 in the Supplementary Material 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.[17]

4.2. Aggregate results

Panel (a) in Fig. 5 presents the responses of gross 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 the response of gross 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. We also estimated impulse responses based on an ICT-shock identified with the Fisher model. The correlation to our baseline ICT-shock is high at 0.72 and the impulse responses remain qualitatively unchanged. Section E in the Supplementary Material contains detailed information.

The different responses of gross 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.[18]

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 panel (b) in Fig. 5. 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 percent. Both the shape and magnitude of responses are highly similar across the groups of sectors, notwithstanding the

[13] Note that we estimate the equations sector-wise and not in a panel setup. As the ICT-shocks are the same for the three sectors, the prominent issue on dynamic heterogeneity introduced by Canova (2022) does not apply in our case. Nevertheless, we followed Canova's recommendation and estimated the local projection for each sub-sector within one of our three aggregates and averaged the effects afterwards. The resulting point estimates were numerically identical to our baseline responses.

[14] Specifically, the quarterly shocks are transformed to a quarterly index series. Then, we take yearly averages and calculate the annual percentage changes. The robustness section contains an additional shock aggregation procedure together with the resulting impulse responses.

[15] In theory, ICT-shocks can influence the outcome variables through technology spillovers or material inputs. As the focus of this paper is on the former channel, our empirical framework is constructed to rule out material inputs as a possible mediator. In terms of quantity of material inputs, variation is eliminated by using value added instead of gross output, both in the VAR model and in the calculation of sector-specific TFP. Moreover, changes in the quality of material inputs should be reflected in the hedonic price deflators we exploit for the identification of the ICT-shocks. Since the local projections include sector-horizon-specific constants, our empirical strategy only implicitly relies on the weak assumption that any differential changes in the hedonic price adjustment between material inputs and value added need not to be correlated with the ICT-shocks.

[16] The Supplementary Material contains three different bootstrap procedures to estimate the standard errors. All three approaches underpin our baseline results as the inference does not change.

[17] 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.

[18] Note that the effects of employment, ICT investment and TFP do not have to add up to the response for gross value added. First, employment and ICT investment are not quality adjusted in the following. Second, ICT investment only covers a part of overall investment. Our approach, however, works well if we calculate growth contributions of labor and capital services together with TFP. The resulting sums equal the effects for gross value added.

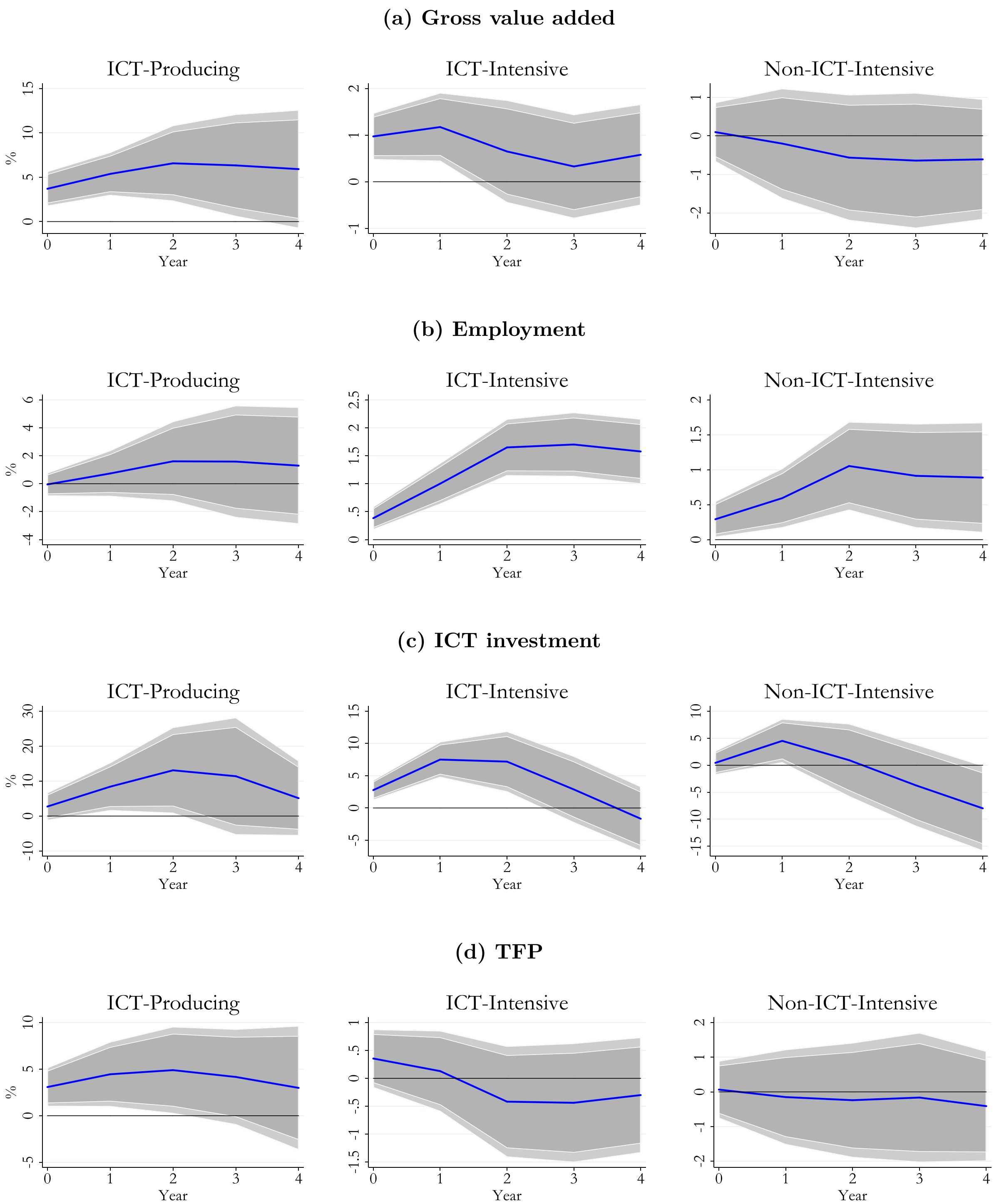

Fig. 5. Effects following an ICT-shock.
Notes: The graph displays the results of a local projection based on an ICT-shock. The solid blue lines show the point estimate, while the shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on Newey-West-corrected standard errors with $h + 1$ lags.

insignificant estimates for ICT-producing sectors 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.

Second, we analyze the importance of the capital side for transmitting ICT-shocks.[19] Panel (c) in Fig. 5 shows the responses of ICT-investment for the three groups of sectors. The ICT-producing sectors invest about 2.4 percent 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 percent, respectively. Afterwards, the level of investment stabilizes. The response for the ICT-intensive sectors is similar. Investment increases contemporaneously by 3.1 percent, rising to more than 8 percent during the following two years. Then, the response reverts and becomes insignificant. The non-ICT-intensive sectors increase their investment in ICT by one percent in the period of the shock, which is barely significant. One year later, the effect becomes strongly significant and increases to 5.4 percent and reverts afterwards.[20]

The evidence suggests that ICT investments of all three groups respond to ICT-shocks, especially with a lag of one or two years.[21] 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, panel (d) in Fig. 5 presents the effects of the ICT-shock on TFP growth. In the ICT-producing sectors, the exogenous ICT-related technological progress increases the technology level in the subsequent two years. The maximum effect occurs two years later, showing an increase of 5.2 percent. 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.[22]

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 percent on impact. While the contemporaneous response is economically sizeable compared to the unconditional dispersion of the 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 technological growth which subsided by the mid-2000s (Gordon and Sayed, 2020; Fernald, 2015; Cette et al., 2016).

Motivated by these considerations, Fig. 6 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.[23] 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 percent 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

[19] 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 Eq. (5)). 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.

[20] 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.

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

[22] 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.

[23] 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 Supplementary Material for the ICT-intensive sectors).

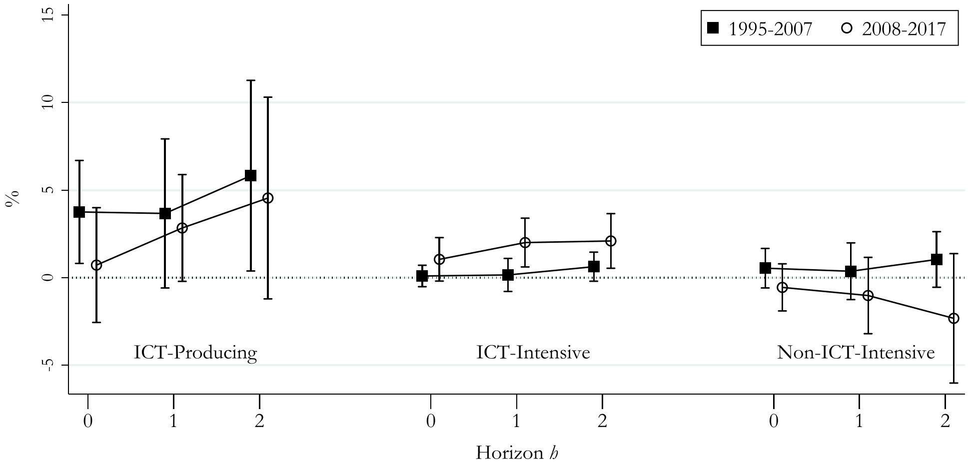

Fig. 6. TFP spillover by sub-period.
Notes: The graph plots the results of a local projection for TFP as described in Section 4.1 for $h = 0, 1, 2$. The results are obtained from two separate sets of regressions based on a split sample: the first sample ranges from 1995 to 2007 and the second from 2008 to 2017. The confidence bands indicate 95 percent confidence intervals, based on Newey-West-corrected standard errors with $h + 1$ lags.

two time periods. Overall, technological gains in the ICT-producing sectors are positive and persistent, independent of the period considered.

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 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 to sectoral TFP.

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 Fig. 2, 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 Figs. 3 and 4). We now 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 panel (d) in Fig. 5 with the point estimates of the responses derived from the respective owner-concept data. Fig. 7 demonstrates these differences in TFP, for the three groups of sectors, ICT-intensive activities without leasing and the leasing sector itself (MN). Contrary to our previous inference based on Newey and West (1987) standard errors, we now obtain standard errors of these coefficient differences using standard bootstrapping methods. According to Montiel Olea and Plagborg-Møller (2021), standard bootstrapping approaches yield consistent confidence intervals for local projections. We calculate

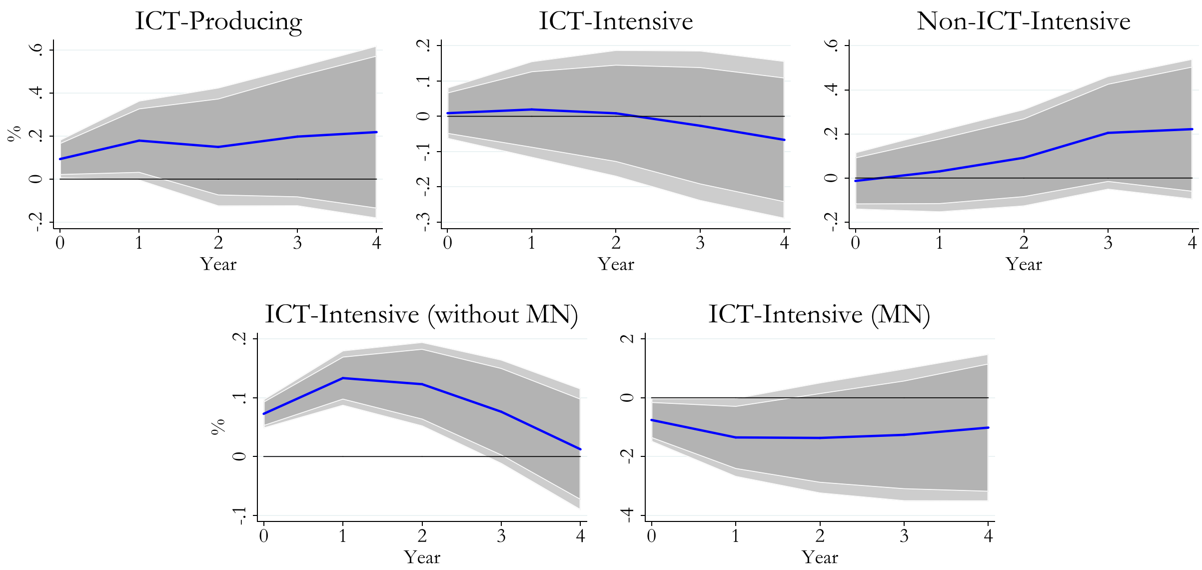

Fig. 7. TFP spillover: owner vs. user concept.
Notes: The plot displays the differences in the point estimates of owner-concept TFP from user-concept TFP. The point estimates are obtained from local projections as described in Section 4.1. The top panels show the differences for each of the three aggregated sectors. The bottom panels show the values for the ICT-intensive sectors without the leasing sector (without MN) and the respective values for the leasing sector (MN). The shaded areas indicate 95 percent and 90 percent confidence intervals, respectively, based on standard bootstrapping.

confidence intervals based on normal-approximations with 200 draws, i.e. the procedure bootstraps standard errors that are then used together with critical values from a normal distribution to obtain these intervals. Bootstrap samples of size N are stratified, i.e. drawn individually within each group.[24]

Overall, the responses differ by up to 0.2 percentage points (upper three panels in Fig. 7). For the ICT-producing and the non-ICT-intensive sectors, the owner concept overestimates the actual response of TFP; the difference for the ICT-producing sector is also statistically different from zero. 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.

Since the leasing sector 'Professional and Business Service Providers' (MN) belongs to the ICT-intensive sectors, we now analyze this sector separately. The bottom-left panel in Fig. 7 shows the difference of conditional responses of TFP among the ICT-intensive sectors without the leasing sector, and the bottom-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 and significantly 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.

The analysis 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 are overestimated for most sectors.

4.5. Robustness checks

In the following, we present a number of robustness checks to validate our baseline results. Detailed information on these checks can be found in the Supplementary Material to this paper. We discuss the sensitivity of the impulse responses arising from the shock identification scheme as well as the variable selection, the assumptions underlying our production function, TFP measurement, and the shock aggregation procedure.

[24] Section D in the Supplementary Material considers two additional bootstrapping methods (percentile and bias-corrected bootstrapping). Both yield almost identical results.

Table 4
Alternative specifications of the VAR model.

Version	Description	Correlation of ICT-Shocks	
		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.

Baseline identification and variable selection. We start by evaluating the sensitivity of the impulse responses to changes in the identification procedure for the ICT-shocks and the variable selection in the SVAR model (see Section E in the Supplementary Material). In sum, we calculate eleven additional shock versions of which we discuss six in the following in more detail.[25] First, we use alternative medium-run restrictions by varying the horizon for which the FEV share is maximized (version 1 to 3 in Table 4). 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 of Uhlig (2004), the latter is used by Francis et al. (2014). Second, we substitute some of the variables used in the SVAR model (versions 4 to 6 in Table 4). 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. Table 4 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. This also holds true for the impulse responses, as shown in the Supplementary Material.

Production function. The extraction of sectoral TFP is based on a Cobb–Douglas production function with constant returns to scale. To back this assumption, we take a closer look at the elasticity estimates provided by the Competitiveness Research Network (CompNet, see Section F in the Supplementary Material). The kernel densities of these estimates underpin that the constant returns to scale assumption is adequate. By applying their elasticity estimates to our data, we find that the resulting TFP estimates are highly correlated with our baseline. Given these alternative estimates of TFP, we re-estimated our local projections and find that our main statements remain the same.

TFP measurement. (Mis-)Measurement of TFP has been identified as a key concern in the associated literature. For example, Basu et al. (2006) and Fernald (2014) argue that TFP estimates are biased because of unobserved factor utilization. We tackle this issue by using the series of Comin et al. (2020), who adjust TFP estimates by survey-based capacity utilization measures (see Section G in the Supplementary Material). Our baseline results for the ICT-producing and non-ICT-intensive sectors hold. However, the responses are smaller in magnitude. For ICT-intensive sectors, the results are almost identical. While the responses are quite similar for horizons equal to or greater than one year, the initial response for $h = 0$ is zero. We provide three possible explanations why these quantitative differences occur. First, our data set contains a finer grid of sectors and thus a more granular measurement of TFP. Second, not for all German service sectors, capacity utilization measures are available, thus, they have to approximated by other aggregates. If sectoral cycles are not equal, this approximation might be misleading. Third, the model's parameters to backcast capacity utilization for the total service sector are identified for the period following 2011 until the end of 2019, which has been characterized by a long-lasting upswing and includes no recession.

Shock aggregation. Ottonello and Winberry (2020) stress the role of applying different weights to quarterly shocks when aggregating them to an annual series. In our baseline, we use equal quarterly weights to aggregate our shocks. The aggregation rule by Ottonello and Winberry (2020) gives quarterly shocks a higher weight, the closer they occur before the end of the period. In our case this means that the shock in the fourth quarter of the given year gets a higher weight than the one from the first quarter. In Section H of the Supplementary Material we discuss this issue and find that the correlation between our baseline annual shock measure and the annual measure calculated according to Ottonello and Winberry (2020) is 0.86. The impulse responses based on these shocks are consistent with our baseline results.

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

[25] The Supplementary Material includes these additional robustness checks next to the ones discussed here. Among others, we vary the length of the estimation period, assume different bounds for the medium-run restrictions, or specify the VAR in levels instead of log-differences.

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 other 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., 2021). The dramatic increase in teleworking has allowed firms to lower costs by reducing expenditure on office space and traveling. In addition, evidence suggests that teleworking increases productivity and job satisfaction (Bloom et al., 2015; Barrero et al., 2021), 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 goods 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., 2021). 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 collateralize 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, 2022). 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., 2021). 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.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We can provide aggregate data, statistics and replication files. However, some microdata are confidential and can only be accessed in a data center.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2022.104277.

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