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Unraveling the Productivity Paradox: Evidence for Germany

Abstract

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JEL Classification: O40, E24, C32, O30

Keywords: labor productivity, technology shocks, Digitization, Structural VARs, purified TFP

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Unraveling the Productivity Paradox: Evidence for Germany*

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May 19, 2021

Abstract

Despite massive digitization efforts, the German economy has experienced a marked slowdown in its productivity growth. This paper empirically analyzes three prominent explanations for this development. First, using a novel quarterly utilization-adjusted total factor productivity measure for the German economy, we find that the slowdown in U.S. productivity growth since the mid-2000s had a negligible impact on the German productivity trend. Second, the structural shift towards services in the German economy explains a sizeable share of the weaker aggregate productivity gains. This transformation process is associated with a strong labor market performance. And third, employing a novel identification procedure, we show that technological progress in the German information and communication technology (ICT) producing sector stimulates aggregate employment growth. Its effect on aggregate productivity is, however, small.

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1 Introduction

Since the 1970s all major advanced economies have shared a similar experience: a decline of productivity growth rates. This decline has become even more pronounced well before the onset of the financial crisis of 2008/09. Some commentators have already concluded that the world's economic growth potential might suffer from a case of secular stagnation (Gordon, 2015; Summers, 2014). However, the deceleration has not proceeded completely synchronously across countries. This heterogeneity not only casts some doubts regarding this explanation, but also provides analysts with the opportunity to scrutinize it more deeply.

Germany is a particularly interesting case, as its economic performance provides an impression of ambivalence. On the one hand, it even realized declining unemployment during the Eurozone crisis and experienced a protracted economic expansion with increasing employment afterwards. Many German industrial companies are viable competitors in world markets, carried by their engineering competencies and their fast pace of developing and adopting new technologies, epitomized in the expression "Industry 4.0". On the other hand, potential growth and in particular productivity growth have remained quite modest despite considerable investments into information and communication technology (ICT) capital.

In this paper, we examine this productivity paradox. Specifically, we study three prominent explanations using state of the art empirical methods both regarding data construction and empirical identification procedures.

A first potential explanation is that slower productivity progress in the U.S., commonly known as the global frontier of technology and knowledge (Cette et al., 2016), triggers reduced productivity growth. Starting around 1995, the U.S., unlike other countries, experienced an acceleration in productivity growth. In the following decade, the U.S. economy realized a burst of innovation and massive reallocation of production factors related to the production and use of ICT. However, since the mid-2000s, U.S. productivity growth has once again fallen back behind the figures of other countries.[1]

To study the spillover effects on productivity growth in Germany and other major European countries, we construct novel quarterly time series for utilization-adjusted total factor productivity (TFP). The construction of such purified TFP measures is inspired by a series provided by Fernald (2014) for the U.S., which gained much attention in the literature. For other countries, however, such data does not exist. Given the presumably high demand for

[1] Among the explanations for this development in the U.S. are financial constraints in the wake of the Great Recession (Anzoategui et al., 2019; Fort et al., 2013), a return to normal productivity growth after ICT had provided an exceptional boost to productivity around the millennium (Fernald, 2015; Gordon, 2012), an increasing productivity gap within industries (Andrews et al., 2015) coming along with declining business dynamism (Decker et al., 2016) as well as problems with measuring productivity properly (Byrne et al., 2016; Syverson, 2017).

purified TFP measures, our paper thus provides a methodological contribution.[2] To control for capacity utilization, we rely on estimates presented by Comin et al. (2020) for major European countries. Identifying exogenous U.S. technological progress using an SVAR model with Fernald's and our own purified TFP measures, we find that the sluggish productivity trend in the U.S. exerted negligible effects on productivity growth in Germany, France, and Italy. Only for the United Kingdom, we identify positive spillover effects. Consequently, it is sensible to analyze German productivity data and their domestic sources separately from U.S. developments.

Therefore, as a second potential explanation, we analyze the effects of the strong German labor performance on aggregate productivity. Employment increased from 39.3 million people in 2005, the year with the highest recorded unemployment rate in German post-war history, to 45.3 million in 2019. Some studies even talk about the "German labor market miracle" (Burda, 2016). New jobs were mainly created in the services sectors, where labor productivity growth is notably lower than in the manufacturing sector. We conduct a disaggregated analysis at the sector level to account for this composition effect precipitated by the structural shifts (de Avillez, 2012). Our results suggest that a sizeable part of the slowdown in German productivity growth is a side effect of the labor market performance since the year 2005. The integration of almost six million workers into the labor market attenuated productivity growth.

In a third analysis, we study the effects of digitization on the German economy. Higher investment in ICT can raise productivity growth via many channels. Most directly, it creates aggregate productivity gains by raising productivity growth in the industries that produce ICT goods. A higher ICT-capital intensity can lift growth in productivity also indirectly by fostering complementary innovations, such as business organization, or by enabling new business ideas. In this case, firms take advantage of an improved ability to manage information and communications (Bloom et al., 2012). In addition, reallocation movements towards higher-productivity establishments can raise productivity, as shown by Foster et al. (2006) for the U.S. retail sector.

We focus on the question as to how technological progress originating from producers of ICT goods and services is transmitted to other sectors of the economy using a novel identification procedure based on the relative price of ICT goods and services in a structural VAR model with medium-run restrictions. This identification approach to detect technological progress in the ICT producing sector constitutes a further methodological contribution.

[2]The quarterly purified TFP measure and the Solow residual for Germany, France, Italy, and the United Kingdom described in this paper are available at the authors' websites (`https://sites.google.com/view/steffen-elstner/ptfp-data`).

According to our results, technological progress originating from the ICT-producing sector had significantly positive effects on both GDP and employment. This result corroborates the common intuition that digitization is a driving force of economic prosperity. The net effect on labor productivity growth is modest, however, as the positive effects on output and labor input almost cancel each other out. Thus, technology shocks in the ICT-producing sector apparently act like investment-specific technology shocks. Fisher (2006), Justiniano et al. (2011), and Altig et al. (2011) find similar results for the U.S. Moreover, for the years after 2012, only limited productivity growth originated in the ICT-producing sectors. The decline in the intensity in these impulses also contributes to the explanation of the decelerated German productivity growth.

We structure our analysis as follows. In Section 2, we introduce our productivity measures. In particular, we explain the construction of our quarterly series of purified TFP. Section 3 presents econometric results regarding the link between U.S. and German productivity growth. Section 4 analyzes the effects of the recent process of tertiarization in the German labor market. Section 5 studies the importance of information technologies on German productivity growth. Section 6 concludes.

2 Measuring technology improvements

Productivity can be measured in various ways. The relative usefulness different productivity measures possess for particular research questions depends on data availability and on the credibility of the necessary assumptions underlying their construction. In the remainder of this paper, we thus focus on total factor productivity (TFP) as an economy-wide measure and on labor productivity when we conduct disaggregated analyses at the industry level. In this section, we compare these measures. In particular, we expound the construction of our quarterly utilization-adjusted TFP growth series for major European countries.

2.1 Labor productivity and the Solow residual

The easiest way to study productivity developments is to consider labor productivity. As a single factor productivity measure, output is divided by the number of hours worked or employment. Other input factors such as human capital or physical capital are not considered. Increases in these variables result in a higher growth rate of labor productivity which does not directly reflect improvements in technology. It is therefore an incomplete measure for technological progress.

Nonetheless, due to the low data requirements, it is easy to perform studies at a disaggregated level using labor productivity. In such analyses, data for the input factor capital or other variables are often not available. Furthermore, the weights for the corresponding industries are simply the shares of these industries in total hours or total employment. Figure 1 shows hourly labor productivity as cumulative values for Germany, France, Italy, and the United Kingdom. It is obvious, that the growth of labor productivity has declined in all countries. The productivity slowdown is especially pronounced in Italy and the United Kingdom.

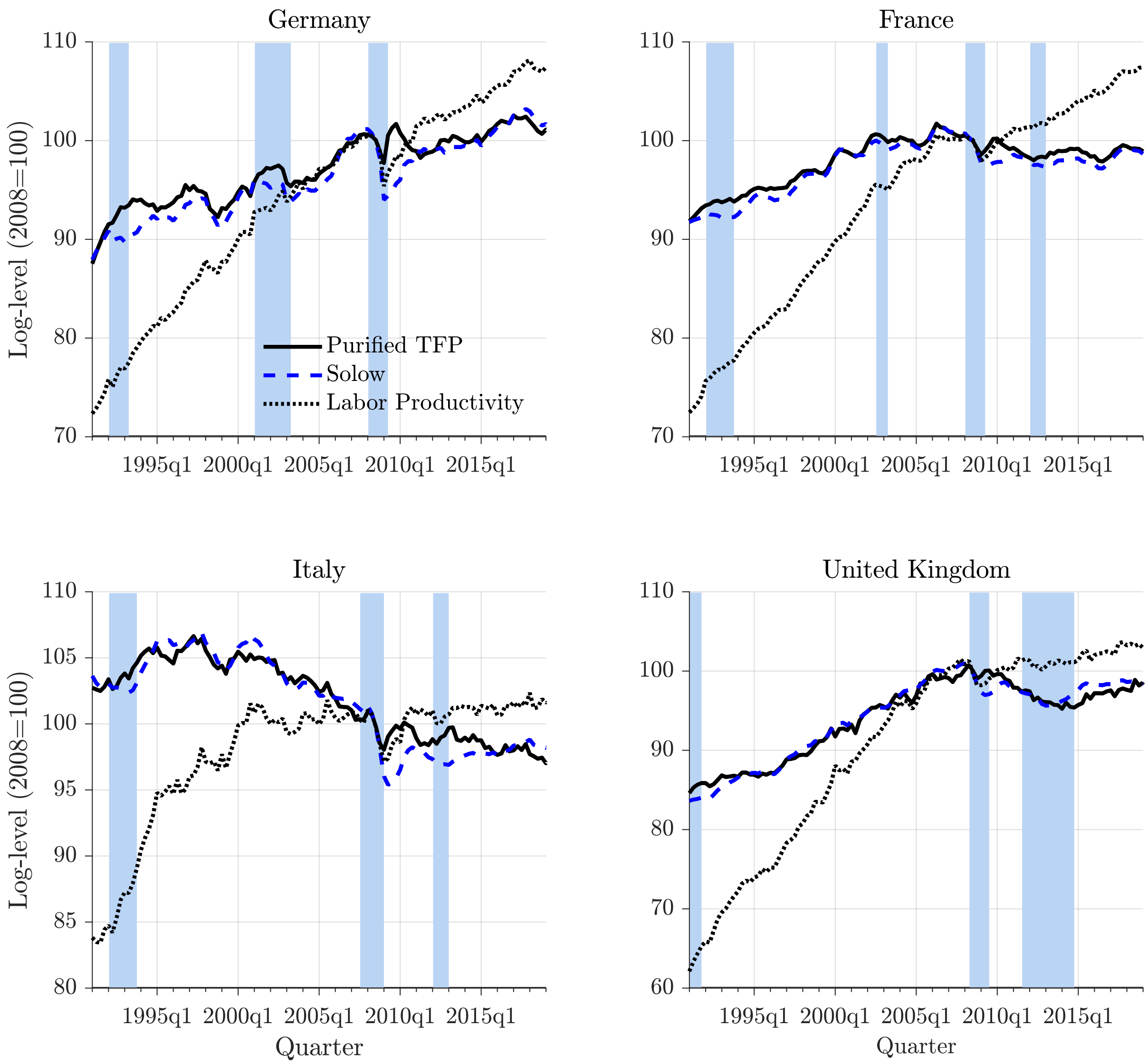
In contrast to labor productivity, the computation of TFP depends on several assumptions. In a growth accounting framework, it is conventionally measured by the Solow residual which is defined as that part of output growth which is not explained by the growth of the considered input factors. The literature discusses several shortcomings of the Solow residual as a measure for technological progress. First, the Solow residual depends on the specification of the production function including other assumptions on the economy (e.g., markups or structural change).

Second, while several input factors like employment or hours worked are often available quarterly, at least at the aggregate level, this is not the case for capital stock or capital services. To estimate this input factor, assumptions are necessary, e.g., on the rate of depreciation. This complicates studies at the disaggregate level to a large extent. Particularly for studies at a quarterly frequency, one needs to find a balance between using a simple productivity measure or using a Solow residual which is constructed on the basis of only moderately plausible identification assumptions.

Third, even when input factors are measured correctly and the production function resembles reality, the Solow residual captures many other things besides technological change. For example, it picks up cyclical effects. When output is temporarily weak in a recession, firms typically do not reduce the number of workers or machines to the same extent. Instead, they employ them less intensively, e.g., by reducing the number of shifts. Consequently, the Solow residual captures such effects which are unrelated to technology. Therefore, it underestimates (overestimates) technological progress if factor utilization decreases (increases). This creates an important bias in the Solow residual as a technology measure. We address this bias and construct a quarterly TFP measure adjusted for such factor utilization for four European countries in Section 2.2.

We use this purified TFP (PTFP) measure in Section 3 to study spillover effects of U.S. technology on major European countries. In our disaggregated analyses at the industry level in Sections 4 and 5, we rely on labor productivity instead. In these analyses, we assess the necessary identification assumptions to compute industrial TFP or PTFP measures as being

Figure 1: Productivity developments in major European countries



Notes: This figure compares our quarterly measure for purified TFP for the major European countries with the Solow residual and labor productivity. It shows the log-levels of the considered variables (annual average of 2008 = 100). Full lines are our quarterly PTFP measures. The blue dashed lines display our quarterly series for the Solow residual. Labor productivity is measured as output per hour worked and shown with dotted lines. Shaded regions reflect recessions as dated by the German Council of Economic Experts (GCEE) for Germany, the Conference Board for France and the United Kingdom, and the Economic Cycle Research Institute (ECRI) for Italy.

too demanding. Moreover, when we focus on the effects of structural shifts in the German economy, we consider long-term averages. In these cases, changes in factor utilization are less of a concern. Finally, the industry-specific weights for labor productivity are easy to compute.

2.2 Quarterly purified TFP measures for European countries

In this section, we describe the construction of our quarterly PTFP measures for Germany, France, Italy and the United Kingdom. Our analysis is inspired by Fernald (2014) who provides a quarterly PTFP measure for the U.S. economy. His measure is heavily cited in the literature addressing the effects of anticipated and unanticipated U.S. technology gains.[3] To the best of our knowledge, no such quarterly PTFP measures exist for European countries.

According to Fernald (2014) PTFP growth is computed as follows:

$$\Delta\ln PTFP_t = \Delta\ln TFP_t + \Delta\ln u_t, \tag{1}$$

where TFP_t defines the usual Solow residual, $PTFP_t$ denotes purified TFP, and u_t denotes factor utilization. To derive the latter, Fernald (2014) resorts to annual estimates by Basu et al. (2006) and Basu et al. (2013) and applies them to quarterly data. These studies rely on hours-per-worker growth as a proxy for factor utilization.

We construct our PTFP measure by proceeding in two steps that we explain in more detail below. First, we determine quarterly time series for the Solow residual. To this end, we interpolate the annual Solow residuals provided by the EU-Klems database using self-constructed quarterly TFP measures. The advantage of this approach is that we end up with a time series that delivers the same annual growth rates as the original EU-Klems data. Second, we draw on the estimates provided by Comin et al. (2020) to determine an aggregate measure of factor utilization. These estimates are based on a survey-based utilization proxy in three broad sectors: durable manufacturing, non-durable manufacturing and non-manufacturing.[4]

To construct our quarterly measures of TFP, we first extend the individual annual time series of the EU-Klems database to obtain a sample running from 1991 to 2019. To do so, we regress the annual growth rates of the EU-Klems TFP data on estimates of TFP growth

[3]Fernald frequently updates the adjusted TFP series based on new data and, less frequently, implements methodological changes. A summary of the literature regarding U.S. technology shocks is provided by Ramey (2016).

[4]See Comin et al. (2020) for details on the (preliminary) data and the instrumental variable estimation procedure.

from the Penn World Table which starts earlier and ends later (Feenstra et al., 2015).[5] In a second step, we construct quarterly auxiliary TFP measures using the production elasticities of the Penn World Tables.[6] Furthermore, we use quarterly real GDP data from the OECD and construct quarterly series for hours worked using data from Eurostat and the data by Ohanian and Raffo (2012) who provide internationally consistent series for hours worked. To construct a series for the capital stock on a quarterly basis, we use investment data published by the OECD and apply the perpetual inventory approach outlined in Imbs (1999).

Assuming a Cobb-Douglas production function, we are able to determine the auxiliary TFP-series. The annual averages of this auxiliary TFP series are highly correlated with the main EU-Klems TFP series. In a final step, we use the Chow-Lin interpolation method to translate the annual TFP data from EU-Klems in quarterly time series. We interpolate the data in levels and obtain a quarterly estimate for $\Delta \ln TFP_t$.

To proxy the change in factor utilization, we refer to Comin et al. (2020) and rely on a weighted change in industrial capacity utilization:

$$\Delta \ln u_t = \sum_{i=0}^{n} \gamma_i \hat{\beta}_i \, \Delta \ln cu_{i,t} \tag{2}$$

where $cu_{i,t}$ denotes capacity utilization in industry i discussed further below, γ_i is the industry weight (Domar weight)[7], and $\hat{\beta}_i$ is the elasticity of gross output on capacity utilization in industry i. The estimated elasticities are provided by Comin et al. (2020) for all four European countries. They report them for the three sectors durable manufacturing, non-durable manufacturing and non-manufacturing.[8]

For capacity utilization, we use quarterly time series based on survey data for different industries, provided by Eurostat. We assign these industries to the three sectors so that we can rely on the estimates by Comin et al. (2020).[9] While detailed data for the manufacturing sectors is available over the whole sample period starting in 1991Q1, this is not the case for the services sector and for construction. The time series for capacity utilization in the services sector start in 2010 or 2011 for the four countries. Therefore, we have to backcast this series for the remaining sample. Our approach differs from that proposed by Comin et al. (2020) who only rely on capacity utilization in the manufacturing sector in their backcasting procedure. In addition to this variable, we also use information from the business situation

[5] Data and the sample periods per country are reported in Appendix A.

[6] We use the time series average for the considered period.

[7] The Domar weight is the ratio of the industry's gross output divided by gross value added of the total economy. See footnote 11 in Fernald (2014). To avoid sudden shifts in the weighting but to allow for structural shifts, we rely on five-years rolling windows.

[8] See Table B2 in the Appendix.

[9] In Table B1 in the Appendix, we report how industries are assigned to sectors.

Table 1: Correlations of our quarterly series with estimates by Comin et al. (2020)

	Germany	France	Italy	United Kingdom
Factor utilization				
Baseline	0.96	0.75	0.93	0.83
Alternative	0.96	0.79	0.90	0.91
Purified TFP				
Baseline	0.76	0.40	0.53	0.67
Alternative	0.87	0.90	0.94	0.90

Notes: This tables presents correlations between the annual percentage changes of our series for factor utilization and purified TFP with the respective results by Comin et al. (2020). As an alternative to our baseline procedure, we backcast the time series for capacity utilization in the services and construction sector with the contemporaneous level of manufacturing capacity utilization.

of firms in the services sector as suggested by Göttert and Wollmershäuser (2021). These balances are available from the year 2000 onwards.

Specifically, for the period starting in the year 2000, we regress the level of capacity utilization in the services sector on the balance of the business situation and the level of capacity utilization in manufacturing. The regression includes contemporaneous values and the four lags of the latter two variables. We do not consider insignificant variables in the regression. For the remaining years in the 1990s, the regression includes only capacity utilization in the manufacturing sector.

For the construction sector, we use utilization data provided by the institutes Insee and IFO for France and Germany respectively. For Italy and the United Kingdom, we simply translate the balance of business situation in the construction sector into a measure of capacity utilization using the empirical relationships between both variables observed in France and Germany.

To facilitate the comparison between our approach and the results by Comin et al. (2020), we also present findings of an alternative specification. Here we backcast capacity utilization in the services and in the construction sectors solely on the basis of the contemporaneous level of manufacturing capacity utilization.

The upper part of Table 1 summarizes the correlations between the annual percentage changes of our final quarterly series of factor utilization $\Delta \ln u_t$, and the results by Comin et al. (2020). When using our preferred backcast procedure as our baseline, the correlations are already quite high in particular for Germany (0.96) and Italy (0.93). The correlations even increase when we resort to the capacity utilization for the manufacturing sector also for services and construction (alternative specification).[10]

[10] The remaining differences stem from the fact that we use five-year rolling windows for industry weights to consider structural shifts and data for the whole economy whereas Comin et al. (2020) focus on the market economy.

Combining the quarterly estimates for $\Delta\ln\ TFP_t$ and $\Delta\ln\ u_t$, we obtain the PTFP measures. The lower part of Table 1 shows the correlations between these final series. For our preferred backcast procedure, the correlations are still high for Germany (0.76) and the United Kingdom (0.67). For France and Italy, the relationships between both PTFP measures are robustly positive but far from perfect. The reason lies in the backcast procedure. Using the approach by Comin et al. (2020), we obtain correlations of 0.9 or above for almost all countries. However, we think that our backcast procedure is better suited for quarterly data as it is plausible to assume that the services sector to some extent lags behind the development in the manufacturing sector. Furthermore, the approach of Comin et al. (2020) defines a special case of our procedure as we also allow for contemporaneous effects. In the remainder of the paper, we nonetheless present results for both quarterly series.

Figure 1 relates these quarterly measures for PTFP to the Solow residual and labor productivity for Germany, France, Italy, and the United Kingdom. The PTFP series show a lower volatility than the unadjusted Solow residual. A comparison of the two measures during the financial crisis of 2008/09 shows that the purified TFP measure decreases less strongly in particular in Germany, Italy, and the United Kingdom. This reflects that factor utilization was adjusted significantly during the crisis.

3 Explanation 1: U.S. productivity slowdown

3.1 Motivation: The U.S. as the technology frontier

The contemporaneous deceleration of productivity growth among advanced countries in the last decades, in particular since the mid-2000s, raises the question as to whether there are common forces behind that development. The U.S. is commonly considered as the global frontier of technology and knowledge (Cette et al., 2016; Growiec, 2012). A comparison of TFP levels between major advanced countries also indicates the productivity lead of the U.S. economy in various economic sectors (Elstner and Rujin, 2019). Thus, it seems plausible that a trend towards a lower intensity of technological innovations in the U.S. causes declines in productivity growth in other industrial countries.

This idea motivates our first analysis. In particular, we want to explore whether the recent slowdown in U.S. productivity growth that started in the mid-2000s caused a deceleration in productivity growth in major European countries. To answer that question, we try to figure out whether U.S. technology spills over to other industrial countries in general. Therefore, we need to identify exogenous changes in U.S. technology (henceforth denoted as U.S. technology shocks) and analyze their impact on our measures of PTFP. The challenge of the analysis is to single out (exogenous) changes in U.S. total factor productivity that are neither contaminated by U.S. non-technological factors, e.g., demand shocks, nor by technology gains originating from other major countries.

3.2 Empirical model: A structural time-series analysis

To study spillover effects of U.S. technology shocks, we estimate country-specific SVAR models for each of the four European countries. They contain three variables in first log-differences: U.S. PTFP constructed by Fernald (2014), our PTFP measure for the country under consideration, and a weighted PTFP measure of the four European countries to proxy developments in the rest of the world (ROW PTFP).[11] For the weighting, we resort to five-year rolling windows of the countries' shares in world GDP based on purchasing power parities provided by the IMF. We use seasonally adjusted quarterly data covering a sample period running from 1991q1 to 2019q4. In addition, we include a constant and four lags.

We estimate this model using seemingly unrelated regressions (SUR): the estimation equations of U.S. PTFP and ROW PTFP do not contain the lags of the country-specific PTFP measure. On the one hand, this allows for controlling for European technology spillovers which affect U.S. technology. On the other hand, this specification ensures that the sequences of U.S. technology shocks are the same for all countries under consideration.

The advantage of using PTFP measures is that non-technological changes in productivity are ruled out by construction. Accordingly, by using the PTFP measure of Fernald (2014), we assume that we have already controlled for non-technology factors in U.S. technology growth. However, we still need to separate U.S.-specific (idiosyncratic) technology components from global (common) elements. We do so, by applying the medium-run identification procedure proposed by Uhlig (2004a,b). The resulting series of U.S. technology shocks contains those changes that explain the largest share of fluctuations in U.S. PTFP over a certain time span. In our baseline estimations, we consider a forecast horizon running from three to ten years.[12] We explain this procedure in detail in Appendix C.[13]

[11] We use a broader measure for the Solow residual and labor productivity including additional countries in a robustness check (see Figure D1 in the Appendix).

[12] As we estimate the SVARs in first log-differences, we use cumulated impulse responses to determine the forecast error variance which is necessary for the medium-run identification.

[13] In our opinion, a Cholesky identification which implies a zero-impact restriction of ROW PTFP on U.S. PTFP is problematic. This assumption rules out that technology gains in the major European countries affect the U.S. technology level in the same period. Nonetheless, when considering this identification, our main statements still hold (see Figure D3 in the Appendix).

3.3 Results: Negligible pass-through of U.S. technology changes

Figure 2 shows the dynamic reactions of technology following an exogeneous change in U.S. technology in the four European countries Germany, France, Italy, and the United Kingdom. We normalize the technology impulse to reflect an increase of PTFP in the U.S. by one percent after 20 quarters. For the European countries, we show the responses using the two PTFP measures that we described in Section 2. To account for conditional heteroscedasticity in the data, we construct our confidence bands using the recursive design wild bootstrap procedure proposed by Gonçalves and Kilian (2004).

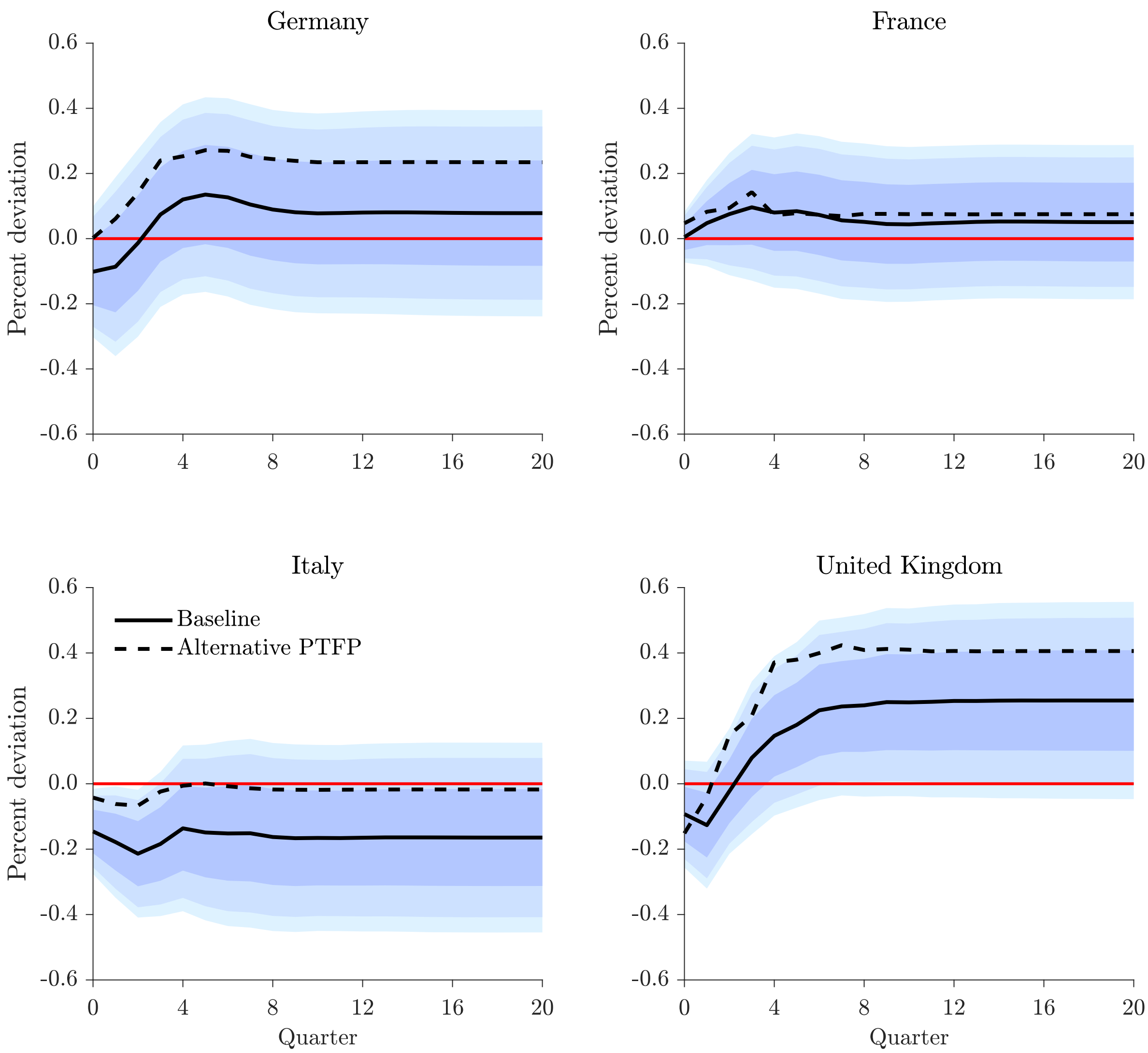
Apart from the United Kingdom, we find rather small productivity spillover effects of U.S. technology shocks. In our baseline estimations, the effects are positive but not significantly different from zero for Germany and France. For Italy, the point estimate is negative, but insignificant. In contrast to this, for the United Kingdom, we find positive spillover effects resulting in a permanent increase of PTFP by 0.2 percent. These effects are statistically significant at a 10-percent confidence level. Overall, this corroborates the findings by Elstner and Rujin (2019) who stress the negligible pass-through of U.S. technology shocks to other industrial countries.

As an alternative PTFP measure, we draw on our second series, in which we backcast the time series for services and construction on the basis of the contemporaneous level of manufacturing capacity utilization (see Table 1). Our main statements also hold for this measure. The point estimates are almost zero over the whole period for Italy and France. We find a higher, albeit insignificant reaction of approximately 0.2 percent after 20 quarters for Germany. The positive spillover effect for the United Kingdom becomes even more pronounced. In this specification, productivity increases permanently by 0.4 percent.

To check the robustness of our results, we perform further analyses. Instead of estimating the responses of PTFP, we use two other measures for productivity: the unadjusted Solow residual as well as labor productivity (see Figure D2 in the Appendix). In addition, we include more lags (8 instead of 4) and use different forecast horizons for our medium-run identification procedure (see Figure D3 in the Appendix). Additionally, we consider broader measures to control for productivity changes in the rest of the world by including a weighted Solow residual or labor productivity for 13 advanced countries into our SVAR models (see Figure D1 in the Appendix). Irrespective of the concrete specification chosen, we only find insignificant or small spillover effects for Germany, France, and Italy as well as positive effects for the United Kingdom.

Our results are closely related to the findings of Imbs (1999) and Huo et al. (2020). Both studies estimate PTFPs based on different utilization variables and show that these measures are uncorrelated across countries. They thus conclude that international technological

Figure 2: The effects of U.S. technology shocks on PTFP in European countries



Notes: The figure shows the accumulated responses of purified TFP (PTFP) in major European countries after an exogenous increase in U.S. TFP (technology shock). The U.S. technology shock amounts to a one percent increase in U.S. PTFP after 20 quarters. Full lines are point estimates using our baseline PTFP measure, dashed lines are point estimates using our alternative PTFP measure. The SVAR models contain U.S. PTFP, the PTFP measure for the country under consideration and ROW PTFP. We estimate our SVAR model with quarterly data beginning with the first quarter of 1991 and ending in the fourth quarter of 2019. All variables are expressed in log-differences and the SVAR model includes four lags and a constant. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004).

propagation does not generate much output comovement. In contrast to our work, these studies determine their empirical results on the basis of a correlation analysis.

In summary, these results suggest that the sluggish U.S. productivity development since the mid-2000s had only small effects on German productivity growth. In the further analysis, it is thus reasonable to abstract from possible spillover effects that might originate from U.S. productivity shocks. Therefore, we focus on two potential domestic explanations: structural shifts on the labor market and the impact of digitization.

4 Explanation 2: Structural shift towards services

4.1 Motivation: Employment increase by over 15 percent

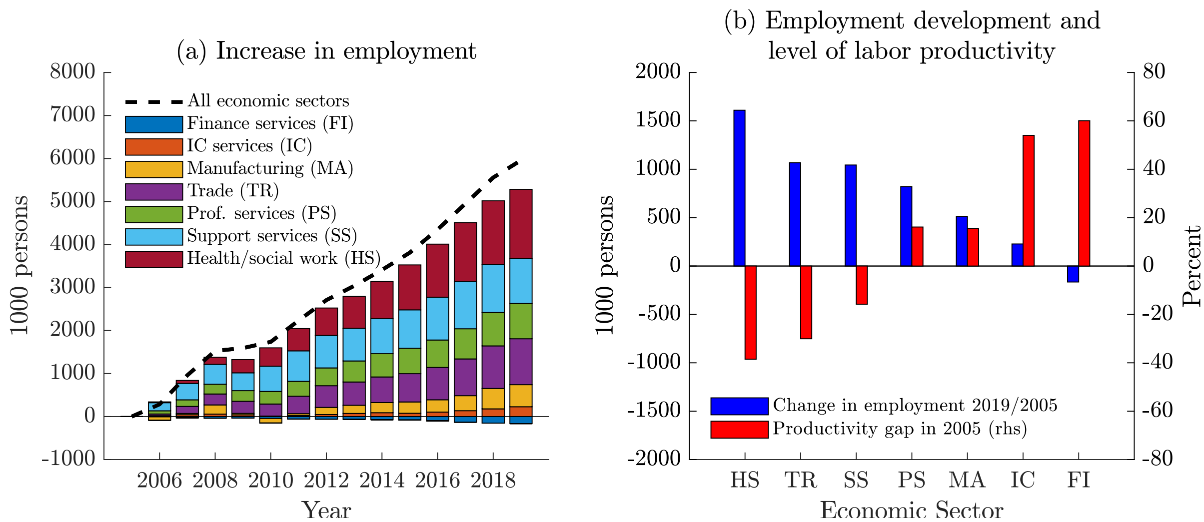
Since our analyses suggest that the slowdown in U.S. productivity growth had only limited effects on German productivity, other explanations are needed for the deceleration of Germany productivity growth. The German economy evolved quite differently from the U.S., and other large European countries such as France, Italy or Spain. A particularly remarkable facet of this development was the strong performance of the labor market in the years during and after the Great Recession. Starting around 2005, Germany experienced a protracted transition to a new structural labor market equilibrium, with higher employment, especially in the services sector, and lower unemployment rates.

From 2005 to 2019, German employment increased by almost six million workers, i.e., by over 15 percent. During this time period, total hours worked only increased by 11.2 percent, since many of the new jobs were part-time jobs. Burda (2016) and Burda and Seele (2020) conclude that the large German labor market reforms that phased in over the period of 2003 to 2005 play a major role in explaining the labor market trend since the mid-2000s.[14] They even talk about the “German labor market miracle”.

Figure 3a displays the sectoral composition of this massive employment growth. New jobs were mainly created in the services sectors, not in the highly productive manufacturing sectors; employment growth was strongest in the sectors trade, transportation and accommo-

[14] These labor market reforms (“Hartz reforms”) were an important part of a comprehensive reform package dubbed “Agenda 2010” that also comprised reforms in the tax system and the social security systems. The Hartz reforms consisted of four packages, see Burda and Hunt (2011) or Jacobi and Kluve (2007) for details. The package “Hartz I” deregulated the temporary working agencies, “Hartz II” increased the incentives of the unemployed to become self-employed. The aim of “Hartz III” was to improve the matching efficiency on the labor market by restructuring the Federal Employment Agency. Finally, the major reform package “Hartz IV” attempted to strengthen the incentives of unemployed workers to search for a job. Among others, Krause and Uhlig (2012), Krebs and Scheffel (2013), Launov and Wälde (2016), Gadatsch et al. (2016), Hartung et al. (2018), Carrillo-Tudela et al. (2021), and Hochmuth et al. (2021) analyze different packages of these reforms, partially with dissenting conclusions.

Figure 3: Development of employment and labor productivity in selected economic sectors



Notes: The left panel shows the accumulated change of employment compared to 2005. For selected economic sectors, the right panel depicts the change in employment between 2005 and 2019 on the left axis, and the difference to the average productivity level in 2005 on the right axis. Labor productivity is defined as real gross value added per worker. We use data from Destatis.

dation, health and social work, administrative as well as support services. Thus, jobs were created disproportionately often in labor-intensive and less productive services sectors (see Figure 3b). We analyze whether the decelerated productivity growth of the last decade could reflect this structural shift towards the services sectors. By keeping sectoral compositions constant, we calculate a counterfactual development of labor productivity.

4.2 Empirical model: A counterfactual path of productivity expansion

It will be prohibitively difficult to construct a counterfactual capturing the development of sector-specific productivity in the hypothetical absence of the German labor market miracle. Yet, by means of a disaggregated analysis at the sector level, we can at least account for the composition effect exerted by the associated structural shifts (de Avillez, 2012). Specifically, we construct a counterfactual aggregate productivity development by taking the developments within individual sectors ("within sector-specific effects") at face value and holding the sectoral composition constant. The difference between the actual and the constructed counterfactual development then captures the effect of the employment shifts between sectors ("reallocation effect"). Arguably, it is the development net of the reallocation effect which should be in the focus of our considerations regarding productivity growth.

In our analysis, we consider 20 sub-sectors for which we have data until the year 2019. The counterfactual development of total labor productivity over time is constructed with reference to a benchmark year 0 as follows:

$$\left(\frac{LP_t^{total} - LP_0^{total}}{LP_0^{total}}\right) = \underbrace{\sum_{i=1}^{20}\left(\frac{LP_t^i - LP_0^i}{LP_0^{total}}\right)n_0^i}_{\text{within sector-specific effects}} + \underbrace{\sum_{i=1}^{20}\left(n_t^i - n_0^i\right)\frac{LP_t^i}{LP_0^{total}}}_{\text{reallocation effect}} \tag{3}$$

with LP_t^{total} denoting aggregate labor productivity at time t and LP_t^i representing the labor productivity of sub-sector i at time t. Finally, n_t^i is the relative proportion of the labor force or hours worked in sub-sector i.

4.3 Results: Composition effect explains a large part of productivity slowdown

Table 2 reports detailed growth contributions to labor productivity for the two periods 1995 to 2005 and 2005 to 2019, respectively. We construct the productivity figures per person employed and per hour. Given our focus on Germany, it seems wise to exclude the first years after German reunification that witnessed a strong catchup process in East Germany. Therefore, we exclude the years before 1995. The implementation of the largest labor market reforms that Germany experienced after its reunification ("Hartz reforms") was finished in the year 2005. This is the reason why we split our sample in this year.

Apparently, the reallocation effect has not been responsible for the majority of productivity advances that were realized since 1995. Rather, the productivity gains over the past 25 years have largely resulted from developments within the individual sectors. Yet, the reallocation effect affects our assessment of the deceleration of productivity growth, since it first provided a slightly positive contribution to labor productivity in the period from 1995 to 2005, as employment increasingly shifted to the productive economic sectors. Thereafter, its contribution was rather negative, due to the structural shift towards the relatively unproductive services sectors.

Specifically, the growth contributions arising from the reallocation effect are negative for the years between 2005 and 2019. Compared to the previous 10 years, this negative reallocation effect has caused the annual increase in macroeconomic productivity (person concept) to decline by around 0.4 percentage points since the year 2005. This result is the same whether we construct the productivity figures per hour or per person employed. The analysis of the within sector-specific effects shows that in comparison to the period 1995 to 2005, between 2005 and 2019 the combined growth contributions of the less productive

Table 2: Growth contributions to aggregate labor productivity (in percentage points)

	Share	Per person employed		Per hour	
	(in percent)	1995-2005	2005-2019	1995-2005	2005-2019
Within sector-specific growth contributions					
Manufacturing	22.2	0.6	0.3	0.7	0.3
Services sector	70.1	0.2	0.4	0.8	0.6
including:					
Wholesale and retail trade, transport and storage, accommodation	16.3	0.3	0.1	0.5	0.2
Information and communication	4.6	0.2	0.2	0.2	0.2
Professional, scientific and technical activities	6.5	-0.2	-0.1	-0.1	-0.1
Administrative and support service activities	4.3	-0.1	0.0	0.0	0.0
Human health and social work activities	6.6	0.0	0.0	0.1	0.0
Reallocation effect		0.1	-0.2	0.2	-0.2
Development of labor productivity (in percent)					
Actual development		1.1	0.5	1.7	0.7
Development without structural shifts		1.0	0.7	1.6	0.9

Notes: The calculations of the within sector-specific growth contributions and the reallocation effects are based on Equation 3. The development without structural shifts shows the development of aggregate labor productivity without the reallocation effect. The share of the corresponding sector in total gross value added refers to the year 2005. Please note the difference at the aggregate level between gross domestic product and gross value added. We use data from Destatis.

sectors trade, transportation and accommodation, health and social work, administrative and support services have annually shaved off 0.2 percentage points of productivity growth per person employed.

These results indicate that the annual decline in the growth rate of productivity per person employed, from 1.1 percent during the period 1995 to 2005 to only 0.5 percent since 2005, can largely be explained by the composition effect resulting from the structural shifts in the labor market. A similar conclusion emerges in the analysis of hourly productivity. The productivity gain generated by the manufacturing sector has declined considerably by 0.4 percentage points since the year 2005. And yet, some of the deceleration still remains to be explained.

5 Explanation 3: Low productivity effects of ICT

5.1 Motivation: Weak transmission of technological progress to other sectors

Our results from Section 4 suggest that a large part of the slowdown in German productivity growth reflects a composition effect, induced by the labor market integration of almost six million workers. The perceived widespread digitization of the German economy, caused by large technology gains in ICT, apparently did not offset these dampening influences on productivity growth. In order to move towards a resolution of this remaining productivity paradox, we analyze the effects of digitization on productivity growth in more detail. It turns out that, to understand this sluggish reaction to digitization, we need to address both elements of labor productivity separately, economic output and employment. Additionally, we distinguish between the ICT-producing sector and the rest of the economy.

We are particularly interested as to how technological progress originating from the ICT-producing sector is transmitted to other economic sectors of the economy. Higher investment in ICT should raise productivity growth in the industries that produce ICT goods most directly. This technological progress causes a decline in the relative price of ICT investment goods and, thus, affects capital deepening in ICT-intensive industries, i.e., industries that make greater use of ICT. This channel is often related to investment-specific technological change, as Greenwood et al. (1997) and Fisher (2006) emphasize.

Studies using growth accounting frameworks to determine the contribution of ICT to productivity growth show that in Germany, the ICT-producing and ICT-intensive economic sectors contributed relatively little to aggregate labor productivity growth (Eicher and Roehn, 2007). By contrast, U.S. productivity growth in the second half of the 1990s was heavily concentrated in the ICT-producing manufacturing sector, as quality-adjusted computer prices began to fall rapidly (Jorgenson, 2001). Stiroh (2002) shows with U.S. industry data that the gains in productivity in the ICT-producing sectors were followed by significant productivity surges in ICT-intensive sectors like wholesale and retail trade or business services effects at the turn of the century.

To study how technological progress originating from producers of ICT goods and services is transmitted to other sectors of the economy, we propose a novel approach for identifying exogenous technological changes originating from ICT (ICT technology shocks) by combining a structural vector autoregressive (SVAR) model with medium-run restrictions and the relative price of ICT goods and services. Thereby, from a methodological perspective, we suggest a method that tries to provide evidence regarding the economic effects caused by ICT-related technological progress.

5.2 Empirical model: Two-step identification procedure

Model specification

To classify the ICT sector, we adopt the definition by the German Federal Statistical Office (Destatis, 2017) which follows the OECD definition for the ICT-producing sector by combining manufacturing and services industries. It comprises manufacturing of computer, electronic and optical products as well as the services sectors telecommunication and IT services (computer programming, consultancy, related activities).[15] We subsume the remaining industries into a "non-ICT sector".

To answer our research question, we first determine technological changes that have long-run effects on labor productivity using a SVAR model. Second, we isolate ICT technology shocks from other productivity advancements (neutral technology shocks). We distinguish between both types of technology shocks by resorting to the relative price of produced value added between the ICT and the non-ICT sector, $Price_t^{ratio}$. ICT technology shocks exert strong short run effects on $Price_t^{ratio}$, while this is not the case for neutral technology shocks. This assumption refers to the hedonic price measurement of Destatis, that tries to incorporate ICT-related technology gains in the price deflators of the industries in the ICT sector.

Our approach is motivated by the literature studying the effects of investment-specific technology shocks (Fisher, 2006). In contrast to Fisher (2006), we incorporate two labor productivity measures in our analysis, one for the ICT sector, LP_t^{ICT}, and one for the non-ICT sector, LP_t^{nonICT}. We further impose a different restriction regarding the horizon of the price effects of ICT technology shocks in our baseline model. Our SVAR model has five variables. We consider LP_t^{ICT}, LP_t^{nonICT}, $Price_t^{ratio}$, hours per worker, and total employment.[16] We estimate our SVAR model with quarterly data beginning in the first quarter of 1991 and ending in the fourth quarter of 2017.[17]

We additionally face the problem that some time series are only available at an annual frequency. To construct the data set, it is necessary to determine quarterly time series for gross value added, the price deflators and working hours for the ICT and non-ICT sector. As Destatis only provides annual data for the individual economic sectors, we interpolate

[15] Due to data limitations, we are not able to incorporate the wholesale of ICT, software publishing and the repair of computers and communication equipment in our measure. In the year 2015, our considered ICT sector generated about 70 percent of the sales in the total ICT sector defined by Destatis (2017). The remaining 30 percent are almost entirely due to the missing ICT wholesaling. Regarding investment expenditures, our sector definition encompasses more than 97 percent of the total ICT sector.

[16] Our main findings do not change if we use total hours worked instead of hours per worker and total employment.

[17] An earlier starting point of our sample would not be useful as Destatis has not conducted a hedonic price adjustment for ICT goods prior to 1991 which is crucial for our identification. Our sample ends in 2017 as there is no further data available for the ICT sector.

these annual time series by using the Chow-Lin interpolation procedure and higher frequency indicators. Details are provided in Appendix E. All variables are expressed in log-differences and the SVAR model includes four lags and a constant.

Identification of ICT technology shocks

To identify ICT technology shocks, ε_t^{ICT}, we use an identification scheme that proceeds in two steps. In a first step, we use medium-run restrictions to separate all types of technology shocks from non-technology factors. In a second step, we extract only those technology shocks stemming from the ICT sector from these shocks.

Step 1: Using our SVAR model with five variables, we identify all shocks related to technology. We use them as auxiliary shocks. To do so, we apply the medium-run identification procedure proposed by Uhlig (2004a). Analogous to Section 3.2, we first select candidates for "shocks" that account for the largest forecast error variance (FEV) of our target variables over a specific forecast horizon.

We single out three auxiliary shocks u_t^{ICT}, u_t^{nonICT}, and u_t^{price} that maximize the FEV of LP_t^{ICT}, LP_t^{nonICT}, and $Price_t^{ratio}$, respectively. For u_t^{ICT} and u_t^{nonICT}, we consider a medium-run forecast horizon running from 12 to 40 quarters, which is in line with Uhlig (2004a). For the price ratio, we focus on a shorter forecast horizon running from 0 to 8 quarters because the hedonic price measurement by Destatis should capture adjustments in the short run.[18]

Step 2: The resulting auxiliary shocks are still correlated with each other due to the partial identification nature of medium-run restrictions. Therefore, we attach a second step to extract only ICT-related technology shocks. Conceptually, this step can be split in two parts. First, we obtain neutral technology shocks, ε_t^N, by regressing u_t^{nonICT} on u_t^{price}. By construction, this residual is not the main driver of fluctuations in the relative price. Second, we regress u_t^{ICT} on these neutral technology shocks ε_t^N. The residuals from this second regression, ε_t^{ICT}, are uncorrelated with neutral technology shocks. Therefore, we use this shock series as exogenous ICT-related changes in the technology level of the ICT sector.

Technically, we consolidate both steps by applying two QR-decompositions to the three eigenvectors that define the auxiliary shocks. Appendix F discusses more details on this procedure.

[18] In a robustness check, we vary these horizons for productivities and the price level, see Figure G1 in the Appendix.

5.3 Results: Positive effects on GDP and employment cushion productivity growth

Figures 4a and 4b depict the accumulated impulse response functions of labor productivity in the non-ICT and the ICT sector after an ICT technology shock. The impulse response functions suggest that such shock leads to a sizeable and permanent increase in labor productivity in the ICT sector, whereas the reaction in the non-ICT sector is insignificant throughout. According to the point estimates, the initial positive reaction of productivity in the non-ICT sector even turns into the opposite after one year. At first glance, it therefore seems that technological progress in the ICT sector has no effects on the remaining economy.[19]

Figures 4c and 4d display the historical contributions of the ICT technology shocks on labor productivity growth in both sectors for the years 1995 to 2017. Two results stand out: First, despite the fact that ICT technology shocks seem to play a crucial role in explaining the movements in annual labor productivity growth in the ICT sector, we have not seen strong positive effects in recent years. From a historical perspective, the strongest contributions were observed in the years 1998 and 2007. As well, the actual growth rates do not suggest that the ICT sector has experienced significant productivity gains in recent years. To some extent, this observation challenges the popular impression that the pace of digitization has accelerated recently ("digital revolution"). Second, the effects of ICT technology shocks on the productivity growth rates in the non-ICT sector are limited. This is hardly surprising, as the corresponding impulse response function was already insignificant.

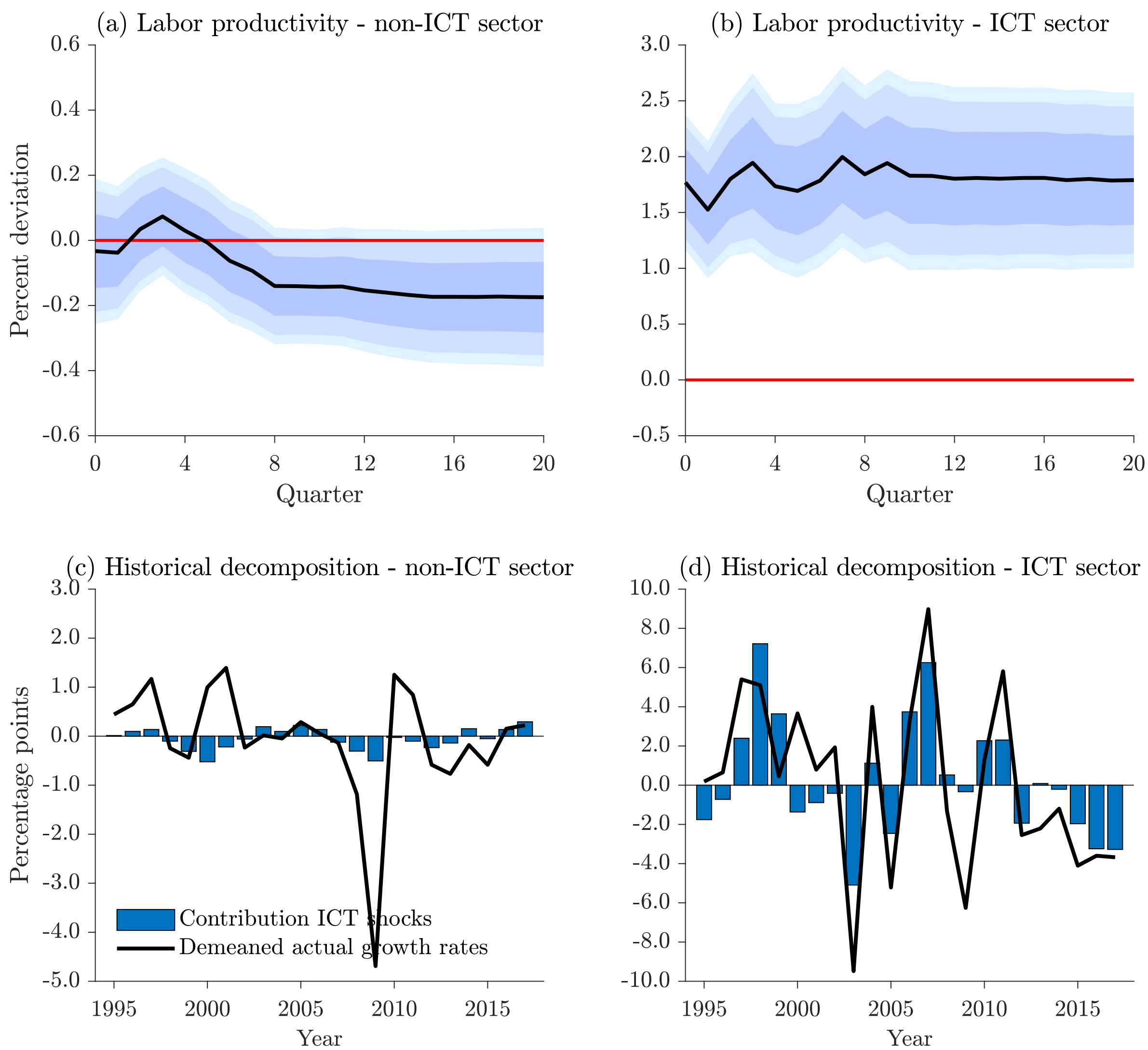
After all, these results suggest that technological progress originating in the ICT sector was rather small in the years after 2012. Furthermore, the transmission of productivity advancements from the ICT sector to the non-ICT sector apparently tends to be quite modest. These results might be an explanation for the productivity paradox.

But what are the reasons for these findings? Figure 5 provides a possible answer. It displays the reactions of gross value added and employment of the total economy after an ICT technology shock. The impulse response function for gross value added is determined by using a subset SVAR in which we impose the restrictions that the respective variable is not included in the equations of the initial SVAR model. Our results indicate that both production and employment rise considerably after an ICT technology shock. Furthermore, the size of both dynamic reactions is almost the same. As a result, the net effect on productivity is almost zero.[20]

[19]For neutral technology shocks, we find permanent positive reactions for labor productivity in both sectors. Results are available upon request.

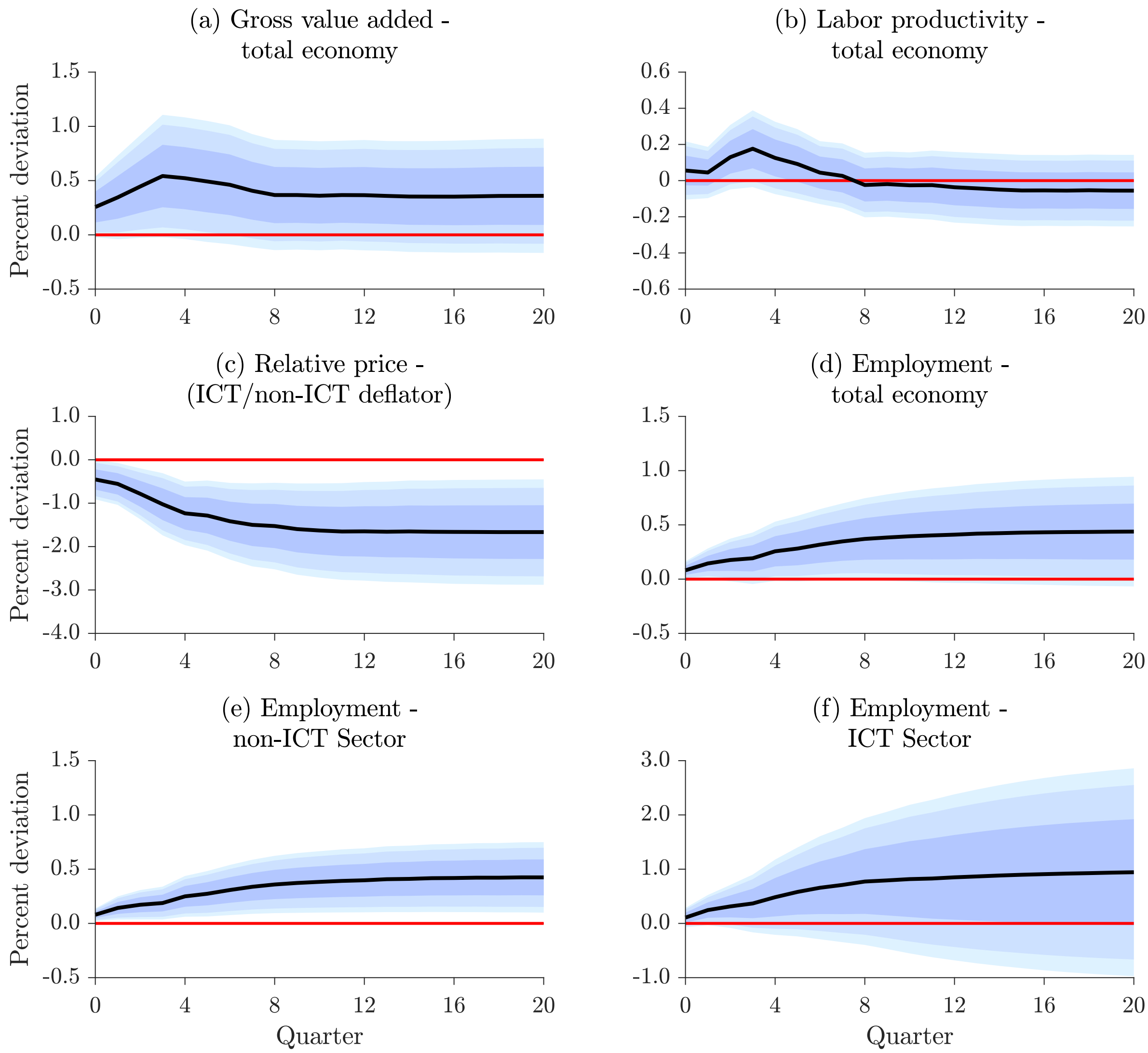
[20]Elstner et al. (2020) analyze the effects of ICT related technological change at a more disaggregate level using local projections. To determine ICT technology shocks, they use our identification method but a different VAR model and time sample. They find similar results.

Figure 4: Effects of an ICT technology shock



Notes: The upper two panels depict accumulated impulse response functions after an ICT technology shock identified by using our two-step procedure. The lower two panels show historical decompositions. The SVAR model contains labor productivity of the non-ICT sector and the ICT sector, the relative price of produced value added between the ICT sector and the non-ICT sector, hours per worker and total employment. We estimate the SVAR model with quarterly data beginning with the first quarter of 1991 and ending in the fourth quarter of 2017. All variables are expressed in log-differences and the SVAR model includes four lags and a constant. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004).

Figure 5: Responses of macroeconomic variables to an ICT technology shock



Notes: This figure depicts the accumulated impulse response functions for several macroeconomic variables after an ICT technology shock identified by using our two-step procedure. The SVAR model contains labor productivity for the non-ICT sector and the ICT sector, the relative price of produced value added between the ICT sector and the non-ICT sector, hours per worker and total employment. The impulse response functions of employment in the non-ICT and ICT sector are determined by using a subset SVAR in which we impose the restrictions that these variables are not included in the equations of the initial SVAR model. We estimate our SVAR model with quarterly data beginning with the first quarter of 1991 and ending in the fourth quarter of 2017. All variables are expressed in log-differences and the SVAR model includes four lags and a constant. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004).

This result is in line with theoretical and empirical predictions. Fisher (2006) and Altig et al. (2011) find similar results for the U.S. Interestingly, theoretical DSGE models such as Smets and Wouters (2007) predict similar outcomes. In these models, after an investment specific technology shock labor input rises by almost the same amount as output. The intuition behind this result is that the new investment goods lead to a higher labor demand as the marginal product of labor increases. Moreover, a higher demand for more productive investment goods raises the real interest rate which causes private households to consume less and work more.

We check how much our conclusions depend on our identification assumptions. First, we vary the forecast horizons used for our medium-run identification procedure (see Figure G1 in the Appendix). Second, we include additional variables in our SVAR model. Figure G2 in the Appendix shows the results. The findings are in line with our main results. To sum up, they show that the digitization of the German economy seems to have strong positive effects on German GDP and employment. However, it seems questionable whether the new ICT goods exert a sizeable positive effect on productivity.

6 Conclusions

This paper addresses the question as to why the German economy has experienced a marked slowdown in productivity growth in recent years, despite the general perception that increasing digitization causes rapid technological change. The growth rate of productivity per person employed decreased from 1.1 percent during the period 1995 to 2005 to only 0.5 percent since 2005. A similar conclusion emerges in the analysis of hourly productivity. Our analysis provides the following explanations:

(i) We find only small spillover effects from U.S. technology changes on German productivity growth. This suggests that the German situation seems to be special as compared to other advanced countries.

(ii) A sizeable part of the slowdown in German productivity growth is a side effect of the labor market performance since the year 2005. The integration of almost six million people into the labor market caused an attenuating effect on productivity growth as it induced a structural shift towards the services sector. Reallocation between more productive and less productive sectors of the economy accounts for some 0.4 percentage points of the annual productivity growth decline since the year 2005.

(iii) Technological progress originating in the ICT-producing sector has significant positive effects on GDP and employment. The net effect on labor productivity, however, is modest. Consequently, increasing digitization leads to higher production and employment, but not to sizably higher productivity. For the years after 2012, technological progress in the ICT-producing sectors seems to be low, which might be an additional explanation for the German productivity paradox.

While our analysis provides several plausible answers to the German productivity paradox, it raises further research questions. One possible question concerns the limited spillover effects in labor productivity between the U.S. and German economy. A deeper look into industry data could provide further insights regarding this point. Furthermore, we think that more research with respect to the reasons for the permanent shift in the productivity level of the highly export-oriented German manufacturing is needed. One explanation could lie in the link between world trade, global value added and productivity growth.

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Appendix

A Data definitions and sources

Table A1: Variables used in Sections 2 and 3: Description and sources

Variable	Description	Source
Utilization-adjusted quarterly TFP series for the U.S.	Quarterly data series for the U.S. business sector, adjusted for variations in factor utilization, labor effort and capital's work-week; constant prices; seasonally adjusted; data availability: 1947:1–2021:1; downloadable from `http://www.johnfernald.net/TFP`	Fernald (2014)
TFP series (EU-Klems)	Annual data series; constant prices; data availability: Germany 1997–2015, France 1982–2015, Italy 1997–2014, United Kingdom 1999–2015	EU-Klems database
TFP series (PWT)	Annual data series; constant prices; data availability: 1970–2019; used to extend the annual time series of the EU-Klems database; downloadable from `www.ggdc.net/pwt`	Penn World Tables, version 10.0, Feenstra et al. (2015)
Hours worked (Eurostat)	Quarterly data series; seasonally adjusted; data availability: Germany and France 1991:1–2019:4, Italy and UK 1995:1–2019:4	Eurostat
Hours worked (Ohanian/Raffo)	Quarterly data series; seasonally adjusted; data availability: 1960:1–2016:4 (for the U.K.: 1971:1-2016:4); used to extend the annual time series from Eurostat; downloadable from `http://andrearaffo.com/araffo/Research.html`	Ohanian and Raffo (2012)
GDP	Quarterly data series; constant prices; seasonally adjusted; 1970:1–2019:4	OECD-Economic Outlook database
Value added	Annual data series; nominal prices; data availability: Germany, Italy and United Kingdom 1995-2017, France 1990-2017	OECD-Economic Outlook database
Gross output	Annual data series; nominal prices; data availability: Germany, Italy and United Kingdom 1995-2017, France 1990-2017	OECD-Economic Outlook database
Production elasticities	Annual data series; data availability: 1970–2019; downloadable from `www.ggdc.net/pwt`	Penn World Tables, version 10.0, Feenstra et al. (2015)
Gross fixed capital formation (investment)	Quarterly data series; constant prices; seasonally adjusted; data availability: 1970:1–2019:1; used to construct a quarterly series for the capital stock	OECD

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Table A1 – *Continued from previous page*

Variable	**Description**	**Source**
Countries' shares in world GDP	Gross domestic product based on purchasing-power-parity (PPP), share of world total; annual data series; data availability: 1985–2020	IMF, World Economic Outlook Database, October 2020
Capacity utilization	Survey data for industries; quarterly data series; seasonally adjusted; data availability for the manufacturing sector: Germany, France and Italy 1991:1–2019:4, UK 1994:3–2019:4, for the services sector: Germany 2011:1–2020:4, France 2011:4–2019:4, Italy 2010:1–2019:4, UK 2011:3–2019:4, for the construction sector: Germany and France 1991:1–2019:4	Eurostat
Business situation of firms in the services sector	Survey data for industries; quarterly data series; seasonally adjusted; data availability: Germany 1995:2–2019:4, France 1991:1–2019:4, Italy 1998:1–2019:4, UK 1997:1–2019:4	Eurostat

Notes: All series were downloaded from the cited sources in March 2021 at the most recent vintage available at that time.

Table A2: Variables used in Section 5: Description and sources

Variable	**Description**	**Source**
Gross value added ICT manufacturing	Annual time series for ICT manufacturing is converted into a quarterly data series using the real production index for the manufacture of computer, electronic and optical products (c.e.o. products), Chow-Lin procedure, the annual correlation between both time series is 0.89; constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Federal Statistical Office (Destatis)
Deflator ICT manufacturing	Deflator gross value added corresponds to nominal gross value added divided by real gross value added; annual time series for ICT manufacturing is converted into a quarterly series using the producer price index of c.e.o. products, Chow-Lin procedure, the annual correlation between both time series is 0.69; seasonally adjusted; period 1991:1–2017:4	Destatis
Hours worked ICT manufacturing	Quarterly data series is constructed using the hours worked series for the total manufacturing, Chow-Lin procedure, the annual correlation between both time series is 0.95; seasonally adjusted; period 1991:1–2017:4	Destatis
Employment ICT manufacturing	Quarterly data series is constructed using the employment series for the total manufacturing, Chow-Lin procedure, the annual correlation between both time series is 0.95; seasonally and working day adjusted; period 1991:1–2017:4	Destatis

Continued on next page

Table A2 – *Continued from previous page*

Variable	**Description**	**Source**
Gross value added ICT services	Annual time series for the two ICT sub-sectors are converted into a quarterly data series using the real gross value added time series for the total German information and communication sector (ICT sector), Chow-Lin procedure, the annual correlations between both time series are 0.76 (telecommunication) and 0.83 (IT services); constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Nominal gross value added ICT services	Quarterly data series are constructed using the nominal gross value added time series for the total IC sector, Chow-Lin procedure, the correlations between these time series are 0.79 (telecommunication) and 0.75 (IT services); constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Hours worked ICT services	Quarterly data series are constructed using the hours worked series for the total IC sector, Chow-Lin procedure, the annual correlations between these time series are 0.69 (telecommunication) and 0.74 (IT services); constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Employment ICT services	Quarterly data series are constructed using the employment series for the total IC sector, Chow-Lin procedure, the annual correlations between these time series are 0.53 (telecommunication) and 0.85 (IT services); constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Gross value added total ICT sector	Growth rate is computed using the sum of the weighted quarterly growth rates of real gross value added of the ICT manufacturing and the ICT services, the corresponding weights are the proportions in nominal gross value added of all three ICT sectors of the previous quarter; period 1991:1–2017:4	Destatis
Private consumption	Final consumption expenditures of households; constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Equipment investment	Gross fixed capital formation: machinery and equipment; constant prices; seasonally and working day adjusted; period 1991:1–2017:4	Destatis
Terms of trade	Ratio between export and import deflator; seasonally and working day adjusted; period 1991:1–2017:4	Destatis

Notes: ICT manufacturing corresponds to manufacture of computer, electronic and optical products. ICT service sector includes the two service sectors telecommunication and IT services (computer programming, consultancy and related activities). All series were downloaded from the cited sources in May 2020 at the most recent vintage available at that time.

B Assignment of industries to sectors and utilization adjustment coefficients

Table B1: Composition of the three broad sectors

Industry sub-sectors	**NACE Codes**
Nun-durable manufacturing	
Food products, beverages, tobacco products	C10–12
Textiles, wearing apparel, leather and related products	C13–15
Products of wood, cork, and paper; printing and reproduction	C16–18
Chemicals and chemical products; pharmaceuticals	C20–21
Rubber, plastic, and other non-metallic mineral products	C22–23
Durable manufacturing	
Basic metals; fabricated metal products	C24–25
Computer, electronic and optical products; electrical equipment	C26–27
Machinery and equipment	C28
Motor vehicles, trailers and semi-trailers; other transport equipment	C29–30
Furniture; other manufacturing; repair and installation of machinery and equipment	C31–33
Non-manufacturing	
Electricity, gas and water supply	D,E
Construction	F
Wholesale and retail trade; repair of motor vehicles and motorcycles	G
Transportation and storage	H
Accommodation and food service activities	I
Information and communication	J
Financial and insurance activities	K
Professional, scientific and technical activities; administrative and support service activities	M,N
Arts, entertainment and recreation; other service activities	R,S

Notes: The table lists the industry sub-sectors and NACE Codes that form the three broad sectors for which Comin et al. (2020) provides estimates which we use to determine an aggregate measure of capacity utilization in Section 2.2.

Table B2: Estimates for utilization adjustment coefficients by Comin et al. (2020)

	Germany	France	Italy	United Kingdom
Elasticities $\hat{\beta}$				
Non-durable manufacturing	0.562	0.070	0.400	0.119
Durable manufacturing	0.392	0.255	0.337	0.228
Non-manufacturing	0.122	0.203	0.201	0.376

Notes: This tables presents the elasticities $\hat{\beta}_i$ for the three broad sectors used in Equation 2. The estimates for utilization adjustment coefficients are extracted from Comin et al. (2020), Table 7 ("Utilization adjustment regressions (survey-based utilization proxy)".

C Identification of U.S. technology shocks

In this Appendix, we explain in more detail the identification of exogenous U.S. technology changes that we use in Section 3.2. We apply the medium-run identification procedure proposed by Uhlig (2004a,b). This procedure extracts the structural shock that accounts for the largest forecast error variance share of fluctuations in U.S. PTFP over a certain time span.

In reduced form, the moving average representation of Y_t – which is a $k \times 1$ vector of endogenous variables at time t where we order U.S. purified TFP first – is given by:

$$Y_t = C(L)\, u_t. \tag{C1}$$

The vector of prediction errors is denoted by u_t with a covariance matrix of $\sum_u$. The vector of structural shocks ε_t can be represented as a linear combination of prediction errors $u_t = A\varepsilon_t$. To derive ε_t, the impact matrix A must satisfy $\sum_u = AA'$. Because of the symmetry of $\sum_u$ the solution is not unique. By conducting a Cholesky decomposition of $\sum_u$, we obtain a matrix $\widetilde{A}$. This allows us to condense the entire space of acceptable impact matrices to $A = \widetilde{A}Q$, where Q is a $k \times k$ orthonormal matrix ($QQ' = I$). The resulting structural moving average representation of Y_t is:

$$Y_t = C(L)\, \widetilde{A} Q \varepsilon_t. \tag{C2}$$

The goal of the identification approach by Uhlig (2004a) is to select the structural shock that accounts for the largest forecast error variance share of some target variable $y_{i,t}$ in Y_t over a forecast horizon $h = \underline{h} \leq \overline{h}$. Following Uhlig (2004a), we set the starting point $\underline{h}$ of this forecast horizon to 12 quarters, and the ending point $\overline{h}$ to 40 quarters.

The forecasting equation of $y_{i,t}$ for h steps ahead can be written as:

$$y_{i,t+h} - E_t y_{i,t+h} = e_i' \left[\sum_{l=0}^{h-1} C_l \widetilde{A} Q \varepsilon_{t+h-l} \right], \tag{C3}$$

where e_i is a column vector with one in the i-th position and zeros elsewhere. The maximization problem that determines the shock that explains most of the forecast error variance of the i-th variable in Y_t is:

$$q_1^* = arg\ max_{q_1} e_i' \left[\sum_{h=\underline{h}}^{\overline{h}} \sum_{l=0}^{h-1} C_l \widetilde{A} q_1 q_1' \widetilde{A'} C_l' \right] e_i \quad s.t. \quad q_1' q_1 = 1, \tag{C4}$$

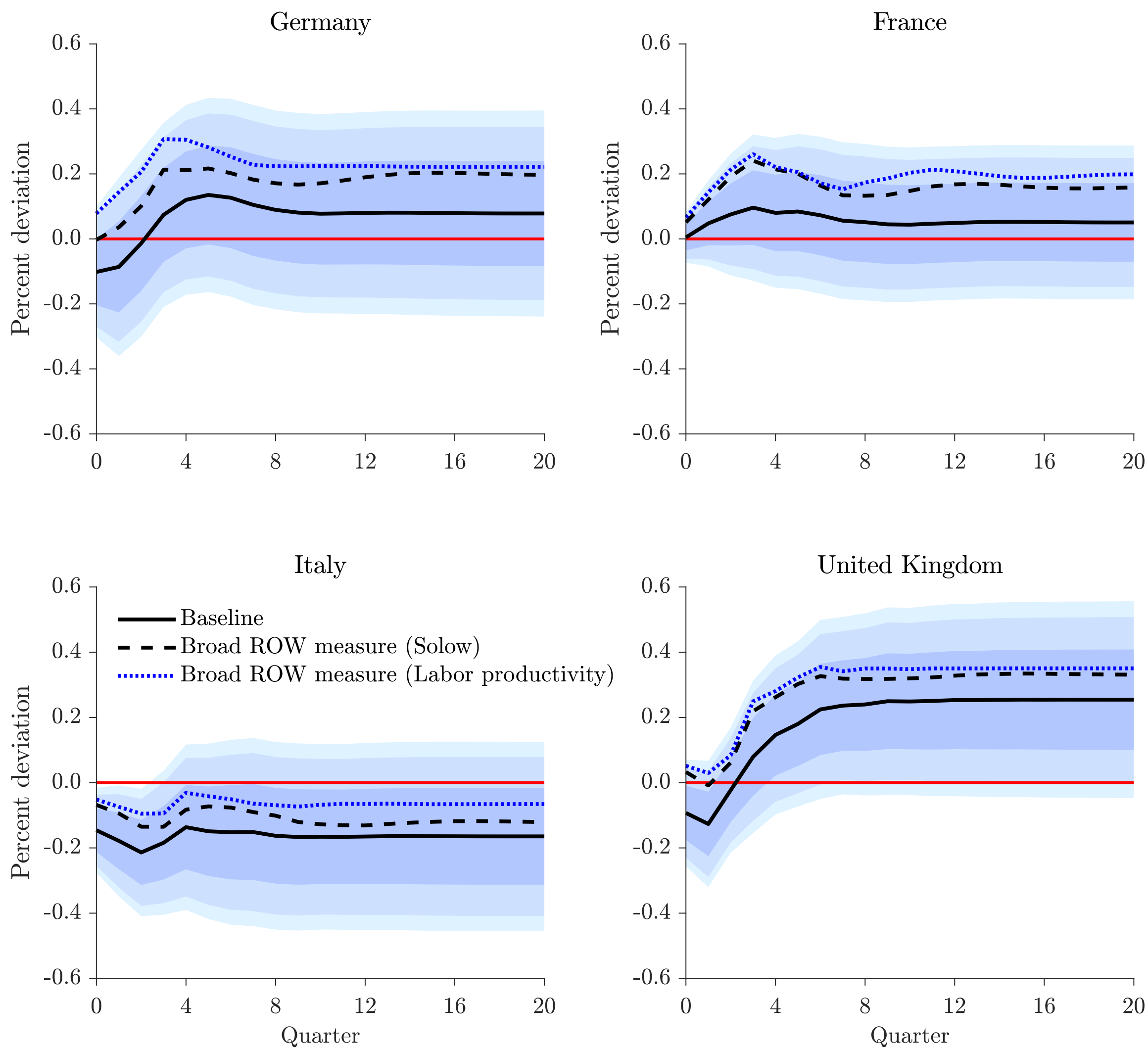
where q_1 is a vector of unit length that represents a column of Q. This problem can be expressed as $Sq_1 = \lambda q_1$, where

$$S = \sum_{h=\underline{h}}^{\overline{h}} \sum_{l=0}^{h-1} \left(C_l \widetilde{A} \right)' (e_i e_i') \left(C_l \widetilde{A} \right). \tag{C5}$$

By solving for the eigenvector q_1 with the maximal eigenvalue λ of the matrix S, we receive the structural shock associated with the largest forecast error variance of $y_{i,t}$ over our forecast horizon $h = \underline{h} \leq \overline{h}$.

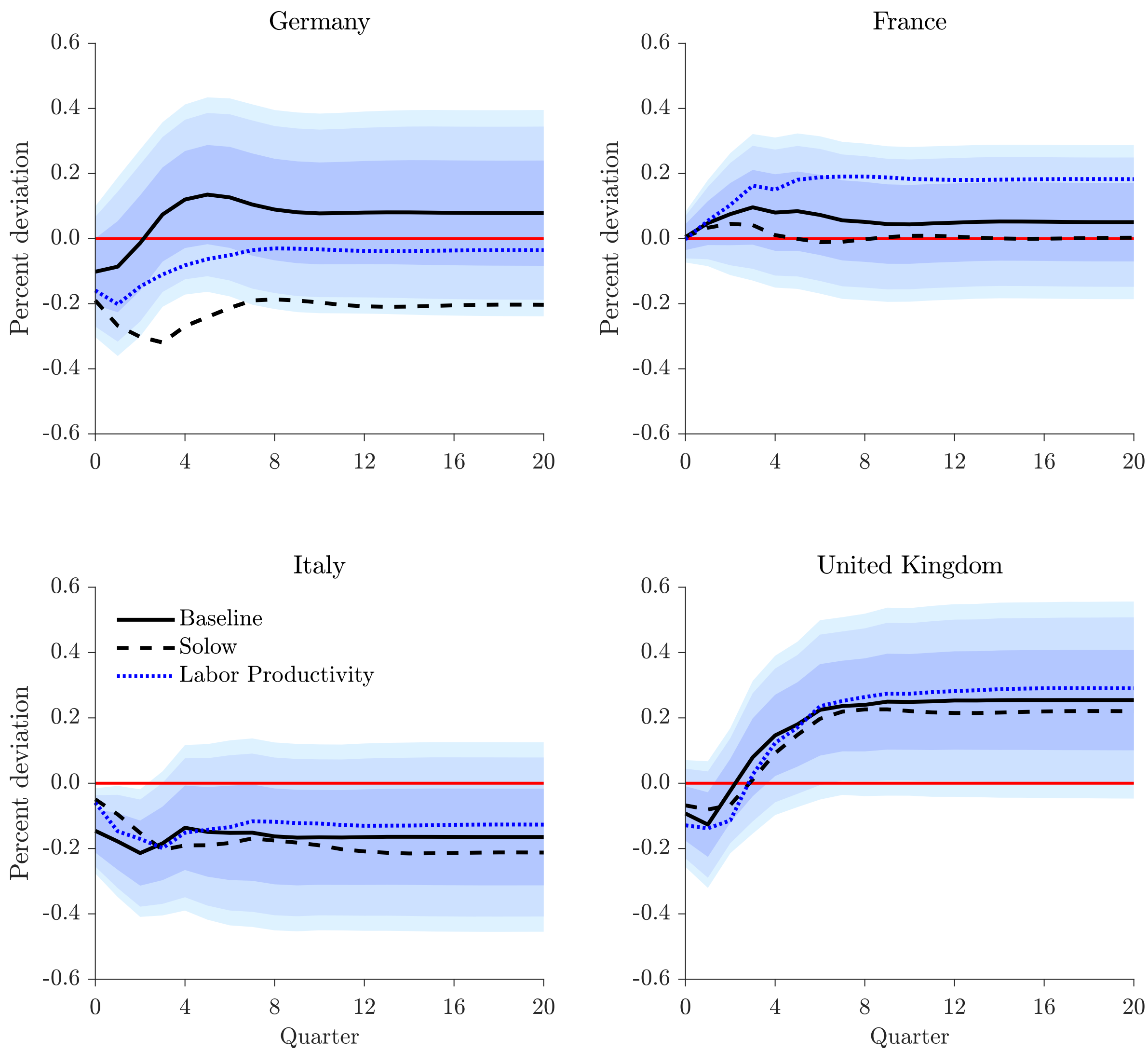
D International spillover effects: Robustness checks

Figure D1: Robustness check: Effects of U.S. technology shocks on PTFP measures in European countries, broader measure for the rest of the world



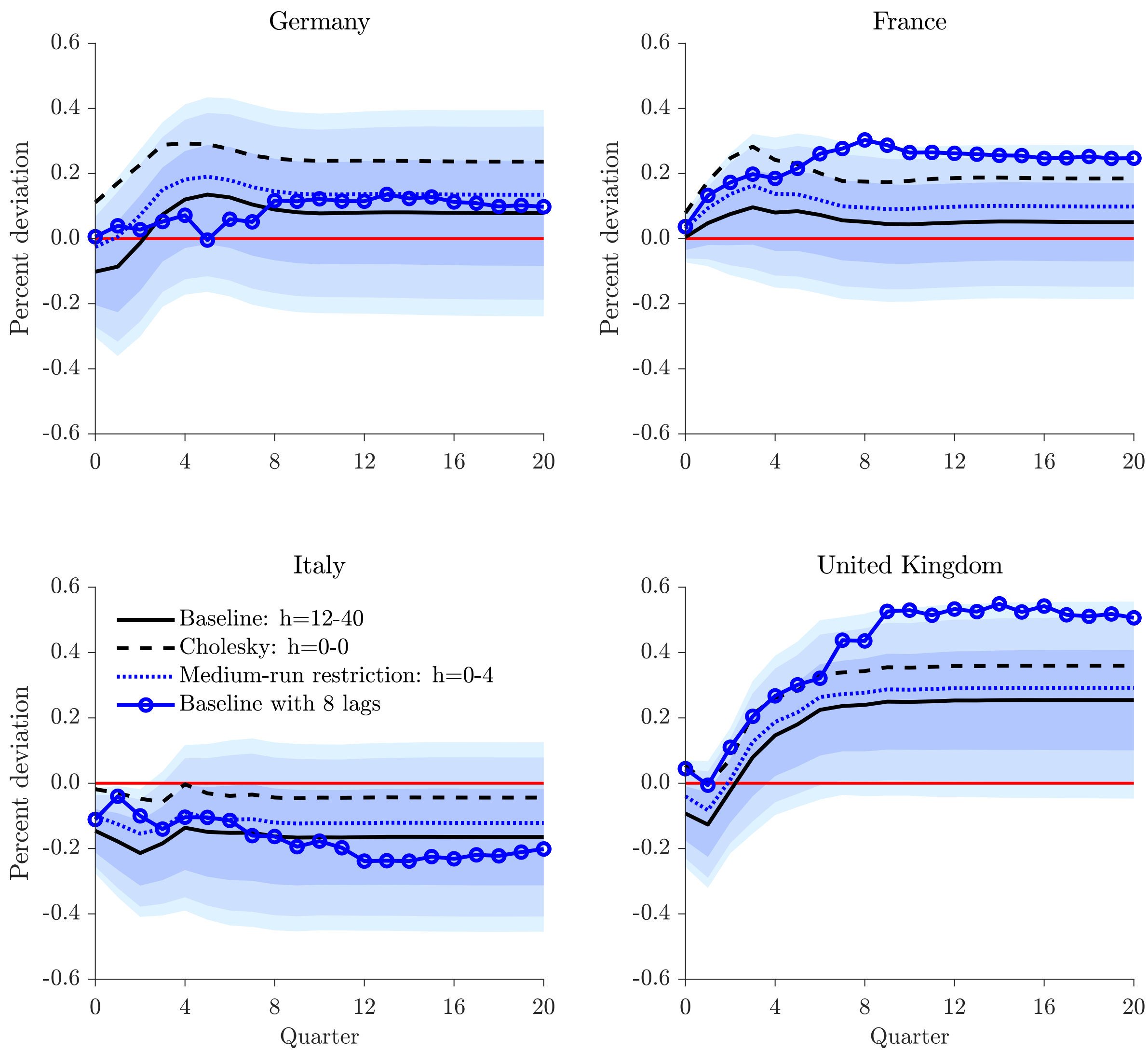
Notes: The figure shows the accumulated responses of purified TFP (PTFP) in major European countries after an exogenous increase in U.S. TFP (technology shock) for different measures for the rest of the world (ROW). The U.S. technology shock amounts to a one percent increase in U.S. PTFP after 20 quarters. Full lines are point estimates using our baseline SVAR model, dashed lines are point estimates from a specification where we include a weighted Solow residual for the 13 countries Australia, Austria, Canada, Germany, Finland, France, Ireland, Italy, Japan, South Korea, Sweden, and the United Kingdom instead of the weighted PTFP measure for the four European countries, dotted blue lines are point estimates from a specification where we include weighted labor productivity for these 13 countries. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004), and refer to the baseline specification.

Figure D2: Robustness check: Effects of U.S. technology shocks on different productivity measures in European countries



Notes: The figure shows the accumulated responses of different country-specific technology measures in major European countries after an exogenous increase in U.S. TFP (technology shock). The U.S. technology shock amounts to a one percent increase in U.S. PTFP after 20 quarters. Full lines are point estimates using our baseline PTFP measure, dashed lines are point estimates using the Solow residual, dotted blue lines are point estimates using hourly labor productivity. These measures are also used for the average European productivity measure that enters the SVAR model. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004), and refer to the baseline specification.

Figure D3: Robustness check: Effects of U.S. technology shocks on PTFP measures in European countries, model specifications



Notes: The figure shows the accumulated responses of purified TFP (PTFP) in major European countries after an exogenous increase in U.S. TFP (technology shock) for different identification assumptions. The U.S. technology shock amounts to a one percent increase in U.S. PTFP after 20 quarters. Full lines are point estimates using our baseline SVAR model. Dashed lines are point estimates from an identification procedure using a Cholesky decomposition. Dotted blue lines refer to a specification where we set the starting point of the forecast horizon to 0 quarters, and the ending point to 4 quarters. Blue lines with circles are point estimates from our baseline estimation with 8 instead of 4 lags. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004), and refer to the baseline specification.

E Determining quarterly time series for the ICT sector

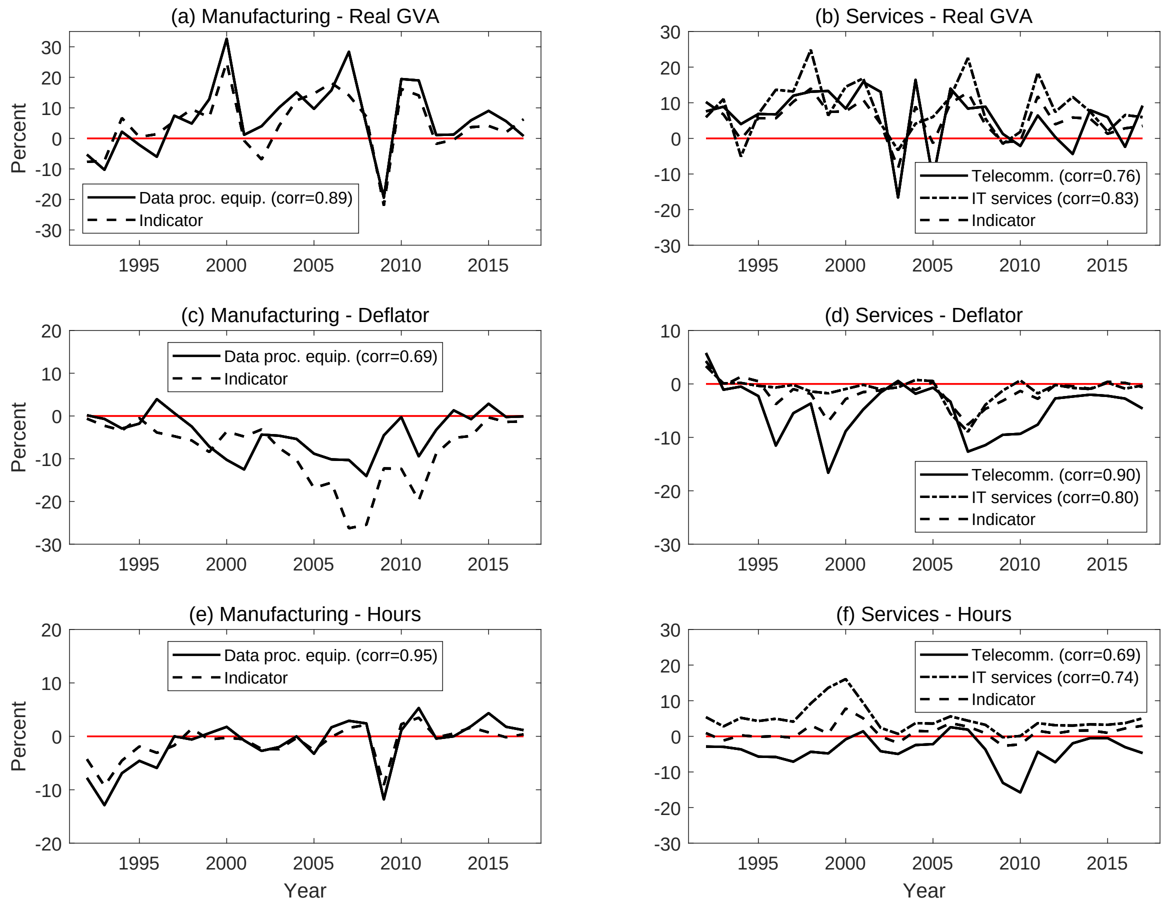
To construct the data set in Section 5, we need to determine quarterly time series for gross value added, the price deflators and working hours for the ICT and the non-ICT sector. To this end, we interpolate the annual data provided by Destatis using the Chow-Lin interpolation procedure and higher frequency indicators. As a prerequisite, these indicators have to possess a high time-series correlation with our considered main series at an annual basis. For the ICT manufacturing economic sector, we use the industrial production index and the producer price index for manufacturing of computer, electronic and optical products as indicators for real gross value added and the price deflator. As our measure of total hours worked, we use total manufacturing hours. For both ICT services sectors, we use corresponding time series of the total ICT sector as the respective indicator series for gross value added (nominal and real) and hours worked.[21]

To gauge the validity of our constructed series, each panel of Figure E1 compares the single indicator series with our main series, together with the correlation coefficient of the time series. All indicator series are highly correlated with their respective main series, all correlation coefficients exceed 0.7 at an annual level. For the total hours worked and gross value added series for the manufacture of electronic and optical products, we even find correlation coefficients of 0.9 or above. With these indicator series at hand, we determine quarterly time series for real gross value added, the price deflators and working hours for all three economic sectors that form the ICT sector using the Chow-Lin interpolation procedure.

In a next step, we use the quarterly time series of all these ICT-producing sectors to construct the aggregate time series for the total ICT sector. We consider that the real gross value time series has to be constructed as a chain index. It is then possible to determine the corresponding data series for the non-ICT sector by using the aggregated time series for the ICT sector and the quarterly time series for the total economy.

[21] Besides telecommunication and IT services, the total ICT services sector contains the industries publishing activities, motion picture, video and television program production, sound recording, music publishing activities as well as programming and broadcasting activities.

Figure E1: Comparison between main- and indicator series used for Chow-Lin interpolation



Notes: This figure presents the annual growth rates for the time period 1992 to 2017. The abbreviation "Data proc. equip." defines manufacturing of computer, electronic and optical products. For the ICT manufacturing sector, we use the production index and producer price index for manufacturing of computer, electronic and optical products as indicators for real gross value added and the deflator. For total hours worked, we employ as indicator the hours series regarding total manufacturing. The abbreviation "IT services" contains computer programming, consultancy and related activities. For both ICT services sectors, we use corresponding time series of the total ICT sector as the respective indicator series for gross value added (nominal and real) and hours worked. In each panel, we present for each time series of the respective ICT industry the correlation coefficient with the corresponding indicator. The data source is Destatis.

F QR-decompositions to extract the ICT technology shocks

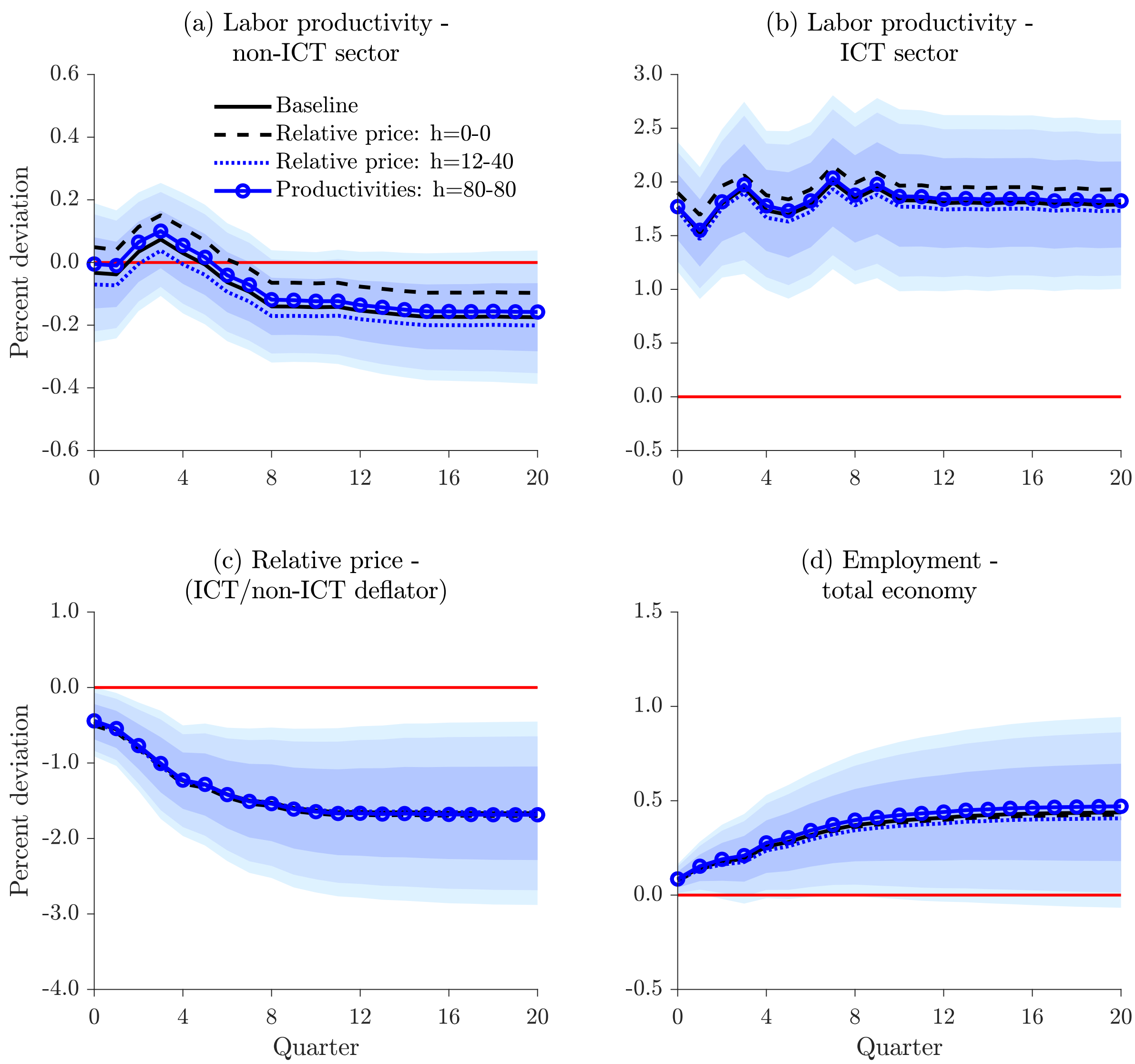
In step 2 of our identification procedure in Section 5.2, we extract ICT-related technology shocks. To do so, we apply two QR-decompositions to the three eigenvectors that define the auxiliary shocks u_t^{ICT}, u_t^{nonICT}, and u_t^{price}. Conceptually, this is equivalent to estimating two separate regressions as explained in Section 5.2.

Part 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 sector (u_t^{price} and u_t^{nonICT}). Ordering the eigenvector related to the relative price first, and the vector related to productivity of the non-ICT sector second, the first eigenvector remains unchanged. The resulting second vector is obtained by subtracting its projection over the first one. This is equivalent to the first regression in step 2.

Part 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 sector (u_t^{ICT}). 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 technology shock.

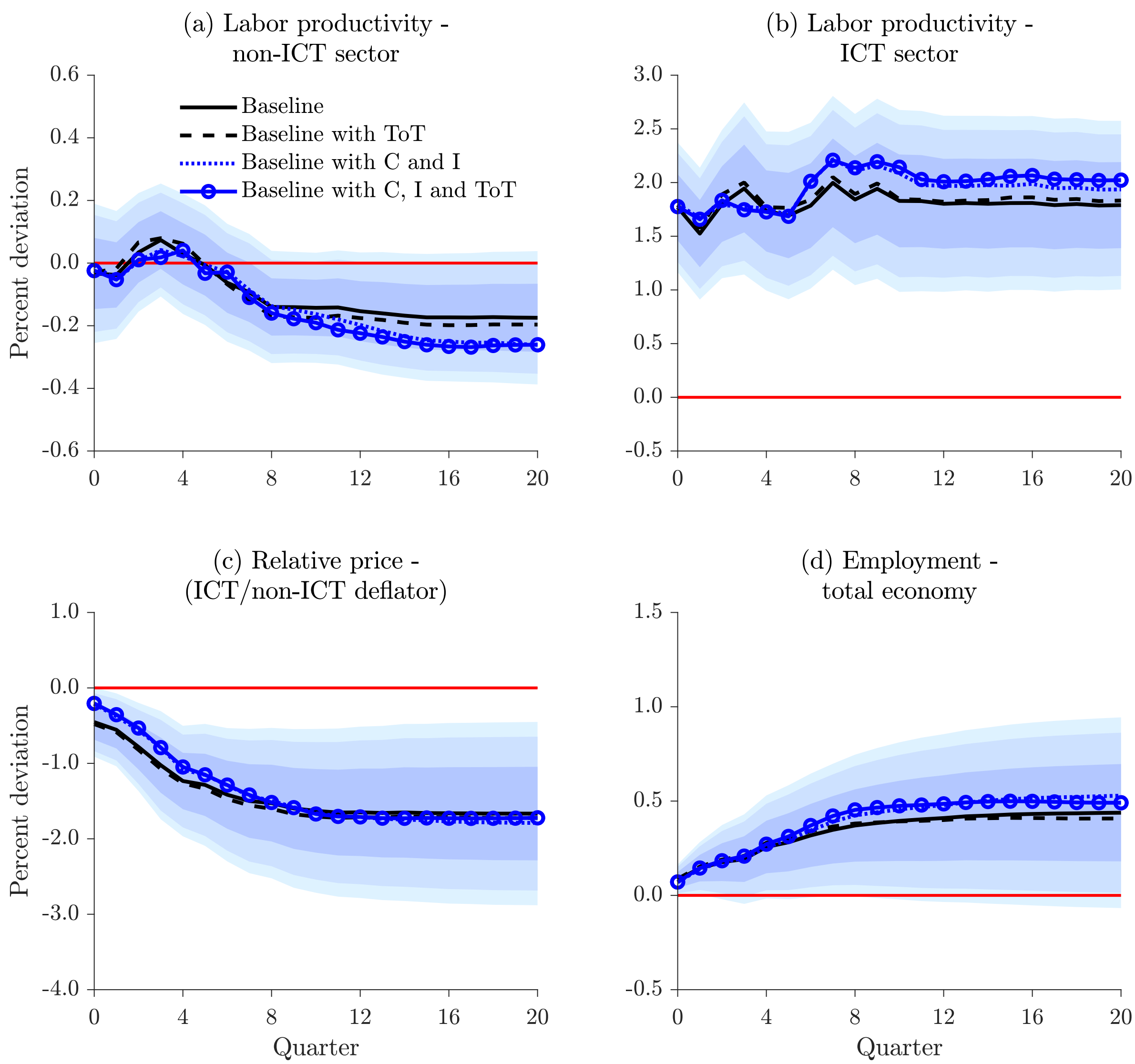
G Digitization and productivity: Robustness checks

Figure G1: Robustness check: Effects of an ICT technology shock, model specifications



Notes: The panels depict accumulated impulse response functions after an ICT technology shock identified using our two-step procedure with varying identification assumptions regarding the forecast horizon for the medium-run restrictions. Full lines are point estimates using our baseline model. Dashed lines are point estimates from an identification procedure using a Cholesky decomposition for the relative price. Dotted blue lines refer to a specification where we set the starting point of the forecast horizon to 12 quarters, and the ending point to 40 quarters for the relative price. Blue lines with circles refer to a specification where we set the starting and ending point of the forecast horizon to 80 quarters for the labor productivities in the ICT and non-ICT sector. Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004), and refer to the baseline specification.

Figure G2: Robustness check: Effects of an ICT technology shock, larger SVAR model



Notes: The panels depict accumulated impulse response functions after an ICT technology shock identified using our two-step procedure with including additional variables in our SVAR model. Full lines are point estimates using our baseline SVAR model with five variables (labor productivity of the non-ICT sector and the ICT sector, the relative price of produced value added between the ICT sector and the non-ICT sector, hours per worker and total employment). Dashed lines are point estimates from a specification including the terms of trade defined as the ratio of the export and the import deflator (ToT) as additional variable. Dotted blue lines refer to a specification with consumption (C) and investment (I) as additional variables. Blue lines with circles are point estimates from a specification with all three variables as additional variables (ToT, C, and I). Blue shaded areas: 68%, 90%, and 95% confidence bands are constructed using a recursive design wild bootstrap, see Gonçalves and Kilian (2004), and refer to the baseline specification.