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The Consequences of U.S. Technology Changes for Productivity in Advanced Economies

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Steffen Elstner and Svetlana Rujin¹

The Consequences of U.S. Technology Changes for Productivity in Advanced Economies

Abstract

Since at least the mid-2000's, many advanced economies have experienced low productivity growth. This development is often related to the declining productivity gains at the technology frontier, which is commonly assumed to be determined by the U.S. We challenge this explanation by studying the effects of changes in U.S. technology on the productivity level in other advanced economies. Overall, we find positive but small spillover effects of U.S. technology shocks. The elasticity of foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one for many countries. The recent U.S. productivity slowdown, therefore, had a limited effect on productivity developments in advanced economies. Furthermore, our results suggest that institutional factors are not able to explain cross-country differences in the size of the spillover effects. If any, regulation of the service sector seems to play a role.

JEL Classification: O40, E24, C32, F00

Keywords: Labor productivity; international spillover effects; technology shocks; structural VARs

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1 Introduction

Since at least the mid-2000's, many advanced economies have experienced low productivity growth. This development is often related to the declining productivity gains at the technology frontier, which is commonly assumed to be determined by the U.S. (IMF, 2015). This paper challenges this explanation and poses the questions (i) whether sizable productivity spillovers of U.S. technology gains on advanced economies exist, and (ii) whether institutional rigidities of labor, product, and financial markets in the corresponding economies have a quantitative importance for shaping these effects?

These research questions are motivated by Keller (2010), who documents that for most countries, foreign sources of technology are estimated to account for around 90 percent of domestic productivity growth. Furthermore, new technologies originate from a small number of countries that determine the pattern of worldwide technology transmission. Since the U.S. is commonly regarded as the world technology frontier, the focus of this paper is on productivity spillovers of U.S. technology gains on advanced economies. Additionally, we scrutinize the work of Cetto, Fernald, and Mojon (2016), who state that while the U.S. experienced a burst of innovation related to the use of new technologies at the turn of the millenium, the continental European economies were falling back relative to the U.S. level at varying rates. In this context, the authors highlight the role of labor and product market regulations in shaping the transmission of ideas and innovations across borders.

To provide insights into how technological innovations in the U.S. economy affect labor productivity in advanced countries, we focus on technology spillovers rather than on technology diffusion. The latter is a process that spans over decades. Comin, Hobijn, and Rovito (2008) and Comin and Hobijn (2010) estimate that, on average, the time lags in the diffusion of new technologies amount to 45 years. In contrast to this, the spillover effects become apparent in a shorter period of time. Hence, we consider a time horizon for the transmission of U.S. technology gains of up to 10 years.

The recent slowdown in U.S. productivity growth has become subject of extensive research. Fernald (2015) finds two structural breaks the mean of U.S. hourly productivity growth in the post-1973 time period.¹ Thus, while the average productivity growth in the period 1995 to 2003 amounted to 2.5 percent, it dropped to 1.0 percent in the period 2004 to 2017. The corresponding numbers for utilization-adjusted total factor productivity (TFP) growth in the business sector are 2.0 percent and 0.5 percent, respectively. Existing contributions explain this phenomenon through the lens of the role of financial frictions (Anzoategui, Comin, Gertler, and Martinez, 2018), a lack of major innovations (Fernald, 2015; Gordon, 2012), problems regarding technology diffusion (Andrews, Criscuolo, and Gal, 2015; Decker, Haltiwanger, Jarmin, and Miranda, 2014), and measurement issues (Byrne, Fernald, and Reinsdorf, 2016; Syverson, 2017; Kurmann and Sims, 2017). One contribution of our study is, therefore, that we address this

¹Using the Bai-Perron test for multiple structural changes in the mean of the quarterly growth rates, Fernald (2015) finds structural breaks in the fourth quarter of 1995 and in the fourth quarter of 2003.

issue from an international perspective and provide elasticities that show how strongly the technology-driven slowdown in U.S. productivity growth affected the productivity figures in other advanced economies.

To date, much of the literature has focused on international differences in the productivity levels. [Acemoglu and Zilibotti \(2001\)](#) argue that the technology-skill mismatch can explain a substantial fraction of the cross-country productivity differences even in the absence of any barriers to technology transfer. [Hall and Jones \(1999\)](#) provide insights into productivity differences across countries using the aggregate production function approach. The authors document that while differences in each element of the production function are important—that is, human capital and physical capital—the so-called productivity residual is the element that plays the key role.² [Hall and Jones \(1999\)](#) show that gaps in productivity residuals across countries are driven by differences in institutions and government policies, which the authors label as social infrastructure.

Similarly, using the aggregate production function approach, [Lagos \(2006\)](#) shows that labor market institutions can affect this function in general and the level of measured TFP in particular. This idea finds support in [Dabla-Norris, Guo, Haksar, Kim, Kochhar, Wiseman, and Zdzienicka \(2015\)](#) and [Cette et al. \(2016\)](#), who highlight the role of labor and product market regulations for technology spillovers across borders. Thus, while technology transfer keeps countries from drifting indefinitely far from each other, institutional barriers generally push the economies further from the frontier. Structural rigidities in product and labor markets can affect productivity via various channels. Missing competition could prevent the creation of ideas and the adoption of new technologies. Furthermore, highly regulated product and labor markets impede the efficient allocation of resources in the economies. Therefore, it seems instructive to analyze the relationship between the degree of goods and labor market rigidities and the size of international productivity spillovers.

However, far less attention has been paid on international productivity spillovers originating from the U.S. One exception is the work by [Rabanal, Rubio-Ramírez, and Tuesta \(2011\)](#), who find that the technology processes in the U.S. and other advanced economies converge slowly over time with important consequences for the volatility of the real exchange rate. Other empirical studies addressing the international transmission of U.S. technology shocks focus on the effects on international prices, GDP, private consumption or the trade balance ([Corsetti, Dedola, and Leduc, 2008](#); [Enders and Müller, 2009](#); [Keller, 2010](#); [Miyamoto and Nguyen, 2017](#)).

In our empirical analysis, we study the spillover effects of U.S. technology shocks for 13 advanced economies over the time period 1970 to 2016. To do so, we rely on the direct utilization-adjusted technology measure for the U.S. proposed by [Fernald \(2014\)](#). In country-specific vector autoregressive models (VAR), we examine the dynamic effects of changes in this technology measure on hourly labor productivity in advanced economies. We then use indicators

²[Hall and Jones \(1999\)](#) show that different capital intensities in the two countries of their focus contributed a factor of 1.5 to the income differences, while different levels of educational attainment contributed a factor of 3.1. The remaining difference—a factor of 7.7—is captured by the productivity residual.

of non-price competitiveness to analyze the relationship between international differences in the transmission of U.S. technology shocks and institutional rigidities. Finally, we show that other identification approaches, like those proposed by Galí (1999) and Uhlig (2004), yield similar results.

The main results of our analysis are as follows: first, we do not find large productivity spillover effects of U.S. technology shocks. For most countries, these effects are not significantly different from zero. Furthermore, the elasticity of foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one for many countries. This picture is robust across all structural VAR (SVAR) specifications and identification approaches. We stress the importance of this finding as technology (knowledge) has the feature of non-rivalry (Keller, 2004). In a setting with perfect competition and without structural rigidities, technological innovations in the U.S. should increase the level of technology in other countries by the same magnitude after the same time. In sum, these results suggest that there is an incomplete pass-through of the U.S. technology shocks to other countries. Therefore, the recent U.S. productivity slowdown had a limited effect on developments in advanced countries. In contrast to these findings, Rabanal et al. (2011) find a slow, but complete transmission of the U.S. technological advances to the rest of the world.

Second, though the magnitudes of the U.S. technology spillovers vary across countries, the differences in international productivity responses are not significant. Also when we use indicators of non-price competitiveness to cluster countries into groups characterized by high and low degree of institutional rigidity and contrast the results, we are not able to find significant cross-country differences regarding the size of the U.S. productivity spillover effects. This result contradicts the finding in Cette et al. (2016), who stress the importance of labor and product market regulations in shaping the transmission of new technologies across countries. If any, regulation of the service sectors seems to play a role.

This paper is organized as follows: Section 2 provides evidence on the U.S. as technology frontier. Section 3 describes our empirical approach and Section 4 presents our baseline results. In Section 5 we provide evidence from institutional and macroeconomic characteristics. In Section 6 we test the sensitivity of our baseline results. Finally, Section 7 concludes the analysis.

2 The U.S. as technology frontier

The focus on international productivity spillovers resulting from U.S. technology gains is motivated by the fact that the U.S. economy is largely considered as the global technology frontier (Cette et al., 2016; Growiec, 2012; IMF, 2015). Inklaar and Diewert (2016) corroborate this statement by providing estimates of internationally comparable TFP levels for several economies. The authors analyze dispersion in international TFP measures using industry-level data on real value added over the time period 1995–2011. The main data source is the World Input-Output Database (Timmer, Dietzenbacher, Los, Stehrer, and De Vries, 2015).

Table 1: **Productivity gaps**
Percentage deviations from the U.S. TFP-level

	(1) Market sector		(2) Tradable sector		(3) Non-tradable sector	
	1995	2010	1995	2010	1995	2010
Australia	-29.0	-35.4	-24.0	-10.5	-31.0	-44.9
Austria	-34.0	-36.2	-31.0	-34.9	-36.0	-37.3
Canada	-27.0	-44.9	-24.0	-34.9	-29.0	-50.0
Germany	-16.0	-22.8	9.0	-2.6	-27.0	-32.2
Finland	-42.0	-41.7	-32.0	-34.2	-48.0	-45.8
France	-15.0	-33.9	-16.0	-34.2	-14.0	-32.2
Ireland	-37.0	-22.0	-23.0	1.3	-45.0	-33.9
Italy	-55.0	-60.6	-38.0	-54.6	-62.0	-62.7
Japan	-33.0	-58.3	-8.0	-43.4	-43.0	-63.6
South Korea	-46.0	-66.1	-21.0	-52.0	-58.0	-73.7
Sweden	-21.0	-26.0	16.0	3.9	-36.0	-36.4
U.K.	-17.0	-20.5	-3.0	-13.8	-23.0	-22.0

Notes: Productivity levels are determined by [Inklaar and Diewert \(2016\)](#). Data for Norway are not available.

Table 1 reports the results. [Inklaar and Diewert \(2016\)](#) distinguish between a tradable and a non-tradable sector. The tradable sector refers to the industries producing market-oriented goods and the non-tradable sector covers market-oriented service industries. The aggregate of these two sectors represents the market sector.

The entries in Table 1 represent percentage deviations of international TFP measures from the U.S. TFP level for the years 1995 and 2010, respectively. Overall, negative productivity gaps suggest that selected countries are less productive than the U.S. The productivity lead of the U.S. economy is particularly pronounced in the non-tradable sector, and it became even larger in the time period from 1995 to 2010 with respect to many countries. For example, [Inklaar and Diewert \(2016\)](#) report that the negative productivity gap in Italy’s market sector in 2010 was of 60 percent. A similar conclusion can be drawn for Japan and South Korea. For Germany, the U.K., and Ireland, the productivity gaps are significantly smaller with roughly 20 percent.

In addition to these findings, [Dabla-Norris et al. \(2015\)](#) document sector-level patterns in TFP growth rates across advanced economies. The authors show that the U.S. economy represents the technology frontier in finance, business, and personal services, whereas Germany represents the technology frontier in manufacturing. Moreover, [Comin et al. \(2008\)](#) provide evidence that the U.S. also leads the world in the intensity of use of a broad range of technologies. Their results show that, for many countries, the degree to which they use various technologies, including electricity, cars, trucks, and phones, lags the technology usage level in the U.S. by several decades.³

³[Comin et al. \(2008\)](#) use data for 185 countries in their analysis. According to this study, usage lags measure how many years ago the technologies that the authors consider were used in the U.S. at the same intensity as they are used in the foreign countries. [Comin et al. \(2008\)](#) show that technology usage disparities might account for a large part of cross-country TFP differentials.

3 Empirical framework

We determine our baseline results from a SVAR model that relies on a quarterly utilization-adjusted TFP series for the U.S. business sector (purified TFP) proposed by [Fernald \(2014\)](#).⁴ We label this SVAR as the Fernald model. Fernald’s quarterly purified TFP series is closely related to the annual technology measure derived in [Basu, Fernald, and Kimball \(2006\)](#). Using disaggregate information at the industry-level, [Fernald \(2014\)](#) obtains purified TFP from a growth-accounting exercise that accounts for varying utilization of capital and labor. Hence, the Fernald model does not require an explicit control for demand-related movements in the technology measure, which is an advantage compared to other identification approaches.⁵

We estimate for each country i at a time a three-variable SVAR that includes: purified TFP and a measure of capacity utilization for the U.S. computed by [Fernald \(2014\)](#), and real hourly labor productivity for country i .⁶ All models include a constant and four lags. All variables are expressed in log first differences. We use seasonally adjusted quarterly data that cover 13 advanced economies over the sample period 1970:1–2016:4 unless otherwise indicated. Determined by the availability of quarterly measures of total hours in the Ohanian-Raffo dataset ([Ohanian and Raffo, 2012](#)), which we require for the computation of hourly labor productivity for country i , we consider the following countries: Australia, Austria, Canada, Finland, France, Germany, Ireland, Italy, Japan, Norway, South Korea, Sweden (1974:1–2016:4), and the U.K. (1971:1–2016:4).⁷

The estimation of the U.S. productivity spillover effects hinges on three assumptions: first, we treat each country i as a small economy relative to the U.S., and thus assume that shocks in these countries have no effect on U.S. variables. Hence, labor productivity for country i is not included in the equations for the U.S. variables: purified TFP and capacity utilization. Consequently, the VAR is estimated as a subset system of equations using the method of seemingly unrelated regressions. This assumption guarantees that for each country i the sequence of U.S. technology shocks is the same.

Second, we assume that labor productivity in country i is affected contemporaneously by the two U.S. variables. Additionally, changes in U.S. capacity utilization have no contemporaneous effect on purified TFP, as this measure is already utilization-adjusted. Consequently, to estimate the effects of changes in purified TFP on labor productivity for the advanced economies, the Fernald model uses a recursive VAR ordering with the U.S. technology measure

⁴[Corsetti et al. \(2008\)](#), [Enders and Müller \(2009\)](#) and [Miyamoto and Nguyen \(2017\)](#) use SVARs to study the international transmission of technology shocks. In contrast to our study, however, they are particularly interested in the effects of technology shocks on GDP, private consumption, trade balance, and the terms of trade.

⁵In the robustness section, we check the sensitivity of our baseline results with respect to alternative identification schemes that include hourly labor productivity. Thus, we employ the long-run identification approach proposed by [Galí \(1999\)](#), the medium-run identification approach proposed by [Uhlig \(2004\)](#), and a Proxy-SVAR model put forward by [Mertens and Ravn \(2013, 2014\)](#).

⁶Using a bivariate SVAR framework with purified TFP for the U.S. and hourly labor productivity for country i does not affect our baseline results.

⁷We exclude Spain from the analysis due to the much later starting date of the hours series in 1995:1.

Table 2: **Correlations with the U.S. neutral technology shocks**

The U.S. neutral technology shocks				
	<i>Fernald model</i>	<i>Galí model</i>	<i>Uhlig model</i>	<i>Proxy-SVAR</i>
<i>The U.S. neutral technology shocks</i>				
Fernald model	1.00			
Galí model	0.76	1.00		
Uhlig model	0.77	0.99	1.00	
Proxy-SVAR	0.78	0.98	0.99	1.00
<i>Galí model, aggregate data</i>				
G6	-0.05	-0.02	- 0.01	0.01
G13	0.02	-0.01	0.00	0.02
<i>Galí model, OECD countries</i>				
Austria	0.13	0.08	0.10	0.14
Australia	0.14	0.17	0.17	0.18
Canada	0.16	0.13	0.12	0.19
Germany	0.04	-0.05	-0.04	-0.02
Finland	0.08	0.07	0.07	0.09
France	0.14	0.08	0.09	0.12
Ireland	0.08	0.06	0.06	0.05
Italy	-0.03	-0.06	-0.05	-0.04
Japan	-0.06	-0.03	-0.02	-0.01
South Korea	0.04	0.08	0.08	0.09
Norway	0.04	0.06	0.06	0.05
Sweden	-0.01	0.00	0.00	0.01
U.K.	0.06	0.09	0.09	0.10

Notes: This table reports the correlations of the U.S. neutral technology shocks obtained from different identification schemes with technology shocks for the two country groupings and 13 countries, respectively. The G6 country group includes: Canada, Germany, France, Italy, Japan, and the U.K. The G13 country group includes all countries considered in our sample. The identification of technology shocks is described in [Section 3](#) and [Section 6](#). Technology shocks for the two country groupings and each of the 13 countries are obtained from bivariate SVARs with long-run restrictions that include quarterly series on hourly labor productivity and total hours worked adjusted for the working-age population. All variables are specified in log first differences and all SVARs include four lags. Sample period is 1970:1–2016:4. We compute the correlations using GDP-weighted technology shocks for 13 countries. The weights are country-level shares in the nominal GDP for the group of 13 countries. The correlations between the U.S. technology shocks obtained from the Fernald model and country-specific and aggregate technology shocks from the Uhlig model (not reported in this table) are equal to those obtained for the Galí model. Data sources: [Ohanian and Raffo \(2012\)](#); <http://andrearaffo.com/araffo/Research.html>, Fernald (2014); <http://www.johnfernald.net/TFP>, Federal Reserve Economic Data (FRED), and OECD.

ordered first, followed by the U.S. capacity utilization and hourly labor productivity for country i . We thus apply the Cholesky decomposition to obtain impulse response functions (IRFs) of labor productivity for country i to a U.S. technology shock.

Our final assumption concerns the measure of U.S. technology shocks. It is plausible that changes in U.S. purified TFP can capture a U.S.-specific (idiosyncratic) and a global (common) component. In our baseline calculations, we assume that U.S. technology shocks are solely driven by the U.S.-specific component. To check the plausibility of this assumption, we determine correlation coefficients of the U.S. purified TFP series with technology measures for other countries. Since quarterly measures of purified TFP are not available for other countries, we need to rely on technology shocks derived from country-level SVARs with hourly labor

productivity and total hours worked adjusted for the working-age population.⁸ For each country i we identify technology shocks using the long-run identification scheme proposed by Galí (1999) and the medium-run identification scheme proposed by Uhlig (2004).

Table 2 summarizes the results and shows that the correlation coefficients of U.S. purified TFP and the country-specific technology shocks determined with long-run identification scheme are close to zero. Thus, there is no evidence that U.S. purified TFP is affected by foreign technology shocks. We find almost identical results for the foreign technology shocks determined with approach proposed by Uhlig (2004).⁹

4 Results

This section presents our baseline results.¹⁰ Since we focus on the long-run effects of the U.S. technology shocks on foreign labor productivity, we standardize the U.S. technology shock such that the structural shock induces a one percent increase in purified TFP after 20 quarters.¹¹ Figure 1 illustrates the accumulated IRFs of foreign labor productivity following a U.S. technology shock for the major six economies: Japan, Germany, the U.K., France, Italy, and Canada. The 95%-confidence intervals are based on a recursive-design wild bootstrap procedure proposed by Gonçalves and Kilian (2004).

Our first main result is that the long-run U.S. productivity spillover effects are positive across all countries. We find the largest effects for Italy, France, and Japan. In contrast, the response of labor productivity in Canada remains subdued throughout the entire horizon. Miyamoto and Nguyen (2017) report similar results: Canadian labor productivity increases slightly and not significantly following a positive permanent U.S. technology shock.

Second, the point estimates of the impulse responses at a one- and five-year horizon for all countries considered in our analysis that are illustrated in Figure 2 imply that the elasticity of foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one.

For illustration purposes, we add to the figure dotted lines that represent the cross-sectional averages of the IRFs of labor productivity and the corresponding 95%-confidence intervals. Particularly, the average 95%-confidence intervals illustrate our result that the elasticity of foreign labor productivity with respect to a U.S. technology shock is significantly smaller than one for the majority of countries. This implies that a one percent increase in the U.S. technology causes an increase in foreign productivity of less than one percent. There is, however, some indication that the effects become larger over time. Thus, on average across all countries, the response of foreign labor productivity to a U.S. technology shock is of 0.19 percent at the one-year horizon and it increases to 0.30 at the five-year horizon. Given these findings, we

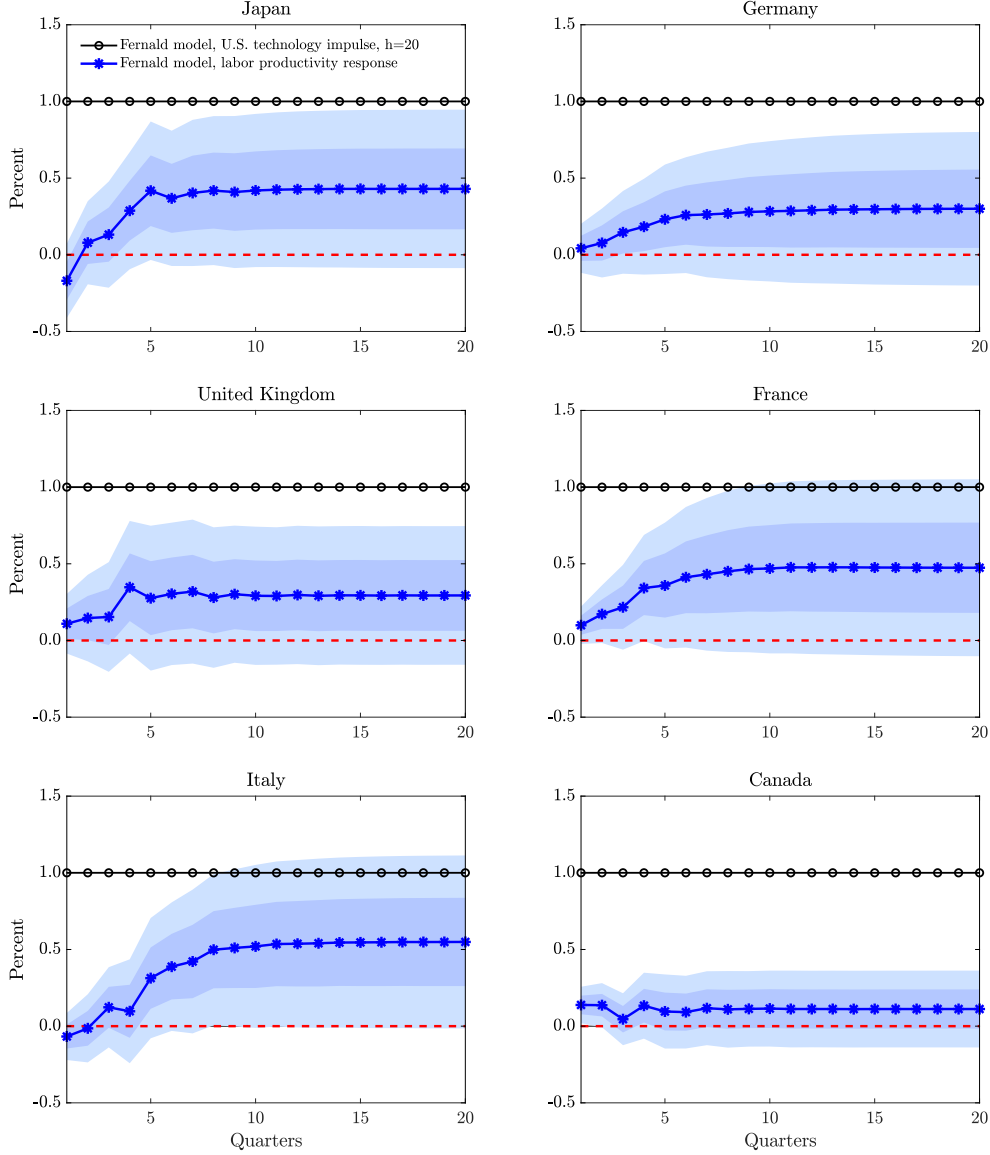
⁸The data are from the Ohanian–Raffo dataset (Ohanian and Raffo, 2012).

⁹The results are not reported in Table 2 and available upon request.

¹⁰We leave a detailed description of the data definitions and sources to the data appendix.

¹¹We also computed the IRFs for a time horizon of 40 quarters. Our baseline statements are unaffected by this modification.

Figure 1: Productivity spillover effects of a U.S. technology shock



Notes: This figure shows the accumulated IRFs of labor productivity to a U.S. technology shock for major advanced economies. The Fernald model includes purified TFP and capacity utilization for the U.S., followed by labor productivity for the respective foreign country. We use a Cholesky decomposition to estimate the productivity spillover effects of a U.S. technology shock. All models are estimated as subset VARs on a country-by-country basis. We standardize the U.S. technology shock such that the structural shock induces a one percent increase in purified TFP after 20 quarters. All models include four lags and all variables are expressed in log first differences. We use seasonally adjusted data for the sample period 1970:1–2016:4. Shaded areas represent the 68% and 95%-confidence intervals based on a recursive-design wild bootstrap procedure proposed by Gonçalves and Kilian (2004). Data sources are provided in the [data appendix](#).

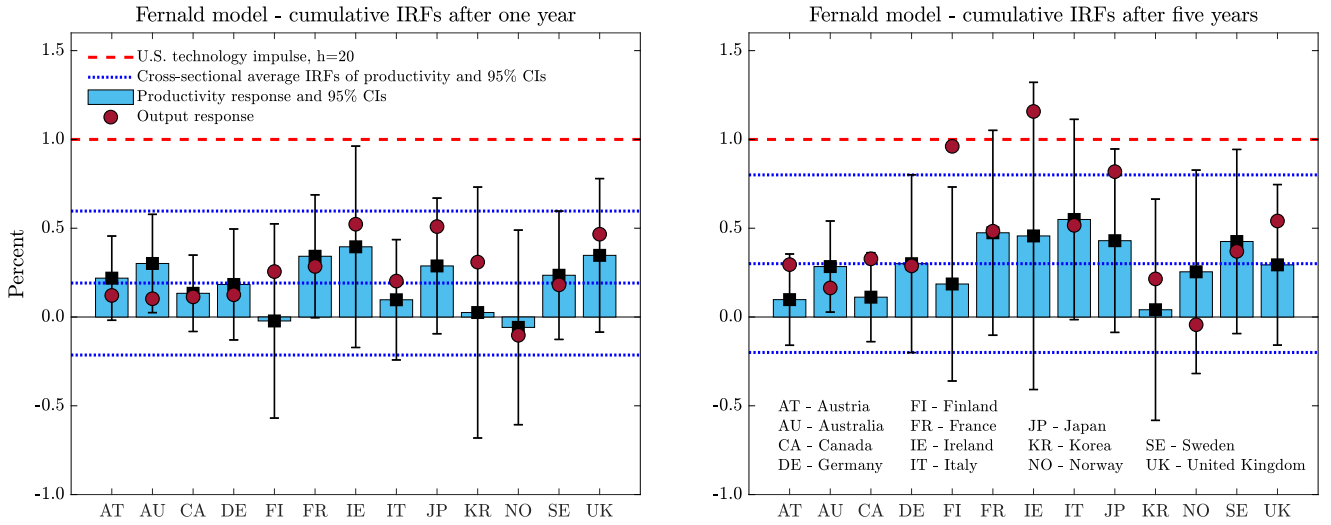
conclude that the recent slowdown in the U.S productivity growth had only a limited effect on the decline in productivity growth in advanced economies.

Rabanal et al. (2011) adopt a cointegration framework to study the transmission of new technologies across countries. Their study finds that the TFP processes of the U.S. and other advanced economies (rest of the world) converge perfectly but slowly over time. The presence of cointegrated TFP shocks, which implies a full absorption of new technologies across countries independent of their origin, is hard to reconcile with our finding that the long-run elasticity of

foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one.¹²

We stress the importance of this finding, since technology (knowledge) has the feature of non-rivalry (Keller, 2004). In a setting characterized by perfect competition and without structural rigidities, innovations in one country should increase the technology level in all other countries by the same magnitude after same time. Note that in our framework, the one percent mark provides a lower bound, since we consider labor productivity and not a direct measure of technology (like purified TFP) for the single countries. In the neoclassical growth model, positive technology shocks are associated with an increase in capital intensity.

Figure 2: International spillover effects of a U.S. technology shock



Notes: This figure shows the accumulated IRFs of labor productivity (bars) and output (markers) to a U.S. technology shock over a one- and five-year horizon for 13 advanced economies. Labor productivity and output measures for the selected countries enter the model as subset variables, each at a time. Dotted lines represent the cross-sectional average IRFs of labor productivity to a U.S. technology shock and the corresponding 95%-confidence intervals that were originally computed using a recursive-design wild bootstrap procedure proposed by Gonçalves and Kilian (2004). All details concerning the model specification, estimation, and data sources are provided in Section 3 and notes to Figure 1.

While there are qualitative similarities in the U.S. productivity spillover effects across countries, we find some cross-country heterogeneity regarding the magnitude of these effects. However, since the country-specific point estimates lie within the average 95%-confidence intervals denoted by the dotted lines in Figure 2, the point estimates of the impulse responses are not significantly different across countries. Nonetheless, the point estimates at a five-year horizon range between around 0.00 percent in South Korea and roughly 0.50 percent in Italy. In our opinion, these differences warrant some further investigation.

In order to provide a more detailed picture on the transmission mechanism of technology shocks, we additionally show the responses of GDP to these shocks, which are depicted by circle markers in Figure 2. After five years, the spillover effects of U.S. technology shocks

¹²We estimated the Fernald model using variables in log levels and obtained productivity spillover effects significantly smaller than one for the majority of countries.

on output are larger than those on productivity, which means that U.S. productivity gains stimulate labor input in many advanced economies. We further find a positive but not perfect relationship between productivity and output gains across countries.

5 Evidence from institutional characteristics

5.1 Indicators of institutional characteristics

Our baseline results indicate that there is no significant cross-country heterogeneity in the transmission of the U.S. technology gains. Nonetheless, the point estimates after five years vary to some degree and these differences allow some further analysis. In the following we, therefore, scrutinize the statements of [Cette et al. \(2016\)](#) regarding the importance of labor and product market regulations for the transmission of U.S. technology gains. To do so, we estimate the productivity spillover effects of a U.S. technology shock for the groups of countries that have contrasting—that is, flexible or rigid—institutional environments. We thus address the role of institutional rigidity in shaping our baseline outcomes. For this purpose, we refer to earlier work by [van Ark, O’Mahoney, and Timmer \(2008\)](#), [Bouis, Causa, Demmou, Duval, and Zdzienicka \(2012\)](#), [Bourlès, Cette, Lopez, Mairesse, and Nicoletti \(2013\)](#), [Nicoletti and Scarpetta \(2003\)](#), [Dabla-Norris et al. \(2015\)](#), and [Cette, Lopez, and Mairesse \(2016\)](#). These studies address the role of policies promoting competitive pressures in the transmission of ideas and innovations across borders, with a particular focus on international differences in labor and product market institutions. Furthermore, numerous studies find that countries that are more financially developed or have higher quality of institutions experience larger productivity and TFP growth ([Kose, Prasad, and Terrones, 2009](#); [Bekaert, Harvey, and Lundblad, 2011](#)). Hence, we use indicators of non-price competitiveness to analyze the role of international institutional factors in shaping our baseline results.¹³

Concerning labor market institutions, we are interested in the role of institutional aspects that influence job and worker flows (that is, (un)employment rigidities), which are regarded as the most important determinants of labor market adjustments ([Gnocchi, Lagerborg, and Pappa, 2015](#)).¹⁴ To this end, we employ the OECD index on the strictness of employment protection against individual dismissal (based on regular contracts).

To address institutional arrangements that target product and service markets, we use two indicators. The first indicator defines product market regulation for the total economy and measures the degree to which policies promote or inhibit competition in the product markets. The second indicator focuses on regulation in the non-manufacturing sector. It represents the degree of regulation in seven network sectors (aggregated into one indicator of regulation in

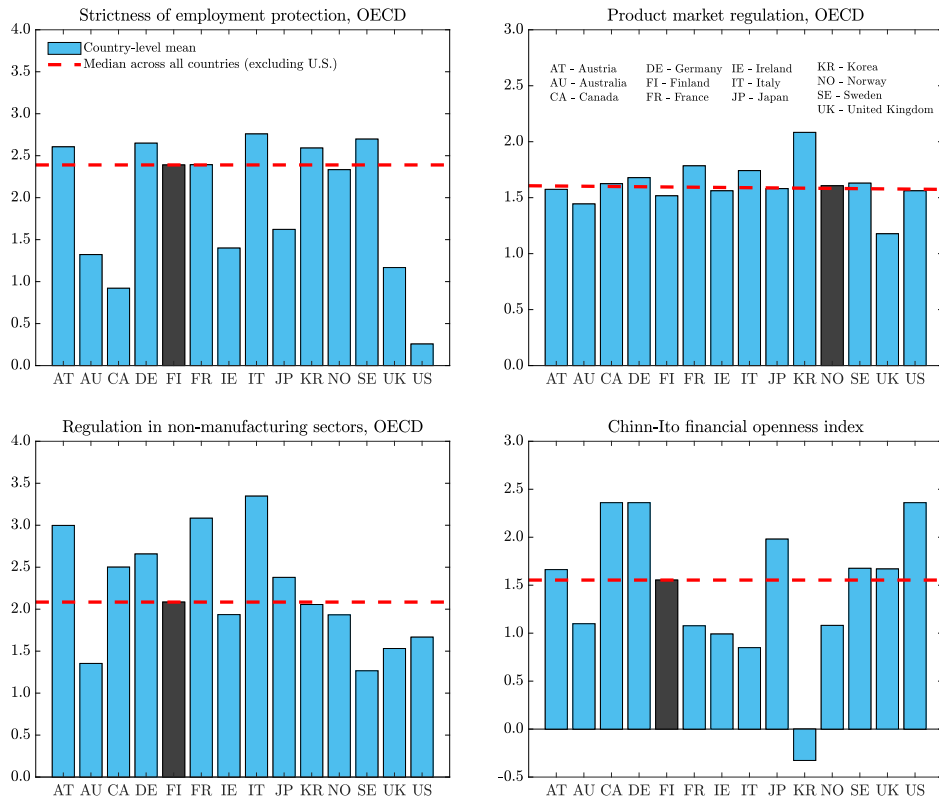
¹³Definitions, sample periods, and sources of the data are summarized in [Table A.1](#).

¹⁴[Rujin \(2019\)](#) shows that technology-induced labor market fluctuations are positively associated with the efficiency and flexibility of the labor market. That is, labor markets characterized by flexible institutional arrangements (fluid labor markets) are more likely to lay off workers or reduce hours worked per worker following a positive technology shock.

energy, transport and communications) and five service sectors (retail distribution, accounting services, legal services, engineering services, and architectural services). Both indicators are from the OECD database and described in [Koske, Wanner, Bitetti, and Barbiero \(2015\)](#).

Finally, we study the relationship between financial openness and international productivity spillovers of U.S. technology shocks. For this purpose, we use the Chinn-Ito index measuring a country's degree of capital account openness, which accounts for regulatory restrictions on cross-border financial transactions ([Chinn and Ito, 2006](#)).

Figure 3: International institutional characteristics



Notes: This figure shows descriptive statistics on international institutional characteristics. The bars represent the country-level averages of institutional indicators and the highlighted bars correspond to the respective median country. The cross-country median value of each indicator (excluding the U.S.) is depicted by the dashed line. The OECD indicator reflecting the strictness of employment protection legislation (EPL) refers to individual and collective dismissals (regular contracts) and covers a time period from 1985 to 2013. The indicator measuring the product market regulation reflects the degree to which policies promote or inhibit competition. The OECD indicator of regulation in non-manufacturing sectors measures regulation at the sector level and covers seven network sectors (telecommunication, electricity, gas, post, rail, air passenger transport, and road freight) and five services sectors (retail distribution, accounting services, legal services, engineering services, and architectural services). The latter two indicators are available for the years 1998, 2003, 2008 and 2013. The Chinn-Ito index of financial openness ([Chinn and Ito, 2006](#)) measures a country's degree of capital account openness and covers the time period from 1970 to 2016. See [data appendix](#) for further details and definitions.

Figure 3 depicts descriptive statistics of these institutional characteristics. The bars represent the time-series averages of the respective institutional indicators for each country. Except for the financial openness index, high values of an indicator point to a highly regulated labor

or product market. Low values signal more flexible market features.¹⁵ Based on this average scores, we compute for each indicator the median value across all countries, excluding the U.S. The black bars define the median-country for the corresponding institutional characteristic. The dashed lines depict the median values for each indicator that help to cluster the remaining countries into "high" and "low" regime groups. Consequently, countries displaying an average value above (below) the corresponding median are classified into high (low) regimes. We include an equal number of countries in each regime-grouping.¹⁶ We also report these results in [Table B.1](#).

In sum, while labor, product, and service markets in major European economies (Germany, France, and Italy) are highly regulated, the opposite applies to Anglo-American countries (Australia, the U.K., and the U.S.). For Canada we observe that the labor market is quite flexible, while the product and services markets are highly regulated. The Japanese economy has flexible labor and product market regulations, whereas competition in the service sectors seems to be quite difficult. Concerning financial openness, Canada, Germany, Japan, and the U.S. have by far the most flexible regulatory policies on cross-border financial transactions.

5.2 The role of institutions

To analyze the differences in the size of the country-specific responses of labor productivity to a U.S. technology shock, we adopt the approach by [Calza, Monacelli, and Stracca \(2013\)](#). We first estimate our baseline model country-by-country and then compute the average impulse responses of labor productivity for the two country sub-groups that we defined in the previous section. We normalize the U.S. technology shock such that the structural shock induces a one percent increase in purified TFP after 20 quarters. [Figure 4](#) illustrates the mean IRFs along with the 95%-confidence intervals for the respective country groups.

The computation of mean IRFs obtained from the country-specific SVARs (mean-group estimator) results in efficiency gains versus SVAR estimates based on standard panel estimation methods, like pooled ordinary least squares or fixed-effect estimation. The estimation of subset SVARs on a country-by-country basis does not only take into account country-specific fixed effects, that is the intercepts, but also results in country-specific estimates of the slope parameters.¹⁷

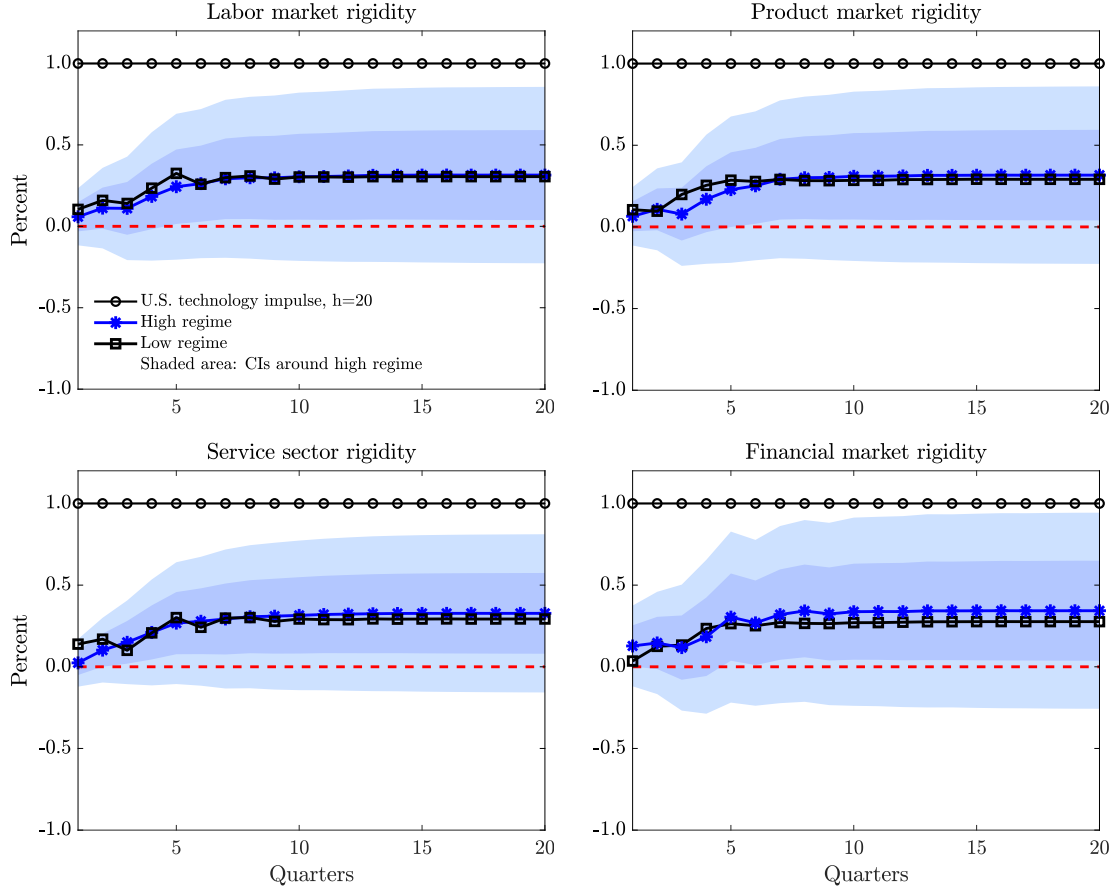
[Figure 4](#) reveals that there are only slight differences in the magnitudes of productivity spillovers between the two country sub-groups and along the four institutional dimensions.

¹⁵For consistency reasons, we use in the following sections a reversed definition of financial market openness and attribute high (low) financial openness to low (high) institutional rigidity.

¹⁶To obtain the same number of countries in each group, we exclude for each institutional characteristic the respective median-country from the analysis.

¹⁷If the true slope parameters differ across countries, the random and fixed effects estimators result in inconsistent and misleading estimates of the coefficients ([Nickell, 1981](#)).

Figure 4: Mean impulse responses to a U.S. technology shock



Notes: This figure displays the average impulse responses of labor productivity to a U.S. technology shock, which are computed over the groups of 6 countries, respectively. The original IRFs were obtained from the estimation of the baseline model on a country-by-country basis (these results are illustrated in [Figure 1](#) and [Figure 2](#)). The classification of countries into "high" and "low" regime groupings is done according to their respective institutional characteristics, which can be found in [Table B.1](#). We use the unit effect normalization of the U.S. technology shock so that a unit increase in the structural shock induces a one percent increase in the observable U.S. technology measure (purified TFP) after 20 quarters. Shaded areas represent the corresponding cross-sectional average 68% and 95%-confidence intervals, which were originally computed using a recursive-design wild bootstrap procedure proposed by [Gonçalves and Kilian \(2004\)](#). All details concerning the model estimation, specification, and data sources are provided in [Section 3](#) and in the notes to [Figure 1](#).

Alternatively, following [Gnocchi et al. \(2015\)](#), we assess the link between productivity spillovers and institutional characteristics based on Spearman rank correlation coefficients.¹⁸ [Table 3](#) reports the results on the Spearman rank correlation coefficients between the one and five years delayed accumulated IRFs of labor productivity with respect to a U.S. technology shock for 13 countries and indicators on institutional characteristics.

In sum, evidence from Spearman rank correlations supports our results in [Figure 4](#) and [Section 4](#). Thus, institutional factors do not seem to be able to explain the cross-country differences in the size of the spillover effects. This evidence is at odds with the statements made by [Cette et al. \(2016\)](#).

¹⁸The advantage of using Spearman's correlation is that it is successful in small samples like ours (which includes 13 cross-sections), since normality is violated, and it is robust to outliers ([Gnocchi et al., 2015](#)).

Table 3: **Evidence from Spearman correlation coefficients**

	Lags	<i>Institutional characteristics</i>			
		Labor market rigidity	Product market rigidity	Service sector rigidity	Financial market rigidity
<i>Baseline IRFs</i>	4	-0.34	-0.35	-0.19	-0.09
	20	0.22	0.15	0.20	0.13

Notes: This table reports the Spearman rank correlation coefficients between the one and five years delayed cumulative IRFs of labor productivity following a U.S. technology shock for 13 advanced economies and indicators on institutional characteristics, respectively. We denote the statistical significance of correlation coefficients by asterisks *, **, *** at 10, 5, and 1 percent level, respectively.

6 Robustness Checks

In this section, we conduct a battery of robustness checks to test the sensitivity of our baseline results. These checks question the identification of the U.S. technology shocks and address certain modifications in the empirical model, that is the sample period chosen for the estimation of the model and the stochastic treatment of variables used in SVARs.

6.1 Identification approach

We check the sensitivity of our baseline results with respect to alternative identification schemes of U.S. technology shocks, which are obtained from: (i) the long-run identification approach proposed by [Galí \(1999\)](#), (ii) the medium-run identification approach proposed by [Uhlig \(2004\)](#), and finally (iii) we use a modified version of a Proxy-SVAR model put forward by [Mertens and Ravn \(2013, 2014\)](#).

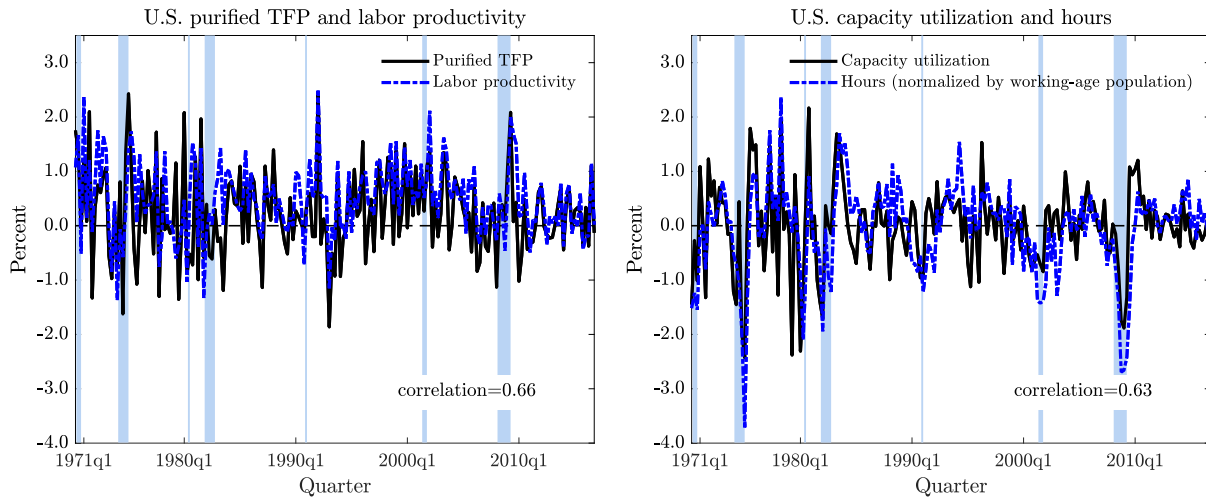
We conduct these robustness checks as [Kurmann and Sims \(2017\)](#) show that the purified TFP series by [Fernald \(2014\)](#) is subject to measurement errors. For example, the time series was heavily revised in 2014 due to changes in the estimate of factor utilization. These modifications led to large and qualitatively important differences in the time series properties among different vintages of purified TFP. Specifically, [Kurmann and Sims \(2017\)](#) show that the correlation coefficients between the growth rates of purified TFP vintages published before 2014 and the later vintages are smaller than 0.6.¹⁹

While the models mentioned above employ different identification assumptions to recover structural shocks, the specification of the VARs is the same across the three models. Hence, we estimate three-variable VARs with hourly labor productivity and total hours worked (normalized by the U.S. working-age population) for the U.S., and hourly labor productivity for country i . All variables are specified in log first differences. The VAR models include a constant and four lags. We exclude labor productivity for country i from the equations for the U.S. variables and estimate the models as a subset system of equations.

¹⁹Furthermore, [Kurmann and Sims \(2017\)](#) show that these revisions led to different results regarding the importance of news shocks for the U.S. business cycle.

In contrast to our baseline model, these three models employ both a different productivity measure for the U.S. and a different instrument series used to isolate business cycle fluctuations. Figure 5 illustrates the time series used in our SVARs. It thus follows that in addition to alternative identification schemes of U.S. technology shocks, we also test the robustness of our baseline results with respect to an alternative specification of the empirical model.

Figure 5: Time series used in VARs



Notes: This figure illustrates the growth rates of the U.S. time series used in SVAR models for the sample period 1970:1–2016:4. The shaded areas define recession periods as defined by the NBER. Data source: Fernald (2014) and Federal Reserve Economic Data (FRED).

The most prominent approach used in the literature is the long-run identification proposed by Galí (1999).²⁰ In his empirical model, Galí (1999) assumes that only U.S. technology shocks can permanently shift the level of the U.S. productivity measure. This assumption, however, has been criticized in some contributions.²¹ To identify the U.S. technology shock, we impose three restrictions: first, the assumption that shocks in country i have no effect on U.S. variables results in two short-run zero restrictions. Second, we impose the restriction that only U.S. technology shocks have a long-run effect on the level of U.S. labor productivity.

Figure 6 illustrates the impulse responses for the group of major advanced economies as well as for the U.S. variables. The upper row of Figure 7 summarizes the results for all 13 countries at a one- and five-year horizon, respectively. The impulse responses obtained from the Galí model are qualitatively and quantitatively in line with our baseline results. Furthermore, the Fernald and Galí models deliver similar structural shock series for the changes in the U.S. technology,

²⁰A summary of studies using the long-run identification of the U.S. technology shocks can be found in Rujin (2019).

²¹Uhlig (2004), Erceg, Guerrieri, and Gust (2005), and Chari, Kehoe, and McGrattan (2008) question Galí's long-run assumption. However, Erceg et al. (2005) conclude that, overall, long-run identification represents a reliable structural approach if the researcher has a reasonable sample length to work with. Furthermore, Galí (2004) and Francis and Ramey (2005) address the issues related to weak identification and show that shocks obtained by long-run restrictions are indeed capturing exogenous variations in technology and appear to be uncorrelated with other key structural shocks.

with a significant correlation coefficient of 0.76.²² However, the results for Japan and South Korea differ between both approaches. For other countries, our results are robust. We report a Spearman correlation coefficient of, respectively, 0.59 and 0.32 for the IRF point estimates for country-specific labor productivity after one and five years. Thus, the relative ranking of the responses does not change substantially between both approaches. The latter implies that the results of the previous section remain unaffected by this alternative identification scheme.

Second, to overcome the shortcomings of the long-run identification scheme, we employ the medium-run identification approach by Uhlig (2004), which maximizes the contribution of technology shocks to the forecast-error variance of productivity at intermediate horizons. The use of the medium-run identification is motivated by the assumption that labor productivity can be shifted in the long-run also by changes in dividend taxation and changes in the social attitude towards the workplace, and not exclusively by technology shocks. To obtain U.S. technology shocks, we employ the assumptions by Uhlig (2004) and identify these shocks as those that maximize the forecast-error variance of labor productivity between three and ten years.

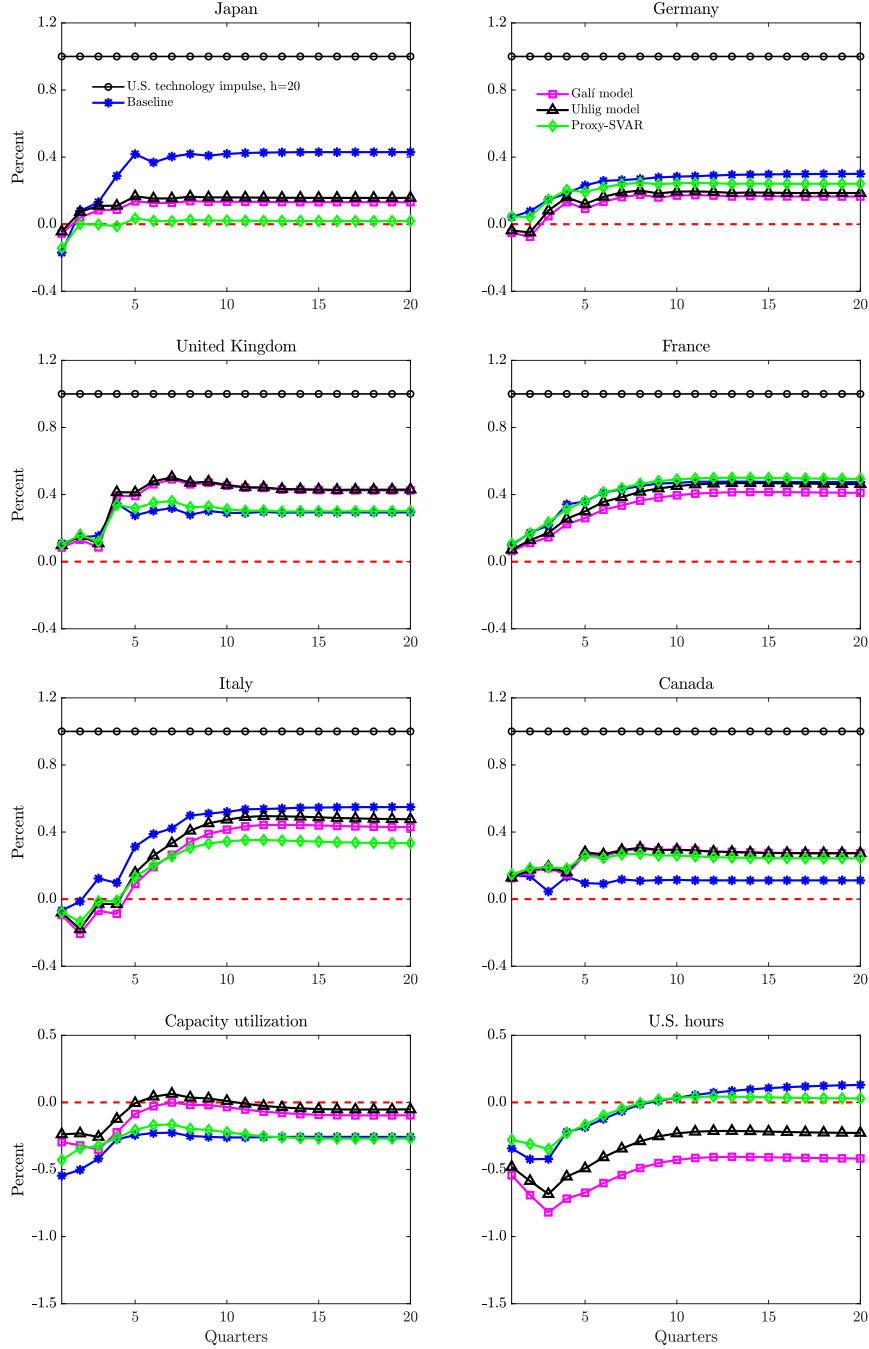
The results are displayed in Figure 6 and in the upper row of Figure 7. The technology shocks obtained from the Uhlig model are highly correlated with our baseline U.S. technology shocks; the correlation coefficient is 0.77. The IRFs obtained from the Uhlig model are very close to the results obtained from the Fernald model. For the U.S. hours, the magnitude of the IRF is now closer to the baseline result (see Figure 6). Also the point estimates illustrated in the upper row of Figure 7 are in line with the baseline results and the Spearman correlation coefficients are high. Consequently, using the medium-run identification approach proposed by Uhlig (2004) does not change our baseline statements.

Finally, we estimate a Proxy-SVAR model where we use purified TFP as an instrument to isolate U.S. technology shocks from U.S. labor productivity. Technology shocks resulting from this identification approach are defined as the unexpected changes in the U.S. labor productivity that have the highest correlation with the instrument series, that is, the purified TFP series. Hence, the correlation of our baseline U.S. technology shocks with the shock series obtained from the Proxy-SVAR model is high (0.78).

The results illustrated in Figure 6 are very close to the baseline IRFs, with the exception of Japan where the long-run productivity effect of the U.S. technology shock is close to zero. The outcomes shown in the upper row of Figure 7 are broadly in line with the baseline results. However, the Spearman correlation coefficients are now weaker. When we exclude the outlier countries from the analysis, that is, Japan and South Korea, the Spearman rank correlations between the baseline results and the results obtained from the alternative identification approaches discussed above increase significantly. Overall, Table B.2 and Figure B.1 show that the results in Section 5 remain unaffected by the exclusion of these two countries from the analysis.

²²Ramey (2016) reports a correlation between the two shock series of 0.68, which is based on a sample starting in 1947.

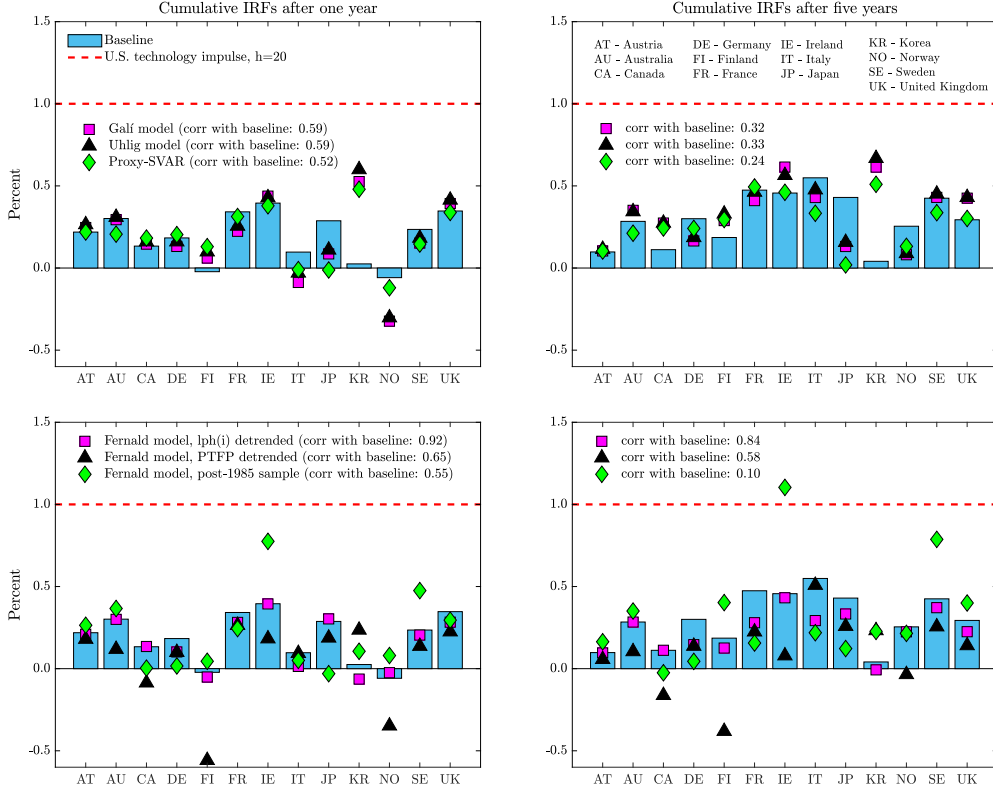
Figure 6: Impulse responses to a U.S. technology shock from different models



Notes: This figure shows the accumulated IRFs of labor productivity for the selected countries, the U.S. capacity utilization and hours following a U.S. technology shock. The Galí model, the Uhlig model, and the Proxy-SVAR include hourly labor productivity and hours adjusted for the working-age population for the U.S. The Galí and Uhlig models use long-run and medium-run identification schemes. The Proxy-SVAR uses purified TFP as instrument to identify U.S. technology shocks. U.S. capacity utilization enters these models as a subset variable. The scale of shocks obtained from these models is normalized to produce a one percent increase in purified TFP after 20 quarters. We use a subset framework to determine the response of purified TFP.

In sum, the results obtained from the three alternative models support our main conclusions related to an overall low elasticity of international labor productivity with respect to the U.S. technology shocks, as well as heterogeneous productivity spillovers across the major advanced economies. Furthermore, the Spearman rank correlations between the point esti-

Figure 7: Robustness checks of the U.S. productivity spillovers



Notes: This figure shows the accumulated IRFs of labor productivity to a U.S. technology shock over a one- and five-year horizon for 13 advanced economies. We also report the Spearman rank correlation coefficients between the IRFs of labor productivity for 13 advanced economies obtained from alternative model specifications and identification schemes and baseline results, respectively. The graphs in the first row illustrate the point estimates obtained from the baseline model (bars) and the markers denote the point estimates obtained from the Galí model, the Uhlig model, and the Proxy-SVAR. The second row illustrates the results obtained from the Fernald model that includes detrended labor productivity for foreign countries and the results obtained from the Fernald model that includes a detrended measure of purified TFP (PTFP). We also show the results obtained from the Fernald model that uses data for the post-1985 sample period. All models are estimated as subset VARs on a country-by-country basis. We normalize the size of the U.S. technology shock such that the structural shock induces a one percent increase in purified TFP after 20 quarters. To determine the response of purified TFP, we use a subset framework. All models include four lags and all variables are expressed in log first differences.

mates obtained from alternative identification schemes and our baseline results confirm the consistency of our key outcomes across countries.

6.2 Specification of the empirical model

Next, we test the sensitivity of our baseline results with respect to alternative stochastic transformations of the variables included in the Fernald model. First, we use detrended growth rates of labor productivity for 13 advanced economies while leaving the U.S. variables unchanged.²³ In the second exercise, we detrend purified TFP to account for breaks in the mean growth rate of the series. For this purpose, we use the break dates documented in Fer-

²³We detrend the growth rates of labor productivity by regressing the respective series on a constant and a linear and quadratic time trend. We use the residuals from these regression equations as our detrended series.

nald (2015): 1973:2, 1995:4, and 2003:4. In a final check, we follow Canova, Lopez-Salido, and Michelacci (2010) and restrict our estimation sample to start in the first quarter of 1985.²⁴

The second row of Figure 7 illustrates the results. Overall, there are no significant differences between the estimated IRFs obtained from the SVARs that employ detrended productivity measures and our baseline results. The relative ranking of the responses remains unchanged. For the IRFs obtained from the models specified with detrended labor productivity for the advanced economies, we report the Spearman correlation coefficients with our baseline result of 0.92 at a one-year horizon and of 0.84 at a five-year horizon.

For the IRFs obtained from the SVARs with detrended purified TFP, the correlations are 0.65 and 0.58, respectively. Concerning the magnitude of the IRFs, we find lower elasticities of foreign labor productivity with respect to a one percent increase in U.S. technology compared with our baseline results.

The results of the robustness check with respect to the later starting date are illustrated in the second row of Figure 7. In contrast to the previous checks, we find that the later starting date of our estimation sample affects the relative ranking of the impulse responses compared with the baseline results; the Spearman correlation coefficient at a five-year horizon is low (0.10).²⁵ However, our key finding that the elasticity of foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one remains unaffected. Furthermore, we again find some heterogeneity in the magnitudes of the IRFs across countries.²⁶

Table 4: **Spearman correlation coefficients for the post-1985 sample period**

	Lags	<i>Institutional characteristics</i>			
		Labor market rigidity	Product market rigidity	Service sector rigidity	Financial market rigidity
<i>Baseline IRFs</i>	4	-0.01	-0.29	-0.54*	0.38
	20	0.01	-0.41	-0.64**	0.43

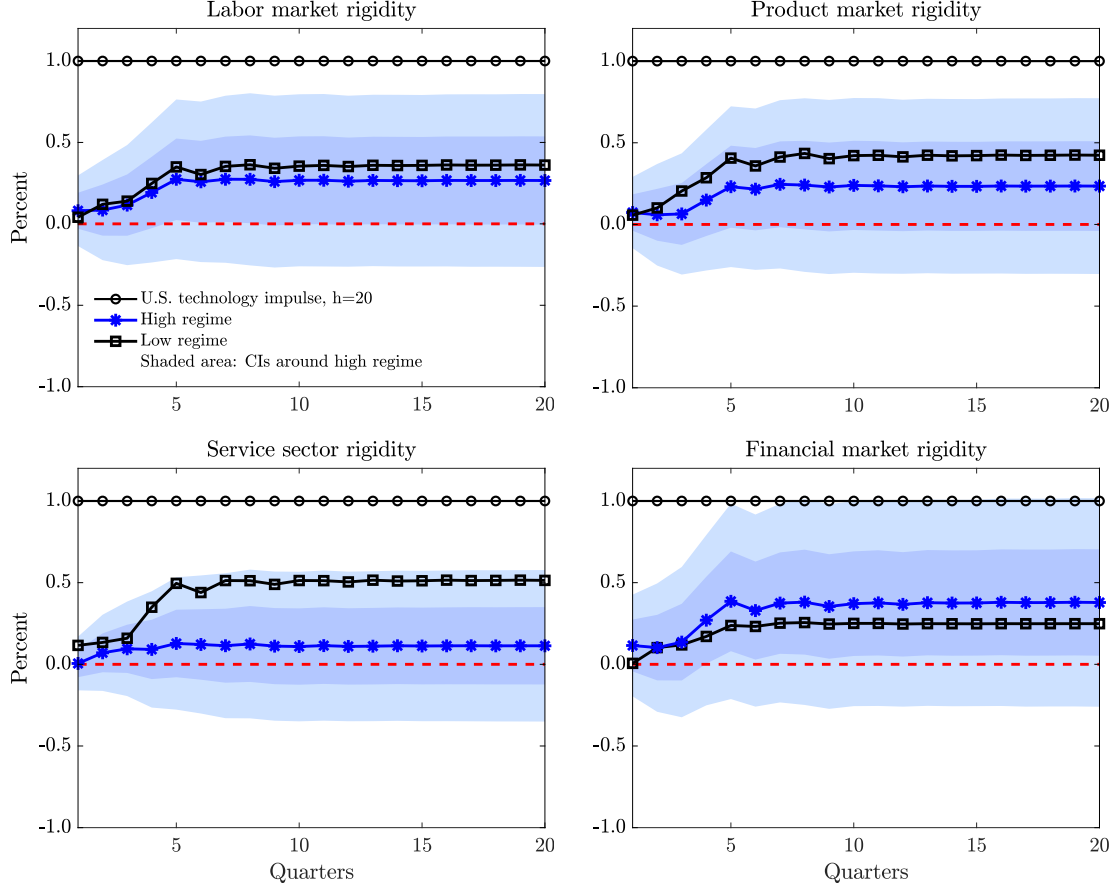
Notes: This table reports the Spearman rank correlation coefficients between the one and five years delayed cumulative IRFs of labor productivity following a U.S. technology shock for 13 advanced economies and indicators on institutional characteristics, respectively. The results were obtained using the data for the post-1985 sample period. We denote the statistical significance of correlation coefficients by asterisks *, **, *** at 10, 5, and 1 percent level, respectively.

²⁴This choice is based on the observation documented in, e.g., Summers (2005), that the volatility of aggregate economic activity has fallen dramatically in most of the industrialized world in that period, which is reflected in lower volatility of macroeconomic variables like GDP and inflation. Furthermore, since the fall of the Iron Curtain and the progressing integration of China into the world economy, there was an increase in the globalization trend. This development has led to a rapid expansion of the global trade, which is considered to be a strong channel for international productivity spillovers (Keller, 2004).

²⁵If we exclude Japan and South Korea from the calculations, the Spearman correlation coefficient increases to 0.26

²⁶In an additional robustness check, we extend our SVAR models to include 16 lags and consider the entire estimation sample spanning from 1970:1 to 2016:4. This generous lag length specification is motivated by the widely documented slow transmission process of new technologies across countries (Smets and Wouters, 2007; Rotemberg, 2003; Rabanal et al., 2011). Therefore, in this robustness check, we allow for delayed effects of up to four years. The results are illustrated in Figure B.2 in the appendix. Our main results are unaffected by this lag selection.

Figure 8: Mean impulse responses to a U.S. technology shocks for the post-1985 sample period



Notes: This figure displays the cross-sectional average impulse responses of labor productivity to a U.S. technology shock, which are computed over the groups of 6 countries, respectively. The original IRFs were obtained from the estimation of the baseline model using data for the post-1985 sample period and on a country-by-country basis. Further details are provided in the notes to Figure 4.

In contrast to our baseline results, we find for the post-1985 period that the mean IRFs computed for the country sub-groups display considerable differences. Figure 8 shows the results. We find a significant difference between the mean IRFs corresponding to the groups of countries with low and high service sector rigidity, which was not the case in our baseline calculations illustrated in Figure 4. Economies with a more flexible service sector benefit to a greater extent from U.S. technology gains compared to economies that adopt a stricter regulation, like France, Germany, and Italy. Finally, the Spearman rank correlation coefficients between the one and five years delayed cumulative IRFs of labor productivity following a U.S. technology shock for 13 advanced economies and indicators on institutional characteristics reported in Table 4 point to a statistically significant negative relationship between institutional rigidity in the service sector and productivity spillovers of U.S. technology shocks for the post-1985 time period.

7 Conclusions

This study adds to the empirical literature on international technology spillovers. Specifically, we provide new evidence regarding the size of international productivity spillover effects originating from the U.S. economy. To do so, we use a direct utilization-adjusted U.S. technology measure and analyze the dynamic effects of changes in this measure on hourly labor productivity in 13 advanced economies.

Overall, we do not find large productivity spillover effects of U.S. technology shocks. Specifically, for most countries, these effects are not significantly different from zero. Moreover, the elasticity of foreign labor productivity with respect to a one percent increase in the U.S. technology level is significantly lower than one for many countries. The finding of low spillover effects is somewhat surprising as technology (knowledge) has the feature of non-rivalry (Keller, 2004). In our opinion, studying the reasons for this incomplete pass-through of U.S. technology gains opens an important avenue for future research. Regarding the sources of the marked slowdown in productivity growth in many advanced economies since the mid-2000's, we conclude that the decline in U.S. productivity growth had only a limited role.

Finally, we find no sizeable cross-country heterogeneity regarding the magnitude of the international U.S. technology spillover effects. Using indicators of non-price competitiveness, we are not able to explain the cross-country differences in the size of the spillover effects by institutional factors. This result contradicts the finding in Cetto et al. (2016), who stress the importance of labor and product market regulations in shaping the transmission of ideas and innovations across countries. If any, regulation of the service sector seems to play a role.

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Appendix A Data definitions and sources

Table A.1: Data sources and definitions

Variable	Sample	Definitions and sources
Fernald (2014) , http://www.johnfernauld.net/TFP		
Utilization-adjusted quarterly-TFP series for the U.S. Business Sector	1970:1–2016:4	The data on inputs, including capital, are used to produce a quarterly series on total factor productivity. In addition, the dataset implements an adjustment for variations in factor utilization–labor effort and the workweek of capital. The utilization adjustment follows Basu et al. (2006) .
Utilization of capital and labor	1970:1–2016:4	Based on the approaches developed by Basu et al. (2006) and Basu, Fernald, Fisher, and Kimball (2013) , Fernald (2014) computes a proxy for variations in factor utilization – labor effort and the workweek of capital.
Ohanian-Raffo dataset: Ohanian and Raffo (2012) , http://andrearaffo.com/arafo/Research.html		
Total hours worked	1970:1–2016:4 1971:1–2016:4 (U.K.) 1974:1–2016:4 (SE)	Total hours worked series are obtained as the product of hours worked per worker and employment.
Population aged 15 to 64	1970:1–2016:4	Time series are from national statistical offices and the OECD-Economic Outlook database.
Real GDP	1970:1–2016:4	Time series are from the OECD-Economic Outlook database.
International institutional characteristics		
Strictness of employment protection, 0 - 6 (strict)	1985–2013 1990–2013 (KR)	The OECD indicator of employment protection is a synthetic indicator of the strictness of regulation on dismissals. It measures the strictness of employment protection against individual dismissal (regular contracts) and is expressed on a scale 0 - 6 (most strict).
Economy-wide product market regulation, 0 - 6 (strict)	1998–2013	This indicator is from the OECD dataset, which represents a comprehensive and internationally-comparable set of indicators that measure the degree to which policies promote or inhibit competition in areas of the product market where competition is viable. They measure the economy-wide regulatory and market environments in 1998, 2003, 2008 and 2013. These indicators are consistent across time and countries and are expressed on a scale from least (0) to most restrictive (6). For further details see Koske et al. (2015)

Table A.1: (*Continued*)

Variable	Sample	Definitions and sources
Sector market regulation, 0 - 6 (strict)	1998–2013	This indicator is from the OECD dataset, which represents a comprehensive and internationally-comparable set of indicators on regulation in non-manufacturing sectors (NMR). These indicators measure regulation at the sector level and cover seven network sectors (telecommunication, electricity, gas, post, rail, air passenger transport, and road freight) and five service sectors (retail distribution, accounting services, legal services, engineering services, and architectural services). The seven indicators of regulation in network sectors are aggregated into one indicator of regulation in energy, transport and communications (ETCR). The indicators for the five service sectors are available for the years 1998, 2003, 2008 and 2013. For further details see Koske et al. (2015)
Chinn-Ito index of financial openness	1970–2016	The index of financial openness was developed by Chinn and Ito (2006) . It measures a country's degree of capital account openness by considering regulatory restrictions on cross-border financial transactions.
Productivity Levels		
Country Productivity Levels	1995 and 2010	Inklaar and Diewert (2016) use the translog GDP methodology for measuring productivity levels across time and adapt it to the multilateral context. The new method is illustrated using an industry level data set and shows productivity dispersion across 12 countries between 1995 and 2010.
Real GDP per hour worked	1970–2016	GDP per hour worked in US Dollars, constant prices, and 2010 PPPs from the OECD.
Gaps in real GDP per hour worked with respect to the U.S.	1970–2016	Gaps are expressed in percent. Data are from the OECD.

Table A.1: (*Continued*)

Variable	Sample	Definitions and sources
Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis		
Nonfarm Business Sector: Real Output Per Hour of All Persons, Index 2009=100, Quarterly, Sea- sonally Adjusted, U.S.	1970:1–2016:4	U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Real Output Per Hour of All Persons [OPHNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OPHNFB
Nonfarm Business Sector: Hours of All Persons, In- dex 2009=100, Quarterly, Seasonally Adjusted, U.S.	1970:1–2016:4	U.S. Bureau of Labor Statistics, Nonfarm Business Sec- tor: Hours of All Persons [HOANBS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/HOANBS
Other variables		
Nominal GDP	1970:1–2016:4	Gross domestic product – expenditure approach, in U.S. dollars, current prices, current PPPs, seasonally adjusted. Data are from the OECD Quarterly National Accounts.

Notes: All definitions are from the original sources. The data set covers 14 countries: Australia (AU), Austria (AT), Canada (CA), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Japan (JP), Norway (NO), South Korea (KR), Sweden (SE), U.K., and the U.S. We exclude Spain from the analysis due to the much later starting date of the hours series which starts in 1995:1.

Appendix B Additional tables and figures

Table B.1: Classification of countries according to institutional characteristics

Country	Labor market rigidity	Product market rigidity	Service sector rigidity	Financial market rigidity
Median (excluding U.S.)	2.39	1.61	2.08	1.55
U.S.	0.26	1.56	1.67	2.36
Austria	high	low	high	low
Australia	low	low	low	high
Canada	low	high	high	low
Germany	high	high	high	low
Finland	<i>median</i>	low	<i>median</i>	<i>median</i>
France	high	high	high	high
Ireland	low	low	low	high
Italy	high	high	high	high
Japan	low	low	high	low
South Korea	high	high	low	high
Norway	low	<i>median</i>	low	high
Sweden	high	high	low	low
U.K.	low	low	low	low

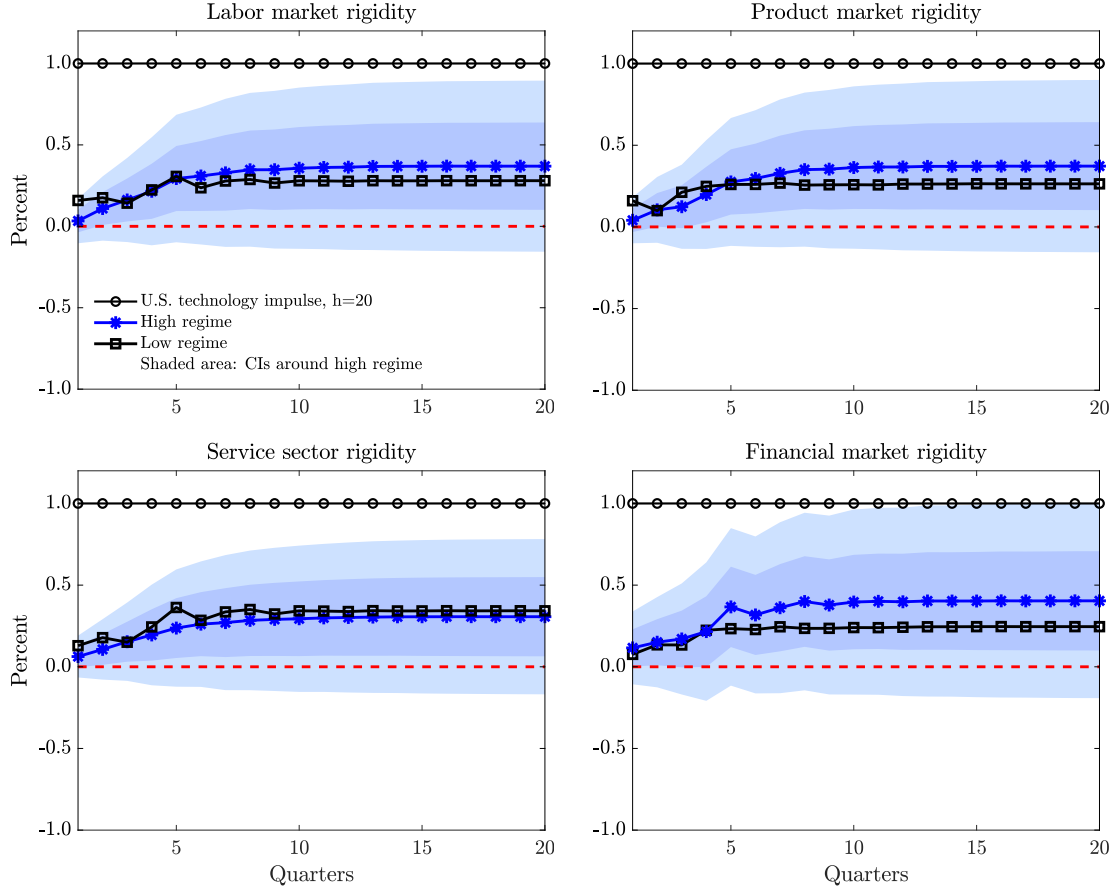
Notes: This table shows the classification of countries into "high" and "low" regimes, based on the respective institutional characteristics. For this purpose, we compute the country-level averages of the respective institutional indicators. Based on these averages, we compute the median value of each indicator (excluding the U.S.). Consequently, countries displaying an average value above (below) the corresponding median are classified into high (low) regimes. To obtain the same number of countries in each regime, we exclude for each institutional characteristic the respective median country. Definitions and sources of the institutional characteristics considered in this table can be found in the [data appendix](#). For consistency reasons, we reversed the definition of financial market openness. We thus attribute high (low) financial openness to low (high) institutional rigidity.

Table B.2: Spearman correlation coefficients excluding Japan and South Korea

		<i>Institutional characteristics</i>			
	Lags	Labor market rigidity	Product market rigidity	Service sector rigidity	Financial market rigidity
<i>Baseline IRFs</i>	4	-0.25	-0.24	-0.25	0.08
	20	0.45	0.50	0.17	0.51

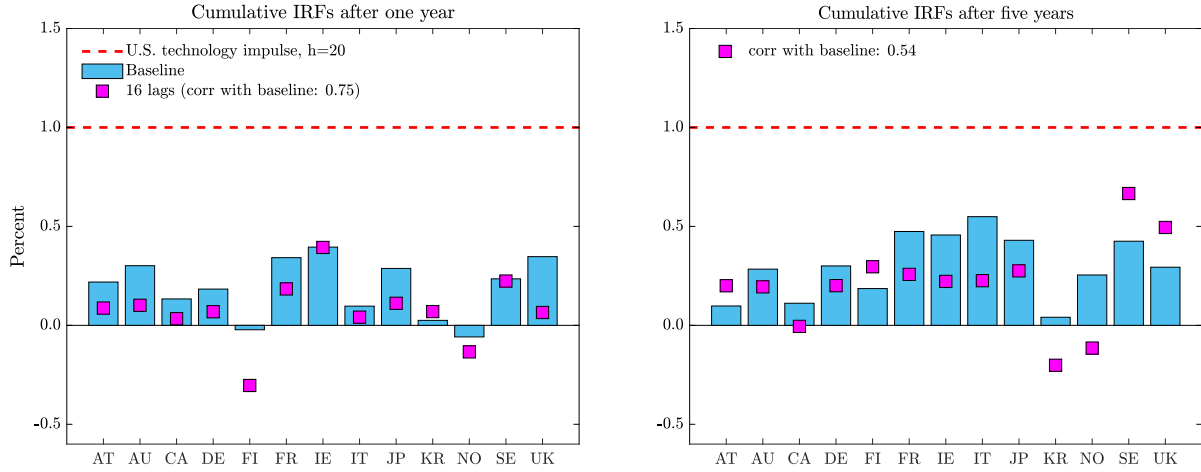
Notes: This table reports the Spearman rank correlation coefficients between the one and five years delayed cumulative IRFs of labor productivity following a U.S. technology shock for 11 advanced economies, excluding Japan and South Korea, and indicators on institutional characteristics, respectively.

Figure B.1: Mean impulse responses to a U.S. technology excluding Japan and South Korea



Notes: This figure displays the cross-sectional average impulse responses of labor productivity to a U.S. technology shock, which are computed over the groups of 5 countries, respectively. Japan and South Korea are excluded from the calculations. The original IRFs were obtained from the estimation of the baseline model on a country-by-country basis (these results are illustrated in [Figure 1](#) and [Figure 2](#)). The classification of countries into "high" and "low" regime groupings is done according to their respective institutional characteristics, which can be found in [Table B.1](#). We use the unit effect normalization of the U.S. technology shock so that a unit increase in $\epsilon_t^{U.S. \text{ tech}}$ induces a one percent increase in the observable U.S. technology measure (purified TFP) after 20 quarters. Shaded areas represent the corresponding cross-sectional average 68% and 95%-confidence intervals, which were originally computed using a recursive-design wild bootstrap procedure proposed by [Gonçalves and Kilian \(2004\)](#). All details concerning the model estimation, specification, and data sources are provided in [Section 3](#) and in the notes to [Figure 1](#).

Figure B.2: The effects of U.S. technology shocks on labor productivity



Notes: This figure shows the accumulated IRFs of labor productivity to a U.S. technology shock over a one- and five-year horizon for 13 advanced economies. The markers illustrate the point estimates obtained from the Fernald model that includes 16 lags. We also report the Spearman rank correlation coefficients between the IRFs of labor productivity for 13 advanced economies obtained from the Fernald model with 16 lags and baseline results, respectively. All models are estimated as subset VARs on a country-by-country basis. We use the unit effect normalization of the U.S. technology shock so that a unit increase in $\epsilon_t^{U.S. tech}$ induces a one percent increase in the observable U.S. technology measure (purified TFP) after 20 quarters. All variables are expressed in log first differences.