IMF STAFF DISCUSSION NOTE

Gone with the Headwinds: Global Productivity

TECHNICAL APPENDICES I-VIII

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The Global Productivity Slowdown: Crisis Legacies and Other Headwinds

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APPENDIX I. THE IMPACT OF DEEP RECESSIONS ON AGGREGATE PRODUCTIVITY[2]

Previous literature has found that financial crises and large recessions can have sizable and persistent effects on output.[3] This note focuses on the specific effects of deep recessions on total factor productivity (TFP). Recessions can have an impact on aggregate productivity through two channels: (i) by affecting productivity at the firm level or, in the analysis below, at the sectoral level (the *within* effect); and (ii) by inducing inter-sectoral reallocation of resources (the *between* effect). This is explored here.

A. Methodology

Aggregate TFP is decomposed into two components, *within*- and *between*-sector productivity following the methodology by McMillan and Rodrick (2011), adapted to study TFP growth by Furceri, Selik, and Schnuker (forthcoming):[4]

$$tfp_{j,t+k} - tfp_{j,t-1} = \sum_{i=1}^{I} w_{i,j,t-1}\left(tfp_{i,j,t+k} - tfp_{i,j,t-1}\right) + \sum_{i=1}^{I} tfp_{i,j,t+k}\left(w_{i,j,t+k} - w_{i,j,t-1}\right)$$

where $tfp_{j,t}$ is the log of aggregate cyclically-adjusted TFP in country *j* at time t, $tfp_{i,j,t}$ is the log of the cyclically-adjusted TFP of sector *i* in country *j*, and $w_{i,j,t}$ is the share of sector *i's* value added.[5] The first right-hand side term is the *within* component—which captures the change in TFP in each sector, keeping the weight of each sector unchanged. The second right-hand side term is the *between* component, which captures the change in TFP resulting from reallocation of resources across different sectors. This *between* component is simply calculated as a residual between aggregate TFP growth and the *within* component, which alleviates the need to compute TFP levels as would be needed if we attempted to measure it directly.

We use the local projections method (Jorda 2005) to study the effect of deep recession on different variables of interest, including aggregate TFP, as well as the *within* and *between* components. Specifically, the following equation is estimated for each horizon $k = 0,1,2,3,4$:

$$x_{t+k,j} - x_{t-1,j} = \alpha_j + \gamma_t + \sum_{s=1}^{2} \delta_s^k \Delta y_{t-s,j} + \beta_k D_{t,j} + \sum_{s=1}^{2} \theta_s^k D_{t-s,j} + \sum_{s=0}^{k-1} \rho_s^k D_{t+k-s,j} + \varepsilon_{t,j}$$

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[2] This technical appendix was prepared by Ksenia Koloskova.

[3] See, for example, Cerra and Saxena (2008).

[4] See also IMF (2015).

[5] These weights are those we also use to compute our aggregate measure of cyclically-adjusted TFP growth. Following the approach described in Basu and others (2006), the weights are given by $w_i/(1\text{-}sm_i)$, in which w_i is the industry' share of gross output, and sm_i is the share of input payments in total costs. The rationale for dividing by 1-sm_i is to take into account productivity gains in intermediate sectors, following Domar (1961). Therefore, the TFP growth rates are weighted by the industry's share of aggregate value added (Basu and others 2006).

where $x_{t+k,j} - x_{t-1,j}$ is the cumulative change of the variable of interest for country *j;* α_j and γ_t are country and time fixed effects, respectively; *D* is a dummy variable which takes value of 1 for beginning of the deep recession, and zero otherwise. Other control variables include (i) past output growth (two lags), (ii) lagged recession dates (two lags), (iii) country-specific trends. The bias correction suggested by Teulings and Zubanov (2014) is followed, by controlling for forward values of the recession dummy between periods t and $t + k - 1$.

B. Data

Country-level data come from Penn World Tables version 9.0 (PWT). For the sector-level analysis, cyclically-adjusted TFP data come from Furceri, Selik, and Schnuker (forthcoming) and Dabla-Norris and others (2015). The cyclical adjustment is applied by extending the approach followed by Basu and others (2006) for the United States to 17 advanced economies for 1970–2010. The sample for our analysis is restricted to years before the global financial crisis. We focus on past recessions of comparable size—by output decline— to the global financial crisis. The countries in the sample include Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, the Netherlands, Portugal, Spain, the United Kingdom, and the United States.

The definition of *deep recessions* is based on the sample of recessions identified in Blanchard, Cerutti, and Summers (2015). Their original quarterly data set contains data on peak and trough dates, with all periods between these dates (inclusive) defined as recessions. Deep recessions are identified as those at the bottom 10 percent of the distribution of episodes, by cumulative output growth in the first eight quarters of the recession (starting from the peak). The deep recession dummy then takes value of 1 in the year of the start of the event,[6] and 0 in all other years. This selection allows us to study whether recessions with large initial output declines (comparable in size to that observed during the global financial crisis) have persistent effects on key macroeconomic variables such as TFP, as opposed to just transitory effects. As a robustness check, we also rerun our analysis with an identification of deep recession episodes based on output contraction in the first four—rather than eight—quarters after the peak.

C. Results

Aggregate Effect

Results for economy-wide variables using Penn World Tables are reported in Appendix Figure 1.1. Output declines by about 10 percent in the medium term during deep recessions. The decline in employment is somewhat delayed, resulting in a sharp fall in labor productivity. In the medium term, employment declines almost by as much as the output. The effects on output and employment appear to be very persistent. Medium-term recovery in labor productivity is driven by the evolution of the capital-to-labor ratio: physical capital declines significantly in the medium term, but by less

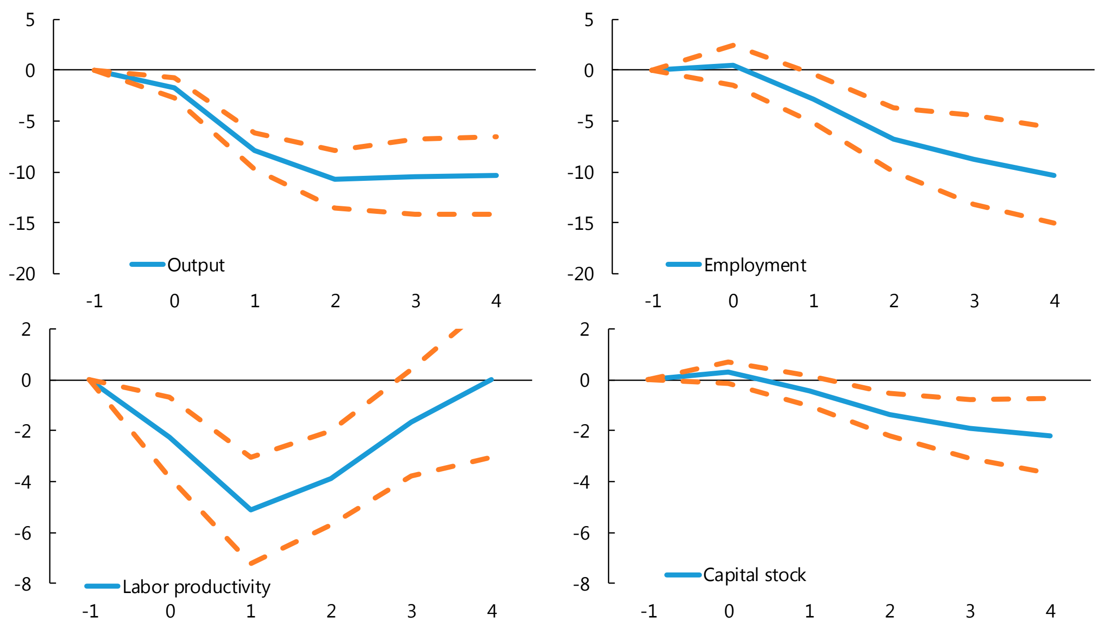
[6] In all identified episodes of deep recessions, the pre-recession peak occurred either in Q1 or Q2. This alleviates potential issue of incorrectly dating the start of a recession when moving from quarterly to annual frequency.

than employment. Since labor productivity goes back to, and the capital-to-labor ratio rises above, pre-recession levels over the medium term, TFP is durably reduced.

The next section reruns this analysis following an alternative approach, which is to estimate the economy-wide TFP loss using sector-level data from KLEMS and then decompose it into its within and between components. The use of sector-level data allows for cyclical adjustment of TFP at the sector level as in Basu, Fernald, and Kimball (2006), which is important to capture the underlying change in productivity since measured TFP fluctuations are typically driven in part by highly procyclical unobserved capacity utilization.

Appendix Figure 1.1. Effects of Recessions on Key Macroeconomic Variables

(Percent)



Sources: Penn World Table 9.0; EU KLEMS and WORLD KLEMS data; Blanchard, Cerutti, and Summers (2015); and IMF staff calculations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. Dashed lines denote 90-percent confidence bands. The effects are estimated using local projections method (Jordà 2005), controlling for past growth, lagged recessions and country-specific trends, and including a bias correction suggested by Teulings and Zubanov (2014).

Sectoral Reallocation

Cyclically-adjusted TFP shows a strong protracted decline during deep recessions, averaging about 5 percent after four years (Appendix Figure 1.2—Panel A).[7] This is somewhat larger than in the

[7] These results contrast with those of Oulton and Sebastia-Barriel (2013), who found permanent output effects, but not permanent TFP impact, of financial crises. The difference owes to our focus on deep recessions rather than on financial crises. Some financial crises are associated with only mild recessions, and conversely some deep recessions are not associated with financial crisis. Rerunning the analysis focusing only on financial crises would yield no significant long-term impact on TFP, in line with Oulton and Sebastia-Barriel (2013).

aggregate analysis performed above, which uses data from Penn World Tables rather than KLEMS. The former encompasses all sectors of the economy, although it is not cyclically adjusted.

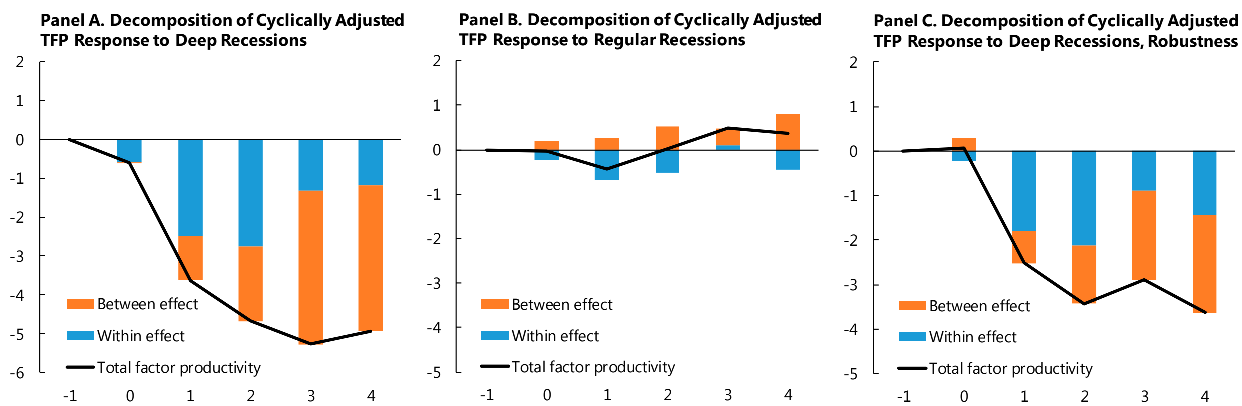
The effect comes from both the *within* and *between* components of TFP growth, with the latter being small initially but gaining prominence over time, possibly reflecting the impact of market dislocation. Complementary analysis of the change in weights of various sectors shows that deep recessions are associated with declining weights for high-productivity manufacturing sectors, such as electrical and optical equipment, machinery, and so on.

A comparison between deep and mild recessions shows that the former have a much larger effect on cyclically-adjusted TFP (Appendix Figure 1.2—Panel B)—the TFP decline is much smaller and short-lived in mild recessions. Moreover, in contrast to the large *between* component identified during deep recessions, the TFP decline during mild recessions is entirely due to the *within* effect. The *between* effect is small and goes in the opposite direction.

A robustness exercise identifying deep recessions on the basis of only their four-quarter cumulative output contraction confirms a large and persistent decline in cyclically adjusted TFP with a significant contribution of the *between* effect (Appendix Figure 1.2—Panel C).

Appendix Figure 1.2. Effects of Recessions on Cyclically Adjusted TFP and Its Components

(Percent)

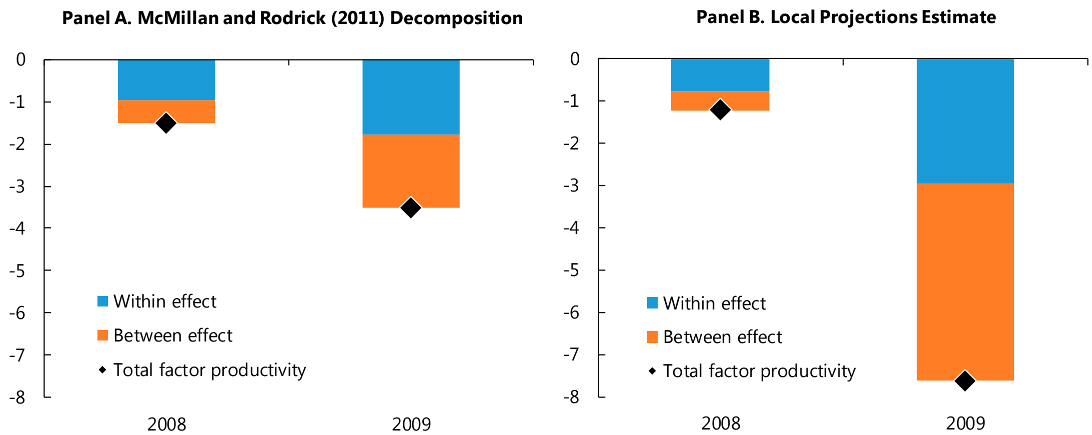


Sources: EU KLEMS and WORLD KLEMS data; Blanchard, Cerutti, and Summers (2015); and IMF staff calculations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. TFP = total factor productivity. The decomposition is based on McMillan and Rodrik (2011). Within effect refers to the contribution of sectoral productivity growth to aggregate productivity growth. Between effect refers to contribution of inter-sectoral reallocation of resources. The effects are estimated using local projections method (Jordà 2005), controlling for past growth, lagged recessions and country-specific trends, and including a bias correction suggested by Teulings and Zubanov (2014). Panel C presents the decomposition based on an alternative definition of deep recessions, using growth in the first 4 quarters after the peak (instead of 8 quarters) to identify the 10 percent of the largest recessions.

A similar decomposition for the global financial crisis indicates that the productivity decline was even larger compared with past deep recessions, and sectoral reallocation (*between* effect) also played an important role (Appendix Figure 1.3). Since sector-level data used here end in 2009 for the most the countries in the sample, only the short-term impact of the global financial crisis can be explored. Both the results based on the above sectoral decomposition and those from a local projection estimation focusing only on the global financial crisis (where the *within* and *between* effects are also regressed on control variables) show a cumulative productivity decline of more than 3 percent, with a significant contribution from the *between* effect, in the first two years. In this regard, the global financial crisis is comparable to previous deep recession episodes.

Appendix Figure 1.3. Cumulative Change in Cyclically Adjusted Total Factor Productivity

(Relative to 2007, percent)



Sources: EU KLEMS and WORLD KLEMS data; Blanchard, Cerutti, and Summers (2015); and IMF staff calculations.
Note: The decomposition is based on McMillan and Rodrik (2011). *Within* effect refers to the contribution of sectoral productivity growth to aggregate productivity growth. *Between* effect refers to the contribution of inter-sectoral reallocation of resources. The effects in the right hand side panel are estimated using local projections method (Jordà 2005), controlling for past growth and lagged global financial crisis dummy, and including a bias correction suggested by Teulings and Zubanov (2014).

References

Blanchard, O., E. Cerutti and L. Summers. 2015. "Inflation and Activity – Two Explorations and their Monetary Policy Implications," IMF Working Papers 15/230, International Monetary Fund.

Cerra, V. and S,C. Saxena. 2008. "Growth Dynamics: The Myth of Economic Recovery," American Economic Review, American Economic Association, vol. 98(1), pages 439–57, March.

Dabla-Norris, E., S. Guo, V. Haksar, M. Kim, K. Kochhar, K. Wiseman, and A. Zdzienicka. 2015. "The New Normal: A Sector-Level Perspective on Productivity Trends in Advanced Economies." Staff Discussion Note 15/03, International Monetary Fund.

Domar, E. 1961. "On the Measurement of Technical Change," Economic Journal, vol. 71(284), pages 710–29.

Furceri, D. S. Kilic Celik and A. Schnucker, forthcoming. "TFP Growth before the Global Financial Crisis: Evidence from a New Database for Advanced Economies," IMF Working Paper, International Monetary Fund.

Jordà, Ò. 2005. "Estimation and Inference of Impulse Responses by Local Projections," American Economic Review, American Economic Association, vol. 95(1), pages 161–182, March.

Kimball, M. S., J.G. Fernald and S. Basu. 2006. "Are Technology Improvements Contractionary?," American Economic Review, American Economic Association, vol. 96(5), pages 1418–1448, December.

McMillan, M. S. and D. Rodrik. 2011. "Globalization, Structural Change and Productivity Growth," NBER Working Papers 17143, National Bureau of Economic Research, Inc.

Teulings, C. N. and N. Zubanov, 2014. "Is Economic Recovery a Myth? Robust Estimation Of Impulse Responses," Journal of Applied Econometrics, John Wiley & Sons, Ltd., vol. 29(3), pages 497–514, 04.

APPENDIX II. THE IMPACT OF FIRM BALANCE SHEET VULNERABILITIES AND CREDIT CONDITIONS ON THE POSTCRISIS PRODUCTIVITY SLOWDOWN[8]

One possible driver of the abrupt slowdown in total factor productivity (TFP) since the global financial crisis is the sharp tightening in credit conditions that took place after the collapse of Lehman Brothers in September 2008 and persisted in a number of countries afterward, not least in Southern Europe during the euro area crisis. Credit conditions may affect aggregate TFP through their impact on *both* firm-level TFP and the efficiency of resource allocation across firms. This appendix focuses on the former channel. Using an extensive cross-country firm-level data set, it investigates whether tighter access to credit postcrisis reduced TFP growth in firms with pre-existing balance sheet vulnerabilities, and thereby weakened aggregate TFP growth given that such "vulnerable" firms were not (on average) lower-productivity-growth firms. The analysis then explores one possible channel: the adverse impact of tighter credit conditions on intangible investment.

Key Variables and Data

The main dataset used for the firm-level analysis is ORBIS, a unique cross-country longitudinal database of both listed and unlisted firms provided by Bureau van Dijk. ORBIS features harmonized and rich information on firms' productive activities (for instance, value-added output, capital stock, employment) and financial situations based on balance sheets and income statements (for instance, debt, assets, tangible and intangible fixed assets, long-term debt).[9]

The main analysis draws from the latest vintage of data collected in 2015, which covers 10 years from 2004 to 2013.[10] We focus on 15 advanced economies for which we also have information on aggregate financial and credit conditions over this period: Austria, Belgium, Denmark, Germany, Spain, France, Greece, Italy, Japan, Korea, the Netherlands, Portugal, Slovenia, the United Kingdom, and the United States. We study firms in the nonfarm, nonfinancial business sector, which corresponds to the two-digit industry codes 5–82 in NACE Rev.2., covering both manufacturing and a number of services sectors including real estate, education, and profession/scientific/technical activities, to name a few.[11]

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[8] This technical appendix was prepared by Romain Duval and Gee Hee Hong.

[9] See Gal (2013), Kalemli-Özcan and others (2015) and Gal and Hijzen (2016) for more detailed descriptions of the data set.

[10] The only exception is the placebo analysis around the time of the 2000 dot-com bubble burst (see below), for which one of the historical vintages of ORBIS containing information before and after 2000 is used.

[11] See Eurostat (2008) for information on the categorization and correspondence with other sector classifications (http://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07–015-EN.PDF).

To ensure consistency and comparability of monetary variables across countries and over time, we adopt the methodology followed by Gal and Hijzen (2016). First, the original data recorded in U.S. dollars are converted into local currency. Nominal variables are then turned into real variables by applying local currency deflators obtained from OECD STAN (ISIC4 version), which are rebased to 2005 U.S. dollars using country-industry level purchasing power parity data obtained from Timmer and Inklaar (2014). In addition, we exclude very small firms (less than three employees), a common practice in studies using firm-level data, due to concerns regarding the reliability of the data as well as the consistency of variables over time. Also, we restrict our analysis to firms that report at least four consecutive periods.

Matched with these firm-level variables are aggregate, country-level financial and credit conditions variables drawn from other sources. The main one is an economy-wide measure of spreads on bank credit default swaps (CDS) in each country in our sample, which is computed as the simple average of CDS spreads across the country's banks.[12] All else equal, banking systems whose CDS spreads rose more around the collapse of Lehman Brothers experienced a larger increase in perceived vulnerabilities and a more adverse shock to credit supply as banks sought to strengthen their balance sheets. We argue that greater exposure to the Lehman bankruptcy as reflected in a larger increase in domestic bank CDS spreads captures an exogenous tightening of credit conditions in the country considered.

The main dependent variable used in the analysis is firm-level TFP growth, which we compute using real value added, real capital stock, and the number of employees available in each firm's balance sheet, and applying the control function suggested by Wooldridge (2009).[13] The real capital stock for each firm is derived from the dynamic evolution of the capital stock following the perpetual inventory method (PIM), using information on depreciation and tangible fixed in the balance sheet (for more details, see Gal 2013, Gal and Hijzen 2016). In addition to identifying the possible channel(s) through which firm-level productivity growth may be affected by financial frictions, we explore their impact on intangible fixed assets as reported in balance sheets.

Two key explanatory variables are chosen that capture two different dimensions of firms' balance sheet vulnerabilities entering the global financial crisis. The first variable captures debt overhang. It is the precrisis average leverage ratio, measured as the ratio of the sum of current liabilities and long-term debt to total assets, averaged from 2003 to 2007. The second variable captures rollover risk, and is measured as the ratio of current liabilities (i.e. debt maturing within a year) to total sales in the 2007 balance sheet. A higher share of debt maturing in 2008 implies greater exposure to rollover risk before the failure of Lehman Brothers. Almeida and others (2009) argue that this variable provides exogenous variation in firms' financial vulnerabilities, as firms could not foresee in 2007 the timing and size of the September 2008 shock to global credit conditions.

[12] Results are robust to considering weighted averages instead.

[13] Wooldridge (2009) provides a single-equation instrumental variable approach to estimate unobserved multi-factor productivity, including intermediate inputs rather than investment as proxies as proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Importantly, TFP growth did *not* systematically differ across firms along these two dimensions before the crisis (as shown in Figure 7 in the main text), which points to exogenous variation in firm vulnerabilities and will allow causal interpretation of the estimated effects. Our confidence in such a causal interpretation will be strengthened by a placebo test around the 2000 recession, which will show no effect of preexisting financial vulnerabilities on postrecession TFP growth.

Empirical Strategy and Findings

Our baseline regression follows a difference-in-differences strategy and compares precrisis and postcrisis TFP growth in more vulnerable versus less vulnerable firms, controlling for country-sector fixed effects to ensure the comparison is performed within each country-sector and the results are not driven by country-sector-specific factors (such as a sharp decline in the output and productivity growth of the construction sector, which was also more leveraged in some countries than in others). This identification strategy bears similarities with Giroud and Mueller (2017), who study the impact of the 2008 credit supply shock on employment in firms in the United States, using the pre-crisis leverage ratio as a measure of firm-specific vulnerability. We also use 2008 as the crisis year. To further assess whether the sharp unforeseen tightening of credit conditions after the collapse of Lehman Brothers reduced TFP growth more in firms that had greater ex-ante balance sheet vulnerabilities, we also exploit the variability in the tightening in credit conditions across countries. We do so by interacting an indicator capturing this degree of tightening, namely the change in average bank CDS spreads between the first and second halves of 2008, with our two measures of firm-specific financial vulnerabilities. By design, the focus is on firms still in business; tighter access to credit may have led some of the more vulnerable firms to exit. But this is not studied here for lack of reliable data on exit using Orbis.

Specifically, the estimated specification is:

$$\Delta TFP_{isc}^{growth} = \alpha_{sc} + \beta_1 Vulnerabilities_i^{PRE} + \beta_2 Vulnerabilities_i^{PRE} * \Delta CDS_c + \gamma' X_i + \varepsilon_{isc} \quad (1)$$

where $\Delta TFP_{isc}^{growth}$denotes the change in average TFP growth between the five years before and five years after the crisis in firm i, in sector s, and country c, $Vulnerabilities_i^{PRE}$ is one of the two firm-specific measures of precrisis vulnerabilities (which may also enter the equation simultaneously), X_i is a set of firm-level controls including age, total assets and earnings (EBITDA) before the financial crisis and ΔCDS_c is the change in the average CDS spread across banks of country c between the first and second halves of 2008. Standard errors are double-clustered at the country-sector and firm levels in all firm-level regressions.

Appendix Table 2.1 reports the results. Both high leverage and high rollover risk are found to have had a large and statistically significant adverse effect on TFP growth postcrisis, as shown in columns (1) to (3). There is also significant interaction between each source of vulnerability and the degree of tightening in credit conditions as measured by the country-wide change in average bank CDS spreads around the collapse of Lehman Brothers, as shown in columns (4) to (6). This indicates that firm-specific vulnerabilities weakened TFP growth more in countries where credit conditions tightened more.

Appendix Table 2.1. Pre-2008 Financial Vulnerabilities and the Change in TFP Growth Between the Precrisis and Postcrisis Periods

	(1)	(2)	(3)	(4)	(5)	(6)
			Δ Total factor productivity growth			
Leverage precrisis	-0.047***		-0.036***	-0.057***		-0.046***
	(0.008)		(0.006)	(0.009)		(0.010)
Leverage precrisis * Δ credit default swap spreads				-0.057***		-0.051***
				(0.015)		(0.021)
Debt maturing 2008		-0.094***	-0.091***		-0.111***	-0.108***
		(0.010)	(0.010)		(0.008)	(0.008)
Debt maturing 2008 * Δ credit default swap spreads					-0.068***	-0.064***
					(0.017)	(0.017)
R-squared	0.149	0.151	0.151	0.163	0.167	0.167
N	134838	134838	134838	104275	104275	104275
Country* sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff estimate.
Note: TFP = total factor productivity, CDS = credit default swap spreads. The dependent variable ` ΔTFP growth' is the difference in the TFP growth rate postcrisis versus `Leverage precrisis' is the average precrisis debt-to-assets ratio. `Debt maturing 2008' is the amount of debt maturing in 2008 divided by average total sales precrisis. Postcrisis starts in 2008. `ΔCDS' is the difference in the average CDS spread of banks in each country two quarters before and two quarters after the Lehman Brothers bankruptcy. Standard errors in parentheses are clustered at the country-sector and firm levels. * = significant at 10% level; ** = significant at 5% level; *** = significant at 1% level.

The magnitudes of these effects are rather large. The estimates in column 3 imply that a firm with a 10 percentage points higher leverage ratio than its less leveraged counterpart experienced a 0.36 percentage point larger drop in TFP growth after the crisis. Likewise, a 10 percentage points higher share of debt maturing in 2008 was associated with a 0.91 percentage point postcrisis decline in TFP growth. This relationship is stronger in countries whose banking sectors were hit harder by the financial crisis and where credit conditions tightened more as a result. Using the estimates in column 6,[14] in the average country a firm with a 10 percentage point higher share of debt maturing in 2008 experienced on average a 1.08 percentage point stronger decline in TFP growth than its less exposed counterpart, but this difference was 1.72 percentage points in a country where the CDS spread rose by 100 basis points more than in the average country.

A crude back-of-the-envelope calculation can help assess the extent to which financial vulnerabilities accounted for the postcrisis drop in within-firm productivity growth. To this end, we

[14] The difference in the coefficient between columns (6) and (3) is due to column (3) reflecting the average firm (not necessarily in the average country) and column (6) reflecting the average firm in the average country.

use the coefficient on the debt maturity variable in column (3) and estimate the loss of TFP growth postcrisis for each firm compared to a hypothetical firm that did face any roll-over risk (had zero short-term debt in 2007) and is conservatively assumed not to have faced financial frictions. We then aggregate up this loss across all firms using their TFP levels as weights. This yields an overall loss that is about one third of the total loss in aggregate within-firm TFP growth after the financial crisis (five years after versus five years before 2008).

As a robustness check for our findings, we run a placebo test. If the effects estimated in Appendix Table 2.1 do indeed reflect the role of the sharp tightening of credit supply conditions during the global financial crisis, they should not show up if one focused instead on regular recessions that were not accompanied by a financial crisis. With this in mind, we use the historical vintages of ORBIS to conduct similar analysis using the year 2000, which saw the burst of the dot com bubble and marked the start of a mild recession in advanced economies. We reestimate specification (1), using as measures of vulnerabilities the average leverage ratio before 2000 and the current liabilities reported in 1999 balance sheets. We find no evidence that financial vulnerabilities before the 2000 recession had any significant impact on TFP growth after the recession (Appendix Table 2.2). This confirms that the results in Appendix Table 2.1 reflect the peculiar nature of the recent global financial crisis.

Appendix Table 2.2. Placebo Test: The Dot Com Bubble

	(1)	(2)	(3)
		Δ Total factor productivity growth	
Leverage prerecession	-0.00383		0.00620
	(0.015)		(0.017)
Debt maturing 2000		-0.0657	-0.0690
		(0.046)	(0.050)
R-squared	0.157	0.157	0.157
N	53200	53200	53200
Country * sector fixed effects	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes

Source: IMF staff estimates.
Note: TFP = total factor productivity. The postrecession period covers 2000–2005. The dependent variable ` ΔTFP growth' is the difference in the TFP growth rate postrecession versus prerecession. `Leverage prerecession' is the average prerecession debt-to-assets ratio. `Debt maturing 2000' is the amount of debt maturing in 2000 divided by average total sales before the recession. Standard errors in parentheses are clustered at the country-sector and firm levels * = significant at 10% level; ** = significant at 5% level; *** = significant at 1% level.

Finally, we explore one potential channel through which financial vulnerabilities could have led to a protracted TFP slowdown, which is by pushing distressed firms to cut their investment in intangibles. A wide range of recent studies have linked investments in intangible assets with productivity since the influential work of Corrado, Hulten and Sichel (2005, 2009). When hit by a financial shock, firms may adjust various types of investment differently depending on expected returns, risks and gestation periods (Holstrom and Tirole 1997; Matsuyama 2007; Garcia-Macia 2016). While most forms of physical capital can be pledged as collateral to get a loan, intangible assets such as R&D or workforce training cannot. Furthermore, investments in intangible assets tend to translate more slowly into sales and to be riskier. Therefore, our hypothesis is that vulnerable firms are more likely to cut investment in intangible assets than physical capital investment when access to financing suddenly tightens.

We use the same difference-in-differences strategy, using as dependent variable the investment in intangible assets as a share of total value added. The specification is as follows:

$$\Delta Inv\_Intan_{isc} = \alpha_{sc} + \beta_1 Vulnerabilities_i^{PRE} + \beta_2 Vulnerabilities_i^{PRE} * \Delta CDS_c + \gamma' X_i + \varepsilon_{isc} \qquad (2)$$

We find that more vulnerable firms indeed reduced their investment in intangible assets more than their less vulnerable counterparts after the crisis, and this gap was again larger in countries where credit conditions tightened more (Appendix Table 2.3).[15]

Appendix Table 2.3. Investment in Intangible Assets

	(1)	(2)	(3)
		Δ Investment in intangible assets	
Leverage precrisis	-0.025***		-0.023***
	(0.004)		(0.004)
Leverage precrisis * Δ credit default swap spreads	-0.047***		-0.043***
	(0.009)		(0.009)
Debt maturing 2008		-0.02***	-0.019***
		(0.002)	(0.002)
Debt maturing 2008 * Δ credit default swap spreads		-0.018***	-0.014***
		(0.004)	(0.004)
R-squared	0.041	0.041	0.045
N	97487	97487	97487
Country * sector fixed effects	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes

Source: IMF staff estimates.
Note: CDS = credit default swap spreads. The dependent variable `Δ Investment in intangible assets' is the difference in the investment in intangible assets as a ratio of value added postcrisis versus precrisis. `Leverage precrisis' is the average precrisis debt-to-assets ratio. `Debt maturing 2008' is the amount of debt maturing in 2008 divided by average total sales precrisis. Postcrisis starts in 2008. `ΔCDS' is the difference in the average CDS spread of banks in each country two quarters before and two quarters after the Lehman Brothers bankruptcy in 2008. Standard errors in parentheses are clustered at the country-sector and firm levels. * = significant at 10% level; ** = significant at 5% level; *** = significant at 1% level.

As a complement, we explore whether distressed firms cut intangible investment more than physical capital investment. To do so, we replace the dependent variable with the share of intangible fixed assets out of total fixed investment, which is the sum of physical (or tangible fixed) assets and intangible fixed assets. Appendix Table 2.4 shows that, relative to their less vulnerable counterparts after the 2008 financial shock, more vulnerable firms reduced intangible

[15] This is consistent with the results of Aghion and others (2012), who find evidence of procyclical R&D spending among financially constrained firms, using French firm-level data.

asset investment to a greater degree than tangible asset investments—the share of intangible assets in total investment declined. Again, this difference was larger in countries where credit conditions tightened more.

Appendix Table 2.4. Share of Intangible Assets

	(1)	(2)	(3)
		Δ Share of intangible assets	
Leverage precrisis	-0.136***		-0.129***
	(0.018)		(0.018)
Leverage precrisis * Δ credit default swap spreads	-0.277***		-0.265***
	(0.043)		(0.043)
Debt maturing 2008		-0.069***	-0.061***
		(0.009)	(0.009)
Debt maturing 2008 * Δ credit default swap spreads		-0.103***	-0.075***
		(0.017)	(0.016)
R-squared	0.382	0.380	0.384
N	101150	101150	101150
Country * sector fixed effects	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes

Source: IMF staff estimates.
Note: CDS = credit default swap spreads. The dependent variable ` Δ Share of intangible assets' is the difference in the share of intangible assets in total capital postcrisis versus precrisis. `Leverage precrisis' is the average precrisis debt over assets ratio. `Debt maturing 2008' is the amount of debt maturing in 2008 divided by average total sales precrisis. Postcrisis starts in 2008. `ΔCDS' is the difference in the average CDS spread of banks in each country two quarters before and two quarters after the Lehman Brothers bankruptcy in 2008. Standard errors in parentheses are clustered at the country-sector and firm levels. * = significant at 10% level; ** = significant at 5% level; *** = significant at 1% level.

References

Aghion, P, P. Askenazy, N. Berman, G. Cette, and L. Eymard. 2012. "Credit Constraints and the Cyclicality of R&D Investment: Evidence from France." *Journal of the European Economic Association* 10 (5): 1001–1024.

Almeida, H. M. Campello, B. Laranjeira, and S. Weisbenner. 2012. "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis." *Critical Finance Review* 1 (1): 3–58.

Corrado, C., C. Hulten and D. Sichel. 2005. Measuring Capital and Technology: An Expanded Framework. In *Measuring Capital in New Economy,* edited by John Haltiwanger, Carol Corrado, and Dan Sichel. Chicago, IL: University of Chicago Press. 114–146.

Corrado, C., C. Hulten, and D. Sichel. 2009. "Intangible Capital and U.S. Economic Wealth." *Review of Income and Wealth* 55: 661–685.

Gal, P. 2013. "Measuring Total Factor Productivity at the Firm Level using OECD-Orbis." OECD Economics Department Working Paper 1049, OECD, Paris.

Gal, P., and A. Hijzen. 2016. "The Short-Term Impact of Product Market Reforms: A Cross-Country Firm-Level Analysis." IMF Working Paper Series, WP/16/116, International Monetary Fund, Washington, DC

Garcia-Macia, D. 2016. "The Financing of Ideas and the Great Deviation." Unpublished. Stanford University.

Giroud, X., and H. Mueller. 2017. "Firm Leverage, Consumer Demand, and Employment Losses during the Great Recession." *Quarterly Journal of Economics* 132 (1): 271–316

Holmstrom, B., and J. Tirole. 1997. "Financial Intermediation, Loanable Funds, and the Real Sector." *The Quarterly Journal of Economics* 112 (3): 663–691.

Inklaar, R., and M. Timmer. 2014. "The Relative Price of Services." *Review of Income and Wealth* 60 (4): 727–746.

Levinsohn, J., and A. Petrin. 2003. "Estimating Production Functions using Inputs to Control for Unobservables." *Review of Economic Studies* 70 (2): 317–341.

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych and S. Yesiltas. 2015. "How to Construct Nationally Representative Firm Level Data from the Orbis Global Database." NBER Working Paper Series 21558, National Bureau of Economic Research,m Cambridge, MA.

Matsuyama, K. 2007. "Credit Traps and Credit Cycles." *American Economic Review* 97 (1): 503–516.

Olley, S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–1297.

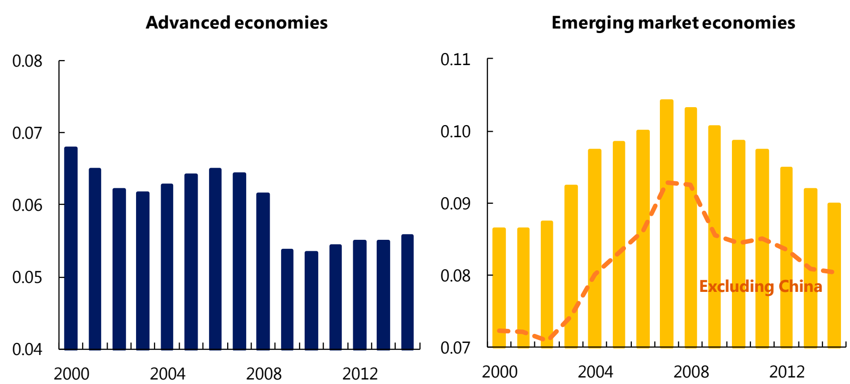
Wooldridge, J. 2009. "On Estimating Firm-Level Production Functions using Proxy Variables to Control for Unobservables." *Economic Letters* 104 (3): 112–114.

APPENDIX III. INVESTMENT AND CAPITAL-EMBODIED INNOVATION[16]

The post-global financial crisis period has been characterized by weak investment across the spectrum of countries—although with different patterns across income groups, meaning a marked level shift in advanced economies and a more gradual weakening in emerging market economies (Appendix Figure 3.1). Weak investment is likely have contributed to the accompanying sluggish output growth not only through its effect on capital accumulation, but also through its effect on total factor productivity (TFP). The notion that capital can affect TFP goes back to Solow (1959), who argued that new capital equipment may enable some innovations to find their way into production. An example of this in the late 1990s and early 2000s is that technological change such as internet use was "embodied" in new and increasingly powerful computers. New investment may also facilitate TFP-enhancing organizational innovations—for instance, just-in-time manufacturing and supply chain management emerged during the 1980s–1990s because of new IT equipment and software.[17] This appendix explores the role that capital embodied technological innovation may have played in the postcrisis global TFP slowdown.

Appendix Figure 3.1. Gross Fixed Capital Formation, 2000–14

(Share of stock of physical capital)



Sources: Penn World Table 9.0; IMF, *World Economic Outlook*; and IMF staff estimates.
Note: Purchasing power parity GDP weighted average of largest 20 economies in each income group is reported.

A. Empirical Approach

The empirical approach to explore the relationship between investment and TFP growth is broadly similar to Wolff (1991),[18] and entails estimating the following simple linear specification in a panel setting:

[16] This technical appendix was prepared by Gustavo Adler.

[17] See further discussions in Wolff (1991) and Greenwood, Hercowitz, and Krusell (1997).

[18] There are two key differences to the work by Wolff (1991): the exercise here focuses on investment as a share of the stock of capital (as opposed to the capital-to-labor ratio); and, more importantly, it seeks to address the likely endogeneity bias with a two-stage least square instrumentation approach.

$$\widehat{TPF_{i,p}} = \alpha + \beta_0 TFP_{i,p_0} + \beta_1 IK_{i,p} + \gamma_i + \delta_p + \varepsilon_{i,p}$$

where $\widehat{TPF_{i,p}}$ denotes average aggregate TFP growth in country i during period p; TFP_{i,p_0} is country i's TFP gap vis-a-vis the United States at the beginning of the period (meant to control for the average rate of productivity catch-up); $IK_{i,p}$ is the average rate of investment (gross fixed capital formation) as a share of the stock of capital; γ_i is a country fixed effect meant to control for relatively time-invariant country characteristics that may affect the rate of technological innovation, such as institutions, trade openness, culture, and so on; and δ_p is a period fixed effect meant to control for common shocks—for example, frontier innovations that affect all countries alike. β_1 is the coefficient of interest, indicating the effect during the period of the average rate of capital accumulation on the average TFP growth rate. To avoid capturing TFP variations arising from the economic cycle, estimations are conducted using low frequency data (that is, averages over relative long time periods). Specifically, individual observations for each country are averages over annual data for the periods 1970–79, 1980–89, 1990–99, 2000–07 and 2008–14.[19]

To address possible endogeneity bias arising from reverse causality (investment responding to TFP shocks), a Two-stage Least Squares (2SLS) approach is implemented. The investment rate is instrumented by population growth and the initial physical capital per capita (measured in comparable purchasing power parity terms). These two variables are likely to drive growth in capital accumulation, but are unlikely to be correlated with TFP growth. As predicted by a standard growth model, population growth should correlate positively with investment—that is, higher population growth should lead to higher investment rates to sustain a constant capital-to-labor ratio—independent of the pace of TFP. On the other hand, the initial stock of capital should correlate negatively with the investment rate, from a convergence perspective, and also be independent of the pace of TFP growth.

Two robustness checks are implemented, by excluding low-income countries—for which data issues can make TFP measures less reliable—and controlling for population aging, given that population growth may be correlated with population aging, which in turn may directly affect TFP growth, as discussed in the main text and Appendix V.

B. Data

The sample encompasses 112 countries—for which there is available data for the proposed instrumentation—over 1970–2014.[20] Data on aggregate TFP (growth and levels) and stock of physical capital come from Penn World Tables 9.0; data on gross fixed capital formation are extracted from the IMF World Economic Outlook database, and population series are from the UN Population Statistics.

C. Results

Appendix Table 3.1 presents the main results, displaying both the results of the first- and second-stage regressions. The instruments are highly statistically significant with the expected

[19] The period 2000–14 is split at 2007 to better control for global financial crisis effects with the period fixed effect.

[20] When controlling for population aging, the sample of countries is reduced to 104.

signs in the first stage. The instrumented investment-to-capital ratio displays both statistically significant and economically meaningful second-stage coefficients. Results for the baseline specification (columns 3 and 4) suggest that a 1 percentage point increase in the investment rate leads, on average, to a TFP increase of about ¼ percent. Moreover, this effect appears to have increased over time, as shown by the results for 1990–2014 (columns 5 and 6). Results are robust to excluding low-income countries from the sample and controlling for population aging. In line with Wolff (1991), these findings provide support to the notion that capital accumulation contributes to output growth not only through capital deepening but also through capital-embodied technological change.

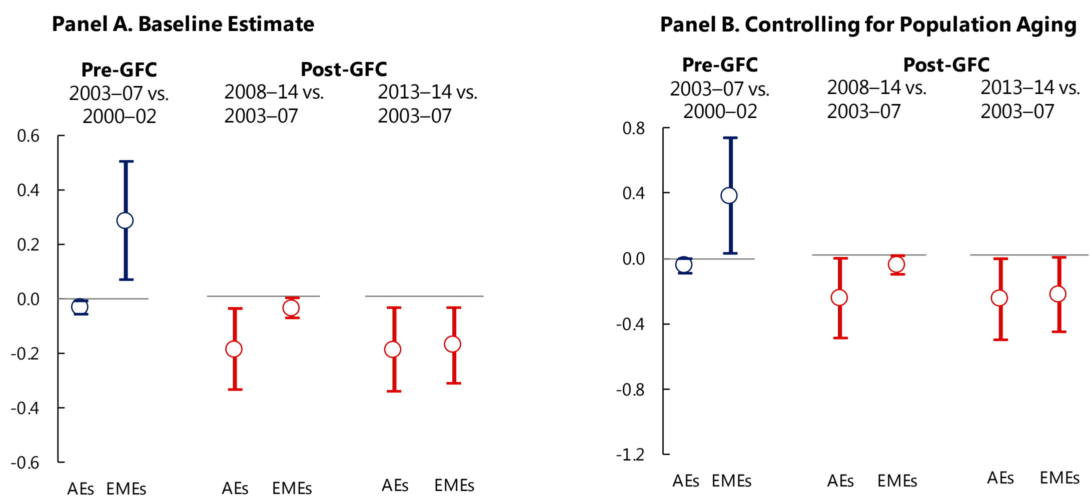
D. Contribution to Recent TFP Growth

Applying these rough estimates to the recent data suggests that weak investment may have been a meaningful driving force behind variations in the pace of TFP growth. As shown in Appendix Figure 3.2, falling investment may have lowered annual TFP growth in advanced economies by as much as 0.2 percent points on average during the period following the global financial crisis. For emerging market economies—which displayed a more gradual weakening in investment over the postcrisis period—the contribution of this channel is muted for the whole post-crisis period but reaches about 0.2 percentage points per year toward the end of the period (again, relative to precrisis TFP growth). This marks a shift from the pace of TFP growth in the years preceding the crisis, when the rise in the investment rate appears to have been an important driver behind the productivity boost in these economies.

Appendix Figure 3.2. Investment and Estimated Impact on Total Factor Productivity Growth Around the Global Financial Crisis

In

(Percent)



Sources: Penn World Table 9.0; IMF, *World Economic Outlook*; and IMF staff estimates.
Note: AEs = advanced economies, EMEs = emerging market economies, and GFC = global financial crisis. Purchasing power parity GDP weighted average of largest 20 economies in each income group is reported.
1/ Estimated contribution of capital accumulation to the change in total factor productivity growth between stated periods. 90-percent confidence bands are reported.

Appendix Table 3.1. Effect of Capital Accumulation on TFP Growth

	Baseline Estimation						Controlling for Population Aging				Excluding Low-Income Countries			
Time period:	1970–2014				1990–2014		1970–2014		1990–2014		1970–2014		1990–2014	
Sample of countries:	All countries				All countries		All countries		All countries		AE and EMEs		AE and EMEs	
			2SLS		2SLS		2SLS		2SLS		2SLS		2SLS	
Method:	OLS		1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
Dependent variable:	Avg. TFP growth	Avg. TFP growth	Avg. I/K	Avg. TFP growth	Avg. I/K	Avg. TFP growth	Avg. I/K	Avg. TFP growth	Avg. I/K	Avg. TFP growth	Avg. I/K	Avg. TFP growth	Avg. I/K	Avg. TFP growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Initial TFP relative to the U.S.	-0.015***	-0.034***	-0.001	-0.034***	-0.010	-0.063***	0.004	-0.036***	0.003	-0.102***	0.002	-0.033***	-0.005	-0.060***
	(0.002)	(0.005)	(0.006)	(0.003)	(0.008)	(0.008)	(0.005)	(0.004)	(0.015)	(0.016)	(0.006)	(0.004)	(0.008)	(0.007)
I/K (average)	0.006	0.088*												
	(0.027)	(0.048)												
I/K (average; instrumented)				**0.243****		**0.428*****		**0.326***		**0.721****		**0.229**		**0.506****
				(0.112)		(0.156)		(0.184)		(0.347)		(0.195)		(0.206)
Instruments														
Population growth			1.038***		0.853***		0.867***		0.875***		0.791***		0.741***	
			(0.237)		(0.203)		(0.215)		(0.244)		(0.271)		(0.208)	
Initial capital per capita			-0.003***		-0.003***		-0.004***		-0.004**		-0.001*		-0.002***	
			(0.001)		(0.001)		(0.001)		(0.002)		(0.001)		(0.001)	
Country fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controlling for population aging	No	No	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Constant	0.013***	0.015***	0.078***	0.004	0.089***	0.010	0.075***	0.013	0.078***	0.028	0.070***	0.008	0.083***	0.009
	(0.003)	(0.005)	(0.006)	(0.008)	(0.006)	(0.012)	(0.005)	(0.013)	(0.009)	(0.026)	(0.007)	(0.013)	(0.007)	(0.014)
Number of observations	487	487	498	487	334	323	365	356	210	201	395	390	259	254
F-statistics	27.78	29.38	13.15	.	9.451	.	11.12	.	4.014	.	13.26	.	5.933	.
R-squared overall	.	0.18	0.09	0.13	0.12	0.07	0.10	0.14	0.10	0.04	0.14	0.17	0.18	0.09
R-squared within	.	0.37	0.20	0.32	0.18	0.38	0.24	0.38	0.17	0.37	0.24	0.34	0.15	0.42
R-squared between	.	0.02	0.05	0.00	0.11	0.00	0.07	0.01	0.09	0.00	0.10	0.02	0.19	0.00
Number of countries	112	112	113	112	113	112	106	104	106	103	87	87	87	87

Source: IMF staff estimations.

Note: AE = advanced economies, EME = emerging market economies, TFP = total factor productivity, I/K = investment-to-capital ratio, OLS = ordinary least squares, and 2SLS = two-stage least squares. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Periods include: 1970–79, 1980–89, 1990–99, 2000–07, 2008–14.

References

Greenwood, J., Z. Hercowitz and P. Krusell,. 1997, "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*. 87 (3), 342–362.

Solow, R. 1959. "Investment and Technical Progress," in K. Arrow, S. Karlin and P. Suppes (eds.), Mathematical Methods in the Social Sciences, Stanford University Press.

Wolff, E. 1991. "Capital Formation and Productivity Convergence Over the Long Run," *American Economic Review* 81 (3), 565–579.

APPENDIX IV: PRODUCTIVITY SPILLOVERS FROM THE TECHNOLOGICAL FRONTIER[21]

This technical appendix empirically assesses the spillovers from frontier TFP growth shocks to TFP growth in other economies. The dynamics of TFP growth in key sectors over the last two decades has raised questions about the role of innovation at the frontier and spillovers, both within and across sectors. A slowdown in TFP growth at the frontier may have contributed to the general TFP slowdown in advanced economies through spillover effects. These are explored next by relying on data on (cyclically-adjusted) TFP growth rates at country-industry-level for a group of 17 advanced economies over 1970–2010.

I. EMPIRICAL STRATEGY

A. Data

TFP growth data at industry level are obtained from Furceri, Kiliç Çelik, and Schnucker (2016) and Dabla-Norris and others (2015). The data are cyclically-adjusted by econometrically correcting for time-varying unobserved utilization in capital and labor and aggregation effects. This correction is essential to properly evaluate the evolution of aggregate TFP growth during the business cycle, and in particular during periods of major expansion and recession (Basu, Fernald, and Kimball 2006; Fernald 2014a, 2014b). Similarly, controlling for aggregation effects is important to correct for sectoral heterogeneity, since the aggregate Solow residual, typically used as a proxy for TFP growth, depends on which sectors change input use the most during the business cycle (Basu and Fernald 1997, 2001; Basu and Kimball 1997; and Hall 1990).[22]

The procedure is applied for a sample of 17 advanced economies[23] over 1970–2010 using industry level data from the EU KLEMS and the WORLD KLEMS databases. These provide internationally comparable data for industry gross output and inputs of capital, labor, hours worked for 24 industries (see Appendix Table 4.1).[24] Country-industry data from EU KLEMS and the WORLD KLEMS are also employed in the analysis constructing the TFP frontier using TFP

[21] This technical appendix was prepared by Marcos Poplawski-Ribeiro.

[22] Furceri, Kiliç Çelik, and Schnucker (2016) estimate disaggregated technology changes at the industry level, following Hall (1990) and Basu and Fernald (2001). They assume cost minimization and relate output growth to the growth of the inputs and compute the utilization-adjusted TFP growth as the difference between the aggregate TFP (Solow residual) and aggregate utilization of factors.

[23] The economies considered are: Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Japan, Ireland, Italy, Korea, the Netherlands, Portugal, Spain, the United Kingdom, and the United States. Data availability limitations preclude the analysis for years since 2010.

[24] Data on the sectors *Publishing, audiovisual and broadcasting activities* (58–60), *Telecommunications* (61), and *IT and other information services* (62–63), are not available for Australia, Canada, Denmark, Greece, Ireland, Korea, and Portugal.

(continued)

levels (see Dabla-Norris and others),[25] and for the analysis on spillover effects through the input channel, as discussed below.

Appendix Table 4.1. Industries Used in the Estimation of Total Factor Productivity Growth

Industry Description	Industry Code
Aggregated Industries	TOT
Information and Communications Technologies Goods and Services	ELECOM
Electrical and optical equipment	26–27
Publishing, audiovisual and broadcasting activities	58–60
Telecommunications	61
Information technology and other information services	62–63
Total Manufacturing, Excluding Electrical	MexElec
Food products, beverages and tobacco	10–12
Textiles, wearing apparel, leather and related prodcuts	13–15
Other manufacturing; repair and installation of machinery and equipment	31–33
Wood and paper products; printing and reproduction of recorded media	16–18
Coke and refined petroleum products	19
Chemicals and chemical products	20–21
Rubber and plastics products, and other non-metallic mineral products	22–23
Basic metals and fabricated metal products, except machinery and equipment	24–25
Machinery and equipment n.e.c.	28
Transport equipment	29–30
Agriculture, forestry and fishing	A
Mining and quarrying	B
Electricity, gas and water supply	D–E
Construction	F
Distribution	DISTR
Wholesale and retail trade and repair of motor vehicles and motorcycles	45
Wholesale trade, except of motor vehicles and motorcycles	46
Retail trade, except of motor vehicles and motorcycles	47
Transport and storage	49–52
Postal and courier activities	53
Finance and Business, Except Real Estate	FINBU
Financial and insurance activities	K
Professional, scientific, technical, administrative and support service activities	M–N
Personal Services	PERS
Accommodation and food service activities	I
Arts, entertainment and recreation	R
Other service activities	S
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	T
Nonmarket Services	NONMAR
Real estate activities	L
Public admin, education and health	OtQ
Public administration and defence; compulsory social security	O
Education	P
Health and social work	Q

Source: EU KLEMS data.
Note: Industries classified using International Standard Industrial Classification, Revision 4.

B. Methodology

The empirical methodology follows the approach proposed by Jordà (2005) and expanded by Teulings and Zubanov (2014), by tracing out the evolution of TFP in the aftermath of TFP shocks at the frontier through the local projection method. As argued by Stock and Watson (2007) and Auerbach and Gorodnichenko (2013), among others, this approach provides a flexible alternative

[25] We are thankful to Vikram Haksar and Minsuk Kim for providing the data on TFP levels.

that does not impose dynamic restrictions embedded in vector autoregressive (autoregressive distributed lag) estimations.

Given the data availability at the country-industry level, the analysis initially focuses on shocks in U.S. industries, assuming that they constitute the TFP frontier. This assumption is relaxed later, using data on TFP levels obtained from Dabla-Norris and others (2015) to construct a time-varying TFP frontier (maximum levels of TFP) at country-industry level for a subset of 11 countries and 18 industries (see Appendix Table 4.2).

Appendix Table 4.2. Industries with Information on Total Factor Productivity Levels, 1970–2007

Industry Description	Industry Code
Accommodation and food service activities	I
Agriculture, forestry and fishing	A
Basic metals and fabricated metal products, except machinery and equipment	24–25
Chemicals and chemical products	20–21
Electrical and optical equipment	26–27
Electricity, gas and water supply	D–E
Financial and insurance activities	K
Food products, beverages and tobacco	10–12
Machinery and equipment not elsewhere classified	28
Mining and quarrying	B
Other manufacturing; repair and installation of machinery and equipment	31–33
Real estate activities	L
Rubber and plastics products, and other non-metallic mineral products	22–23
Telecommunications	61
Textiles, wearing apparel, leather and related prodcuts	13–15
Transport and storage	49–52
Transport equipment	29–30
Wood and paper products; printing and reproduction of recorded media	16–18

Source: EU KLEMS data.

Note: Industries classified using International Standard Industrial Classification, Revision 4. Data available for the following countries: Australia, Austria, Denmark, Germany, Italy, Japan, Netherlands, Spain, Sweden, the United Kingdom, and the United States.

Spillover effects can operate within each industry (through diffusion due to competition or learning) or across industries (input channel). The corresponding econometric specifications used to estimate these TFP spillovers effects are described below.

Intra-industry Spillovers from TFP Shocks in the United States

The first specification investigates the intra-industry spillover effects of U.S. industry TFP level shocks on TFP in the same industry in the other advanced economies in this study. Using the local projection method, separate regressions are estimated at different time horizons $t + k$, as follows:

$$tfp_{i,j,t+k} - tfp_{i,j,t-1} = \alpha_{i,j} + \gamma_t + \beta_k dtfp_{US,j,t} + \delta(L) dtfp_{i,j,t} + \sum_{h=1}^{k} \theta_j dtfp_{US,j,t+h} + \varphi(L) dtfp_{US,j,t} + \varepsilon_{i,t}, \quad (1)$$

where tfp is the log level of cyclically-adjusted TFP for country i and industry j; $\alpha_{i,j}$ are country-industry fixed effects; γ_t are time fixed effects; and $dtfp_{US,j,t}$ is U.S. adjusted TFP growth at the industry level. The specification includes lags of TFP growth in the United States and the other countries. Since variables affecting TFP growth are typically serially correlated, the inclusion of lags allows for controlling for short-term factors that affect the short-term response of TFP growth in a particular country i.

Impulse response functions (IRFs) are computed directly using the estimated coefficients β_k. That coefficient measures the intra-industry (direct) spillover effect of a 1 percent change in a particular industry-level U.S. adjusted TFP level. The 90-percent confidence bands associated with the estimated IRFs are obtained using the estimated standard deviations of the coefficients β_k. Equation (1) is estimated using heteroskedasticity-robust and autocorrelation-robust standard errors.

Inter-industry Spillover from U.S. TFP Shocks

The second specification explores the input channel by exploiting differences across countries and industries in the extent to which inputs from the United States are used in the production process. The specification is:

$$tfp_{i,j,t+k} - tfp_{i,j,t-1} = \alpha_i + \gamma_t + \beta_k \overline{\omega} \times dtfp_{US,s,t} + \delta(L) dtfp_{i,j,t} + \sum_{h=1}^{k} \theta_j dtfp_{US,s,t+H} + \varphi(L) dtfp_{US,s,t} + \varepsilon_{i,t}, \qquad (2)$$

where j is a downstream industry in advanced economies other than the United States; s is the upstream U.S. industry; and $\overline{\omega}$ is a weighting matrix denoting the use of inputs from a U.S. industry s in industry j of country i. Input utilization from the technological frontier has been typically found in the literature to be a key transmission channel for knowledge spillovers (see, for example, Coe and Helpman 1995; Coe, Helpman, and Hoffmaister 2009; Rondeau and Pommier 2012), including in the trade literature, where TFP gains from imported input variety and quality have been highlighted theoretically (such as in Grossman and Helpman 1991; Markusen 1989) and identified empirically (Kasahara and Rodrigue 2008; Topalova and Khandelwal 2011; Amiti and Konings 2013; Halpern and others 2015; Ahn and others 2016).[26]

Input-output matrices are used to construct the weights of U.S. inputs in each downstream sector of the other advanced economies. Due to data limitations, and also to minimize any endogeneity issues, fixed 2005 weights are used. Specifically, each element $\overline{\omega}_{i,j,s}$ of the weighting matrix $\overline{\omega}$ is constructed as:

$$\overline{\omega}_{i,j,s} = \frac{Input\ Industry_{i,j,s,2005}}{\sum_{j=1,i=1}^{J,N} Input\ Industry_{i,j,s,2005}}, \qquad (3)$$

where ω is a weighing element for each j downstream industry in the other advanced economies and upstream industry s in the United States in a $NJ \times S$ weighing matrix $\Omega_{NJ \times S}$. $N = 16$ is the

[26] Other possibilities for country-characteristics with potential knowledge spillover effects (not investigated here) include the country's relative distance from the technology frontier—defined as the gap between the country's total factor productivity and that of the United States—and financial openness vis-à-vis the country-industry frontier.

total number of advanced economies (apart from the United States), $J = 24$ is the number of downstream industries in those countries and $S = [1{,}24]$ is the number of upstream industries in the United States investigated. In the analysis all upstream sectors with available data ($S = J = 24$) are investigated and, by construction, the sum of the elements of $\Omega_{NJ\times S}$ equals to 1.[27]

For each year, the weighting matrix $\Omega_{NJ\times S}$ is then multiplied by the vector of U.S. TFP growth rates for each upstream U.S. industries to obtain the vector of U.S. input shocks for each country-industry for that year:

$$\forall t\colon \overline{\omega} \times dtfp_{US,s,t} = \begin{bmatrix} \omega_{AUS,1,s,2005} & \cdots & \omega_{AUS,1,S,2005} \\ \vdots & \cdots & \vdots \\ \omega_{AUS,24,s,2005} & \cdots & \omega_{AUS,24,S,2005} \\ \vdots & \ddots & \vdots \\ \omega_{UK,1,s,2005} & \cdots & \omega_{UK,1,S,2005} \\ \vdots & \cdots & \vdots \\ \omega_{UK,24,s,2005} & \cdots & \omega_{UK,24,S,2005} \end{bmatrix}_{NJ\times S} \times \begin{bmatrix} dtfp_{US,s,t} \\ \vdots \\ dtfp_{US,S,t} \end{bmatrix}_{S\times 1} . \qquad (4)$$

This provides a vector $NJ \times 1$ of values of weighted averages of U.S. TFP growth rates across all sectors, for all country-industry observations in each year.

II. RESULTS

Appendix Figure 4.1 displays the main results for the two exercises discussed above. Overall, the findings indicate that, historically, a shock to U.S. TFP has had a gradual, increasing, and significant spillover effect on the TFP of the other advanced economies.

The impulse response function (IRF) corresponding to the intra-industry spillover effects are displayed in Panel A. It shows that the average TFP spillover of a particular industry in the United States on the same industry in the other advanced economies is relatively small in the short term but gradually increases over time, reaching about 0.08 percentage points for each 1 percentage point U.S. TFP level shock in the medium term—five years after the shock.[28]

The analysis on inter-industry spillovers is displayed on Panel B. The IRF indicates that a 1 percentage point rise in U.S. TFP in all industries is on average associated with an approximately

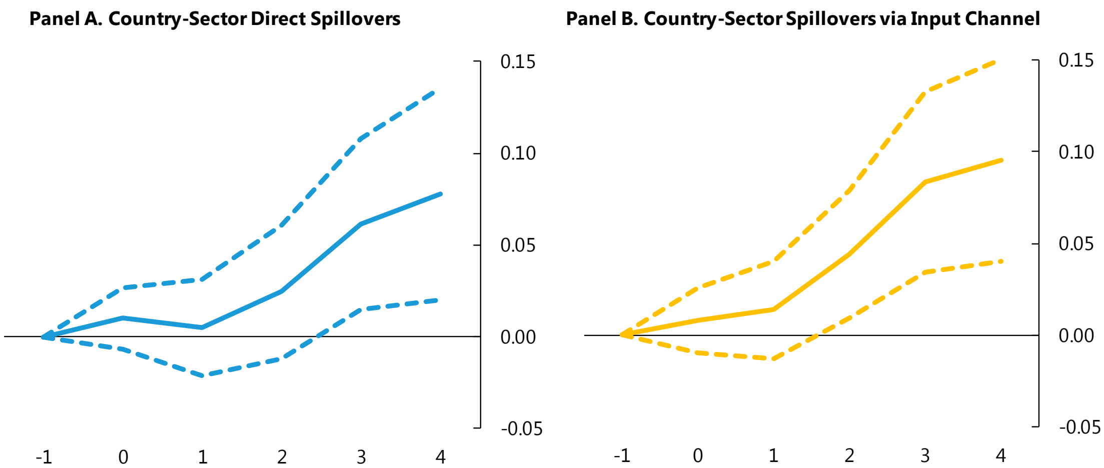
[27] Indeed, two versions of the weighing matrix $\Omega_{NJ\times S}$ are employed in the analysis. The first (baseline) eliminates inputs from an upstream industry in the United States used in a same downstream industry in the other AE. This means that the diagonals of the weighing matrix $\Omega_{NJ\times S}$ are zero, guaranteeing that the analysis is purely inter-industrial. The second version of that matrix includes non-zero values for those diagonals. The results (not shown here and available upon request) indicate very robust and similar effects using both versions of that weighting matrix.

[28] The estimations use a two-lag structure and exclude outliers at the top and bottom 5th percentile of the distribution of the TFP growth level at country-industry-year level for the advanced economies (excluding the United States).

0.1 percentage point increase in TFP in the other advanced economies in the medium term through this input channel.

Appendix Figure 4.1. Spillovers from a One Percentage Point Rise in U.S. TFP Growth to Other Advanced Economies

(Percentage points)



Sources: EU KLEMS and WORLD KLEMS data; IMF staff estimations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. TFP = total factor productivity. Estimates of the intra-industry spillover from the United States (U.S.) TFP growth shocks to other advanced economies for different horizons obtained via local projections method. The input channel is estimated by interacting the U.S. TFP growth shocks with a weighting matrix capturing the importance of each U.S. industry as an input for a particular industry in each other advanced economies. Estimations include country-sector- and year-fixed-effects and exclude top and bottom fifth percentiles of the U.S. TFP growth sample distribution at industry level as outlier treatment. Dashed lines denote 90-percent confidence intervals. Countries considered are Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Japan, Ireland, Italy, Korea, the Netherlands, Portugal, Spain, the United Kingdom, and the United States.

Those two results in Appendix Figure 4.1 indicate a combined (intra- and inter-industry) spillover effect of around 0.2 percentage points in the medium-term for a given 1 percentage point TFP level shock (in all industries) in the United States. This suggests that the observed slowdown in U.S. TFP growth in industries where the United States is the technological leader can partly explain the TFP growth slowdown in the other advanced economies. It should be noted that an average 0.2 percentage point effect of a 1 percentage point TFP shock at the frontier after five years implies that about 4 percent of the gap between the frontier and lagging countries is closed in a year. This is about twice as much as the typical speed of resorption of GDP per capita gaps found in the empirical growth literature (see Barro and Sala-i-Martin 2004).

III. ADDITIONAL RESULTS AND ROBUSTNESS CHECKS

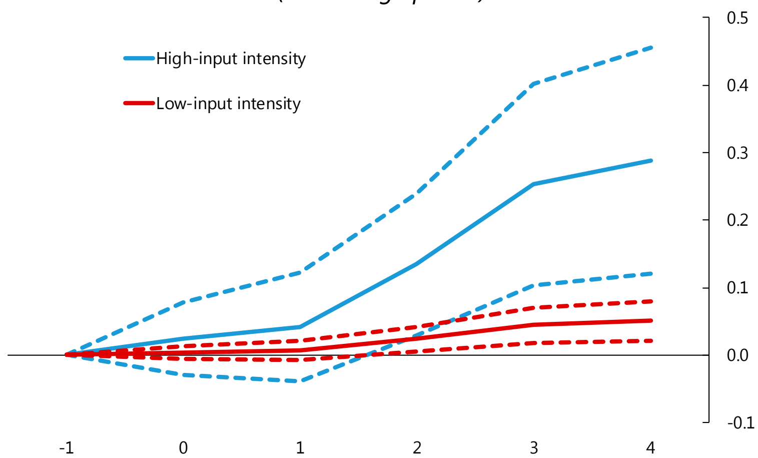
A. High and Low U.S. Input Utilization

The results presented above correspond to a country with an average use of U.S. inputs. However, the variance in U.S. input utilization is relatively high across advanced economies. A rescaling of the effect—in line with a linear specification, as in Equation (2)—for the 25th and 75th

percentiles of the input-intensity weight distribution is shown in Appendix Figure 4.2.[29] These IRFs suggest that TFP spillovers are significantly larger for countries with high U.S. inputs utilization. In particular, the increase in TFP in a country that is relatively strongly linked with the United States (at the 75th percentile) is about six times larger, at 0.23 percentage points, than in a country that has relatively low linkages (at the 25th percentile).

Appendix Figure 4.2. Inter-Industry Spillovers Through the Input Channel (High- and Low-Intensity)

(Percentage points)



Sources: Furceri, Çelik, and Schnucker (2016); EU KLEMS and WORLD KLEMS data; and IMF staff estimations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. TFP = total factor productivity. Input channel is estimated by interacting the United States (U.S.) TFP growth shocks with a weighting matrix capturing the importance of each U.S. industry as an input for a particular industry in each other advanced economies. High- and low-intensity correspond to the 75th and 25th percentiles of the cross-country-industry distribution of the input weights in the sample. Estimations include country-sector- and year-fixed-effects and exclude top and bottom fifth percentiles of the U.S. TFP growth sample distribution at industry level as outlier treatment. Dashed lines denote 90-percent confidence intervals.

B. Average TFP Growth Changes in Advanced Economies

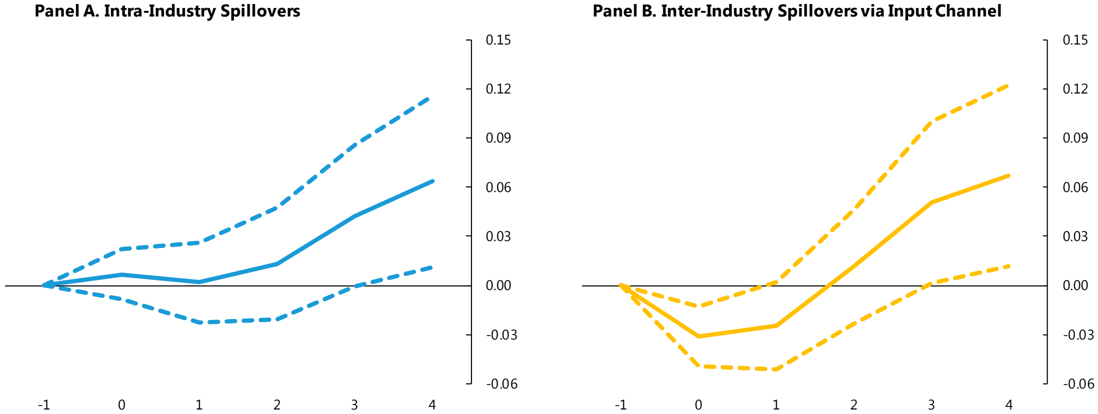
A possible concern in the estimation of Equation (1) is reverse causality and omitted variable bias. That is because changes in TFP in other countries may affect U.S. TFP, or respond to common technological shocks. Thus, a robustness check is implemented by adding the average change in TFP growth across other advanced economies following a U.S. TFP shock as an additional control in the estimation of Equation (1).

Appendix Figure 4.3 displays the corresponding IRFs, which indicate that the estimated medium-term spillover effects are robust to this robustness exercise, and only slightly smaller than the combined effect of 0.2 percentage points found in the previous analysis.

[29] More specifically, this is done by using the same coefficient β_k estimated using Equation (2), but rescaling it by the ratio between the 75th (or 25th) percentile and the average value of the of the United States input intensity across its whole country-industry-year distribution.

Appendix Figure 4.3. Spillovers from U.S. TFP Shocks, Controlling for Average TFP Changes in Other Advanced Economies

(Percentage points)



Sources: Furceri, Çelik, and Schnucker (2016); EU KLEMS and WORLD KLEMS data; and IMF staff estimations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. TFP = total factor productivity. Estimates of the intra-industry relationship between shocks in the United States (U.S.) TFP growth and TFP growth at the country-industry level in other advanced economies for different horizons are obtained via local projection method. The input channel is estimated by interacting the U.S. TFP growth shocks with a weighting matrix capturing the importance of each U.S. industry as an input for a particular industry in each other advanced economies. Estimations include country-industry- and year-fixed-effects and exclude top and bottom fifth percentiles of the U.S. TFP growth sample distribution at industry level as outlier treatment. Dashed lines denote 90-percent confidence intervals.

C. Frontier Analysis

An additional refinement entails relaxing the assumption that the United States is the technological frontier across sectors. This is done by focus on TFP shocks from a time-varying industry frontier. While this is conceptually a clearer exercise than the baseline one presented above, it requires level (rather than growth) TFP data that are more scarce and subject to methodological limitations.[30]

The time-varying frontier is calculated by using the TFP levels from Dabla-Norris and others (2015) and finding the maximum TFP level for each available industry and year across the 11 countries (with available TFP level data). Once these frontier country-industries are identified for each year, their TFP growth rates replace $dtfp_{US,j,t}$ in the estimation of (1) and (2), while making sure that the particular country in the frontier is not included in the left-hand side of those equations and that the United States is inserted in the left-hand side when not identified as being in the frontier.

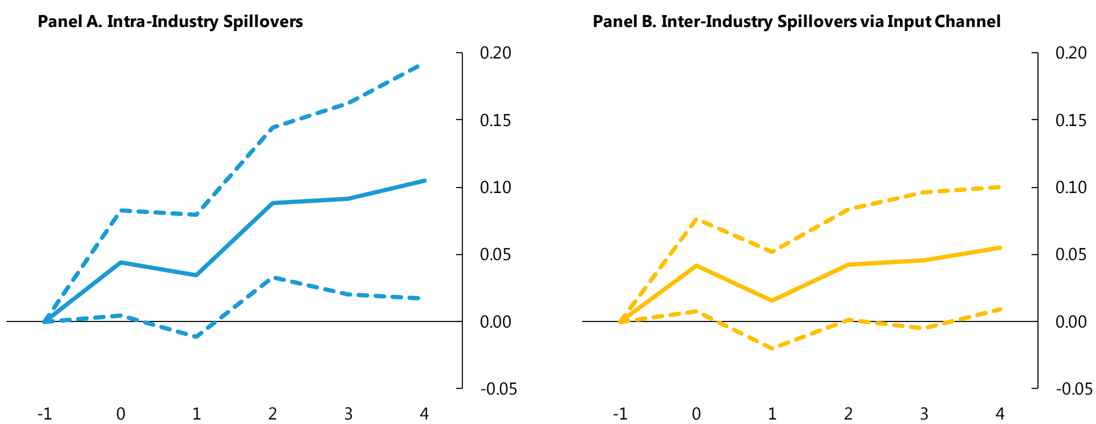
Appendix Figure 4.4 shows the estimated IRFs for both equations over the period 1985–2007. For both the intra- and inter-industry spillover analysis, the IRFs are significant in the medium term, indicating the previous findings are robust to this refinement. A one percent frontier TFP shock leads, on average, to a 0.05 percentage point increase in TFP in other Advanced economies in the

[30] EU-KLEMs provides data on TFP level only for some years (particularly 1996), which were projected forward via an inventory method using TFP growth rates more broadly available. See Appendix Table 4.2 for the list of industries containing information on TFP levels and the Technical Appendix 3 of Dabla-Norris and others (2015) for more details in the construction of this variable.

short term—1 year after the shock—and by about 0.1 percentage points in the medium term—5 years after the shock. For the inter-industry analysis via the input channel, the estimated spillover effects in this refined exercise are slightly lower than in the baseline estimation: a one percent frontier TFP shock leads, on average, to a 0.04 percentage point increase in TFP in other advanced economies in the short term—1 year after the shock—and by about 0.06 percentage points in the medium term—5 years after the shock.

Appendix Figure 4.4. Spillovers from TFP-Frontier Growth Shocks to Other Advanced Economies, 1985–2007

(Percentage points)



Sources: Furceri, Çelik, and Schnucker (2016); EU KLEMS and WORLD KLEMS data; and IMF staff estimations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. TFP = total factor productivity. Estimates of the intra-industry relationship between shocks in the United States (U.S.) TFP growth and TFP growth at the country-industry level in other advanced economies for different horizons are obtained via local projection method. The input channel is estimated by interacting the U.S. TFP growth shocks with a weighting matrix capturing the importance of each U.S. industry as an input for a particular industry in each other advanced economies. Estimations include country-industry- and year-fixed-effects and exclude top and bottom fifth percentiles of the U.S. TFP growth sample distribution at industry level as outlier treatment. The inter-industry spillovers are estimated with one lag instead of two. Dashed lines denote 90-percent confidence intervals.

IV. CONCLUSIONS

This technical appendix estimates intra- and inter-industrial spillover effects from a slowdown of TFP growth at the frontier to TFP in the other advanced economies.

The findings indicate a combined (intra- and inter-industry) spillover effect of around 0.15–0.2 percentage points in the medium-term for a given 1 percentage point TFP shock in the frontier. This suggests that the observed slowdown in U.S. TFP growth, and at the industry-specific technological frontier more broadly, can partly explain a the TFP growth slowdown in the other advanced economies. Indeed, these are robust to calculating an alternative technological frontier using industry data on TFP levels rather than taking the United States as the frontier and to including additional variables in the analysis.

References

Amiti, M., and J. Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review* 97 (5): 1611–38.

Auerbach, A., and Y. Gorodnichenko. 2013. "Measuring the Output Responses to Fiscal Policy." *American Economic Journal: Economic Policy* 4 (2): 1–27.

Basu, S. and J.G. Fernald. 1997. "Aggregate Productivity and Aggregate Technology." International Finance Discussion Paper No. 593, Board of Governors of the Federal Reserve System, Washington, DC.

Barro, R. J. and X. Sala-i-Martin. 2004. "Economic Growth." Second Edition. (MIT Press: Cambridge).

Basu, S., and M. S. Kimball. 1997. "Cyclical Productivity with Unobserved Input Variation." NBER Working Paper No. 5915, National Bureau of Economic Research, Cambridge, MA.

Basu, S., J. G. Fernald, and M. S. Kimball. 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96 (5): 1418–48.

Coe, D.T., and E. Helpman. 1995. "International R&D Spillovers." *European Economic Review* 39 (5): 859–87.

Coe, D. T., E. Helpman, and Alexander W. Hoffmaister. 2009. "International R&D Spillovers and Institutions." *European Economic Review* 53 (7): 723–41.

Dabla-Norris, E., S. Guo, V. Haksar, M. Kim, K.Kochhar, K. Wiseman, and A. Zdzienicka. 2015. "The New Normal: A Sector-Level Perspective on Productivity Trends in Advanced Economies." IMF Staff Discussion Note 15/03, International Monetary Fund, Washington, DC.

Fernald, J. 2014a. "Productivity and Potential Output before, during, and after the Great Recession." In *NBER Macroeconomics Annual 2014*, Vol. 29. Chicago: University of Chicago Press.

Fernald, J. 2014b. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." Working Paper 2012–19, Federal Reserve Bank of San Francisco, San Francisco.

Furceri, D., S. Kiliç Çelik, and A. Schnucker. 2016. "TFP Growth before the Global Financial Crisis: Evidence from a New Database for Advanced Economies." Forthcoming IMF Working Paper, International Monetary Fund: Washington.

Grossman, G. and E. Helpman. 1991. "Quality Ladders in the Theory of Growth." *Review of Economic Studies* 58 (1): 43–61.

Hall, R. E. 1990. "Invariance Properties of Solow's Productivity Residual." In Growth/ Productivity/Unemployment: Essays to celebrate Bob Solow's birthday, edited by Peter Diamond. Cambridge, MA: MIT Press.

Halpern, L., M. Koren, and A. Szeidl. 2015. "Imported Inputs and Productivity." *American Economic Review*, 105 (12): 3660–3703.

Jordà, Ò.. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–82.

Kasahara, H., and J. Rodrigue. 2008. "Does the Use of Imported Intermediates Increase Productivity? Plant-level Evidence." *Journal of Development Economics* 87 (1): 106–18.

Markusen, J. 1989. "Trade in Producer Services and in other Specialized, Intermediate Inputs." *American Economic Review* 79 (1): 85–95.

Rondeau, F., and S. Pommier. 2012. "Factors of R&D Spillovers and European Integration." *Economics Bulletin* 32 (3): 1970–77.

Stock, J. H., and M. W. Watson. 2007. "Why Has U.S. Inflation Become Harder to Forecast?" *Journal of Money, Credit and Banking* 39 (Suppl. 1): 3–33.

Teulings, C. N., and N. Zubanov. 2014. "Is Economic Recovery a Myth? Robust Estimation of Impulse Response Functions." *Journal of Applied Econometrics* 29 (3): 497–514.

Topalova, P. and A. Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." *The Review of Economics and Statistics* 93 (3): 995–1009.

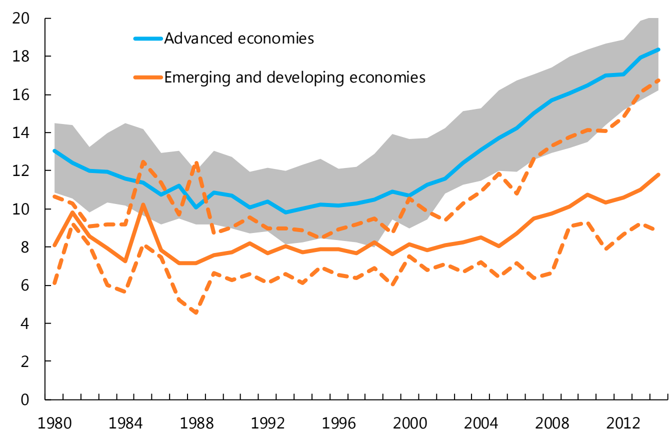
APPENDIX V. LABOR FORCE AGING AND PRODUCTIVITY GROWTH[31]

I. INTRODUCTION

Over the last two decades, many advanced economies and emerging market economies have witnessed the effects of demographic transition on their workforces, as population aging has led to significant increases in the share of most senior workers, particularly in advanced economies (Appendix Figure 5.1).

Appendix Figure 5.1. Share of Elderly (Ages 55–64) to Total Labor Force Participation

(Percent)



Sources: International Labour Organization Labour Statistics; IMF staff estimations.
Note: Solid lines display the median of the distribution of the share of old labor force participation. Shaded area and dashed lines represent the interquartile range.

This secular trend may have direct implications for productivity growth. As stressed in the literature, a worker's productivity varies over her working life, for reasons such as the accumulation of experience over time, depreciation of knowledge, and age-related trends in physical and mental capabilities. On one hand, a mature labor force will have higher average levels of work experience, with positive effects on productivity (Disney 1996). On the other hand, the workforce's stock of skills is likely to become increasingly dated as the average age of workers rises, leading to a decline of innovation and productivity (Dixon 2003; Feyrer 2008; Aksoy and others 2015; Jones 2010). Moreover, if job requirements evolve as a result of structural changes in the economy, older workers may find it more difficult to adapt (OECD 1998), especially with increased penetration of information technologies (Dixon 2003).

However, empirical work on this issue remains scarce and the evidence is somewhat mixed. For example, Feyrer (2008) shows that in the United States, the median age of innovators has been

[31] This technical appendix was prepared by Marcos Poplawski-Ribeiro.

stable at about age 48 over 1975–95, whereas the median age of managers who adopt new ideas is lower at around age 40. Aksoy and others (2015) also show that demographic structure affects innovation, with older workers (in particular the 50–59 age group) having a strong negative impact on the number of patent applications. Consistent with this, Jones (2010) finds that innovation increases with the presence of young and middle-aged cohorts and is reduced by the presence of older cohorts. Other recent papers, based on sector or firm-specific data, yield mixed results. Acemoglu, Akcigitz, and Celik (2014) show that younger managers lead firms to have more innovation as they are more open to product destruction. Göbel and Zwick (2012) find no significant differences in age-productivity profiles between manufacturing and services sectors in Germany, whereas Börsch-Supan and Weiss (2016) find that the productivity of workers in a large car manufacturer in Germany declines at around age 60. Taken together, these results might suggest that aggregate effects could be larger than sector or firm-level effects when externalities linked to workforce aging are taken into account (Feyrer 2007). More recently, Maestas and others (2016) study the relationship between aging and GDP per capita across U.S. states, finding a negative association between them. Acemoglu and Restrepo (2017), on the other hand, explore the issue and conclude that the link between aging and economic growth is not significant, which they explain by the greater incentives to adopt labor-saving innovations in rapidly aging societies. Their findings suggest that the effects of aging have been, at least recently, offset by the adoption of automation technologies.[32]

This technical appendix reassesses the relationship between changes in the share of older workers in the labor force (age 55–64) and total factor productivity (TFP) growth at the country level.

The econometric evidence indicates that aging has played a meaningful role in slowing down TFP growth both for advanced economies and emerging market economies over the last two decades. In particular, the observed increase in the share of older workers may have contributed to the TFP slowdown, on average, by as much as 0.2–0.5 percentage points a year in advanced economies and 0.1 percentage points a year in emerging market economies during the 2000s.

II. EMPIRICAL STRATEGY

The empirical strategy builds on Feyrer (2007) and Aiyar, Ebeke and Shao (2016).[33] Taking Feyrer's specification as a benchmark, this appendix (i) extends the sample coverage to 2014, by using updated data on labor force participation from the International Labour Organization (ILO);

[32] Methodologically, we differ from Acemoglu and Restrepo (2017) in that we (i) focus on TFP rather than GDP per capita; (ii) use a more restrictive definition of aging based on the share of employed workers, (iii) allow for dynamic effects on this relationship by using five-year panel—instead of cross-section—data and techniques (time fixed-effects); and (iv) instrument the latter using past demographic characteristics of the population, as explained in more detail below.

[33] See also related work by Jaimovich and Siu (2009), and Wong (2007).

(continued)

(ii) adds a new identification strategy to instrument labor force aging and estimate its effect on TFP growth; and (iii) refines the approach by focusing on the age structure of employed workers (as opposed to the age structure of the labor force).[34]

A. Data

The analysis focuses on a panel data set composed of at least 31 and at most 60 Advanced economies and emerging market economies over the period 1985–2014.[35]

Drawing on the recent cross-country empirical literature (Feyrer, 2007; Cuaresma, Loichinger, and Gallina, 2016), workforce aging is measured in two alternative ways: (i) the ratio of older workers (aged 55–64) to the total labor force; and (ii) the ratio of older employed workers (ages 55–64) to the total number of employed workers. Data on labor force participation by age group is obtained from a newly updated data set from the ILO, focusing on a selected group of 68 countries (see details in Appendix Table 5.1). Data on employment by age group for a smaller set of 35 advanced economies and emerging market economies is obtained from the OECD Labor Statistics (Appendix Table 5.1).

Appendix Table 5.1. Sample of Economies Included in the Analytical Exercises

Group 1/	Economies 2/	Exercise 3/			
		I	II	III	IV
A	Australia,* Austria,* Belgium,* Canada,* Chile, Czech Republic,* Denmark,* Estonia,* Germany,* Finland,* France,* Hungary, Ireland,* Israel,* Italy,* Japan,* Korea,* Netherlands,* New Zealand,* Norway,* Portugal,* Slovak Republic,* Spain,* Sweden,* Switzerland,* Turkey, United Kingdom,* United States*	X	X	X	X
B	Brazil, Slovenia,* South Africa	X	X	X	
C	Mexico	X		X	X
D	Argentina, Bulgaria, Chile, Costa Rica, Croatia, Dominican Republic, Egypt, Guatemala, Hong Kong SAR,* Honduras, Iceland,* Indonesia, Jamaica, Malta,* Mauritius, Mongolia, Morocco, Panama, Paraguay, Philippines, Poland, Romania, Senegal, Singapore,* Thailand, Tunisia, Ukraine,	X	X		
F	Greece,* Russia			X	X
G	Barbados, Benin, Burundi, Burkina Faso, Cyprus,* Lesotho, Moldova, Peru, Sri Lanka, Uruguay	X			
H	Colombia			X	

Source: IMF staff compilation.
1/ Group of countries according to their use in different analytical exercises.
2/ Asterisk (*) denotes advanced economies as classified by IMF, *World Economic Outlook*.
3/ Analytical exercises performed: I = fixed effects (FE) and ordinary least squares (OLS) estimation with International Labour Organization (ILO) data; II = FE and two-stage least squares (2SLS) estimation with ILO data; III = FE-OLS estimation with Organisation for Economic Co-operation and Development (OECD) data; IV = FE-2SLS estimation with OECD data.

[34] Compared to Aiyar, Ebeke and Shao (2016), this appendix (i) analyzes the effects of changes in (instead of the level of) older worker labor force participation on productivity growth; and (ii) extends their analysis to emerging market economies.
[35] The raw dataset initially covers 202 countries over the period of 1960 to 2014. See Appendix Table 5.1 for the list of all countries actually covered in the analysis once data availability constraints are taken into account.

TFP growth at country level is obtained from the Penn World Table (PWT, 9.0). Finally, population data (total and by age group) and dependency ratios are retrieved from the UN Population Statistics.

B. Methodology

As in Feyrer (2007), the analysis tests whether the TFP level $(TFP)_{i,t}$ in country i at time t is affected by the share older labor force participants in the total labor force, or alternatively, the share of employed older workers (aged 55–64) in total employment. The econometric specification is:

$$log(TFP)_{i,t} = \alpha_i + \gamma_t + \beta w55_{i,t} + \delta yadr_{i,t} + \varphi oadr_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

where α_i is a time-invariant country fixed effect; γ_t is a time fixed effect common to all countries; $oadr_{i,t}$ $(yadr_{i,t})$ is the old- (young-) age dependency ratio. Both ratios are additional controls for the effect of aging on TFP levels.[36]

Given that aging is a slow-moving process that is likely to affect TFP only gradually, all variables in Equation (1) are measured as non-overlapping at five-year averages. Moreover, to deal with the fact that log(TFP) is I(1), the estimation of (1) is done in first-differences (Δ):

$$\Delta log(TFP)_{i,t} = \alpha_i + \gamma_t + \beta \Delta w55_{i,t-1} + \delta \Delta yadr_{i,t} + \varphi \Delta oadr_{i,t} + \varepsilon_{i,t}, \qquad (2)$$

where standard errors are clustered by country to correct for serial correlation in the error term, which is further attenuated by the use of 5-year averages.

Equation (2) is initially estimated using panel fixed-effects ordinary least squares (FE-OLS). However, a potential issue is the endogeneity of the share of older workers (or that of older labor force participants) to TFP. Experienced individuals may supply more labor in response to wage-augmenting technological innovations. At the same time, higher income arising from faster aggregate productivity growth may induce older workers to leave the labor force. Hence, the direction of the possible endogeneity bias is unclear. As in Aiyar, Ebeke and Shao (2016), the share of older workers is instrumented—as one of the alternative specifications for equation (2)—by the 10- to 14-year lagged share of the population aged 45–54 years. Such variable should be highly correlated to the share of workers aged 55–64 a decade later, but orthogonal to future technological innovations. The instrumental variable specification is estimated via panel fixed-effect two-stage least squares (FE-2SLS).

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[36] Those dependency ratios are obtained here by dividing the share of young (0–14 years-old) and old (65+ years-old) population to the active population. They aim to capture several other channels through which a higher dependency ratio (that is, fewer workers in a fixed population) could affect productivity, such as lower aggregate savings (life cycle theory) and thereby lower investment rates, pressures on public finances via age-related spending increases, greater aggregate volatility (Jaimovich and Siu, 2009), and structural transformation (Siliverstovs and others 2011). See Aiyar, Ebeke and Shao (2016) for a detailed discussion.

III. RESULTS

Appendix Table 5.2 reports the estimated relationship between our demographic variable of interest and TFP growth over 1985–2014. The results are reported for both the FE-OLS and FE-2SLS (instrumental variable) estimators. Moreover, different data sets are used to check the robustness of the findings.

The results show that aging can meaningfully slowdown TFP growth in advanced economies and emerging market economies. For example, the significant coefficient of older labor force participation in the OLS regression in Column (1) indicates that a 1 percentage point increase in the share of 55–64 years-old age group leads to a statistically significant cumulative decrease in TFP of about 0.7 percentage points over five years (that is, about 0.15 per year).

This negative OLS coefficient remains statistically significant when OECD data are used for older labor force participation as shown in column (3). The coefficient in that column is higher as the country sample includes only Advanced economies and EMs, possibly because these economies have been more affected by the population aging than low-income countries (see Appendix Figure 5.1). For older employed workers—a variable that should be more directly connected to the efficiency of the production process *a priori*—the coefficient using OLS is not significant as shown in column (4). This indicates issues with the endogeneity of that variable and challenges in estimating such relationship using OLS.

The robustness of the results increases by using the FE-2SLS estimator. All coefficients become statistically significant and are quantitatively larger in this case, indicating a downward bias of the (OLS) estimates when not dealing with the endogeneity. In particular, when using the OECD data set and country sample—Appendix Table 5.2, Column (8)—the estimation suggests that a 1 percentage point increase in the share of older workers in the labor force leads to a statistically significant cumulative decrease in TFP growth of about 1.8 percentage points over five years (that is, about 0.35 percentage points per year).

To illustrate the economic significance of those results, Appendix Figure 5.2 depicts the estimated contribution of aging to average annual TFP growth in the 2000s, under the alternative estimations.[37] In all cases, the estimates point to economically sizable adverse effects of aging, of some 0.2–0.5 percentage points in advanced economies and about 0.1 percentage points in emerging market economies.

[37] The solid dots are constructed by using the estimates from columns (4) and (8) of Appendix Table 5.1 and taking the difference in the average share of older labor force in the 1990s (13.8 percent of the total labor force) minus the average share of older labor force in the 2000s (10.6 percent of the total labor force).

Appendix Table 5.2. Effects of an Increasingly Elderly Labor Force on Productivity (TFP) Growth, 1985–2014

Panel estimation method	Fixed Effects -OLS				Fixed Effects - Instrumental Variable			
Labor variables database	ILO[a]	ILO[a,b]	OECD[c]	OECD[c]	ILO[a]	ILO[a,b]	OECD[c]	OECD[c]
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ share of old labor force	-0.864**	-0.873**			-2.166**	-2.449**		
	(0.390)	(0.405)			(1.074)	(1.175)		
Δ share of old labor force $_{t-1}$			-0.909**				-1.702*	
			(0.355)				(0.960)	
Δ share of old employed workers $_{t-1}$				-0.641				-1.774*
				(0.404)				(0.956)
Δ old dependency ratio	-0.019***	-0.020***	-0.008*	-0.009	-0.029***	-0.033***	-0.006	-0.006
	(0.006)	(0.006)	(0.005)	(0.006)	(0.009)	(0.010)	(0.004)	(0.004)
Δ young dependency ratio	-0.006*	-0.008***	-0.003	-0.001	-0.004	-0.007**	-0.007*	-0.008*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Adjusted R-squared[d]	0.21	0.24	0.45	0.44	0.16	0.15	0.26	0.23
Regression F-statistic	9.80	9.35	15.96	15.66	6.93	6.54	11.70	11.64
Anderson correlations (underidentification) LR statistic					19.90	17.19	19.44	16.14
Anderson correlations LR test p-value					0.00	0.00	0.00	0.00
Cragg-Donald chi-square (weak identification) statistic					20.91	17.99	21.18	17.32
Cragg-Donald chi-square test p-value					0.00	0.00	0.00	0.00
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	73	68	36	36	63	57	32	32
Number of observations	274	257	151	151	264	246	147	147

Source: IMF staff estimates.

Notes: Significance at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; time- and country fixed-effects not reported in the table. Instrumental variable is here the 10 to 14 years lagged share of population at age 44–54 years-old to total population. All overidentification tests reject the null hypothesis. List of countries included in the analyses reported in Table 1.

[a] Sample includes all IMF *World Economic Outlook* economies with data available excluding Greece, Latvia, Lithuania, Luxembourg, Serbia, and Zimbabwe, and excludes top and percentile of the TFP growth rates distribution as outlier treatments.

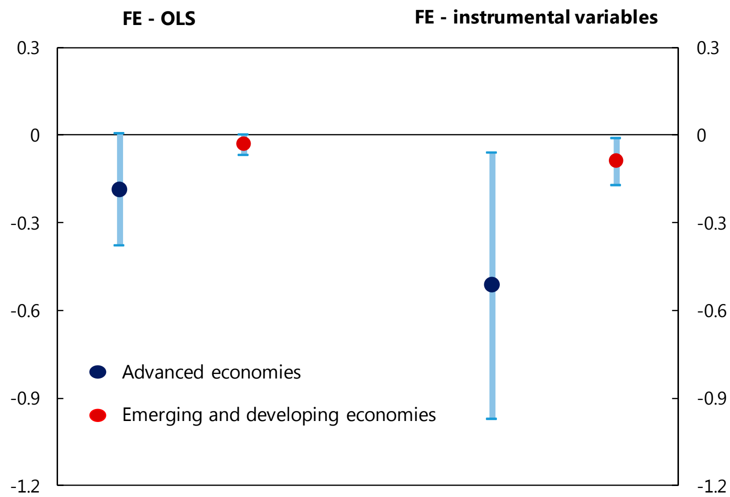
[b] Sample further excludes countries with less than 1 million people in 2014.

[c] Sample includes all OECD economies with data available excluding Latvia and countries with less than 1 million people in 2014.

[d] For estimations with instrumental variables, the centered R-squared is reported.

Appendix Figure 5.2. Estimated Effect on TFP Growth of Change in Share of Elderly Labor Force (Aged 55–64) Between the 1990s and the 2000s

(Annual average, percent)



Sources: International Labour Organization Labour Statistics; IMF staff estimations.
Note: TFP = total factor productivity, FE= fixed effects, and OLS = ordinary least squares. Vertical lines indicate the 90-percent confidence bands. Average effects for each income group are based on observed changes in the share of old employed workers, and the estimated effects on TFP growth.

IV. Conclusions

This technical appendix has explored the relationship between labor force aging and TFP growth in a panel setting composed of advanced economies and emerging market economies over 1985–2014. The evidence indicates that aging can meaningfully slowdown TFP growth in advanced economies and emerging market economies. The observed increase in the share of older workers in the labor force may have contributed to the TFP slowdown, on average, by as much as 0.2–0.5 percentage points a year in advanced economies and 0.1 percentage points a year in emerging market economies during the 2000s. Given the projected demographic trends, the findings indicate that population aging will remain a drag on productivity growth in the years to come.

References

Acemoglu D., U. Akcigitz, U., and M.A. Celik. 2014. Young, Restless and Creative: Openness to Disruption and Creative Innovations. NBER Working Paper No. 19894, February.

Aiyar, S., C. Ebeke, and X. Shao. 2016. "The Impact of Workforce Aging on European Productivity." IMF Working Paper No. 16/238, International Monetary Fund, Washington, DC.

Aksoy, Y., E.S. Basso, T. Grasl, and R.P. Smith. 2015. "Demographic Structure and Macroeconomic Trends." Birkbeck Working Papers in Economics and Finance 1501.

Cuaresma, C., Loichinger, E., and V. Gallina. 2016. Aging and Income Convergence in Europe: A Survey Of The Literature And Insights From A Demographic Projection Exercise. *Economic Systems, Elsevier* 40 (1): 4–17.

Disney, R. 1996. Can We Afford to Grow Older? A Perspective on the Economics of Aging. Cambridge, MA: MIT Press.

Dixon, S. 2003. Implications of Population Ageing for the Labour Market. *Labour Market Trends*, February.

Feyrer, J. 2007. Demographics and Productivity, *The Review of Economics and Statistics. MIT Press* 89 (1): 100–109.

Feyrer, J. 2008. Aggregate Evidence on the Link Between Age Structure and Productivity. *Population and Development Review* 34 (supp): 78–99.

Göbel, C., and T. Zwick. 2012. Age and Productivity: Sector Differences, *De Economist*, Vol. 160(1), pp. 35–57, March.

Jaimovich, N., and H. Siu. 2009. The Young, the Old, and the Restless: Demographics and Business Cycle Volatility. *American Economic Review* 99 (3): 804–26.

Jones, B., 2010. "Age and Great Invention." *The Review of Economics and Statistics*, *MIT Press* 92 (1): 1–14.

Maestas, N., K. J. Mullen, and D. Powell. 2016. "The Effect of Population Aging on Economic Growth, the Labor Force and Productivity." NBER Working Paper No. 22452, National Bureau of Economic Research, Cambridge, MA.

Siliverstovs, B., K. Kholodilin, and U. Thiessen. 2011. Does Aging Influence Structural Change? Evidence from panel data, *Economic Systems* 35 (2): 244–260.

Wong, W. K. 2007. Economic Growth: A Channel Decomposition Exercise. *B.E. Journal of Macroeconomics* 7 (1).

APPENDIX VI. TRADE AND PRODUCTIVITY GROWTH[38]

Anemic global productivity growth in recent years has been accompanied by a slowdown in global trade. While the trade slowdown is first and foremost the result of weak economic activity, waning trade liberalization efforts and the maturation of global supply chains have also been a driving factor (IMF 2016). Irrespective of its sources, however, the trade slowdown itself can have potentially important implications for productivity, through two main channels:

- Import penetration. With stronger foreign competition increasing pressure on domestic firms to produce more efficiently or to innovate; and imported inputs expanding the variety of and enhancing the quality of the intermediate goods to which firms have access;

- Exports, which can improve firm-level productivity through exposure to competition or improved access to foreign markets.

These channels can operate both at the firm level—by inducing firms to adapt more efficient production processes, improve product quality, or undertake specific investments—and at the sectoral level, by inducing a reallocation of resources toward more productive firms within a sector. The relevance of these effects on productivity growth are explored in this technical appendix.

A. Empirical Strategy

The empirical strategy entails using the opening of China to international trade over the last two decades as an exogenous shock to identify the effects of greater trade integration on productivity, using country-sector level data on trade and productivity.

In order to identify the respective effects of export and import—both vis-a-vis China—on productivity at the country-sector level, the following empirical specification is considered:

$$\ln TFP_{ist} = \beta_1 IMP_{is,t-l}^{CHN} + \beta_2 EXP_{is,t-l}^{CHN} + FE_{is} + FE_{it} + \varepsilon_{ist}, \qquad (2)$$

where subscripts i, s, t denote country, sector, and year, respectively. The dependent variable $\ln TFP_{ist}$ denotes log total factor productivity (TFP) in country i and sector s in year t, while $IMP_{is,t-l}^{CHN}$and $EXP_{is,t-l}^{CHN}$ are the corresponding country-sector-level imports from China (as a ratio to total domestic output) and exports to China (as a ratio to total domestic output), both lagged l years. The specification also includes country-sector (FE_{is}) and country-year fixed effects (FE_{it}).

[38] This technical appendix was prepared by Jaebin Ahn, and is based on Ahn and Duval (forthcoming).

The latter control for any variation that is common to all sectors of a country's economy, including for instance exchange rate shocks, aggregate output growth or reforms in other areas. The country-industry fixed effects allow us to control for industry-specific factors, including, for instance, cross-country differences in the growth of certain sectors that could arise for instance from differences in comparative advantage. This specification with fixed effects is tantamount to asking how changes in trade with China in a given sector and country are associated with changes in productivity levels in that country-sector.

To address potential endogeneity bias in the simple OLS estimates, we follow Autor, Dorn, and Hanson (2013) by instrumenting imports from China in a given country-sector with average imports from China in the same sector but other countries of the sample. Likewise, we propose the average exports to China in other countries as an instrumental variable for exports to China in any given country-sector. In so doing, we aim to exploit exogenous portions of imports from China (supply-driven) and exports to China (demand-driven) in 2SLS procedures.

B. Data

We combine the country-sector-year-level TFP data from the EU KLEMS and World KLEMS databases with the corresponding trade data from the World Input Output Database (WIOD). This data set provides annual information on sectoral input, output, TFP as well as export (by destination countries) and import (by source countries) over 1995–2011, covering 18 manufacturing and non-manufacturing sectors across 18 advanced economies.[39]

C. Estimation Results

Appendix Table 6.1 presents the baseline regression results from both simple OLS (columns 1–3) and 2SLS (columns 4–6), showing the impact of imports from China and exports to China on TFP.

[39] The sample of includes: Australia, Austria, Canada, Czech Republic, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Korea, Netherlands, Slovenia, Spain, Sweden, United Kingdom, and the United States of America.

Appendix Table 6.1. Estimates of Effect of Trade on Total Factor Productivity

	OLS			2SLS		
Dependent variable: [ln (TFP)ist]	(1)	(2)	(3)	(4)	(5)	(6)
(Imports from China/Total ouput)*100ist-1	0.006 **		0.005 *	0.017 ***		0.009 ***
	(0.003)		(0.003)	(0.006)		(0.003)
(Exports to China/Total outputs)*100ist-1		0.051 ***	0.048 ***		0.129 ***	0.112 ***
		(0.012)	(0.011)		(0.040)	(0.037)
First stage F-stats				62.4	36.9	32.9; 22.4
First stage p-value				0.00	0.00	0.00; 0.00
Obs	3,543	3,543	3,543	3,543	3,543	3,543

Source: IMF staff estimates.

Note: OLS = ordinary least squares, 2SLS = two-stage least squares. The dependent variable is log total factor productivity (TFP) in country *i* and sector *s* in year *t*. Independent variables are corresponding country-sector-level imports from China (as a ratio to total domestic output) and total exports to China (as a ratio to total domestic output), both lagged one year. The average value of imports from China relative to domestic output in all other countries and the average value of exports to China relative to domestic output in all other countries, both lagged one year, are used as instrumental variables for corresponding variables in columns (4)-(6). Country-sector as well as country-year fixed effects are included in all columns. Robust standard errors clustered at country-sector level are provided in parentheses.

D. Contributions to TFP Growth

The median country-sector in the sample experienced cumulative TFP growth of 14.7 percent between 1995 and 2007. During the same period, a median increase in the ratio of imports from China to total domestic output was 0.84 percentage points, whereas the increase in the ratio of exports to China to total domestic output was 0.3 percentage points. Following the methodology employed in Autor, Dorn, and Hanson (2013), we quantify that an exogenous portion of an increase in the ratio of imports from China to domestic output was 70 percent, while that in the ratio of exports to China was 30 percent.[40] Taking the benchmark semi-elasticity of 0.9 and 11.2 from imports and exports, respectively (column (6) in Appendix Table 6.1), we conclude that the exogenous variation in trade with China could explain up to 10 percent of the total increase in TFP growth (or 1.5 percent growth in level) in median country-sector.[41]

[40] For details, see Appendix B.A in Autor, Dorn, and Hanson (2013).

[41] (0.84*0.7)*0.9+(0.3*0.3)*11.2=1.5

References

Ahn, J., and R. Duval. Forthcoming. "Trading with China: Productivity Gains, Job Losses." IMF Working Paper, International Monetary Fund, Washington, DC.

Autor, D., D. Dorn, and G. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–68.

International Monetary Fund. 2016. "Global Trade: What's Behind the Slowdown?" *World Economic Outlook*, Chapter 2, October.

APPENDIX VII. IMPACT OF MIGRATION ON PRODUCTIVITY IN RECEIVING COUNTRIES[42]

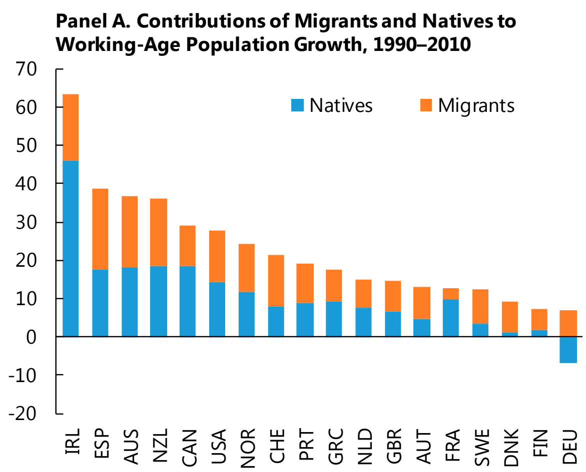
This appendix studies the impact of immigration on labor productivity and its components, with a focus on advanced economies. It builds on the recent work by Jaumotte, Koloskova and Saxena (2016). In line with previous literature, the analysis finds that migration can lead to economically meaningful long-term productivity gains.[43] These findings indicate that migration policies can be important not only in addressing adverse demographic challenges (population aging) but also in boosting aggregate productivity.

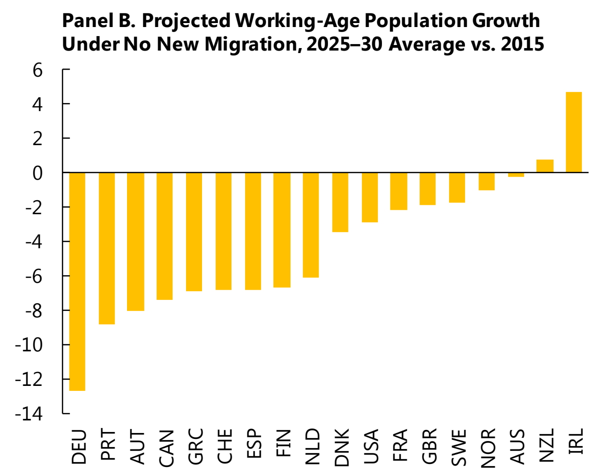
A. Migrants and Working-Age Population

Migration has already played an important role in mitigating the shrinking labor force in some advanced economies. Between 1990 and 2015, immigrants contributed about ½ of the growth in working-age population in many of these economies (Appendix Figure 7.1—Panel A), boosting the ratio of working age-to-total population.

Appendix Figure 7.1. Migration and Working-Age Population in Advanced Economies

(Percent)





Source: Jaumotte, Koloskova, and Saxena (2016).

Note: Data labels in the figure use International Organization for Standardization (ISO) country codes. Working-age population refers to age group 15–64. Sample of countries includes Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Ireland, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[42] This technical appendix was prepared by Ksenia Koloskova, building on Jaumotte, Koloskova, and Saxena (2016).

[43] Ortega and Peri (2014) study the long-run impact of immigration share on incomes per capita in a large cross-section of countries and find that the effect mainly operates through total factor productivity. Alesina, Harnoss, and Rapoport (2016) focus on the birthplace diversity aspect of migration, and find positive effects of skilled immigrants diversity on total factor productivity.

With adverse demographics projections for most advanced economies, the role of immigration in maintaining a favorable demographic structure is likely to become even more important in the coming years. In the absence of further migration, the United Nations projects that working-age population will decline by as much as 5–10 percent in a large group of advanced economies—including large systemic economies such as Germany, Australia, Canada—over the next 10–15 years (Appendix Figure 7.1—Panel B).

In addition to mitigating population aging, immigration can arguably play a role in boosting aggregate productivity, in part because migrants are typically younger than the natives, but also through other channels such as innovation and complementarity of skills with natives. This is the focus of the following section, which assesses empirically the effect of immigration on labor productivity.

B. Methodology

Following Jaumotte, Koloskova, and Saxena (2016), the effect of migration on the variables of interest (output per worker, TFP, and so on) is estimated using the following specification:

$$\ln y_{dt} = \beta_0 + \beta_M MSH_{dt} + \beta_S \ln S_{dt} + \beta_C Controls_{dt} + \mu_d + \theta_t + \varepsilon_{dt} \qquad (1)$$

where y is the variable of interest, d is the destination country, t is time; MSH_{dt} is the migration share of defined as the number of foreign born adults relative to the destination country's adult population. Throughout the analysis, migration is defined according to the country of birth rather than citizenship, as the latter can change with naturalization and legislation regulating the acquisition of citizenship typically varies among countries and time. Throughout the analysis, both migrants and population refer to individuals aged 25 and older. S_{dt} is the total population of the destination country (which allows to control for country size); $Controls_{dt}$ is a vector of other control variables such as the share of population with high and medium skills, trade openness, young dependency ratio and age structure of the working-age population (lagged by 5 years to mitigate endogeneity problems); μ_d denotes the destination country fixed effects; θ_t is the common time fixed effect, and ε_{dt} is the error term.

Estimation of Equation (1) with an Ordinary Least Squares (OLS) estimator could lead to several potential biases, related to reverse causality, omitted variable, and measurement error. Thus, we estimate it using a Two-stage Least Squares (2SLS) procedure, where the share of migrants is instrumented using the predicted migration shares from an estimated pseudo-gravity model.[44] In addition, total population—one important control in Equation (1)—is instrumented using native

[44] The model predicts bilateral migration shares based on origin countries' push factors, such as economic, political and social factors, and based on bilateral geographic and cultural migration costs (and their interactions). It does not include pull factors specific to the destination country, as they could be correlated with destination country's productivity. Predicted bilateral migration shares from the model are aggregated across origin countries to obtain an instrument for total migration share at destination.

population to clean out the contribution of migration. See Jaumotte, Koloskova, and Saxena (2016) for details.

C. Data

Data on migration comes from the Institute for Employment Research, which reports the immigrant (foreign-born) population for ages 25 years and older, by gender, country of origin, and educational level. The sample covers 18 OECD countries over 1980–2010, with data reported at five-year-intervals.[45] The sample used for the estimation of Equation (1) is based on 1990–2010 data, as the observations in 1980–1985 are used in the gravity model to construct the series for the instrumented migration share starting from 1990.

Data on the shares of population 25 years and older (with high education and secondary school) come from the Barro-Lee data set. Series of young dependency ratio (share of population 0–25 years old in total population) and the age structure of the population of ages 25 and older are constructed using UN population data.

National accounts data, such as labor productivity (GDP per worker), the capital-to-labor ratio, the human capital measure, and TFP are from the Penn World Tables version 9.0.

D. Results

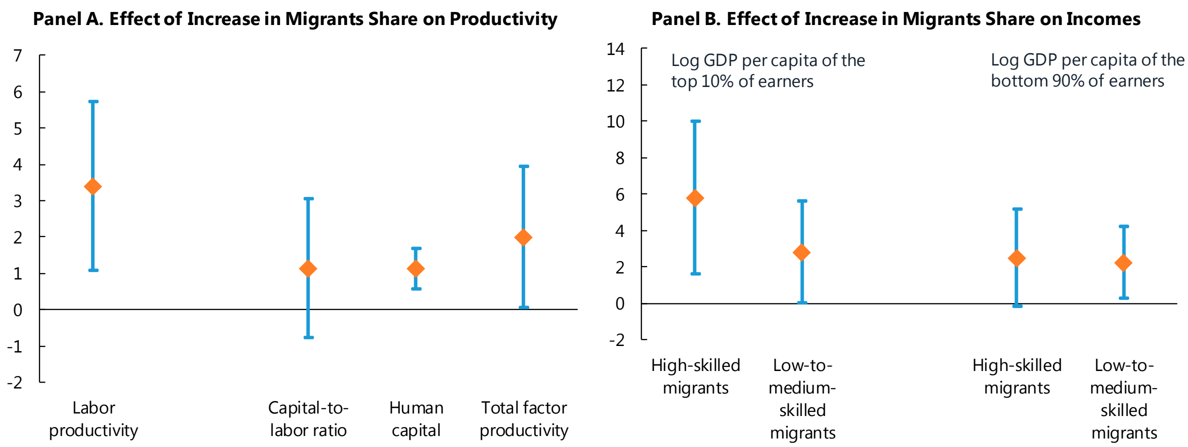
Appendix Figure 7.2 presents the key findings, summarizing the estimated effects of immigration on labor productivity (output per worker) and its components (capital-to-labor ratio, human capital, and TFP). Appendix Table 7.1 reports the second stage results both for the baseline specification—columns (1), (3), (5), and (7)—and for results correcting the standard errors for the possible presence of weak instruments—columns (2), (4), (6), and (8).[46] Results of the gravity model—used to construct the instrument of migration—and further details are reported in Jaumotte, Koloskova and Saxena (2016).

[45] The sample includes Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Ireland, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[46] One concern about the estimates relates to the possible weakness of the instruments (as indicated by the Kleinbergen-Paap statistic in comparison to the Stock and Yogo threshold), and the possible violation of the assumption of independently identically distributed (iid) error terms. To address these concerns, we construct standard errors consistent with weak instruments. Results are presented in columns (2), (4), (6), (8) and are similar in magnitude and significance to those of the baseline estimation.

Appendix Figure 7.2. Impact of Migration on Productivity and Incomes

(Percent change per 1 percentage point increase in migrants share)



Sources: Jaumotte, Koloskova, and Saxena (2016); IMF staff calculations.
Note: The estimation is based on a two-stage least squares approach, where the migration share is instrumented using a gravity-type model of bilateral migration flows. For details, see Jaumotte, Koloskova, and Saxena (2016). The estimation of the effect on labor productivity, capital-to-labor ratio, human capital and total factor productivity controls for the total population size, the share of population with tertiary and secondary education, young age dependency ratio, and the age structure of the working-age population (defined as 25+ years old). The estimation of the effect on inequality controls for the total population size, the share of population with tertiary and secondary education, trade openness, and share of information and communications technologies in total capital stock.

Contribution of Migrants to Labor Productivity

The results suggest that migrants can contribute directly to labor productivity through channels not related to the age structure. In the long term, a higher share of immigrants leads to higher labor productivity, even after controlling for the young dependency ratio and the age structure of the working-age population. The effect comes mainly through higher human capital and TFP—with a 1 percentage point increase in the share of migrants leading to a 1 percent increase in the level of human capital and a 2 percent increase in level of TFP in the long term. Meanwhile, the increase in the capital-to-labor ratio is not statistically significant—indicating that physical capital adjusts to the increased labor force in the long term.

Previous work has found that increased human capital and productivity come partly from the addition of high-skilled migrants—who bring diverse skills and different technology to their new home countries—but also from the effect of a larger stock of low-skilled immigrants. As extensively documented in previous work (see Peri 2016 for a survey), low-skilled migrants can contribute to aggregate human capital and productivity by: (i) filling in labor shortages, for example in non-tradable services, and thus helping to exploit complementarities with natives' skills; (ii) taking more manual and routine tasks, thus allowing natives to take occupations which require more complex (abstract and communication) skills, in which they may have comparative advantage (see, for example, D'Amuri and Peri 2014); (iii) by increasing the supply of household and childcare services, which help boost labor supply of high-skilled females (for example, see Cortes and Tessada 2011).

Distribution of Gains from Migration

Beyond the aggregate effects, a key concern about immigration—especially of low-skilled workers—has been the impact it may carry on low income natives (and income distribution more generally). As shown in Jaumotte, Koloskova and Saxena (2016), immigration increases average per capita income for both the top 10 and bottom 90 percent of earners—although high-skilled immigration tends to benefit high income earners more, possibly due to stronger synergies between high-skilled migrants and high-skilled natives. Moreover, there is no evidence that inequality within the bottom 90 percent—captured by the Gini coefficient—increases with immigration. While this does not exclude that natives in some occupations might be affected by immigration, especially in the short term, it suggests that such effects are not significant at the macro level over a longer horizon.

Appendix Table 7.1. Effect of Immigration on Labor Productivity and Its Component

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log labor productivity	Log labor productivity	Log capital-to-labor ratio	Log capital-to-labor ratio	Human capital	Human capital	TFP	TFP
	Baseline IV	Weak IV consistent CI	Baseline IV	Weak IV consistent CI	Baseline IV	Weak IV consistent CI	Baseline IV	Weak IV consistent CI
Migration share	3.41***	4.35***	1.13	1.15	1.12***	1.05**	2.00**	2.94**
	(2.870)	(2.611)	(1.155)	(0.852)	(3.901)	(2.548)	(2.017)	(2.227)
Ln pop (Ln nat pop in (2), (4), (6), (8))	0.93	0.90	0.02	0.02	-0.07	-0.07	0.93*	0.90**
	(1.448)	(1.489)	(0.047)	(0.047)	(-0.487)	(-0.482)	(1.915)	(1.978)
Share of population high skilled	0.15	0.13	0.20	0.20	0.13	0.14	0.03	0.01
	(0.422)	(0.405)	(0.765)	(0.765)	(1.281)	(1.277)	(0.112)	(0.067)
Share of population medium skilled	0.37*	0.36**	0.10	0.10	0.15***	0.15***	0.31*	0.30*
	(1.957)	(2.018)	(0.694)	(0.718)	(2.898)	(3.007)	(1.866)	(1.881)
Trade openness and age structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	90	90	90	90	90	90	90	90
R-squared	0.763	0.775	0.893	0.893	0.826	0.824	0.557	0.577
Number of destinations	18	18	18	18	18	18	18	18
Excluded instruments	MSH Ln nat pop	MSH	MSH Ln nat pop	MSH	MSH Ln nat pop	MSH	MSH Ln nat pop	MSH
Underidentification test *P*-val	0.00721	0.00574	0.00721	0.00574	0.00721	0.00574	0.00721	0.00574
Kleibergen-Paap rk Wald *F*-stat	3.891	8.651	3.891	8.651	3.891	8.651	3.891	8.651
Stock-Yogo 10% max IV size	7.03	16.38	7.03	7.03	7.03	16.38	7.03	16.38
Stock-Yogo 15% max IV size	4.58	8.96	4.58	4.58	4.58	8.96	4.58	8.96
Weak IV 95% AR-based confidence set		[2.04126, ...]		[-1.14731, ...]		[.413427, ...]		[.9005, ...]

Source: IMF staff estimates.

Note: Robust t-statistics are reported in parentheses. *** denotes significance at the one percent level, ** at the 5 percent level, and * at the 10 percent level. MSH denotes the gravity-predicted migration share from Jaumotte, Koloskova, and Saxena (2016). All regressions include country and time fixed effects. Trade openness is defined as the sum of exports and imports relative to GDP, controlling for total population (lagged by five years to avoid endogeneity). Age structure includes young dependency ratio and the shares of population ages 25-24, 35-44, 45-54 and 55-64 in the population older than 25, all lagged by five years to avoid endogeneity.

References

Alesina, A., J. Harnoss and H. Rapoport. 2016. *Journal of Economic Growth* 21 (2): 101–138.

Cortés, P. and J.Tessada. 2011. "Low-Skilled Immigration and the Labor Supply of Highly Skilled Women." *American Economic Journal: Applied Economics, American Economic Association* 3 (3): 88–123.

D'Amuri, F. and G. Peri. 2014. "Immigration, Jobs, and Employment Protection: Evidence from Europe Before and During the Great Recession." *Journal of the European Economic Association, European Economic Association* 12 (2): 432–464, 04.

Jaumotte, F., K. Koloskova and S. C. Saxena. 2016. “Impact of Migration on Income Levels in Advanced Economies.” Spillover Note 8, International Monetary Fund, Washington.

Ortega, F. and G. Peri. 2014. "Openness and Income: The Roles Of Trade and Migration." *Journal of International Economics, Elsevier* 92 (2): 231–251.

Peri, G. 2016. "Immigrants, Productivity, and Labor Markets." *Journal of Economic Perspectives* 30 (4): 3–30.

APPENDIX VIII. THE IMPACT OF STRUCTURAL REFORMS ON PRODUCTIVITY[47]

There are several ways in which deregulation can have an impact on productivity (see Nicoletti and Scarpetta 2005 for a review of theoretical literature): (i) by reducing slack in the use of resources; (ii) by facilitating technology diffusion and adoption; (iii) by increasing incentives to innovate. Previous industry-level studies have empirically documented that product and labor market structural reforms tend to increase output and productivity (Bouis, Duval and Eugster 2016; Nicoletti and Scarpetta 2005; Bassanini, Nunziata, and Venn 2009). This note studies the impact of labor and product market reforms on total factor productivity and other key macroeconomic variables at the macro level. The analysis is based on a new narrative-approach data set on *major* structural reforms by Duval and others (Forthcoming)—as opposed to OECD indicators typically used in earlier studies. Moreover, following IMF 2016, the analysis uses a dynamic approach to capture the fact that the positive impact of reforms can build up gradually over time.

A. Methodology

Given their likely lagged effects, the impact of reforms on macroeconomic outcomes is estimated at different time horizons, $k = [0,4]$, using the local projections method (Jorda 2005). Specifically, the following specification is estimates for each horizon *k*:

$$y_{t+k,i} - y_{t-1,i} = \alpha_i + \gamma_t + \beta_k R_{i,t} + \theta_k X_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $y_{t+k,i} - y_{t-1,i}$ denotes the change of the variable of interest (for example, TFP) in levels between *t-1* and *t+k*; α_i and γ_t are country- and time-fixed effects; $R_{i,t}$ is a dummy variable that captures the implementation of a structural reform at time *t*. The latter can be a product market or an employment protection legislation reform. Control variables $X_{i,t}$ include two lags of GDP growth, contemporaneous and past crisis dummies (defined as annual growth below -3 percent), three lags of the relevant reform variable, and leads of the reform variable from period t until period $t + k - 1$ to correct a possible bias that arises from using the local projection method, as suggested by Teulings and Zubanov (2014). The methodology is applied to construct impulse responses of TFP, output, employment, and labor productivity.

The employment protection legislation reform dummy takes values {1; 0; -1}, denoting a deregulating reform, absence of a reform, or a reversal of a reform.

For product market reform, the analysis focuses on major deregulation in seven network industries: gas, electricity, telecom, post services, rail, airlines, and road transportation. The

[47] This technical appendix was prepared by Ksenia Koloskova.

product market reform dummy takes value of 1 if there were at least two reforms over three years in one or more of the seven network industries, and zero otherwise.

B. Data

The TFP measure is obtained from Penn World Tables version 9.0. Structural reforms data are from Duval and others (Forthcoming). The sample covers 1970–2013 and data are an unbalanced panel. The analysis includes 26 advanced economies for which the structural reforms data are available: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

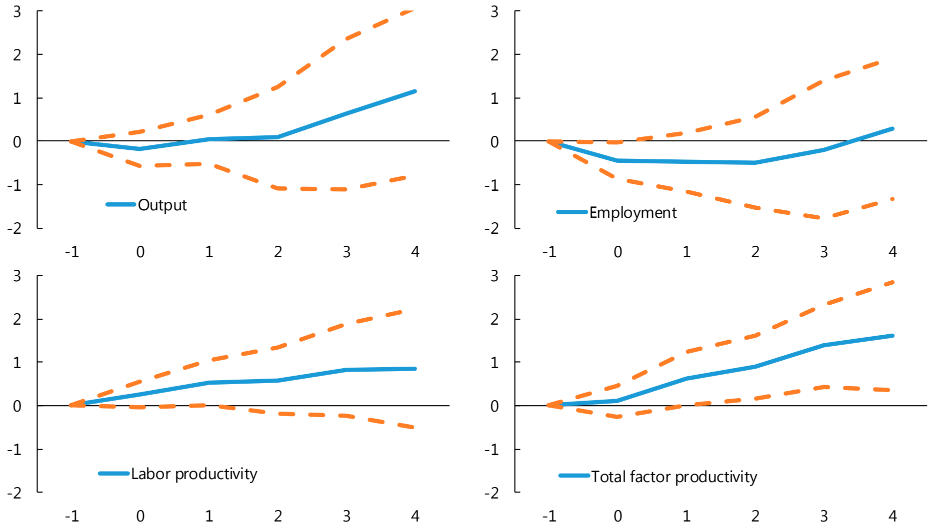
C. Results

Employment Protection Legislation Reforms (Regular Contracts)

The results of the analysis using equation (1) for output and some of its components are reported in Appendix Figure 8.1. Employment protection legislation reforms do not show a significant near-term impact on output nor employment, although this reflects the role of initial conditions. Indeed, the effects of reforms differ substantially under strong and weak economic conditions (see IMF 2016). Both variables show a significant decline if the reforms are undertaken under weak economic conditions, and a significant increase otherwise. Overall, this implies a muted impact on labor productivity. Capital deepening declines in the medium term as the relaxation of employment regulation induces substitution toward labor. At the same time, employment protection legislation reforms have unambiguously positive effects on TFP. Lifting strict employment protection legislation facilitates hiring and firing process, improving labor allocation and increasing total factor productivity.

Appendix Figure 8.1. Effect of Employment Protection Legislation Reforms

(Percent)



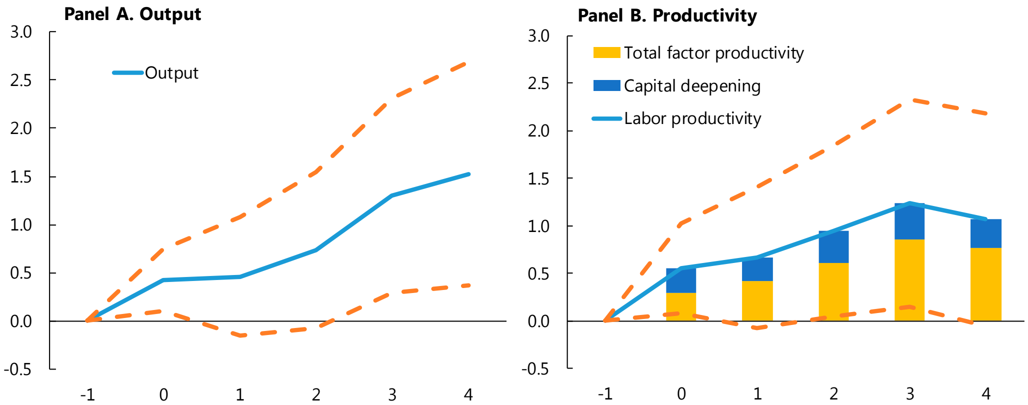
Sources: Penn World Table 9.0; Duval and others (forthcoming); and IMF staff calculations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. Dashed lines denote 90-percent confidence bands. The effects are estimated using local projections method (Jordà 2005), controlling for lagged growth, past reforms, crisis dummies and using a bias correction suggested by Teulings and Zubanov (2014).

Product Market Reforms

In line with the findings in IMF (2016), product market reforms can significantly increase output in the medium term, and raise labor productivity (Appendix Figure 8.2). This effect reflects both increased capital deepening and TFP, with TFP explaining about two-thirds of the total increase in labor productivity. Statistical significance decreases, however, once the labor productivity is divided between these two components. These findings are consistent with those from sector- and firm-level analysis in IMF (2016). As shown in the latter, product market reforms can facilitate new firms' entry, and result in higher employment and investment by incumbent firms. These reforms also have significant output spillovers to upstream and downstream sectors.

Appendix Figure 8.2. Effect of Product Market Reforms

(Percent)



Sources: Penn World Table 9.0; Duval and others (forthcoming); and IMF staff calculations.
Note: Years after the shock on the x-axis, t = 0 is the year of the shock. Dashed lines denote 90-percent confidence bands. The effects are estimated using local projections method (Jordà 2005), controlling for lagged growth, past reforms, crisis dummies and using a bias correction suggested by Teulings and Zubanov (2014).

References

Bassanini, A., L. Nunziata and D. Venn. 2009. "Job Protection Legislation and Productivity Growth in OECD Countries." *Economic Policy* 24: 349–402.

Bouis, R., R. Duval and J. Eugster. 2016. "Product Market Deregulation and Growth; New Country-Industry-Level Evidence." IMF Working Papers 16/114, International Monetary Fund, Washington, DC.

Duval, R., D. Furceri, B. Hu, J. Jalles, and H. Nguyen. Forthcoming. "A New Narrative Database of Product and Labor Market Reforms in Advanced Economies." IMF Working Paper, Washington, DC.

Nicoletti, G. and S. Scarpetta. 2005. "Regulation and Economic Performance: Product Market Reforms and Productivity in the OECD." OECD Economics Department Working Papers 460, OECD, Paris.

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

Teulings, C. N., and N. Zubanov. 2014. "Is Economic Recovery a Myth? Robust Estimation of Impulse Responses." *Journal of Applied Econometrics* 29 (3): 497–514.