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Technology and Demand Drivers of Productivity Dynamics in Developed and Emerging Market Economies

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Abstract

Frequently, factors other than structural developments in technology and production efficiency drive changes in labor productivity in advanced and emerging market and developing economies (EMDEs). This paper uses a new method to extract technology shocks that excludes these influences, resulting in lasting improvements in labor productivity. The same methodology in turn is used to identify a stylized example of the effects of a demand shock on productivity. Technology innovations are accompanied by higher and more rapidly increasing rates of investment in EMDEs relative to advanced economies, suggesting that positive technological developments are often capital-embodied in the former economies. Employment falls in both advanced economies and EMDEs following positive technology developments, with the effect smaller but more persistent in EMDEs. Uncorrelated technological developments across economies suggest that global synchronization of labor productivity growth is due to cyclical (demand) influences. Demand drivers of labor productivity are found to have highly persistent effects in EMDEs and some advanced economies. Unlike technology shocks, however, demand shocks influence labor productivity only through the capital deepening channel, particularly in economies with low capacity for counter-cyclical fiscal policy. Overall, non-technological factors accounted for most of the fall in labor productivity growth during 2007-08 and around one-third of the longer-term productivity decline after the global financial crisis.

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Technology and Demand Drivers of Productivity Dynamics in Developed and Emerging Market Economies*

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1 Introduction

Productivity growth in advanced economies (AEs) and emerging and developing economies (EMDEs) has undergone many surges and declines historically, usually coinciding with global recessions and slowdown events (Dieppe, 2020). Productivity growth has been less volatile in advanced economies but has followed a similar series of rapid growth gains and slowdowns (Fernald, 2007).

A wide range of factors can affect productivity growth. This paper will disentangle the influences of lasting changes to productivity, "technology", from temporary or demand-side influences for a large number of economies.We use 'technology' as a catchall phrase for the *most* persistent driver of productivity. Improvements in productivity due to factors such as better technologies, or organizational and institutional changes, are important drivers of sustained productivity improvements. Non-technology factors can also affect productivity growth. For example, demand-led changes in productivity are likely to have played a role in the pre-2008 surge and the subsequent decline in global productivity growth during the Global Financial Crisis (GFC), and are once again expected to operate during the recent COVID-19 pandemic. Both types of shock are of interest to policymakers and are explored in this paper.

To identify the dominant driver of lasting productivity changes, it is necessary to abstract from temporary and business-cycle influences. There are two established approaches to removing these influences from labor productivity and total factor productivity (hereafter, TFP): first, a utilization-adjustment of TFP, and second, structural vector-autoregressions (VARs) that identify the dominant drivers of long-run influences on labor productivity. The latter approach is the focus of this paper.

A standard growth accounting analysis of productivity developments only provides a partial insight into the drivers of large swings in productivity growth or slower-moving trend changes. One component of labor productivity, TFP, will reflect demand-driven cyclical influences such as changing labor and capital utilization as well as technological and organizational changes (Basu et al., 2006; Fernald and Wang, 2016).[1] To account for the intensive margin of labor inputs, researchers typically scale the factor inputs using observable proxies for factor utilization. For example, average hours per worker, electricity usage, and surveys of capacity utilization can provide insight, individually and collectively, into how labor effort and capital utilization vary (Burnside et al., 1996; Imbs, 1999; Shapiro, 1993). This approach has also been extended using industry-level data to account for industry heterogeneity. However, data requirements for this approach—in particular, annual data on the sectoral distribution of hours-worked, employment, and capital—are prohibitive for many advanced economies and most EMDEs, which makes it impossible to conduct a broad-based analysis across many economies.[2]

Structural VARs (SVARs) take an alternative approach to removing cyclical or demand-led

[1] In the United States, one-half of TFP growth variability has been attributed to non-technology factors Basu et al. (2006).

[2] Basu et al. (2006), Huo et al. (2020), and Comin et al. (2019) have implemented these for advanced economies, but not for EMDEs. A second difficulty with this approach is the possible presence of a wide range of structural relationships between different inputs to production, preventing the broad-based application of this methodology. For example, an inflexible labor market around the number of hours worked makes it a poor proxy for utilization.

components of productivity growth. They identify the dominant persistent and permanent variations in productivity. These are assumed to reflect lasting structural influences on productivity, such as technological innovation, or organizational changes. This paper uses a new spectral SVAR identification methodology that identifies technology shocks as those that drive the largest proportion of low (long-run) frequency labor productivity variation. The SVAR approach effectively filters through other less persistent changes in productivity or changes that drive only a small proportion of long-run productivity variation.[3] Demand shocks could also have persistent effects on productivity growth, which are not ruled out in our SVAR identification. An example of a persistent demand shock is identified using a modification of the approach for identifying technology shocks. Importantly, the persistence of the effect of the identified demand driver is found to vary across countries according to their capacity to enact counter-cyclical fiscal policy.[4]

Finally, the literature has pointed towards evidence that a large proportion of cross-country synchronization of labor productivity growth is driven by business-cycle factors as opposed to technology spillovers (Huo et al., 2020; Imbs, 1999). Accordingly, using the identified technology measure, we assess whether these findings also apply to our expanded dataset covering EMDEs.

We address the following questions:

- How can researchers identify technological and non-technological factors driving productivity developments across a wide range of countries? Are the macroeconomic responses to these shocks different across developed and developing economies?

- Can non-technology shocks have a persistent impact on labor productivity, especially in EMDEs? If yes, are there defining features associated with countries having persistent (or less persistent) impulse responses?

- After removing the cyclical and other non-technological components from labor productivity, how synchronized are the technology-driven productivity components across countries?

We make multiple contributions to the literature, which has until now focused on advanced economies. This paper is the first study to separate technology and non-technology drivers of productivity across a broad range of countries using a new spectral SVAR approach introduced by Dieppe et al. (2019, 2021). Panel and individual VARs are estimated and identified for over 100 advanced and emerging economies, an unprecedented country sample relative to the existing literature which has generally focused on the G-7 advanced economies.[5] This paper also uncovers non-technology shocks that may have persistent effects on advanced economy and EMDE labor productivity levels through the capital-deepening channel and country-characteristics that govern the degree of persistence. We are also the first to assess the synchronization of productivity growth across a broad range of countries for measures that remove non-technology drivers of productivity

[3] A survey of the SVAR literature has found that technology shocks account for between 1 and 55 percent of variations in output in the US (Ramey, 2016).

[4] While not explicitly modeling demand shocks, a range of studies have documented the existence of lasting negative effects on output and productivity from financial, currency, and political crises (Dieppe, 2020; Cerra and Saxena, 2008; Jordà et al., 2013; Reinhart and Rogoff, 2014).

[5] Previous studies have focused on a small subset of advanced economies. For example, Elstner and Rujin (2019); and Galí (1999) apply long-run restriction-identified SVARs to G-7 economies only.

fluctuations. The existing literature focuses on advanced economy synchronization, whereas this study also considers a wide range of EMDEs (Imbs, 1999; Huo et al., 2020).

The following findings emerge:

- Technology changes have contributed up to 80 percent of the variation of productivity growth at long (10 years) horizons in advanced economies and EMDEs. Non-technology factors, including demand-side factors, can also have highly persistent, but smaller, effects at this horizon.

- Technology shocks in EMDEs are accompanied by larger and more rapid increases in investment than in advanced economies, suggesting that technological developments are often capital-embodied in these economies. Positive technology shocks also lead to lower employment and consumer price inflation in both groups of economies in the short-term. However, the falls in prices and employment are more persistent in EMDEs than in advanced economies.

- There is weak technology transmission across economies. The synchronization of the technology measure of productivity across countries is lower than for un-adjusted measures of labor productivity and TFP growth. This supports the finding of the slow-moving nature of technology diffusion and convergence across economies (Comin and Hobijn, 2010; Kindberg-Hanlon and Okou, 2020). Common productivity developments are therefore largely a business-cycle phenomenon through common demand factors, which operated strongly during the GFC, when non-technology shocks explained over half of the immediate fall in productivity growth.

- Non-technology shocks dominate short-term productivity fluctuations but can have persistent effects on productivity in advanced economies and EMDEs, with the effects magnified for countries having weak fiscal positions. This supports similar conclusions in Bachmann and Sims (2012) and Jordà et al. (2020), who find evidence that monetary and fiscal policy can have long-lasting effects on the productivity of advanced economies.

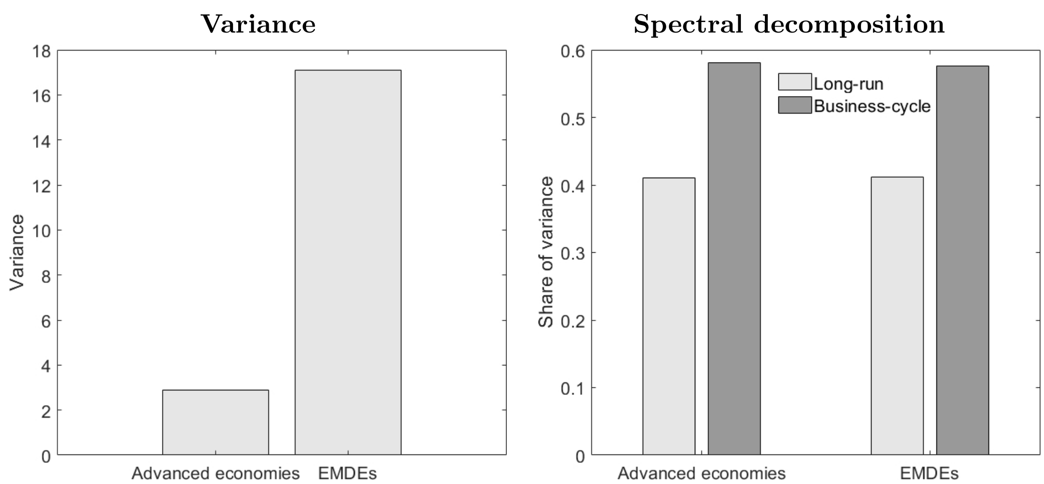
Our exploration starts by examining the cyclical and volatile nature of productivity growth before turning to the methodology (and its panel extension) that we use to identify technological innovations. We then proceed to explore the implications of the identified technological—and, by extension, non-technological—drivers of productivity, along with their cross-country synchronization.

2 Cyclicality and Volatility of Productivity: Some Observations

Labor productivity and TFP growth are generally procyclical, with troughs coinciding with recessions and peaks during periods of strong employment growth (World Bank, 2020).[6] Labor productivity is significantly more volatile in EMDEs than in advanced economies, by up to a factor of 6 times (see left panel of Figure 1).[7] However, business cycle fluctuations are found to be just as important in driving the volatility of labor productivity in EMDEs and in advanced economies; typically, business cycle fluctuations are assumed as those that last between 2 - 8 years.[8] In both EMDEs and advanced economies, fluctuations that rise and fall over the course of the business cycle account for 60 percent of the variation of productivity growth, while long-lasting changes account for the remaining 40 percent (see right panel of Figure 1).

The volatility of labor productivity growth is largely accounted for by TFP across both advanced economies and EMDEs, where TFP accounts for 75 - 80 percent of the variance of labor productivity growth (Figure 2).[9] The high proportion of volatility present in TFP growth reflects its role as a residual, explaining all productivity variation not driven by slower-moving developments in the capital stock and human capital.

Figure 1: Variance and Spectrum of Labor Productivity Variance



Note: Median variance of labor productivity growth between 1980-2018 in advanced economies and EMDEs. Spectral decomposition shows the contribution to the variance of labor productivity growth of low-frequency (>8 years) and business-cycle frequency components (2-8 years).

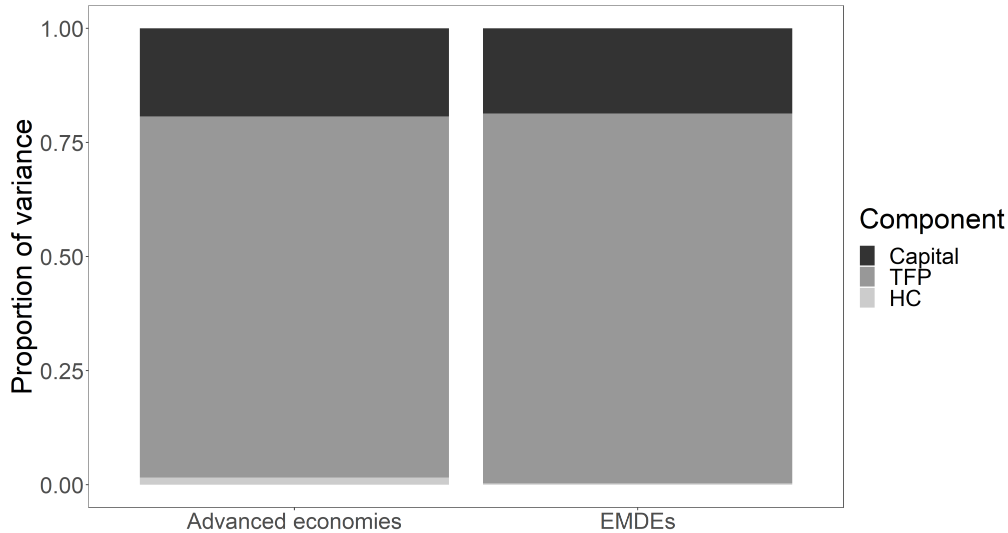
[6] However, in the United States, there is some evidence that TFP is becoming increasingly a-cyclical (Biddle, 2014; Fernald and Wang, 2016). For advanced economies in general, there are strong cyclical patterns, including a sharp fall and rebound during and in the aftermath of the global financial crisis.

[7] The literature has documented a higher vulnerability of EMDE output to shocks relative to advanced economies (García-Cicco et al., 2010; Neumeyer and Perri, 2005).

[8] See Christiano and Fitzgerald (2003) and Sargent (1987).

[9] See Sprauge (2020) who finds comparable numbers for the USA.

Figure 2: Decomposition of labor productivity variance



Note: Contributions of TFP, capital deepening, and human capital contributions to labor productivity variance in the median advanced economy and EMDE during 1980-2018. Does not account for covariance between contributions.

A variety of reasons exist for the existence of procyclicality in TFP and labor productivity, and the difficulties with associating either measure with structural developments such as technological or organizational change. For example, labor effort can rise during periods of strong demand without a change in measured labor inputs, while labor hoarding during downturns can leave workers idle, lowering measured TFP and productivity. In addition, capital inputs are measured without taking account of utilization; factories and machines may also be left unused during downturns, while measured capital inputs remain unchanged. Measured as a residual, TFP often includes changing utilization without appropriate adjustments (Basu et al., 2006; Imbs, 1999).

3 Empirical Approach

3.1 Spectral SVAR Approach

A new spectral identification approach is used to identify technology shocks as the impetus that drives the largest share of low-frequency (long-term) labor productivity fluctuations. This identification serves to "look through" non-structural developments in productivity such as changing utilization rates. The identified lasting changes in productivity will be referred to as "technology", as is common in the literature, although it could capture a range of influences.[10] This identification does not impose the condition that no other shock can have a long-lasting impact on productivity, as is typically the case with long-run SVAR identifications. A similar methodology has been used to assess shocks that drive business cycle movements in a range of macroeconomic variables

[10] See also Chen and Wemy (2015), Fisher (2006), Francis and Ramey (2005).

(Angeletos and Dellas, 2020).

Identifications of technology shocks using the long-run identification of Galí (1999) have been found to be subject to substantial bias where non-technology shocks account for a non-trivial proportion of output fluctuations (Chari et al., 2008). In contrast, the spectral identification method tends to be more robust than other SVAR identifications of technology shocks in the presence of large confounding business-cycle shocks to productivity growth (Dieppe et al., 2019, 2021). The spectral SVAR identification is applied to a VAR containing the log of labor productivity, log employment per capita, consumption as a share of GDP, investment as a share of GDP, consumer price inflation, and monetary policy rates (when available). For illustrative purposes, TFP is also included in the VAR to observe differences relative to the response of labor productivity to the technology shock.

A Fourier transform is used to estimate the contributions of potential structural shocks at various frequencies. Effectively this involves the application of a band-pass filter (Christiano et al., 2003) using the reduced-form coefficients of a VAR, identifying the spectral density of the variables within a particular frequency band. The technology shock is then identified as the shock that explains the largest share of the variance of labor productivity at the desired (*long-horizon*) frequency.

Identifying technology shocks through restrictions that explain the majority of low (long-term) frequency volatility of productivity is a novel approach. This methodology has previously been used to assess the types of shocks that drive the business cycle. For example, Angeletos and Dellas (2020) find that a single shock drives the majority of the variance of a range of macroeconomic variables at business cycle frequencies, and DiCecio and Owyang (2010) use a similar methodology to identify technology shocks.

A VAR representation of the spectral density of Y is generated using the Wold representation of the VAR (assuming it is invertible):

$$Y_t = \left(I - \left(B_1 L + B_2 L^2 + \dots B_p L^p\right)\right)^{-1} u_t = D u_t, \tag{1}$$

where B are the reduced-form VAR coefficients and (assuming invertibility) D represents the MA coefficients on the reduced form innovations u at each horizon. By post-multiplying Y_t by $Y_{t-\tau}$, a series of autocorrelations are generated, which in turn can generate the spectral density of the endogenous variables at frequency ω, based on the reduced-form MA coefficients $D\left(e^{-i\tau\omega}\right) = \left(I - \left(B_1 L e^{-i\omega} + B_2 L^2 e^{-i2\omega} + \dots B_p L^p e^{-ip\omega}\right)\right)^{-1}$:

$$S_{YY}(\omega) = D\left(e^{-i\tau\omega}\right) \Sigma_u D\left(e^{-i\tau\omega}\right)' = \sum_{\tau=-\infty}^{\infty} \gamma(\tau)\, e^{-i\tau\omega}. \tag{2}$$

To assess the spectral density within a frequency band, $S_{YY}(\omega)$ is integrated over the band of interest $\omega = [\underline{\omega}, \bar{\omega}]$

To identify technology, the band is restricted to frequencies that are longer than 10 years in order to exclude business cycle frequencies. The shock that maximizes the variance of labor productivity over the desired frequency is the eigenvector associated with the largest eigenvalue of $S_{YY}(\omega)$, see (Uhlig, 2003); equation 3 demonstrates the maximization problem. Later, in the exercise identifying the primary business-cycle driver of investment, frequencies of 2 - 8 years are chosen.

$$\max f(\alpha) = \frac{\varphi_i' \left(D\left(e^{-i\tau\omega}\right) \alpha\alpha\prime D\left(e^{-i\tau\omega}\right)' \right) \varphi_i}{\varphi_i' \left(S_{YY}(\omega)\right) \varphi_i} \quad s.t. \quad \alpha'\alpha = 1 \tag{3}$$

Where φ_i is an indicator vector that selects the i^{th} impulse response vector. The solution to this maximization problem is the eigenvector associated with the largest eigenvalue of the denominator (which is $S_{YY}(\omega)$), evaluated over the relevant frequency $\omega = [\underline{\omega}, \bar{\omega}]$.

Given the limited sample size under consideration, and in a modification relative to existing implementations of spectral VAR methodologies, the MA-coefficient matrix D and τ are constrained to the 1 - 10-year horizon, which has been shown to reduce estimation bias (Dieppe et al., 2019, 2021; Francis et al., 2014). That is, we instead maximize $f^k(\alpha)$, where k reflects the horizon limit of the MA coefficients up to $k = 10$ years.

3.2 Panel VAR Framework

We extend this new spectral identification approach to a panel VAR, which takes the form:

$$Y_t^n = C^n + \sum_{\tau=1}^{k} B_\tau Y_{t-\tau}^n + u_t, \tag{4}$$

where C^n, the constant, varies across countries, n, while the slope coefficients B, and the variance-covariance matrix of residuals Σ_u are both assumed to be common across economies. Additionally, dummy variables are included in certain economies during periods where inflation exceeds 20 percent. The estimated parameters B and Σ_u can then be used to identify the effects of technology shocks using the spectral identification for each group.

4 Data and Estimation

Typically, technology-identifying SVARs have been applied to quarterly datasets. Data shortcomings for EMDEs (with typically less than 10 years of quarterly data on employment or productivity) pose severe constraints. Hence, annual data are used to estimate the VARs. This choice significantly lengthens the period over which the VAR is estimated for many EMDEs. The time span of the data is critical for identifying technology shocks as those that drive long-term developments in productivity. Separately, the literature typically uses total hours worked. However, this type of data is largely unavailable for EMDEs for sufficiently long time spans. Instead, the estimations here rely on employment to ensure the comparability of results.

The VARs are estimated over the maximum length of data available for each country. Data on macroeconomic aggregates such as GDP and employment are taken from the World Bank's World Development Indicators (WDI) database and The Conference Board's Total Economy Database

Table 1: Median Sample Periods

Regions	**Labor Prod.**	**TFP**	**Spectral**
AEs	1962-2018	1951-2018	1973-2018
EMDEs	1972-2018	1971-2018	1981-2018
LICs	1981-2018	1981-2018	1981-2018

(TED). Data on capital services and human capital are taken from the Penn World Table 9.1, and they are used to estimate TFP (Dieppe et al., 2020b). This results in an unbalanced panel of 30 advanced economies and 96 EMDEs. The average sample length is just under 40 years for EMDEs and 45 years for advanced economies (Table 1).

Both individual and panel VAR estimations are performed. The panel VAR estimation is performed separately for both advanced economies and EMDEs to illustrate the typical effects of technology and primary business-cycle shocks on representative economies in both groups.

In the standard specification, two lags of the endogenous variables are included in the VAR estimations. This is the minimum number of lags required to account for cyclical processes (which can be described as an AR(2) process). Results are robust to including four lags (accounting for four years of data).

5 Technology Shocks: Dominant Long-Run Drivers of Productivity

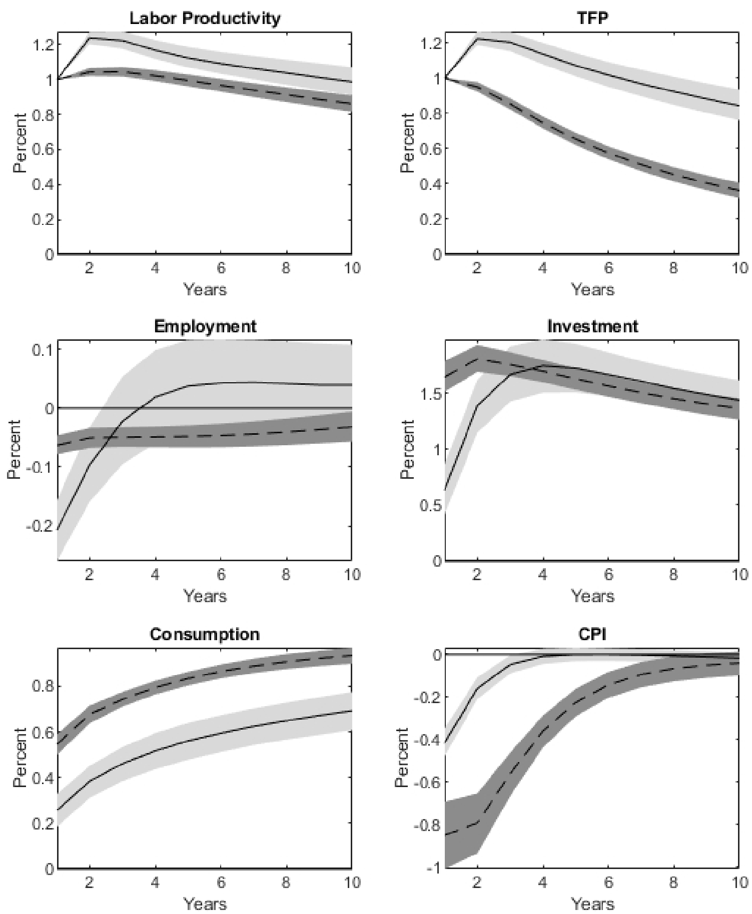
For our sample of countries and over the time period studied, the impulse responses to technology shocks exhibit many similarities but invariably differ in magnitude and persistence across advanced economies and EMDEs.

Despite our methodology placing no restriction on the direction of the impact of technology shocks on the variables contained in the VAR, the impulse response functions (IRFs) for both advanced economies and EMDEs are generally consistent with theory and previous findings for technology shocks in advanced economies (Ramey, 2016). A technology shock raises the level of labor productivity persistently in advanced economies and EMDEs (Figure 3). We find it prudent to scale IRFs by the effect of the technology shock on labor productivity given the greater volatility of EMDEs over our sample period. The greater impact of technology shocks on EMDE labor productivity is likely to reflect the higher volatility of productivity growth and the high vulnerability of EMDEs to shocks with long-lasting effects on output (Aguiar and Gopinath, 2007).

TFP responds immediately to a technology shock in both advanced economies and EMDEs, explaining the majority of the improvement in labor productivity (in contrast to a capital-deepening driven improvement). As investment responds to higher production efficiency, some of the TFP boost in EMDEs fades and the increase in labor productivity is increasingly driven by capital deepening.

The remaining IRFs are also scaled to the response of labor productivity to an improvement in technology. They can, therefore, be interpreted as the impact on each variable for each one percent technology-driven boost to labor productivity, aiding the comparison between the two groups.

Figure 3: Technology Shock IRFs



Note: Light shading and solid line shows the advanced economy IRFs. Dark shading and dashed line show the EMDE IRFs. 16-84th percentile confidence intervals. The labor productivity and TFP IRFs are scaled to the initial impact of the shock. All other IRFs are scaled to the effects of the technology shock on labor productivity.

Impact of technology on employment. Technology-driven improvements in labor productivity reduce employment in the short-run, a finding that is well-established for the United States and some economies in Europe (Basu et al., 2006; Francis and Ramey, 2005; Galí, 1999). A one percent technology-driven increase in labor productivity lowers employment by 0.2 percent on average in the first year in advanced economies and 0.1 percent in EMDEs. However, the negative response is more persistent in EMDEs than in advanced economies, where the IRF becomes positive after three years. The persistence in EMDEs is likely to reflect difficulties in matching workers to new jobs following a labor-substituting productivity shock. Those economies with the most persistent effects on productivity have tended to have larger increases in the share of workers in the industrial sector in recent decades (Kindberg-Hanlon, 2021; Dieppe et al., 2020a).

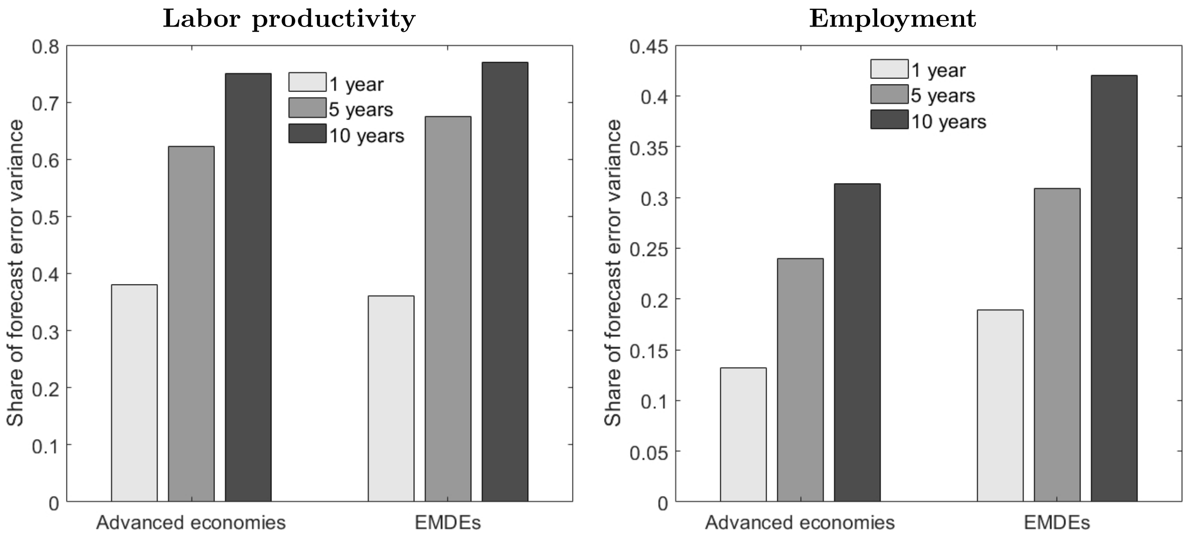
Impact of technology on investment and consumption. Investment and consumption rise in response to technology improvements. In advanced economies and EMDEs, investment rises more than one for one in response to the technology shock after the first few years. The response is more rapid and larger in emerging markets, responding by 2.5 times the response of investment in advanced economies in the first year of the shock. This suggests that new technological change in these economies may often be capital-embodied or initiated into the production process alongside new investment (Hulten, 1992).

Impact of technology shock on consumer prices. As efficiency improves, prices fall in both EMDEs and advanced economies following a positive technology development. The effect is larger and more persistent in EMDEs. This is likely to be a result of less well-anchored inflation expectations in EMDEs than in advanced economies over the sample period, due to weaker or more recently-introduced inflation-targeting monetary policy frameworks (Kose et al., 2018).

5.1 Analyzing Technology Shocks: Importance in Explaining Productivity and Employment Fluctuations.

A forecast error variance decomposition (FEVD) quantifies the contribution of technology shocks to the variation of labor productivity at different time horizons (see Figure 4). By construction, technological developments explain a large portion of the variation of productivity over long horizons (around 75 percent after 10 years in both advanced economies and EMDEs). Initially, however, technology shocks explain just under 40 percent of the variation of labor productivity of the median country of advanced economies and EMDEs, respectively. This leaves over-half of productivity growth variation in the near-term and one-quarter of variation in the long-term explained by other non-technology shocks. The contribution of technology shocks to labor productivity growth has significantly lower volatility than TFP and labor productivity growth, averaging around half the level of volatility of labor productivity and two-thirds of TFP growth in both advanced economies and EMDEs (Figure 5). This is consistent with the literature on utilization-adjusted TFP, where the volatility of the adjusted measure is lower than TFP to a similar degree (Basu et al., 2006).

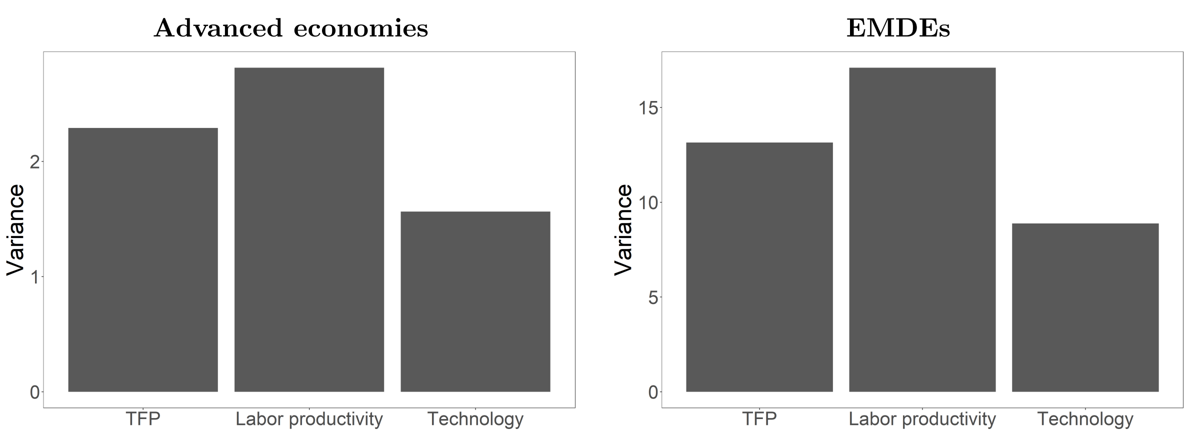
Figure 4: Forecast error variance of labor productivity and employment driven by technology



Note: Share of forecast error variance driven by technology in the median advanced economy and EMDE.

Employment is adversely impacted following a positive technology shock, particularly in the near term in advanced economies but more persistently in EMDEs. The effect is sizable as a driver of employment variation, although smaller than other non-technology drivers of employment (see Figure 4). Over 10 years, technology shocks account for one-third of the variation of advanced economy employment. Technology shocks are larger drivers of the variation of employment in EMDEs, explaining 35-45 percent of the forecast error variance at the 10-year horizon, due to the increased persistence of its effects.

Figure 5: Variance of productivity measures and technology contribution to labor productivity growth

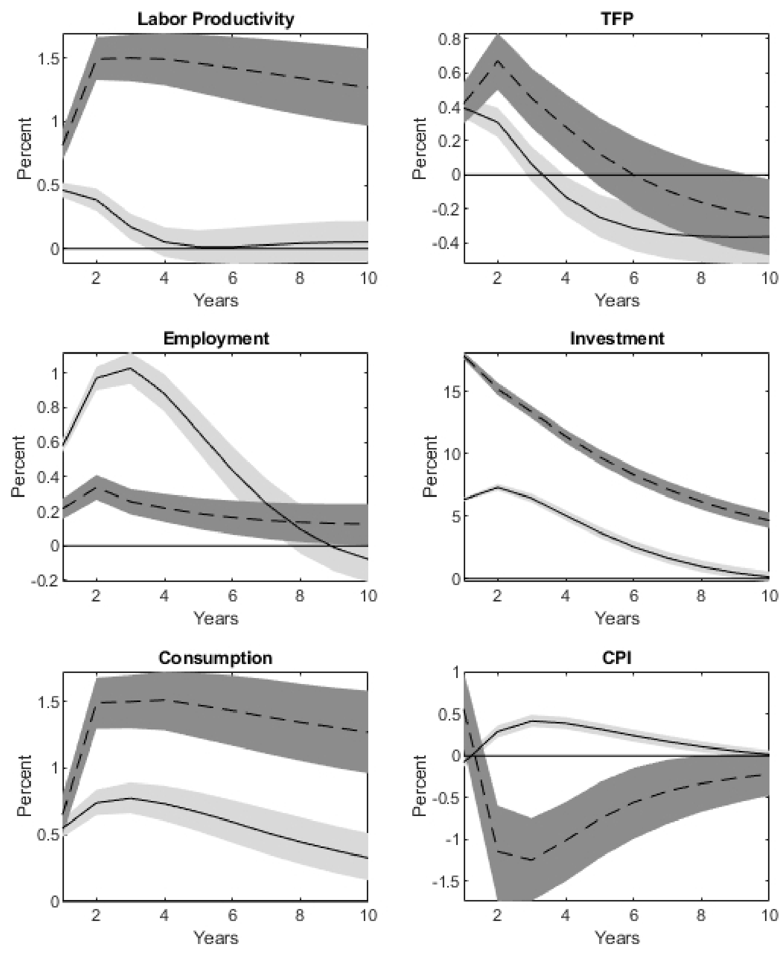


Note: The variance of TFP growth, labor productivity growth, and the contribution of the technology shock to labor productivity growth in the median advanced economy and EMDE.

6 Non-Technology "Demand" Shocks: Business-Cycle Drivers of Productivity

The SVAR identifies the dominant driver of long-run productivity developments whose features are consistent with many typical supply-side shocks. However, many of the productivity surges observed in advanced economies and EMDEs have not been associated with falling employment or consumer prices. While productivity and investment often co-move in both advanced economies and EMDEs over the business-cycle they are usually accompanied by rising prices and employment (Boz et al., 2015; Stock and Watson, 1999). In addition, the SVAR-identified technology shocks explain three-quarters of the variation of labor productivity over long-horizons, leaving a role for other shocks to also generate persistent changes in labor productivity. A large range of influences

Figure 6: Business-Cycle, Investment-Identified Demand Shock IRFs



Note: Light shading and solid line shows the advanced economy IRFs. Dark shading and dashed line show the EMDE IRFs. 16-84th percentile confidence intervals. IRFs are responses to the shock that maximizes the business-cycle frequency (2-8 years) variance of the share of investment in GDP.

could potentially drive business-cycle fluctuations in the economy. These include, for example, changes in expectations on the returns to investment, government spending or tax change, commodity prices, and terms of trade changes, as well as a range of other shocks that affect aggregate demand.[11]

To illustrate the effects of a typical business-cycle shock, the SVAR identifies the shock that drives the majority of fluctuations in investment at business-cycle frequencies. This contrasts with the long-run frequencies used to identify technology shocks. Fluctuating *animal spirits* are often cited as the drivers of large changes in investment growth and have long been assumed to be the principal driver of the business cycle since the introduction of Keynesian economics (Justiniano et al., 2010; Keynes, 1936).[12]

We specifically target investment to demonstrate the effects of a *demand shock* on productivity. In contrast, we find that the shock targeting business-cycle inflation variation resembles an adverse cost-push supply shock in both advanced economies and EMDEs, while the shock targeting employment resembles a positive labor-supply shock in EMDEs and a positive demand shock in advanced economies (see Appendix A).

Advanced economies. A typical demand shock in advanced economies causes labor productivity to rise initially but fade after several years, in contrast to the effects of the identified technology shock (see Figure 6). This is largely due to a fall in the level of TFP after an initial boost (likely reflecting cyclical changes in utilization, as predicted). While TFP contracts from year-3 onward, the impact on labor productivity falls to zero, reflecting the offsetting effect of higher investment that boosts the capital stock. In contrast to the effect of the identified technology shock, employment initially rises, but the effect subsides. The initial boost to consumption and investment also fades over a 10-year horizon, in contrast to the persistent boost from a technology shock to these variables. Finally, consumer prices initially rise, in line with responses expected from a typical positive demand-development.

EMDEs. EMDEs exhibit many similar responses to a demand shock as in advanced economies, but the identified shock has more persistent effects on labor productivity. The initial boost to TFP falls away as in advanced economies. However, labor productivity remains higher as the persistent effects of higher investment raise the ratio of capital to labor. The persistently higher level of labor productivity also allows for a longer-term rise in consumption.

The finding that demand shocks can have highly persistent effects on productivity and output over the long-run has also been found in several related contexts. In advanced economies, monetary policy, which is often assumed to have neutral effects on real variables such as productivity over the long run, has been found to have highly persistent effects on capital deepening and TFP at horizons over 10 years (Jordà et al., 2020; Moran and Queralto, 2018). Government spending shocks have

[11] A range of non-technology shocks exist, many of which are not-necessarily demand-driven. For example, a labor supply shock may result in lower consumer prices and labor productivity, as the price of labor falls relative to capital. This would contrast with the technology shock identified by the SVAR, however, which reduces the quantity of labor employed in production.

[12] Changing expectations about future innovations ("News") has also been cited as a key driver of the business cycle, resulting in large swings in investment growth (Beaudry and Portier, 2014). In addition, demand-side factors have also been found to dominate the volatility of output in the short-run for G7 economies (den Haan and Sumner, 2004).

been found to have highly persistent effects on productivity and output when economies are in recession (Bachmann and Sims, 2012; Fatás and Summers, 2018).

The persistent increase in productivity in EMDEs is entirely driven by capital deepening, with a decline in TFP occurring after less than 5 years following the shock. Therefore, there is little evidence that demand-driven shocks can drive sustained improvements in the efficiency of production, although they can boost welfare by increasing capital deepening. Equally, demand factors are frequently likely to be negative, often reversing earlier gains and driving persistent falls in productivity. This highlights the importance of various forms of demand-management in EMDEs. For example, negative demand shocks can drive highly persistent falls in labor productivity in these economies.

6.1 Analyzing Demand Shocks: Fiscal Capacity

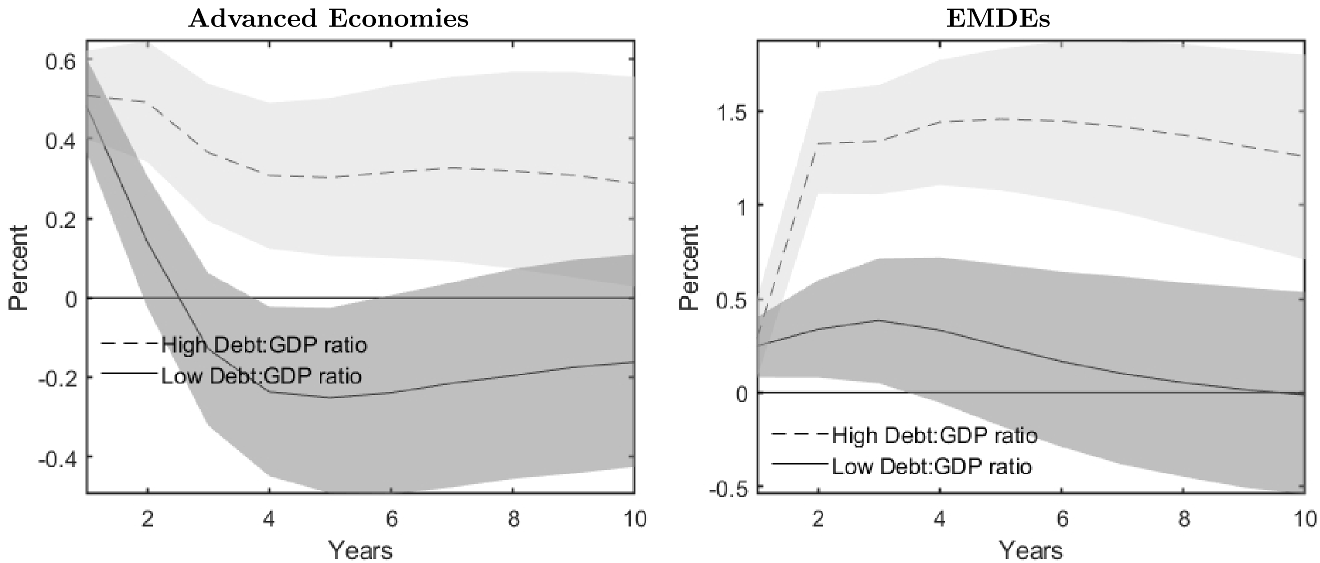
We investigate potential factors that could account for the more persistent labor productivity response of EMDEs to the demand shock that maximizes investment volatility at the business cycle frequency. In particular, we investigate the possibility that fiscal policies in EMDEs are more pro-cyclical, and therefore, these countries are less able to offset demand shocks. EMDEs have historically been more likely to accommodate demand booms, spending revenue gains and conducting more procyclical fiscal policy; countercyclical frameworks have been introduced in many EMDEs only in the past two decades (Abiad et al., 2012; Frankel et al., 2013).

Two measures are used to assess the capacity of economies to conduct countercyclical fiscal policy in recent decades. The first is to rank countries by their debt-to-GDP ratios. Economies are ordered by their average debt-to-GDP ratio from 1990-2018. Those in the top quartile, in both groups, are considered "high debt-to-GDP" economies, while those in the bottom quartile are considered "low debt-to-GDP" economies. Our second measure ranks and selects countries by their average primary balance since 1990, when data are widely available. Economies are ordered by their average primary balance (as percent of GDP) from 1990-2018. Those in the top half of the distribution in both groups are classified as "high fiscal space" economies, while those in the bottom half are considered "low fiscal space" economies.[13] We caution against interpreting our results as causal since there are potential endogeneity issues. For example, a weak primary fiscal balance could arise because an economy is subject to more persistent negative shocks that significantly reduce tax revenues.

Both sets of impulse responses (see Figures 7 and 8) suggest that demand shocks have more fleeting effects on labor productivity in economies that have historically had stronger fiscal positions and low aggregate debt. Developed and emerging economies are better able to offset cyclical influences if their fiscal houses are in order. Unsurprisingly, the magnitude and persistence are largest for EMDEs with the worst fiscal metrics relative to advanced economies.

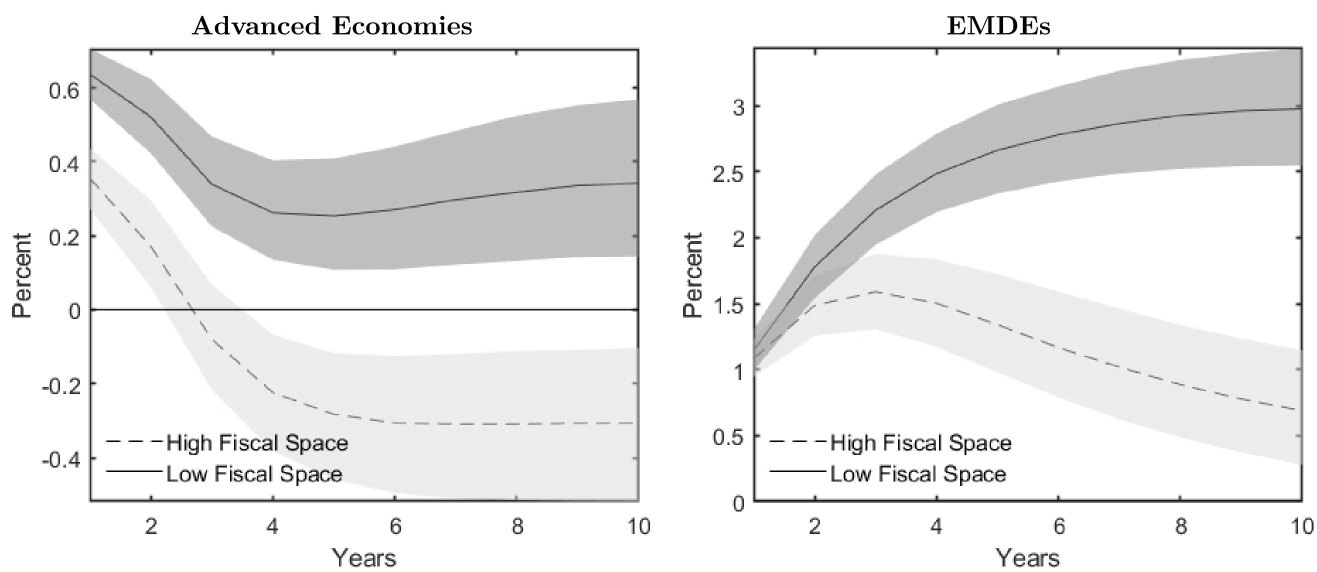
[13] Notice that both samples are not the same since data on debt-to-GDP ratios are available for a much larger proportion of EMDEs (95 available) than data on government primary balances (50 EMDEs). For this reason, the panel VARs are estimated for the top and bottom quartiles of the debt-to-GDP ratio ranking but the top and bottom half of the distribution is used for the smaller sample for primary balances.

Figure 7: Demand Shock IRFs: High and Low Change Level of Debt-to-GDP Ratios



Note: For advanced economies and EMDEs separately, economies are ordered by their average debt-to-GDP ratio from 1990-99 to 2010-18. Those in the top quartile in both groups are considered "High debt-to-GDP" economies, while those in the bottom quartile are considered "Low". Sample includes 30 advanced economies and 95 EMDEs.

Figure 8: Demand Shock IRFs: High and Low Average Primary Balance (% GDP)



Note: For advanced economies and EMDEs separately, economies are ordered by their average primary balance (% GDP) from 1990-99 to 2010-18. Those in the top half of the distribution in both groups are considered "High fiscal space" economies, while those in the bottom half are considered "Low". Sample includes 30 advanced economies and 50 EMDEs.

7 Exploring Similarities in Productivity Dynamics

In this section, we explore the contributions of the identified technology shocks to labor productivity growth and contrast them with the contributions of non-technology shocks such as the above-identified business-cycle investment shock. We first examine the historical decomposition of labor productivity growth in advanced economies and EMDEs, highlighting the importance of each innovation to productivity dynamics over the sample period. We then explore the synchronization of labor productivity across economies to gauge the degrees of spillovers between countries and across regions, and the extent to which they are driven by technology shocks or cyclical factors.

7.1 Historical Decomposition: Comparing the Drivers of Productivity

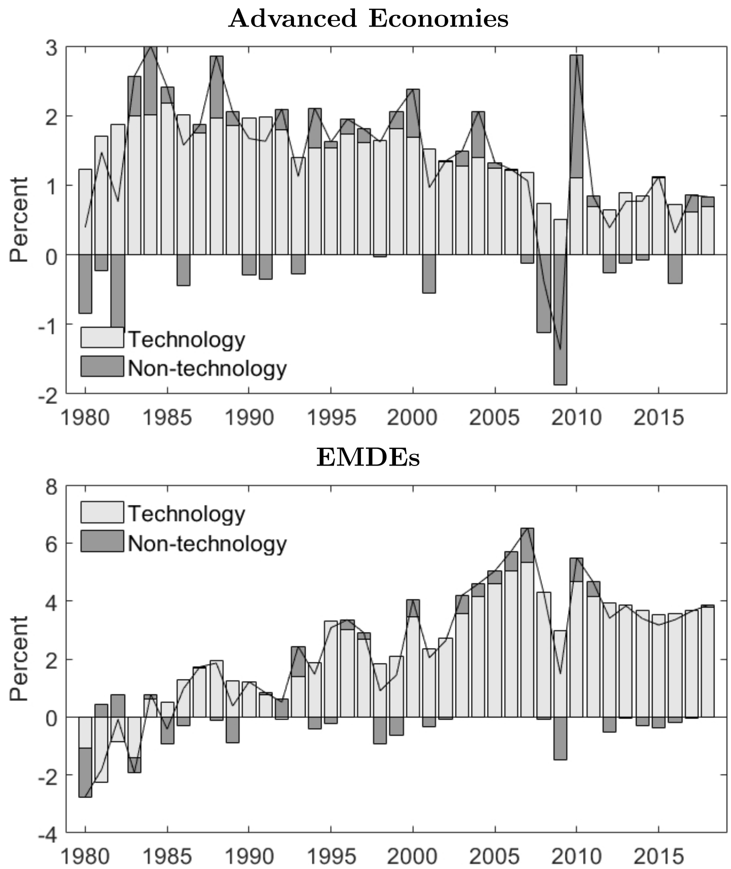
Several distinctions have already been explored between the effects of technology and non-technology drivers of productivity. Using the SVAR, the contribution of technological developments to labor productivity can be separated from the contributions of non-technological demand factors.

Historical decomposition of labor productivity growth can be written as a function of the structural shocks identified through the spectral identification ϵ_t, initial condition X_0 (which accounts for the lack of data prior to the start of the sample), and the constant, C.

$$Y_t = \sum_{i=0}^{t-1} F^i \epsilon_{t-i} + A^t X_0 + C. \tag{5}$$

In the decomposition shown in Figure 9, the identified technology shock, initial condition, and constants are included in the technology category, given that they reflect average rates of growth and persistent effects from initial conditions. The effects of all other shocks are included in the non-technology category. The estimation used for the historical decomposition includes labor productivity in growth rates, rather than in log-levels as in the estimation of impulse responses. This is because the effects of initial conditions can be substantial in I(1) or highly persistent processes such as labor productivity levels. In the estimation using growth rates, the effects of the initial condition are minimal given the stationary nature of productivity growth.

Figure 9: Shock decomposition of labor productivity growth

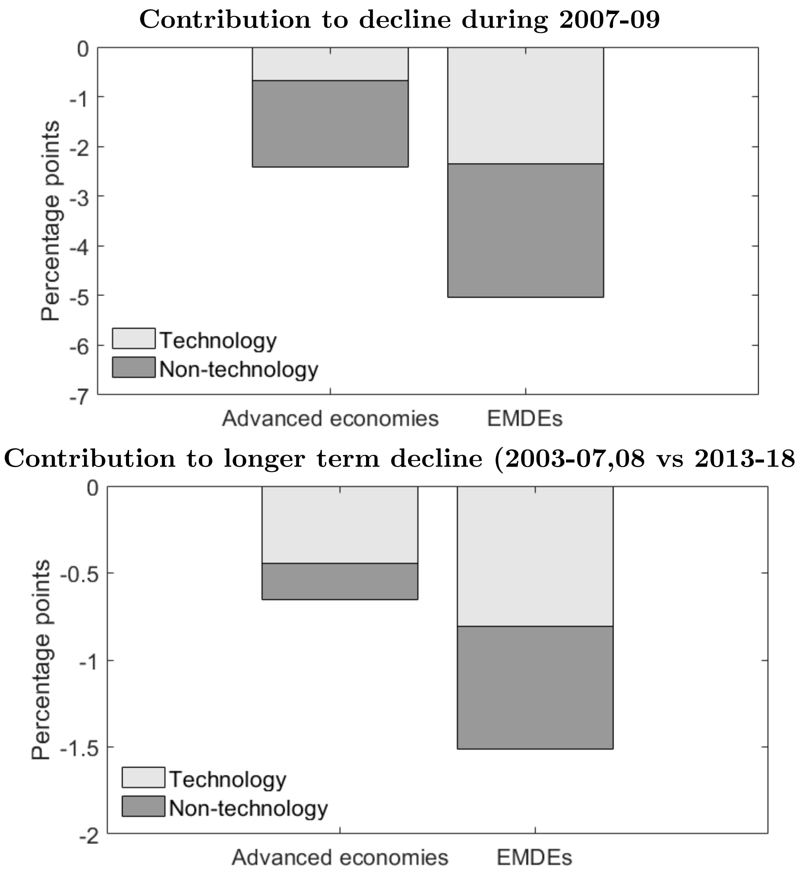


Note: GDP-weighted decomposition of labor productivity growth into the SVAR-identified technology shock and non-technology factors. The technology contribution includes the identified technology shock, the initial condition, and the constant. Non-technology factors are defined as the residual between labor productivity growth and the contribution of the technology shock, initial condition, and constant to labor productivity growth.

Advanced economies. The decline in the contribution of technology shocks to labor productivity growth began before the global financial crisis, starting in 2000. This is consistent with the fading of the ICT boom in the United States by the early 2000s that has compounded a steady trend decline in productivity in western Europe since the 1990s (Cette et al., 2016). In addition, positive non-technology developments have faded relative to their levels in the late-1990s ahead of the end of the dot-com boom, and in the mid-2000s, ahead of the global financial crisis.

Non-technology shocks explain most (over three-quarters) of the sharp decline in productivity growth during the financial crisis between 2007 and 2009 (Figure 10). More generally, the contributions of non-technological factors have been negative, or fallen close to zero, in each of the global recessions or slowdowns over the past 40 years (in 1982, 1991, 1998, 2001, and 2009; see, for example, Kose and Terrones (2015)). Longer-term, technology developments account for two-thirds of the 0.6 percentage point decline in advanced-economy labor productivity growth since the global financial crisis (2003-07 vs 2013-18); see the bottom panel of Figure 10. Since 2007, the contribution of technology developments to productivity growth has been lower in every year compared to the pre-2007 average, suggesting a degree of permanent scarring from economic disruptions associated with the global financial crisis (Adler et al., 2017; Anzoategui et al., 2019).

Figure 10: Shock decomposition of labor productivity growth change during and following the global financial crisis



Note: GDP-weighted decomposition of the change in labor productivity growth during the periods specified into the SVAR-identified technology shock and non-technology factors. The technology contribution includes the identified technology shock, the initial condition, and the constant. Non-technology factors are defined as the residual between labor productivity growth and the contribution of the technology shock, initial condition, and constant to labor productivity growth.

EMDEs The post-GFC decline in EMDE productivity growth is also driven by a mix of technology and non-technology shocks; see Figure 9 and the top panel of Figure 10. Just over half of the fall in labor productivity growth during 2007-09 was driven by non-technology shocks. Previous labor productivity contractions, frequently driven by episodes of debt-related financial distress, alongside various structural macroeconomic challenges, are interpreted as a mix of lasting structural factors reflected by the SVAR technology shocks and transitory factors. Productivity growth rose sharply in the mid-1990s, following debt crises affecting many commodity-exporting economies in Latin America and the Caribbean and Sub-Saharan Africa in the 1980s, further compounded by volatility following the breakup of the Soviet Union (Federal Deposit Insurance Corporation, 1997; Kaminsky and Pereira, 1996). As these crises faded, the contribution of technology grew rapidly, partially resulting from institutional reforms and rapid global trade and production integration, particularly in Asia (Baldwin, 2013; Subramanian and Kessler, 2013; World Bank, 2019). The contribution of technology post-crisis has remained strong relative to contributions in the 1980s and 1990s, although the contribution of non-technology factors has been zero or negative for much of the post-crisis period.

7.2 Synchronization of Productivity: Technology versus Non-Technology Drivers

The decomposition of productivity growth into technology-driven and non-technology driven factors allows a deeper exploration of the drivers of global labor productivity synchronization. Productivity growth has declined in both advanced economies and EMDEs since the global financial crisis, and in all EMDE regions (World Bank, 2020). This broad-based fall suggests the presence of common factors or spillovers. A large body of literature has already documented the co-movement of output across economies.[14] The strong correlation between output growth and labor productivity growth (70 percent on average in our sample) suggests the possibility of common determinants of productivity developments across economies. The cross-country synchronization of labor productivity growth, and the extent to which it is driven by structural factors captured by the SVAR-identified measure of technology, or business-cycle factors, has been so far under-explored. The literature that does exist has focused on advanced economy synchronization and has found some co-movement in cyclical drivers of productivity but little in structural measures.

In advanced economies, utilization-adjusted TFP, a similar measure to SVAR-identified technology, has been found to be uncorrelated across countries, while unadjusted measures of TFP are correlated (Huo et al., 2020; Imbs, 1999). Structural VARs point to the presence of cointegration between TFP in the United States and other economies but with slow and limited spillovers (Mandelman et al., 2011; Miyamoto and Nguyen, 2017). In a broader dataset, utilization-adjusted U.S. TFP has been found to have spillover effects on TFP growth in other advanced economies but only at very gradual rates (Adler et al., 2017). Using data for patents and R&D spending as proxies for productivity-enhancing technology adoption, some cross-country spillovers have been identified (Keller, 2010). Finally, in a factor modeling framework, TFP growth has been found to be one of the most important correlates of common developments in G7 GDP growth (Crucini et al., 2011) and a GDP factor estimated for a broader range of 117 economies (Abate and Serven, 2019).

An alternative and growing strand of the literature has highlighted the role of slow technological diffusion between leading and lagging firms across advanced economies (Organisation for Economic Co-operation and Development, 2015; Andrews et al., 2015; Cirera and Maloney, 2017). Long lags in the adoption and intensity of use of new technologies have been found to explain

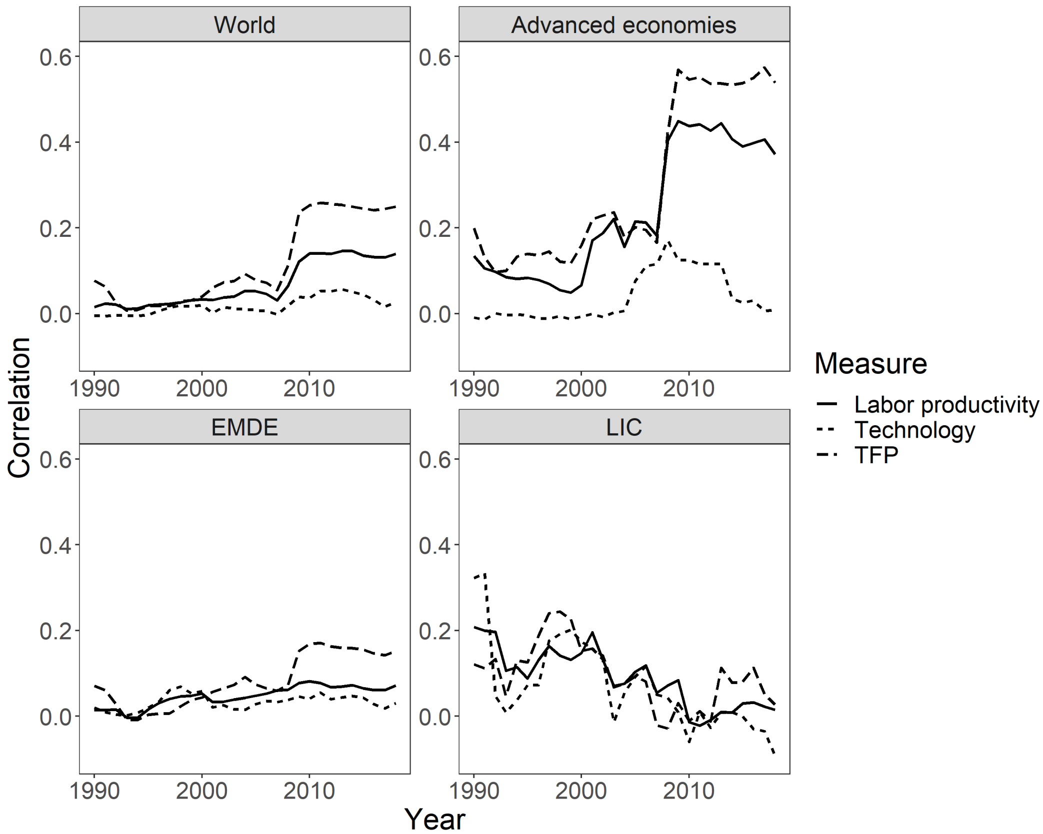
[14] See, for example, Francis et al. (2017), Francis et al. (2019), and Kose et al. (2003).

a material proportion of cross-country income divergence (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Both approaches, based on firm and country-level data, emphasize that structural improvements in productivity can diffuse across borders only over long time-lags, implying that structural measures of productivity synchronization are low.

Cross-country correlations provide an insight into the extent to which different measures of productivity are synchronized. This approach is applied to labor productivity growth and TFP growth, as well as the SVAR-identified technology measures contribution to labor productivity growth. These can provide important insights into how synchronized each measure is between country pairs, with average correlations providing a summary statistic within groups of economies (International Monetary Fund, 2013).

The average 10-year rolling correlations between all bilateral pairs for each measure of productivity growth suggest that global synchronization was very low prior to the global financial crisis (see Figure 11). During the crisis and its immediate aftermath, correlations rose for all measures of productivity growth. Correlations between those measures with sizable demand-driven cyclical components (labor productivity and TFP growth) were considerably higher than those for the SVAR-identified structural technology shocks, similar to previous findings for advanced economies (Huo et al., 2020; Imbs, 1999). These structural measures have returned to zero in advanced economies and EMDEs in recent years, while they remain high for labor productivity and TFP. Based on these correlations, productivity synchronization in both EMDEs and advanced economies appears to be a largely cyclical phenomenon. Advanced economies featured higher cross-country correlations of labor productivity and TFP than EMDEs. Since 2005, Low Income Country (LIC) productivity growth has been largely unsynchronized, even during the global financial crisis, plausibly reflecting limited trade integration and the effects of idiosyncratic shocks. The poorest EMDEs are largely unaffected by both global fluctuations in demand and technology spillovers.

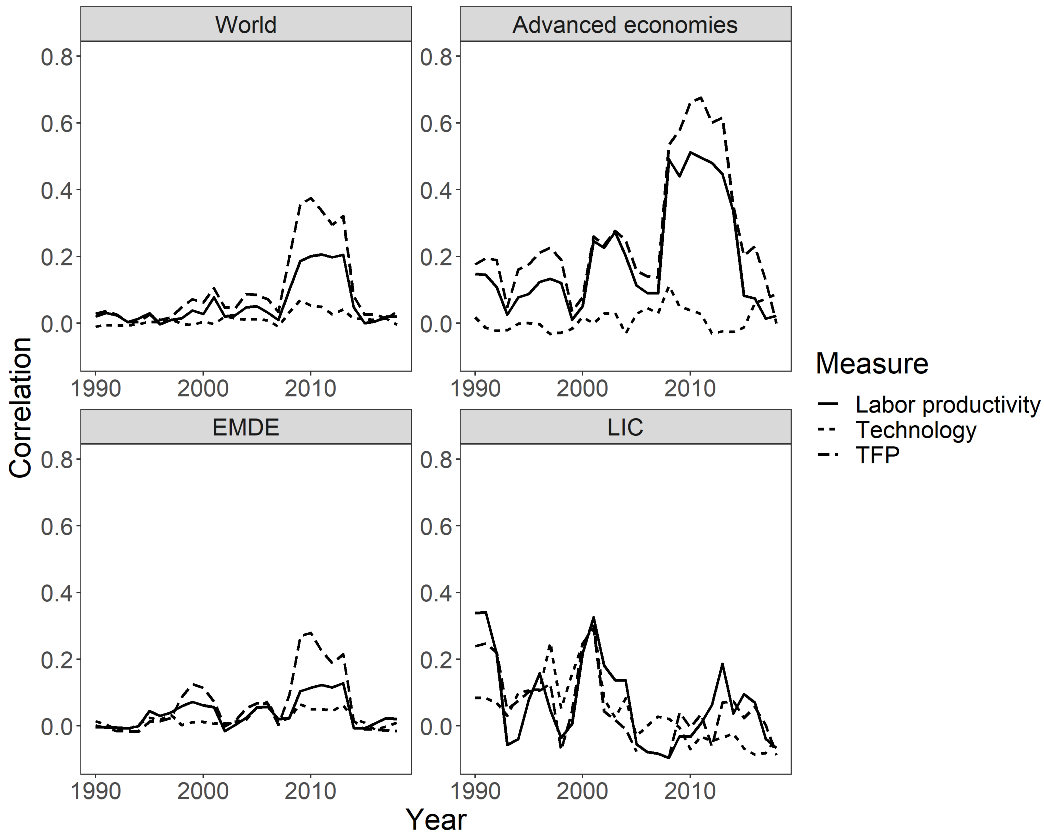
Figure 11: 10-year Rolling Correlations of Productivity Measures



Note: 10-year rolling correlation of labor productivity, TFP, and the contribution of technology shocks to labor productivity.

As a robustness check, we find that using a 5-year rolling window produces similar qualitative findings as above, as shown in Figure 12. Reducing the window from 10-years produces a shorter-lived degree of correlation in advanced economies and EMDEs following the global financial crisis, suggesting that the increase in synchronization was temporary and faded soon after the global recession.

Figure 12: 5-year Rolling Correlations of Productivity Measures



Note: 5-year rolling correlation of labor productivity, TFP, and the contribution of technology shocks to labor productivity.

8 Conclusion

The creation of a new SVAR-identified measure of technology and separate demand driver of labor productivity growth across a broad set of advanced economies and EMDEs enables a deeper understanding of how different drivers of productivity developments can result in different outcomes. A range of findings emerge.

The SVAR-identified technology measure dominates long-run productivity variation. These developments lower prices and come at a cost of falling employment in the short-run as production efficiency improves and input requirements fall. We find that technological improvements are accompanied by larger and more rapid increases in investment in EMDEs than in advanced economies. This suggests that technology improvements in the former are more likely to be capital-embodied, or incorporated alongside new capital goods.

Non-technology drivers of labor productivity operate primarily through channels such as increased capital deepening and factor utilization, with no lasting effect on TFP. In the case identified in this paper, the demand driver of productivity raises prices and employment. Non-technology contributions to productivity have consistently fallen during global recession events in advanced economies and EMDEs.

The impact on labor productivity of the dominant business-cycle driver of investment is highly persistent in advanced economies and EMDEs with a low average capacity for fiscal stimulus in recent decades. These findings support the use of demand management policies to offset negative shocks, while also using prudent fiscal policies to generate higher tax revenues during upturns. The lasting productivity damage that even short-term demand shocks can cause calls for room to allow active deployment of fiscal and monetary policy to support activity. This will require a strengthening of monetary and fiscal policy frameworks in those economies where fiscal policy has operated in a procyclical manner. Fiscal rules and medium-term budgetary frameworks can limit risks for debt sustainability (Kose et al., 2019). For commodity exporters, the creation or expansion of sovereign wealth funds, as well as better prioritization of spending, could help avoid procyclical spending in response to commodity price fluctuations (Mohaddes and Raissi, 2017).

The SVAR-identified technology developments are uncorrelated across countries, in contrast to labor productivity and TFP growth. The latter are found to have been correlated across countries, particularly at the time of the global financial crisis. These correlated measures include the effects of cyclical developments on labor productivity in contrast to the technology measure, which excludes them. Cyclical shocks such as demand-led changes in labor productivity are therefore found to be the primary driver of cross-country labor productivity synchronization. There is little evidence of a common "rising tide" of structural productivity developments driven by a global technology factor. EMDEs may foster trade integration, FDI, and economic flexibility so they can benefit to a greater extent from technology spillovers, which currently appear to be limited in many economies (Kindberg-Hanlon and Okou, 2020).

A Appendix - Other Business-Cycle Anatomy

This paper has focused on the low-frequency drivers of labor productivity and business cycle drivers of investment and contrasted the response to both shocks between advanced economies and EMDEs. Using a similar framework, Angeletos and Dellas (2020) demonstrated that the shocks that target business-cycle fluctuations in unemployment (their baseline variable of interest), GDP, investment, hours, and consumption produce impulse responses that are indistinguishable in shape and often in magnitude. Here we examine the impulse responses to the shocks that target employment and inflation, comparing them to our benchmark investment shock.

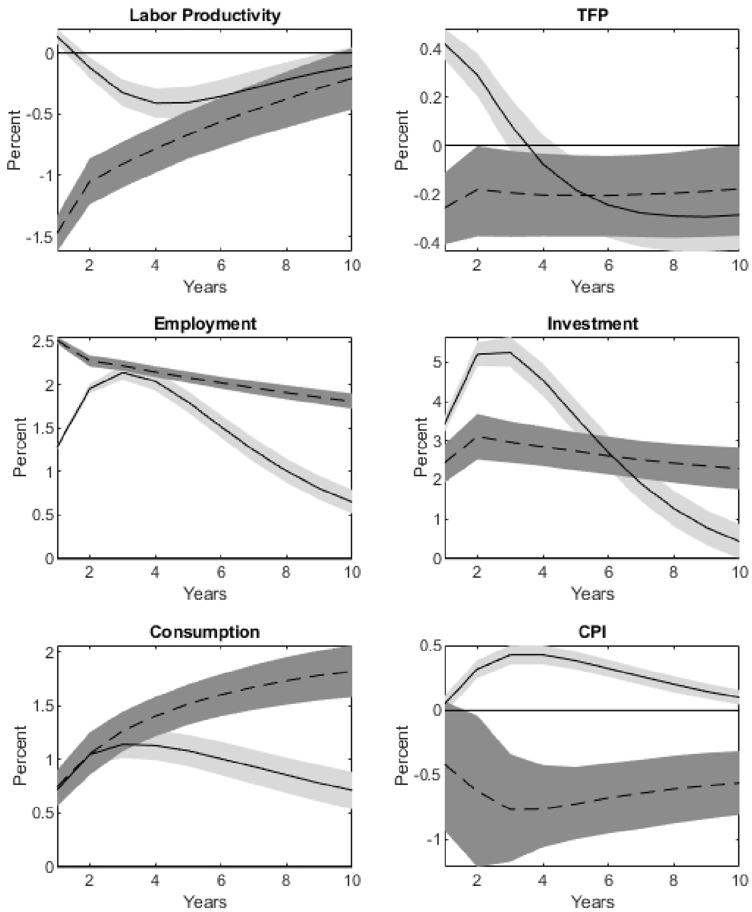
A.1 Employment Business-Cycle Shock

Similar to Angeletos and Dellas (2020), we find that for advanced economies, the shock that targets business-cycle fluctuations in employment produces impulse responses similar in shape and magnitude as their counterparts to the investment shock with one exception: the response of labor productivity (Figure 13). Here, we find labor productivity rises on impact before quickly turning negative, compared to its response to the dominant investment shock where it stays positive or close to zero throughout. Similar to the dominant investment shock, TFP also becomes negative after several years while the remaining variables respond persistently positively.

For EMDEs, we find some striking differences between the investment and employment-targeting shock. The dominant shock captured here is a positive labor supply shock, which reduces consumer prices through an increased labor supply, even while productivity (labor and TFP) falls. This is in contrast to the positive demand shock captured in advanced economies and the positive demand shock captured by the investment-targeting shock in both regions.

Overall, our findings are similar to those of Angeletos and Dellas (2020) for advanced economies, where the shock driving the majority of fluctuations in labor markets and of investment are similar. However, this is not the case for emerging market economies.

Figure 13: Dominant Employment Business-Cycle Shock

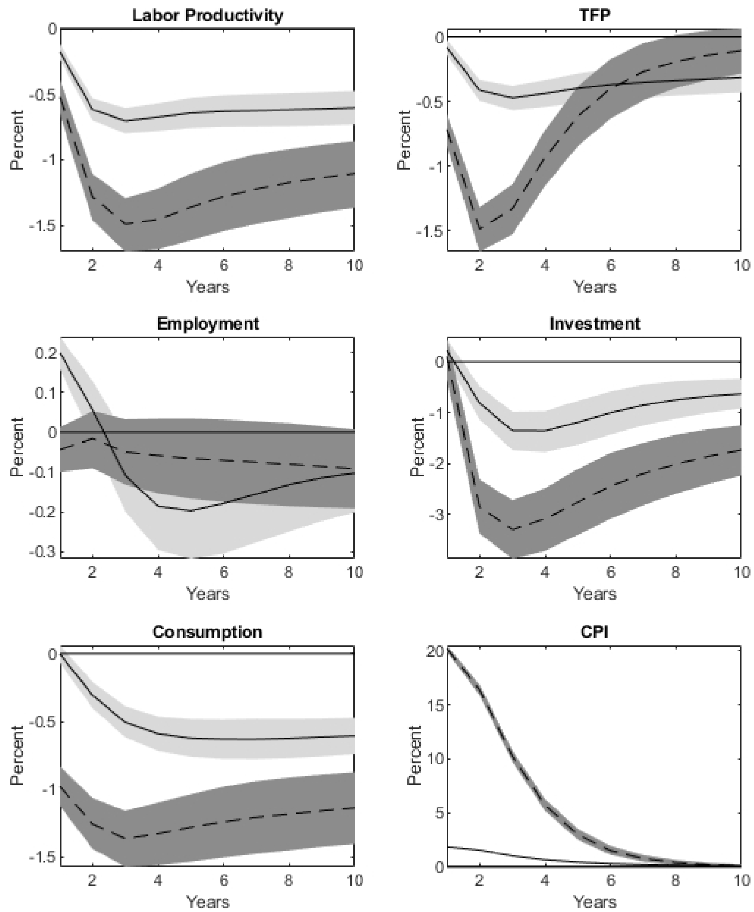


Note: Light shading and solid line shows the advanced economy IRFs. Dark shading and dashed line show the EMDE IRFs. 16-84th percentile confidence intervals. IRFs are responses to the shock that maximizes the business-cycle frequency (2-8 years) variance of employment.

A.2 Inflation Business-Cycle Shock

Like Angeletos and Dellas (2020), we also find a disconnect between the business cycle shocks that drive real variables and the shock that drives inflation. Roughly, the shock driving the majority of business cycle fluctuations in consumer prices takes the form of a negative supply, or cost-push shock, which increases prices while reducing productivity, employment, investment, and consumption (Figure 14). In contrast to the investment-targeting demand shock for advanced economies, the persistence of the negative effects on real variables is much higher.

Figure 14: Dominant CPI Business-Cycle Shock



Note: Light shading and solid line shows the advanced economy IRFs. Dark shading and dashed line show the EMDE IRFs. 16-84th percentile confidence intervals. IRFs are responses to the shock that maximizes the business-cycle frequency (2-8 years) variance of consumer price inflation.

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