CHAPTER 6

Productivity: Technology, Demand, and Employment Trade-Offs

Lasting per capita income growth and poverty reduction depend on sustained growth in labor productivity, which is driven by technological progress, often embedded in new investment, capital deepening, and structural change. The productivity growth slowdown over the past decade reflects weakening in all these drivers. The consequences of the COVID-19 pandemic including the current deep recession, suggest negative repercussions for labor productivity. However, COVID-19 could catalyze rapid technological innovation and structural change. Nonetheless, the resulting income gains might not be equitably distributed, partly because of the possible effects of innovation on employment. Following technological improvements during 1980-2018, employment declined in 70 percent of emerging market and developing economies (EMDEs) and 90 percent of advanced economies. The largest negative effects occurred in economies where employment was concentrated in industry, which tends to be more amenable to labor-saving innovation than other sectors. Cyclical fluctuations in activity can also have persistent effects on productivity, particularly in countries with weak fiscal positions. These findings indicate the importance of retraining programs and effective social safety nets to lower transition costs for workers displaced by technology advancements, as well as the strengthening of fiscal positions to ensure adequate space for stabilization policy.

Introduction

Productivity growth in advanced economies and emerging market and developing economies (EMDEs) has undergone many surges and declines in recent decades, usually coinciding with economic upswings and slowdowns respectively. In the four largest surges since 1980, annual labor productivity growth in EMDEs rose by at least 3 percentage points, and it fell by nearly 2 percentage points in the subsequent slowdowns (Figure 6.1). Productivity growth has been less volatile in advanced economies but has followed a similar pattern of rapid growth gains in upswings followed by slowdowns. Such short-term swings reflect cyclical fluctuations in labor and capacity utilization (Basu, Fernald, and Kimball 2006; Fernald and Wang 2016).[1]

The COVID-19 pandemic has likely dealt a severe blow to labor productivity by triggering the deepest global recession since World War II. If past recessions are any guide, labor productivity is likely to rebound in a cyclical upturn as the global economy recovers but remain below the pre-pandemic trend for many years to come.[2] However, the global recession resulting from shocks related to COVID-19 may drive a larger decline in productivity growth even than experienced during the global financial crisis (World Bank 2020, Chapter 2).

Note: This chapter was prepared by Alistair Dieppe, Neville Francis, and Gene Kindberg-Hanlon. Research assistance was provided by Aygul Evdokimova and Yi Li.

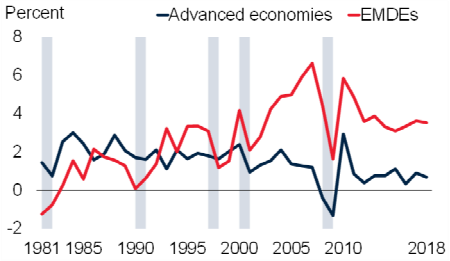
[1] In the United States, one-half of TFP growth variability has been attributed to demand-driven factors (Basu, Fernald, and Kimball 2006).

[2] Many studies have documented the persistent negative output effects of financial, currency, and political crises (Cerra and Saxena 2008; Jordà, Schularick, and Taylor 2013; Reinhart and Rogoff 2009).

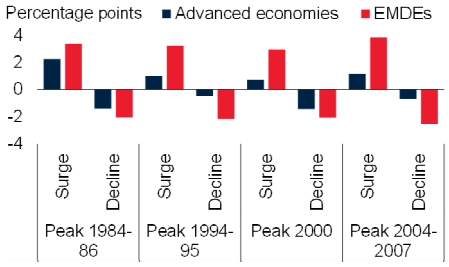
FIGURE 6.1 Global labor productivity surges and declines

Over the past 40 years, labor productivity growth in advanced economies and EMDEs has undergone several cycles of surges and subsequent declines. Surges in labor productivity growth have tended to occur during cyclical upswings and declines in downturns. The most recent surge and decline in productivity growth, and the largest in EMDEs since 1980, occurred in the runup to, and following, the global financial crisis.

A. Advanced economy and EMDE labor productivity growth



B. Labor productivity surges and declines following global slowdowns



Source: Conference Board; Kose and Terrones (2015); Penn World Table; World Bank, World Development Indicators.

A. Labor productivity growth in advanced economies and EMDEs constructed as GDP-weighted average growth rates, measured at 2010 prices and market exchange rates. Shaded regions indicate global recessions and slowdowns (1982, 1991, 1998, 2001, 2009), as defined in Kose and Terrones (2015).

B. Each surge in productivity shows the increase in productivity growth from its lowest point to its peak rate in advanced economies and EMDEs, with the lowest point being the weakest rate of growth in the 5 years preceding its peak. The decline is calculated as the decline to the lowest rate of growth in the 5-years following the peak of productivity growth. Peaks do not always occur in the same year in advanced economies and EMDEs. The range over which these peaks occur is indicated on the x-axis.

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Yet, lasting per capita income growth and poverty reduction depend on sustained labor productivity growth, stripped of such short-lived swings. Sustained labor productivity growth may be driven by capital-deepening (growth of capital per unit of labor input) or by technological and organizational changes, including the adoption of more efficient methods of production, in some cases incorporated through capital investment (Hulten 1992).

The COVID-19 pandemic may trigger lasting organizational and technological changes to the way businesses operate. These could be adverse to productivity growth if they erode capital or disrupt the accumulation of physical or human capital (Chapter 2). However, pandemic-induced structural changes could also have productivity-enhancing effects, such as a "cleansing" effect, eliminating the least efficient firms and encouraging the adoption of more efficient production technologies (Caballero and Hammour 1994).[3] While such effects could result in faster overall per capita income gains, they may also displace workers from their current roles, increasing income inequality.

Against this backdrop, this chapter reports disentangles long-term productivity changes from short-term, cyclical productivity fluctuations using structural vector auto-

[3] The threat of labor shortages due to social distancing could foster a wave of automation in certain industries (Leduc and Liu 2020).

regressions (SVARs). Throughout this chapter, the long-term drivers of productivity growth will be referred to as "technology," as is common in the literature.[4] Changes in technology, in this sense, occur not only as a result of technical innovations but also when there are organizational or institutional changes to the production process.[5]

Focus. This chapter addresses the following questions:

- How much do long-term changes and business cycle fluctuations each contribute to changes in labor productivity growth?
- What are the effects of long-term changes in labor productivity growth on employment and other variables?
- What are the lasting effects of demand-driven cyclical fluctuations in labor productivity growth?
- What are the policy implications?

Contribution to the literature

This chapter makes multiple contributions to a literature that has primarily focused on advanced economies.

First, this chapter is the first study to identify "technology" drivers of labor productivity growth in a comprehensive cross-country sample of 30 advanced economies and 96 EMDEs.[6] Other studies have restricted themselves to a decomposition of labor productivity growth into its growth accounting components, or have only examined the role of cyclically-adjusted TFP growth or econometrically identified measures of changes in technology in a small number of advanced economies.[7]

Second, this chapter is the first study to estimate the effects of technological change on aggregate employment across a broad range of EMDEs and advanced economies. It is also the first to examine the extent of technology-driven job losses outside the G7 economies and to determine the correlates of their scale and persistence, in contrast to earlier studies that focused on a narrower set of advanced economies (Box 6.1).[8]

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[4] More specifically, they are referred to as "technology shocks," or unanticipated changes in labor productivity. These may include "investment-specific" technologies. See also Chen and Wemy (2015), Fisher (2006), Francis and Ramey (2005).

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

[6] Previous studies have focused on a small subset of advanced economies. For example, Rujin (2019) and Galí (1999) apply long-run restriction-identified SVARs to G7 economies only.

[7] Coibion, Gorodnichenko, and Ulate (2017); Fernald (2014); Goodridge, Haskel, and Wallis (2018); OECD (2015); World Bank (2018b).

[8] Some studies have examined the link between productivity growth and employment growth in a reduced-form framework in a broad set of economies including some EMDEs, but have not separately identified the differential impact of technology and demand-driven changes in productivity (Beaudry and Collard 2003; Boulhol and Turner 2009).

Third, this chapter is the first study to illustrate the persistent effects of demand shocks on labor productivity and its components in a wide range of EMDEs and advanced economies. Previous studies have examined a smaller subset of productivity growth drivers over shorter time horizons or have used data for fewer and mostly advanced economies (Aslam et al. 2016; Dabla-Norris et al. 2015; Fornero, Kirchner, and Andres 2014). This complements the analysis of Chapter 3, which explores a set of specific adverse events, some of which also constitute demand shocks.

Main findings

The chapter reports several novel findings.

First, long-term, "technological" drivers of productivity accounted for a large portion of labor productivity variation in the period 1980-2018: for about 40 percent of the one-year-ahead forecast error variance of labor productivity and 60-75 percent of the five- to ten-year-ahead forecast error variance of labor productivity. The cyclical, non-technological component of productivity growth accounts for the remainder and largely reflected volatile total factor productivity growth.

Second, in around 70 percent of EMDEs and 90 percent of advanced economies, employment fell initially after technology-driven productivity improvements. These employment losses were larger but less persistent in advanced economies than in EMDEs. Such employment losses were also larger in economies with larger increases in industry's share of employment since the 1990s, possibly because industry is particularly amenable to labor-saving innovations such as automation.

Third, this chapter highlights the persistent effects that cyclical developments driven by demand shocks can have on productivity. While such developments may unwind faster than technology shocks, their impact on productivity can last well beyond the typical 2-8 year duration of a business cycle. Demand-driven fluctuations in productivity growth have historically been considered to be neutral in the long run, with rising efficiency of production in cyclical upswings reversed in downswings. This chapter's contrasting finding is in line with a growing literature uncovering persistent effects on productivity in advanced economies from a range of demand-side developments.[9]

Fourth, policy options are available to promote the equitable sharing across the economy of gains from technology-driven productivity growth. These include measures to ensure that technological change does not lead to prolonged unemployment and measures that encourage diversification of skills. Training and retraining can encourage the accumulation of worker skills that complement new technologies, including in sectors conducive to automation. Adequate social protection provisions can help temporarily displaced workers transition to new sectors.

[9] Bachmann and Sims (2012) and Jordà, Singh, and Taylor (2020) find evidence that monetary and fiscal policy-induced expansions and contractions have had long-lasting effects on advanced economy productivity, in contrast to traditional assumptions of neutrality at long horizons.

Methodology. A new structural vector autoregression (SVAR) approach, before now only applied in studies of a few advanced economies, allows a decomposition of labor productivity into long-term drivers and drivers that operate at business cycle frequencies (Dieppe, Francis, and Kindberg-Hanlon 2019; Angeletos, Collard, and Dellas 2018a). The SVAR includes the log-level of labor productivity, the log of employment per capita, consumption as a share of GDP, investment as a share of GDP, consumer price inflation, and monetary policy interest rates where available (Francis et al. 2014).[10] For illustrative purposes, total factor productivity (TFP) is also included to show how labor productivity and TFP individually react to a technology shock.[11] Panel estimations for advanced economies and EMDEs were run with country fixed effects as well as a series of country-specific estimations. Technology shocks are defined as shocks that explain the largest share of the variance of labor productivity at the horizon of more than ten years; demand shocks are those that explain the largest share at horizons of 2-8 years (Annex 6.1).[12] Chapter 3 offers some examples of such demand shocks.

Data. This chapter uses a dataset broad enough to capture global productivity developments. Data on capital services and human capital are taken from the Penn World Table 9.1, while data on other macroeconomic aggregates such as GDP and employment are from the World Bank's World Development Indicators (WDI) database and The Conference Board's Total Economy Database (TED). Consistent annual data are available for 1980-2018 for 103 economies, of which 74 are EMDEs and 29 are advanced economies, for labor productivity, and as a basis for estimates for TFP and capital services (Chapter 1). Labor productivity is measured as output per worker. Data requirements to estimate SVAR technology shocks require additional variables, resulting in an unbalanced, but broader, panel of 30 advanced economies and 96 EMDEs.[13] The average sample length is 40 years for EMDEs and 45 years for advanced economies.

Drivers of productivity: Technology versus demand shocks

The productivity surge which peaked in 2004 and 2007 in advanced economies and EMDEs, respectively, was the largest since at least 1980 in EMDEs (World Bank 2020). It was followed by the steepest and most prolonged decline in EMDE productivity growth since 1980 (Chapter 1).

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[10] Checks on robustness to the inclusion of exchange rate and cyclically adjusted primary balance are shown in Annex 6.1. They do not materially affect IRFs but do result in shorter and more unbalanced data.

[11] TFP estimates are taken from Chapter 1. An alternative approach to identify the long-run drivers of productivity takes into account changes in the utilization of labor and capital in the calculation of TFP growth. Basu, Fernald, and Kimball (2006), Duval et al. (2020), Levchenko and Pandalai-Nayar (2018), and Comin et al. (2019) have implemented this approach for advanced economies other than the US, but not for EMDEs.

[12] Typically, business cycles are assumed to last 2-8 years (Christiano and Fitzgerald 2003; Sargent 1987).

[13] Typically, technology-identifying SVARs have been applied to quarterly datasets. Data shortcomings for EMDEs—with typically less than 20 years of quarterly data on employment or productivity—impose severe constraints. Hence, annual data are used to estimate the SVARs. This choice significantly lengthens the time period over which the VAR is estimated for many EMDEs.

The methodology described above is used to decompose variations in labor productivity growth into business cycle fluctuations and longer-term trends. In EMDEs, 60 percent of the variation of labor productivity growth between 1980 and 2018 consisted of business cycle fluctuations (of between 2 and 8 years), with just 40 percent representing longer-lasting (Figure 6.2). Over longer horizons, however, in part by construction, technology shocks become more important drivers of labor productivity. Thus at the five- or ten-year horizon, technology shocks accounted for 60-75 percent of the forecast error variance decomposition of labor productivity, both for advanced economies and EMDEs.

At least half of the immediate slowdown in productivity growth in EMDEs after the 2008 global financial crisis was attributable to cyclical factors such as weaker investment and reduced factor utilization (Chapter 1). Longer-term, most of the slowdown in EMDEs is structural, reflecting weaker technological development and adoption (Figure 6.3). In advanced economies, two-thirds of the slowdown is explained by structural factors. The contributions vary across EMDE regions.

Effects of technology shocks

Response of productivity to technology shocks. The impulse responses suggest an economically meaningful and statistically significant effect of technology shocks on labor productivity growth over the long-term (Figure 6.4). Initially, almost all of the boost to labor productivity in both EMDEs and advanced economies is accounted for by TFP.[14] The proportion accounted for by TFP falls over time as investment rises, increasing the capital stock per worker.

Short-term macroeconomic responses to a technology shock. Alongside a sustained improvement in labor productivity and TFP, the level of consumption and investment are found to rise, while consumer price inflation and employment are found to fall initially.[15] Employment falls by 0.1-0.2 percent in the next year in response to a technology shock which boosts labor productivity by 1 percent.[16] These initial employment losses are statistically significant in the panel estimations, in one-half of individual-country estimations for advanced economies, and in one-third of those for EMDEs. In EMDEs, investment initially responds twice as strongly as in labor productivity to a technology shock, suggesting that technological change in these

[14] The labor productivity and TFP responses are scaled to the initial impact on each variable respectively. The scaling of the IRFs obscures the substantial difference in the size of the shocks in advanced economies compared to EMDEs. A one standard deviation technology shock raises the level of productivity by around 1.5 percent over 10 years in advanced economies and around 4.5 percent in EMDEs.

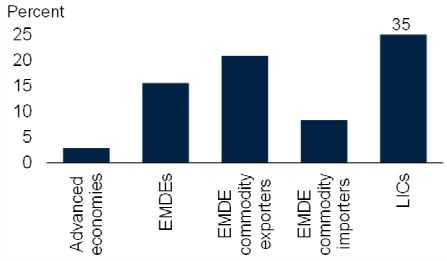
[15] Overall, the impulse response functions for both advanced economies and EMDEs are consistent with theory and similar to typical responses in previous findings for positive technology shocks in advanced economies (Ramey 2016). The more persistent fall in inflation in EMDEs is likely to be a result of less well anchored inflation expectations (Kose et al. 2018).

[16] The finding that technology-driven improvements in labor productivity reduce employment in the short-run is well-established for the United States and some economies in Europe (Basu, Fernald, and Kimball 2006; Francis and Ramey 2005; Galí 1999).

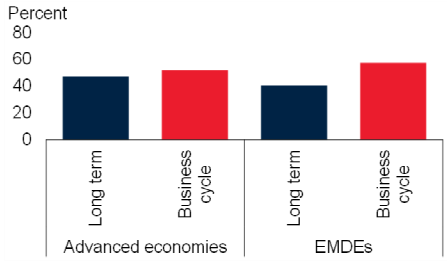
FIGURE 6.2 Decomposition of labor productivity variation

In EMDEs, 60 percent of the variation of labor productivity growth since 1980 is estimated to have consisted of business cycle fluctuations, with just 40 percent being longer-lasting, technological changes. Over longer horizons, however, in part by construction, technology shocks become more important. At the five- or ten-year horizon, technology shocks account for 60-75 percent of the forecast error variance decomposition of labor productivity, both for advanced economies and EMDEs.

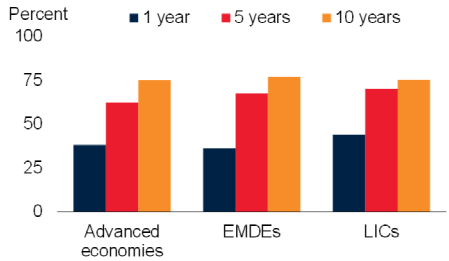
A. Variance of labor productivity growth



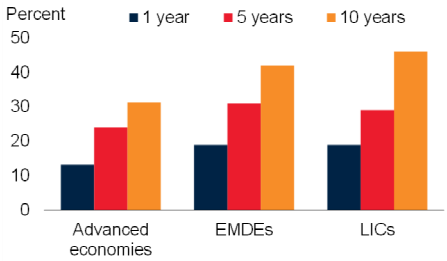
B. Share of long-term and business-cycle variation in labor productivity growth



C. Forecast error variance of labor productivity: Share explained by technology



D. Forecast error variance of employment: Share explained by technology



Source: Conference Board; Penn World Table; World Bank, World Development Indicators.
A. Median variance of labor productivity in each group of economies. Y-axis cropped at 25, while median LIC labor productivity is 35.
B. Applying spectral decomposition, the variance of each series is decomposed into components that reflect long-term and business-cycle frequencies. Here, business-cycle frequencies are classified as those lasting between 2 and 8 years, while long-term frequencies include the variance contributed by fluctuations at frequencies longer than 8 years. Frequencies at 2 years are negligible and excluded (annual data cannot be decomposed into frequencies higher than 2 years).
C.D. Median of forecast error variance contribution to labor productivity or employment at the 1, 5, and 10-year horizon.
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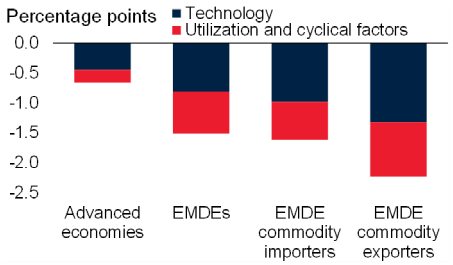
economies may often be capital-embodied or introduced into the production process alongside new investment (Hulten 1992). This contrasts with advanced economies, where the investment response builds over time. Consumption rises significantly by 0.3 percent (advanced economies) to 0.5 percent (EMDEs) after the technology shock, as incomes grow and consumer price inflation declines.

Long-term macroeconomic response to a technology shock. Over time, the adverse employment effects of the technology shock taper off while the consumption gains continue to build. Employment in advanced economies is no longer economically or statistically significantly different from before the technology shock after three years and, in EMDEs for longer. The more persistent employment losses in EMDEs may reflect

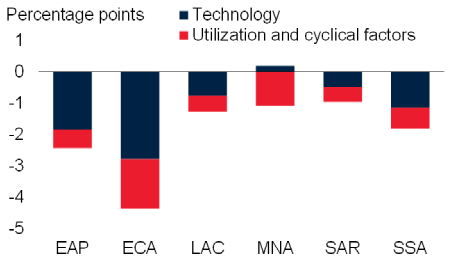
FIGURE 6.3 Contribution of cyclicality to labor productivity slowdown

Cyclical factors such as changes in aggregate demand pressures and factor utilization explain less than one-half of the longer-term post-crisis slowdown in labor productivity growth. A "technology" measure of labor productivity growth which removes these cyclical factors, has declined significantly since the global financial crisis but by different magnitudes across EMDE regions, suggesting different degrees of scarring from the crisis.

A. Slowdown 2013-18 relative to pre-crisis: Advanced economies and EMDEs



B. Productivity growth 2013-18 relative to pre-crisis: EMDE regions



Source: World Bank.

Note: The "technology" contribution to labor productivity growth consists of the contribution of the Spectral SVAR-identified technology shock in addition to the contribution from the constant and initial condition in the VAR, which can also be considered long-term processes. Utilization and cyclical factor contributions are defined as the residual of the contribution of "technology" and labor productivity growth. See Annex 6.1 for further details.

A.B. Pre-crisis period defined as 2003-07 for advanced economies, and 2003-08 for EMDEs.

B. EAP = East Asia and Pacific, ECA = Europe and Central Asia, LAC = Latin America and the Caribbean, MNA = Middle East and North Africa, SAR = South Asia, SSA = Sub-Saharan Africa.

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difficulties in finding new roles for workers following a labor-substituting productivity shock. Meanwhile, consumption continues to grow until it reaches 0.7 percent (advanced economies) to 0.9 percent (EMDEs) above the pre-shock level after 10 years. Disinflation unwinds in less than a decade (Figure 6.4).[17]

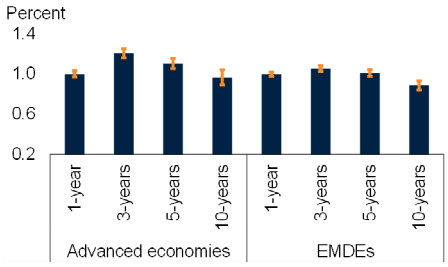
Channels for technology-induced employment losses. The literature has identified a variety of channels through which advances in production technology can result in changes in employment (Box 6.1). Technology can be either a substitute or a complement for labor, and therefore can boost job opportunities as well as reduce them (Autor 2015). New technologies may substitute for labor, for example, where the costs of updating existing production technologies with the existing workforce become prohibitively high relative to the cost of automating capital (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018). Employment losses are more likely in sectors where tasks are easily automated. Several studies of advanced economies have found evidence of increased employment in recent decades in service sector occupations involving tasks that are less easily automated, such as professional services and creative roles (Acemoglu 1999; Autor et al. 2013; Goos, Manning, and Salomons 2014).

[17] Each IRF is scaled to the response of labor productivity to an improvement in technology (Figure 6.4). The IRFs can therefore be interpreted as the impact on each variable for each 1 percent boost to labor productivity. For the labor productivity and TFP IRFs, the scaling is relative to the initial impact on each variable respectively.

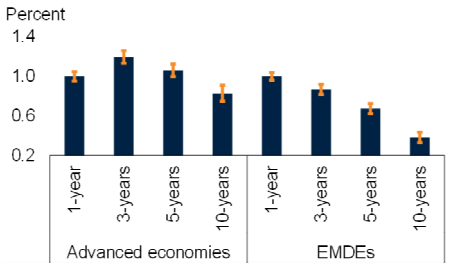
FIGURE 6.4 Productivity effects of technology shocks

Labor productivity and TFP increase following a positive technology shock, but employment initially falls, with the effects in EMDEs fading away only after 10 years. Investment adjusts rapidly to a positive technology shock, as higher returns increase the incentive to boost the capital stock, while consumption increases more gradually. Inflation falls following a positive technology shock, as an improvement in the efficiency of production reduces costs and increases supply.

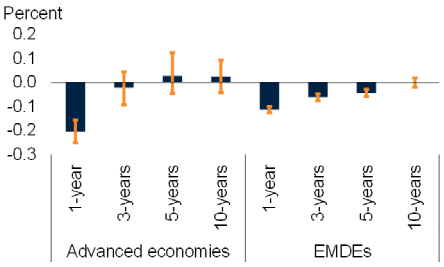
A. Scaled impulse response of labor productivity to a technology shock



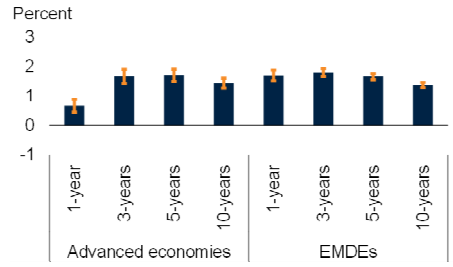
B. Scaled impulse response of TFP to a technology shock



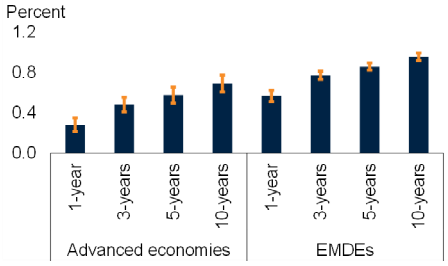
C. Scaled impulse response of employment to a technology shock



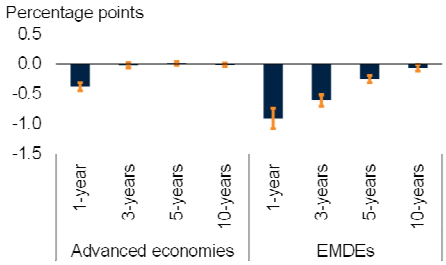
D. Scaled impulse response of investment to a technology shock



E. Scaled impulse response of consumption to a technology shock



F. Scaled impulse response of consumer price inflation to a technology shock



Source: World Bank.

Note: Panel-VAR estimates of impulse responses from a technology shock identified using the Spectral VAR methodology. Panel estimations with fixed effects are performed separately for advanced economies and EMDEs. All impulse responses except TFP are scaled to the size of the impact on labor productivity. Therefore, each IRF can be viewed as the response of the variable for each one-percent increase in labor productivity. The labor productivity and TFP responses are scaled to the initial impact on each variable respectively. The scaling of the IRFs obscures the substantial difference in the size of the shocks in advanced economies compared to EMDEs. A one standard deviation technology shock raises the level of productivity by around 1.5 percent over 10 years in advanced economies and around 4.5 percent in EMDEs. Consumption and investment responses are calculated as the sum of the impact on labor productivity and employment (which approximates to output) added to the impulse on the share of consumption or investment in GDP (measured in logs).

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Country characteristics associated with larger technology-induced employment losses. Economies with larger increases in the share of employment in the industrial sector since the 1990s have tended to suffer larger and more prolonged aggregate job losses from new productivity-enhancing technologies (Figure 6.5).[18] This may reflect a failure to reallocate workers who have lost jobs to sectors where automation has been less prevalent. Technology-induced employment losses were also more severe in countries with smaller FDI inflows and, in the short term, in higher-productivity countries and those less open to global trade.

Effects of demand shocks

Although demand shocks are, by construction, short-lived, their effects can be long-lived. Over a 10-year horizon, demand shocks accounted for about one-quarter to one-third of labor productivity variation between 1980 and 2018.

Demand shocks can be caused by changes in expectations about the returns to investment, changes in government spending or taxes, changes in monetary conditions, externally-driven changes in commodity prices and terms of trade, or changes in "animal spirits" affecting investment behavior (Justiniano, Primiceri, and Tambalotti 2010; Keynes 1936).[19] While the methodology used here does not explicitly identify demand shocks from other factors that can drive business-cycle fluctuations, the resulting characteristics are consistent with those associated with a typical demand shock.[20] Below we consider changes in animal spirits as a determinant of investment behavior and show that their productivity effects can be highly persistent through the capital-deepening channel. Annex 6.2 examines as a second example the effects of commodity-price fluctuations, a key demand-driven determinant of productivity developments in EMDE commodity exporters.

Response of labor productivity to demand shocks. In advanced economies, a positive demand shock raises labor productivity only for a couple of years, after which the effect fades. In contrast, in EMDEs, positive demand shocks are associated with sustained productivity gains (Figure 6.6): A decade after a 1-standard deviation positive demand shock, labor productivity remains about 1 percent higher.

Long-term responses to demand shocks. In advanced economies, the rapid reversal of labor productivity gains arising from positive demand shocks largely reflects a

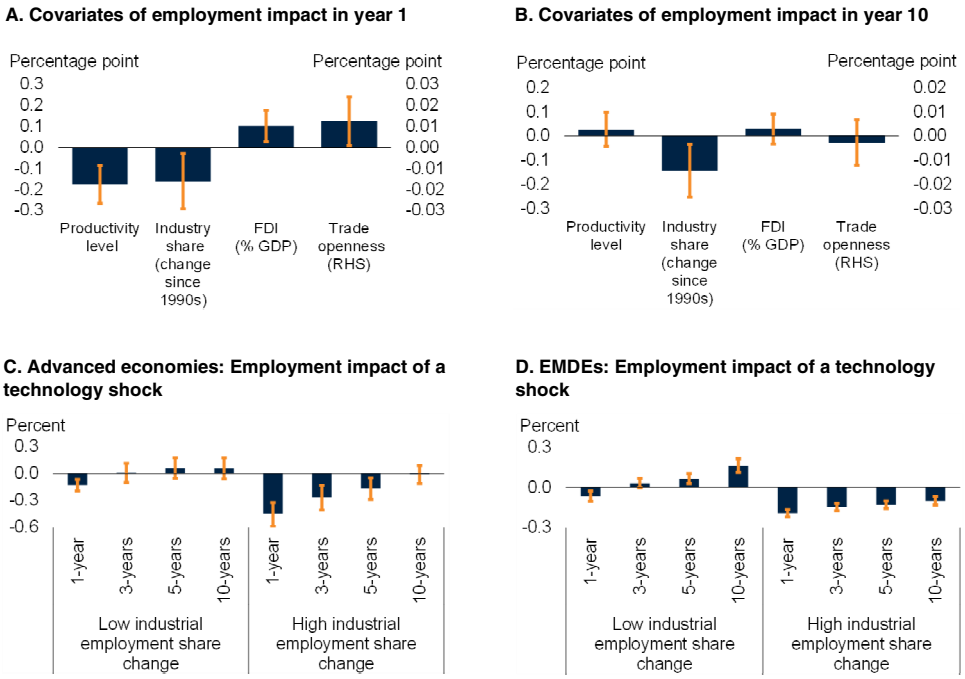
[18] Evidence from the United States suggests that technological displacement leads workers to leave the labor force as well as employment, and also results in smaller flows of new workers into the labor force (Cortes et al. 2020).

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

[20] Angeletos, Collard, and Dellas (2018a) identify a common driver of unemployment, investment, consumption and output at business cycle frequencies in the United States using the same technique. They find similar characteristics to those identified in the panel-VAR framework here across advanced economies and EMDEs. They attribute the resulting responses to "confidence" shocks, which cause co-movement of investment and consumption at the targeted frequencies (Angeletos, Collard, and Dellas 2018b).

FIGURE 6.5 Employment effects of technology developments

Technology-induced employment losses were larger in economies with higher productivity (advanced economies), larger increases in the share of employment in industry, less openness to trade, and smaller FDI inflows.



Source: World Bank.

A. B. Coefficient estimated in a regression of the correlates of the employment impact of a technology innovation at the one year and 10-year horizon. Productivity level is measured in log-units of output per worker measured in US dollars at 2010 prices and exchange rates, industry share shows the effect of a 10 percentage point increase in the share of industrial sector employment between 1990-99 and 2010-18, FDI is the average net inflow relative to GDP during 1990-2018 (showing the effect of a 10 percentage point increase), while trade openness is exports and imports as a share of GDP during 1990-2018, also scaled to show the effect of a 10 percentage point increase. Orange lines show the 95 percent confidence interval.

C. D. Panel VAR estimation of the employment impact of a technology innovation in two separate groups. "High industrial employment share change" are those who are in the top quartile of changes in employment share in industry between 1990-9 and 2010-2018. "Low industrial employment share change" includes economies in the bottom quartile of changes in the share of industrial employment over the same time horizon. IRFs are scaled to reflect the employment impact per percentage point increase in labor productivity at each horizon.

Click here to download charts and data.

contraction of TFP and fading investment after an initial boost. Initial employment gains fade in less than a decade, as do gains in consumption and the initial surge in inflation. In EMDEs, however, the effects of demand shocks are more persistent. TFP and employment gains fade but investment remains 4 percent higher and consumption around 1 percent higher a decade after a positive demand shock that generates a 1 percent increase in labor productivity (Figure 6.6).

Country characteristics associated with larger demand-driven productivity losses. One reason for less persistent effects on productivity from demand shocks in advanced

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs?

New technologies can both substitute for, and complement, labor. Evidence from a large global sample of economies suggests that the substitution effect dominates in the short-run. A typical one percent technology-driven improvement in labor productivity reduces employment in the first year by 0.2 percent in advanced economies and 0.1 percent in emerging and developing economies (EMDEs). Advanced economies have been more affected in the short run by employment-displacing technological change, but the disruption in the labor market in EMDEs has been more persistent. Economies where the share of industrial employment has increased the most (or decreased the least) in recent decades have been more subject to employment-displacing technologies and have experienced larger and more persistent negative effects on employment. Trends towards greater automation and digitalization are growing in EMDEs, increasing the importance of measures to improve the labor force skill-base to better complement the introduction of new technologies, while ensuring adequate social safety nets for transitioning workers.

Introduction

Productivity-enhancing technological innovation is key for reducing poverty and raising living standards. However, concerns are frequently raised about how the gains from new technologies are shared, and about their impact on employment. Currently, concerns are perhaps highest around the automation of manufacturing jobs and digitalization of repetitive tasks, but historically many innovations have been accompanied by the threat of job losses (World Bank 2019). In the early industrialization of the United Kingdom, the "Luddites" famously destroyed newly invented machines such as the "Spinning Jenny," used to improve the efficiency of textile production in the early 19th century (Mantoux 2006). Over the long run, the benefits from industrialization through improved productivity have outweighed transition costs, and the actions of the Luddites look misplaced. Technological progress can be both a substitute and a complement for labor, and can also boost real incomes, so that it can boost job opportunities as well as reduce them (Autor 2015). However, certain segments of the labor market can be harmed by technological change, suffering losses of real incomes or jobs, at least temporarily. And where the skills needed to accompany new technologies are unavailable, or demand for new labor tasks does not rise sufficiently, aggregate employment can be persistently lower for a long period.

A large literature has attempted to assess the impact of technological change on employment within affected sectors, but so far, the effects on aggregate

Note: This box was prepared by Gene Kindberg-Hanlon, with research assistance from Aygul Evdokimova.

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

employment have been under-explored, particularly in EMDEs. This box reviews the literature and employs recently developed statistical techniques using structural vector auto-regressions (SVARs) to assess the impact of technology improvements on aggregate employment. This is the first exercise to employ these techniques on EMDE data, estimating effects across 96 EMDEs and 30 advanced economies. The scale of the sample also allows for an exploration of the factors that explain cross-economy differences in the effects of new technologies on employment.

This box addresses the following three questions:

- Is there evidence from the literature that new production technologies can reduce employment?
- What is the estimated effect of productivity-enhancing technological change on employment and how does this vary between advanced economies and EMDEs?
- How should policymakers respond?

Literature

Theory. Productivity-improving technologies generate two opposing forces on employment: first a substitution effect, where new technologies can replace the need for workers; and second, an income effect, where increases in the profitability of production increase the demand for labor in the affected or other sectors (Aghion and Howitt 1994). The extent to which the income effects offset automation effect will depend crucially on the type of tasks required to complement new technologies and associated capital assets, and the supply of workers with the appropriate skills for these tasks (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018). Search-and-matching models have been used to show that new technologies can increase unemployment when the costs of updating existing technology become prohibitively high, labor market flexibility is low, or the skills required to accompany new technologies become increasingly novel (Mortensen and Pissarides 1998; Restrepo 2015).

Sectoral evidence. A large body of evidence has shown that jobs have become increasingly polarized into low- and high-skill occupations in the U.S. and Europe in recent decades, as a combination of automation and offshoring has reduced demand for middle and low-skilled workers performing routine and codifiable jobs (Acemoglu 1999; Autor et al. 2013; Goos, Manning, and

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

Salomons 2014).[1] Many of these lost occupations were in the industrial sector, even as value-added produced by the sector remained resilient—in the United States, employment of machine operators, assemblers, and other production employees fell by over one-third every 10 years between 1980 and 2005 (Autor and Dorn 2013). In a study of 16 European economies during 1993-2010, the share of employment accounted for by industrial sector occupations fell by nearly 10 percentage points (Goos, Manning, and Salomons 2014). In the United States and France, the increased use of robotics is found to be inversely related to industrial employment levels since 1990 and 2010, respectively (Acemoglu, LeLarge, and Restrepo 2020; Acemoglu and Restrepo 2020). Some service sector occupations are also found to have been negatively affected by this trend in both regions, notably middle-skilled jobs such as office clerks. However, codifiable middle- and low-skill jobs have been (at least partially) replaced by higher demand for both low-skill service sector jobs, which are less easy to automate, and higher-skill jobs that complement new technologies. SVAR analysis of sectoral manufacturing data for advanced economies has also found negative effects on total hours worked of developments that have driven persistent positive TFP growth (Chang and Hong 2006; Khan and Tsoukalas 2013; Park 2012).

General equilibrium impacts of technological progress on employment. Several studies of the U.S. economy have found that technological progress has caused *aggregate* and not just sectoral employment to fall. During the so-called "jobless recoveries" in the U.S. after the recessions of 1991, 2001, and 2008, where the employment rate fell overall, declines in employment were concentrated in middle-skill and automatable jobs, particularly in the manufacturing sector (Charles, Hurst, and Notowidigdo 2016; Jaimovich and Siu 2020). It has been further argued that even high-skilled workers have been substituted by newer technologies and pushed into lower-skilled positions (Beaudry, Green, and Sand 2016). There remains controversy over the net effect on total employment of technological change. In some advanced economy studies, the fall in employment in the sector where innovation occurs are offset by employment gains in other sectors (Autor and Salomons 2018).

EMDE evidence. There have been few studies of the effects of technological change on employment in EMDEs. In part this is because EMDEs have been large beneficiaries of outsourcing from advanced economies: many manufacturing and "codifiable" service sector jobs have moved to EMDEs

[1] While offshoring is a separate phenomenon from the technological displacement of workers, technological advances have lowered the costs of offshoring both information-based tasks and manufacturing jobs (Blinder and Krueger 2013).

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

(Maloney and Molina 2016).[2] What technology-influenced change does appear to be occurring has increased the share of routine semi-skilled jobs in many EMDEs, in contrast to the fall in the share of these types of jobs in advanced economies (World Bank 2019). That said, large increases in manufacturing productivity have resulted in "premature deindustrialization" in EMDEs, with the shares of employment in the industrial sector rising by less, or falling at much lower levels of income per capita than has occurred in the past, particularly in the development of today's advanced economies (Rodrik 2016). That could suggest that productivity-enhancing technology in the manufacturing sector has reduced employment relative to a counterfactual, which would have been otherwise higher still.

Estimating the effects of technology shocks on employment

Many of the recent studies of the effects of productivity-improving technological change on employment have concerned the effects of progress in information technology (IT) and manufacturing technology in the U.S. and Europe on codifiable jobs in recent decades. There has been no broader assessment of the effects of technological progress on employment in a wide range of countries. To assess the effects of technical progress on employment a range of countries, we turn to SVAR techniques, which have already been used extensively to estimate the relationship between "technology shocks" and total hours worked in the U.S. and some European economies, finding a negative impact on total hours worked (See Table A.6.1.2 for a summary of published findings). In some cases, the loss of jobs in the United States following an SVAR-identified technology shock has been attributed to "creative destruction," with labor tasks being replaced by new technologies (Canova, Lopez-Salido, and Michelacci 2013; Michelacci and Lopez-Salido 2007).

Methodology. Here, productivity-enhancing developments in technology are identified as developments that bring persistent changes in labor productivity and which drive most of the variation in long-run productivity (Annex 6.1).[3] The implicit assumption in this exercise is that technological innovations are the dominant long-run driver of improvements in labor productivity. The VAR has

[2] The term "codifiable jobs" generally refers to those consisting of repetitive tasks that are vulnerable to automation.

[3] Specifically, the SVAR identifies a "technology" shock as the shock which drives the largest proportion of low-frequency variation in labor productivity (frequencies below 10-years). This has been found to be more robust than traditional long-run restrictions in identifying technology shocks (Dieppe, Francis, and Kindberg-Hanlon 2019).

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

the same specification as that used in the main chapter text and contains output per worker, employment per capita, consumption and investment as shares of GDP, the short-term interest rate (where available), and consumer price inflation. The VARs are estimated across 30 advanced economies and 96 EMDEs. Panel VAR estimations are performed to show general impulse responses for groups of economies, while individual estimations are used to examine the extent to which findings are broad-based.

Effects of productivity-enhancing technologies on employment

For both the average advanced economy and the average EMDE, an SVAR-identified positive technology development results in a sustained increase in labor productivity over a 10-year horizon (Figure 6.1.1).[4] While productivity and output increase, the short-term impact on employment is negative and statistically significant in both advanced economies and EMDEs. Employment falls by 0.2 percent in the first year in advanced economies for each one percent boost to labor productivity, before returning to its original level by year three (Figure 6.1.1). In EMDEs, employment falls by 0.1 percent initially but the fall is more persistent and employment remains below its original level at the 5-year horizon. Therefore, while on average technological change in EMDEs seems to have had a smaller initial negative impact on employment, EMDEs have been less successful at restoring employment levels over long horizons.[5] The smaller negative employment effect in EMDEs is consistent with the finding in the literature that the displacement of low and middle-skilled workers has primarily been an advanced-economy phenomenon.

The finding of falling employment following technological improvements is broad-based across advanced economies, EMDEs, and regions. Estimates for individual economies show that 90 percent of advanced economies have experienced a negative impact on employment in year 1, with statistically significant falls in 50 percent of them. In EMDEs, 70 percent of economies experienced a fall in the first year, statistically significant in 30 percent of cases.

[4] The larger impact of technology shocks on productivity in EMDEs reflects higher average EMDE productivity growth over the past 20 years as well as the higher volatility of the data.

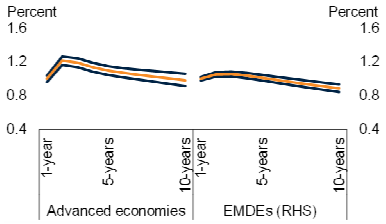
[5] For robustness, the same specification is estimated for advanced economies using data on total hours worked instead of employment (for EMDEs, data for hours worked are only available for one-quarter of the sample and frequently show little deviation from labor input measured by employment). The average of the median impacts on total hours worked following a technology shock matches the impact on employment very closely. In addition, despite using annual data in our VAR exercises, a statistically significant negative impact on hours is found for the U.S. which lasts for one year, matching the results of the U.S. literature (using quarterly data).

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

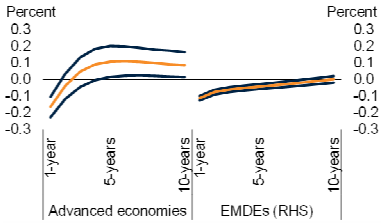
FIGURE 6.1.1 Impact of a positive technology innovation

"Technology" improvements result in a sustained increase in labor productivity in advanced economies and EMDEs. Employment declines in 90 percent of advanced economies and three-quarters of EMDEs, although the fall is statistically significant in only one-third of EMDEs. The estimated impact on employment of a technology shock that boosts productivity by 1 percent is -0.1 to -0.2 percent in the first year—it is smaller in EMDEs but it persists there for longer.

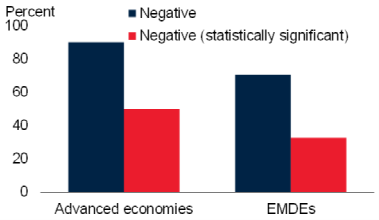
A. Labor productivity impact of technology shocks



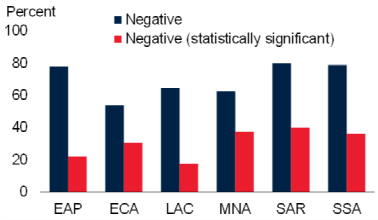
B. Change in employment per 1 percent productivity gain



C. Proportion of economies with negative employment impact in year 1: AE and EMDEs



D. Proportion of economies with negative employment impact in year 1: EMDE regions



Source: World Bank.
A.B. Based on a separate panel VAR estimation for 30 advanced economies and 96 EMDEs, including fixed effects for each economy. Error bars show 16th to 84th percentiles.
A. Impact on labor productivity is scaled to the side of the initial impact—due to the higher variation of labor productivity in EMDEs, a one standard deviation technology shock boost labor productivity by 5 percent, relative to 1.7 percent in advanced economies (Annex 6.1).
B. Impact on employment per one percent increase in labor productivity driven by the identified technology shock.
C.D. Based on individual VAR estimations. The proportion of economies where the median of the IRF is negative in the dark blue bars, and proportion where the 84th percentile is below zero in year 1 in the red bars.
Click here to download charts and data.

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

The finding is also consistent in all EMDE regions: more than half of the economies in each region experienced negative employment impacts.

What country features are associated with prolonged technology-driven employment losses?

Both advanced economies and EMDEs are thus found to have experienced job losses following advances in technology. Of primary concern for policymakers are first, the scale of initial losses, and second, whether employment recovers quickly, including through the movement of labor to new activities, or whether there are long-lasting scarring effects on the labor force, such as a long-lasting decline in participation rates. The degree and duration of labor market disruption in each economy may depend on multiple factors. These include the types of technologies introduced over the sample period and the degree to which they substitute for, or complement, skilled or unskilled labor, and the policies implemented by the governments to facilitate labor mobility, including the promotion of training and retraining.

A regression is performed on the size of the estimated employment impact and a range of covariates that could determine the size and persistence of job losses. Higher average productivity levels over the estimation sample are found to be negatively related to the employment impact of technology shocks: more productive economies seem to have been more subject to labor-displacing technologies (Figure 6.1.2). Secondly, the change in the share of industrial employment since 1990 (when these data begin for a broad range of countries) is also negatively related to the employment impact, both in the short term (after one year), and long term (at the 10-year horizon). Third, higher average degrees of trade openness and FDI inflows are associated with fewer job losses following a technology shock. These findings are further explored below.

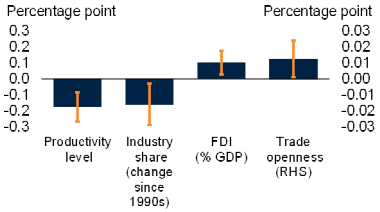
Growth of industrial employment shares. The change in the share of employment in industry since the 1990s is a key correlate of both the size of the employment impact from the SVAR-identified technology shock and its persistence (Figure 6.1.2). A panel VAR is used to estimate employment losses following positive technology developments in economies in the top and bottom quartiles of growth in industrial sector employment since the 1990s. In advanced economies, the share of employment in industry has declined since the 1990s. However, those economies where the declines have been smallest (including France, Germany, and the United States) have experienced negative employment impacts of technological advances four times larger than the economies where the declines have been largest (including Singapore, Spain, and the United Kingdom).

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

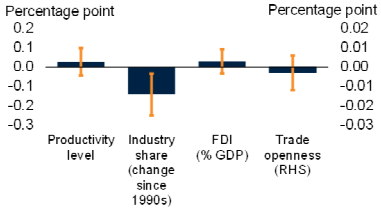
FIGURE 6.1.2 Covariates of the impact of technology on employment

Economies with a larger increase in the share of workers in industry since the 1990s have experienced larger and more persistent job losses from productivity-enhancing technology developments. Trade openness and FDI inflows are positively related to the employment impact in year 1 but do not affect the persistence of the employment impact.

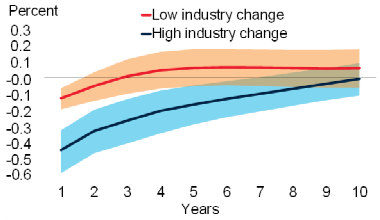
A. Covariates of employment impact in year 1



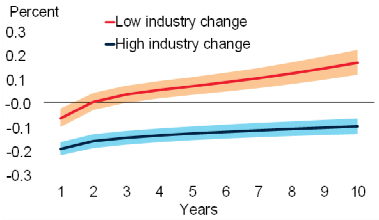
B. Covariates of employment impact in year 10



C. Advanced economies: High and low change in industrial employment share: Employment IRFs



D. EMDEs: High and low increase in industrial employment share: Employment IRFs



Source: World Bank.

Note. Impulse response functions from panel VAR estimations with fixed-effects.

A.B. Coefficients estimated in a regression of the correlates of the employment impact of a technology innovation at the one-year and 10-year horizons. Productivity level is measured in log-units of output per worker measured in U.S. dollars at 2010 prices and exchange rates, industry share shows the effect of a 10 percentage point increase in the share of industrial sector employment between 1990-99 and 2010-18, FDI is the average net inflow relative to GDP during 1990-2018 (showing the effect of a 10 percentage point increase), while trade openness is exports plus imports as a ratio to GDP during 1990-2018, also scaled to show the effect of a 10 percentage point increase.

C.D. These show panel VAR estimations of the employment impact of a technology innovation in two separate groups. "High industry change" economies are those that are in the top quartile of changes in industry's share of employment between 1990-9 and 2010-2018. "Low industry change" are economies in the bottom quartile of changes in the share of industrial employment over the same time horizon. Quartiles calculated for advanced economies and EMDEs separately. IRFs are scaled to reflect the employment impact per percentage point increase in labor productivity at each horizon. Shaded areas reflect 68% confidence bands.

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BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

In EMDEs, the industrial share of employment has risen since the 1990s in half of those in the sample,. In those EMDEs with the largest increases (including China, India, and Vietnam), declines in employment in response to positive productivity developments were three times larger than in those with the largest declines (including Argentina, Romania and South Africa).[6] However, as indicated earlier, the scale of job losses was significantly smaller in EMDEs than in advanced economies.

These findings link directly to much of the literature on the effects of new technologies on employment, which has found that routine manufacturing jobs (and routine service sector jobs) have been at the highest risk of being lost through changes in technology, including automation. Those economies with increasing industrial employment shares in the industrial sector since the 1990s will have been at the highest risk from automation. In addition, those economies with increasing employment shares in this sector may have had the least success in increasing employment in other sectors following job losses in the industrial sector. For example, the share of employment in industry will fall if jobs are replaced by new technologies in that sector. It will fall by even more if affected workers are re-employed in sectors that are less affected by automation. Countries that successfully redeploy workers to new roles will see stronger aggregate employment growth and a smaller share of workers in sectors such as industry where workers may be most at risk of technology-driven displacement. On average, those economies where industrial employment as a proportion of the total workforce has fallen by more have experienced larger increases in aggregate employment and the labor force since 1990 (Figure 6.1.3).

International trade and investment. A regression of the employment impact of changes in technology on a range of covariates finds that trade openness and FDI inflows are *positively* correlated with the employment impact in year 1: higher levels of both variables are associated with fewer job losses or more gains in employment from productivity-enhancing changes in technology (Figure 6.1.2). FDI, particularly when it is export-focused, has been associated with job generation (Waldkirch, Nunnenkamp, and Bremont 2009). More generally, FDI has been found to be associated with increased employment and skill-upgrading in the host country in EMDEs in a range of studies (Hale and Xu 2016).

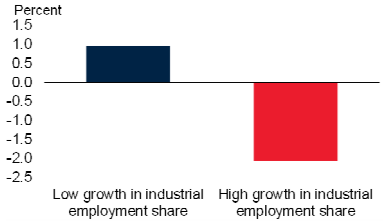
[6] The industrial sector is defined as including mining and construction as well as manufacturing, so that it includes production of some commodities.. The share of primary commodities in total exports shows no relationship with the scale of job losses following an SVAR-identified technology shock, however, suggesting that manufacturing is the primary driver of the results for the industrial sector

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

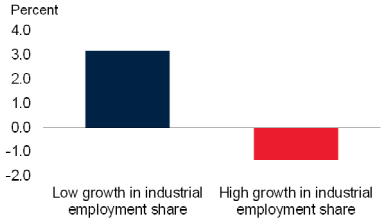
FIGURE 6.1.3 Share of workers in industry and aggregate employment

Employment growth since 1990 is negatively correlated across economies with the increase in the industrial sector's share of employment. This is likely to reflect differences in success with the redeployment of technology-displaced workers into sectors that have been less affected by automation.

A. Employment growth in economies with high and low growth in the industrial sector's share of employment



B. High and low growth in the share of employment in industry and aggregate labor force growth



Source: World Bank, World Development Indicators.

Note: Sample of 100 advanced economies and EMDEs. The y-axis shows the percentage point change in the ratio of employment to the working-age population (15-64), and the change in the ratio of the labor force to the working-age population between 1990-99 and 2010-18. The labor force includes those that are employed and unemployed. Those economies with above-median growth in the share of workers in industry between 1990-99 and 2010-18 are classified as "High growth," while those with below-median growth are classified as "low growth."

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Future risks and policy options

Technology-driven employment losses have been found to be larger but less persistent in advanced economies than in EMDEs. Increases in the industrial sector's share of employment is a key correlate of larger and more persistent falls in employment. As EMDEs have continued to gain an increasing share of global industrial activity and reached higher income levels, they may have become more exposed to risks of employment dislocation from new technologies. This section considers these risks and policies that can help manage them.

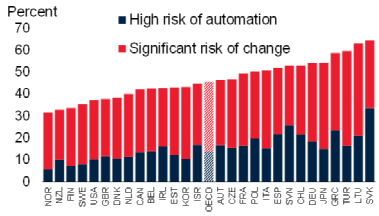
Estimates of jobs at risk. The analysis in this chapter is backward-looking, New trends towards digitalization of tasks and automation could accelerate the adoption of labor-replacing technologies. For advanced economies, there are a wide range of estimates of the proportion of jobs at risk of automation. Arntz, Gregory, and Zierahn (2016) find that 9 percent of jobs across 21 OECD economies are at high risk of automation. A broader study of 32 economies,

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

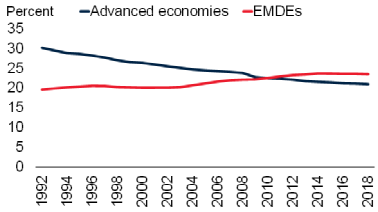
FIGURE 6.1.4 Risks of future employment disruption in EMDEs

Some estimates suggest that 14 percent of jobs in OECD economies, including some EMDEs, are at high risk of automation, and that a further 32 percent are at risk of significant change due to automation. The jobs at risk are primarily in the manufacturing and agricultural sectors, although increasingly service sector roles such as food preparation and transportation are at risk. As EMDE employment increasingly shifts towards the industrial sector, jobs in these economies may be increasingly at risk from automation.

A. OECD estimates of jobs at risk of automation



B. Share of employment in industry



Source: Nedelkoska and Quintini (2018); World Bank, World Development Indicators.
A. Estimates from Nedelkoska and Quintini (2018). "High risk" reflects an estimated probability of over 70 percent that the role will be automated. "Significant risk of change" estimates a probability of between 50 and 70 percent that the role will subject to significant change due to automation.
B. Share of employment in industry in 17 advanced economies and 105 EMDEs, weighted by total employment in each economy.
Click here to download charts and data.

including several EMDEs, has found that on average 14 percent of jobs are at high risk of automation, with a further 32 percent at risk of significant change due to new technologies (Figure 6.1.4). The jobs found to be at risk in this study are primarily in manufacturing (the largest component of industry). However, other sectors are also at risk, including agriculture, and increasingly in the service sector, including food services and transport, and middle-skilled office clerk positions (Nedelkoska and Quintini 2018; OECD 2019).[7] This literature does not take into account new jobs that could be created by the introduction of new technologies given that they are gross, rather than net, effects. However, as shown in this box, the net impact of new technologies on jobs tends to be negative in the short run and can be persistent in EMDEs. So far, no studies have estimated the

[7] Frey and Osborne (2017) find that 47 percent of occupations in the U.S. are at risk of automation.

BOX 6.1 Do productivity-enhancing improvements in technology threaten jobs? *(continued)*

likely impact of expected future technological change on a large sample of EMDE labor markets. As EMDEs acquire an increasing share of global industrial employment, it is likely that they will increasingly face similar challenges from automation (Figure 6.1.4.B).

Policies to manage technology-driven labor market disruption. A more highly educated and trained workforce will reduce the fall in employment following the adoption of skill-biased production processes. Many EMDEs need to make improvements at early stages of education to build a foundation for more advanced levels of education and training (World Bank 2018a, 2019). Education at the early stages of childhood development is currently underprovided in many EMDEs and is critical to the development of language and cognitive skills that are crucial for further education. Many EMDEs also suffer from an underprovision of universities; apprenticeships; other facilities for training and re-training; and continuing adult education. Government efforts to expand provision in these areas can bring high social returns as well as large private returns, in terms of wage premia, to the workers who take advantage of them, in addition to enabling better adaptation to changing production technologies.

Different sectors, or even different industries within manufacturing, may be more or less exposed to risks of automation. For those economies seeking to expand the scale of their manufacturing sector because of its historic role in driving rapid productivity gains, textiles, garments and footwear production may seem attractive options because they have been less affected by automation so far (Hallward-Driemeier and Nayyar 2017). However, the risk of future automation in such industries may be high. Economies may also focus on service sectors that support the manufacturing process but are less vulnerable to automation, such as designing, selling, and supporting the production of manufactured goods.

Adequate social protection should be provided to ensure that those who are displaced from their employment can increase their opportunities to transition to new industries. In LICs, less than 20 percent of workers are covered by social insurance, in part due to large informal sectors (World Bank 2019). Encouraging both private savings and social insurance schemes for unemployment can provide a safety net for displaced workers and encourage workers to take advantage of new employment opportunities that may entail risks for them.

economies than in EMDEs may be the presence of more robust fiscal frameworks. 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, Vegh, and Vuletin 2013). In both advanced economies and EMDEs with weak fiscal positions (government debt in the top quartile or above-median primary deficits), negative demand shocks significantly lowered labor productivity whereas the effect either dissipated or was much weaker in advanced economies and EMDEs with strong fiscal positions (Figure 6.7). The persistent decline in labor productivity largely reflected lower capital accumulation, not TFP, in countries with weaker fiscal positions.

Conclusion and policy messages

This chapter offers several novel findings. First, long-term, "technological" drivers of productivity have accounted for a considerable portion of labor productivity variation since 1980: for about 40 percent of the one-year-ahead forecast error variance of labor productivity and 60-75 percent of the five- to ten-year-ahead forecast error variance. Second, employment has typically fallen, at least initially, after technology-driven productivity improvements. These employment losses were larger but less persistent in advanced economies than in EMDEs. Third, while demand shocks may unwind faster than technology shocks, their impact on productivity can be long-lasting. These findings point to two policy priorities.

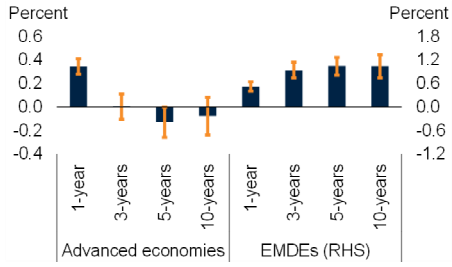
While technological progress is generally beneficial in the long term, it may initially be disruptive to employment (Arntz, Gregory, and Zierahn 2016; Autor 2015; World Bank 2019). The appropriate policy response is three-pronged: first, policies to encourage and support the training and retraining of workers to equip them with the skills required by new technologies; second, policies to mitigate the negative effects on transitioning workers; and third demand management to maintain full employment. The COVID-19 pandemic and resulting global recession may trigger another wave of restructuring and technological innovation, as firms adjust to social distancing and new restrictions on doing business, or search for efficiency savings to remain competitive. EMDEs, in particular, will need to ensure that workers are equipped with skills to complement new technologies, rather than be replaced by them (World Bank 2018a).

Universities, vocational training facilities, on-the-job training, and continued learning are often underprovided in many EMDEs, and there are potentially high social returns to their expansion. Many EMDEs also need to make improvements at earlier stages of education in order to build a foundation for the more advanced education that will enable workers to adapt to skill requirements associated with new technologies (World Bank 2018a, 2019). Adequate social protection can help those displaced by technological change to transition into new industries. For example, in LICs, fewer than 20 percent of workers are covered by social insurance, in part due to large informal sectors in these economies (World Bank 2019). Encouraging private savings, including

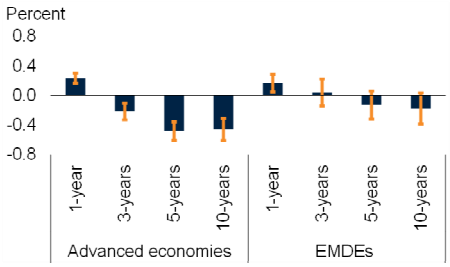
FIGURE 6.6 Effects of demand shocks

In advanced economies, positive demand shocks lifted labor productivity, investment, consumption and employment only temporarily. In EMDEs, positive demand shocks lifted labor productivity, investment, and consumption (but not employment) for a decade.

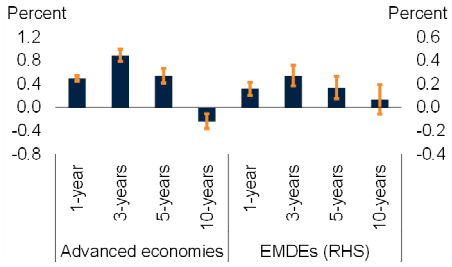
A. Scaled response of labor productivity to demand shock



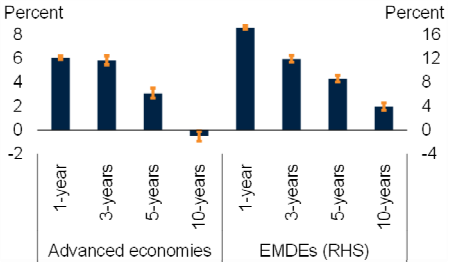
B. Scaled response of TFP to a demand shock



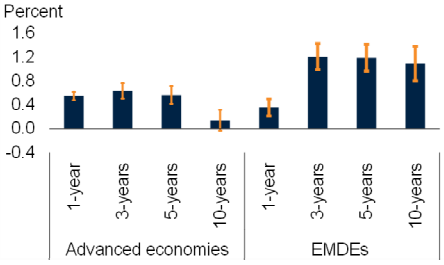
C. Scaled response of employment to demand shock



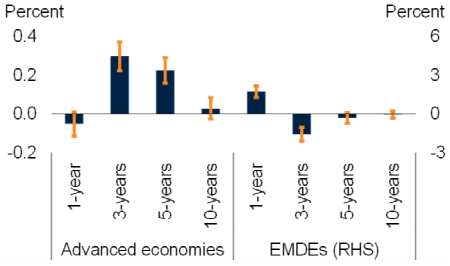
D. Scaled response of investment to demand shock



E. Scaled response of consumption to demand shock



F. Scaled response of consumer price inflation to demand shock



Source: World Bank.

Note: Panel VAR estimation of the impulse-responses to the shock driving the largest proportion of business-cycle variation in investment, identified using the Spectral methodology. See Annex 6.1 for further details. Responses show each variable in levels, except for inflation, which shows the percentage point change in the growth of consumer prices. Consumption and investment responses are calculated as the sum of the impact on labor productivity and employment (which approximates to output) added to the impulse on the share of consumption or investment in GDP (measured in logs).

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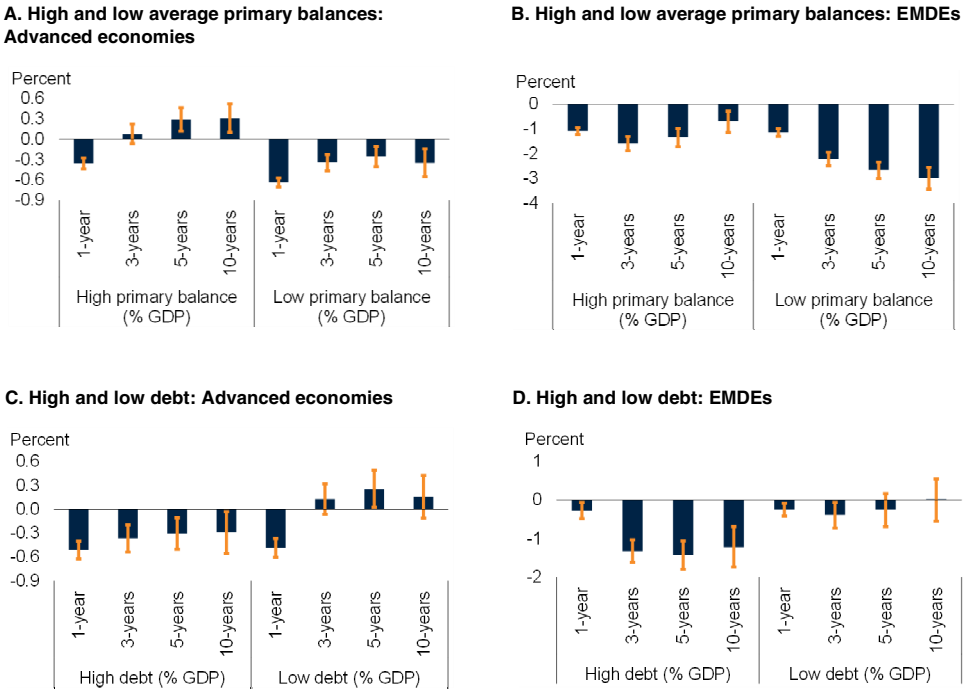
FIGURE 6.7 Negative demand shocks, labor productivity, and fiscal space

In both advanced economies and EMDEs, negative demand shocks have had more persistent effects on labor productivity in those economies with weaker fiscal positions higher government debt and wider primary deficits.



Source: World Bank.

Note: Panel VAR estimation of the impulse responses to the shock driving the largest proportion of business-cycle variation in investment, identified using the Spectral methodology. See Annex 6.1 for further details. IRFs are a response to a negative one standard deviation shock.

A.B. 30 advanced economies and 50 EMDEs are grouped into the top half and bottom half of the distribution of their average primary balances during 1990-2018.

C.D. 30 advanced economies and 95 EMDEs are grouped into a top and bottom quartile by their average government debt-to-GDP ratio during 1990-2018.

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through initiatives that expand financial inclusion, and expanding unemployment insurance programs in the formal and informal sectors can strengthen the safety net.

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 the shoring up of fiscal positions once economic recovery from the pandemic is well established, a strengthening of monetary and fiscal policy frameworks, and effective supervision and regulation to ensure a resilient financial system (Chapter 1; 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 findings above point to two directions for future research. First, future studies could examine peak and trough episodes in individual countries to see whether and how they correspond with significant technological and demand-driven events. The analysis could also examine in greater depth the types of employment that are most vulnerable to disruption from technology and demand shocks, especially in EMDEs. Second, this chapter points to important differences in the long-term effects of shocks, and future research could explore which characteristics of EMDEs cause these differences; for example, differences in institutional factors like educational and legal systems; economic differences in monetary and fiscal policies, trading partners, and trade compositions; and development differences like the sophistication of stock markets and levels of industrialization. Finally, the sectoral dimension could be further explored.

This chapter has focused on the role of short- and long-term shocks in driving labor productivity. However, the literature has also identified sectoral reallocation as an important driver of labor productivity. This is examined in the next chapter.

ANNEX 6.1 SVAR identification of 'technology' drivers of productivity

This annex describes the spectral technology SVAR procedures in greater detail.

Spectral identification

Supply-side "Technology" shocks are identified as those that explain the majority of productivity fluctuations at frequencies longer than 10 years—this approach disregards fluctuations at higher (shorter) frequencies and is, therefore, robust to contamination in economies where productivity is affected by many other factors. This approach identifies long-lasting innovations to labor productivity, assuming that these highly persistent changes are likely to be driven by structural factors such as new production technologies. Historically, long-run restrictions have been used to identify technology shocks, however, this type of restriction has been found to perform poorly in short samples and in volatile data compared to the spectral identification used in this chapter.[1]

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 and Fitzgerald 2003) to 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 which explains the largest share of variance of productivity at the desired frequency.

[1] Long-run restrictions imposed on a finite sample can lead to biased and inefficient estimates (Chari, Kehoe, and McGrattan 2008; Erceg, Guerrieri, and Gust 2005; Francis et al. 2014), especially around structural breaks (Fernald 2007) and have been shown to perform poorly except in situations where technology shocks explain the large majority of productivity developments (Chari, Kehoe, and McGrattan 2008; Dieppe, Francis, and Kindberg-Hanlon 2019).

Identifying technology shocks through restrictions that explain the majority of low (long-term) frequency volatility of productivity is a novel approach. However, this methodology has been used to assess the types of shocks that drive the business cycle - for example, Angeletos, Collard, and Dellas (2018a) 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):

$$Y_t = [I - (A_1 L + A_2 L^2 + \ldots A_p L^p)]^{-1} \mu_t = D\mu_t = D_0 \mu_t + D_1 \mu_{t-1} \ldots$$

Where A is the reduced-form VAR coefficients and D are the MA coefficients on the reduced form innovations (μ) 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 VAR coefficients:

$$S_{YY}(\omega) = D(e^{-i\tau\omega})\Sigma_\mu D(e^{-i\tau\omega})' = \sum_{\tau=-\infty}^{\infty} \gamma(\tau) e^{-i\tau\omega}$$

To assess the spectral density within a frequency band, the spectrum can be summed within the band of interest:

$$S_{YY}(\text{band}) = \sum_{\text{Lower bound}}^{\text{Upper bound}} S_{YY}(\omega)$$

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

Given the limited sample size under consideration, the MA-coefficient matrix D is constrained to the 1-10 year horizon, which has been shown to reduce estimation bias (Dieppe, Francis, and Kindberg-Hanlon 2019; Francis et al. 2014).

Estimation

Each VAR is estimated using annual data. Table A.6.1.1 provides summary statistics on the data length available in each income group.

TABLE A.6.1.1 Median sample periods

	Spectral SVAR
AEs	1973-2018
EMDEs	1981-2018
LICs	1981-2018

Panel VAR framework for IRFs

A panel VAR is used to estimate the IRFs shown in several figures. Here, advanced economies and EMDEs are separately estimated in panel estimations to illustrate the "typical" effects of technology and primary business-cycle shocks on economies in both groups, and also for some subgroups (for example, high and low industrial employment share change economies).

The estimation takes the form $Y_t^n = C^n + \sum_{\tau=1}^{k} B_\tau Y_{t-1}^n + u_t$

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

Robustness of lag-length. 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, including the employment impact of SVAR-identified technology shocks, are robust to including four lags (accounting for four years of data).

Robustness to additional variables. Including additional variables does not materially change impulse responses but does reduce data availability. For advanced economies, including the log-change in the exchange rate and the IMF estimated cyclically-adjusted primary balance results in similar employment effects to the core specification used in Figure 6.4. In EMDEs, data availability for cyclically-adjusted primary balances is poor prior to 2000, so only the log change in the exchange rate is included. Once again, IRFs are largely the same as in the core specification, with the exception of the inflation response, which is smaller.

Robustness to sample time period. Results for both the technology shock and demand shock are robust to changing time periods. Using data for just the past 25 years results in a technology shock that reduces employment by 0.1 percent for each 1 percent boost to labor productivity in EMDEs, and a 0.2 percent reduction in advanced economies. Excluding the financial crisis and post-financial crisis periods in the panel estimation of the demand shock for EMDEs continues to result in a persistent impact on labor productivity (but not TFP), while the advanced economy impulse response for labor productivity fades within the 10-year horizon, as in the whole sample estimation.

TABLE A.6.1.2 SVAR literature summary of technology shocks on employment

Study	Coverage	Methodology and measure of labor input	Finding—Sign of effect on labor input	Finding—Persistence
Galí (1999); Gali (2005)	G7 economies	Long-run identifications. Effect on hours worked.	Negative initial impact in all economies except Japan.	Persistent negative impact to 3 years in Italy, UK, Germany, and France. Less than one year in Canada and the U.S.. No significance levels are shown.
Christiano, Eichenbaum, and Vigfusson (2003)	U.S.	Long-run. Effect on hours. In contrast to many other long-run identifications, hours are measured in log-levels, not log-differences.	Positive	Not persistent
Francis and Ramey (2005)	U.S.	Long-run. Effect on hours worked.	Negative	Persistent in some specifications but not statistically significant.
Francis (2009)	U.K.	Long-run. Effect on hours worked.	Negative	Negative impact for one year
Collard and Dellas (2007)	U.S.	Long-run. Effect on hours worked.	Negative	Persistent in some specifications to the five-year horizon but not statistically significant.
Dupaigne and Fève (2009)	G7	Long-run. Effect on employment	Negative except for the U.S. Positive for aggregated data for G7.	Persistently negative in Italy, France, and the UK for three years. Only statistically significant persistence in Italy.
Francis et al. (2014)	U.S.	Max-Share. Effect on hours worked.	Negative	Negative impact for less than 2 years.
Fisher (2006)	U.S.	Long-run, with separate identifications for neutral technology shocks and investment-specific technology shocks.	Negative for both neutral and investment-specific technology shock.	Effects fade in less than two years.
Canova, Lopez-Salido, and Michelacci (2010)	U.S.	Long-run, with separate identifications for neutral technology shocks and investment-specific technology shocks. Effect on hours.	Negative for neutral technology shocks. Positive for investment-specific technology shocks	Neutral technology shocks have persistent effects for 5-6 years.
Canova, Lopez-Salido, and Michelacci (2013)	U.S.	Long-run. Long-run, with separate identifications for neutral technology shocks and investment-specific technology shocks. Effect on hours and unemployment, job separation rates and job-finding rates.	A rise in job separation rate drives unemployment higher.	Unemployment rate persistently higher for over 5 years in response to neutral technology shock, due to the slow recovery of the job-finding rate.
Rujin (2019)	G7	Long-run identification. Effects on hours and employment	Negative effects on employment and hours in Canada, Germany, the U.S., France, Italy. Neutral effects on employment in Japan and France but negative effects on hours.	Persistent negative effects in the U.S., Canada, UK, France, Germany, Italy.

ANNEX 6.2 Commodity-driven productivity developments

Two-thirds of EMDEs depend significantly on agriculture or mining (including oil drilling) and quarrying for export revenues, and more than half of the world's poor live in such commodity-exporting EMDEs. Therefore, externally driven fluctuations in commodity demand and prices have potentially important implications for productivity growth in EMDEs. Beginning in 2000, commodity prices surged in the run-up to the global financial crisis, then began declining in 2011. A 50 percent fall in energy prices in 2014-15 weighed on prospects for returns on investment in commodity exporters. These price changes have driven large fluctuations in productivity growth (Kose et al. 2017).

Most energy price fluctuations historically have been attributed to global demand rather than supply-side factors (Kilian 2009; Kilian and Hicks 2013; Kilian and Murphy 2014). A large proportion of movements in agricultural and metals prices in recent decades have also been estimated to have been related mainly to common global demand factors such as the increasing consumption of these products in Asia, particularly China (Chiaie, Ferrara, and Giannone 2017; Gervais, Kolet, and Lalonde 2010).

Previous analysis has generally found that commodity price changes explain over half of the volatility of investment in commodity-exporting EMDEs (Fernández, González, and Rodríguez 2018; Kose 2002).[1] The evidence on the impact of commodity price changes on TFP growth is varied, with some studies finding little evidence of any short-term or long-term effect of commodity price changes on TFP in exporters (Aslam et al. 2016). Other studies find some synchronization of TFP with commodity prices (Kataryniuk and Martínez-Martín 2018).

Methodology. The "local projection" methodology of Jordà (2005) is used to assess the impact of commodity price changes on a range of productivity measures. The local projection is estimated up to a horizon of 10 years and controls for developments in global demand that could be driving commodity price changes by using export-weighted GDP growth for each economy (Annex 6.3). The estimation is performed on the components of labor productivity growth in the growth accounting framework—the contributions of capital deepening and TFP growth—thus allowing a deeper examination of the transmission of commodity price fluctuations to productivity. The local projection estimates are obtained separately for exporters of agricultural products and exporters of metals and energy using the World Bank's Pink Sheet measures of real commodity prices for each category.

Effects of commodity price shocks on agricultural exporters. Commodity price changes have had highly persistent effects on labor productivity in EMDE agricultural exporters (Figure A.6.2.1). Following a 10 percent agricultural price rise in real terms, labor

[1] Drechsel and Tenreyro (2018) find, for Argentina, that up to 60 percent of the variance of investment growth could be explained by commodity price fluctuations.

productivity and GDP in EMDE agricultural exporters have tended to be 2.0-2.5 percent higher after 10 years.[2] This rise is accounted for by capital deepening and TFP growth in similar proportions.

Metals exporters. In metals exporters, the effect on labor productivity, reaching 1.1 percent after 5 years, is smaller than for agricultural exporters and less persistent. In this case, most of the rise is accounted for by increased capital deepening, and the effects fade after five years.[3] The effect on TFP growth is neutral in the long-term.

Oil exporters. For oil exporters, oil price rises boost GDP growth temporarily and capital deepening persistently but do not improve labor productivity due to a corresponding fall in TFP growth. Following a 10 percent rise in oil prices, GDP is 0.8 percent higher after 5 years, with a similar increase in the contribution of capital deepening to labor productivity growth. However, TFP falls by 0.8 percent after 5 years and 1.5 percent after 10 years.

Persistent effects on TFP in agriculture. Rising agricultural prices can trigger structural improvements in labor productivity through several channels. The agriculture sector generally has the lowest productivity level across sectors, often significantly lower than mining-related activities, and so may benefit from higher demand to implement newer technologies and more capital into the production process where producers are often finance-constrained (Chapter 7). In addition, rising incomes in the agricultural sector can facilitate reallocation to more productive and efficient sectors by increasing demand for manufacturing and service-sector products (Emerick 2018).

Capital deepening dominates in extractive commodity producers. Sectoral analysis has also found that rising commodity prices are often accompanied by declining within-sector TFP in the extractives sector, along with rising capital deepening and muted effects on sectoral reallocation (Aslam et al. 2016). One reason for the decline in TFP in response to rising prices is that they incentivize the extraction of increasingly capital-intensive and low-return land resources, reducing the efficiency of production (Byrne, Fernald, and Reinsdorf 2016; Dabla-Norris et al. 2015).[4] SVAR evidence for a range of metals exporters finds effects of metals price changes on GDP of a similar magnitude to the local projection estimates in this chapter (Fornero, Kirchner, and Andres 2014). These are also found to operate primarily through the investment channel (not affecting TFP) and to begin to fade near the 5-year horizon.

[2] Examining the effects of commodity price shocks at the 7-year horizon, Aslam et al. (2016) find similar evidence of persistent productivity and output effects in agricultural goods exporters, and less evidence of persistence in a combined sample of metals and oil exporters.

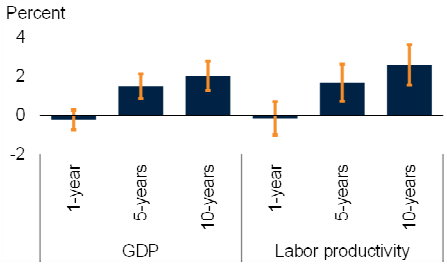
[3] This is consistent with previous analysis of the effects of changing metals prices in Chile, a major copper-exporter, with the effects of price changes on labor productivity fading after 5 years and no effect on TFP (Eyraud 2015).

[4] In the United States, TFP in the mining sector has tended to decrease following oil price increases as it has become economic to drill in less-accessible sources. Byrne, Fernald, and Reinsdorf (2016) estimate that TFP growth measures are understated by about 5 basis points per year in the years following the introduction of fracking in the Unites States, not accounting for the changing quality of natural resources used in production.

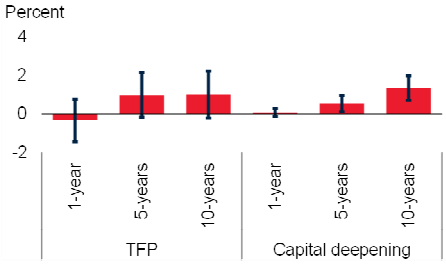
FIGURE A.6.2.1 Effects of commodity prices on productivity in EMDEs

Commodity price shocks are key drivers of productivity growth in commodity-exporting EMDEs. In agricultural and metal exporters, labor productivity is estimated to rise by 1- 2 percent after five years following a 10 percent rise in commodity prices, with the effect lasting for 10 years and rising further in agricultural goods exporters. Most of the effect is accounted for by capital deepening in the case of metals exporters, while agricultural goods exporters experience persistently higher TFP growth. In oil exporters, GDP rises sharply following a 10 percent rise in oil prices, while there is also a significant increase in the contribution of capital deepening, but productivity is relatively unchanged, with a statistically significant decline in TFP offsetting these gains.

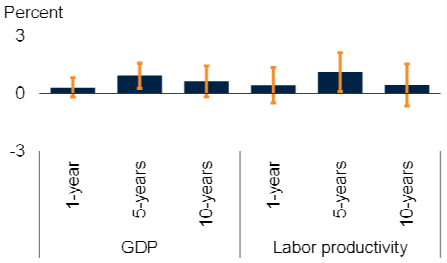
A. Agriculture exporters: GDP and labor productivity



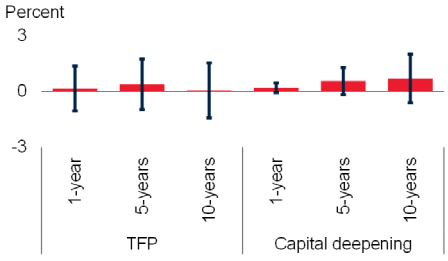
B. Agriculture exporters: TFP and capital deepening



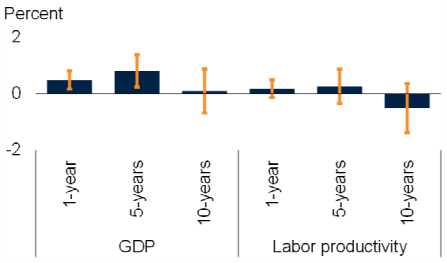
C. Metals exporters: GDP and labor productivity



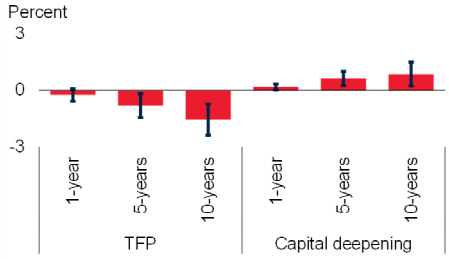
D. Metals exporters: TFP and capital deepening



E. Oil exporters: GDP and labor productivity



F. Oil exporters: TFP and capital deepening



Source: World Bank, Penn World Table, Haver Analytics.

Note: Local projection estimates of commodity price shock on the level of GDP, productivity growth accounting components. The response is the cumulative change in the level of each variable to a 10 percent rise in real commodity prices. The commodity price is measured as the log-change in the World Bank's Pink book real commodity price series for agricultural goods, metals, and energy products for each group of economies respectively. The specification controls for external demand, and lags of the endogenous variable and shock. "Capital deepening" reflects the contribution of capital deepening to labor productivity. Local projections are performed on 15 agricultural exporters, 10 metals exporters, and 14 oil exporters with all measures available since at least 1990. Further details are available in Annex 6.3.

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To summarize, demand drivers can have smaller, but still important, longer-term effects on labor productivity, particularly in economies with little fiscal space and in commodity exporters. Historically, with the exception of agricultural goods exporters, these longer-run effects have occurred primarily through capital deepening, with evidence of some negative effects of positive demand shocks on the overall efficiency of production (TFP).

ANNEX 6.3 Commodity-driven productivity developments: Methodology

A local projection model was used to estimate the effects of commodity price changes on GDP, labor productivity, capital deepening and TFP. The model follows Jordà (2005) in estimating impulse responses over a series of horizons, in this case from one to 10 years. Agricultural, metals, and energy exporters are separately estimated in panel specifications using fixed effects. Commodity price (real U.S. dollar indices) changes are assumed to be exogenous to each country in the specification. However, this property may be violated where individual economies are associated with the price change, for example, due to supply disruptions in individual economies that are large enough to influence global commodity prices.

In addition, the local projection specification controls for changes in global demand conditions which may be driving the commodity price change, including those that occur before and after the commodity price shock under examination. This control is constructed as an export-weighted aggregate of global GDP growth of each country under consideration.

The outcome variable y_t reflects the log-level of GDP, labor productivity, the cumulative contribution of capital deepening to labor productivity growth, and the log level of TFP. In addition to controlling for global demand (D_t), the specification controls for lagged values of the growth of the outcome variable (dy_{t-1}) and lagged values of the commodity price series (Δp^{com}_{t-1}) to reduce bias associated with serial correlation of commodity price changes and the productivity variables. The estimation is performed for each period h from 1 to 10 years.

$$y_{t+h} - y_{t-1} = \alpha^{i}_{h} + \beta_{h}\Delta p^{com}_{t} + \gamma^{p}_{h}\Delta p^{com}_{t-1} + \gamma^{y}_{h} dy_{t-1} + \sum_{i=0}^{1}\gamma^{d}_{i} D_{t-i} + \sum_{j=1}^{h}\gamma^{d}_{i} D_{t+j} + \epsilon_{t+h}$$

It has been argued that for a true IRF representation, subsequent developments in the shock of interest should be controlled for (Alloza, Gonzalo, and Sanz 2019). Including leading changes in commodity price changes results in larger impacts, but does not alter the qualitative channels through which price shocks operate, or the qualitative differences between the transmission channels in each type of commodity exporter.

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