CHAPTER 7

Sectoral Sources of Productivity Growth

Sectoral reallocation—the shift of labor from low- to high-productivity sectors—has accounted for about two-fifths of overall labor productivity growth in emerging market and developing economies (EMDEs) between 1995 and 2017. Over 2013-17, productivity gains from reallocation slowed as productivity gaps narrowed between different sectors. The disruptions caused by the COVID-19 pandemic may further exacerbate this slowdown. Over the medium-term, policy measures to improve agricultural productivity, such as actions to improve infrastructure and strengthen land property rights, and steps to facilitate the reallocation of workers to other sectors, can raise productivity.

Introduction

Factor reallocation towards higher-productivity sectors have long been recognized as one of the most powerful drivers of overall productivity growth (Baumol 1967). They have been identified as an important driver of productivity growth in many emerging market and developing economies (EMDEs), including in regions as diverse as Sub-Saharan Africa (SSA) and East Asia and Pacific (EAP; Cusolito and Maloney 2018; de Vries, de Vries, and Timmer 2015). The transfer of labor out of agriculture into higher-productivity industry has long been recognized as a major source of productivity growth in the industrialization process, and in recent decades shift of labor from agriculture into manufacturing and services have been credited as a major contributor to rapid productivity growth, especially in East Asia, including China (Helble et al. 2019).

After several decades of reallocation out of agriculture, the sector in 2017 accounts for 30 percent of employment in EMDEs—compared with 50 percent less than two decades ago—and less than 10 percent of value-added. In low-income countries (LICs), however, agriculture still accounts for over 60 percent of employment, partly explaining the low overall productivity observed in these countries (Caselli 2005; Restuccia, Yang, and Zhu 2008).

After rapid growth of services sectors in EMDEs over the preceding two decades, in 2017 they accounted for about 40 percent of employment, still below their 75 percent share in advanced economies. Productivity growth in services sectors was the main source of overall productivity growth in EMDEs in the period following the global financial crisis (GFC), accounting for almost two-thirds of overall productivity growth in the average EMDE (compared with one-fifth accounted for by industry) and more than nine-tenths in the average LIC.

Note: This chapter was prepared by Alistair Dieppe, and Hideaki Matsuoka. Cedric Okou authored the box. Bala Bhaskar Naidu Kalimili and Charles Yao Kouadio Kouame helped compile the sectoral database. Research assistance was provided by Xinyue Wang.

Productivity gains through factor reallocation have slowed after 2008, after contributing to the steepest and most prolonged slowdown in EMDE productivity growth since the 1980s (Chapter 1).[1] The COVID-19 pandemic may slow reallocation further. The widespread restrictions on physical interaction and mobility that have been introduced by governments to combat the COVID-19 pandemic, together with self-imposed restraints with similar effects, may not only damage within-sector productivity through its effects on health, business models, and workplace practices, but also reduce inter-sectoral factor mobility and the associated gains in productivity growth (World Bank 2020).

Against this backdrop, this chapter addresses the following questions :

- How large are productivity gaps across sectors?
- What has been the role of sectoral reallocation in overall labor productivity growth?
- How might government policies help raise sectoral productivity growth?

Contributions

This chapter extends the literature in two dimensions.

First, the chapter employs the most comprehensive dataset of sectoral labor productivity available, with data for nine sectors.[2] Past analysis had limited country or time coverage.[3] The updated dataset includes sufficient recent data to allow an analysis of developments following the GFC.

Second, the rich sectoral detail allows an analysis of the heterogeneity of industrial and services subsectors within and across countries, as well as within-sector and between-sector developments that are sensitive to aggregation bias (de Vries et al. 2012; Üngör 2017). This sectoral analysis is complemented by firm-level analysis that points to drivers of within-sector productivity growth (Box 7.1).

Main findings. The chapter offers several novel findings:

First, the chapter documents large productivity gaps across the nine sectors and also across countries within each of the nine sectors. In the average EMDE, productivity in agriculture, the lowest-productivity sector, is 85 percent lower than the average productivity. In advanced economies, the corresponding difference is considerably narrower. Agriculture accounts for less than 10 percent of value-added and around 30 percent of employment in EMDEs. The gap between EMDE and advanced-economy

[1] Unless otherwise indicated, productivity is defined in this chapter as value added per worker.

[2] The nine sectors distinguished in the dataset are agriculture, mining, manufacturing, utilities, construction, trade services, transport services, financial and business services, and government and personal services. Annex 7.1 provides additional details.

[3] McMillan, Rodrik, and Verduzco-Gallo (2014) and Diao, McMillan, and Rodrik (2017) employ 38 and 39 countries; Martins (2019) use 7 sectors and 169 countries, International Monetary Fund (2018) use 10 sectors and 62 countries and (McCullough 2017) have 16 sectors for U.S. and EU10.

productivity is particularly wide in agriculture, with EMDES less than 20 percent of advanced economies. This partly reflects slow technology adoption in the agriculture sector in some of the poorest EMDEs. Within manufacturing, productivity is highest among firms with a high share of exports in output. Those that operate in a conducive business environment are also closer to the global technology frontier (Box 7.1).

Second, sectoral reallocation accounted for two-fifths of overall productivity gains between 1995-2017. This shift lost momentum after the GFC. This slowing sectoral reallocation accounted for two-fifths of the productivity growth slowdown in EMDEs between 2013-2017. By curtailing labor mobility as well as economic activity, the COVID-19 pandemic may further slow sectoral reallocation.

Third, policies can both rekindle sectoral reallocation and boost productivity in low-productivity sectors. Policies to support labor mobility and capital investment include: improving the quality of, and access to, education; promoting good governance and reducing the costs of doing business; strengthening institutional and managerial capabilities; reducing distortions, such as anticompetitive regulations and subsidies; supporting research and development; and removing infrastructure bottlenecks. Given the low productivity of EMDE agricultural sectors and agriculture's role as the primary employer in LICs, policies to raise productivity in this sector, such as actions to strengthen infrastructure and improve land property rights, could pay particularly significant dividends.

Methodology. The chapter estimates a "shift-share" decomposition of overall labor productivity growth in an economy into within- and between-sector components (Padilla-Pérez and Villarreal 2017; Wong 2006).[4] *Within-sector* productivity growth captures that part of overall labor productivity growth that is due to productivity improvements within sectors. This may reflect the effects of improvements in human capital, investments in physical capital, technological advances, and the reallocation of resources from the least to the most productive firms within each sector. Between-sector productivity growth captures the part of overall labor productivity growth that is driven by the reallocation of resources between sectors—both between sectors with different productivity levels (static sectoral effect), and between sectors with different productivity *growth rates* (dynamic sectoral effect).

Data. The database includes value added and employment for nine sectors during 1975-2017 in 103 countries: 34 advanced economies and 69 EMDEs, of which nine are low-income countries. For 94 countries, of which 60 are EMDEs, the database is balanced for 1995-2017. The nine sectors include three primary sectors (agriculture, forestry, fishing); four industrial sectors (mining, utilities, manufacturing, constructions), and four services sectors (wholesale and retail trade, transport, financial and business services, other services). The database combines data from the World Bank's World Development Indicators database, the OECD STAN database, KLEMS, the Groningen Growth Development Center database (de Vries, Timmer, and de Vries 2015), and the

[4] See the Annex 7.1 for details.

Expanded Africa Sector Database (Mensah and Szirmai 2018). The APO Productivity Database, UN data, ILOSTAT, and national sources are used for supplementary purposes. Following (Wong 2006), local currency value-added is converted to U.S. dollars using the 2011 PPP exchange rate obtained from Penn World Table for international comparisons of productivity levels.[5]

Sectoral productivity gaps

Still wide productivity differentials across sectors. Productivity differs widely across sectors, offering large potential productivity gains by factor reallocation across sectors (Figure 7.1; Gollin, Lagakos, and Waugh 2014; Rodrik 2013). Productivity in mining is usually high because the sector is highly capital intensive and dominated by major global companies. Productivity in agriculture tends to be lowest, in part due to the proportion of smallholder ownership and family farms (Cusolito and Maloney 2018; Fuglie et al. 2020; Lowder, Skoet, and Raney 2016).[6] But there are also some services subsectors, such as trade services, with productivity below that of manufacturing.

In the average EMDE, productivity in the lowest-productivity sector—agriculture, which accounts for 10 percent of value-added and 32 percent of employment—is 85 percent lower than the average productivity.[7] In advanced economies, the corresponding difference is considerably narrower.

Over time, the productivity gap between the agricultural sector and other higher productivity sectors has narrowed. Thus productivity in higher-productivity sectors, relative to productivity in agriculture, declined in the average EMDE from 350 percent in 1995 to 310 percent in 2017 and, in the average LIC, from 500 percent in 1995 to 400 percent in 2017.

Wide sectoral productivity differentials across countries. Productivity in all sectors is lower in EMDEs than in advanced economies, and lower again in LICs. Agriculture productivity in EMDEs is 20 percent of advanced-economy productivity. In part, this gap reflects slow technology adoption in the agriculture sector in some of the poorest EMDEs, which tend to be characterized by smallholder ownership and family farms (Lowder, Skoet, and Raney 2016). In mining, where production is dominated globally

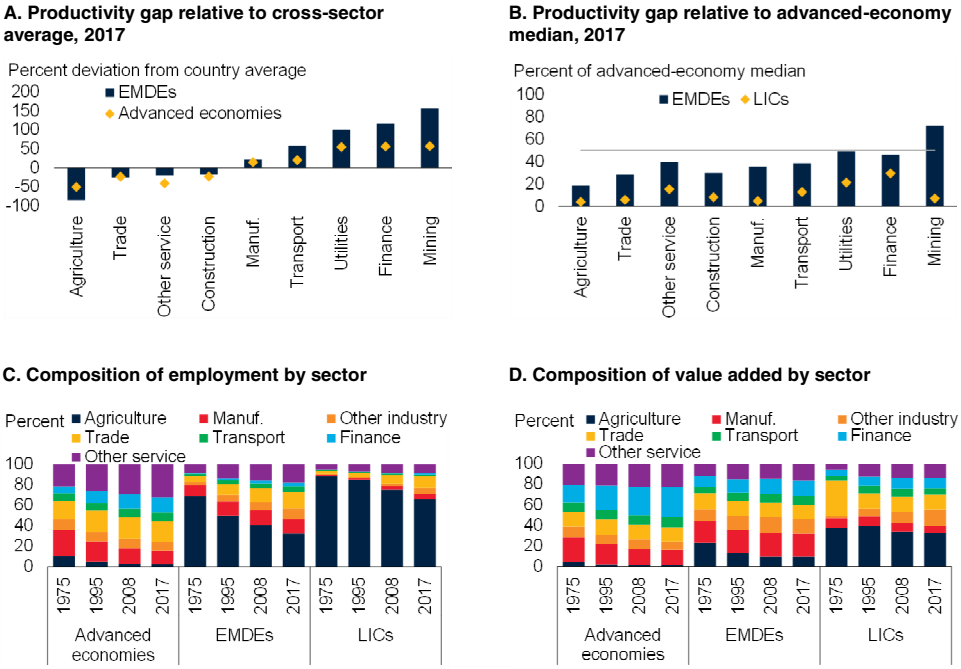
[5] van Biesebroeck (2009) builds expenditure-based sector-specific PPP estimates for OECD countries, using detailed price data.

[6] Mechanization tends to increase agricultural labor productivity through both capital deepening and embodied new technology, but mechanization in LICs is often hindered by frictions such as untitled land (Chen, 2017). Also, Restuccia, Yang, and Zhu (2008) show that agricultural labor productivity is positively associated with the use of relatively advanced intermediate inputs (e.g., modern fertilizers and high-yield seeds) and argue that certain distortions in factor markets may severely dampen the incentives for their use.

[7] This is consistent with findings by Bartelsman and Doms (2000) and Levchenko and Zhang (2016). As agricultural workers often do not work full time in agriculture, the sectoral gap is diminished if productivity is measured per hours worked instead of per worker (Gollin, Lagakos, and Waugh 2014). However, even after taking into account hours worked and human capital per worker, a large sectoral gap remains for a large number of countries (Hicks et al. 2017).

FIGURE 7.1 Sectoral labor composition and productivity gaps

EMDEs are characterized by large, albeit narrowing, productivity gaps across sectors. Gaps are larger in EMDEs than advanced economies. The share of agricultural employment in advanced economies has been small for several decades and continues to decline, whereas the services sector continues to increase. In EMDEs, the share of the agriculture sector has nearly halved since 1975 but remains large in LICs.



Source: APO; EASD; GGDC; ILO; KLEMS; national sources; OECD; United Nations; World Bank.
Note: Based on samples of 94 countries during 1995-99 and 103 countries during 2003-17. Median of the country-specific productivity within indicated country groupings. "Finance" includes business services; "Other service" includes government and personal services.
A.B. Average labor productivity is value-added per worker based on 2017 data. Horizontal line indicates 50 percent.
Click here to download data and charts.

by a few large companies, the productivity gap is considerably narrower (about 70 percent). Productivity gaps between advanced economies and EMDEs have narrowed only a little or have actually widened in agriculture, manufacturing, and utilities.

Sectoral productivity growth

Heterogeneous sectoral productivity growth. In the most recent sub-period examined, 2013-17, the sectors with the fastest growing productivity in the average EMDE were agriculture, trade, and transport services, with annual growth rates between 1.5 and 3.0 percent (Figure 7.2). This differs from the period before the GFC, 2003-08, when manufacturing was the sector with strong productivity growth. Productivity growth was near-zero or negative in both sub-periods in finance and in the more recent sub-period

in mining, and other services. In advanced economies, post-2013 productivity growth was strongest in mining and manufacturing, notwithstanding a slowdown in manufacturing, and near-zero in utilities, finance, and other services.

Sectoral productivity growth slowdown. In EMDEs, productivity growth slowed post-crisis (2013-17) from its pre-crisis (2003-08) rates in one-half of the sectors. The sector with the steepest slowdown, of over 2 percentage points was manufacturing. The regions that experienced the sharpest slowdown were Latin American and the Caribbean (LAC) and South Asia (SAR). In SAR and SSA, and in the LICs, the productivity slowdown in agriculture was particularly marked as commodity prices collapsed. In contrast, EMDE productivity growth increased slightly up in 2013-17 in construction, and utilities. In the advanced economies, productivity growth strengthened post-GFC in sectors such as trade, transport, utilities and construction.

Sectoral contributions to post-crisis productivity growth slowdown. Overall labor productivity growth in EMDEs accelerated ahead of the GFC but subsequently slowed (Chapter 1).[8] More than one-third of the post-GFC slowdown in overall productivity growth in the average EMDE is accounted for by slower growth in the manufacturing sector and another one-third by the finance and trade services sectors combined.[9] This partly reflects the persistent weakness of global trade after the GFC as well as the disruptions to global finance wrought by the financial crisis itself. 2010-2017, services accounted for two-thirds of productivity growth in EMDEs compared with one-fifth in the case of manufacturing.

Roles of between- and within-sector productivity gains. Between 1995 and 2017, advanced-economy productivity growth was almost entirely driven by within-sector productivity gains, whereas two-fifths of EMDE productivity growth, and more than one-half of LICs' productivity growth, was driven by sectoral reallocation (Figure 7.3).

In advanced economies, within-sector productivity growth in this period occurred mainly in the manufacturing, trade, and finance sectors.[10] Overall within-sector productivity growth slowed to 0.9 percent a year during 2013-17. This was compounded by slower reallocation-driven productivity gains (Duernecker, Herrendorf, and Valentinyi 2017).

In EMDEs, within-sector productivity growth accounted for about three-fifths of overall productivity growth since 1995. Within-sector growth was broad-based across sectors, reflecting gains in agriculture as well as trade, transport, and government and personal services. Between-sector productivity gains mainly reflected moves out of agriculture and manufacturing into services. The share of workers employed in

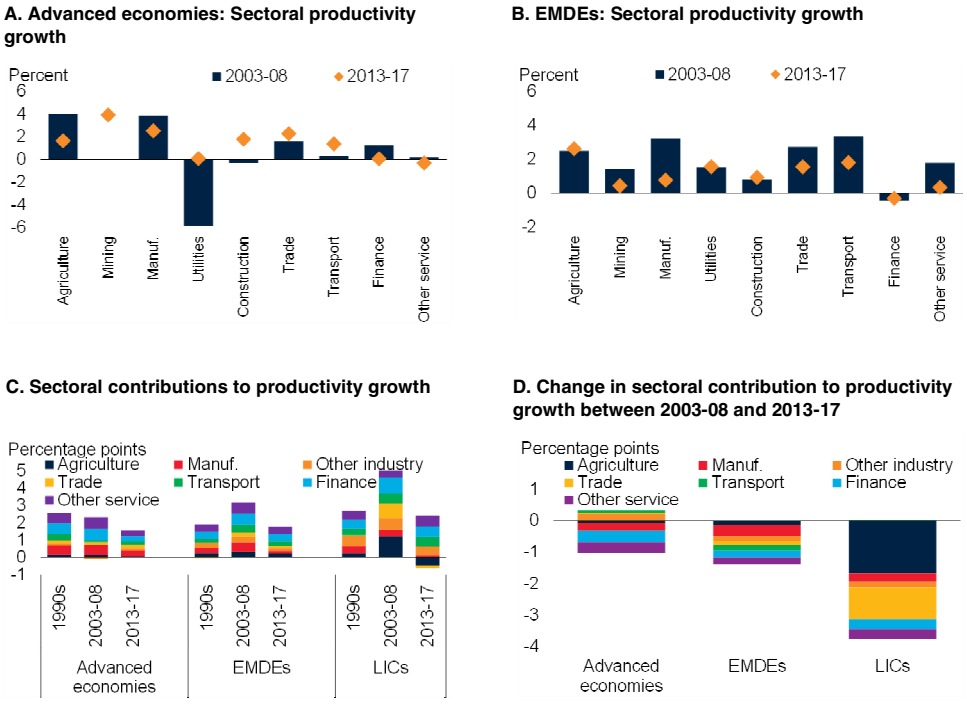
[8] This finding is broadly in line with the evidence in Hallward-Driemeier and Nayyar (2017).

[9] Sectoral productivity contributions are calculated by the difference between sectoral value-added contributions and sectoral employment contributions.

[10] In addition, prior to the GFC, productivity growth was boosted by shifts of factors of production to financial and business services, offsetting the negative effect of the decline in the share of employment in the manufacturing sector.

FIGURE 7.2 Sectoral labor productivity growth

In EMDEs, labor productivity growth slowed in most sectors following the global financial crisis, most markedly in manufacturing and non-financial services. In LICs, slower productivity growth in agriculture accounted for most of the overall productivity growth slowdown after the global financial crisis.



Source: APO; EASD; GGDC; ILO; KLEMS; national sources; OECD; United Nations; World Bank.
Note: "Other industry" includes mining, utilities, and construction; "Finance" includes business services; "Other service" includes government and personal services. All medians.
Click here to download data and charts.

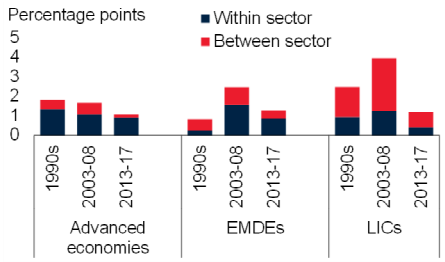
agriculture fell from about 70 percent in 1975 to about 30 percent in 2017. The effect of sectoral reallocations was particularly large in SSA but also important in SAR and EAP (McMillan, Rodrik, and Verduzco-Gallo 2014, and Diao, McMillan, and Rodrik 2017). In the post-GFC period, productivity gains from sectoral reallocation declined across most EMDE regions compared to the pre-GFC period. In the EMDE, slowing sectoral reallocation accounted for two-fifths of the slowdown in productivity growth between 2013-17 and 2003-08.

In LICs, sectoral reallocation accounted for more than one-half of overall productivity growth between 1995 and 2017 but, as in other EMDEs, it lost momentum after the GFC. The contribution of sectoral reallocation to productivity growth declined from 2.7 percentage points a year during 2003-08 to 0.8 percentage points during 2013-17. Whereas between-sector productivity gains in LICs in the pre-GFC period reflected a

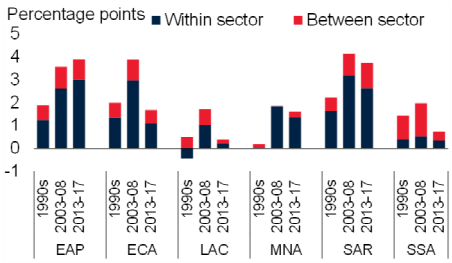
FIGURE 7.3 Between- and within-sector sources of productivity growth

While overall productivity growth in advanced economies has predominantly originated within sectors, between-sector gains have accounted for a sizable portion of both EMDE productivity growth, and its post-global financial crisis slowdown. In EMDEs, between-sector productivity gains have involved shifts out of agriculture into higher-productivity sectors that have differed over time .

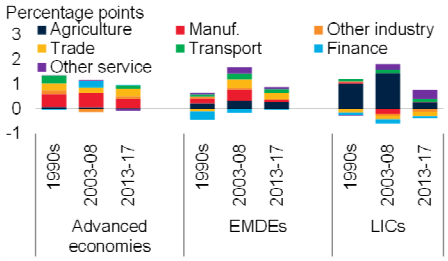
A. Within- and between-sector contributions to productivity growth



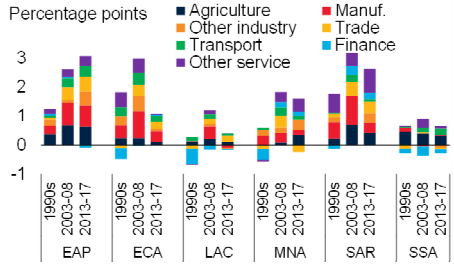
B. Within- and between-sector contributions to productivity growth: Regions



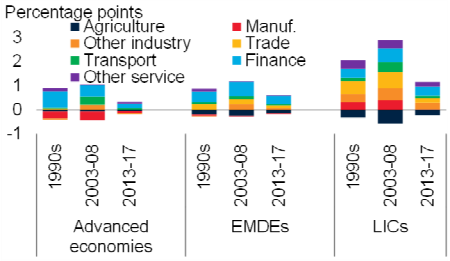
C. Contributions of within-sector growth



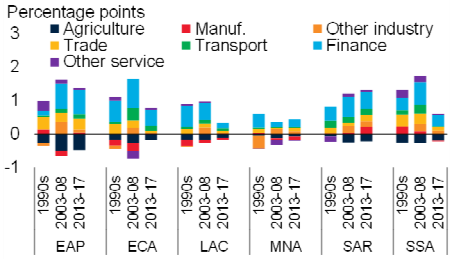
D. Contributions of within-sector growth: Regions



E. Contributions of between-sector growth



F. Contributions of between-sector growth: Regions



Source: APO; EASD; GGDC; ILO; KLEMS; national sources; OECD; United Nations; World Bank.

Note: Based on samples of 94 countries during 1995-1999 and 103 countries during 2003-2017. Median of the country-specific productivity.

A-F. Growth within sector shows the contribution of initial real value-added weighted productivity growth rate and between sector growth effect give the contribution arising from changes in the change in employment share. Median of the country-specific contributions. "Other industry" includes mining, utilities, and construction; "Finance" includes business services; "Other service" includes government and personal services.

Click here to download data and charts.

broad-based shift out of agriculture, in the post-GFC period the shift was mainly into services such as trade services and finance , with only limited shifts into manufacturing. The slowdown in between-sector productivity gains was compounded by a slowdown in the contribution of within-sector productivity gains from 1.2 percentage point a year in 2003-08 to 0.4 percentage point in 2013-17.

Sources of fading sectoral reallocation. In some commodity exporters, especially in LAC and SSA, the slowdown in sectoral reallocation after the GFC partly reflected lower absorption of labor by the services and construction sectors as weaker global commodity prices weighed on domestic demand (Diao et al. 2017). In EAP, it also reflected slower economic growth as productive overcapacity was gradually unwound.[11] In Europe and Central Asia (ECA), higher-productivity manufacturing, financial, and mining sectors suffered during the euro area debt crisis and the commodity price collapse in 2014-16. Meanwhile, in SAR, the move of labor out of low-productivity agriculture into more productive sectors accelerated as rapid urbanization continued and strong consumption growth fueled employment growth in higher-productivity trade services. While labor has continued to move out of agriculture in EMDEs, this process has slowed in all EMDE regions other than SAR.[12]

The COVID-19 pandemic has inflicted a severe shock on the global economy. Economic and financial disruptions like those that have resulted from the pandemic can increase sectoral reallocation, as workers shift from sectors most adversely affected to those less adversely, or favorably, affected (Foster, Grim, and Haltiwanger 2016). But the constraints on mobility resulting from the pandemic, together with the failure, at least in the short term, of job creation to keep pace with job destruction, seem likely to slow the process of reallocation (Barrero, Bloom, and Davis 2020; Chodorow-Reich and Wieland 2020).[13] If the COVID-19 pandemic discourages mobility out of agriculture into urban centers, productivity gains from sectoral reallocation may well slow, particularly in LICs (Hale et al. 2020; World Bank 2020). During the 2014-16 Ebola outbreak in West Africa, for example, the movement of labor out of agriculture slowed in Liberia and Sierra Leone.

Leapfrogging and de-industrialization. In decades past, the economic development of advanced economies typically involved a period of industrialization, as labor moved out of the agricultural sector into manufacturing, and a subsequent period of de-

[11] As highlighted in Chapter 6, this suggests a risk that productivity growth may slow in these regions as demand loses momentum.

[12] Alvarez-Cuadrado and Poschke (2011); Duarte and Restuccia (2007, 2010); Herrendorf, Rogerson, and Valentinyi (2013); Imrohoroglu et al. (2014); and Üngör (2013, 2017) show that productivity improvements in the agricultural sector, along with low income elasticity of demandfor food, explain most of the declines in agriculture's employment share in a closed economy. The move out of agriculture also depends on the extent of economic integration of the domestic economy and with global markets as well as the degree of subsidization and other barriers to reallocation (Barrett et al. 2017; Dercon and Christiaensen 2011; Rodrik 2016). In an open economy context, Uy et al. (2013) argue the role of international trade is quantitatively important for explaining sectoral re-allocation.

[13] Foster, Grim, and Haltiwanger (2016) found in the United States that reallocation effects increased in recessions prior to the GFC.

industrialization, as labor moved into the services sector.[14] However, in some EMDEs, labor has recently shifted directly from agriculture into services, a phenomenon dubbed "leapfrogging" (Rodrik 2016). In three EMDE regions (ECA, LAC, and MNA), labor has not only moved out of agriculture (as a share of labor) but also out of industry–another case of "de-industrialization" (Rodrik 2016). In these regions, employment has largely shifted into construction (MNA), finance (ECA, LAC) and trade services (ECA, MNA). Since some of these sectors, especially construction and trade services, have lower productivity than manufacturing, this has resulted in a sharply lower (ECA) or even negative (LAC, MNA) contribution of between-sector sources of productivity growth.

Leapfrogging has been encouraged by rapid growth in demand for services and slower growth in demand for labor-intensive manufactured goods (Eichengreen and Gupta 2013). In LICs, leapfrogging has primarily consisted of growth in traditional (personal) services. Especially in commodity-reliant countries, the increase in incomes arising from the commodity price boom during the 2000s may have boosted the demand for services, along with services employment (Rodrik 2015, 2018).[15] Leapfrogging has included the growth of modern services (financial, communication, computer, technical, legal, advertising and business) that have benefitted from the application of information technologies as well as the ability to trade across borders.[16] In the past, labor-intensive manufacturing traditionally absorbed significant quantities of unskilled labor (Stiglitz 2018).[17] The scope for unskilled labor to move into manufacturing has diminished because of rising global competition, robotization, and artificial intelligence (Bernard and Jones 1996; Eichengreen and Gupta 2013; Matsuyama 2009).

Policy implications

The redistribution of labor across sectors has been an important engine of productivity growth in EMDEs in recent decades. The sizable productivity gaps between different sectors that remain indicate that this source of growth still has significant potential. Yet there are obstacles. For example, the increasing complexity and automation of manufacturing processes, with their increased requirements of skilled labor, may make it increasingly difficult for countries to achieve gains in overall productivity from shifts in employment to high productivity sectors. This is among the considerations that point to the need for policies to support productivity growth across three dimensions:

[14] Manufacturing increases during low stages of development as capital is accumulated. At the next stage higher incomes drive up demand for services, while rising labor costs make domestic manufacturing less competitive: Boppart (2014); Buera and Kaboski (2009); Duarte and Restuccia (2010); and Herrendorf, Rogerson, and Valentinyi (2013, 2014).

[15] After the commodity boom, the contribution of between-sector growth in LAC and SSA fell in 2013-17.

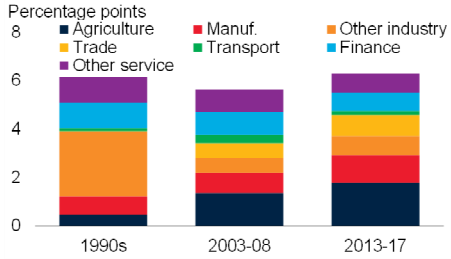
[16] Those services industries with the fastest productivity growth tend to be among the most intensive users of information and communication technologies (Stiroh 2002). Recent advances in those technologies are likely to have played an important role in boosting the productivity in the sectors that use them (Bosworth and Triplett 2003, 2007; Duernecker et al. 2017; Jorgenson and Timmer 2011). This second wave has occurred also in those LICs that are democracies and have high trade and financial openness (Rodrik 2016).

[17] It should be noted that refining and processing of extractives are sometimes classified as manufacturing in resource-rich countries.

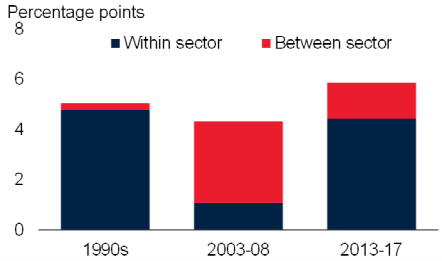
FIGURE 7.4 Policies

Vietnam's agricultural reform shifted employment toward manufacturing, trade, and other services, providing a significant boost to overall productivity growth.

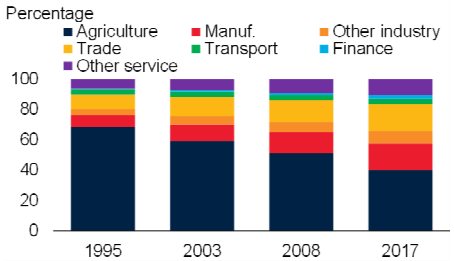
A. Sectoral contributions to productivity growth in Vietnam



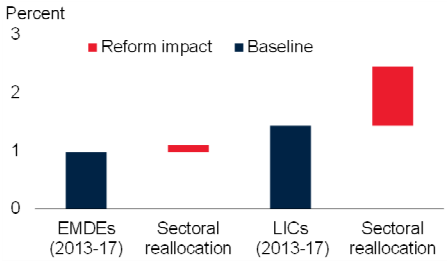
B. Within and between sector contributions to productivity growth in Vietnam



C. Sectoral employment shares in Vietnam



D. Productivity increase in sectoral reallocation scenario



Source: APO; EASD; GGDC; ILO; KLEMS; National sources; OECD; United Nations; World Bank.
D. The reform scenario assumes that the sectoral reallocation reform is calibrated for China and Vietnam, which experienced successful structural change during 2003-2008. More specifically, it assumes a decrease in the share of employment in the agriculture sector by 15 percent, a corresponding increase in the share of manufacturing and trade sectors.
Click here to download data and charts.

Improving agricultural productivity. While productivity in agriculture has been improving in EMDEs and LICs, it is still well below levels in advanced economies. Given that agriculture remains the primary employer in most LICs, raising productivity in this sector is key to boosting employment in other sectors, raising overall productivity, and reducing poverty. The experience of countries such as Vietnam suggests that agricultural productivity can be improved through targeted measures that improve the infrastructure that serves the sector, ensure secure land tenures, and promote access to finance (Figure 7.4).[18] If other EMDEs replicated the reallocation of

[18] Agricultural reforms in Vietnam have included the legalization of private economic activity, giving farms greater exposure to markets and competition by eliminating price controls and the state procurement system, strengthened household land property rights, relaxed restrictions on external and internal trade of agricultural goods and inputs, such as fertilizers. Vietnam succeeded with the expansion of manufacturing employment partly also through the liberalization of foreign investment. Foreign-owned firms, mainly labor-intensive manufacturing, accounted for over half of all exports by 2010, up from about a quarter in 1995 (McCaig and Pavcnik 2013).

BOX 7.1 Patterns of total factor productivity: A firm perspective

There is substantial variation in firm-level total factor productivity (TFP) across industries and across regions. Weak firm productivity in emerging markets and developing economies (EMDEs) partly reflects the divergence between a few highly productive firms and a large number of firms that operate far from the productivity frontier. The difference between frontier and laggard firms is, on average, larger in EMDEs than in advanced economies. Among EMDE firms, large firms tend to be more productive than small firms. Firms in technology-intensive industries, mainly located in East Asia and Pacific (EAP), Europe and Central Asia (ECA), and South Asia (SAR), tend to be more productive than firms in more traditional sectors. Measures to promote exports and improve business climates can help close the observed TFP gap.

Introduction

Firm-level productivity in emerging markets and developing economies (EMDEs) has been low relative to advanced economies, and growth has lost momentum over the past decade. This has diminished prospects among many EMDEs to catch up with the advanced economies.[1]

Numerous factors have been identified as underlying the low firm-level productivity observed in EMDEs: weak institutions and pervasive informality, slow technology innovation and adoption, subdued investment and poor quality infrastructure, low human capital and poor firm management practices, protectionist trade policies and weak economic integration (Cusolito and Maloney 2018; World Bank 2019a, 2019b).[2] Moreover, outdated technologies, lagging innovation, misallocation of labor to inefficient sectors, and market rigidities weigh on productivity and contribute to dispersion in total factor productivity (TFP) across countries (Araujo, Vostroknutova, and Wacker 2017; Bahar 2018; Syverson 2011). In some EMDEs, low participation in global value chains, or lack of openness to foreign direct investment and migration, has resulted in missed opportunities for a productivity boost through the transfer of innovative processes and managerial capabilities (Goldberg et al. 2010; Wolitzky 2018).

This box undertakes a cross-sectional study to analyze firm-level TFP patterns, and maps these to firm characteristics in EMDEs to address the following questions:

Note: This box was prepared by Cedric Okou.

[1] See Andrews, Criscuolo, and Gal (2016); Bloom et al. 2010; Cusolito and Maloney (2018).

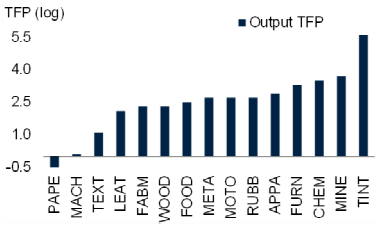
[2] Many studies focus on labor productivity, which depends on both TFP and capital per worker—also known as capital deepening.

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

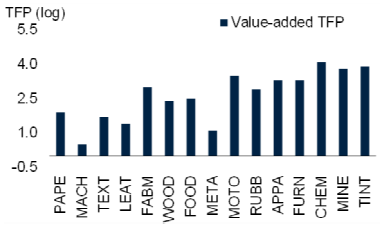
FIGURE 7.1.1 Firm TFP and distance-to-frontier in EMDEs by industry

Firms in technology-intensive industry (TINT) have higher average TFP. These technology-intensive firms are also more tightly clustered around their industry-specific frontier than firms in other sectors.

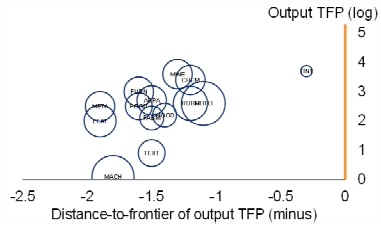
A. Output TFP estimates, by industry



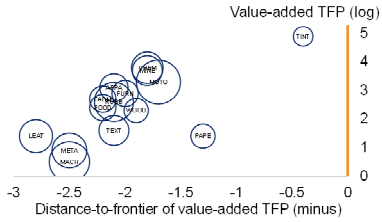
B. Value-added TFP estimates, by industry



C. Distance-to-frontier and average output TFP, by industry



D. Distance-to-frontier and average value-added TFP, by industry



Source: World Bank (Enterprise Surveys).

Note: Firm-level TFP is computed using a Cobb-Douglas production function, assuming that elasticities of output with respect to inputs are the same across countries in a given income group. The distance-to-frontier of TFP is computed within each industry, excluding the top 2.5 percent of firms. For each sector, the location shows the average and the size of the marker (circle) is proportional to one standard deviation of distance to frontier of TFP. Averages and standard deviations are computed using survey weights. Sample includes 15,181 firms in 108 EMDEs, including 20 LICs, for the period 2007-17. Table A.7.3.1 contains a description of each industry: APPA = apparel, CHEM = chemicals, FABM = fabricated metals, FOOD = food, FURN = furniture, LEAT = leather, MACH = non-electrical machinery, META = metals, MINE = non-metallic minerals, MOTO = motor vehicles, PAPE = paper, RUBB = rubber, TEXT = textiles, TINT = technology-intensive, WOOD = wood. The technology-intensive industry (TINT) includes firms in computing and electrical machinery, precision equipment, electronics, information, and communication sectors.

A.B. In the manufacture of paper (PAPE) industry, the value-added TFP is positive and much higher than the corresponding (negative) output TFP due to a relatively high elasticity of output with respect to intermediate inputs.

C.D. Distance-to-frontier of firm-level TFP (minus) and TFP (log), by industry. The right-hand-side y-axis represent the frontier.

Click here to download data and charts.

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

- How does firm-level TFP vary across EMDE sectors and regions?
- What firm characteristics account for the dispersion in TFP?

TFP variation across sectors and regions

Productivity varies across firms, within sectors, and across regions (Bloom et al. 2010; Goñi and Maloney 2017). By focusing on TFP, differences due to capital deepening or other factor inputs can be abstracted from. This allows to identify where TFP dispersion and gaps are the largest, and where steps are needed to improve productivity. Firm-level TFP data are obtained from surveys conducted by the World Bank from 2007 to 2017 (Cusolito et al. 2018). The database of survey results contains TFP for 15,181 manufacturing firms in 108 EMDEs, including 20 low-income countries (LICs). A cross-sectional analysis of the firm-level TFP database is undertaken, which complements longitudinal studies that use micro-level panel data, but with a smaller country coverage (Dall'Olio et al. 2014; Di Mauro et al. 2018).[3] Two measures of TFP are constructed: output and value-added revenue TFP measures. The latter is obtained by subtracting the value of intermediate inputs (materials, electricity, etc.) from output before computing TFP (Cusolito and Maloney 2018; Cusolito et al. 2018). TFP measurement challenges are discussed in Annex 7.3.

TFP across sectors. Differences in firm-level TFP across sectors have been frequently emphasized in the literature.[4] On average, firms in technology-intensive industries have higher TFP than those in other sectors (Figure 7.1.1.A-B). Technology-intensive industries, denoted by TINT (as in Fernald 2015), include computing and electrical machinery, precision equipment, electronics, information, and communication sectors (Table A.7.3.1). One explanation for this observation is that firms operating in a technology-intensive industry rely more on research and development (R&D) and network linkages than physical assets, and as such can reap the benefits of technology to boost productivity (Chevalier, Lecat, and Oulton 2012; Vaaler and McNamara 2010).

Distance to TFP frontier across sectors. TFP dispersion may signal rigidities in the generation, transfer and acquisition of technology across firms in a sector (Bahar 2018; Cette, Corde, and Lecat 2018). To assess within-sector productivity

[3] This analysis does not explore the time series dimension because World Bank's firm output and input data used to construct TFP estimates were collected at different time in different countries. For example, these firm surveys were conducted in 2007 in South Africa and in 2017 in Ecuador. Moreover, the number of surveyed firms in many countries is small, which does not allow to conduct robust within and cross-country comparisons.

[4] See for example, Bartelsman and Doms (2000); Bahar (2016); Levchenko and Zhang (2016); Restuccia and Rogerson (2013).

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

dispersion, a firm's distance to an industry-specific TFP frontier is computed.[5] Firms in basic manufacturing industries, such as non-electrical machinery (MACH), textiles (TEXT), leather (LEAT), and basic metals (META), are not only on average less productive than firms in other sectors, but also relatively far from their industry-specific frontiers (Figure 7.1.1.C-D). By contrast, firms in technology-intensive industries (TINT) are more tightly clustered around their industry-specific frontiers and more productive.[6]

TFP across regions. Across regions, firms in East Asia and Pacific (EAP) are, on average, more productive than those in other regions (Figure 7.1.2.A). EAP also has the highest proportion of large size firms and firms exporting more than half of their sales (Figure 7.1.2.C-D). Most firms in technology-intensive industries are located in EAP, Europe and Central Asia (ECA), and South Asia (SAR) (Figure 7.1.2.B). Perceptions of corruption and licensing as obstacles for firm operation seem to correlate negatively with total factor productivity (Figure 7.1.2.E-F).

Robustness of TFP dispersion. Substantial TFP dispersion may signal misallocation of factor inputs or rigidities in the generation, transfer, and acquisition of technology across firms (Hsieh and Klenow 2009; Restuccia and Rogerson 2008; Bahar 2016). However, commonly used dispersion metrics can also reflect mismeasurements, quality differences, adjustment costs, markups, and investment risks, among other factors. Recent evidence shows that half of the dispersion is unrelated to misallocation, and driven rather by markups and technology wedges (Cusolito and Maloney 2018). Thus, dispersion results should be interpreted with caution. Nonetheless, the variation in distance to frontier in technology-intensive industries is less than one-fifth of that in basic manufacturing industries (leather, metals, machinery), suggesting that firms in technology-intensive industries are much closer to their sector-specific frontier.

Firm characteristics associated with higher TFP growth

Heterogeneous characteristics related to entering, incumbent, and exiting firms can explain the observed patterns of TFP dispersion (Bartelsman and Doms 2000). A large and expanding literature points to three broad categories of correlates of sectoral TFP dispersion in EMDEs: within-firm upgrading and spillovers, and regulatory environment.

---

[5] For a given firm i, the distance to an industry-specific TFP frontier (97.5th quantile) is computed as $DTF_i = TFP_{0.975} - TFP_{i \leq 0.975}$. The top 2.5 percent firm-level TFP values are dropped to minimize the impact of extreme values. Results are robust to alternative 1 and 5 percent cutoffs of top firm TFP values.

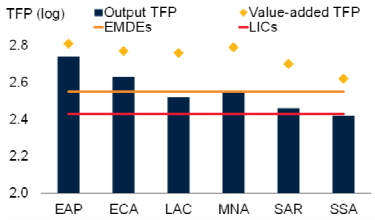
[6] This finding is broadly in line with the evidence in Hallward-Driemeier and Nayyar (2017).

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

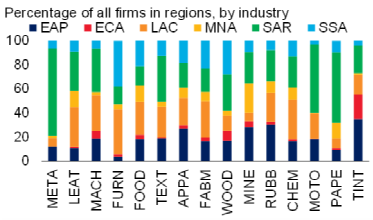
FIGURE 7.1.2 Firm TFP by regions

Firms in EAP are more productive than those located in other EMDE regions. EAP also has the highest share of large size firms and those exporting more than half of their sales. Most firms in technology-intensive industry (TINT) are located in EAP, ECA, and SAR. Perceptions of corruption and licensing as obstacles for firm operation seem to correlate negatively with total factor productivity (TFP).

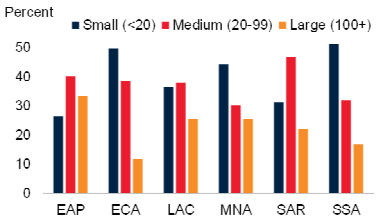
A. Firm-level TFP, by region



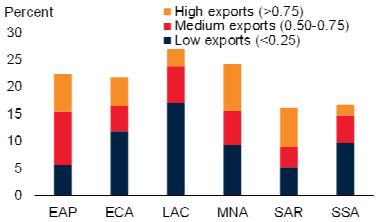
B. Percentage of firms in each region, by industry



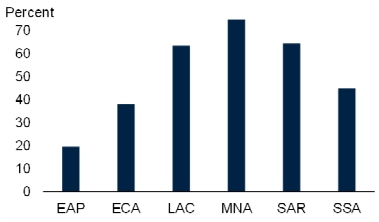
C. Firm size, by region



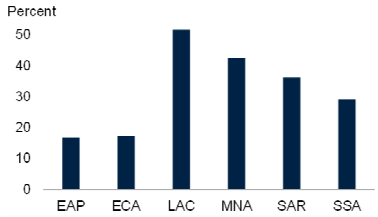
D. Exporting firms, by region



E. Perception of corruption, by region



F. Perception of licensing obstacle, by region



Source: World Bank (Enterprise Surveys).

Note: Firm-level TFP is computed using a Cobb-Douglas production function, assuming elasticities of output with respect to inputs are the same across countries in a given income group. Unweighted regional averages are computed. Sample includes 15,181 firms in 108 EMDEs, including 20 LICs, for the period 2007-17. 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, and SSA = Sub-Saharan Africa.

A. Solid lines are averages of output TFP (log) for EMDEs (orange) and LICs (red). EMDEs = emerging markets and developing economies, LICs = low-income countries.

B. Bars show in each industry the percentage of firms in each region, by industry (Table A.7.3.1).

C.D. Firm size in terms of number of employees (D) and Share of exporting firms (C). High, medium, and low exports firms export more than 75 percent, between 50 and 75, and up to 25 percent of their sales, respectively.

E. Share of firms that perceive corruption as an obstacle for their operations.

F. Share of firms that perceive licensing and permits as an obstacle for their operations.

Click here to download data and charts.

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

Within-firm upgrading and technology spillovers. Controlling for both size and exports, firms in the technology-intensive industry are on average much closer to the TFP frontier than firms in traditional industries such as non-electric machinery, food, and non-metallic minerals industries (Figure 7.1.3.A-B). Knowledge, experience, R&D, and information technology can raise TFP through improvements in product quality and production process upgrading within firms.[7] Firms with a large number of employees are significantly closer to the TFP frontier, as larger firms can invest more in R&D and bring together a richer set of ideas. On average, the productivity of a firm in the highest quartile of size is about 12 and 22 percent closer to output and value-added TFP frontiers relative to a firm in the lowest quartile of size (Figure 7.1.3.C). Moreover, technology in frontier firms can have positive spillovers for productivity in other firms through agglomeration linkages and cross-border flows of goods, capital and people. Firms can reap agglomeration benefits by emulating the best production practices and organization structures of "nearby" highly productive firms (Dercon et al. 2004; Syverson 2011). Knowledge is also transferred through contacts with other firms, courtesy of trade, foreign direct investment, and migration.[8] Firms with a high share of exports are significantly closer to the TFP frontier. A firm in the top quartile of exports, measured as a share of exports in total sales, is about 4 and 6 percent closer to output and value-added TFP frontiers relative to a firm in the lowest quartile of exports (Figure 7.1.3.C). Enabling effective innovation policies appears critical to boosting innovation gains (Cirera and Maloney 2017).

Regulatory environment. Institutions reflect political and legal forces that shape social and economic environments. Regulations and policies affect firms' productivity through incentives to acquire human capital, physical capital, and technology (Bartelsman and Doms 2000; Kouamé and Tapsoba 2018). Firm productivity tends to drop in poorly regulated markets, due to adverse incentives and the lack of creative destruction (Goldberg et al. 2010). In contrast, improvements in the business environment are associated with lower distance to TFP frontier, even after controlling for firm characteristics. Conducive regulatory practices—reflected in highest quartile values of business freedom index—may entail up to 9 percent reduction in the distance-to-frontier of TFP relative firms in the lowest quartile. Similarly, high quality governance—proxied by the top quartile estimates of control of corruption index—is associated with up to 12

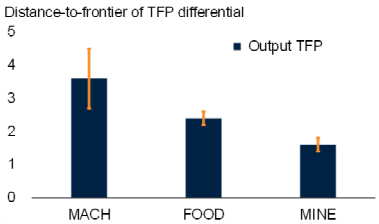
[7] See Atkin, Khandelwal, and Osman (2017); Brynjolfsson and Hitt (1995); Goldberg et al. (2010).
[8] See De Loecker (2007); Foster-McGregor, Isaksson, and Kaulich (2016).

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

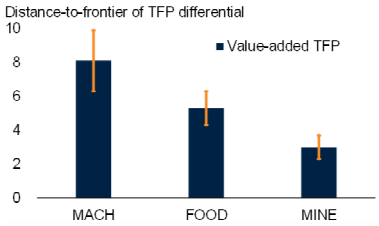
FIGURE 7.1.3 Distance-to-frontier of TFP, firm characteristics, and regulations

On average, a firm in the technology-intensive industry (TINT) is significantly closer to the frontier than a firm in non-electric machinery (MACH), food (FOOD), and non-metallic minerals (MINE) industries. As firms grow by their number of employees and ratios of exports to sales, they move closer to the TFP frontier. A conducive business environment supports TFP. Improvements in business freedom and control of corruption tend to reduce the distance-to-frontier of TFP.

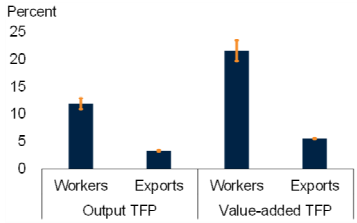
A. Distance to output TFP frontier differential between traditional industries and the technology-intensive industry



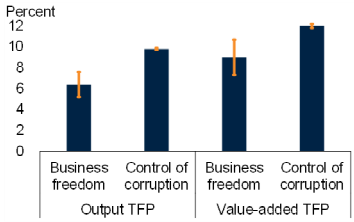
B. Distance to value-added TFP frontier differential between traditional industries and the technology-intensive industry



C. Distance to TFP frontier differential between firms in lowest and highest quartile of firm size and exports



D. Distance to TFP frontier differential between firms in lowest and highest quartile of business environment



Source: World Bank (Enterprise Surveys).

Note: The distance-to-frontier (DTF) of TFP is computed within each industry (Table A.7.3.1), excluding the top 2.5 percent of firms. Sample includes 15,181 firms in 108 EMDEs, including 20 LICs, for the period 2007-17. Based on OLS regressions of the DTF of TFP (dependent variable) on industry dummies (Panel A-C) and business environment quality (Panel D), controlling for firm characteristics and using the technology-intensive industry (TINT) as the base category (Annex 7.3).

A.B Distance-to-frontier of TFP differential between traditional industries, such as manufacturing of non-electric machinery (MACH), food (FOOD), and non-metallic minerals (MINE), and the technology-intensive (TINT) industry, controlling for firm characteristics (firm size and exports).

C. Distance to TFP frontier differential between the median firm in the lowest quartile and highest quartile of firms in terms of firm size (number of workers) and exports (share of exports in total sales). A positive DTF differential implies that firms in the lowest quartile in terms of size and exports are far from the frontier relative to firms in the highest quartile. The lowest quartile of exports is zero, as more than half of firms have no exports.

D. Distance to TFP frontier differential between the median firm in the lowest quartile and highest quartile of firms in terms of business freedom and control of corruption index, controlling for firm characteristics. A positive DTF differential implies that firms in the lowest quartile in terms of business freedom and control of corruption are far from the frontier relative to firms in the highest quartile.

Click here to download data and charts.

BOX 7.1 Patterns of total factor productivity: A firm perspective *(continued)*

percent drop in the distance to TFP frontier relative to firms in the bottom quartile (Figure 7.1.3.D).

Conclusion

The dispersion of firm-level TFP within and across industries in emerging markets and developing economies (EMDEs) is associated with various firm characteristics. TFP dispersion correlates negatively with firm size, partly because large firms can invest more in R&D to innovate. Exports also facilitate the transfer and adoption of new technologies, and therefore, can help close the gap between laggards and frontier firms. Moreover, a conducive business climate characterized by a greater freedom in entrepreneurship and less corruption can support TFP improvements. Undertaking policies to support R&D and innovation, promote exports, combat corruption, increase the ease of doing business, appears critical to boosting productivity.

labor from agriculture to manufacturing and services that occurred in China and Vietnam during 2003-08, it is estimated that this would lift their overall productivity growth by 0.1 percentage points a year (and by 1.0 percentage points a year in LICs).

Opportunities in services. Such secular trends as the declining employment share in manufacturing and the rise of automation may make manufacturing-led development increasingly challenging (Hallward-Driemeier and Nayyar 2017; Sinha 2016). On the other hand, many high value-added services sectors such as finance, information and communications technology, legal, and accounting, and legal services, provide opportunities for rapid productivity catch-up growth (Maloney and Nayyar 2018). However, governments have found it difficult to identify which sectors might play this role. The complexity and scale of interventions to foster new areas have often challenged their capacity to manage risks such as political capture by special interests (Hsieh and Klenow 2009).

Reduce barriers to reallocations. Supporting the efficient allocation of resources through the removal of market distortions can yield significant productivity gains—some estimates suggest that productivity in firms in India and China may be 30 to 60 percent lower than it could be if misallocation of capital and labor across sectors were eliminated (Hsieh and Klenow 2009). Reducing regulatory complexity and burdens, as well as reassessing the role of state-owned enterprises, can improve the ability of new firms to enter and compete in high-productivity sectors. Reducing subsidies, including energy

subsidies, can also reduce the misallocation of resources into low-productivity and inefficient energy-intensive sectors. Many high productivity manufacturing and service sectors activities are becoming increasingly skill intensive. Significant investment in human capital, including at the tertiary education level, would increase the ability of workers to be mobile across sectors and to work with new and more productive technologies (Chapter 2). Firms in EMDEs can update and improve their management styles and benefit from technology spillovers by participating in global value chains (Box 7.1). Furthermore, removing barriers to migration can help facilitate structural transformation.[19]

Future research. This chapter's findings point to three new directions for future research. First, the dataset used would allow a more granular assessment of the impact of the GFC, other major economic shocks, and country-specific recessions on the pace of labor reallocation and within-sector productivity growth. This could include differentiation between the nine sectors by their sensitivity to macroeconomic or financial stress. Second, the dataset could be used to assess whether countries that "leap-frogged" the manufacturing sector benefited from stronger productivity growth over long periods or during times of economic stress. Third, future research could tackle the endogeneity of sectoral reallocation. For example, an improvement in agricultural productivity could allow a reduction in agriculture's share of employment and facilitate between-sector productivity growth. In this case the causal contribution of agriculture productivity growth to overall productivity growth could be found to be larger (and that of sectoral reallocation smaller) than simple growth-accounting suggests.

ANNEX 7.1 Data and methodology

Data. The database consists of sectoral and aggregate labor productivity statistics for 103 countries, and nine sectors covering the period up to 2017 (Tables A.7.1.1 and A.7.1.2). Compared with the literature using nine-sector data, it employs a large and diverse sample of countries (Table A.7.1.3). The database combines data from World Bank World Development Indicators, the OECD STAN database, KLEMS, the Groningen Growth Development Center (GGDC) database (de Vries, Timmer, and de Vries 2015), and the Expanded Africa Sector Database (EASD; Mensah and Szirmai 2018) for value-added data and employment. The APO Productivity Database, UN data, ILOSTAT, and National sources are used for supplementary purposes. Following (Wong 2006), local currency value-added is converted to U.S. dollars using 2011 PPP

[19] Restuccia, Yang, and Zhu (2008) argue that obstacles to migration reduce labor flows out of agriculture. Artuc et al. (2015) estimate, from data for eight major sectors that the labor mobility costs of labor market frictions are larger in EMDEs than those in advanced economies. Bryan and Morten (2019), using Indonesian data show that reducing migration costs to the U.S. level, a high-mobility benchmark, leads to a 7 percentage point increase in productivity growth.

exchange rate obtained from Penn World Table for the international comparison of productivity levels.[1]

Shift-share analysis. Wong (2006), this chapter employs a shift-share-analysis which decomposes aggregate labor productivity into the growth within a sector and shifts between sectors:

$$\underbrace{\frac{\Delta y}{y}}_{\substack{\textit{Aggregate}\\ \textit{Productivity}\\ \textit{Growth}}} = \underbrace{\sum_{j=1}^{k}\frac{Y_j}{Y}\left[\frac{\Delta y_j}{y_j}\right]}_{\substack{\textit{Within}\\ \textit{Sectoral}\\ \textit{Effect}}} + \underbrace{\underbrace{\sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\Delta s_j}_{\substack{\textit{Static}\\ \textit{Sectoral}\\ \textit{Effect}}} + \underbrace{\sum_{j=1}^{k}\left[\frac{y_i}{y}\right]\left[\frac{\Delta y_j}{y_j}\right]\Delta s_j}_{\substack{\textit{Dynamic}\\ \textit{Sectoral}\\ \textit{Effect}}}}_{\substack{\textit{Between}\\ \textit{Sectoral}\\ \textit{Effect}}}, \qquad (1)$$

where y is aggregate labor productivity, yj is labor productivity of sector j, Yj is initial value-added of sector j, sj is the employment share of sector j. Between sector effects are driven by the change in employment share. They are further decomposed into those which are due to the reallocation of sources to sectors which higher productivity levels (static sectoral effect), and those due to reallocation toward sectors with higher productivity growth (dynamic sectoral effect).

TABLE A.7.1.1 Sample coverage (9-sector labor productivity)

Advanced Economies			
Country	**Group**	**Period**	**Source**
Australia	AEs	1975-2018	OECD/APO/ILO
Austria	AEs	1970-2017	OECD/KLEMS/ILO
Belgium	AEs	1975-2017	OECD/ILO
Canada	AEs	1970-2018	OECD/ILO/own estimates
China, Hong Kong SAR	AEs	1974-2018	GGDC/APO/Haver/ILO
Cyprus	AEs	1995-2018	OECD/KLEMS/ILO
Czech Republic	AEs	1993-2017	OECD/ILO
Denmark	AEs	1970-2017	OECD/ILO
Estonia	AEs	1995-2017	OECD/KLEMS
Finland	AEs	1975-2017	OECD/ILO
France	AEs	1970-2017	OECD/ILO
Germany	AEs	1970-2017	OECD/ILO
Greece	AEs	1995-2017	OECD/ILO

[1] Van Biesebroeck (2009) builds an expenditure-based sector-specific PPP in OECD countries, using detailed price data.

TABLE A.7.1.1 Sample coverage (9-sector labor productivity) *(continued)*

Advanced Economies			
Country	Group	Period	Source
Iceland	AEs	1994-2018	OECD/Haver/own estimates
Ireland	AEs	1995-2018	OECD/ILO
Italy	AEs	1970-2017	OECD/GGDC/ILO
Japan	AEs	1973-2017	OECD/Haver/ILO
Latvia	AEs	1995-2017	OECD/KLEMS/ILO
Lithuania	AEs	1995-2018	OECD/ILO
Luxembourg	AEs	1970-2018	OECD/KLEMS/ILO
Netherlands	AEs	1970-2017	OECD/KLEMS/ILO
New Zealand	AEs	1990-2018	OECD/Haver/own estimates
Norway	AEs	1970-2017	OECD/ILO
Portugal	AEs	1995-2017	OECD/ILO
Republic of Korea	AEs	1963-2018	OECD/GGDC/ILO
Singapore	AEs	1970-2018	GGDC/APO
Slovakia	AEs	1995-2017	OECD
Slovenia	AEs	1995-2018	OECD/ILO
Spain	AEs	1970-2018	OECD/KLEMS/ILO
Sweden	AEs	1970-2018	OECD/KLEMS/ILO
Switzerland	AEs	1992-2018	OECD/ILO
Taiwan	AEs	1963-2018	GGDC/APO/ILO/National source
United Kingdom	AEs	1960-2017	OECD/GGDC/ILO
United States	AEs	1950-2017	OECD/KLEMS/ILO

Emerging markets and developing economies			
Country	Group	period	Source
China	EAP	1952-2017	GGDC/APO/Haver/ILO/Own estimates
Fiji	EAP	1977-2018	APO/UN/ILO/National source
Indonesia	EAP	1971-2018	GGDC/APO/UN/ILO/National source
Lao PDR	EAP	1990-2017	APO/UN/ILO
Malaysia	EAP	1975-2018	GGDC/APO/UN/ILO/National source
Mongolia	EAP	1970-2018	APO/UN/ILO/National source
Philippines	EAP	1971-2018	GGDC/APO/UN/ILO/National source
Thailand	EAP	1960-2018	GGDC/APO/UN/ILO/National source
Viet Nam	EAP	1990-2017	APO/UN/ILO
Azerbaijan	ECA	2001-2018	ILO/National source
Bulgaria	ECA	1995-2017	ILO/National source
Croatia	ECA	1995-2017	ILO/National source
Georgia	ECA	2003-2018	ILO/National source
Hungary	ECA	1995-2017	ILO/National source
Montenegro	ECA	2000-2018	ILO/National source
Poland	ECA	1995-2018	ILO/National source
Romania	ECA	1995-2018	ILO/National source
Russia	ECA	1995-2018	KLEMS/Haver/ILO/National source
Serbia	ECA	1995-2018	ILO/National source
Turkey	ECA	1988-2018	OECD/APO/ILO/National source
Argentina	LAC	1990-2018	GGDC/KLEMS/WDI/Haver
Belize	LAC	1991-2018	ILO/National source
Bolivia	LAC	1991-2018	ILO/National source
Brazil	LAC	1970-2018	GGDC/KLEMS/Haver/ILO/National source
Chile	LAC	1950-2018	GGDC/UN/ILO/National source
Colombia	LAC	1950-2018	GGDC/KLEMS/UN/ILO/National source

TABLE A.7.1.1 Sample coverage (9-sector labor productivity) *(continued)*

Emerging markets and developing economies			
Country	**Group**	**period**	**Source**
Costa Rica	LAC	1950-2018	OECD/GGDC/ILO/National source
Dominican Republic	LAC	1991-2018	ILO/National source
Ecuador	LAC	1991-2017	ILO/National source
Guatemala	LAC	2001-2018	ILO/National source
Honduras	LAC	1991-2018	ILO/National source
Jamaica	LAC	1993-2018	ILO/National source
Mexico	LAC	1950-2018	GGDC/KLEMS/ILO/National source
Paraguay	LAC	1991-2017	ILO/National source
Saint Lucia	LAC	1991-2018	ILO/National source
St. Vincent and the Grenadines	LAC	1991-2018	ILO/National source
Uruguay	LAC	1997-2018	ILO/National source
Algeria	MNA	1999-2018	ILO/National source
Egypt	MNA	1960-2018	GGDC/Haver/ILO/National source
Iran	MNA	1991-2017	ILO/National source
Jordan	MNA	1992-2018	ILO/National source
Morocco	MNA	1970-2018	GGDC/Haver/ILO
Qatar	MNA	1986-2018	APO/UN/ILO/National source
Bangladesh	SAR	1991-2018	ILO/National source
India	SAR	1960-2017	GGDC/APO/ILO/National source
Nepal	SAR	2001-2018	ILO/National source
Pakistan	SAR	1970-2018	APO/UN/ILO/National source
Sri Lanka	SAR	1971-2018	APO/UN/ILO/National source
Angola	SSA	2002-2017	ILO/National source
Botswana	SSA	1964-2017	EASD/ILO/National source
Burkina Faso	SSA	1970-2017	EASD/ILO/Own estimates
Cameroon	SSA	1965-2018	EASD/ILO/Haver
Eswatini	SSA	1991-2018	UN/ILO/National source
Ethiopia	SSA	1961-2017	EASD/ILO/National source
Ghana	SSA	1960-2018	EASD/ILO/National source
Kenya	SSA	1969-2018	EASD/ILO/National source
Lesotho	SSA	1970-2018	EASD/ILO/National source
Malawi	SSA	1966-2017	EASD/ILO/Own estimates
Mauritius	SSA	1970-2018	EASD/ILO/National source
Mozambique	SSA	1970-2018	EASD/ILO/National source
Namibia	SSA	1960-2018	EASD/ILO/National source
Nigeria	SSA	1960-2018	EASD/ILO/National source
Rwanda	SSA	1970-2018	EASD/ILO/National source
Senegal	SSA	1970-2017	EASD/ILO/Own estimates
Sierra Leone	SSA	2001-2018	ILO/National source
South Africa	SSA	1960-2018	EASD/ILO/National source
Uganda	SSA	1990-2018	EASD/ILO/National source
United Republic of Tanzania	SSA	1960-2017	EASD/ILO/National source
Zambia	SSA	1965-2018	EASD/Haver/ILO

Note: OECD = OECD STAN database etc., KLEMS = World KLEMS (EU, LAC, and Russia); GGDC = the Groningen Growth Development Center database (Timmer, de Vries, and de Vries 2015); EASD = Expanded Africa Sector Database (Mensah and Szirmai 2018); APO = APO Productivity Database; UN = UN data; ILO = ILOSTAT.

TABLE A.7.1.2 Nine-sector categories

Sector name	Description
1.Agriculture	Agriculture, forestry, and fishing
2.Mining	Mining and quarrying
3.Manufacturing	Manufacturing
4.Utilities	Electricity, gas, steam and air conditioning supply
5.Construction	Construction
6.Trade services	Wholesale and retail trade; repair of motor vehicles and motorcycles; Accommodation and food service activities
7.Transport services	Transportation and storage; Information and communication
8.Financial and Business services	Financial and insurance activities; Real estate activities; Professional, scientific and technical activities; Administrative and support service activities
9.Other services	Public administration and defense; compulsory social security; Education; Human health and social work activities; Arts, entertainment and recreation; Other service activities; Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; Activities of extraterritorial organizations and bodies

Source: APO; EASD; GGDC; ILO; KLEMS; National sources; OECD; United Nations; World Bank.

TABLE A.7.1.3 Comparison with other studies using nine-sector labor productivity

	Period	Country coverage	Group coverage
This study	2003-2017	103	34 AEs 69 EMDEs 9 LICs
	1995-2017	94	34 AEs 60 EMDEs 7 LICs
	1975-2017	54	21 AEs 33 EMDEs 6 LICs
IMF (2018)	1965-2010	62	19 AEs 43EMDEs 2 LICs
	(1965-2015)	(39)	(19 AEs 20 EMDEs 0 LICs)
Mcmillan, Rodrik, and Verduzco-Gallo (2014)	1990-2005	38	13 AEs 25 EMDEs 2 LICs
Diao, McMillan, and Rodrik (2017)	2000-2010	39	13 AEs 26 EMDEs 3 LICs

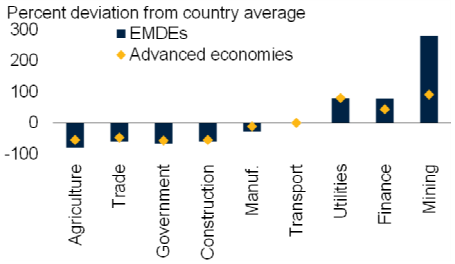
ANNEX 7.2 Marginal productivity gap

Large productivity gaps do not necessarily imply inefficiencies in the allocation of resources across sectors or potential gains from the reallocation of workers. Even if average productivity were the same across sectors, there could still be gains from reallocation if the labor shares of value-added vary across sectors. Under the assumption that labor markets are competitive, efficiency implies the equalization of marginal labor productivities across sectors (Fuglie et al. 2020; Sinha 2016; Vollrath 2009). That is, employment should shift across sectors until the marginal productivity of hiring an extra employee is equalized. If marginal labor productivities differ significantly there can be gains from sectoral reallocation.

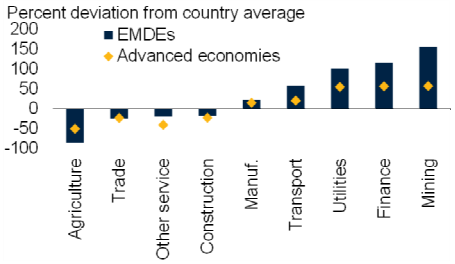
FIGURE A.7.2.1 Marginal productivity gaps

Marginal productivity gaps are broadly similar to average productivity gaps. Negative gaps in agriculture, construction, and trade services, along with positive gaps in the finance and utilities sectors may be signs of allocative inefficiencies. They suggest that reforms to increase intersectoral mobility might substantially improve aggregate labor productivity and incomes.

A. Marginal productivity gap: Advanced economies and EMDEs



B. Average productivity gap: Advanced economies and EMDEs



Source: APO; EASD; GGDC; ILO; KLEMS; national sources; OECD; United Nations; World Bank.
A. Marginal productivity is calculated by the average labor productivity multiplied by the value-added labor share. Setting distortions in transport services at zero gives the relative distortion in eight sectors, although transport service is not assumed to be undistorted.
B. Average labor productivity is value-added per worker based on 2017 data. "Finance" includes business services; "Other service" includes government and personal services. Based on 2017 data.
Click here to download data and charts.

Marginal productivity gaps, "distortions," are calculated as average productivity multiplied by the estimated value-added labor shares following (Sinha 2016).[2] To compute these gaps across sectors, the transport services sector is used as the reference sector relative to which marginal productivity gaps are normalized to zero for that sector (this does not imply that the transport service sector itself is undistorted).[3] The calculated gaps are indicative of (relative) distortions: a negative value of the marginal productivity gap can be interpreted as a subsidy or support to that sector, whereas a positive gap reflects barriers such as taxes, entry regulations, and access to credit.

The marginal productivity gaps for the agriculture, construction, trade, government services, and manufacturing sectors are negative (Figure A.7.2.1). This in part likely reflects protections such as price interventions in the agricultural sector, which have often been large—for example, in LAC (Üngör 2017). The manufacturing sector in EMDEs too has been supported in many countries with tax concessions, relatively low tariffs, price controls, regulations on foreign trade, and foreign currency regulations (Tybout 2000). Finance and utilities are quite heavily regulated. Overall, the estimated marginal productivity gaps are broadly in line with the average productivity gaps, and larger in EMDEs than in advanced economies. Furthermore, the distortions in the

[2] Based on the first-order condition from the firm's optimization.

[3] This normalization is done purely in order to simplify the quantitative results. The allocations remain independent of any normalization.

finance sector in LICs are particularly large. These findings are in line with the literature.[4]

ANNEX 7.3 Firm TFP data, estimates and methodology

Data. The World Bank Enterprise Surveys (ES) collect firm-level data from surveys conducted with more than 129,000 firms in 127 countries, including 71,000 manufacturing firms over a period spanning 2007 to 2017. This box uses revenue TFP constructed for 15,181 manufacturing firms for which output, input, and firm characteristics data are available (Cusolito et al. 2018). The sample covers 108 EMDEs.

TFP estimates. The underlying assumption is that sector-specific elasticities of output with respect to inputs are the same across economies in a given income group.[5] Firm-level revenue TFP estimates are computed in each sector s by pooling all firms i across economies c.[6] The weighted regressions, using survey weights, exploit the log transform of a Cobb-Douglas production function and, therefore, TFP estimates can assume negative and positive values. The ES dataset provides two estimates of firm-level TFP, output TFP and value-added TFP.

Output TFP is estimated as:

$$TFPR_{sci}^{YKNM} = ln(Y_{sci}) - \begin{bmatrix} \alpha_{s,K}\, ln(K_{sci}) + \alpha_{s,N}\, ln(N_{sci}) + \alpha_{s,M}\, ln(M_{sci}) \\ + interaction\ \&\ quadratic\ terms \end{bmatrix}. \quad (1)$$

Value-added TFP is estimated as:

$$TFPR_{sci}^{VAKN} = ln(VA_{sci}) - \begin{bmatrix} \alpha_{s,K}\, ln(K_{sci}) + \alpha_{s,N}\, ln(N_{sci}) \\ + interaction\ \&\ quadratic\ terms \end{bmatrix}, \quad (2)$$

where Y is the firm's output, K is the input capital, N is the input labor, M is intermediate materials, and VA is the firm's value-added (Cusolito et al. 2018).[7] Two-

[4] Vollrath (2009) shows that the ratio of marginal product of labor in industry to that of agriculture ranges from a low of a low of 1.67 in Australia to a high of 16.84 in Kenya. De Vries (2014) measures large distortions in Brazil's retail sector and find taxes and difficulty in access to credit are related with distortions to output and capital. Moreover, Dennis & Işcan (2011) find that the rate of structural change (i.e., the reallocation of labor from low to high productivity sectors) is slow in countries with large distortions in agriculture, and Restuccia, Yang, and Zhu (2008) find that wage wedges, measured as differences in average wage across sectors, significantly slow the process of structural change.

[5] This assumption implies that firm-level TFP are not directly comparable to aggregate TFP from macro panel data.

[6] Firms are grouped in 2-digit ISIC code industries for the estimation. To allow for comparison, values (collected in local currency units) are converted to US dollars using the corresponding exchange rate and then deflated using the 2009 GDP deflator for the United States [$LCU/(FX \times defl_{2009}^{US})$].

[7] The value of (log) intermediate inputs (materials, electricity) is subtracted from the (log) output to obtain the (log) value added. Thus, output and value-added TFP are the same when elasticities of intermediate inputs with respect to output ($\alpha_{s,M}$ in equation 1) is equal to one, but different otherwise. Interaction and quadratic terms are included to control for possible non-linearities. Due to information lacking on self-reported inputs in the World Bank Enterprise Survey dataset, TFP values are not available for some firms in the manufacturing sector. Extreme observations are also removed in the upper tail of the firm-level TFP distribution in Sub-Saharan Africa.

digit ISIC codes are used to define 15 industries (Table A.7.3.1). Firms in electrical machinery, precision equipment, electronics, information, and communication sectors are grouped into a single technology-intensive industry denoted by TINT.

Measurement challenges. TFP captures the efficiency in production not explained by shifts in inputs—capital, labor, intermediate materials. At least four key issues arise when estimating TFP at the firm level. First, a large negative productivity shock may lead a firm to reduce input quantities (simultaneity) or to liquidate (selection).[8] Basic ordinary least squares estimates are therefore biased due to the potential correlation between inputs and productivity. To alleviate the endogeneity problem of input choices and selection bias, existing techniques use firm-specific fixed effects (Pavcnik 2002), instrumental variables (Wooldridge 2009), or two-stage estimation schemes with auxiliary variables (Olley and Pakes 1996; Imrohoroglu and Tuzel 2014; Levinsohn and Petrin 2003; Satpathy, Chatterjee, and Mahakud 2017). Second, common firm-level TFP measures are based on revenues and line item costs rather than physical outputs and inputs. Revenue-based TFP (TFPR) measures conflate productivity and market power, especially in a context of imperfect competition in input markets (Foster, Haltiwanger, and Syverson 2008; Andrews, Criscuolo, and Gal 2016). TFPR estimates are biased when output prices are correlated with inputs choice. Markups-corrected or physical TFP (TFPQ) estimates, obtained by deflating firm-level sales by corresponding prices, can help purge the confounding price effects (Cusolito and Maloney 2018; Van Beveren 2012). Third, a given firm may produce various products using distinct technologies (Bernard, Redding, and Schott 2010; Goldberg et al. 2010). Thus, specifying a single production function for a multi-product firm is rather restrictive and yields biased TFP estimates. Using granular product-level data, if available, to back out firm-level TFP can help account for the diversity in a firm's production mix. Fourth, young, small, and less productive establishments can be under-represented in the sample of firms due to a lack of information. A limited sample representativeness may distort the distribution of firm-level TFP and restrict what can be inferred from the evidence (Andrews, Criscuolo, and Gal 2016). Particular caution is warranted when interpreting the evidence of TFP dispersion among firms.

Methodology. The fitted specification is

$$DTF_i^g = \theta_0 + \sum_g \rho_g I(g \in G \setminus \{ref\}) + \Sigma_{j=1}^{J} \gamma_j X_{ij} + \upsilon_i \ , \qquad (3)$$

where DTF_i^g is the distance-to-frontier of TFP for firm i in industry g, θ_0 stands for the constant term, $ref = TINT$ is the reference industry, and coefficients ρ_g are interpreted relatively to the reference group. X_{ij} is firm i's jth characteristic such as GDP per capita (in 2009 U.S. dollars per worker), size (number of employees), exports (as a proportion of total sales), and business climate (control of corruption, business freedom). The error term is denoted by υ_i.

[8] Selection and simultaneity problems occur when a firm's decision regarding continuation of operations and quantities of inputs is guided by its productivity.

TABLE A.7.3.1 Definitions of industries

2-digit ISIC	Label	Description	Sample
15 and 16	FOOD	Manufacturing of food products and beverages, and manufacturing of tobacco products	3,552
17	TEXT	Manufacturing of textiles	1,074
18	APPA	Manufacture of wearing apparel; dressing and dyeing of fur	1,912
19	LEAT	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	397
20	WOOD	Manufacturing of wood and of products of wood and cork, except furniture; manufacturing of articles of straw and plaiting materials	368
21	PAPE	Manufacturing of paper and paper products	132
22, 30, 31, 32, and 33	TINT= MEDI +OFFI	Publishing, printing and reproduction of recorded media, Manufacturing of office, accounting and computing machinery, manufacturing of electrical machinery and apparatus n.e.c., manufacturing of radio, television and communication equipment and apparatus, and manufacturing of medical, precision and optical instruments, watches and clocks	177
23 and 24	CHEM	Manufacturing of coke, refined petroleum products and nuclear fuel, and manufacturing of chemicals and chemical products	1,250
25	RUBB	Manufacturing of rubber and plastics products	1,174
26	MINE	Manufacturing of other non-metallic mineral products	1,007
27	META	Manufacturing of basic metals	475
28	FABM	Manufacturing of fabricated metal products, except machinery and equipment	1,519
29	MACH	Manufacturing of machinery and equipment not elsewhere classified	844
34 and 35	MOTO	Manufacturing of motor vehicles, trailers and semi-trailers, and manufacturing of other transport equipment	367
36	FURN	Manufacturing of furniture; manufacturing not elsewhere classified	933
		Total	15,181

Source: Cusolito et al. (2018); World Bank Enterprise Surveys, World Bank.

References

Alvarez-Cuadrado, F., and M. Poschke. 2011. "Structural Change Out of Agriculture: Labor Push versus Labor Pull." *American Economic Journal: Macroeconomics* 3 (3): 127–58.

Andrews, D., C. Criscuolo, and P. Gal. 2016. "The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy." OECD Productivity Working Paper 05, Organization for Economic Co-operation and Development, Paris.

Araujo, J. T., E. Vostroknutova, and K. Wacker. 2017. "Productivity Growth in Latin America and the Caribbean: Exploring the Macro-Micro Linkages." Discussion Paper 19, World Bank, Washington, DC.

Artuc, E., D. Lederman, and G. Porto. 2015. "A Mapping of Labor Mobility Costs in the Developing World." *Journal of International Economics* 95 (1): 28–41.

Atkin, D., A. K. Khandelwal, and A. Osman. 2017. "Exporting and Firm Performance: Evidence from a Randomized Experiment." *The Quarterly Journal of Economics* 132 (2): 551–615.

Bahar, D. 2016. "Using Firm-Level Data to Study Growth and Dispersion in Total Factor Productivity," Brookings and Center for International Development, Washington, DC.

Bahar, D. 2018. "The Middle Productivity Trap: Dynamics of Productivity Dispersion." *Economics Letters* 167: 60–66.

Bahar, D., and M. A. Santos. 2018. "One More Resource Curse: Dutch Disease and Export Concentration." *Journal of Development Economics* 132 (1): 102–14.

Barrero, J. M., N. Bloom, and S. J. Davis. 2020. "COVID-19 Is Also a Reallocation Shock." *SSRN Electronic Journal*. Available at SSRN: https://ssrn.com/abstract=3592953.

Barrett, C. B., L. Christiaensen, M. Sheahan, and A. Shimeles. 2017. "On the Structural Transformation of Rural Africa." *Journal of African Economies* 26 (1): 11–35.

Bartelsman, E. J., and M. Doms. 2000. "Understanding Productivity: Lessons from Longitudinal Microdata." *Journal of Economic Literature* 38 (3): 569–94.

Baumol, W. J. 1967. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *American Economic Review* 57 (3): 415–26.

Bernard, A. B., and C. I. Jones. 1996. "Technology and Convergence Author." *The Economic Journal* 106 (437): 1037–44.

Bernard, A. B., S. J. Redding, and P. K. Schott. 2010. "Multi-Product Firms and Product Switching." *American Economic Review* 100 (1): 70–97.

Beveren, I. Van. 2012. "Total Factor Productivity Estimation: A Practical Review." *Journal of Economic Surveys* 26 (1): 98–128.

Bloom, N., A. Mahajan, D. McKenzie, and J. Roberts. 2010. "Why do firms in developing countries have low productivity?" *American Economic Review* 100(2), 619–23.

Boppart, T. 2014. "Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non-Gorman Preferences." *Econometrica* 82 (6): 2167–96.

Bosworth, B. P., and J. E. Triplett. 2003. "Productivity Measurement Issues in Services Industries: 'Baumol's Disease' Has Been Cured." *Economic Policy Review* 9 (3): 23–33.

Bosworth, B. P., and J. E. Triplett. 2007. "The Early 21st Century U.S. Productivity Expansion Is Still in Services." *International Productivity Monitor* 14: 3–19.

Bryan, G., and M. Morten. 2019. "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia." *Journal of Political Economy* 127 (5): 2229–68.

Brynjolfsson, E., and L. Hitt. 1995. "Information Technology as a Factor of Production: The Role of Differences among Firms." *Economics of Innovation and New Technology* 3 (3–4): 183–99.

Buera, F. J., and J. P. Kaboski. 2009. "Can Traditional Theories of Structural Change Fit The Data?" *Journal of the European Economic Association* 7 (2–3): 469–77.

Caselli, F. 2005. "Accounting for Cross-Country Income Differences." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven N. Durlauf, 679–741. Amsterdam: Elsevier.

Cette, G., S. Corde, and R. Lecat. 2018. "Firm-Level Productivity Dispersion and Convergence." *Economics Letters* 166: 76–78.

Chen, C. 2017. "Untitled Land, Occupational Choice, and Agricultural Productivity." *American Economic Journal: Macroeconomics* 9 (4): 91–121.

Chevalier, P. A., R. Lecat, and N. Oulton. 2012. "Convergence of Firm-Level Productivity, Globalisation and Information Technology: Evidence from France." *Economics Letters* 116 (2): 244–46.

Chodorow-Reich, G., and J. Wieland. 2020. "Secular Labor Reallocation and Business Cycles." *Journal of Political Economy* 128 (6): 2245–87.

Cirera, X., and W. F. Maloney. 2017. *The Innovation Paradox: Developing-Country Capabilities and the Unrealized Promise of Technological Catch-Up*. Washington, DC: The World Bank.

Cusolito, A. P., D. C. Francis, N. Karalashvili, and J. R. Meza. 2018. "Firm Level Productivity Estimates." Methodological Note. World Bank, Washington, DC.

Cusolito, A. P., and W. F. Maloney. 2018. *Productivity Revisited - Shifting Paradigms in Analysis and Policy*. Washington, DC: World Bank.

Dall'Olio, A., M. Iootty, N. Kanehira, and F. Saliola. 2014. "Enterprise Productivity a Three-Speed Europe." ECB Working Paper 1748, European Central Bank, Frankfurt.

De Loecker, J. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia." *Journal of International Economics* 73 (1): 69–98.

de Vries, G. , K. de Vries, and M. Timmer. 2015. "Structural Transformation in Africa: Static Gains, Dynamic Losses." *Journal of Development Studies* 51 (6): 674–88.

de Vries, G. J., A. A. Erumban, M. P. Timmer, I. Voskoboynikov, and H. X. Wu. 2012. "Deconstructing the BRICs: Structural Transformation and Aggregate Productivity Growth." *Journal of Comparative Economics* 40 (2): 211–27.

Dennis, B. N., and T. B. Işcan. 2011. "Agricultural Distortions, Structural Change, and Economic Growth: A Cross-Country Analysis." *American Journal of Agricultural Economics* 93 (3): 881–901.

Dercon, S., and L. Christiaensen. 2011. "Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia." *Journal of Development Economics* 96 (2): 159–73.

Dercon, S., M. Fafchamps, C. Pattillo, R. Oostendorp, J. Willem Gunning, P. Collier, A. Zeufack, et al. 2004. "Do African Manufacturing Firms Learn from Exporting?" *Journal of Development Studies* 40 (3): 115–41.

Diao, X., M. McMillan, and D. Rodrik. 2017. "The Recent Growth Boom in Developing Economies: A Structural Change Perspective." NBER Working Paper 23132, National Bureau of Economic Research, Cambridge, MA.

Di Mauro, F., B. Mottironi, G. Ottaviano, and A. Zona-mattioli. 2018. "Living with Lower Productivity Growth: Impact on Exports." Working Paper 18–10, Peterson Institute for International Economics, Washington, DC.

Duarte, M., and D. Restuccia. 2007. "The Structural Transformation and Aggregate Productivity in Portugal." *Portuguese Economic Journal* 6 (1): 23–46.

Duarte, M., and D. Restuccia. 2010. "The Role of the Structural Transformation in Aggregate Productivity." *Quarterly Journal of Economics* 125 (February): 129–173.

Duernecker, G., B. Herrendorf, and A. Valentinyi. 2017. "Structural Change within the Service Sector and the Future of Baumol's Disease." CEPR Discussion Paper DP12467, The Center for Economic Policy Research, London.

Eichengreen, B., and P. Gupta. 2013. "The Two Waves of Service-Sector Growth." *Oxford Economic Papers* 65 (1): 96–123.

Fernald, J. 2015. "Productivity and Potential Output Before, During, and After the Great Recession." Working Paper Series 01-51, Federal Reserve Bank of San Francisco.

Foster, L., C. Grim, and J. Haltiwanger. 2016. "Reallocation in the Great Recession: Cleansing or Not?" *Journal of Labor Economics* 34 (S1): S293–331.

Foster, L., J. Haltiwanger, and C. Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98(1): 394–425.

Foster-McGregor, N., A. Isaksson, and F. Kaulich. 2016. "Importing, Productivity and Absorptive Capacity in Sub-Saharan African Manufacturing and Services Firms." *Open Economies Review* 27 (1): 87–117.

Fuglie, K., M. Gautam, A. Goyal, and W. F. Maloney. 2020. *Harvesting Prosperity: Technology and Productivity Growth in Agriculture*. Washington, DC: World Bank.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova. 2010. "Multi-Product Firms and Product Turnover in the Developing World: Evidence from India." *Review of Economic Statistics* 92 (4): 1042–49.

Gollin, D., D. Lagakos, and M. E. Waugh. 2014. "The Agricultural Productivity Gap." *Quarterly Journal of Economics* 129 (2): 939–93.

Goñi, E., and W. F. Maloney. 2017. "Why Don't Poor Countries Do R&D? Varying Rates of Factor Returns across the Development Process." *European Economic Review* 94 (May): 126–47.

Hale, T., A. Petherick, T. Phillips, and S. Webster. 2020. "Variation in Government Responses to COVID-19." BSG Working Paper 2020/31, Blavatnik School of Government, University of Oxford, U.K.

Hallward-Driemeier, M., and G. Nayyar. 2017. *Trouble in the Making? The Future of Manufacturing-Led Development*. Washington, DC: World Bank.

Helble, M., L. Q. Trinh, T. T. Le, T. Long, and T. T. Le. 2019. "Sectoral and Skill Contributions to Labor Productivity in Asia." ADBI Working Paper 929, Asian Development Bank Institute, Manila.

Herrendorf, B., R. Rogerson, and Á. Valentinyi. 2013. "Two Perspectives on Preferences and Structural." *American Economic Review* 103 (7): 2752–89.

Herrendorf, B., R. Rogerson, and Á. Valentinyi. 2014. "Growth and Structural Transformation." In *Handbook of Economic Growth Vol. 2*, edited by P. Aghion and S. Durlauf, 855–941. Amsterdam: Elsevier.

Hicks, J. H., M. Kleemans, N. Y. Li, E. Miguel, D. Albouy, J. Alvarez, L. Beaman, et al. 2017. "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata." NBER Working Paper 23253, National Bureau of Economic Research, Cambridge, MA.

Hsieh, C.-T., and P. J. Klenow. 2009. "Misallocation and Manufactring TFP in China and India." *Quarterly Journal of Economics* 124 (4): 1403–48.

IMF (International Monetary Fund). 2018. *World Economic Outlook: Cyclical Upswing, Structural Change*. Washington, DC: International Monetary Fund.

Imrohoroğlu, A., S. Imrohoroglu, and M. Üngör. 2014. "Agricultural Productivity and Growth in Turkey." *Macroeconomic Dynamics* 18 (5): 998–1017.

Imrohoroğlu, A., and S. Tuzel. 2014. "Firm-Level Productivity, Risk, and Return." *Management Science* 60 (8): 2073–90.

Jorgenson, D. W., and M. P. Timmer. 2011. "Structural Change in Advanced Nations: A New Set of Stylised Facts." *Scandinavian Journal of Economics* 113 (1): 1–29.

Kouamé, W. A., and S. J. Tapsoba. 2018. "Structural Reforms and Firms' Productivity: Evidence from Developing Countries." IMF Working Paper 18/63, International Monetary Fund, Washington, DC.

Levchenko, A., and J. Zhang. 2016. "The Evolution of Comparative Advantage: Measurement and Welfare Implications." *Journal of Monetary Economics* 78 (April): 96–111.

Levinsohn, J., and A. Petrin. 2003. "Estimating Production Function Using Inputs to Control For." *The Review of Economic Studies* 70: 317–41.

Lowder, S. K., J. Skoet, and T. Raney. 2016. "The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide." *World Development* 87 (November): 16–29.

Maloney, W. F., and G. Nayyar. 2018. "Industrial Policy, Information, and Government Capacity." *The World Bank Research Observer* 33 (2): 189–217.

Martins, P. M. G. 2019. "Structural Change: Pace, Patterns and Determinants." *Review of Development Economics* 23 (1): 1–32.

Matsuyama, K. 2009. "Structural Change in an Interdependent World: A Global View of Manufacturing Decline." *Journal of the European Economic Association* 7 (2–3): 478–86.

McCaig, B., and N. Pavcnik. 2013. "Moving out of Agriculture: Structural Change in Vietnam." NBER Working Paper 19616, National Bureau of Economic Research, Cambridge, MA.

McCullough, E. B. 2017. "Labor Productivity and Employment Gaps in Sub-Saharan Africa." *Food Policy* 67 (February): 133–52.

Mcmillan, M., D. Rodrik, and Í. Verduzco-Gallo. 2014. "Globalization, Structural Change, and Productivity Growth, with an Update on Africa." *World Development* 63 (2014): 11–32.

Mensah, E. B., and A. Szirmai. 2018. "Africa Sector Database (ASD): Expansion and Update." UNU-MERIT Working Paper 020, Maastricht, Netherland.

Olley, G. S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–97.

Padilla-Pérez, R., and F. G. Villarreal. 2017. "Structural Change and Productivity Growth in Mexico, 1990–2014." *Structural Change and Economic Dynamics* 41 (March): 53–63.

Pavcnik, N. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *The Review of Economic Studies* 69 (1): 245–76.

Restuccia, D., and R. Rogerson. 2008. "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments." *Review of Economic Dynamics* 11 (4): 707–20.

Restuccia, D., and R. Rogerson. 2013. "Misallocation and Productivity." *Review of Economic Dynamics* 16 (1): 1–10.

Restuccia, D., D. T. Yang, and X. Zhu. 2008. "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis." *Journal of Monetary Economics* 55 (2): 234–50.

Rodrik, D. 2013. "Unconditional Convergence in Manufacturing." *Quarterly Journal of Economics* 128 (1): 165–204.

Rodrik, D. 2016. "Premature Deindustrialization." *Journal of Economic Growth* 21 (1): 1–33.

Rodrik, D. 2018. "An African Growth Miracle?" *Journal of African Economies* 27 (1): 10–27.

Satpathy, L. D., B. Chatterjee, and J. Mahakud. 2017. "Firm Characteristics and Total Factor

Productivity: Evidence from Indian Manufacturing Firms." *The Journal of Applied Economic Research* 11 (1): 77–98.

Sinha, R. 2016. "Sectoral Productivity Gaps and Aggregate Productivity." Policy Research Working Paper 7737, World Bank, Washington, DC.

Solow, R. M. 1987. "We'd Better Watch Out." Book review of *The Myth of the Post-Industrial Economy*, by S. S. Cohen and J. Zysman. New York Times, July 12.

Stiglitz, J. E. 2018. "From Manufacturing-Led Export Growth to a Twenty-First-Century Inclusive Growth Strategy: Explaining the Demise of a Successful Growth Model and What to Do about It." WIDER Working Paper Series 2018/176, UNU-WIDER, Maastricht, Netherland.

Stiroh, K. 2002. "Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?" *American Economic Review* 92 (5): 1559–76.

Syverson, C. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49 (2): 326–365.

Tybout, J. R. 2000. "Manufacturing Firms in Developing Countries: How Well Do They Do, and Why?" *Journal of Economic Literature* 38 (1): 11–44.

Üngör, M. 2013. "De-Agriculturalization as a Result of Productivity Growth in Agriculture." *Economics Letters* 119 (2): 141–45.

Üngör, M. 2017. "Productivity Growth and Labor Reallocation: Latin America versus East Asia." *Review of Economic Dynamics* 24 (March): 25–42.

Uy, T., K. M. Yi, and J. Zhang. 2013. "Structural Change in an Open Economy." *Journal of Monetary Economics* 60 (6): 667–82.

Vaaler, P. M., and G. McNamara. 2010. "Are Technology-Intensive Industries More Dynamically Competitive? No and Yes." *Organization Science* 21 (1): 271–89.

van Biesebroeck, J. 2009. "Disaggregate Productivity Comparisons: Sectoral Convergence in OECD Countries." *Journal of Productivity Analysis* 32 (2): 63–79.

Vollrath, D. 2009. "How Important Are Dual Economy Effects for Aggregate Productivity?" *Journal of Development Economics* 88 (2): 325–34.

Wolitzky, A. 2018. "Learning form Others' Outcomes." *American Economic Review* 108 (10): 2763–2801.

Wong, W.-K. 2006. "OECD Convergence: A Sectoral Decomposition Exercise." *Economics Letters* 2 (93): 210–14.

Wooldridge, J. M. 2009. "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables." *Economics Letters* 104 (3): 112–14.

World Bank. 2019a. *Global Economic Prospects: Darkening Skies*. January. Washington, DC: World Bank.

World Bank. 2019b. *Global Economic Prospects: Heightened Tensions, Subdued Investment*. June. Washington, DC: World Bank.

World Bank. 2020. *Africa's Pulse: An Analysis of Issues Shaping Africa's Economic Future.* Spring. Washington, DC: World Bank.