Sectoral Decomposition of Convergence in Labor Productivity:A Re-examination from a New Dataset*

Alistair Dieppe†and Hideaki Matsuoka‡

Abstract

This paper investigates how the sector-specific source or the changing sectoral composition of labor productivity has contributed to β-convergence, using a newly constructed eight-sector database. The main findings are twofold. First, both within and sectoral reallocation have become important drivers of β-convergence in labor productivity. Second, agricultural productivity growth has been a significant contributor to β-convergence, whereas catch-up in other sectors has only contributed a small amount to convergence. The strong growth of the agriculture sector has been the most important driver of aggregate productivity convergence even though agricultural productivity itself in low-income countries is not converging to that in advanced economies.

JEL Classification: O1,O11,O4
Keywords:Labor productivity, Shift-share decomposition, βdecomposition, New sectoral database

*This paper should not be reported as representing the views of the European Central Bank nor Ministry of Finance Japan. The views expressed are those of the authors and do not necessarily reflect those of the ECB, Ministry of Finance Japan, the World Bank, its Executive Directors, or the countries they represent. We gratefully acknowledge financial support from the PHRD fund. We are grateful for valuable comments from Gaaitzen de Vries, Iikka Korhonen and participants at Emerging Markets Workshop organized by BOFIT and Winter School 2021 organized by Centre for Development Economics Delhi School of Economics and The Econometric Society.

†**Alistair Dieppe**, European Central Bank, GERMANY. Email:alistair.dieppe@ecb.europa.eu

‡**Hideaki Matsuoka**, orcid.org/0000-0002-7837-1413. Ministry of Finance, Policy Research Institute, JAPAN. Email: hideaki.matsuoka@mof.go.jp

1 Introduction

In low-income countries (hereafter "LICs"), a high share of employment and low labor productivity in agriculture are mainly responsible for low aggregate productivity.[1] The average share of employment in the agriculture sector in LICs is high, at over 65 percent in 2018, compared to just 3 percent in advanced economies. The level of agricultural productivity in LICs is only 4 percent of advanced-economy productivity (Figures 1 and 2). [2] However, even if agricultural labor productivity does not converge to the frontier, the labor reallocation to other sectors with higher productivity levels could be an important engine of aggregate convergence. For example, the East Asia and Pacific (EAP) region has experienced a rapid 'de-agriculturalization' over 40 years. Within countries, the productivity gaps across sectors in LICs have remained larger than advanced economies over the last 20 years.[3]

There is a large body of literature on the determinants of structural change using the multi-sector general equilibrium model. Two traditional explanations for structural change are the representative household with non-homothetic preference (Kongsamut et al. (2001)) and the firms with differential productivity growth rates (Ngai and Pissarides (2007)). Their basic mechanism is that the relative price related to the differential productivity allocates total expenditures across any goods and services. Given these demands, relatively higher productivity growth sheds labor and due to gross complementarity, labor shifts to slower-productivity growth. For example, Alvarez-Cuadrado and Poschke (2011), Duarte and Restuccia (2010), and Herrendorf et al. (2013) with non-homothetic preference consider "Engel's law" which refers to low income elasticity for food produced by the agriculture sector. They show that the productivity improvement in the agriculture sector combined with Engel's law explains most of the declines in agricultural employment share. Also, Üngör (2013) finds that productivity growth in agriculture, combined with the subsistence level of consumption, is able to explain most of the declines in agricultural employment share in several countries. Also, an improvement in agricultural productivity increases incomes and the demand for other goods, encouraging a shift of labor into other sectors (Eberhardt and Vollrath (2018), Gollin et al. (2007), and Diao et al. (2018)). However, the theoretical ambiguity on the role of agricultural productivity growth in structural change is captured by the formulation of Matsuyama (1992), which shows opposite effects in closed economies and small open economies. Increased agricultural productivity in open economies lead to comparative advantage and result in specialization in agriculture, thus pulling labor into agricultural sector. McArthur and McCord (2017) show that if countries are serial expoters, increased yields lead to increases in the labor share in agriculture by regression analysis.

Given the ongoing structural change in Africa and low-income countries (as shown by Diao et al. (2017) and Rodrik (2018)), understanding the role of structural change in aggregate convergence is the focus of this paper. In assessing the contribution of structural change to convergence, it is important to recognize that industry and service sectors are made up of

[1]Unless otherwise indicated, productivity is defined in this paper as value added per worker because it is impossible to get sectoral hours data for a lot of countries. The classification by income follows World Bank (2021). Low-income countries are part of emerging markets and developing economies (EMDEs). ,

[2]This partially reflects that slow technology adoption in the agriculture sector in LICs is due to the high proportion of smallholder ownership and family farms (Lowder et al., 2016). Although mechanization increases agricultural labor productivity due to both capital deepening and TFP, mechanization in poor countries is hindered by frictions such as untitled land, which is a prevalent feature of poor countries(Chen, 2020). Furthermore, Restuccia et al. (2008) show that agricultural labor productivity is positively associated with the use of intermediate inputs (e.g., modern fertilizers and high-yield seeds) and argue that certain distortions in factor markets such may severely dampen the incentives for their use (see Dennis and Işcan (2011), for example).

[3]As agricultural workers often do not work full time in agriculture, the sectoral gap is diminished if productivity is measured per hours instead of per worker (Gollin et al., 2014). However, even after taking hours and human capital per worker by sector, a large sectoral gap remains for a large number of countries Hamory et al. (2021).

a highly heterogeneous set of activities that vary widely in their skill- and capital-intensity as well as their productivity. Understanding these differences is essential to help the policies that can foster sustained productivity growth. This paper investigates how the sector-specific source or the changing sectoral composition (i.e., structural change) has contributed to the β-convergence. This paper extends the literature in two dimensions:

1. It constructs a new sectoral dataset for 8 sectors and 91 countries over 1995-2018 (and for 60 countries over 1975-2018). This is the first comprehensive database covering a broad range of both advanced economies and emerging and developing economies (EMDEs) over a long time period. This more detailed dataset and a more recent sectoral decomposition improves the scope to assess the contribution of structural change in productivity convergence, particularly as the estimates are sensitive to the level of aggregation (Üngör (2017)).

2. This paper is the first to decompose the β-convergence into contributions from within-sector productivity growth and from between-sector productivity growth, for a large number of countries ranging from advanced economies to low-income countries, whereas Wong (2006) have only focused on advanced economies.

The paper starts by describing the new dataset. Then this data is used to decompose aggregate productivity growth into within- and between-sector contributions. The main section examines convergence across countries and examines the extent within and between sectoral reallocation are contributing to convergence. Two robustness exercises are undertaken which support the main findings. The final section concludes with a summary of major findings, policy implications and a discussion of future research directions.

2 Data and empirical strategy

2.1 Data

The database consists of sectoral and aggregate labor productivity statistics for 91 countries, and 8 sectors covering the period up to 2018.[4] Compared with the literature using sectoral datasets, it employs a large and diverse sample of countries.[5] The database combines data from the APO Productivity Database, the OECD STAN database, the OECD National Accounts, and the GGDC/UNU-WIDER Economic Transformation Database (ETD, de Vries et al. (2021)) for value-added data and employment. In addition, this database is extrapolated backwards using annual growth rates from KLEMS, the GGDC 10-Sector database (GGDC, de Vries et al. (2015)) or the Expanded Africa Sector Database (EASD, Mensah and Szirmai (2018)) to construct a long time series dataset. Also, if there is no available employment data, ILO modelled estimates are supplementary employed. See the Appendix for more details. [6]

2.2 Within sector and between sector effects

Following de Vries et al. (2012), McMillan et al. (2014) and Diao et al. (2017), we start by employing a shift-share-analysis which decomposes aggregate labor productivity into the

[4] The eight sectors distinguished in the dataset are agriculture, mining, manufacturing, utilities, construction, trade services, transport and financial services, and government and personal services. According to Economic Transformation Database, Business services include "Information and communication" whereas those in other databases are included in transport service." Hence, we combined transport and financial services to construct a long time series database.

[5] McMillan et al. (2014) and Diao et al. (2017) employ 38 and 39 countries; IMF (2018) use 10 sectors and 62 countries.

[6] Database available for download here: datacatalog.worldbank.org

within sector and between sector effects:

$$\underbrace{\frac{\Delta y}{y}}_{Aggregate\ Labor\ Productivity} = \underbrace{\sum_{j=1}^{k}\frac{Y_j}{Y}\left[\frac{\Delta y_j}{y_j}\right]}_{Within-j} + \underbrace{\underbrace{\sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\Delta s_j}_{Static} + \underbrace{\sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\left[\frac{\Delta y_j}{y_j}\right]\Delta s_j}_{Dynamic}}_{Between} \tag{1}$$

where Δ denotes change, y is aggregate labor productivity, y_j is labor productivity of sector j, Y_j is initial value-added of sector j, s_j 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 with higher productivity levels (static sectoral effect), and those due to reallocation toward sectors with higher productivity growth (dynamic sectoral effect). Within-sector productivity growth may reflect the effects of improvements in human capital, investments in physical capital, technological advantages, or the reallocation of resources from the least to the most productive firms within each sector.

2.3 Decomposition of β-convergence

The unconditional (beta) convergence hypothesis suggests that productivity catch-up growth may occur fastest where productivity differentials are the largest across countries. Following Wong (2002) and Wong (2006), this β-convergence can be decomposed into the contribution of the within-sector growth and that of sectoral reallocation.[7] The decomposition consists of two steps: First, regressing aggregate labor productivity growth $(\Delta y/y)$ on the logarithm of initial aggregate labor productivity (y) gives the β-convergence. [8]

$$\frac{\Delta y}{y} = \alpha + \beta \ln(y) + \varepsilon \tag{2}$$

Second, as the OLS estimater $(\alpha,\beta)' = (X'X)^{-1}X'\frac{\Delta y}{y}$, substituting equation (1) into this gives

(3)

$$(\alpha,\beta)' = (X'X)^{-1}X'\left\{\sum_{j=1}^{k}\frac{Y_j}{Y}\left[\frac{\Delta y_j}{y_j}\right] + \sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\Delta s_j + \sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\left[\frac{\Delta y_j}{y_j}\right]\Delta s_j\right\}$$

$$= \underbrace{(X'X)^{-1}X'\sum_{j=1}^{k}\frac{Y_j}{Y}\left[\frac{\Delta y_j}{y_j}\right]}_{(\alpha_{within},\beta_{within})'} + \underbrace{\underbrace{(X'X)^{-1}X'\sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\Delta s_j}_{(\alpha_{static},\beta_{static})'} + \underbrace{(X'X)^{-1}X'\sum_{j=1}^{k}\left[\frac{y_j}{y}\right]\left[\frac{\Delta y_j}{y_j}\right]\Delta s_j}_{(\alpha_{dynamic},\beta_{dynamic})'}}_{(\alpha_{Between},\beta_{Between})'}$$

Hence, the beta β coefficients obtained in the first step can be decomposed into a sum of coefficients of the within sector effect, the static and dynamic sector effects.

We also examine the regressions for sector-specific convergence;

$$\frac{\Delta y_j}{y_j} = \alpha_j + \beta_j \ln(y_j) + \varepsilon_j \tag{4}$$

[7] Other studies decomposing convergence employ an accounting approach. They calculate the difference of each component (1) between the frontier and all sample countries. (e.g., Bernard and Jones (1996) and Harchaoui and Üngör (2016) use the United States as the frontier and Caselli and Tenreyro (2005) use France. In contrast, Wong (2006) employs an econometric approach. Its advantage is to understand that the components are statistically significant or not.

[8] Following McMillan et al. (2014) , local currency value-added is converted to U.S. dollars using the nominal PPP exchange rate obtained from the Penn World Table for initial labor aggregate productivity (y).

Even if sector labor productivity itself has not converged to the corresponding frontier across sectors, the labor reallocation to other sectors with higher productivity levels could be an important engine of aggregate convergence.[9]

3 Results

3.1 Within sector and between sector effects

Figure 3 shows the decomposition of the aggregate productivity into within-sector productivity growth and between-sector productivity growth. Productivity growth in advanced economies had been almost entirely driven by within-sector productivity growth mainly in the manufacturing, transport and finance sectors. However, since the 2000s both within-sector and between-sector productivity growth have slowed. In contrast, in EMDEs, productivity growth has been supported by both within-sector and between-sector changes over 40 years. The within sector growth has been broad-based-including in agriculture as well as manufacturing, trade, transport and finance services, while the between-sector productivity gains mainly reflected a move out of agriculture into services. In particular, the share of workers employed in agriculture fell from about 70 percent in 1975 to about 30 percent in 2018. In LICs, between-sector productivity gains in LICs reflected a broad-based shift out of agriculture into services such as trade, transport and finance. During the 2010s, the contribution of between-sector slowed down due to small movement to higher productivity sectors such as manufacturing and trade.

Figure 4 shows that contributions of the between-sector effect have been non-negligible in the East Asia and Pacific (EAP), European and Central Asia (ECA), South Asia (SAR) and Sub-Saharan Africa (SSA) regions whereas those in Latin America and Caribbean (LAC) and Middle East and North Africa (MENA) have been small. [10]

3.2 Baseline regression

3.2.1 β-convergence

Table 1 and Figure 5 show the results with three different balanced panel datasets: 60 countries in 1975-2018, 60 countries in 1975-1995, and 91 countries in 1995-2018. At the aggregate level, regression (2) shows there has been weak unconditional convergence prior to 1995. However, since the late 1990s aggregate convergence emerges (Table 1 and Figure 5). Over this period, countries with lower initial levels of productivity have begun to catch up to high-productivity economies. Nonetheless, at the estimated rate of convergence it would take about 140 years for countries at the bottom 10 percent of the productivity distribution to reach the level of the top 10 percent.[11]

[9] While the methodology developed by Wong (2002) can avoid the sectoral PPP-conversion factor problem because it compares only sectoral growth rates and shares -not levels- across countries, this problem remains issue in the sector-specific convergence. Van Biesebroeck (2009) builds an expenditure-based sector-specific PPP in OECD countries, using detailed price data and Inklaar and Timmer (2009) constucts the sector-specific value-added PPPs in twenty advanced OECD countries, using industry-specific relative output and intermediate inputs.

[10] de Vries et al. (2012) distinguish unregistered activities by sector in Brazil and show that it matters for the relative role of structural change. They show that without making the formal/informal split structural change appeared to contribute only a little to aggregate productivity growth. After allowing for employment reallocation towards formal activities, the positive effects of structural change are much higher. Hence, formalization of economic activities in Brazil were related to positive structural change post 2000. McArthur and McCord (2017)

[11] 137 years ≒(ln(0.9)/ln(0.1)-1)/0.695/100, using Table 1.

3.2.2 Decomposing within and between sector convergence

Even though many sectors are not converging to the frontier, the reallocation of labor to other sectors with higher productivity levels could be an important engine of aggregate convergence. Estimating the decomposition of aggregate convergence from regression (3) suggests that since 1995 both within and between sector effects have become important drivers of aggregate convergence in labor productivity (Table 1 and Figure 5). This reflects larger productivity improvements in many sectors in EMDEs (especially the LICs) compared to advanced economies as well the fact that many EMDEs experienced rapid sectoral shifts from agricultural sectors over the last few decades.

Looking across the sectors, agricultural productivity growth has been a significant contributor to aggregate convergence, whereas catch-up in other sectors has only contributed a small amount to convergence. Given the share of value-added in the agriculture sector in LICs is large (Figure 1), the strong growth of the agriculture sector has been the most important driver of the aggregate productivity convergence. Our result is in line with Ivanic and Martin (2018) and Ligon and Sadoulet (2018) which illustrate that the increase in agricultural productivity has a larger poverty-reduction effect than increases in other sectors.

3.2.3 Sectoral convergence

The same exercise is undertaken to examine convergence across sectors (Table 2). Examining this using this study's extensive data suggests the following:

- **Agriculture sector:** Over the entire sample, there is no evidence for unconditional convergence in the agriculture sector. This is line with Kinfemichael and Morshed (2019). Hence, agricultural productivity itself in LICs is not converging to advanced economies. However, this does not mean that the growth of the agriculture sector is not important driver of aggregate productivity convergence because the result of decomposing within and between sector convergence in previous section shows that the agricultural productivity growth has been a significant contributor to aggregate convergence.

- **Industry sectors (Mining, Manufacturing, Utilities and Construction):** There is evidence of unconditional convergence in many of the industry sectors. Over the second half of the sample (1995-2018) there is clear evidence of convergence in the mining sector because this seems to some degree to be due to the commodity price boom during the 2000s. The finding of unconditional convergence in the manufacturing sector is line with Rodrik (2013) using UNIDO data.[12] However, the estimated convergence rate is low. Diao et al. (2021) reveal a dichotomy between larger firms in the manufacturing sector that exhibit superior productivity performance but do not expand employment much in countries such as Tanzania and Ethiopia.

- **Service sectors (Trade, Transport and Finance and others):** There is evidence of unconditional convergence across many service sectors (IMF (2018); Kinfemichael and Morshed (2019)). The transport and financial services sectors show convergence across three different balanced panel datasets. Although there has been evidence of convergence in trade services (wholesale, retail trade, accommodation, and food services), their coefficients are smaller than those of the transport and financial services sectors. Lagakos (2016) argued that in the retail trade sector, developing countries

[12] However, Rodrik (2013) acknowledges that the "convergence results that follow should be read as applying to the more formal, organized parts of manufacturing and not to micro-enterprises or informal firms. In developing countries, enterprises with fewer than 5 or 10 employees are often not included." UNIDO reported that there is a significant difference between UNIDO and the national account.

rationally choose "traditional technologies" with low measured labor productivity instead of "modern technologies" with high productivity across two dimensions. First, low car ownership rates among households in poor countries cause modern stores to locate further than traditional stores from residential centers less attractive. This situation is related with "appropriate technology" suggested by Basu and Weil (1998) and Acemoglu and Zilibotti (2001). Second, traditional retail technologies offer an opportunity for entrepreneurs to operate informally, thus earning a price advantage over modern retail technologies, which are larger in scale and cannot evade taxes as easily as smaller, traditional stores.

3.3 Robustness analysis

3.3.1 Robustness 1: Time-varying regression

The baseline results were based on three sample periods (1975-2018, 1975-1995, and 1995-2018). For robustness and to provide further insights, a rolling window methodology is employed in which regressions (2) and (3) are estimated with OLS over the 10-year rolling window. This results in 34 regressions. Figure 6 shows the time-varying contributions of within and between sector effects on aggregate convergence. The result is line with the baseline regressions. The between sector effects have contributed to aggregate convergence largely and continuously since 1990s. In addition, the within sector growth has played an important role in aggregate convergence since 2000. Furthermore, agricultural productivity growth has been a significant contributor to aggregate convergence since the late 1980s (Figure 6). Finally, due to the commodity price boom during the 2000s, the productivity in the mining sector had also contributed although its contribution subsequently declined.

3.3.2 Robustness 2: Catch-up to the United States

Following Bernard and Jones (1996), another robustness check examines the accounting decomposition for each country relative to the United States. A measure of within and between-sector catch-up is computed by subtracting the productivity growth in the other countries for each sector as follows:

$$(5)\quad \frac{\Delta y_{other}}{y_{other}} - \frac{\Delta y_{us}}{y_{us}} = \sum_{j=1}^{k}(Within_{other,j} - Within_{US,j}) + \sum_{j=1}^{k}(Between_{other,j} - Between_{US,j})$$

where the notations are the same as in equation (1).

Figure 7 shows the between sector effects in EMDEs and LICs have contributed to convergence largely since 1995 while that was not the case between 1975 to 1995. This finding is line with the baseline. Figure 8 shows that both East Asia and Pacific (EAP) and South Asia (SAR) experienced both within- and between-sector catch-up whereas there has been divergence of the within sector effect in the Latin America and Caribbean (LAC), Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA) regions before 2010. In those countries, the within sector effects in the manufacturing sector have not been converging to the U.S. (Kinfemichael and Morshed (2019) and Diao et al. (2021)).

4 Conclusion

This paper investigates how the sector-specific source or the changing sectoral composition has contributed to aggregate productivity and convergence, constructing a new 8-sector database. The main findings are twofold. First, both within and sectoral reallocation have become important drivers of aggregate convergence in labor productivity. This reflects larger productivity improvements in many sectors in EMDEs (especially the LICs) compared to advanced economies as well the fact that many EMDEs experienced rapid sectoral shifts from agricultural sectors over the last few decades. Second, agricultural productivity growth has been a significant contributor to aggregate convergence. The strong growth of the agriculture sector has been the most important driver of aggregate productivity convergence even though agricultural productivity itself in LICs is weakly converging to advanced economies. Our result is in line with the literature that illustrates that the increase in agricultural productivity has a larger poverty-reduction effect than increases in other sectors. Although the potential productivity gains from sectoral reallocation have become more challenging to achieve, there would still be important payoffs from policies including developing human capital; promoting good governance; reducing distortions such as uncompetitive regulations and subsidies and promoting exports. [13] In addition, removing barriers to migration can also help to facilitate structural transformation. [14] Given the low level of productivity in EMDE agricultural sectors and its role as the primary employer in LICs, policies to raise agricultural productivity would pay significant dividends. [15] These polices would include improving infrastructure and land property rights.

[13]Some studies investigate determinants of structural change. Martins (2019) shows that the physical and human capital play an important role in boosting structural change by regression analysis with panel data. Święcki (2017) studies the quantitative contribution of four channels: (i) sector-biased technological progress, (ii) nonhomothetic tastes, (iii) international trade and (iv) changing wedges between factor costs across sectors. They construct a three-sector model (agriculture-manufacture-services), calibrating it for 45 diverse countries. He finds that international trade and changes in relative factor costs across sectors are important for individual countries but their impact on the relocation of labor is less systematic whereas sector-biased technological change is the most important and nonhomothetic preferences are key to accounting for movement of labor out of agriculture.

[14]Artuc et al. (2015) show the estimated labor mobility costs caused by labor market frictions in EMDEs are a larger burden than those in advanced economies, using the data with eight major sectors. Bryan and Morten (2019), using Indonesia data show that reducing migration costs to the US level, a high-mobility benchmark, leads to a 7 percentage point increase in productivity growth. Empirically, regress the structural-term on employment rigidity index and raw materials' share in exports and so on and find that there is a statistically significant impact of the employment rigidity.

[15]McArthur and McCord (2017) and Bustos et al. (2016) show that the improvement of agricultural productivity through fertilizer or agricultural technical change is a driver of structural change .

References

Acemoglu, D., and F. Zilibotti. 2001. "Productivity Differences." *The Quarterly Journal of Economics* 116:563–606.

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

Artuc, E., D. Lederman, and G. Porto. 2015. "A mapping of labor mobility costs in the developing world." *Journal of International Economics* 95:28–41.

Basu, S., and D.N. Weil. 1998. "Appropriate Technology and Growth." *The Quarterly Journal of Economics* 113:1025–1054.

Bernard, A., and C. Jones. 1996. "Productivity across Industries and Countries: Time Series Theory and Evidence." *The Review of Economics and Statistics* 78:135–146.

Bryan, G., and M. Morten. 2019. "The aggregate productivity effects of internal migration: Evidence from Indonesia." *Journal of Political Economy* 127:2229–2268.

Bustos, P., B. Caprettini, J. Ponticelli, D. Atkin, F. Buera, V. Carvalho, G. Gancia, G. Grossman, J.C. Hallak, C.T. Hsieh, J. Kaboski, N. Pavcnik, J. Pinho De Melo, A. Rodríguez-Clare, S. Tenreyro, J. Ventura, and K.M. Yi. 2016. "Agricultural Productivity and Structural Transformation: Evidence from Brazil." *American Economic Review* 106:1320–1365.

Caselli, F., and S. Tenreyro. 2005. "Is Poland the Next Spain?" NBER Working Paper 11045, National Bureau of Economic Research, Cambridge, MA.

Chen, C. 2020. "Technology Adoption, Capital Deepening, and International Productivity Differences." *Journal of Development Economics* 143:1–26.

de Vries, G., L. Arfelt, D. Drees, M. Godemann, C. Hamilton, B. Jessen-Thiesen, A. Kaya, H. Kruse, E. Mensah, and P. Woltjer. 2021. "The Economic Transformation Database (ETD): content, sources, and methods." WIDER Technical Note 2/2021, United Nations University World Institute for Development Economics Research, Helsinki, Finland.

de Vries, G., M. Timmer, and K. de Vries. 2015. "Structural Transformation in Africa: Static Gains, Dynamic Losses." *Journal of Development Studies* 51:674–688.

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* 40:211–227.

Dennis, B.N., and T.B. Işcan. 2011. "Agricultural distortions, structural change, and economic growth: A cross-country analysis." *American Journal of Agricultural Economics* 93:881–901.

Diao, X., M. Ellis, M. McMillan, and D. Rodrik. 2021. "Africa's Manufacturing Puzzle: Evidence from Tanzanian and Ethiopian Firms." NBER Working Paper 28344, National Bureau of Economic Research, Cambridge, MA.

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., Cambridge, MA.

Diao, X., M. McMillan, and S. Wangwe. 2018. "Agricultural Labour Productivity and Industrialisation: Lessons for Africa." *Journal of African Economies* 27:28–65.

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

Eberhardt, M., and D. Vollrath. 2018. "The Effect of Agricultural Technology on the Speed of Development." *World Development* 109:483–496.

Gollin, D., D. Lagakos, and M.E. Waugh. 2014. "The Agricultural Productivity Gap." *Quarterly Journal of Economics* 129:939–993.

Gollin, D., S.L. Parente, and R. Rogerson. 2007. "The food problem and the evolution of international income levels." *Journal of Monetary Economics* 54:1230–1255.

Hamory, J., M. Kleemans, N. Li, and E. Miguel. 2021. "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata." *Journal of the European Economic Association* 19:1522–1555.

Harchaoui, T.M., and M. Üngör. 2016. "Sectoral sources of sub-Saharan Africa's convergence." *Applied Economics Letters* 23:642–651.

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

IMF. 2018. "Manufacturing Jobs: Implications for Productivity and Inequality." In *World Economic Outlook April 2018: Cyclical Upswing, Structural Change*. Washington, DC: IMF.

Inklaar, R., and M.P. Timmer. 2009. "Productivity Convergence Across Industries And Countries: The Importance Of Theory-Based Measurement." *Macroeconomic Dynamics* 13:218–240.

Ivanic, M., and W. Martin. 2018. "Sectoral Productivity Growth and Poverty Reduction: National and Global Impacts." *World Development* 109:429–439.

Kinfemichael, B., and A. Morshed. 2019. "Unconditional convergence of labor productivity in the service sector." *Journal of Macroeconomics* 59:217–229.

Kongsamut, P., S. Rebelo, and D. Xie. 2001. "Beyond Balanced Growth." *Review of Economic Studies* 68:869–882.

Lagakos, D. 2016. "Explaining Cross-Country Productivity Differences in Retail Trade." *Journal of Political Economy* 124:579–620.

Ligon, E., and E. Sadoulet. 2018. "Estimating the Relative Benefits of Agricultural Growth on the Distribution of Expenditures." *World Development* 109:417–428.

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

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

Matsuyama, K. 1992. "Agricultural Productivity, Comparative Advantage, and Economic Growth." *Journal of Economic Theory* 58:317—334.

McArthur, J., and G. McCord. 2017. "Fertilizing growth: Agricultural inputs and their effects in economic development." *Journal of Development Economics* 127:133—152.

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

Mensah, E.B., and A. Szirmai. 2018. "Africa Sector Database (ASD): Expansion and Update." MERIT Working Papers 2018-020, United Nations University - Maastricht Economic and Social Research Institute on Innovation and Technology, Maastricht, Netherland.

Ngai, R., and C. Pissarides. 2007. "Structural Change in a Multisector Model of Growth." *American Economic Review* 97:429–443.

Restuccia, D., D.T. Yang, and X. Zhu. 2008. "Agriculture and aggregate productivity: A quantitative cross-country analysis." *Journal of Monetary Economics* 55:234–250.

Rodrik, D. 2018. "An African growth miracle?" *Journal of African Economies* 27:10–27.

—. 2013. "Unconditional convergence in manufacturing." *Quarterly Journal of Economics* 128:165–204.

Święcki, T. 2017. "Determinants of structural change." *Review of Economic Dynamics* 24:95–131.

Üngör, M. 2013. "De-agriculturalization as a result of productivity growth in agriculture." *Economics Letters* 119:141–145.

—. 2017. "Productivity growth and labor reallocation: Latin America versus East Asia." *Review of Economic Dynamics* 24:25–42.

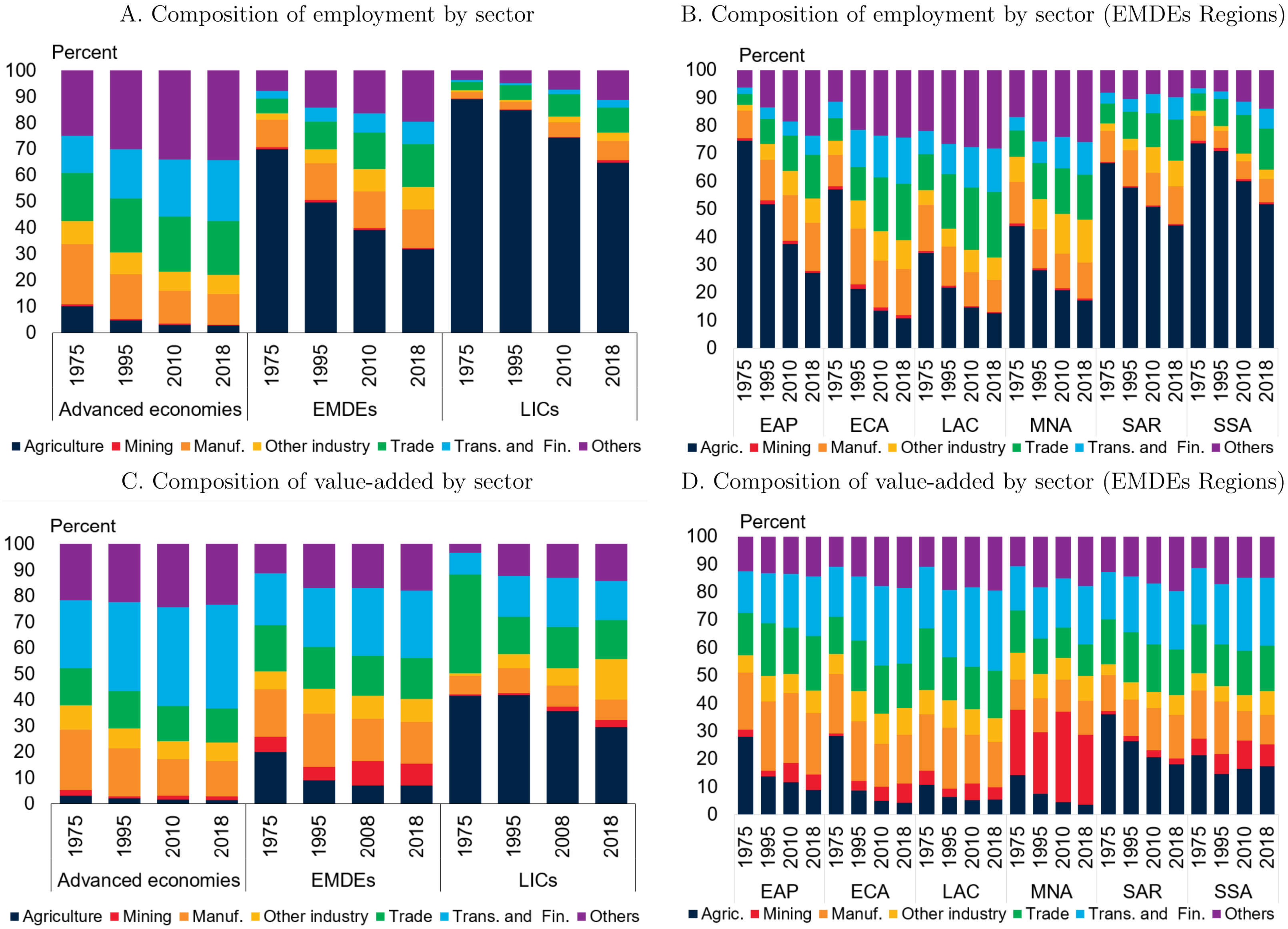
Van Biesebroeck, J. 2009. "Disaggregate productivity comparisons: Sectoral convergence in OECD countries." *Journal of Productivity Analysis* 32:63–79.

Wong, W.K. 2006. "OECD convergence: A sectoral decomposition exercise." *Economics Letters* 93:210–214.

—. 2002. "The Manufacturing Sector did contribute to convergence among OECD countries." NUS Department of Economics Working Paper No.0215, National University of Singapore, Singapore.

World Bank. 2021. *Global Economic Prospects,January 2021*. Washington, DC: World Bank.

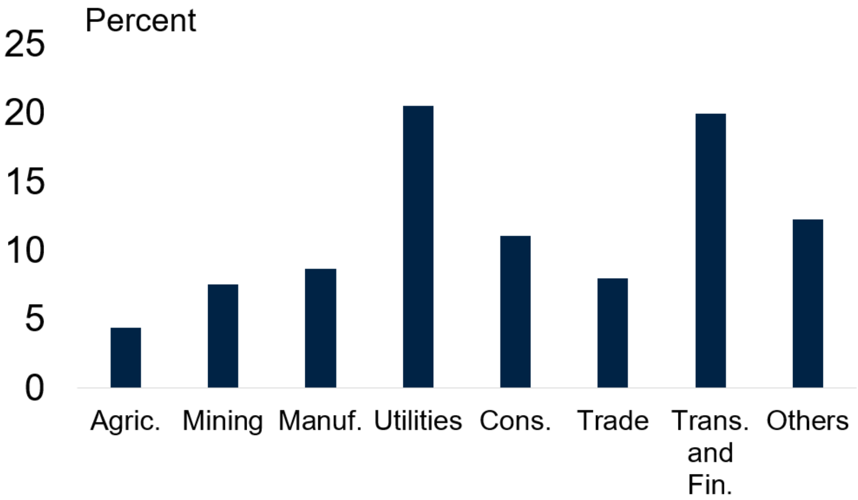
Figure 1: Employment share



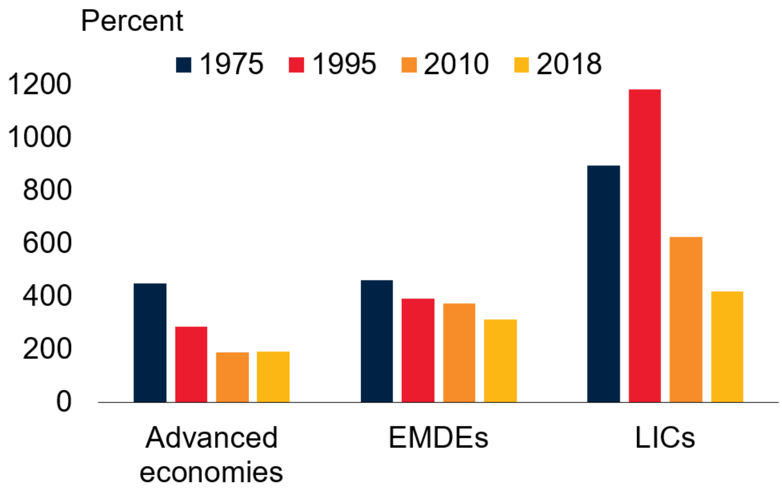
Notes: “Trans. and Fin.” illustrate transport and finance services; "Other industry" includes utilities and construction; "Others" include government and personal services.

Figure 2: Sectoral gap across countries and within countries

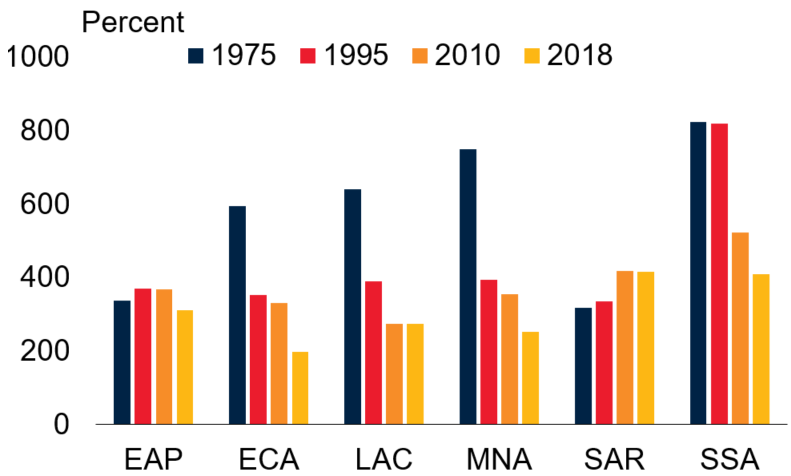
A. Sectoral productivity gap between advanced economies and LICs



B. Agricultural productivity gap

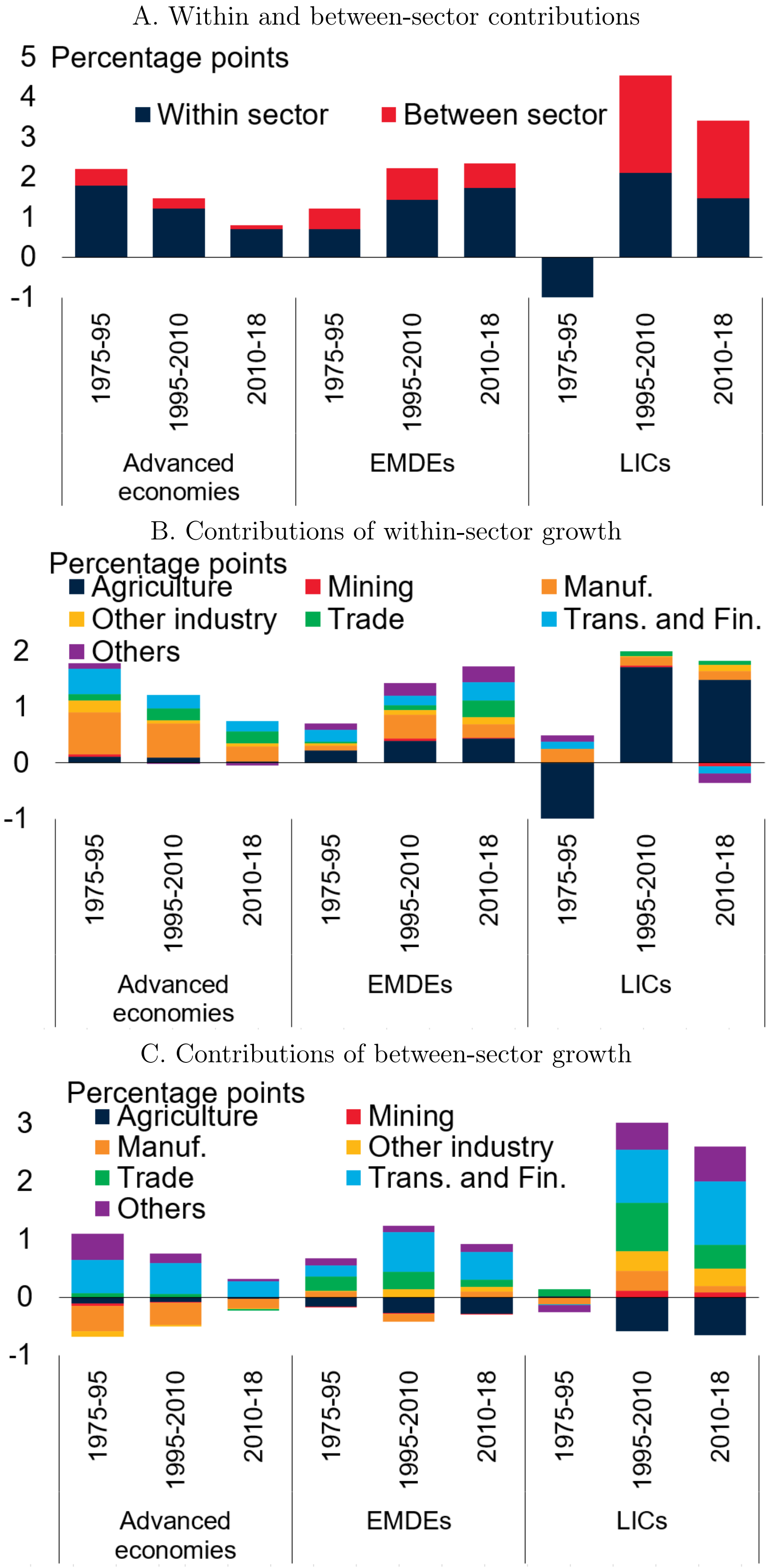


C. Agricultural productivity gap (EMDEs Regions)



Notes: A. Sectoral gap is defined as the ratio of median of sectoral productivity in LICs to that in advanced economies. B.C Agricultural productivity gap is defined as the ratio of non-agricultural productivity to agricultural productivity. "Others" include government and personal services.

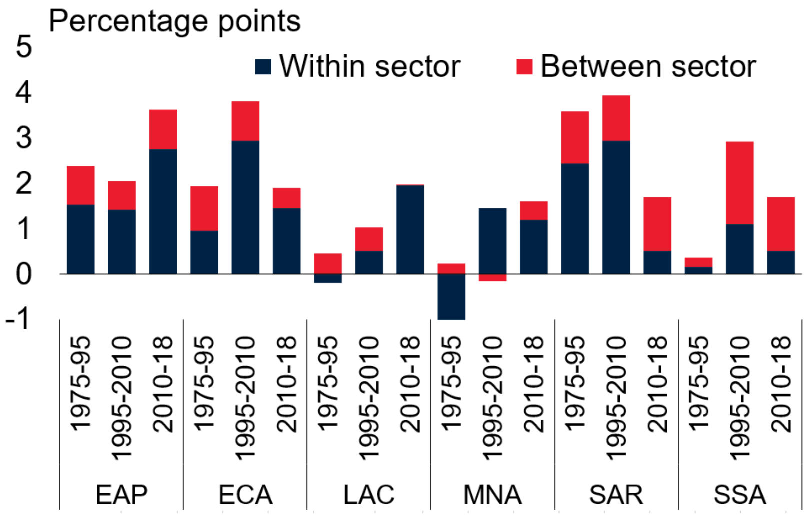
Figure 3: Within sector and between sector effects



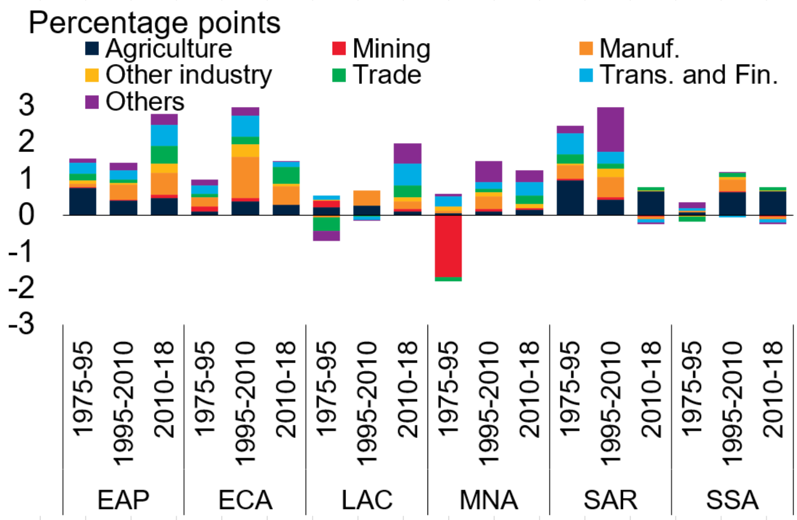
Notes: A.B.C. The decomposition is based on the equation(1). Median contribution to productivity growth. “Trans. and Fin.” illustrate transport and finance services; "Other industry" includes utilities and construction; "Others" include government and personal services.

Figure 4: Within sector and between sector effects (EMDEs Regions)

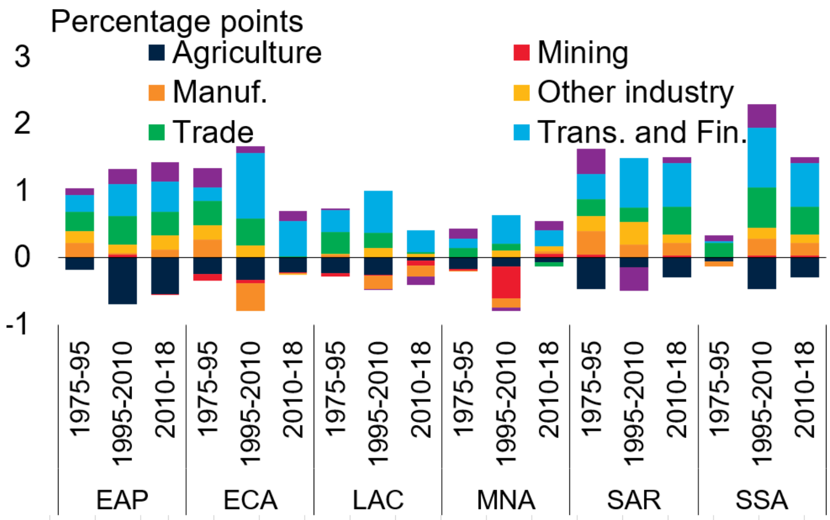
A. Within and between-sector contributions



B. Contributions of within-sector growth (EMDEs Regions)



C. Contributions of between-sector growth (EMDEs Regions)



Notes: A.B.C. The decomposition is based on the equation (1). Median contribution to productivity growth. “Trans. and Fin.” illustrate transport and finance services;"Other industry" includes utilities, and construction; "Others" include government and personal services.

Table 1: Decomposition of aggregate convergence

	1975-2018		1975-1995		1995-2018	
Sector	β	R^2	β	R^2	β	R^2
Aggregate	-0.976**	0.238	-0.289*	0.088	-0.695***	0.266
	(0.484)		(0.155)		(0.234)	
1. Agriculture	-0.255***	0.308	-0.0874***	0.113	-0.181***	0.331
	(0.0493)		(0.0316)		(0.0270)	
2. Mining	-0.0264	0.025	-0.00213	0.000	-0.0388	0.025
	(0.0212)		(0.0304)		(0.0254)	
3. Manufacturing	-0.122***	0.105	-0.0231	0.018	-0.0628*	0.032
	(0.0460)		(0.0223)		(0.0361)	
4. Utilities	-0.0138	0.033	0.00134	0.002	-0.0162**	0.043
	(0.00967)		(0.00418)		(0.00798)	
5. Construction	-0.000995	0.001	0.00263	0.002	-0.00448	0.004
	(0.00534)		(0.00802)		(0.00722)	
6. Trade services	-0.0300**	0.097	-0.0174	0.022	-0.0251	0.028
	(0.0118)		(0.0149)		(0.0155)	
7. Transport and Finance services	-0.0633***	0.137	-0.0142	0.008	-0.0520**	0.054
	(0.0206)		(0.0203)		(0.0229)	
8. Other services	-0.0399*	0.046	-0.00798	0.004	-0.0507**	0.044
	(0.000236)		(0.0156)		(0.0247)	
Total within sectoral effect	-0.551***	0.207	-0.148	0.039	-0.431***	0.171
(1+2+3+4+5+6+7+8)	(0.139)		(0.0953)		(0.0995)	
Static sectoral effect	-0.148	0.014	-0.0516	0.001	-0.277**	0.043
	(0.162)		(0.207)		(0.138)	
Dynamic sectoral effect	-0.276*	0.050	-0.0890	0.004	0.0134	0.000
	(0.155)		(0.179)		(0.115)	
Observations		60		60		91

Notes: Regressions (2) and (3) are estimated. The standard errors are reported in parentheses. The constant terms are not reported.***p<0.01, *p<0.05, *p<0.1

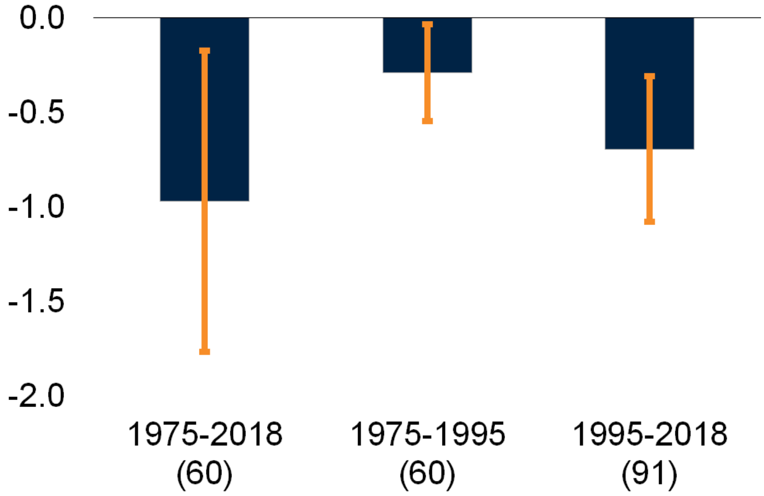
Table 2: Sector-specific convergence

	1975-2018		1975-1995		1995-2018	
Sector	β	R^2	β	R^2	β	R^2
Agriculture	-0.169	0.014	0.151	0.013	-0.212	0.006
	(0.235)		(0.162)		(0.152)	
Mining	-4.800*	0.053	-0.0909	0.001	-3.575**	0.077
	(2.692)		(0.335)		(1.716)	
Manufacturing	-1.126*	0.124	-0.304	0.036	-0.520**	0.062
	(0.616)		(0.228)		(0.253)	
Utilities	-2.024*	0.039	-0.559	0.039	-1.937*	0.033
	(1.169)		(0.405)		(1.097)	
Construction	-0.301*	0.018	-0.223*	0.038	-0.0881	0.003
	(0.174)		(0.115)		(0.212)	
Trade services	-0.448**	0.193	-0.252**	0.069	-0.317*	0.047
	(0.181)		(0.106)		(0.191)	
Finance and business services	-0.847***	0.335	-0.385**	0.127	-0.516***	0.196
	(0.286)		(0.146)		(0.176)	
Other services	-0.406*	0.125	-0.0583	0.005	-0.605**	0.111
	(0.210)		(0.0931)		(0.00275)	
Observations		60		60		91

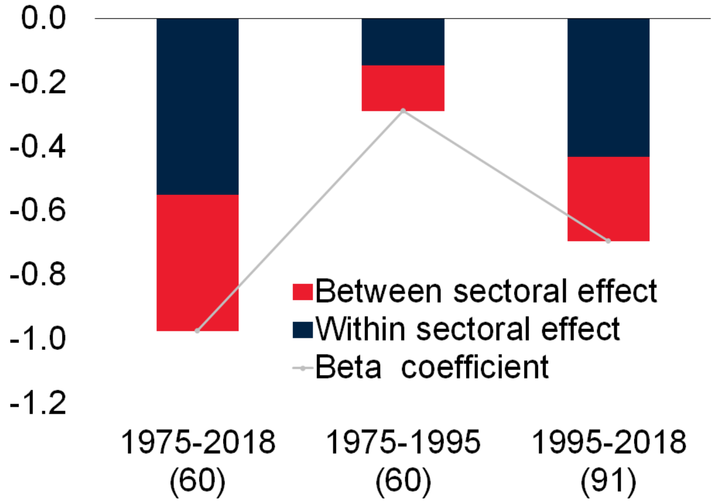
Notes: Regression (4) is estimated. The standard errors are reported in parentheses. The constant terms are not reported.***p<0.01, *p<0.05, *p<0.1

Figure 5: Decomposition of β-convergence

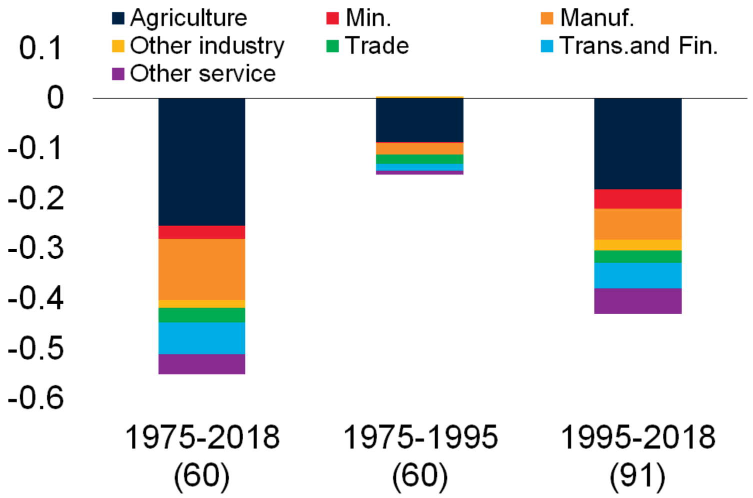
A. β-convergence



B. Decomposition of aggregate convergence



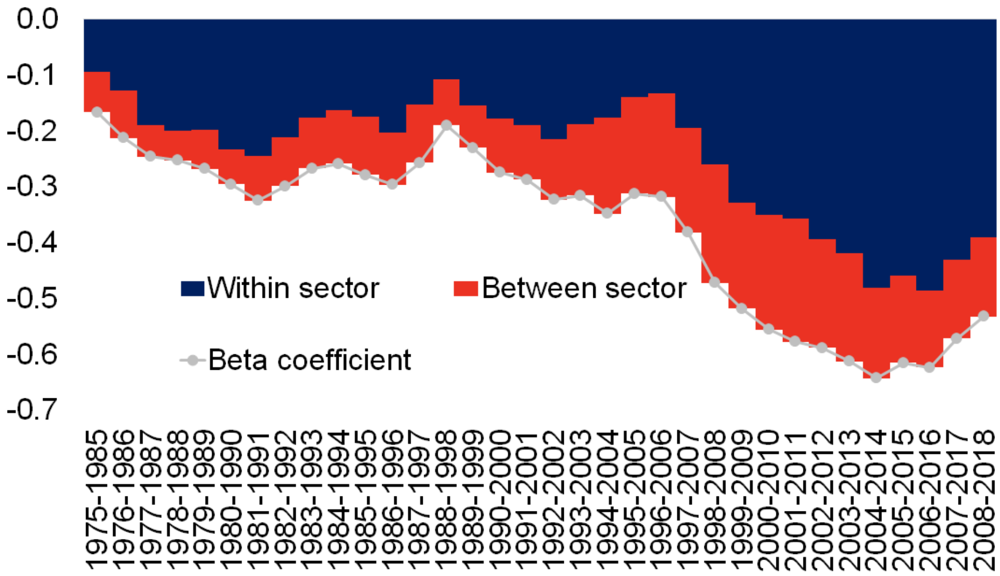
C. Contributions of sector-specific within effects on aggregate convergence



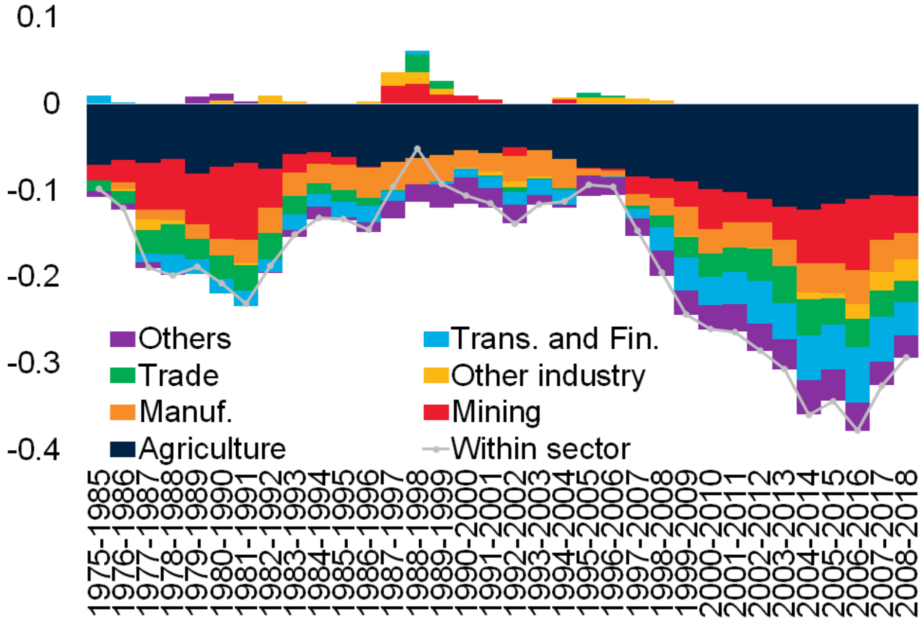
Notes: A. Cross-section regressions (2) are estimated with OLS. The sample size is reported in parentheses. Vertical lines denote 90 percent confidence intervals. B.C. The decomposition is based on the Cross-section regressions (3). “Trans. and Fin.” illustrate transport and finance services;"Other industry" includes utilities, and construction; "Other service" include government and personal services. Residual is the difference between the β and the sum of estimated between and within effects.

Figure 6: Robustness check 1: Time-varing contributions

A. Decomposition of β-convergence



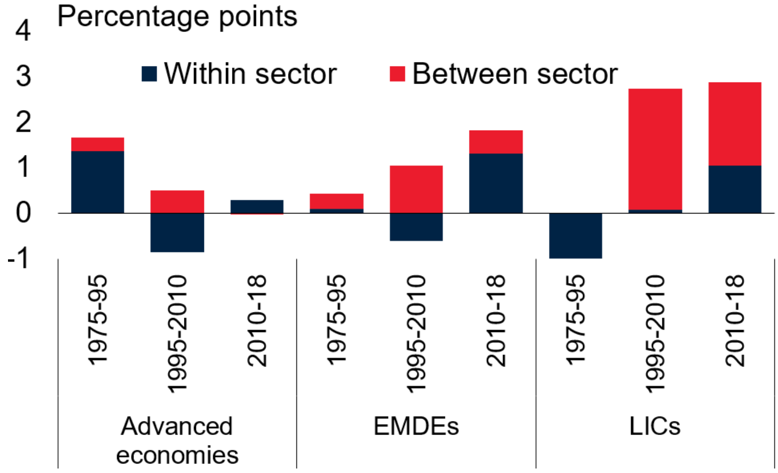
B. Contributions of sector-specific within effects on aggregate convergence



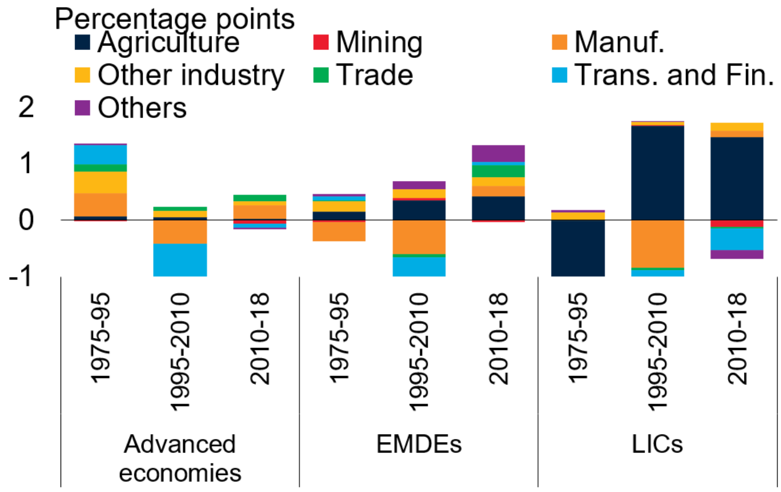
Notes: A. B. Cross-section regressions (2) and (3) are estimated over the 10-year rolling window. The sample size varys through overlapping windows. Residual is the difference between the β and the sum of estimated between and within effects. B. “Trans. and Fin.” illustrate transport and finance services;"Other industry" includes utilities and construction; "Others" include government and personal services.

Figure 7: Robustness check 2: Catch-up to the United States

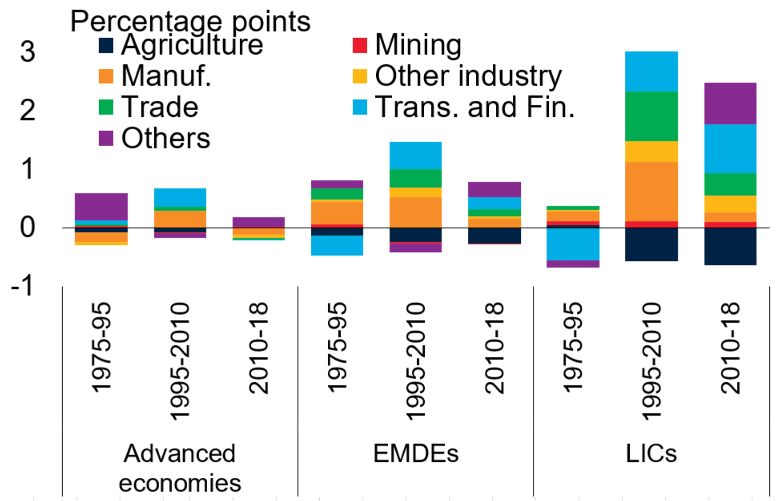
A. Contributions of between-sector growth



B. Contributions of within-sector growth



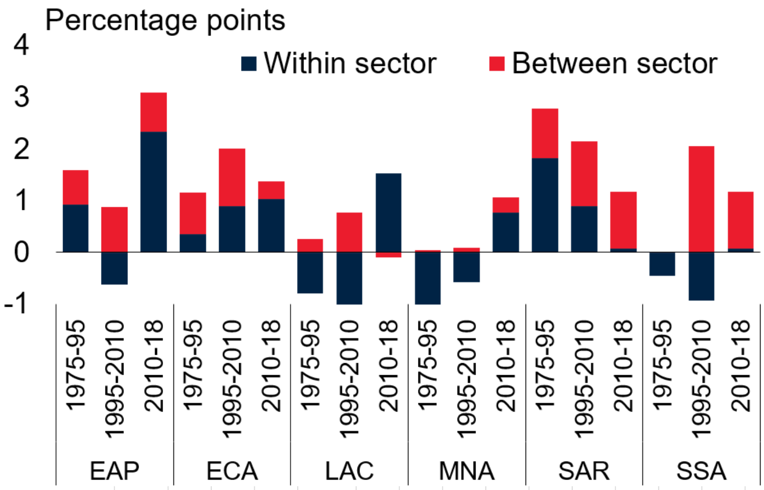
C. Contributions of between-sector growth



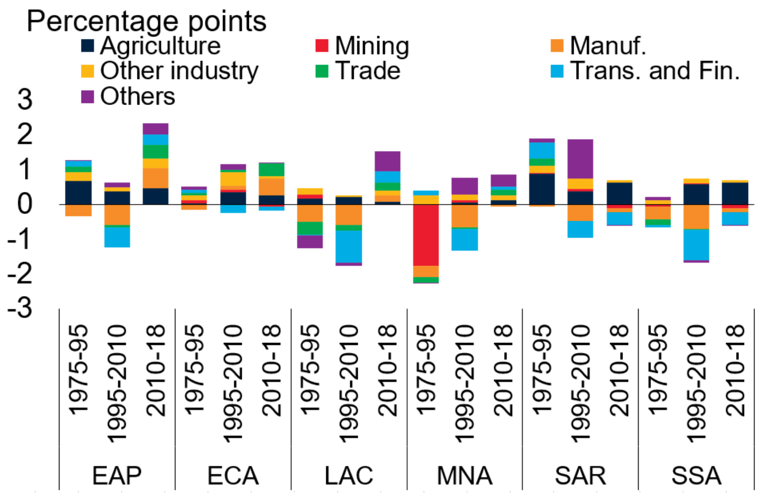
Notes: A.B.C. The decomposition is based on the equation (5). Median contribution to productivity growth. "Trans. and Fin." illustrate transport and finance services; "Other industry" includes utilities and construction; "Others" include government and personal services.

Figure 8: Robustness check 2: Catch-up to the United States (EMDEs Regions)

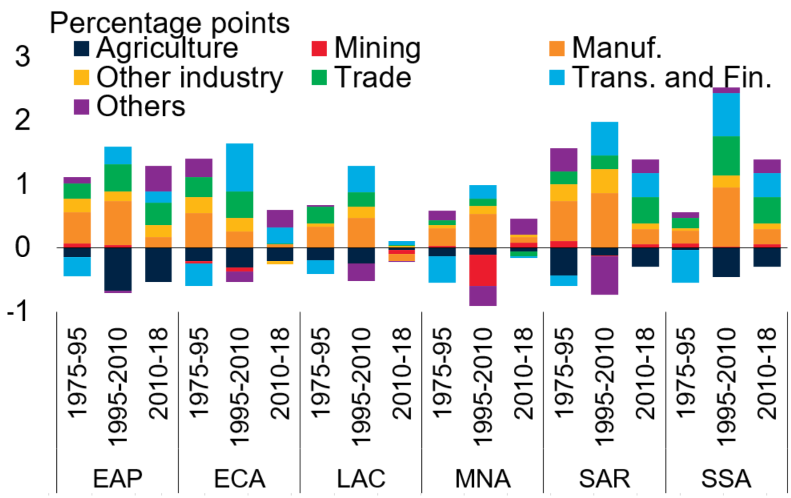
A. Contributions of between-sector growth



B. Contributions of within-sector growth



C. Contributions of between-sector growth



Notes: A.B.C. The decomposition is based on the equation (5). Median contribution to productivity growth. “Trans. and Fin.” illustrate transport and finance services; "Other industry" includes utilities and construction; "Others" include government and personal services.

Table A.1: Comparison with other studies decomposing convergence

Appendix

	Period	Country coverage	Group coverage
This study	1995-2018	91	31 AEs 60 EMDEs
	1975-2018	60	17 AEs 43 EMDEs
Wong (2006)	1970-1990	13	13AEs
Bernard and Jones (1996)	1970-1987	14	14 AEs
Harchaoui and Üngör (2016)	1970-2010	11	11 EMDEs
Caselli and Tenreyro (2005)	1960-2000	27	22 AEs 5 EMDEs

Notes:AEs=advanced economies, EMDEs=emerging markets and developing economies. LICs: low-income countries.

Table A.2: 8-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 and Financial services	Transportation and storage; Information and communication; Financial and insurance activities;Real estate activities; Professional, scientific and technical activities; Administrative and support service activities
8.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

Sources: APO; EASD; ETD; GGDC; KLEMS; OECD.

Table A.3: Sectoral database

Country	Group1	Group2	Period	Source
Australia	AEs	AEs	1975-2018	APO
Austria	AEs	AEs	1970-2018	OECD STAN/KLEMS
Belgium	AEs	AEs	1970-2018	OECD STAN/KLEMS
Czech Republic	AEs	AEs	1993-2018	OECD National Accounts
Cyprus	AEs	AEs	1995-2019	OECD National Accounts/ILO
Denmark	AEs	AEs	1970-2018	OECD STAN
Estonia	AEs	AEs	1995-2018	OECD STAN
Finland	AEs	AEs	1975-2018	OECD STAN
France	AEs	AEs	1970-2018	OECD STAN/OECD National Accounts
Germany	AEs	AEs	1970-2018	OECD STAN/KLEMS
Greece	AEs	AEs	1995-2019	OECD National Accounts
Ireland	AEs	AEs	1995-2019	OECD National Accounts
Israel	AEs	AEs	1990-2018	ETD
Italy	AEs	AEs	1970-2018	OECD STAN/KLEMS
Japan	AEs	AEs	1970-2018	APO
Latvia	AEs	AEs	1995-2018	OECD STAN
Lithuania	AEs	AEs	1995-2018	OECD STAN
Luxembourg	AEs	AEs	1970-2018	OECD STAN/KLEMS
Netherlands	AEs	AEs	1970-2018	OECD STAN/KLEMS
New Zealand	AEs	AEs	1989-2018	OECD STAN
Norway	AEs	AEs	1970-2018	OECD STAN
Portugal	AEs	AEs	1995-2018	OECD STAN
Korea, Rep.	AEs	AEs	1970-2018	APO
Slovak Republic	AEs	AEs	1995-2018	OECD STAN
Slovenia	AEs	AEs	1995-2018	OECD STAN
Spain	AEs	AEs	1970-2018	OECD STAN/KLEMS
Sweden	AEs	AEs	1970-2019	OECD National Accounts
Switzerland	AEs	AEs	1995-2018	OECD STAN
Taiwan, China	AEs	AEs	1970-2018	APO
United Kingdom	AEs	AEs	1970-2018	OECD STAN/KLEMS
United States	AEs	AEs	1970-2018	OECD STAN/KLEMS
Cambodia	EMDEs	EAP	1970-2018	APO
China	EMDEs	EAP	1970-2018	APO
Fiji	EMDEs	EAP	1970-2018	APO
Indonesia	EMDEs	EAP	1970-2018	APO
Lao PDR	EMDEs	EAP	1970-2018	APO
Malaysia	EMDEs	EAP	1970-2018	APO
Mongolia	EMDEs	EAP	1970-2018	APO
Philippines	EMDEs	EAP	1970-2018	APO
Myanmar	EMDEs	EAP	1970-2018	APO
Thailand	EMDEs	EAP	1970-2018	APO
Vietnam	EMDEs	EAP	1970-2018	APO
Bulgaria	EMDEs	ECA	1995-2019	OECD National Accounts/ILO
Croatia	EMDEs	ECA	1995-2019	OECD National Accounts/ILO
Hungary	EMDEs	ECA	1995-2018	OECD STAN
Poland	EMDEs	ECA	1995-2019	OECD National Accounts
Romania	EMDEs	ECA	1995-2018	OECD National Accounts
Russian Federation	EMDEs	ECA	1995-2018	OECD National Accounts/KLEMS/ILO
Serbia	EMDEs	ECA	1995-2018	OECD National Accounts/ILO
Turkey	EMDEs	ECA	1970-2018	APO

Table A.4: Sectoral database (continued)

Country	Group1	Group2	period	Source
Argentina	EMDEs	LAC	1990-2018	ETD
Bolivia	EMDEs	LAC	1990-2018	ETD
Brazil	EMDEs	LAC	1990-2018	ETD
Chile	EMDEs	LAC	1951-2018	GGDC/ETD
Colombia	EMDEs	LAC	1950-2018	GGDC/ETD
Costa Rica	EMDEs	LAC	1950-2018	GGDC/ETD
Ecuador	EMDEs	LAC	1990-2018	ETD
Mexico	EMDEs	LAC	1950-2018	GGDC/ETD
Peru	EMDEs	LAC	1990-2018	ETD
Bahrain	EMDEs	MNA	1970-2018	APO
Egypt, Arab Rep.	EMDEs	MNA	1960-2018	GGDC/ETD
Iran, Islamic Rep.	EMDEs	MNA	1970-2018	APO
Morocco	EMDEs	MNA	1970-2018	GGDC/ETD
Oman	EMDEs	MNA	1991-2018	APO
Qatar	EMDEs	MNA	1986-2018	APO
Saudi Arabia	EMDEs	MNA	1991-2018	APO
United Arab Emirates	EMDEs	MNA	1970-2018	APO
Tunisia	EMDEs	MNA	1990-2018	ETD
Bangladesh	EMDEs	SAR	1970-2018	APO
Bhutan	EMDEs	SAR	1970-2018	APO
India	EMDEs	SAR	1970-2018	APO
Nepal	EMDEs	SAR	1970-2018	APO
Pakistan	EMDEs	SAR	1970-2018	APO
Sri Lanka	EMDEs	SAR	1970-2018	APO
Cameroon	EMDEs	SSA	1965-2018	EASD/ETD
Ghana	EMDEs	SSA	1960-2018	EASD/ETD
Kenya	EMDEs	SSA	1969-2018	EASD/ETD
Lesotho	EMDEs	SSA	1970-2018	EASD/ETD
Mauritius	EMDEs	SSA	1970-2018	EASD/ETD
Namibia	EMDEs	SSA	1965-2018	EASD/ETD
Nigeria	EMDEs	SSA	1960-2018	EASD/ETD
Senegal	EMDEs	SSA	1970-2018	EASD/ETD
South Africa	EMDEs	SSA	1960-2018	EASD/ETD
Tanzania	EMDEs	SSA	1960-2018	EASD/ETD
Zambia	EMDEs	SSA	1965-2018	EASD/ETD
Burkina Faso	EMDEs (LICs)	SSA	1970-2018	EASD/ETD
Ethiopia	EMDEs (LICs)	SSA	1961-2018	EASD/ETD
Malawi	EMDEs (LICs)	SSA	1966-2018	EASD/ETD
Mozambique	EMDEs (LICs)	SSA	1970-2018	EASD/ETD
Rwanda	EMDEs (LICs)	SSA	1970-2018	EASD/ETD
Uganda	EMDEs (LICs)	SSA	1990-2018	ETD

Notes:AEs:advanced economies. EMDEs:emerging markets and developing economies. LICs: low-income countries. EAP: East Asia and Pacific, ECA:European and Central Asia, LAC:Latin America and Caribbean, SAR:South Asia, MNA:Middle East and North Africa, SSA: Sub-Saharan Africa

Table A.5: Data construction from multiple sources

	Country	Description
1	Austria, Belgium, Germany, Italy, Luxembourg, Netherlands, Spain, United Kingdom, United States	OECD STAN or National Accounts data is backwards extrapolated using annual growth rates from EU KLEMS.
2	Chile, Colombia, Costa Rica Mexico, Arab Republic of Egypt, Morocco, Burkina Faso, Cameroon, Ghana, Ethiopia, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Zambia	ETD data is backwards extrapolated using annual growth rates from GGDC or EASD.
3	Cyprus, Bulgaria, Croatia, Serbia	As OECD Employment data is not available, ILO modelled estimates are supplementarily employed.
4	France	OECD STAN data in 2018 is forwards extrapolated using annual growth rates from OECD national Accounts data.
5	Russian Federation	OECD National Accounts data is backwards extrapolated using annual growth rates from KLEMS and ILO modelled estimates.

Table A.6: Data sources

Database	URL
APO Productivity Database	https://www.apo-tokyo.org/wedo/productivity-measurement/
OECD STAN database and National Accounts	https://stats.oecd.org/
WORLD KLEMS Data	http://www.worldklems.net/data.htm (Russia, March 2017 Release)
EU KLEMS Growth and Productivity Accounts	http://www.euklems.net/ (November 2009 Release)
GGDC/UNU-WIDER Economic Transformation Database (ETD)	https://www.rug.nl/ggdc/structuralchange/etd/
GGDC 10-Sector database (GGDC)	https://www.rug.nl/ggdc/structuralchange/previous-sector-database/10-sector-2014
Expanded Africa Sector Database (EASD)	https://www.merit.unu.edu/docs/EASD.xlsx
ILOSTAT databases	https://ilostat.ilo.org/data/bulk/ (ILO modelled estimates, Nov. 2020)
Penn World Table version 10.0	https://www.rug.nl/ggdc/productivity/pwt/?lang=en