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Asia-Pacific's Structural Transformation: The Past and Prospects

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Asia-Pacific's Structural Transformation: The Past and Prospects[1]

The Asia and Pacific region has enjoyed rapid economic and human development gains over the past three decades. Though it has benefited from demographic tailwinds, investment and productivity growth have been the key to these gains. The critical role of structural transformation, that is, workers moving out of agriculture into other, higher-productivity sectors in achieving productivity growth, is often underappreciated. Movement into manufacturing in particular, helped by rapid international trade integration, has been a hallmark of structural transformation in the region. However, services have played a bigger role across the region over the last three decades. Looking ahead, enabling continued transformation will be critical. As per capita incomes rise further, the move into services will likely become even more prominent. Ensuring a shift towards more productive services will require investment in education and training to supply the needed skills, especially to allow workers to adapt to the wave of new technologies, including AI. Continued international integration in services would be key, with an eye on boosting tradability and competition in services. In many economies, enhancing agricultural productivity will still be important to promote transformation and growth, along with lowering barriers to workers and resources moving across sectors. Policies to raise labor force participation, especially among elderly workers and women, will be critical to mitigate the impact of population aging and decline in much of the region.

Asia and the Pacific at the Crossroads of Growth

The Asia-Pacific region has undergone rapid development over the last three decades. Between 1990 and 2023, its GDP per capita more than doubled and its contribution to world GDP growth increased from about a quarter to about two-thirds. The share of those in the region living in poverty fell from over 25 percent to less than 5 percent, while life expectancy increased significantly, especially in low-income developing economies (Figure 1).

However, several developments raise questions about whether such rapid progress can be sustained. For example, labor force growth is projected to slow across the region, and productivity and investment have slowed in many economies since the global financial crisis. Merchandise trade growth has plateaued after the global financial crisis, and geoeconomic fragmentation could turn the region's high degree of trade and global value chain integration into a vulnerability.

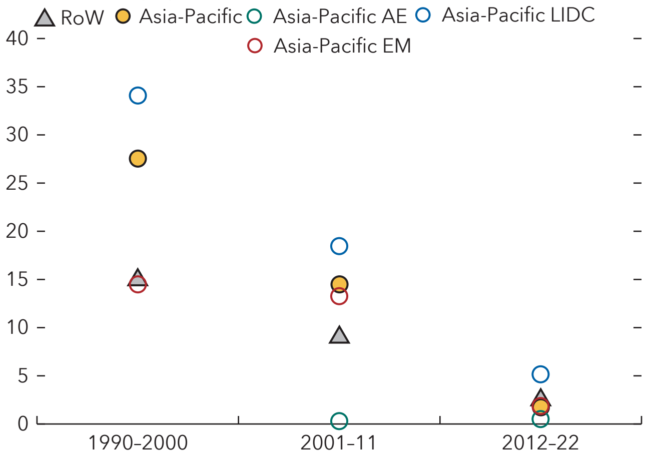
Against this background, this chapter asks two questions: what has driven Asia's rapid growth and transformation over the last three decades, and how will that play out going forward? It first analyzes the drivers of growth and economic transformation using growth and development accounting tools, with a focus on the reallocation of economic activity across sectors. The region has seen strong growth accompanied by an export-led rise of manufacturing—Japan and Korea are prime examples from decades before—so the chapter also examines the role of trade and foreign direct investment (FDI) in supporting such transformation. The chapter then examines prospects for growth in the medium to long term and assesses the implications of a continuation of reallocation trends for growth. The last section concludes and discusses policy implications.

The main findings are:

[1] Chikako Baba (co-lead), Natasha Che, Federico Diez, Rahul Giri (lead), Tristan Hennig, Shujaat Khan, Anne Oeking (co-lead), and Weining Xin, with contributions from Emmanouil Kitsios, under the guidance of Alasdair Scott and Johannes Wiegand. We thank Akos Valentinyi for data and guidance on methodological issues.

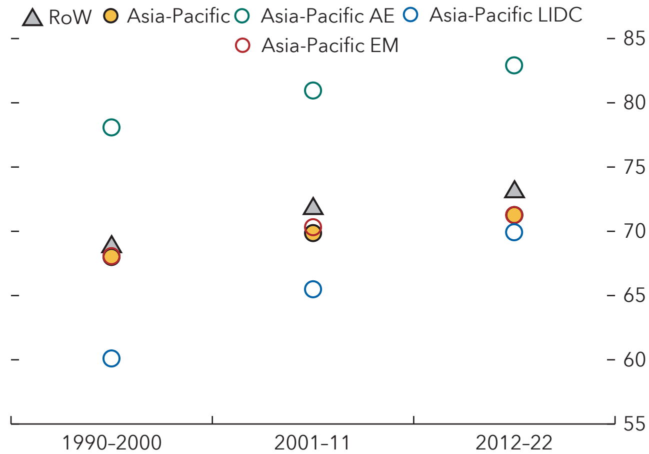
Figure 1. Asia-Pacific Human Development Outcomes

1. Poverty Headcount Ratio
(Percent of population)



Sources: World Bank World Development Indicators; and IMF staff calculations.
Note: The dots and triangles show the median of the population living on less than $2.15 a day at 2017 purchasing power adjusted prices. Asia EM includes CHN, IND, IDN, MYS, PHL, LKA, and THA. Asia AE includes AUS, JPN, and KOR. Asia LIDC includes BGD, LAO, MNG, and VNM. Data for JPN and KOR were unavailable for 1990–2000, hence Asia AE is not shown in that time period. RoW denotes rest of the world.

2. Life Expectancy at Birth
(Years)



Sources: World Bank World Development Indicators; and IMF staff calculations.
Note: The dots and triangle show the median of life expectancy at birth. Asia EM includes BRN, CHN, FJI, FSM, IND, IDN, MDV, MHL, MYS, PHL, LKA, THA, TLS, TON, TUV, VUT, and WSM. Asia AE includes AUS, HKG, JPN, KOR, MAC, NZL, and SGP. Asia LIDC includes BGD, BTN, KHM, KIR, LAO, MNG, MMR, NPL, PNG, SLB, and VNM. RoW denotes rest of the world.

- Increases in total factor productivity (TFP) and human capital have contributed positively to growth across the region. Capital investment and a growing pool of workers have made substantial contributions to growth in Asian emerging markets (EMs) and low-income developing countries (LIDCs). Growth in advanced economies (AEs) in Asia and the Pacific has relied more on productivity improvements, and also higher labor force participation to offset less favorable demographics.
- A significant contribution to growth has come from productivity growth due to structural transformation. Workers have left agriculture to work in more productive sectors. The region—especially South-East Asia—has invested very intensely in manufacturing, more so than other countries at the same stages of development, facilitated importantly by openness to trade. But service sectors have been crucial—in fact, some have generated more employment than has manufacturing.
- Without improvements in productivity and participation, demographic shifts are expected to slow growth rates over the next 10-20 years. More countries are likely to shift to more services-based economies. A shift into services need not slow productivity; in fact, there is likely more potential for countries to improve their services sector productivity than other sectors—but the key is moving into more productive services.

The focus of the chapter is on growth and productivity. The analysis that follows raises many additional questions about job creation, skill matching, and income distribution that, while extremely important, are outside the scope of this chapter. We also do not attempt to adjudicate the long-standing debates about the roles of government policies in driving growth and structural transformation, and in particular the export-led rise of manufacturing.

Looking in the Rear-View Mirror: Drivers of Growth in the Asia-Pacific Region

Growth from an Aggregate Lens—the Role of Factor Inputs and Productivity

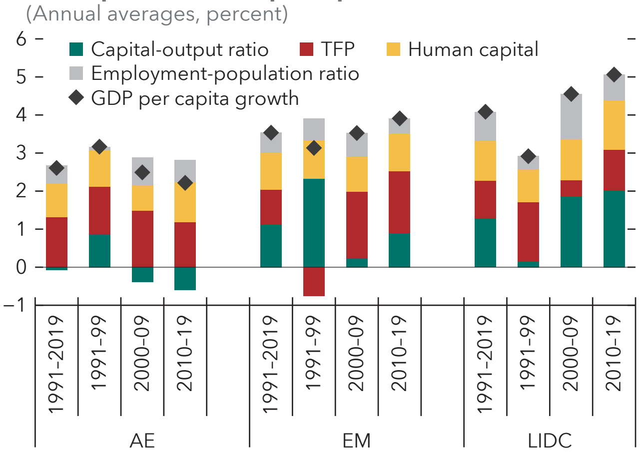
Given the positive correlation between developmental outcomes and per capita income, the chapter focuses on decomposition of per capita GDP growth (detailed in Annex A). The decomposition shows important differences in the drivers of GDP per capita growth in countries across the region (Figure 2, panel 1):

- Per capita growth has been slowest in AEs over the past three decades and has been driven mainly by TFP and human capital. The contribution of the capital-to-output ratio has been marginally negative for the whole period,[2] which largely accounts for the slowing growth over the three decades.
- By contrast, in EMs, an increase in the capital-output ratio has been the most prominent growth factor in the 1990s. Increases in human capital and TFP have made the largest contributions over the last two decades, resembling the pattern seen in AEs.
- Finally, LIDCs have been the fastest-growing group. TFP growth has been the main growth driver in the 1990s, whereas higher capital-to-output ratios have been the main force behind the growth acceleration after 2000, supported by continuous increases in human capital.

How have demographics shaped the consistently positive growth contribution of labor, as measured by the employment-population ratio? The drivers of these contributions differ notably between advanced and other economies (Figure 2, panel 2). In AEs, a decline in the share of the population of working age has been offset by higher labor force participation rates. In EMs and LIDCs, increases in employment-population ratios have been mainly attributable to the demographic dividend (that is, increases in the share of the population of working age). A larger share of the population of working age also contributes to capital accumulation via higher savings

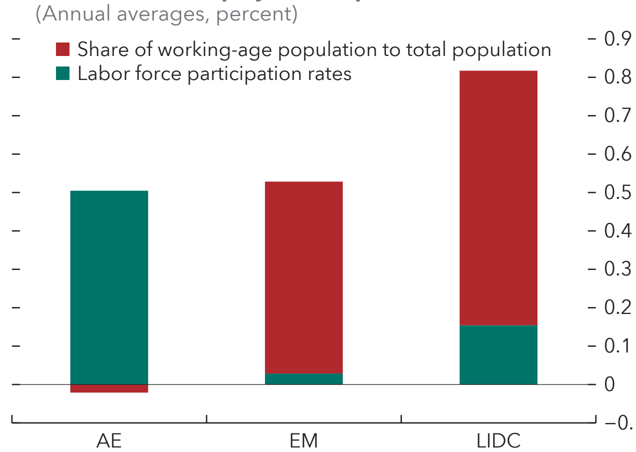
Figure 2. Sources of Growth in Asia-Pacific, 1991–2019

1. Decomposition of GDP per Capita Growth
(Annual averages, percent)



Sources: International Labour Organization; Penn World Table version 10.01; United Nations; and IMF staff calculations.
Note: Aggregate groups based on simple averages and current income group classification. See Annex A for derivation of GDP per capita growth into the components. AE = advanced economy; EM = emerging market; LIDC = low-income developing country; TFP = total factor productivity.

2. Breakdown of Employment-Population Ratio
(Annual averages, percent)



Sources: International Labour Organization; Penn World Table version 10.01; United Nations; and IMF staff calculations.
Note: AE = advanced economy; EM = emerging market; LIDC = low-income developing country.

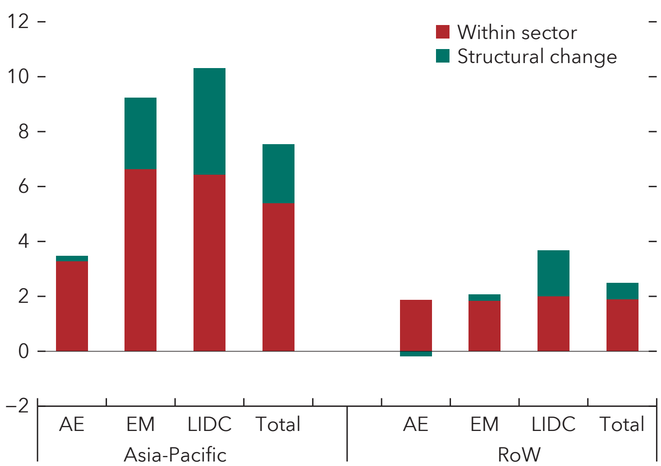
[2] This is similar to the finding of Jones (2022) for the United States.

rates and can free up resources for human capital improvements (Ogawa and others 2021). Indeed, the increase in labor supply has been accompanied by increases in human capital, with this total labor effectiveness strongly contributing to overall per-capita growth improvements.

Growth from a Sectoral Lens—the Role of Reallocation Across Sectors

Aggregate productivity growth, measured by value-added per worker,[3] can be decomposed into two components (Annex A): (i) labor productivity growth in each sector or within-sector productivity growth, and (ii) re-allocation of labor across sectors—here referred to as structural change or transformation. The latter contributes positively to aggregate growth when labor moves from sectors with low value added per worker to those with high value added per worker (see Annex A for data and definitions).

Figure 3. Contribution of Structural Change to Productivity Growth, 1990–2018
(Change between 1990 and 2018 relative to 1990)



Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: Aggregate groups based on simple averages. RoW denotes rest of the world.

Both components have contributed positively to aggregate labor productivity growth in most Asian economies (Figure 3). Structural change has been most important for Asian LIDCs, where it has accounted for nearly two-fifths of aggregate productivity growth on average (45 percent from 1990 to 2000 and 26 percent from 2010 to 2018). For EMs, the contribution has been a bit lower at 28 percent. Growth in AEs has been driven largely by productivity growth within sectors.

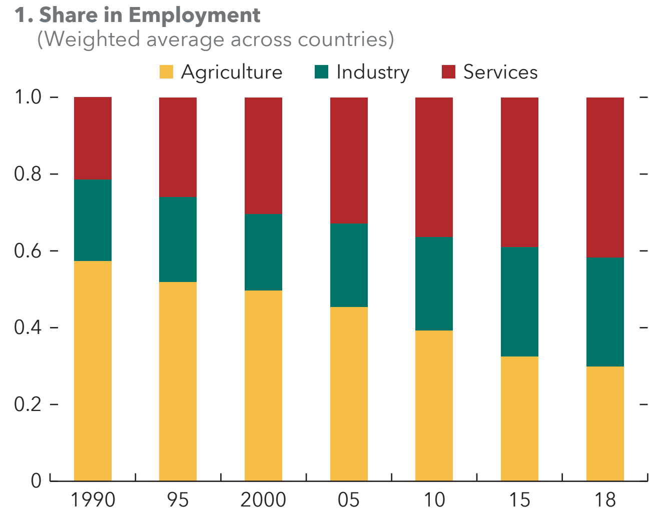
What is behind the significant contribution from structural transformation? We measure structural transformation in the chapter mostly by the reallocation of labor across sectors; the reallocation of production (value added) across sectors is also used to highlight certain sectoral trends (see Herrendorf and others 2014 for a discussion of different ways to measure structural change). A rapid shift of workers out of agriculture into industry and services has been crucial (Figure 4, panel 1). The share of employment in agriculture almost halved from 1990 to 2018, mainly driven by LIDCs and EMs, although the share remains high in most LIDCs and some EMs, such as India, Indonesia, and Thailand.

As a result of this transformation, Asia-Pacific economies—especially those in South-East Asia—became more heavily industrialized than peers in other parts of the world, in terms of both value-added (Figure 4, panel 2) and employment (Annex Figure B.1, panel 1). This has mainly been driven by manufacturing, rather than expansions of other industry sub-sectors (mining, utilities, and construction). Rapid integration into global supply chains and the creation of regional supply chains have been instrumental in boosting greater industrialization. Sharp reductions in shipping and communications costs enabled the "unbundling" (Baldwin and Forslid 2020) of goods production across supply chains. Asia-Pacific economies—especially those in South-East Asia—were able to take advantage of these trends more than those in other regions, whether by natural advantage (cheap and plentiful labor), good timing, or government policies.[4] This international integration has been accompanied by a steady

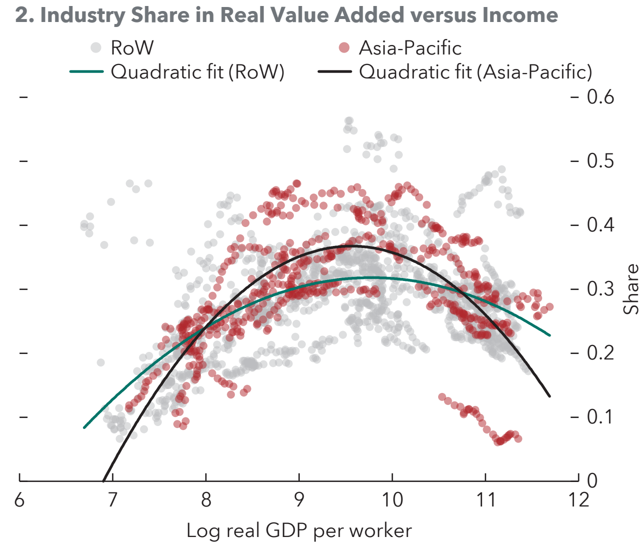
[3] Data on other factor inputs are not available at the sector level for a large set of countries; this restricts the analysis to labor productivity.

[4] There is ongoing debate about the role of government policies. Many Asian countries initially adopted import-substitution strategies that generally delivered weak economic outcomes (Krueger 1985). Some countries turned to export-oriented industrial policies; the remarkable growth of the "East Asian miracles" has led to debate on whether market failures meant that industrial policies were instrumental to those economies' successes (Rodrik and others 1995; Stiglitz 1996), or that the East Asian experiences could be explained by rapid capital and skilled labor accumulation (Krugman 1994). Empirical work has been far from conclusive, hampered by a lack of data and identification issues (Juhász and others 2023).

Figure 4. Reallocation out of Agriculture and Industrialization in Asia-Pacific, 1990–2018



Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: See Annex A for definition of sectors.



Sources: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: RoW denotes rest of the world. Quadratic fit refers to a second-order polynomial fit.

decline of tariffs on manufacturing imports (Figure 5, panel 1). Access to global markets has allowed countries to overcome the constraints on sectoral development imposed by limited domestic demand.[5] Analysis shows that a 10 percent of GDP increase in manufacturing exports was associated with an increase in the manufacturing share of domestic value-added by 6 percentage points on average after four years (Figure 5, panel 2).

The concentration in industry of many Asian countries has meant that the shares of value-added (Figure 6) and employment (Annex Figure B.1, panel 2) in services have been relatively low compared to those of peers in the rest of the world at similar income levels. But that does not mean that services have not been important: they have absorbed a bigger fraction of the workers released from agriculture since 1990 than has industry. As a result, the share of services in employment has doubled (Figure 7, panel 1), with the surge most pronounced in tradable services (finance, business, trade, and transport). This trend is particularly strong in EMs (Annex Figure B.2, panel 1);[6] AEs have continued to shift towards services. In LIDCs, industry's share of employment has risen at a pace comparable with that of services, driven both by manufacturing and non-tradable industry (construction and utilities). For the region as a whole, tradable services have the highest value-added share across sectors (Figure 7, panel 2) and will likely eclipse agriculture to become the sector with the highest employment share. In contrast, manufacturing's share of value added has fallen for the region post the global financial crisis, driven by EMs (Annex Figure B.2, panel 2), while the employment share of manufacturing for the region has largely been stagnant. Industry's share of employment has increased due to construction and utilities.

What is behind these sectoral shifts? Economic development is usually thought to start with an increase in agricultural productivity, which releases labor to other sectors once subsistence food demand is met. Industry is usually thought to absorb these workers initially (due to falling relative prices from its faster productivity growth and an income elasticity that is higher than agriculture's, albeit lower than that of services). As incomes rise

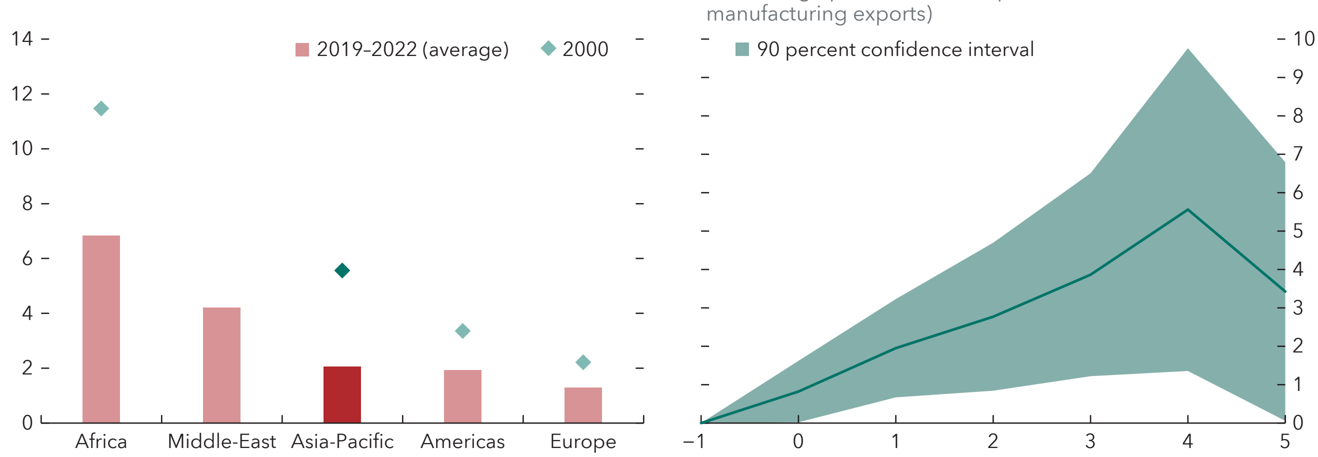
[5] See Matsuyama (2009); Uy, Yi, and Zhang (2013); Betts, Giri, and Verma (2017); and Sposi, Yi, and Zhang (2021) for structural models underscoring the importance of trade for structural transformation.

[6] A rising share of services is apparent in all Asia-Pacific EMs. While Malaysia and Philippines have the top two largest shares of tradable services in employment, China exhibits the fastest growth. India has a considerably larger value-added share of tradable services relative to employment share when compared with other EMs.

Figure 5. Trade and Industrialization

1. Effectively Applied Tariffs on Manufacturing Imports
(Percent)

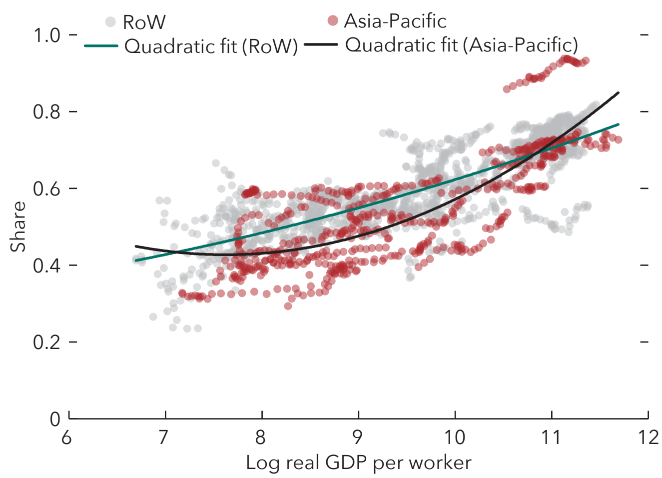
2. Change in Manufacturing Share of Value-Added
(Percentage points, after a 10 percent of GDP increase in manufacturing exports)



Sources: World Integrated Trade Solution; and IMF staff calculations.
Note: Import weighted.

Sources: BACI database; ESCAP-World Bank Trade Cost Database; GGDC/UNU-WIDER Economic Transformation Database; and IMF staff estimates.
Note: The line shows the change in manufacturing share of value added, in percentage points, after a 10 percent of GDP increase in manufacturing exports in year $t-1$, and the shaded area shows the 90 percent confidence interval. See Annex A for details.

Figure 6. Services Share in Real Value Added versus Income, 1990–2018



Sources: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: RoW denotes rest of the world. Quadratic fit refers to a second-order polynomial fit.

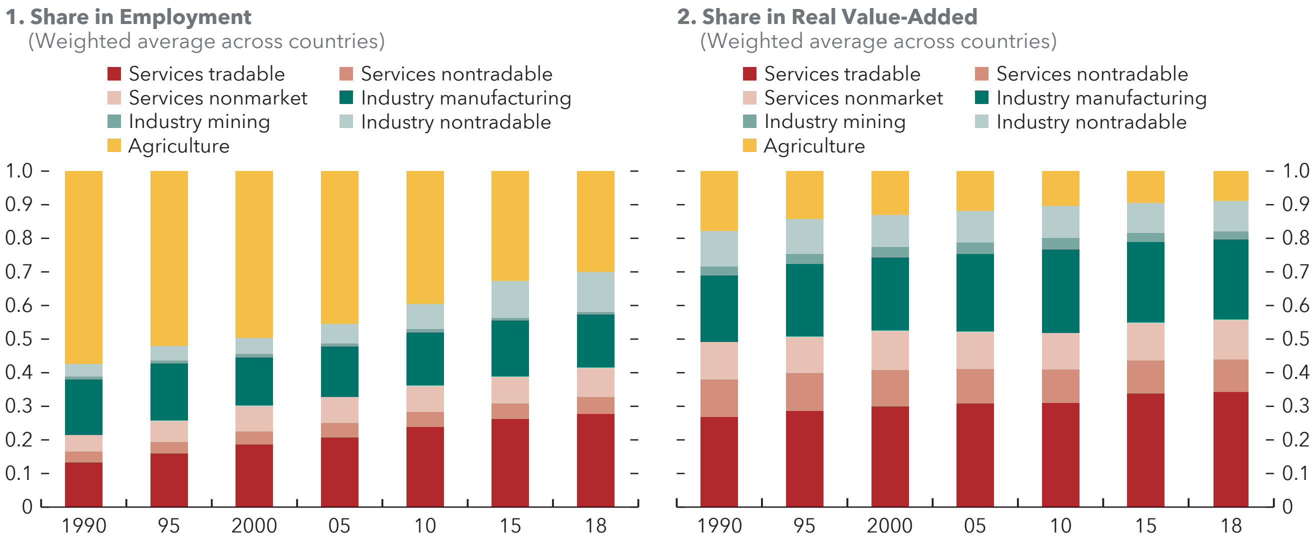
further, services—which typically have higher income elasticities—experience larger increases in demand, and hence absorb more workers (even though slower productivity growth in the services sector implies rising prices relative to industry and agriculture).[7] This is because services and products of industry and agriculture are typically complements in consumption baskets. Therefore, industry's share of output and employment declines, resulting in a hump-shaped pattern of industrialization. Thus, in the traditional narrative, economies move first into light manufacturing, then into heavy industry, and only then into services.[8]

However, this progression need not hold always and everywhere—actual outcomes depend on the relative strengths of productivity growth and income effects, and in the short term on adjustment frictions, market distortions, and so on. They also depend crucially on openness to trade

[7] Differences in the level of informality could play a role in explaining productivity differences across sectors if some sectors systematically tend to be more informal than others, given the typically lower productivity of informal enterprises. The dataset used for this chapter pays particular attention to challenges arising from informality while obtaining measures of sectoral value-added and employment from national accounts and labor force surveys/census data, respectively.

[8] See Herrendorf and others (2014) for a comprehensive literature review and Sposi and others (2018) for analysis of additional mechanisms behind structural change.

Figure 7. Rising Importance of Tradable Services in Asia-Pacific, 1990–2018



Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: See Annex A for definition of sectors.

Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: See Annex A for definition of sectors.

(Matsuyama 2009; Rodrik 2016). Trade provides access to foreign demand and hence supports reallocation to sectors with faster productivity growth, usually considered to be industry. As result, trade can boost industrialization beyond what the size of the domestic market would allow. In practice, different patterns have emerged: East and South-East Asia has become highly industrialized, following in the footsteps of Japan and Korea. But in South Asia (as in most of Africa and Latin America; see Chapter 3 of the April 2018 *World Economic Outlook*) industrialization has been slower. Some other economies (for example, Australia and New Zealand) have also moved directly from agriculture to services (Annex Figure B.3).[9]

Looking Ahead: Prospects for Future Transformation and Growth

The Implications of More Structural Transformation

What does reallocation out of agriculture mean for aggregate productivity? From the perspective of supply side factors, agricultural productivity is relatively low in Asian economies. Specifically, productivity gaps in agriculture in the region are almost always larger than aggregate productivity gaps (measured by GDP per worker relative to the frontier) and have not changed much since 1990 (Figure 8).[10] A relatively high level of agriculture protectionism could be one cause of low agricultural productivity (Figure 9), among many factors. Reallocation out of agriculture would, thus, improve aggregate productivity, as productivity gaps must be smaller in non-agricultural sector(s).

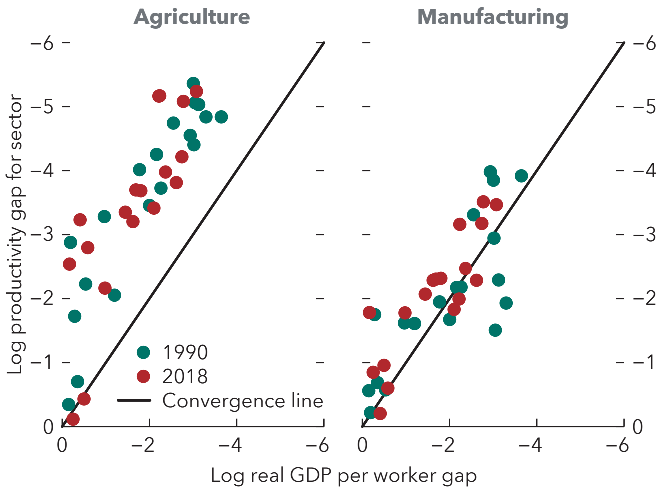
Is Manufacturing Necessarily the Way Forward?

The traditional narrative suggests that moving resources to manufacturing would result in the biggest increase in growth. In turn, this rests on an assumption that services are less productive—often referred to as the Baumol effect (Baumol 1967). This assumption has two important caveats: first, the services sector is in fact

[9] Some explanations for departures from the traditional pattern include reallocation stemming from demand for products of modern sectors rather than productivity improvements in those sectors (Diao and others 2017), greater role of income effects (Comin and others 2021) and imported de-industrialization due to rapid decline in price of manufactures resulting from globalization (Rodrik 2016).

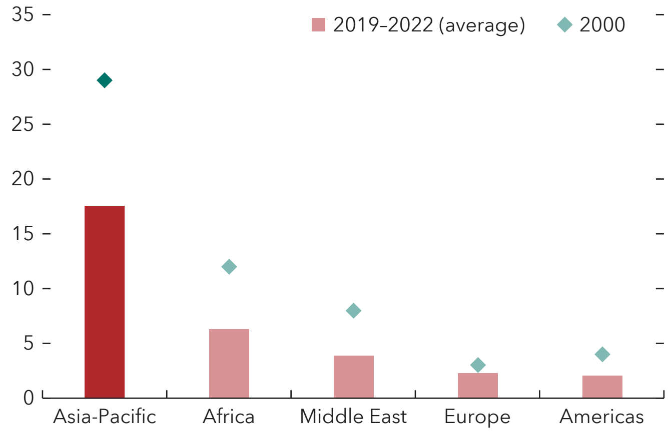
[10] This result is consistent with findings of Restuccia and others (2008), based on Food and Agricultural Organization (FAO).

Figure 8. Productivity Gaps by Sector
(Log difference)



Sources: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: The figure plots a country's productivity gaps from the global frontier for agriculture (left) and manufacturing (right) on *y*-axis, relative to the country's aggregate productivity gap on *x*-axis. The global frontier is calculated as the average productivity of the top three most productive countries. Productivity is measured as value-added per worker in constant PPP prices.

Figure 9. Effectively Applied Tariffs on Agriculture Imports
(Percent)



Sources: World Integrated Trade Solution; and IMF staff calculations.
Note: Import weighted.

very heterogenous, and second, productivity is subject to measurement problems (see Duarte and Restuccia 2022). The data used for this chapter address some of the measurement problems, owing to calculating sectoral purchasing power parity (PPP) prices rather than relying on the same PPP price for all sectors, and because they detail different services subsectors—this matters for comparisons of manufacturing and services productivity levels below.

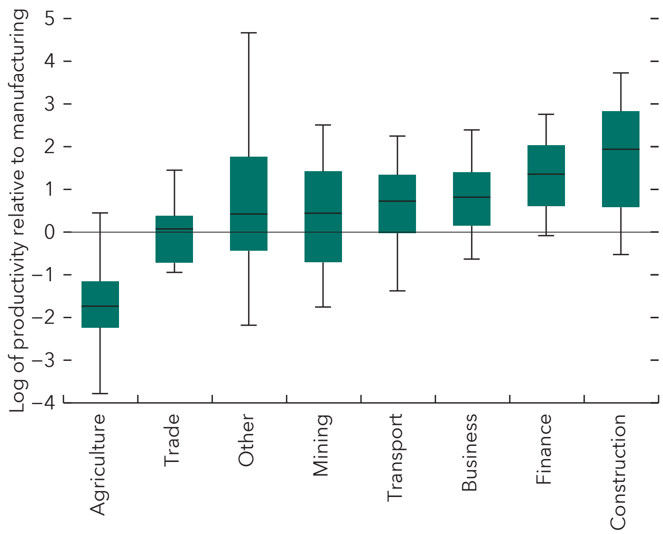
To begin with manufacturing: the evidence for Asian economies shows that while productivity gaps in manufacturing are smaller than those in agriculture (consistent with the higher level of international integration), they are not smaller than *aggregate* gaps (Figure 8). They also appear to have *increased* somewhat from 1990 to 2018. This implies that, although a shift to manufacturing from agriculture would improve aggregate productivity, it might not cause the *largest* increase in aggregate productivity (unless manufacturing productivity were to increase relative to the frontier).

What of productivity in services? Using PPP price indices allows cross-country comparison of subsector productivity levels and shows that services—especially "modern" tradable services (business and finance)—are *more* productive in Asian economies than manufacturing (Figure 10).[11]

The evidence so far indicates that manufacturing productivity gaps are not smaller than aggregate gaps—a *static* comparison. Nonetheless, manufacturing is often thought to be critical *dynamically* for developing economies to catch up to advanced economies' income levels. This is referred to as unconditional β-convergence. Testing (see Annex A for specification and regression results) shows evidence of unconditional β-convergence for services,

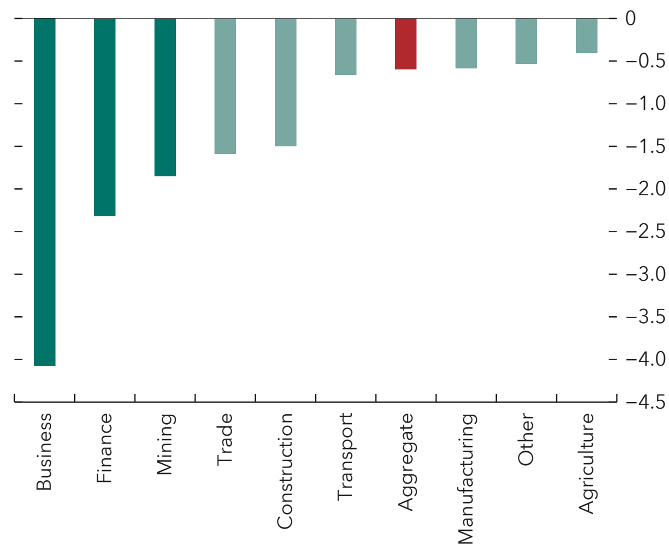
[11] This result holds for countries at different income levels, but the gap relative to manufacturing shrinks with income level, and dispersion of productivity increases with income level (Annex Figure B.4, panel 2). The higher productivity of modern tradable services is also observed in 1990 (Annex figure B.4, panel 1). Labor productivity is a broader measure of productivity than TFP, and would be affected by capital, human capital as well as TFP itself.

Figure 10. Labor Productivity Relative to Manufacturing, 2018
(Log of ratio of a sector's labor productivity relative to that of manufacturing)



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; and IMF staff calculations.
Note: Real estate services are excluded due to extremely large variation. Government and Utilities are excluded because of challenges of measuring prices, including due to large public sector presence. Productivity is measured as value-added per worker in constant PPP prices.

Figure 11. Unconditional Convergence by Sub-Sectors, 1990–2018
(Percentage points)



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; Penn World Table 10.01; and IMF staff calculations.
Note: Chart shows coefficient from regressing annual change in log labor productivity on initial labor productivity and year fixed effects for the period 1990–2018. A light shaded bar indicates that the coefficient is not statistically significant at 90% confidence level (see Annex A for specification and regression results). Real estate services are excluded due to extremely large variation. Government and Utilities are excluded because of challenges of measuring prices, including due to large public sector presence. Productivity is measured as value-added per worker in constant PPP prices.

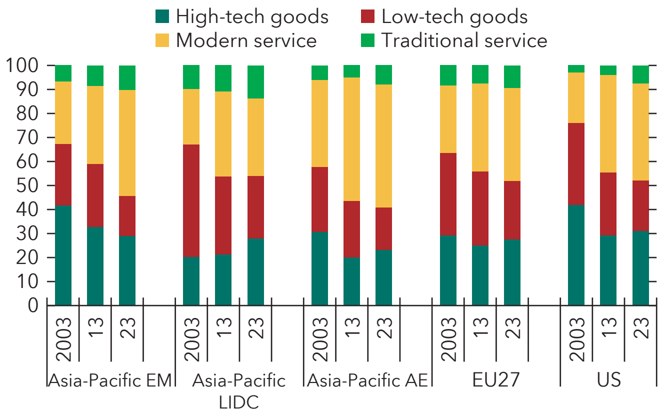
especially modern tradable services, but not for agriculture and manufacturing (Figure 11).[12] Thus, unconditional convergence to the frontier for the Asian economies has been driven by modern tradable services rather than manufacturing.[13]

[12] Conditional on accounting for country-specificities (via country-fixed effects), proxying for differences across countries in geography, institutions, and relative strength of policy frameworks, there is evidence for convergence for most sectors, with the pace of convergence for manufacturing and agriculture exceeding that of tradable services. It is not clear whether inclusion of fixed effects is appropriate in testing for convergence—see for instance Barro (2015); Kremer, Willis, and You (2021); and Acemoglu and Molina (2021). Nonetheless, convergence process can take long periods. In fact, the aggregate unconditional convergence coefficient implies a very slow convergence process, consistent with Herrendorf and others (2022).

[13] A related concept is σ–convergence: as countries converge to the frontier, dispersion in productivities across countries also declines. Asia exhibits σ–convergence for services, particularly business and finance, but not for agriculture and manufacturing (Annex Figure B.5).

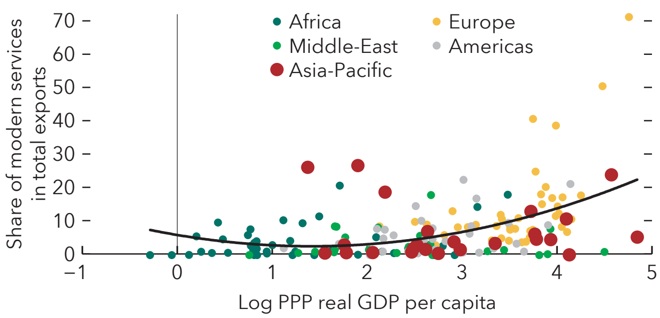
Figure 12. Tradability of Services

1. Share in FDI Projects
(Percent)



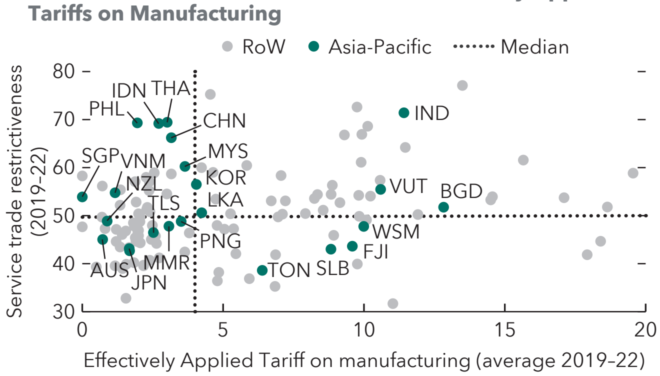
Sources: fDi Markets; and IMF staff calculations.
Note: High- and low-tech manufacturing classification is based on the R&D intensity of production following Galindo-Rueda and Verger 2016. Modern services include financial, real estate, ICT, and business services.

2. Share of Modern Services in Exports versus Income, 2019
(Percent)



Sources: BACI database; International Trade in Services database (Loungani and others 2017); Penn World Table version 10.01; *World Economic Outlook*; and IMF staff calculations.

3. Services Trade Restrictiveness versus Effectively Applied Tariffs on Manufacturing



Sources: Borchert and others 2020; World Bank-WTO Service Trade Restrictions Index (Baiker and others 2023); World Integrated Trade Solution; and IMF staff calculations.
Note: Modern services trade restrictiveness is based on services trade policy measures on communication, financial, and professional services. Countries are surveyed in 2019–22. RoW denotes rest of the world.

The empirical evidence here does not imply that there are no benefits to manufacturing, and there is room for debate about the role of manufacturing in driving growth. Nonetheless, the empirical evidence suggests that the Baumol effect does not necessarily hold, and hence that manufacturing is not necessarily the only way forward.[14]

An increasing role for services?

Theory also suggests additional forces would increase the role of services. First, the demand for services will more than proportionately increase as incomes rise. The largest shift will likely be in EMs followed by LIDCs; AEs are already services dominated.

In addition, the increasing tradability of services will likely boost demand for countries that have a comparative advantage in this area. Digital technology is a key driver behind making services more tradable (Baldwin 2019); indeed, services trade growth has outpaced goods trade growth since the global financial crisis. To date, traditional services such as tourism and transport account for much of Asian service exports but shares of "modern" services—information and communication technology (ICT), business operations, intellectual property, financial services—are steadily increasing, as evidenced by their rising share of FDI projects (Figure 12, panel 1). These developments vary greatly across countries, with countries like India and the Philippines leading the region's EMs in the provision of ICT and business services. Richer countries tend, in general,

[14] In an influential paper, Rodrik (2013) does find evidence for unconditional convergence for manufacturing. The data in that paper are sourced from large formal enterprises, whereas the data in our exercise have been harmonized to take informality into account as best as possible. In addition, Rodrik (2013) is forced to adopt the strong assumption that the law of one price holds, whereas the testing in this chapter uses sectoral PPP prices to compare real value-added across sectors and countries. Our findings are consistent with those of Herrendorf and others (2022), who, using very similar data, find a lack of unconditional convergence for agriculture and manufacturing. An innovation is using sectoral PPP data for more years. Chapter 3 of the April 2018 *World Economic Outlook* finds evidence for convergence among market services and manufacturing but not for agriculture. However, the set of countries is smaller (39) and the sectoral PPP prices are available only for 2005 and only for nine sectors.

to have a higher share of modern service exports in total exports—but many countries in Asia and the Pacific lag their peers in this respect (Figure 12, panel 2). One factor is likely services trade restrictions: less modern service-oriented and more heavily industrialized countries—typically those in East and South-East Asia—tend to lag in liberalization of modern services, while they are notably open in manufacturing (Figure 12, panel 3; see also Constantinescu, Mattoo, and Ruta 2018).

To illustrate, comparative-static simulations using the Rodrik (2016) model (Annex C) show that a doubling of the services exports-to-GDP ratio by 2040 would double the decline in manufacturing share of employment for Asia. For context, the service exports-to-GDP ratio increased from about 1.5 percent in 1990 to 4.7 percent in 2018. On the other hand, the manufacturing trade balance for Asia would have to increase by a factor of about 1.5 relative to current levels to simply *maintain* manufacturing's employment shares. This stands in stark contrast with slowing growth of merchandise trade after the global financial crisis as well as trends to reshoring and rising geoeconomic fragmentation.

Overall, the evidence suggests that the forces driving structural change in the region will likely result in continued declines in the output and employment shares of agriculture as incomes rise and increases in the shares of services. A transition to greater services shares need not impede the catch-up to advanced economy income levels. This transition is underway among the EMs where the shift of employment towards services has been the quickest. As underscored earlier, LIDCs in Asia appear to be shifting out of agriculture towards industry and services at a comparable pace, and hence are undergoing the canonical phase of industrialization. It remains to be seen if their peak industrialization would be comparable to historical averages.

Advancing Productivity to Mitigate Demographic Shifts

What are Asia's growth prospects looking ahead? To answer this question, this section uses the growth accounting framework from above to project medium-term GDP growth rates (Annex A).

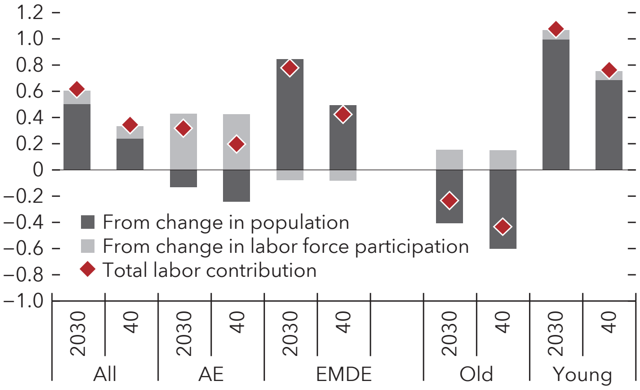
Rapidly ageing populations are projected to gradually reverse Asia's demographic dividend. In AEs, ageing will be partially buffered by positive net migration, most notable in countries such as Australia or Singapore, as well as by increases in labor force participation, especially among females and the elderly (Figure 13, panel 1). For some emerging markets and developing economies (EMDEs), labor force participation will be a small drag to total labor supply, mostly because of falling participation rates among the young as they pursue higher education, and in some cases still low and even slowing female participation. Some Asia-Pacific economies are already old, but many more are projected to follow suit, even as working age populations will continue to grow for now (Figure 13, panel 2). Overall, demographic factors would have negative effects on trend growth.[15] To illustrate:

- Employment-to-population ratios would decline. So too would the contributions from human capital, even though further skills accumulation would continue to have a sizeable impact overall. Together, these two factors are projected to contribute 0.2 percentage points less on average to annual per-capita growth by 2040 than currently.
- The reduction in labor supply would also imply a reduction in physical investment; the contribution from capital-to-output ratios is projected to decline by 0.5 percentage points.
- Historical TFP trends imply slower TFP growth going forward, contributing 0.4 percentage points less on average to annual per capita growth by 2040.
- The sum of these contributions implies that potential per capita GDP growth across the region could decline to around 2 percent by 2040 (Figure 13, panel 3). This results in corresponding aggregate GDP growth of around 2.2 percent, contrasting sharply with the 4 percent average growth seen in 2023. It would imply a cumulative output loss of almost 20 percent by 2040, compared with the level of GDP implied by continuing at current growth rates. The slowdown would be largest in EMDEs: these have yet to experience the

[15] While this note abstracts from analyzing the effects of climate change on potential growth, it could be an additional factor affecting long-term growth and structural transformation (see, for example, Kahn and others 2019).

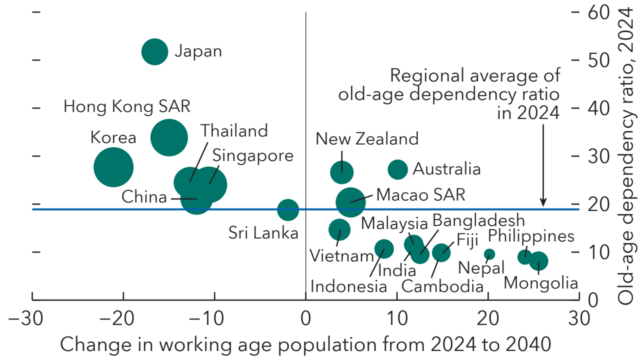
Figure 13. Growth Projections and Contributions to Growth

1. Projected Change in Labor Supply
(Percentage points)



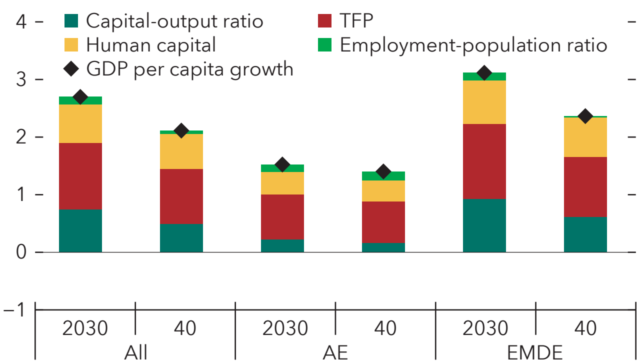
Sources: United Nations World Population Prospects 2022; International Labour Organization; Penn World Table version 10.01; and IMF staff calculations.
Note: Old populations defined as those with shrinking working age population (15–64) over the time horizon 2024 to 2040. Projections of labor supply based on projections of working age population and cohort-gender specific labor force participation rates.

2. Demographic Developments Across Asia
(Percent)



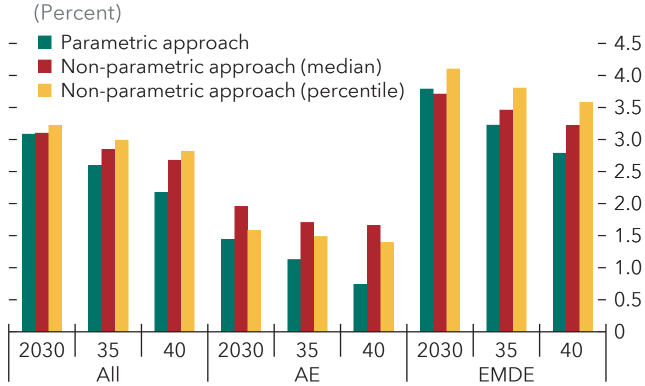
Sources: United Nation World Population Prospects 2022; and IMF staff calculations.
Note: Working age population defined as population ages 15–64. Old-age dependency ratio is defined as ratio of population 65+ to working age population. Bubble size shows the projected change in the old-age dependency ratio between 2024 and 2040 percentage points.

3. Projected Average Potential GDP Per Capita Growth
(Percent)



Sources: International Labour Organization; Penn World Table version 10.01; United Nations; and IMF staff calculations.
Note: Aggregate groups based on simple averages.

4. Projected Medium- and Long-Term Aggregate GDP Growth
(Percent)



Sources: Penn World Table version 10.01; International Labour Organization; United Nations; and IMF staff calculations.
Note: Aggregate groups based on simple averages. For the non-parametric approach, "median" assumes the target country will grow at the median rate of its peer group. "Percentile" assumes the target country will maintain its current percentile ranking for growth performance among its peers.

demographic slowdown that many AEs are facing already; in addition, contributions from productivity growth and capital accumulation in those countries are projected to decline more steeply over time. Thus, EMDE aggregate growth is projected to fall to 2.8 percent in 2040, compared to average growth of 5.1 percent in 2023. A downward trend is also likely for AEs, with aggregate growth projected to fall to 0.8 percent in 2040, compared to average growth in 2023 of 1.7 percent.

Several assumptions are necessary to make these projections which are subject to significant uncertainty. As a robustness check, aggregate growth rates are also projected using a non-parametric approach called Dynamic Time Warping (DTW, Annex A) that is not contingent on such assumptions and instead uses the historical growth trajectories of peer countries with similar economic conditions to project growth. This shows a similar reduction in growth rates over time (Figure 13, panel 4).

The DTW approach nonetheless also projects somewhat higher levels of potential growth rates over the medium and long term. One question is whether the potential effect of future structural transformation is adequately accounted for in the growth accounting exercise—the DTW could be capturing structural transformations in similar past experiences, leading to slightly higher growth rate projections.

Simulations of aggregate labor productivity based on the empirical evidence in the preceding section gives some support that further structural transformation could boost productivity, mitigating the effects on aggregate growth. The lack of unconditional convergence in agriculture and manufacturing implies that labor productivity growth for Asia in these goods sectors would be the same as those in frontier economies. But labor productivity growth in services is likely to be higher.[16] Assuming that frontier economies' annual growth rates for the three sectors remain the same as those observed from 2008 to 2018, and holding employment shares of the three sectors in Asia unchanged at their 2018 levels, aggregate labor productivity growth would be higher: 3.1 percent, compared to around 2.7 percent implied by the aggregate growth accounting framework.

In sum, demographic factors can be expected to reduce trend growth. But there is a potential upside from further structural transformation. As discussed in the previous section, reallocation of labor towards services will continue. But much would depend on the types of services: a greater shift towards modern tradable services would tend to raise labor productivity further, while a shift towards low-skill labor absorbing services (trade, care, education, and personal and public services) would tend to lower labor productivity.

An important factor not incorporated in growth prospects is the impact of AI, which could have far-reaching consequences for productivity as well as labor markets and income distribution given its high degree of substitutability with labor. The lack of accurate data on adoption of these technologies impedes a systematic analysis. Nonetheless, early estimates suggest that services are likely to face higher exposure to AI and hence could see larger gains in productivity. The effect on aggregate productivity will depend on the importance of more exposed sectors in an economy (Box 1). Moreover, while both advanced and emerging economies are likely to see such growth gains over the near to medium term, EMDEs may have to contend with higher unemployment as the occupations which can be complemented by AI rather than replaced are concentrated in AEs. But AI (like automation) is expected to transform tasks and roles in the labor market—creating new jobs and tasks while making many current jobs obsolete.

Conclusions and Policy Implications

This chapter looks at forces driving growth and prospects for the future in Asia and the Pacific. Two dominant themes emerge: demographics affecting labor supply and structural transformation affecting productivity.

Demographic trends suggest that many countries face lower growth prospects unless they can increase labor force participation, find other workers, or raise productivity. Policies are needed to reduce the impact of aging, including by supporting labor force participation, especially for women, increasing fertility, and facilitating

[16] AEs in the rest of the world are assumed to be the frontier—Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, United Kingdom, and United States. The service sector labor productivity growth rate for Asia for 2018-2040 is the frontier economies' growth rate adjusted upwards for the extent of catch-up to the frontier observed for Asia in services during 1990-2018. See Annex C for details.

migration. Countries that are further along the aging trajectory will have to shift attention to retirement, pension, and healthcare reforms, while ensuring debt sustainability. Here, productivity-enhancing reforms will be even more important and could be supported by technologies such as AI.

Some countries are still young. They are typically less wealthy and may not be able to harness the gains from manufacturing driven growth and job creation as successfully as their predecessors in the region. The increasing skill and capital bias of manufacturing together with the increasingly internationally integrated nature of production could limit the scope for labor-intensive manufacturing going forward (Rodrik 2016; Rodrik and Stiglitz 2024).

Hence, for EMDEs, where structural transformation is a significant source of productivity improvement, policies need to prioritize addressing distortions that inhibit transformation:

- The large and stagnant agricultural productivity gaps relative to the frontier suggest there is room to spur aggregate productivity growth by closing these gaps. LIDCs and EMs with large shares of the workforce in agriculture should prioritize *reforms to boost agricultural productivity* to reinforce reallocation out of agriculture. Options include lowering tariff barriers to promote competition, promoting better access to finance, and reviewing appropriateness of land regulation, property rights, and government interventions in food markets. Policymakers also need to tackle adverse climate change impacts on agricultural productivity. In addition, targeted and flexible social safety nets can support reallocation away from agriculture.
- The transition to a more services-based economy, more pressing for EMs, need not imply that the scope for catching-up with advanced economies' income levels is diminished, but does imply making the transition to highly-productive services, such as modern tradable services. Policymakers could facilitate the transition by *lowering barriers to entry in services*, which would help achieve scale economies. Tradable services (such as telecommunications, logistics and delivery, and financial services) are critical for reducing transaction costs and providing the infrastructure for e-commerce and digital trade. *Addressing the lagging services trade and FDI liberalization* can help to maximize pro-competitive gains and technological spillovers.

Given that within-sector productivity growth is the dominant source of aggregate productivity growth across the income spectrum, though more so for AEs and EMs, *the policy and business environment should be well-aligned with fostering productivity growth*. This entails providing high quality physical infrastructure, improving the business and investment climate, and improving incentives for R&D. Reforms that remove obstacles to the efficient reallocation of factor inputs, across firms within sectors, will support healthy firm growth to achieve efficient size and scale. Chapter 3 of the April 2024 *World Economic Outlook* finds that about two-thirds of the misallocation losses are attributable to structural factors such as ease of market entry and competition, trade openness, financial access, and labor market flexibility. Evidence suggests that misallocation tends to be higher in services.

Some countries may rush into industrial policies targeting certain sectors, in an effort to leverage the changing incentives resulting from geoeconomic fragmentation. Such policies carry the risk of being poorly rationalized, designed, and implemented and potentially involve large fiscal costs,[17] and hence, could exacerbate the misallocation losses both within and across sectors.

Care is needed to make growth more inclusive:

- Productivity-maximizing reallocation may not be able to generate enough jobs, as modern tradable services tend to be intensive in technology and skilled labor. Thus, *improving productivity in low-skill labor absorbing services* will be important to balance job creation with productivity growth (Rodrik and Sandhu 2024), absent which informality and inequality could worsen and productivity growth adversely affected.

[17] See the April 2024 *Fiscal Monitor* for the case for fiscal policy interventions to boost innovation in sectors with higher knowledge spillovers.

- Investing in education and skill development will be a crucial ingredient to (i) supply skills demanded by the more productive sectors, (ii) boost productivity by raising human capital, and (iii) prepare a workforce to leverage new technologies.
- The new technologies have the potential to boost productivity and create new jobs, but they can also bring distributional trade-offs. The chapter finds that EMDEs face greater risk of higher unemployment due to AI adoption. Containing possible negative distributional implications will require a focus on digital infrastructure preparedness, regulatory preparedness and bolstering social safety nets. Box 1 shows that though the large EMs in Asia appear to be better prepared than the average World EM, there are many Asian economies that have significant room to catch-up.

Box 1. The Impact of Artificial Intelligence on Asia

Artificial intelligence (AI) is poised to significantly reshape labor markets across Asia, creating both challenges and opportunities for the region's diverse economies. This box explores the differential impact of AI on Asian labor markets, identifying the roles most vulnerable to AI disruption and the sectors where productivity could be boosted. While both AEs and EMDEs may see aggregate productivity increases from AI adoption, EMDEs could face higher unemployment as the roles that can be complemented rather than replaced by AI are concentrated in AEs. To harness AI's benefits and mitigate risks, proactive policymaking to improve digital infrastructure, education, and innovation will be critical.

Recent advances in the capabilities of artificial intelligence will have implications for labor markets around the world. Machine learning algorithms and, more recently, generative AI models such as OpenAI's GPT-4 and Google's Gemini have demonstrated significant potential to transform work in many economic sectors. While these technologies are expected to provide substantial productivity gains, at least for some workers, they have also raised concerns about job security for roles involving tasks that can now be replaced by AI. This box provides an initial assessment of Asia's labor force exposure to AI and identifies which Asian countries are most likely to benefit from AI-induced productivity gains over the near to medium term. Understanding how the impact of AI depends on country characteristics is crucial for crafting policies that ensure inclusive growth and mitigate potential inequalities caused by AI-driven disruptions.

Box Table 1. Exposure and complementarity by country groups in Asia

	AEs	EMDEs
High exposure, low complementarity	26 percent	18 percent
High exposure, high complementarity	24 percent	9 percent
Low exposure	50 percent	73 percent

Our analysis builds on the findings of previous research examining how artificial intelligence interacts with the abilities required for various job roles. Felten and others (2021) developed the AI Occupational Exposure (AIOE) metric, which evaluates the overlap between the tasks performed by a worker in a given occupation and the capabilities of generative AI. Pizzinelli and others (2024) additionally consider the required skill level and societal context to evaluate how shielded each occupation is from replacement by AI. Looking at both dimensions—exposure and complementarity—provides a nuanced view of how AI might affect jobs by distinguishing between roles where AI serves as an aid versus those at risk of displacement. It is important to note that these two metrics do not account for country-specific factors; therefore, the analysis assumes that the nature of occupations does not vary across countries. We merge the two scores with data on employment by occupation and gender from the International Labour Organization on 21 economies in Asia and the Pacific.[1]

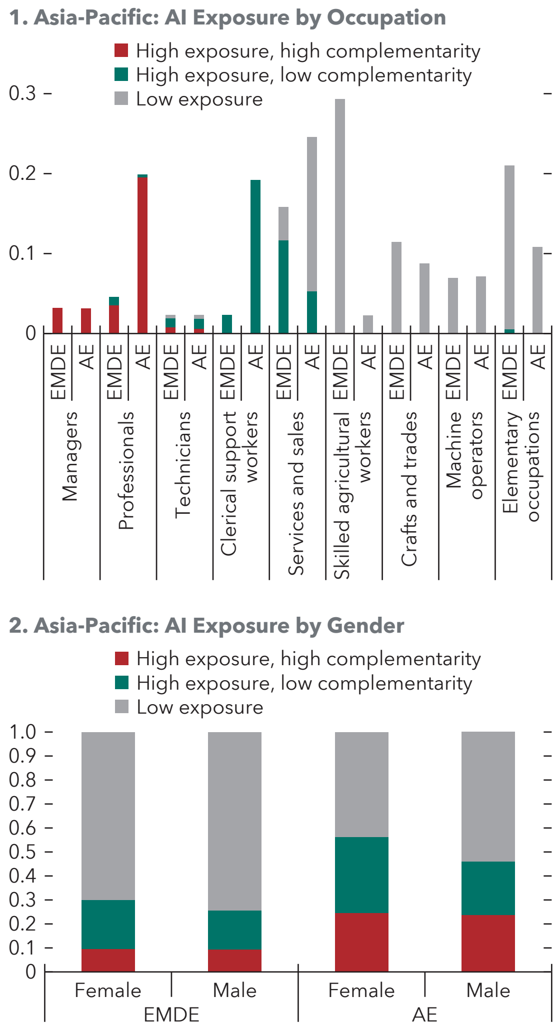
Asia's AEs are more likely to experience shifts in the labor market as a result of AI adoption. We find that roughly half of all jobs in AEs are exposed to AI, compared to only 27 percent in EMDEs. However, there are also more jobs in AEs that are classified as highly complementary, meaning that AI will likely enhance productivity rather than replace these roles. These results suggest that while both AEs and

Prepared by Tristan Hennig and Shujaat Khan.

1 Sample includes AE = AUS, SGP, JPN; EMDE = BGD, BRN, BTN, IDN, IND, KHM, KIR, LAO, LKA, MDV, MNG, PHL, PNG, THA, TLS, TUV, VNM, WSM.

Box 1. *(continued)*

Box Figure 1.1. Labor Markets



Sources: International Labour Organization; and IMF staff calculations.
Note: AI exposure is based on Felten and others (2021), AI complementarity is based on Pizzinelli and others (2024).

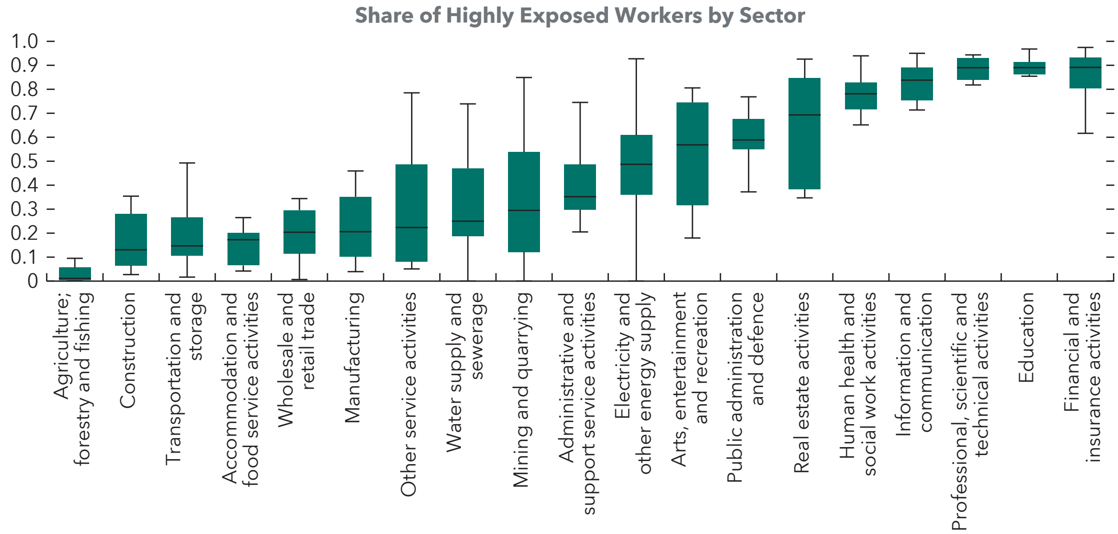
EMDEs will face displacement of jobs by AI, EMDEs have comparatively fewer jobs that can leverage AI for productivity gains. Box Figure 1.1 shows the underlying distribution of occupations and their classification in AEs and EMs. Jobs at risk of displacement are mostly service, sales, and clerical support workers while managers, professionals, and some technicians can expect to benefit from AI. Agricultural workers, the trades, machine operators, and elementary occupations are unlikely to be impacted by AI at this stage. Furthermore, Box Figure 1.2 shows that women are more at risk of disruption from AI as they are more likely to hold jobs in the clerical support and services and sales categories while men are overrepresented in the trades, agriculture and as machine operators.

Education, finance, IT, health, and administration have the highest shares of exposed workers. Box Figure 1.2 shows the share of highly exposed workers by sector, by combining the AI exposure of occupations with data on the occupational composition of each sector; the latter differs across countries. This analysis can help policymakers and business leaders devise strategies for workforce development, sectoral support, and targeted investments to navigate the AI-driven economic transformation. If AI does prove to be a major driver of productivity gains, whether by complementing or replacing workers, those countries with a higher share of value added coming from sectors with many highly exposed workers would see the strongest boost to growth.

The distribution of workers across occupations and sectors is highly likely to change over the long-term as AI is deployed. Box Figures 1.1 and 1.2 present a snapshot of the current state of labor markets in Asia. There is, however, a considerable disagreement in the literature over the longer-term impact of AI on wages and the nature of work. Some (for example, Korinek 2024) argue that artificial general intelligence will eventually substitute all human labor and cause competitive market wages to plummet whereas others (for example, Acemoglu 2024) argue that higher productivity and the creation of new labor-intensive jobs could support the labor share of income over the long run. This box does not to take a stance on this debate but focuses instead on the existing occupations and sectors in Asia that are most likely to be impacted.

Box 1. *(continued)*

Box Figure 1.2. Sectoral Distribution



Sources: International Labour Organization; and IMF staff calculations.
Note: AI exposure is based on Felten and others (2021).

Digital infrastructure, human capital, technological innovation, and legal frameworks will all be relevant for smooth AI adoption. The AI preparedness index (AIPI) developed by Cazzaniga and others (2024) assesses countries' readiness based on these four dimensions. For each dimension, the authors collect a rich set of indicators compiled by different institutions, including sustained human capital investment, inclusive STEM expertise, labor and capital mobility within and across countries, a vibrant R&D ecosystem, and the adaptability of legal frameworks to digital business models. All indicators are normalized to a 0-1 scale and then averaged. The AIPI is the simple average of the four dimensions and Box Figure 1.3 shows the results for Asia.

Big Asian emerging markets, such as China, India, and Indonesia, score better than the world EM average on this index, indicating a relatively strong foundation for AI adoption and the potential to harness AI-driven growth. Asia's AEs also score higher than their peers, with Singapore topping the global list. However, there are also many countries in Asia with significant room to catch up in all four dimensions. As those countries develop, the share of workers employed in the services sector, where adoption of AI is particularly relevant for productivity, is likely to increase, making improvements in those areas all the more important.

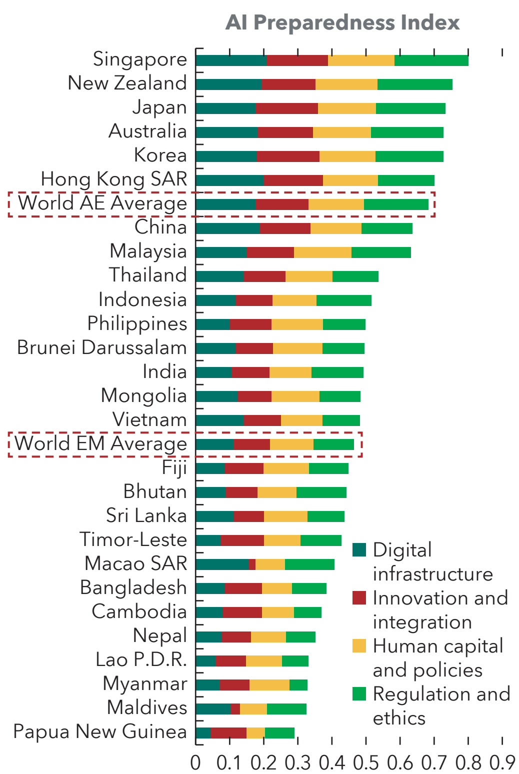
Policymakers, particularly in EMDEs, should take a proactive approach to adopting AI. Investments in digital infrastructure need to be prioritized to ensure widespread internet and technology access. Additionally, policymakers should focus on education and training programs to develop a digitally skilled workforce capable of leveraging AI technologies. This will be particularly relevant in EMDEs, where there currently are relatively few jobs in which AI could increase workers' productivity (Box Table 1). Enhancing innovation capacity through support for research and development, along with creating adaptive regulatory frameworks that promote ethical AI use and data protection, will also be important. Such measures will enable these countries to not only mitigate the risks of AI-induced disruptions but also to capitalize on

Box 1. ***(continued)***

the opportunities for economic growth and improved productivity. Over the medium term, the taxation of capital income may need to be recalibrated if the income share of labor does indeed decline due to the adoption of AI (see Chapter 3 of the April 2024 *World Economic Outlook*).

There are several open questions for future research. Other issues raised in this chapter, such as aging/demographics, could impact the adoption of AI. Certain age groups may be more likely to take up assistance from AI. In countries where aging will lead to labor supply shortages, AI may help bridge the gap. Similarly, how AI interacts with other global transitions and developments happening at the same time, such as climate change or geoeconomic fragmentation, remains an open question.

Box Figure 1.3. AI Preparedness across Asia-Pacific



Source: Cazzaniga and others (2024).

Annex A. Data and Methodology

Aggregate Growth Accounting

This section describes the details of the growth accounting exercise for Asia-Pacific for 1991-2019. The decomposition follows Jones (2022) and considers a semi-endogenous growth model, where the real GDP (Y) is given by $Y = K^{\alpha}(AhL)^{1-\alpha}$, where K stands for the capital stock, A represents TFP, h is human capital, L is employment, and α and $1 - \alpha$ are the capital and labor income shares, respectively. This expression can be rewritten in per capita terms as follows

$$y \equiv \frac{Y}{P} = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} Ah \frac{L}{P}$$

where P represents the population. Further, introducing LF, the working-age population, allows to express GDP per capita as

$$y = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} Ah \frac{L}{LF} \frac{LF}{P}$$

where L/LF proxies the employment rate and LF/P proxies the inverse of dependency ratio. The analysis presented in the main text differentiates the two expressions above with respect to time in order to assess the evolution of growth among Asian countries.

The countries included in the analysis are Australia, Bangladesh, Brunei Darussalam, Cambodia, China, Fiji, Hong Kong SAR, India, Indonesia, Japan, Korea, Lao P.D.R., Malaysia, Maldives, Mongolia, Nepal, New Zealand, Philippines, Singapore, Sri Lanka, Taiwan Province of China, Thailand, and Vietnam. The data come from the Penn World Table (real GDP in 2017 prices, capital stock at 2017 prices, human capital index, employment, population), International Labour Organization (average labor income shares), and the United Nations (working-age labor force and population projections).

Aggregate Growth Projections with Parametric Approach

The parametric approach projects aggregate growth by individually projecting each contributing factor—labor and capital inputs, human capital, and total factor productivity (TFP)—on a country-by-country basis and summarizes over these factors to derive aggregate growth. Decomposition of real GDP growth per capita follows the same expression as in the historical growth accounting part.

The individual contributing factors are assumed to follow their pre-pandemic trends. Specifically:

- **Labor (*L*)**: Country-specific linear regressions are applied for the time period 2000-22 for cohort-gender specific labor force participation rates (LFPR) from the International Labour Organization, to project a linear trend, bound by regional maxima or minima, respectively. Age cohorts include 15-24, 25-54, 55-64 and 65+. In case any cohort-gender LFPR hits the regional maxima or minima during the projection period, a logistic growth regression is used instead to project trends. These LFPRs, multiplied by United Nations demographic projections (World Population Prospects 2022) based on their medium-fertility scenario—which include assumptions on net migration—provide estimates of potential labor inputs.
- **Capital (*K*)**: Capital stock is projected using the perpetual inventory method. Past capital stock data, depreciation rates, and implicit investment data are taken from the Penn World Table (PWT) version 10.01. Linear trends are based on the period 2009-19. This implies increasing depreciation rates for most economies, in line with trends towards more intangible capital which usually requires more input to sustain.
- **Human capital (*h*)**: Human capital—measured by years of schooling and the returns to education based on PWT data—follows its pre-pandemic trend over 2000-19, improving across all economies, irrespective of income group.

- **TFP (A)**: TFP growth is projected based on country-specific linear regressions of TFP levels during the post-global financial crisis period 2009-19. Historical levels are derived as the residual from the production function decomposition as described above.
- **Labor income share ($1 - \alpha$):** Labor income share is assumed as a constant percent of GDP, sourced from International Labour Organization.

The sample includes 20 regional economies: Australia, Bangladesh, Cambodia, China, Fiji, Hong Kong SAR, India, Indonesia, Japan, Korea, Macao SAR, Malaysia, Mongolia, Nepal, New Zealand, Philippines, Singapore, Sri Lanka, Thailand, and Vietnam.

Aggregate Growth Projections with Non-Parametric Approach

Dynamic Time Warping (DTW) is a method for measuring the distance between two temporal sequences which may vary in speed. For instance, similarities between economic indicators over time can be compared, even if they do not have the same volatility pattern or length. The essence of DTW lies in its ability to stretch or compress the time dimension of the sequences to achieve a minimal distance alignment.

The implementation of the algorithm starts with identifying historical country-periods most similar to the target country. Specifically, the forecast is conducted in the following steps:

- Define a "target period" $[t - k + 1, t]$, for the target country. k is the window size for comparison. For this note's exercise, $k = 5$ years and $t = 2019$.
- Use DTW algorithm to calculate the similarity (that is, DTW distance) between the variable values of the target country's target period and those of other countries in their respective historical periods.
- Identify the country-periods with the shortest DTW distances to the target country's target period. Select the top x percent of those country-periods with the shortest distances as projection candidates. In the baseline projection, x is set to 1.
- For each selected projection candidate, identify its growth trajectory for the subsequent y years, where y is the forecast horizon of interest. Aggregate the subsequent growth rates of the projection candidates for each of the y years.

A key step in implementing the forecast algorithm is to calculate the DTW distance between country-period pairs. The calculation of the DTW distance between two time series sequences involves a few steps:

- Step 1: Initialize the cost matrix. Given two time series $X = \{x_1, x_2, ..., x_n\}$ and $Y = \{y_1, y_2, ..., y_m\}$ initialize a cost matrix D of size $n \times m$. In our application, we set $n = m = 5$, with X and Y being the multivariate annual data for 2 different countries at different time.
- Step 2: Calculate the pair-wise distance. For each element x_i from sequence X and y_j from sequence Y, calculate a distance $D[i][j]$. For multivariate data, distances are computed vectorwise and the variables in the sequence are normalized. Different types of distance metrics can be used based on the nature of the data. This note used the Euclidean distance.
- Step 3: Calculate the cumulative Distance recursively. Construct a cumulative cost matrix C where the first row and column of C are initialized as follows:

$$C[1][1] = D[1][1]$$

$$C[i][1] = C[i-1][1] + D[i][1], \text{ for } i = 2, \ldots, n$$

$$C[1][j] = C[1][j-1] + D[1][j], \text{ for } j = 2, \ldots, m$$

Annex Table A.1. Sector Classification Correspondence

ISIC Rev. 4 code	ETD Sector name	ISIC Rev. 4 description
A	Agriculture	Agriculture, forestry, fishing
B	Mining	Mining and quarrying
C	Manufacturing	Manufacturing
D+E	Utilities	Electricity, gas, steam and air conditioning supply; Water supply; sewerage, waste management and remediation activities
F	Construction	Construction
G+I	Trade services	Wholesale and retail trade; repair of motor vehicles and motorcycles; Accommodation and food service activities
H	Transport services	Transportation and storage
J+M+N	Business services	Information and communication; Professional, scientific and technical activities; Administrative and support service activities
K	Financial services	Financial and insurance activities
L	Real estate	Real estate activities
O+P+Q	Government services	Public administration and defense; compulsory social security; Education; Human health and social work activities
R+S+T+U	Other services	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

Fill in the rest of the cumulative cost matrix C by updating each cell $C[i][j]$ based on the pair-wise distance, $D[i][j]$ and the minimum of the cumulative distances from the three adjacent cells: directly above, directly to the left, and diagonally above-left:

$$C[i][j] = D[i][j] + \min(C[i-1][j], C[i][j-1], C[i-1][j-1])$$

Repeat the step to calculate the cumulative distance for each cell until the entire matrix C is filled. The DTW distance between X and Y is represented by the value in the final cell of the cost matrix, $C[n][m]$. This value reflects the minimum cumulative distance needed to align the entire sequences X and Y optimally according to the DTW criteria.

Variables used in identifying similar countries and periods include real GDP growth, GDP per capita, capital-output ratio, consumption-output ratio, labor productivity, and population growth. The data are sourced from the Penn World Table version 10.01, which covers annual national account data for more than 180 countries globally from 1950 to 2019.

Structural Change in Asia: Data

Data on gross value-added (at current national currency prices and at constant 2015 national currency prices) and number of persons engaged for 12 sectors and 51 economies come from the GGDC/UNU-WIDER Economic Transformation Database (ETD). Following Herrendorf and others (2022), ETD data are augmented with data on advanced economies (Australia, Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, New Zealand, Spain, Sweden, United Kingdom, and United States).[1] The expanded ETD (EETD) includes 20 Asian economies: Australia, Bangladesh, Cambodia, China, Hong Kong SAR, India, Indonesia, Japan, Korea, Lao P.D.R., Malaysia, Myanmar, Nepal, New Zealand, Philippines, Singapore, Sri Lanka, Taiwan Province of China, Thailand, and Vietnam. The 12 sectors with the corresponding ISIC rev 4 codes and descriptions are show in Annex Table A.1.

Following the literature, the sectors are assigned to two classifications. First, an aggregate classification into: (i) agriculture (A), (ii) industry (B+C+D+E+F), and (iii) services (rest of the sectors). Second, a disaggregate classification into: (i) agriculture (A), (ii) mining (B), (iii) manufacturing (C), (iv) non-tradable industry (D+E+F), (v) tradable services (G+I+H+J+M+N+K), (vi) non-tradable services (L+ R+S+T+U), and (vii) non-market services (O+P+Q). While the aggregate classification is standard in the literature the disaggregate classification is based on the broad definition of tradable and non-tradable sectors from Inklaar and others (2023). Their tradable industry is separated into manufacturing and mining and their non-tradable services separated into non-market services (government services) and the rest (other services). This classification of services based on tradability also aligns with the classification of Duarte and Restuccia (2020) into traditional and non-traditional services based on income elasticities of relative prices.

The data are supplemented with PPP value-added price indices for the 12 sectors, for the 2005, 2011, and 2017 benchmark years from the 2023 release of the GGDC Productivity Level Database (PLD). Following the PWT methodology (see Feenstra and others 2015) the PPP prices for other years are imputed by interpolating and extrapolating using percentage change in value-added price indices in national units with the PPP price indices for the three benchmark years.

Contribution of Structural Change to Aggregate Labor Productivity Growth

From a sectoral lens aggregate economic growth is a dependent on within-sector productivity growth and the reallocation of resources to high productivity sectors. In the absence of data on capital stocks by sectors, the analysis focuses on labor productivity and measures only reallocation of labor. Specifically, following McMillan, Rodrik and Gallo (2013), aggregate labor productivity growth can be expressed as the sum of two components: (i) weighted sum of productivity growth within individual sectors, where the weights are the employment shares of sectors at the beginning of the time-period and this is the within-sector productivity growth component; and (ii) productivity effect of labor re-allocations across different sectors, which is the structural change component and it is essentially the inner product of productivity levels (at the end of the time period) with the change in employment shares across sectors. Thus, the change in economy-wide labor productivity between year t and $t-k$ can be expressed as

$$\Delta LP_t = \underbrace{\sum_{i=1}^{S} n_{i,t-k} \Delta LP_{i,t}}_{\text{within-sector}} + \quad + \underbrace{\sum_{i=1}^{S} \Delta n_{i,t} LP_{i,t}}_{\text{structural change}} \quad ,$$

where t denotes year, $n_{i,t}$ is the share of sector i in employment, and LP_t and $LP_{i,t}$ denote economy-wide and sector $i(=1, \ldots, S)$ labor productivity, measured as real value added per worker, where real value added is value added in constant 2015 national currency prices (for aggregate value-added and sector i value added, respectively).

Trade and Structural Change

To examine the correlations between manufacturing trade and manufacturing share of value added, the following equation with instrumental variables is estimated:

$$VA_{i,t+h} - VA_{i,t-1} = \beta_{ex}^{h}\, exports_{i,t} + \beta_{im}^{h}\, imports_{i,t} + X_{i,t}\beta_{x}^{h} + \alpha_i + \gamma_t + \varepsilon_{i,t}\,,$$

[1] Missing values for employment and value added in constant prices for New Zealand were imputed using the more aggregated Cross-Country Database of Sectoral Labor Productivity of the World Bank. Outliers for value added for Botswana were adjusted using the relationship between employment growth and value-added growth for prior years.

where $VA_{i,t}$ is the value added share of manufacturing sector in country *i* and year *t*, $exports_{i,t}$ and $imports_{i,t}$ are country *i*'s manufacturing exports and imports, as share of GDP, $X_{i,t}$ includes other explanatory variables including population and GDP per capita and their squared terms (all in logarithmic term) as well as lagged terms of all explanatory variables and the dependent variable (up to three). To address the potential endogeneity issue, $exports_{i,t}$ and $imports_{i,t}$ are instrumented using trade costs of exports and imports from ESCAP-World Bank Trade Cost Database, which measure the comprehensive trade costs that *include all additional costs involved in trading goods internationally with another partner (that is, bilaterally) relative to those involved in trading goods intranationally (that is, internally or domestically)*. Under the assumption that domestic manufacturing sector's share of value added is affected by trade costs only through manufacturing exports and imports, β^h_{ex} and β^h_{im} would measure the cumulative change in manufacturing share of value added *h* years after an exogenous increase in manufacturing exports and imports by 1 percent of GDP, respectively.

A modified equation with manufacturing exports and imports replaced by manufacturing trade balance is also estimated to examine the cumulative change in manufacturing share of value added *h* years after an exogenous increase in manufacturing trade balance by 1 percent of GDP. For modern services sector, the equation is modified to include number of FDI projects (in logarithmic term) and without instrument variables.[2]

The countries included in the analysis are those in the ETD. The data come from the World Economic Outlook Database (real GDP per capita in PPP international dollars and population), ETD (sectoral value added), BACI (sectoral trade), and ESCAP-World Bank Trade Cost Database (trade costs).

Convergence Analysis

The baseline specification for testing unconditional β–convergence for labor productivity in each sector is given by

$$\Delta\log(LP_{jt,t-1}) = \alpha + \beta \log LP_{jt-1} + \gamma_t + \varepsilon_{j,t}\,,$$

where LP denotes labor productivity in constant PPP prices, *j* denotes country, *t* denotes year, and Δ denotes the change between year *t* and *t* – 1. γ_t is the year fixed effect. The coefficient β measures the speed of convergence: $\beta < 0$ implies that a lower initial productivity is associated with higher growth of productivity, allowing low labor productivity countries to catch-up to the high labor productivity countries.

[2] The number of FDI projects is not included in the estimation for manufacturing because of the data availability: it is only available from 2003 when most of the Asia-Pacific countries in the sample have seen the rise of their domestic manufacturing sector. There is no variable measuring the trade barriers to modern services with sufficient coverage, and thus the estimation for modern services is not instrumented.

Annex Table A.2. Manufacturing Share of Value-Added and Manufacturing Trade
Dependent variable: change in manufacturing share of value-added from that in the year t–1, in percentage points

	Year *t*	Year *t+1*	Year *t+2*	Year *t+3*	Year *t+4*	Year *t+5*
Manufacturing Imports (% of GDP), *t*	−0.026	−0.144*	−0.241**	−0.322*	−0.269*	−0.171
	(0.055)	(0.087)	(0.096)	(0.180)	(0.150)	(0.156)
Manufacturing Exports (% of GDP), *t*	0.082*	0.195**	0.277**	0.386**	0.556**	0.343*
	(0.049)	(0.078)	(0.117)	(0.161)	(0.255)	(0.205)
Log(Population), *t*	0.000	0.000	0.000	0.000	32.652	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(74.927)	(0.000)
Log(Population)^2, *t*	−13.525	5.281	−6.421	−13.403	−114.60	−8.959
	(8.252)	(22.476)	(13.059)	(21.798)	(196.584)	(20.226)
Log(GDP per capita), *t*	26.388*	22.280	19.681	14.149	34.795	28.427
	(15.521)	(18.099)	(23.305)	(23.136)	(27.226)	(24.057)
Log(GDP per capita) ^{2}, *t*	−1.522	0.020	1.550	4.165	1.917	0.387
	(2.491)	(3.574)	(4.222)	(4.808)	(5.570)	(3.456)
Manufacturing Imports (% of GDP), *t-1*	0.023	0.102	0.175*	0.225	0.159	0.146
	(0.045)	(0.076)	(0.090)	(0.148)	(0.101)	(0.117)
Manufacturing Imports (% of GDP), *t-2*	0.006	0.033	0.052	0.074*	0.108	0.046
	(0.010)	(0.020)	(0.032)	(0.044)	(0.070)	(0.045)
Manufacturing Exports (% of GDP), *t-1*	−0.055	−0.101	−0.155	−0.265*	−0.564*	−0.388*
	(0.042)	(0.079)	(0.114)	(0.148)	(0.313)	(0.214)
Manufacturing Exports (% of GDP), *t-2*	−0.029	−0.089**	−0.139**	−0.141*	0.011	−0.037
	(0.017)	(0.039)	(0.055)	(0.079)	(0.141)	(0.051)
Log(Population), *t-1*	91.844	0.000	0.000	−102.446	0.000	79.494
	(92.909)	(0.000)	(0.000)	(221.280)	(0.000)	(284.159)
Log(Population), *t-2*	−93.794	−9.700***	−13.974***	88.372	−34.471	−86.115
	(89.928)	(2.850)	(4.358)	(219.279)	(69.276)	(285.619)
Log(Population)^2, *t-1*	17.259*	-7.702	8.767	32.957	200.396	0.000
	(10.075)	(36.837)	(27.155)	(30.941)	(350.276)	(0.000)
Log(Population)^2, *t-2*	−3.749	3.061	−1.793	−19.131	−86.750	8.395
	(8.715)	(14.759)	(14.654)	(19.092)	(154.935)	(20.067)
Log(GDP per capita), *t-1*	−27.605	−26.096	−23.953	−29.014	−82.745	−65.574
	(21.504)	(30.256)	(39.739)	(42.294)	(44.589)	(45.118)
Log(GDP per capita), *t-2*	1.356	3.200	3.172	13.353	45.684	37.421
	(8.042)	(15.421)	(20.643)	(24.163)	(26.097)	(25.778)

Annex Table A.2. Continued

	Year *t*	Year *t+1*	Year *t+2*	Year *t+3*	Year *t+4*	Year *t+5*
Log(GDP per capita)^2, *t-1*	1.203	−0.147	−0.893	−1.976	5.288	3.394
	(3.446)	(5.569)	(6.934)	(7.861)	(7.179)	(5.208)
Log(GDP per capita)^2, *t-2*	0.459	0.18	−0.629	−2.230	−6.887*	−4.309
	(1.399)	(2.662)	(3.621)	(4.350)	(4.059)	(3.554)
Dependent variable, *t-1*	−0.006	−0.217*	−0.436***	−0.378*	−0.099	−0.197
	(0.084)	(0.130)	(0.163)	(0.198)	(0.316)	(0.182)
Dependent variable, *t-2*	−0.089	−0.266**	−0.338**	−0.382**	−0.422	−0.145
	(0.063)	(0.118)	(0.149)	(0.184)	(0.517)	(0.211)
Number of observations	241	232	222	212	200	188
Country and Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: IMF staff estimates.

Note: The table reports the coefficients from regressing the change in manufacturing share of value-added from that in the year *t-1* for each year (from *t* to *t+5*) on the listed explanatory variables. Standard errors in parenthesis are clustered at the country level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Annex Table A.3. Regression Results: Unconditional Convergence

	Convergence coefficient	Observations	Year fixed effects	Country fixed effects
Aggregate	−0.00597**	532	Yes	No
Agriculture	−0.00402	560	Yes	No
Business	−0.0408***	560	Yes	No
Construction	−0.0150	560	Yes	No
Finance	−0.0232***	560	Yes	No
Manufacturing	−0.00583	560	Yes	No
Mining	−0.0185**	560	Yes	No
Other	−0.00532	560	Yes	No
Trade	−0.0159	560	Yes	No
Transport	−0.00661	560	Yes	No

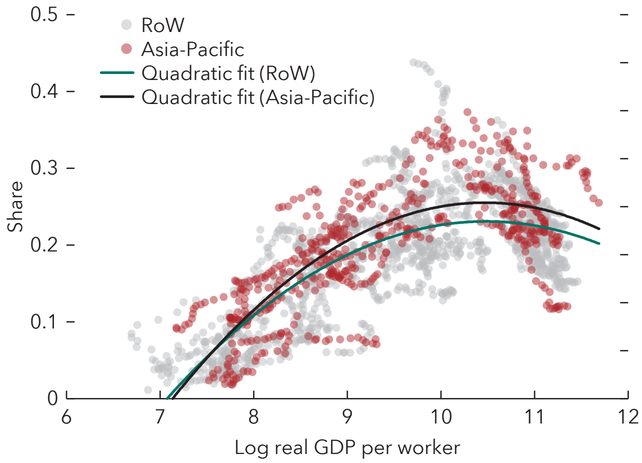
Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; Penn World Table 10.01; and IMF staff calculations.

Note: The table reports the convergence coefficient from regressing the change in logarithm of labor productivity on initial labor productivity for each sector as well as the aggregate economy (titled "Aggregate"). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Annex B. Additional Charts

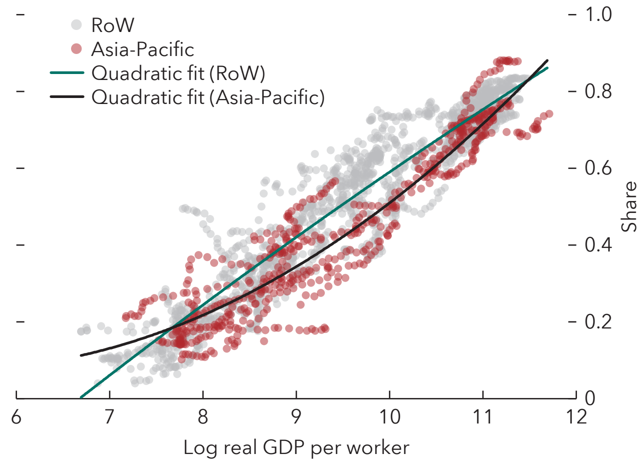
Annex Figure B.1. Structural Change in Asia: Industry and Services

1. Industry Share in Employment versus Income



Sources: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: RoW denotes rest of the world. Quadratic fit refers to a second-order polynomial fit.

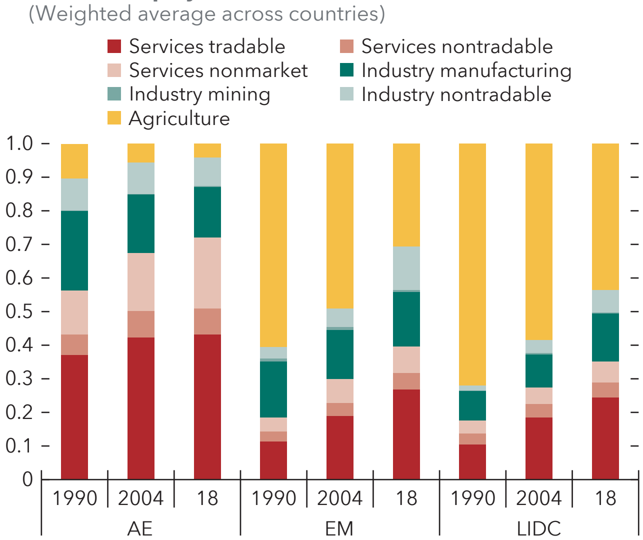
2. Services Share in Employment versus Income



Sources: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: RoW denotes rest of the world. Quadratic fit refers to a second-order polynomial fit.

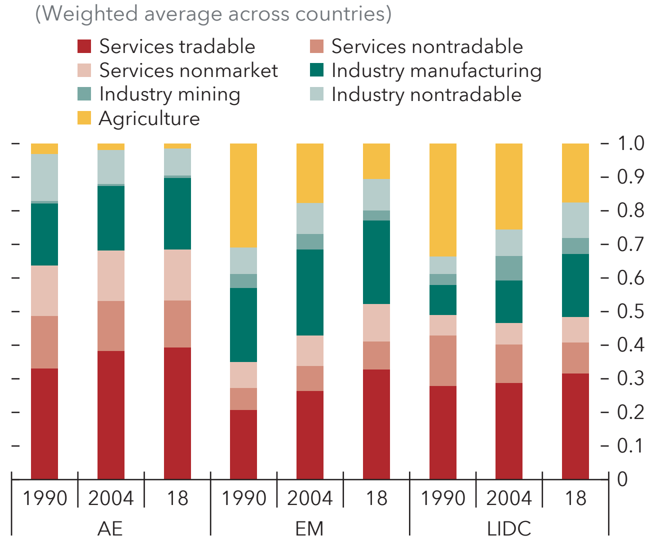
Annex Figure B.2. Re-allocation across Sub-sectors in Asia, by Income Groups

1. Share in Employment
(Weighted average across countries)



Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: See Annex A for definition of sectors.

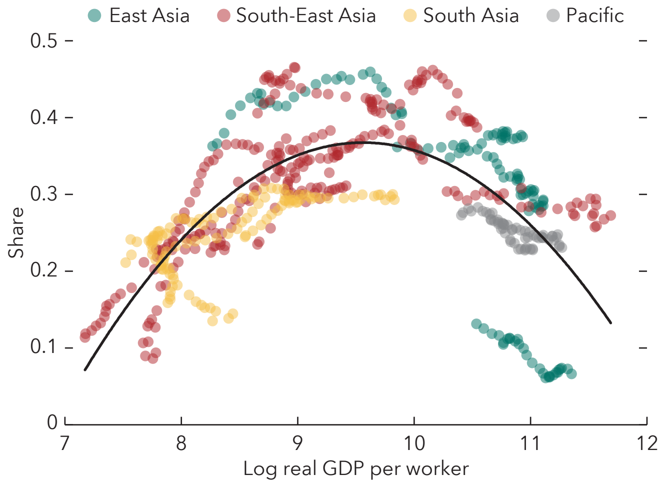
2. Share in Real Value-Added
(Weighted average across countries)



Sources: GGDC/UNU-WIDER Economic Transformation Database; and IMF staff calculations.
Note: See Annex A for definition of sectors.

Annex Figure B.3. Structural Change in Asia: Regional differences in Industrialization

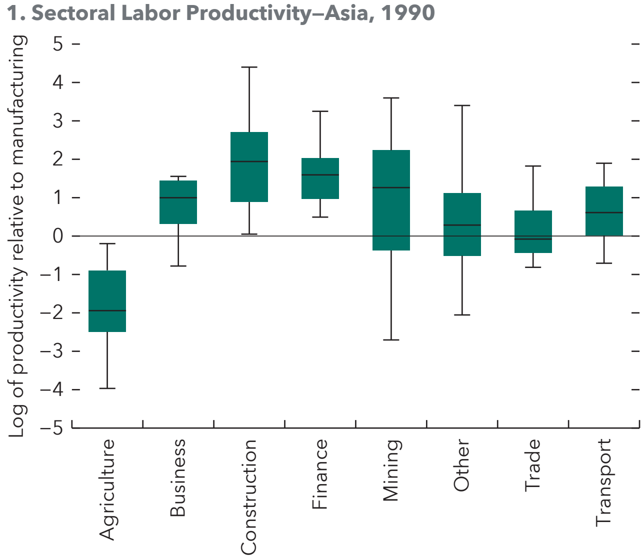
(Industry share in real value-added versus income)



Source: GGDC/UNU-WIDER Economic Transformation Database; Penn World Table version 10.01; and IMF staff calculations.
Note: East Asia includes CHN, HKG, JPN, KOR, TWN; South-East Asia includes IDN, KHM, LAO, MMR, MYS, PHL, SGP, THA, VNM; South Asia includes BGD, IND, LKA, NPL; Pacific includes AUS, NZL.

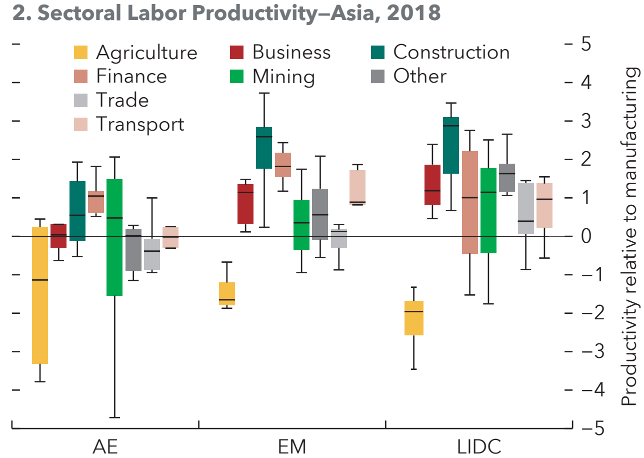
Annex Figure B.4. Labor Productivity Relative to Manufacturing

1. Sectoral Labor Productivity–Asia, 1990



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; and IMF staff calculations.
Note: Real estate services are excluded due to extremely large variation. Government and Utilities are excluded because of challenges of measuring prices, including due to large public sector presence. Productivity is measured as value-added per worker in constant PPP prices.

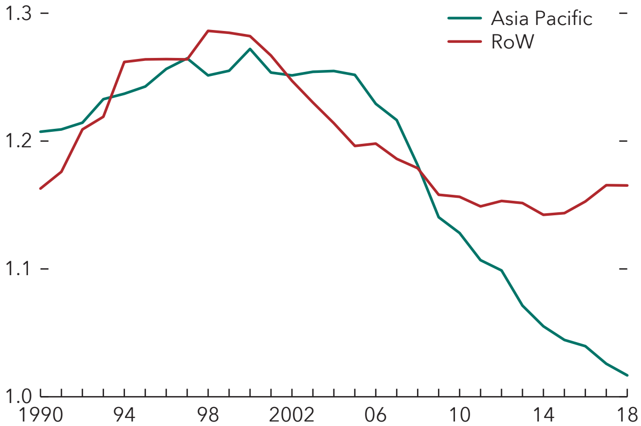
2. Sectoral Labor Productivity–Asia, 2018



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; and IMF staff calculations.
Note: Real estate services are excluded due to extremely large variation. Government and Utilities are excluded because of challenges of measuring prices, including due to large public sector presence. Productivity is measured as value-added per worker in constant PPP prices.

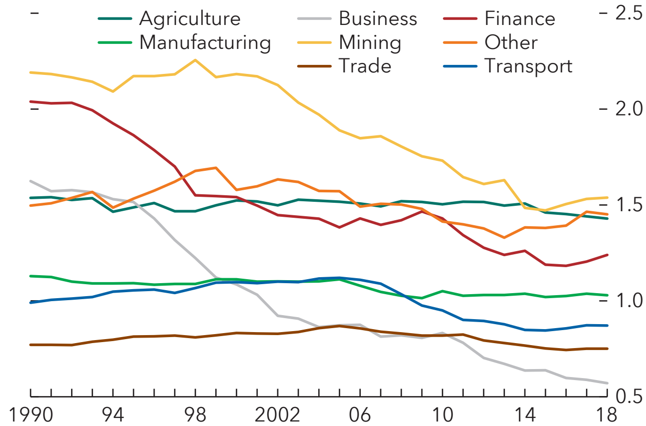
Annex Figure B.5. σ–Convergence in Asia
(Standard deviation across countries)

1. Dispersion of Aggregate Log Productivity



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; and IMF staff calculations.
Note: Productivity is measured as value-added per worker in constant PPP prices.

2. Dispersion of Sectoral Log Productivity



Sources: GGDC/UNU-WIDER Economic Transformation Database; GGDC Productivity Level Database; and IMF staff calculations.
Note: Real estate services are excluded due to extremely large variation. Government and Utilities are excluded because of challenges of measuring prices, including due to large public sector presence. Productivity is measured as value-added per worker in constant PPP prices.

Annex C. Counterfactual Simulations

The framework of Rodrik (2016) is used to analyze the interplay of the key factors influencing structural change—sectoral labor productivity growth and sectoral trade. It is augmented to allow for services to be tradable and account for the trade balance and no just exports. The augmented model is used to conduct comparative static counterfactuals conditional on (a) assumed growth in productivities for manufacturing and services, and (b) assumed growth in trade balances for manufacturing and services. The augmented framework is not a dynamic general equilibrium framework, and it abstracts from multilateral resistance (competition faced from other countries in a destination market) featured in model of international trade with multiple countries and sectors. The parameterization and assumptions are detailed below.

Production is subject to diminishing returns to labor, the only factor of production, in the two sectors of the economy—manufacturing and non-manufacturing or services—as follows

$$q_m^s = \theta_m \alpha^{\beta_m} \quad \text{and} \quad q_n^s = \theta_n (1-\alpha)^{\beta_n},$$

where α is the employment share of manufacturing sector, θ_m and θ_n denote productivity in the two sectors, and $0 < \beta_m < \beta_n < 1$. Demand features constant elasticity of substitution so that, with the percent changes (represented for a variable x as ($\hat{x} = dx/x$)), the demand for the goods of the two sectors is determined by

$$\hat{q}_m^d - \hat{q}_n^d = -\sigma(\hat{p}_m - \hat{p}_n) \quad ,$$

where $\sigma > 0$ is the elasticity of substitution in consumption between the goods of the two sectors and p_m and p_n are the prices of the two sectors' goods. Finally, market clearing for the two sectors is given by

$$q_m^d + X_m - M_m = q_m^s \quad \text{and} \quad q_n^d + X_n - M_n = q_n^s$$

where X and M are exports and imports, respectively. The change in employment share of manufacturing is

$$d\alpha = \psi\left[\left(\frac{\sigma-\lambda_m}{\sigma}\right)\hat{\theta}_m - \left(\frac{\sigma-\lambda_n}{\sigma}\right)\hat{\theta}_n + \frac{1}{\sigma}\left\{\frac{dt_m}{q_m^d} - \frac{dt_n}{q_n^d}\right\}\right] \tag{1}$$

where $\psi = \left[\frac{1}{\alpha}(1-\beta_m) + \frac{1}{1-\alpha}(1-\beta_n) + \frac{1}{\sigma}\left\{\frac{\lambda_m}{\alpha}\beta_m + \frac{\lambda_n}{1-\alpha}\beta_n\right\}\right]^{-1}$ and t_m and t_n denote the trade balance for the two sectors ($t_m = X_m - M_m$, $t_n = X_n - M_n$) and $\lambda_m = q_m^s/q_m^d$ and $\lambda_n = q_n^s/q_n^d$. Since the rest of the world (or other countries) is not modeled as a trading partner, the model solution requires taking a stand on trade balances in (1).

Parameterization

1. β_m, β_n: these capture the share of labor in value-added and are computed as the average labor share (from Table 2) of Inklaar and others (2023) for the 12 ETD sectors. $\beta_m = 0.43$, $\beta_n = 0.59$.
2. λ_m, λ_n: the goods market clearing conditions implies $\frac{1}{\lambda_m} = 1 - \left(\frac{t_m}{q_m^s}\right)$ and $\frac{1}{\lambda_n} = 1 - \left(\frac{t_n}{q_n^s}\right)$. Thus λ_m and λ_n are determined by the trade balance to value-added ratio for manufacturing and services for the region in 2018. $\lambda_m = 1.25$ and $\lambda_n = 0.99$. For simplicity, these abstract from the issue of different prices of exports, imports, and value-added.
3. $\hat{\theta}_m$, $\hat{\theta}_n$ lack of unconditional convergence in manufacturing implies that productivity growth in manufacturing is the same as the frontier, where the advanced economies in the rest of the world are assumed to be the frontier.[3] The frontier economies' average growth rate of manufacturing and services for 2024-2040 are assumed to be those observed during 2008-2018. Given the evidence of unconditional convergence for services, the service sector productivity growth rate is the frontier economies' growth rate adjusted upwards for the extent of catch-up observed for Asia and the Pacific in services during 1990-2018. $\hat{\theta}_m = 3.5\%$, $\hat{\theta}_n = 2.6\%$.

[3] Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, United Kingdom, and United States.

4. $\frac{dt_m}{q_m^d}, \frac{dt_n}{q_n^d}$: goods market-clearing condition can be manipulated to show that $\frac{dt_m}{q_m^d} = \hat{t}_m\,(\lambda_m - 1)$ and $\frac{dt_n}{q_n^d} = \hat{t}_n\,(\lambda_n - 1)$. Furthermore, $\hat{t}_m = \widehat{\left(\frac{t_m}{Y}\right)}\left[\left(\frac{\hat{Y}}{Y}\right)/\left(\frac{\hat{P}}{P}\right)\right] - 1$, where Y is the aggregate value added (nominal GDP) and P is the aggregate price index of value-added (GDP deflator). Thus, $\hat{t}_m$ is the percent change in manufacturing trade-balance to GDP ratio adjusted by real GDP growth rate over 2024–2040. $\hat{t}_n$ is projected analogously using service-trade balance to GDP percent change. Real GDP growth rate for the region is taken from the aggregate projections. $\widehat{\left(\frac{t_m}{Y}\right)}$ and $\widehat{\left(\frac{t_n}{Y}\right)}$ are projected using exports-to-GDP and imports-to-GDP ratio projections (0.15 and 0.13 for manufacturing, respectively and 0.04 and 0.05 for services, respectively).
5. σ: this is the elasticity of substitution between goods of different sectors. This is chosen to ensure that the model matches the change in manufacturing share of Asian advanced economies during 1990–2018. This yields $\sigma = 0.742$.

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