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Productivity Convergence

Is Anyone Catching Up?

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Abstract

Labor productivity in EMDEs is just under one-fifth of the advanced economy average, while in LICs, it is just 2 percent. Average productivity growth in EMDEs has picked up rapidly since 2000, renewing interest in the convergence hypothesis, which predicts that economies with low productivity should close productivity gaps over time. However, the average rate of convergence remains low, with current growth differentials halving the productivity gap only after over 100 years. Behind the low average pace of convergence lies considerable diversity among groups of countries converging toward different productivity levels (convergence clubs). Many EMDEs have moved into higher-level productivity convergence clubs since 2000, with 16 joining the highest club, primarily consisting of advanced economies. These transitioning EMDEs have been characterized by systematically better initial education levels, greater institutional quality, and high or deepening economic complexity relative to their income level, frequently aided by policies to encourage participation in global value chains. Countries seeking to replicate successes, or continue along rapid convergence paths, face a range of headwinds, including a more challenging environment to gain market share in manufacturing production or to increase global value chain integration.

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Productivity convergence: Is anyone catching up?*

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1 Introduction

Labor productivity in emerging market and developing economies (EMDEs) is less than one-fifth of the level in advanced economies, while in low-income countries (LICs), it is just 2 percent of advanced economy levels. The unconditional convergence hypothesis states that productivity catch-up growth will tend to occur where productivity differentials exist and that they will decline over time. However, this type of convergence may fail to occur for reasons such as the existence of international barriers to technology transfer and differences in saving and investment behavior.[1] Conditional convergence is more restrictive, as catch-up productivity growth may depend on characteristics of economies beyond their initial productivity levels. For example, only economies with characteristics such as high institutional quality and education levels may be able to converge to the frontier.

The large productivity gap between EMDEs and the frontier implies that there is a potential for substantial income gains in EMDEs if either of these hypotheses holds.[2] Historically, productivity gaps have remained stubbornly ingrained, with the bulk of evidence pointing away from unconditional convergence (Johnson and Papageorgiou, Johnson and Papageorgiou). However, falling global poverty rates in recent decades are an encouraging sign that economies near the bottom of the distribution have been making productivity and income gains, helping reduce the proportion of the world's population living in extreme poverty from 36 percent in 1990 to 10 percent in 2015 (World Bank, 2018b). Most of the fall is concentrated in South Asia and in East Asia and Pacific, the two regions with the highest rates of productivity growth among EMDEs.[3]

Faster EMDE productivity growth in recent decades does not itself imply convergence towards the advanced economy frontier, which has also continued to expand. In addition, if the unconditional convergence hypothesis holds, the gains in productivity should be broad-based. More complex dynamics of productivity growth could instead support the convergence club hypothesis, with different clubs of economies converging toward different productivity levels depending on their characteristics.

Finally, productivity growth has already begun to slow following the global financial crisis in EMDEs and faces headwinds from the COVID-19 crisis. The COVID-19-driven global recession is occurring during a period of heightened debt vulnerabilities, while previous pandemics and other major natural disasters have been associated with prolonged declines in labor productivity growth and investment. Commodity prices have also collapsed, adding negative pressure on investment in the large number of commodity-reliant EMDEs, and will remain weak in the event the global recovery in output is drawn out. There are further risks to EMDE convergence if countries adopt inward-looking policies that result in the fragmentation of global trade—integration into global value chains has been a key vehicle for the adoption of more advanced production processes in EMDEs.

Against this backdrop, this chapter examines the following questions.

[1] See Annex A for further details of the theoretical underpinnings of the convergence hypothesis, implied by the models of Solow (1956) and Swan (1956).

[2] Cross-country differences in per capita income, which account for two-thirds of global income equality, largely reflect differentials in labor productivity (World Bank, 2018a).

[3] Over the same time-frame as the productivity-driven reduction in global poverty, global infant mortality has halved and secondary school enrollment has increased by 14 percentage points.

- How has productivity convergence evolved over the past five decades?
- Are there "clubs" of economies following different convergence trajectories?
- What separates economies in successful and unsuccessful clubs?
- What headwinds to convergence face EMDEs, and what are the policy implications?

This chapter makes several contributions to the literature:

First, it expands a reinvigorated literature on income per capita convergence by examining *labor productivity* convergence. The existing literature, which began empirically assessing income convergence in the mid-1980s, has generally found broad-based support for convergence that is conditional on country characteristics, but little support for the unconditional convergence hypothesis. This debate has been re-ignited by the surge in EMDE growth in the 2000s (Patel et al., 2018). The majority of the convergence literature has focused on convergence in income per capita (Barro, 2015; Caselli, 2005; Mankiw et al., 1992). In contrast, the focus in this chapter is on labor productivity convergence, the main driver of lasting per capita income convergence.

Second, this chapter highlights important nonlinearities captured by "convergence clubs" following different convergence paths. The existing literature on convergence clubs thus far has not taken account of the large increase in EMDE productivity growth since 2000 (Battisti and Parmeter, 2012; Bernard and Durlauf, 1995; Pesaran, 2007; Phillips and Sul, 2009). This chapter updates this literature and identifies important changes in the membership of convergence clubs that have occurred in recent decades. Third, this chapter utilizes multiple methodologies and common datasets—previous studies have been hampered by data differences that have made conclusions non-comparable (Johnson et al., 2013). It is also the only recent study of convergence that measures labor productivity at market exchange rates as opposed to PPP-adjusted measures, noting that the latter can be problematic in assessing club convergence (see Annex F).

Fourth, this chapter is one of the few studies examining the drivers of convergence-club membership and transitions, and the only one applied to a global set of economies. Existing studies either focus on European (Bartkowska and Riedl, 2012; Von Lyncker and Thoennessen, 2017) or Chinese regions (Tian et al., 2016) and do not assess the causes of changing club membership over time. In contrast, this study identifies the drivers of convergence club membership and transitions between clubs during 1970-2018.

Main findings. The following findings emerge from the analysis in this chapter.

- **Large productivity gaps**. The gap between advanced economy and EMDE labor productivity levels is large. On average since 2010, labor productivity in EMDEs was just under one-fifth, and in LICs, just 2 percent, of the advanced economy average. EMDE productivity gaps relative to advanced economies widened during the 1970s, 1980s, and 1990s but began to narrow in the 2000s, primarily in EMDE commodity importers.
- **Convergence since 2000**. Examples of economies converging from low levels of labor productivity all the way to the frontier were rare in the latter-half of the 20th century. Since 2000, productivity growth has exceeded the advanced economy average in around 60 percent of EMDEs. However, the productivity gap declined at just 0.5 percent on average per year and

convergence rates have begun to slow. Even at this peak rate, it would take nearly 140 years to halve the initial productivity gap between economies. While the average rate of convergence has been low, convergence rates for economies with good characteristics are substantially higher; new evidence suggests that the conditional convergence rate has accelerated in recent decades.

- **Convergence clubs**. Since 1970, countries have fallen into five distinct convergence clubs. The first club of countries, converging to the highest productivity levels, includes all advanced economies and several middle-income EMDEs that have experienced sustained long periods of robust growth since the 1990s. The second club includes the majority of upper-middle-income EMDEs while the third through fifth clubs include lower-middle and low-income countries.

- **Transition to higher-productivity convergence clubs: successful policies**. Increasing numbers of EMDEs have moved into the highest-level productivity club in recent decades, in contrast to older assessments of club convergence that found few positive convergence club transitions. These countries are found to have had a foundation of systematically better initial education levels and greater political stability, which has helped them deepen the complexity of their economies, with diversified production across a broad range of sectors outside of their original comparative advantage. Several country case studies highlight the importance of export-promotion, global value chain integration and FDI in transitioning to higher-productivity convergence clubs.

- **Challenging environment for convergence models**. EMDEs that have successfully shifted into higher-level productivity clubs have often relied upon manufacturing-led development—efforts to enhance the complexity and diversity of exports can prove to be high-reward but have also frequently been costly failures. This strategy faces increasing challenges due to falling global manufacturing employment and slower trade growth. In addition, a weak outlook for commodity prices and slow improvements in many key covariates of productivity growth, such as institutional quality, urbanization, and educational attainment pose further headwinds to both new and continuing transitions to high productivity levels.

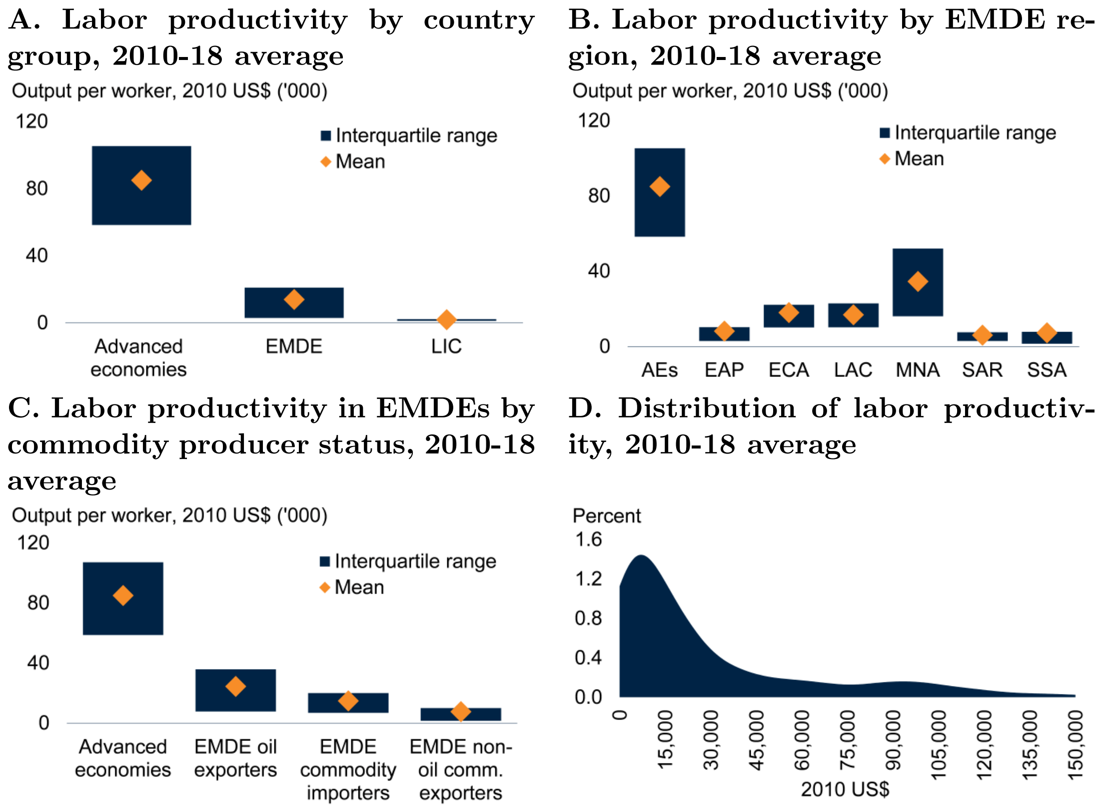
This chapter examines convergence in labor productivity, defined as output per worker (at 2010 prices and exchange rates, Annex B). Labor productivity data are available for 103 countries since 1970, consisting of 29 advanced economies and 74 EMDEs. Labor productivity is more readily measured than total factor productivity (TFP), which can only be estimated on the basis of special assumptions. Labor productivity is also conceptually closer to per capita income, the variable of primary interest in discussions of global average living standards and the global income distribution. The dataset is constructed from national accounts, the World Bank's World Development Indicators, The Conference Board, and the Penn World Table 9.1 (Annex B).

Section 2 discusses the evolution of convergence over time. Section 3 estimates the speed of convergence, both regardless of country characteristics and conditional on country characteristics. Section 4 provides evidence for the presence of club convergence assesses the characteristics of EMDEs who have demonstrated faster degrees of convergence. Section 5 concludes and discusses policy implications.

2 How has productivity convergence evolved?

The gap between advanced economy and EMDE labor productivity levels is large. On average since 2010, labor productivity in EMDEs was just 16 percent, and in LICs, just 2 percent, of the advanced economy average (**Figure 1**). Even the top decile of EMDE output per worker was just 70 percent of the lowest decile of advanced economy labor productivity levels.

Figure 1: **Labor productivity gaps**



A. Labor productivity by country group, 2010-18 average

B. Labor productivity by EMDE region, 2010-18 average

C. Labor productivity in EMDEs by commodity producer status, 2010-18 average

D. Distribution of labor productivity, 2010-18 average

Source: Penn World Table; The Conference Board; World Bank, World Development Indicators.
Note: Productivity defined as output per worker in U.S. dollars (at 2010 prices and exchange rates). Based on 35 advanced economies and 126 EMDEs, of which 27 are LICs.
C. Based on 35 advanced economies, 27 oil exporters, 47 commodity-importing EMDEs and 52 non-oil commodity-exporting EMDEs.
D. Smoothed density estimates of output per worker.

Among EMDE regions, labor productivity is highest in the Middle East and North Africa (MNA), Latin America and the Caribbean (LAC) and Europe and Central Asia (ECA) and lowest in Sub-Saharan Africa (SSA) and South Asia (SAR) (**Figure 1**). On average, MNA produced 41 percent of the output per worker of advanced economies, while output per worker in SSA and SAR was well below the EMDE average, at just 9 and 7 percent of advanced economy productivity, respectively. Other regional features are as follows:

- **EAP** EAP economies are characterized by a relatively low dispersion of productivity levels compared to other EMDE regions, ranging from 2-27 percent of the level in the average advanced economy. This may partly reflect the close economic integration of the region's economies.

- **ECA** Close trade integration with western Europe, strong growth since the deep recessions following the collapse of the Soviet Union, and relatively high initial productivity levels in some cases have led economies in the ECA region to have the second-highest average labor productivity level among EMDE regions. However, there is significant variation, with output per worker in non-oil commodity exporters in the region averaging just one-quarter of the output per worker relative to commodity-importing economies.

- **LAC** In LAC, the labor productivity gap with advanced economies has widened since the 1970s, with labor productivity falling from 23 to 20 percent of the levels in the average advanced economy.

- **MENA** While the region has the highest average labor productivity it also has an exceptionally wide range of labor productivity levels. This ranges from 10 percent of the advanced economy average in Egypt and Morocco to over 100 percent of the advanced economy average in oil-exporting economies such as Qatar.[4]

- **SAR** Despite relying on commodity imports in aggregate, South Asian economies are heavily reliant on the agricultural sector. Agriculture has accounted for 18 percent of value-added since 2010, compared to the EMDE average of 10 percent. In addition, SAR is the region with the largest number of informal workers (World Bank, 2019a). These two factors may help to account for uniformly low labor productivity in EMDEs in the region.

- **SSA** Labor productivity in SSA is among the lowest across EMDE regions. There is a degree of heterogeneity: in its most productive economy, South Africa, labor productivity has been just 29 percent of the advanced-economy average since 2010. However, fragile and conflict-affected economies—14 out of the 39 SSA economies in the sample—had less than half of the labor productivity level of the SSA average.

The stark divide between advanced economy and EMDE labor productivity levels significantly exceeds regional variations among EMDEs—a polarization exists in the distribution of productivity levels, with EMDEs concentrated at the bottom of the distribution, while advanced economies occupy a wide range of significantly higher productivity levels (Quah 1996b, 1997a, **Figure 1**). On average during 2010-18, EMDE productivity was concentrated around $7,000 of output per worker per year, while advanced economies are clustered around a high level of productivity peaking at $95,000, below the United States ($109,000) but above lower-productivity advanced economies such as the Republic of Korea ($48,000). The fact that EMDE and advanced economies cluster around these highly differential productivity levels is strong evidence both for convergence being conditional and for the presence of multiple points of attraction for productivity.

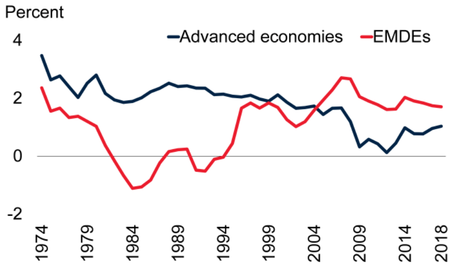
Following a steep decline in EMDE productivity growth in the 1980s and early 1990s, caused by a series of financial crises in SSA and LAC, and the collapse of the Soviet Union, growth rose sharply in the late 1990s (World Bank, 2020a). For the first time since the dataset began in 1970,

[4]Saudi Arabia and Qatar have labor productivity levels that are close to that of the United States, but TFP levels are just half those of the United States as measured in the Penn World Table.

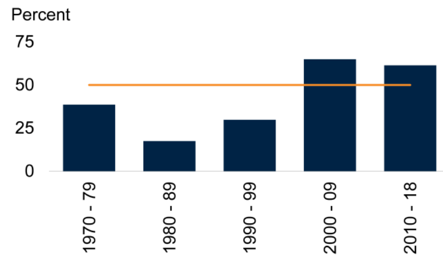
average EMDE productivity growth exceeded that of advanced economies on a nearly continuous basis starting in 2000 (**Figure 2**). The improvement in performance was broad-based, with around 65 percent of EMDEs growing faster than the average advanced economy over the past two decades (Rodrik, 2011). Nevertheless, on average, the productivity gap between advanced economies and EMDEs has closed only modestly since the 1990s.

Figure 2: **Evolution of labor productivity gaps**

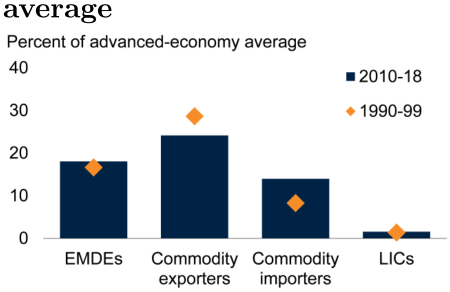
A. Average annual advanced economy and EMDE labor productivity growth (5-year moving average)



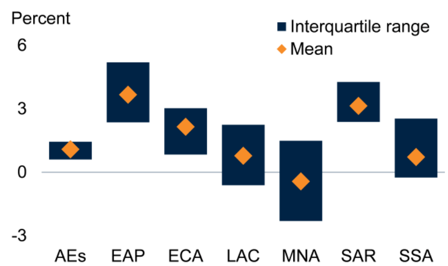
B. Share of EMDEs with a narrowing productivity gap vs advanced economies



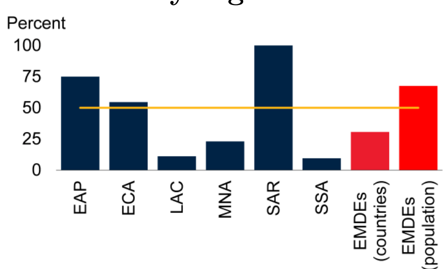
C. Labor productivity in EMDEs by commodity producer status, 2010-18 average



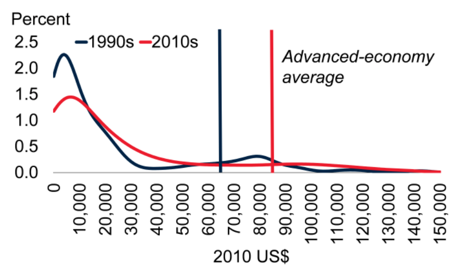
D. Distribution of labor productivity, 2010-18 average



E. Share of EMDEs with narrower productivity gap in 2010-18 than in the 1970s by region



F. Distribution of productivity: 1990s and 2010s



Source: Penn World Table; The Conference Board; World Bank, World Development Indicators.
Note: Productivity is defined as output per worker in U.S. dollars (at 2010 prices and market exchange rates). Based on a sample of 35 advanced economies and 123 EMDEs for a consistent sample since 1990, and 29 advanced economies and 74 EMDEs for a consistent sample since 1970.
A. Simple average of productivity growth in advanced economies and EMDEs.
B. Share of EMDEs with average productivity growth above average advanced-economy productivity growth.
C. GDP-weighted average gap across EMDE groups to average advanced economy productivity level by decade.
D. Mean and interquartile range of productivity growth during 2010-18.
E. Proportion of economies in each region, proportion of all EMDE economies, and proportion of EMDE total population that live in economies with smaller productivity gap with advanced economies during 2010-18 than during the 1970s on average.
F. Smoothed density estimates (Gaussian kernel) of output per worker during 1990-99 and 2010-18.

Progress in closing the productivity gap occurred mainly in commodity-importing EMDEs; commodity exporters, on average, moved further away from the frontier (**Figure 2**). Among the regions, EAP, ECA, and SAR had average productivity growth in 2010-18 that exceeded that of advanced economies by a significant margin. In other regions, many of which have large numbers of commodity exporters, productivity growth was similar to, or below, that of advanced economies.

The faster pace of productivity growth since 2000 has shifted the distribution of productivity levels to the right but has yet to lead to a material proportion of EMDEs reducing the income gap with advanced economies relative to the 1970s, particularly given the lackluster growth experienced in the 1980s and early 1990s. SAR, EAP, and ECA are the only regions where a material proportion of EMDEs have a smaller gap than in the 1970s today. Only one-third of EMDEs have narrowed their productivity gaps over the past 50 years. However, the economies where productivity gaps have narrowed since the 1970s account for around 70 percent of the population of EMDEs: a clear majority of the population of EMDEs live in economies where the productivity gap has narrowed.

Despite the slow progress in closing productivity gaps, absolute productivity levels have improved in many of the poorest economies. Like the productivity distribution in the 2010s, the productivity distribution in the 1990s featured a concentration of countries around low-productivity levels and another concentration close to the average advanced economy productivity level. However, since the 1990s, the share of economies in the lowest productivity region (below $10,000) has almost halved. Using the World Bank's income classifications, around half of the economies classified as "low income" in 1990 are now classified as "lower-middle" or "upper-middle" income economies.[5] And 60 percent of economies are now classified as high or upper-middle-income economies, compared to just 35 percent in 1990. However, World Bank income thresholds are only adjusted for inflation—the threshold for the "high income" classification has remained unchanged in real terms since 1990. Therefore, they do not imply convergence to the frontier but rather a broad-based absolute improvement.

Historical episodes of convergence towards the frontier are rare (Durlauf et al., 2005; Johnson and Papageorgiou, Johnson and Papageorgiou; Rodrik, 2011). Full convergence to the frontier requires sustained high productivity growth over many decades. Just nine economies transitioned into the top quartile of incomes between the 1950s and the post-crisis period.[6] Of these, Equatorial Guinea and Oman benefited from oil and gas exploration; Japan, Cyprus, and Portugal were already close to the highest quartile in 1950; the Republic of Korea, Hong Kong SAR, and Singapore were "Asian Miracle" economies, with their success attributed to a number of factors, including high education levels, strong governance, and industrial policies that included export promotion (Leipziger and Thomas, 1993).

In summary, productivity growth improved for a broad set of EMDEs starting around 2000 but has not yet led to a material reduction in productivity gaps with advanced economies. In some cases, these improvements only partially unwound previous productivity growth underperformance,

[5]See also *Special Focus 2.1* (World Bank, 2019b)

[6]This statement relies on convergence in income per capita instead of labor productivity, allowing a sample of 137 economies since 1950, compared to 103 since 1970 for labor productivity. The Maddison Project database of income per capita for 137 economies since 1950 provides a much wider coverage than the labor productivity database used throughout this chapter – the productivity dataset falls to 49 economies for the same period of data. Output per capita provides a less precise measure of productivity, not accounting for changes in labor force participation or the share of the working-age population.

such that a minority of economies, but a majority of the population, has seen productivity gaps decline since the 1970s. Since the global financial crisis, this surge in productivity growth has declined in several EMDE regions. In addition, historically, sustained convergence to the frontier is rare.

In the following section, formal statistical tests of the convergence hypothesis are undertaken to assess the speed of convergence, before delving into more complex examinations of club convergence.

3 Testing for convergence and its pace

Countries with lower initial levels of productivity have only recently begun to outperform productivity growth in high-productivity economies on a broad basis, suggesting the presence of *unconditional* convergence. This has occurred in recent decades at a slow pace but does not hold over the entire sample. Convergence potential may be hindered by unfavorable characteristics in some economies that hold back productivity growth, such as poor human capital or lack of infrastructure, a phenomenon dubbed "conditional convergence" (Barro and Sala-i Martin, 1992). This section explores the pace of unconditional and conditional convergence in a more formal statistical framework.

3.1 Unconditional convergence

Unconditional convergence can be assessed using a "β-convergence" regression, which posits that productivity growth depends on its initial level:

$$y_{iT} - y_{i0} = c + \beta y_{i0} + \epsilon_{iT}$$

where y is the natural log of output per worker at both time "T" and the initial period "0" under consideration and the disturbance term ϵ_{iT} captures shocks to productivity in country i that are unrelated to convergence drivers of productivity growth. The hypothesis that $\beta < 0$ implies that lower initial productivity produces faster cumulative growth (between time 0 and time T). When all countries have access to the same technology, those with higher marginal returns to capital—i.e. capital-scarce poorer economies—should benefit from greater capital accumulation and higher growth. The coefficient β can then be converted to an annual rate of convergence, the percent fall in the average productivity gap that is estimated to have occurred each year.[7]

Early estimates of β-convergence found little evidence of its existence, often instead finding that initial income was positively related to the subsequent rate of growth (Baumol, 1986; Barro, 1991; Dowrick, 1992).[8] More recent tests for unconditional convergence show tentative evidence in support of the hypothesis. In tests on data from the late 1990s onwards, a statistically significant negative coefficient on initial income has been found (Patel et al., 2018; Roy et al., 2016). Additionally, in manufacturing, evidence in support of statistically significant unconditional convergence has also been found (Rodrik, 2013).

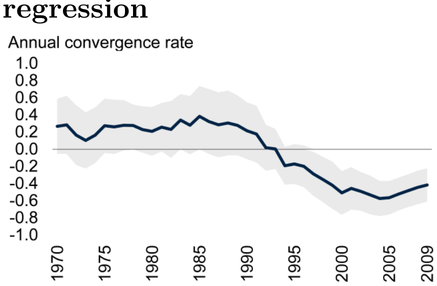
[7]This is computed as $(-1) * ln\,(\beta + 1)\,T$, where T is the number of years under consideration, as in Barro and Sala-i Martin (1992).

[8]Barro (1991) and Barro and Sala-i Martin (1992) apply the unconditional convergence testing procedure to US states and the OECD, while Sala-i Martin (1996) applies the procedure to Japanese Prefectures and European regions. All studies have found little evidence of unconditional convergence.

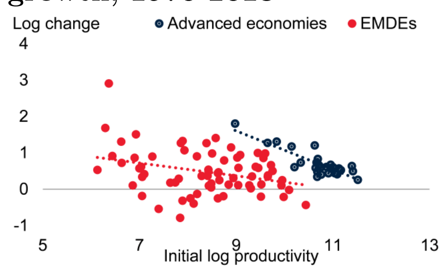
Globally, there has been little evidence of enduring unconditional productivity convergence until the most recent two decades, where the negative coefficient on initial productivity becomes statistically significant (**Figure 3**). Although statistically significant in recent decades, the estimated pace of convergence is slow, with the average economy closing just 0.5 percent of the productivity gap since 2010. At this rate, it would take nearly 140 years to close just half of the initial productivity gap between economies on average. In contrast, within the group of advanced economies, unconditional convergence is statistically significant and there is a clear relationship between initial labor productivity and subsequent growth (**Figure 3**). Within advanced economies, labor productivity converged at a rate of 2 percent per year in the 1980s and 1990s, requiring less than 40 years to close half of the outstanding productivity gaps, although the rate of convergence has declined in recent decades as residual gaps became smaller. Even among EMDEs, a modest rate of convergence (0.5 percent) is detected over the last decade. This is evidence that within groups with similar characteristics, economies tend to converge towards a similar productivity level.

Figure 3: **Conditional and unconditional convergence**

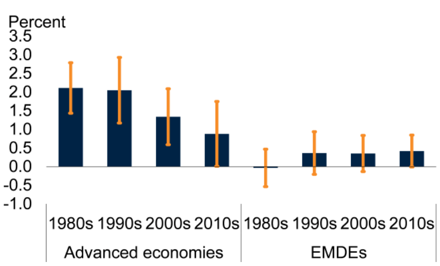
A. Convergence rate implied by β-regression



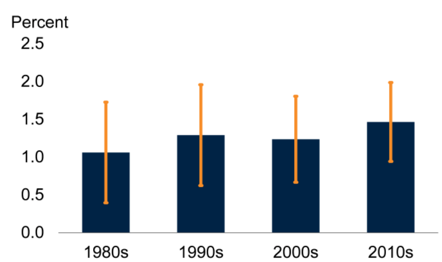
B. Initial log labor productivity and growth, 1970-2018



C. Unconditional annual convergence rate *within* advanced economies and EMDEs



D. Conditional annual convergence rate: all economies



Source: Penn World Table; The Conference Board; World Bank, World Development Indicators.
Note: Based on data for 98 economies, consisting of 29 advanced economies and 69 EMDEs. Sample excludes 6 EMDE oil exporters with productivity levels above those of the United States in the 1970s.
A. Gray shaded area indicates 95 percent confidence intervals. Estimation performed over 10-year rolling windows in the specification $log\Delta y_t = c + \beta log y_{t-10} + \epsilon_t$ where y is output per worker. X-axis indicates start year of regression sample. Negative value indicates productivity gaps are declining at rate indicated. Regression coefficient converted to a convergence rate using the transformation $\beta = e^{-\lambda T} - 1$, where λ is the annual convergence rate and T is the number of years over which the regression is estimated.
B. Dotted line indicates a fitted relationship between initial log productivity level and subsequent productivity growth.
C. Annual percent decline in productivity gaps, derived from a β-regression containing only advanced economies or EMDEs. Convergence rate indicated is based on productivity growth since the previous decade.
D. Annual convergence rate implied by a β-regression which controls for a number of country features, including average years of education, a commodity-exporter dummy, economic complexity (Hidalgo and Hausmann 2009 measure), trade openness, investment as a share of GDP and a measure of political stability (Annex C)

3.2 Conditional convergence

Much of the literature has found evidence that once country characteristics are controlled for, the coefficient on initial income becomes negative and statistically significant. Tests for conditional convergence use a similar regression specification as tests for unconditional convergence but control for country characteristics:

$$y_{iT} - y_{i0} = c + \beta y_{i0} + \gamma X_i + \epsilon_{iT}$$

where X_i is a set of country characteristics. These country characteristics include the initial levels and changes in variables relating to factors such as educational attainment, trade openness, natural resources, demographics, population health, and governance.

Controlling for the level of human capital available across economies, as measured by average years of education, has been found to result in statistically significant convergence (Barro and Lee, 1994; Mankiw et al., 1992). Other than direct inputs into the production function, a range of additional factors have also been found to be important controls for assessing convergence. These have included trade openness and export orientation (Dollar and Kraay, 2003; Frankel and Romer, 1999; Sachs and Warner, 1995), good institutions (Rodrik, 2004), natural resources and other geographical factors (Easterly and Levine, 2001, 2003; Sachs and Warner, 2001), and economic or export complexity (Hausmann et al., 2007; Hidalgo and Hausmann, 2009).

Consistent rates of convergence have also been found when controlling for country characteristics. The "rule of 2 percent" was coined after a common rate of annual income convergence across U.S. states, and separately countries, was identified when controls for factors such as educational levels and political stability were included (Barro and Sala-i Martin, 1992). Most studies have found results within a range of 1 to 3 percent per annum (Durlauf et al., 2005). An annual convergence rate of 2 percent implies that half of any initial difference in productivity levels will disappear after 35 years.

The results of a conditional convergence regression, containing typical country-characteristics used in the literature, show that lower initial incomes were associated with higher productivity growth in each decade since the 1980s.[9] The convergence rate is estimated to have increased over time, peaking at 1.5 percent per year over the past decade, which if sustained would halve the productivity gap in just under 50 years (**Figure 3**). Previous studies, including recent tests for club convergence, have documented similar rates of conditional convergence but have yet to document the acceleration in pace in recent decades (Johnson and Papageorgiou, Johnson and Papageorgiou). The panel specification, covering all decades, shows an annual convergence rate of 1.3 percent, within with the range of 1-3 percent found in surveys of the literature of growth regressions on income per capita (Annex C).[10]

Estimates conditional on other characteristics, such as the level of education and investment,

[9] See Annex C for further details. Regression includes controls for average levels of education, trade openness, the economic complexity index of Hidalgo and Hausmann (2009), commodity exporter status, the level of investment as a share of output, and political stability.

[10] Most of these studies have performed these exercises on PPP-adjusted measures of income per capita. This alternative measure results in estimates of a convergence rate of 1.7 percent using the same specification. However, PPP-adjustment may be inappropriate for measuring output per worker. Many economies have substantially faster productivity growth measured using time-varying PPP adjustments compared to national accounts measures (Box A).

suggest that convergence rates have been much faster and rising in recent decades. However, the conditional convergence concept is less useful as a generalized measure of convergence progress among EMDEs, as it suggests that economies may be on many different productivity paths dependent on their characteristics. A deeper examination of which economies are experiencing fast rates of convergence due to their characteristics can be explored through club convergence analysis.

4 Convergence clubs

In general, the β-convergence framework underlying the unconditional and conditional convergence results faces limitations in distinguishing between multiple attraction points that may exist for productivity levels in different economies, such that even in cases where the coefficient is negative, economies may not be converging to a common level of productivity, and there may not even be a reduction in the dispersion of productivity levels (Bernard and Jones, 1996; Phillips and Sul, 2007; Quah, 1993).[11] Therefore, the analysis of convergent behavior across economies is better explored in an alternative framework. Tests for convergence clubs—groups of economies that are converging to one of a range of attraction points, and which likely share common characteristics— are less prone to the failings of the β-convergence framework (Quah, 1993, 1997; Durlauf and Johnson, 1995).

The early literature on the existence of convergence clubs extended the β–convergence framework to assess whether different groups of economies converged at different values for β, finding evidence that this parameter was not stable between groups (Durlauf and Johnson, 1995; Canova, 2004). The literature then extended into two primary categories of approaches, which are both applied in this chapter.

Distributional analysis: commonalities in productivity levels. Studies conducting distributional analysis have explored whether economies can be subdivided into statistically-distinct distributions (mixture modeling), with much of the literature focusing on the distribution of per capita income and not productivity. Countries' per capita income levels appeared to fall into two to four different distributions, with limited transitions between them.[12] Studies that included additional variables to help inform the clustering of labor productivity—TFP, human capital, or physical capital—similarly identified 2-3 clusters during the decades 1960-2000 (Battisti and Parmeter, 2013). The gap between different clusters appears to have widened since the 1970s (Pittau and Zelli, 2006). Distributional analysis has more generally found evidence of increasing divergence between groups of economies.

Time series analysis: commonalities in trajectories. Studies conducting time series analysis have typically tested for cointegration and more recently used factor model structures to test for convergence. Cointegration tests of output per capita have tended to find little evidence for convergence of income per capita in either advanced economies or wider samples of 140 advanced economies and EMDEs between 1950 and 2000 (Bernard and Durlauf, 1995; Bernard and Jones,

[11] Even simple modifications to the standard β-convergence framework expose some of its weaknesses. For example, an additional squared measure of initial income suggests that those with an initial income below one-sixth of the US exhibit different behavior than for those economies above this level (Chatterji, 1992). Separately, in a partially linear regression model, no evidence has been found of convergence for countries with income below \$1800 per annum (Liu and Stengos, 1999).

[12] See Pittau and Zelli (2006), Henderson et al. (2008), and Battisti and Parmeter (2013).

1996; Pesaran, 2007). However, evidence is found for convergence in per capita income growth rates in the cointegration testing framework, suggesting that income gaps do not increase over time. More recently, a factor model-framework for club convergence testing has been proposed which is less liable to make false rejections of the formation of convergence clubs than previous time-series approaches. In a dataset spanning 1970-2003 for income per capita in 152 economies, evidence was found for the existence of 5 convergence clubs, with the first dominated by advanced economies (Phillips and Sul, 2007, 2009).

4.1 Convergence clubs: Commonalities in productivity *levels*

The first strand of the literature can identify clubs of economies well in an ex-post sense: those economies who have converged over time towards common attraction points will have similar productivity levels and thus be found to have been in a convergence club. Updating the distributional analysis literature to the post-2000 period, when EMDE productivity growth has picked up substantially relative to earlier decades, results in a similar number of clubs relative to earlier estimates (4 in the most recent period). However, relative to earlier studies, 10 faster-growing EMDEs have separated from the lowest productivity club over the past decade to join a convergence club consisting of many middle-income EMDEs (Annex D). The period of faster productivity growth in EMDEs has resulted in new convergence club dynamics—a more comprehensive examination in the following section of both the level of productivity and the trajectory of productivity over time provides greater clarity over the development of convergence clubs in recent decades.

4.2 Convergence clubs: Commonalities in productivity *trajectories*

Common productivity trajectories. The clubs identified above capture common productivity levels at different points in time. However, these same productivity levels can be achieved along very different trajectories— a low-productivity economy may be on a growth path that is convergent with high-productivity economies in the future but may not be considered to be in a similar convergence club based on a snapshot of productivity levels alone. This section identifies commonalities in the trajectories of productivity over time: countries in the same convergence club are on paths that converge towards similar productivity levels, even if productivity differentials are high in the period under examination.

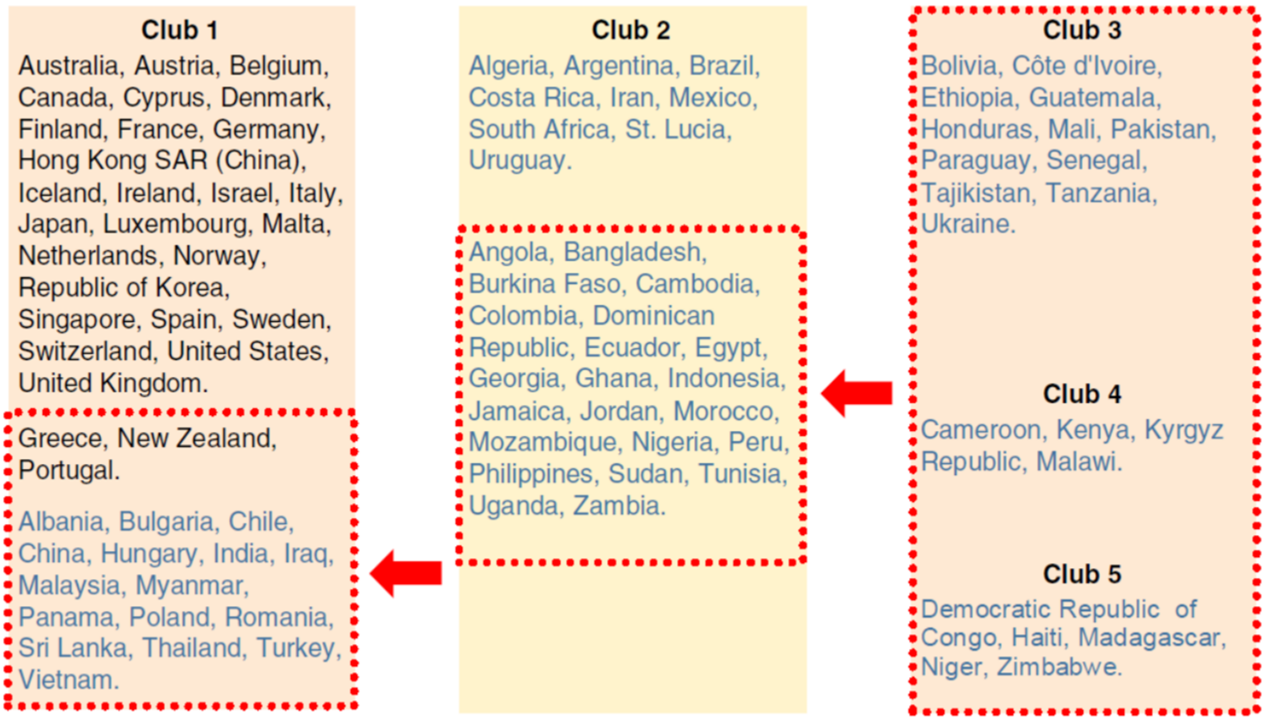
Methodology. Labor productivity (in logs) is modeled as a country-specific weighting on a common factor μ_t, which reflects the common productivity attraction point that club members are drawn to (Phillips and Sul 2009):

$$y_{it} = b_{it}\mu_t$$

Countries in the same convergence club will initially feature different coefficients b_{it}, reflecting their varying distance from a common attraction point. For a group of economies to form a convergence "club", their deviations from the common attraction point should fall over time. Using an iterative procedure, the methodology tests combinations of economies for common convergence dynamics; economies that do not display falling productivity gaps are discarded until groups are found that do (Annex E). Data are available for 29 advanced economies and 68 EMDEs for

1970-2018. Results. Since 1970, countries have fallen into 5 distinct convergence clubs in which productivity moved along a similar trajectory and where productivity differentials were falling over time. Several countries have moved into faster-productivity clubs since 2000 (**Figure 4**).

Figure 4: **Convergence clubs, 1970-2018 and transitions relative to the early-sample estimation of convergence clubs (1970-2000)**



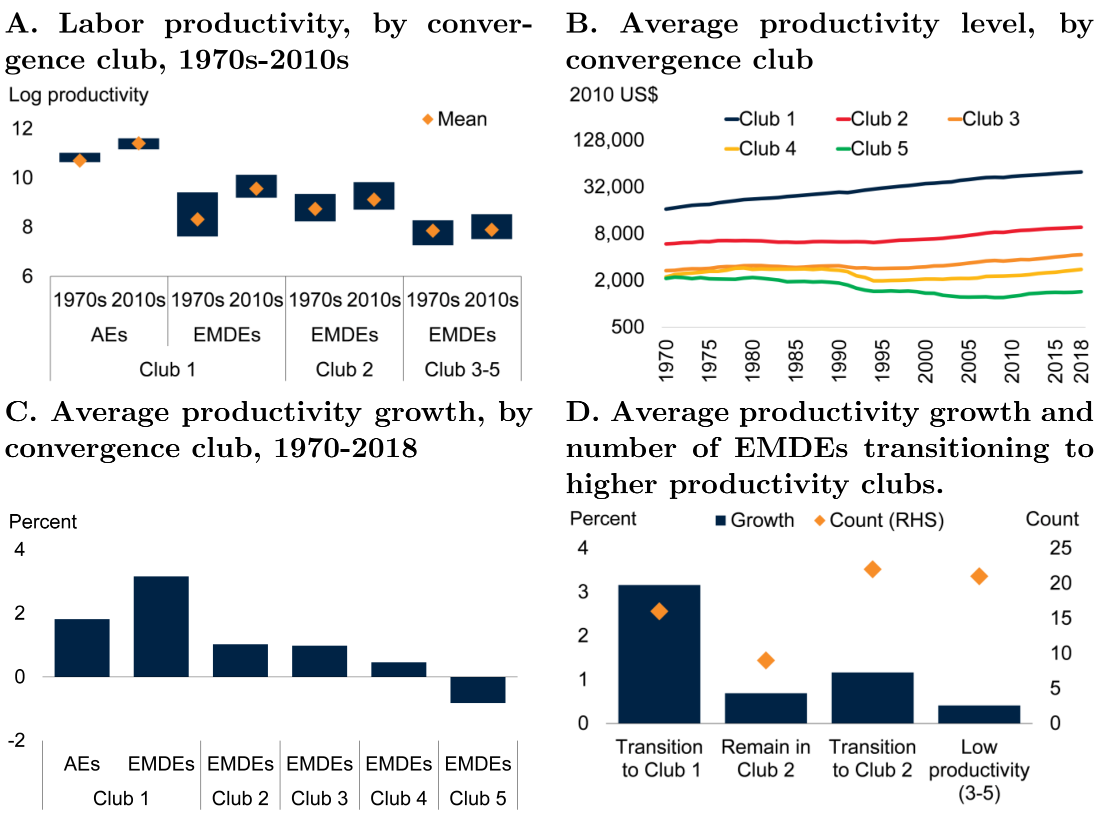
Source: World Bank
Note: The figures show the club composition when estimated over the whole sample (1970-2018). The red and blue dotted boxes show economies that were in a lower convergence club in the first half of the sample 1970-2000 (e.g. moved from Club 2 to Club 1). Blue text indicates advanced economies while red economies are EMDEs.

Clusters during 1970-2018. The first club (Club 1) consists of economies converging towards the highest productivity level. It includes all advanced economies, several upper-middle-income EMDEs that have sustained long periods of robust growth, and three lower or lower-middle-income economies with rapid productivity growth (**Figure 4**). This club initially had a broad range of productivity levels in 1970 which had narrowed by 2010 as low-productivity economies caught-up. The second club includes the majority of upper-middle-income, or near upper-middle-income EMDEs, converging towards an intermediate level of productivity. Lower clubs consist primarily of lower-middle and low-income economies that have persisted in a low-productivity low-growth state. Advanced economy members of the high-productivity Club 1 have achieved average productivity growth of around 2 percent since 1970, rising to 3 percent for EMDE Club 1 members —just over twice the average productivity growth of EMDEs in Clubs 2 and 3 and in contrast to stagnant productivity levels in lower-productivity convergence clubs 4-5 (**Figure 5**). The economies in each club tend to be geographically diverse.

Changes over time. When estimating convergence clubs separately for the period 1970-2000, the decades during which average EMDE productivity growth fell short of the advanced-economy average, no EMDEs were estimated to be in a convergence club with advanced economies. In this earlier period, the second club included a combination of advanced economies and middle-income EMDEs (**Figure 4**). Three advanced economies (Greece, New Zealand, and Portugal) and 16 middle-income EMDEs (including China, India, and Turkey) in this club have since moved to Club 1, converging towards the highest productivity levels, and 22 middle-income EMDEs (including Indonesia) have moved to the second-highest productivity club (**Figures 4 & 5**). Earlier studies using the same methodology to 2003 found that just 4 of the economies identified as transitioning to Club 1 in this study had done so based on the earlier sample (Phillips and Sul, 2009).

Alternatively, using PPP-adjusted measures of labor productivity levels, as opposed to labor productivity measured at market exchange rates, results in an additional 5 EMDEs being estimated to have joined the highest productivity level convergence club. However, large discrepancies with national accounts measures of productivity growth suggest some caution should be used in interpreting these results (Annex F).

Figure 5: **Characteristics of convergence clubs**



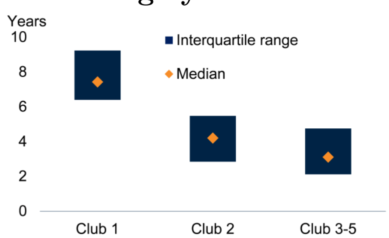
Source: World Bank.
Note: Based on convergence clubs estimated as in Phillips and Sul (2009).
A. Unweighted average log-productivity levels during 1970-79 and 2010-18. Blue bars show interquartile range.
B. Unweighted average productivity level in each identified convergence club.
C. Simple average of productivity growth over the sample 1970-2018. All members of clubs 2-5 are EMDEs.
D. "Transition to 1" group includes EMDEs which have joined convergence Club 1 during the whole-sample estimation relative to the early-sample estimation (1970-2000). "Club 2 remainer" economies are those which are in Club 2 in both estimations. "Transition to 2" economies joined Club 2 from lower clubs in the early-sample estimation, while "Low productivity (3-5)" economies are estimated to be in lower clubs in both samples.

4.3 Country characteristics associated with convergence club membership

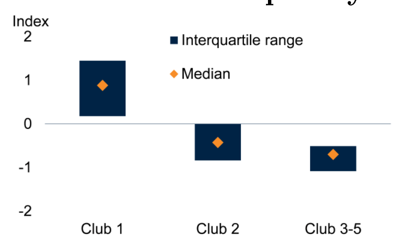
Several country characteristics—including higher levels of education, greater economic complexity, and greater political stability—have been systematically associated with more favorable long-term productivity trajectories.[13] This is consistent with findings in the literature that have associated higher productivity or per capita income with a better-educated labor force (Rodrik, 1994), greater diversification and complexity of exported goods (Hausmann et al., 2007; Hausmann and Hidalgo, 2010) and better institutions, governance, and stability (Hall and Jones, 1999; Rodrik, 2004).[14]

Figure 6: **Key characteristics of convergence clubs**

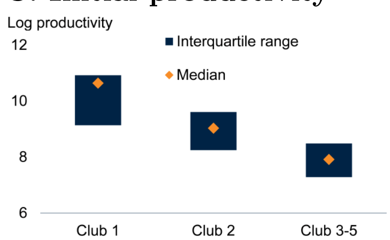
A. Average years of education



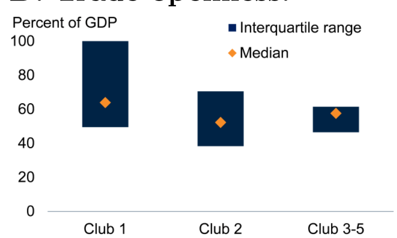
B. Economic complexity index



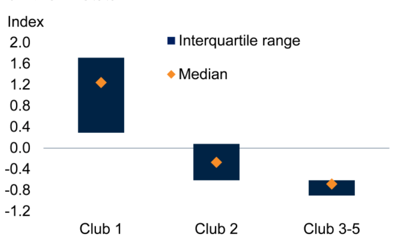
C. Initial productivity



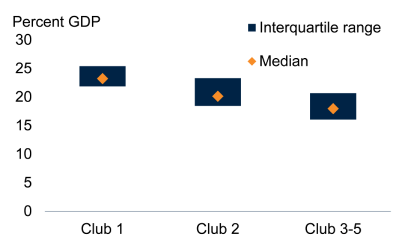
D. Trade openness.



E. Perceptions of government effectiveness



F. Investment



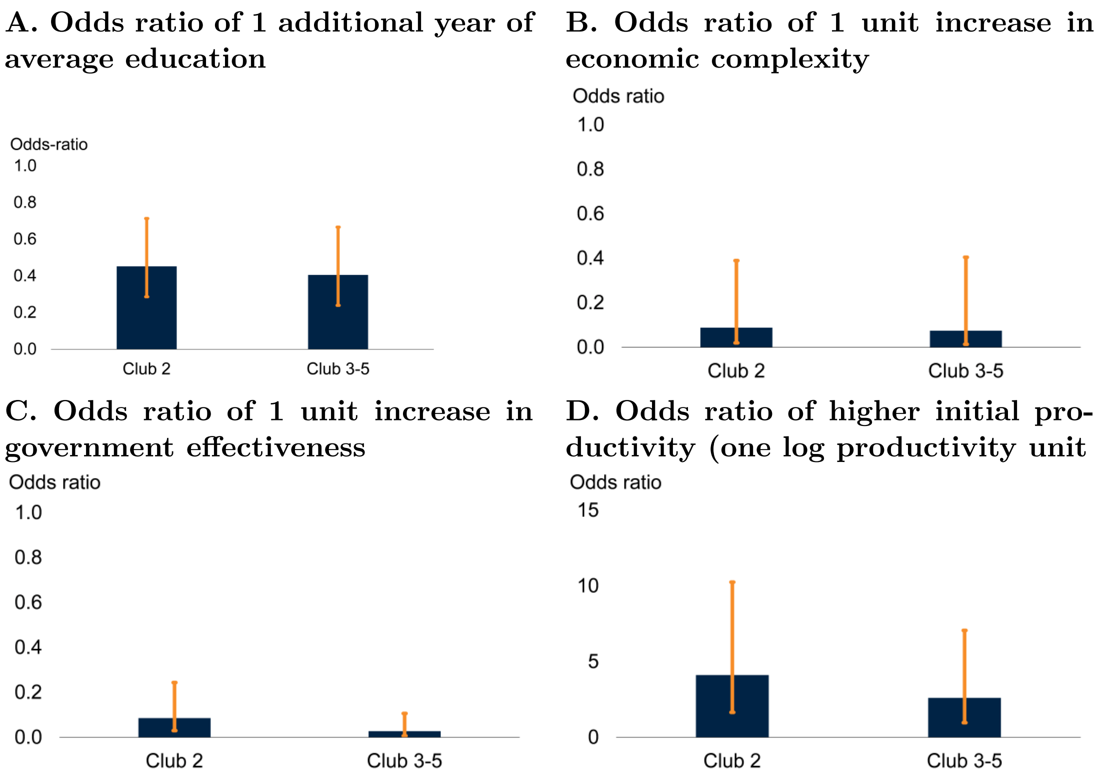
Sources: Barro and Lee (2015); Hausmann and Hidalgo (2009); World Bank, Worldwide Governance Indicators.
Notes: Average between 1970 and 2017, except for C, with 1970-1980 used for initial productivity and E. which is only available since 1995.
A. Average years of schooling for males and females from (Barro and Lee, 2015).
B. Economic complexity index of Hidalgo and Hausmann (2009).
D. Exports and imports in percent of GDP.
E. Government effectiveness survey from the World Bank's Worldwide Governance indicators.
F. Gross fixed capital formation in percent of GDP.

[13]Similar results are found for the determinants of the convergence clubs found using the distributional clustering approach. The results are available in Annex D.

[14]Economic complexity is a measure of two concepts: the diversity and the ubiquity of the products an economy is able to produce. Diversity reflects the range of products the economy in question produces, while ubiquity reflects the number of other economies producing those products. For example, an economy specializing in just food products (produced by many other economies) will score poorly in the ECI.

On average, members of Club 1 had significantly higher levels of education, greater economic complexity, higher initial labor productivity, and stronger perceptions of government effectiveness than members of other clubs (**Figure 6**). In contrast, there were significant overlaps between the interquartile range of clubs for trade-openness and the investment-to-GDP ratio, suggesting that these characteristics were less decisive in determining club membership.

Figure 7: **Country characteristics associated with membership of Clubs 2-5 relative to the membership of fast-convergence Club 1**



Sources: Barro and Lee (2015), World Bank World Development Indicators, Hausmann and Hidalgo (2009), World Bank Worldwide Governance Indicators.
Note: Covariates are calculated as their average value during 1970-90 in the multinomial logit estimation, with the exception of the WGI measure of political stability, which uses the 1990s average due to data availability. The "Odds-ratio" measures the impact of a one unit increase in each covariate on the probability of membership of each convergence club relative to Club 1. An odds ratio of more than 1 implies that the characteristic makes membership of Clubs 2-5 more likely relative to membership in Club 1. A ratio of less than one means an increase in the covariate reduces the likelihood of being in Clubs 2 or 3-5 relative to Club 1. Orange lines show 95 percent confidence interval.

The determinants of club membership are more formally examined in a multinomial logit model (Annex E). In this approach, the conditional probability of membership of a particular club relative to the highest-productivity Club 1 is estimated for Club 2 and an amalgamation of clubs 3-5 to ensure sufficiently consistent club sizes. A one-year increase in the average length of education, a one standard deviation increase in the economic complexity index (ECI), or a unit increase in the index of government effectiveness perceptions substantially reduces the probability of membership of Clubs 2-5 relative to Club 1; the ratio of the probability of being a member of Clubs 2-5 relative to Club 1 more than halves (**Figure 7**). Higher initial productivity levels increase the probability of membership of a lower-productivity convergence club, once other country characteristics are controlled for. That is, countries with high levels of initial productivity but median levels of the other characteristics are more likely to be in a lower convergence club.[15]

4.4 Country characteristics associated with transitioning to higher convergence clubs

In this section, the pre-conditions for transitioning to a higher convergence club are examined, using the 16 EMDEs who transitioned to Club 1 as informative examples. In this exercise, the problem of endogeneity is less of a concern than in the previous exercise when examining the determinants of club membership.[16] However, the results are consistent with the country features associated with higher-productivity club membership. Multiple approaches suggest that better initial education, deepening economic complexity, and stronger institutions were associated with successful transitions.

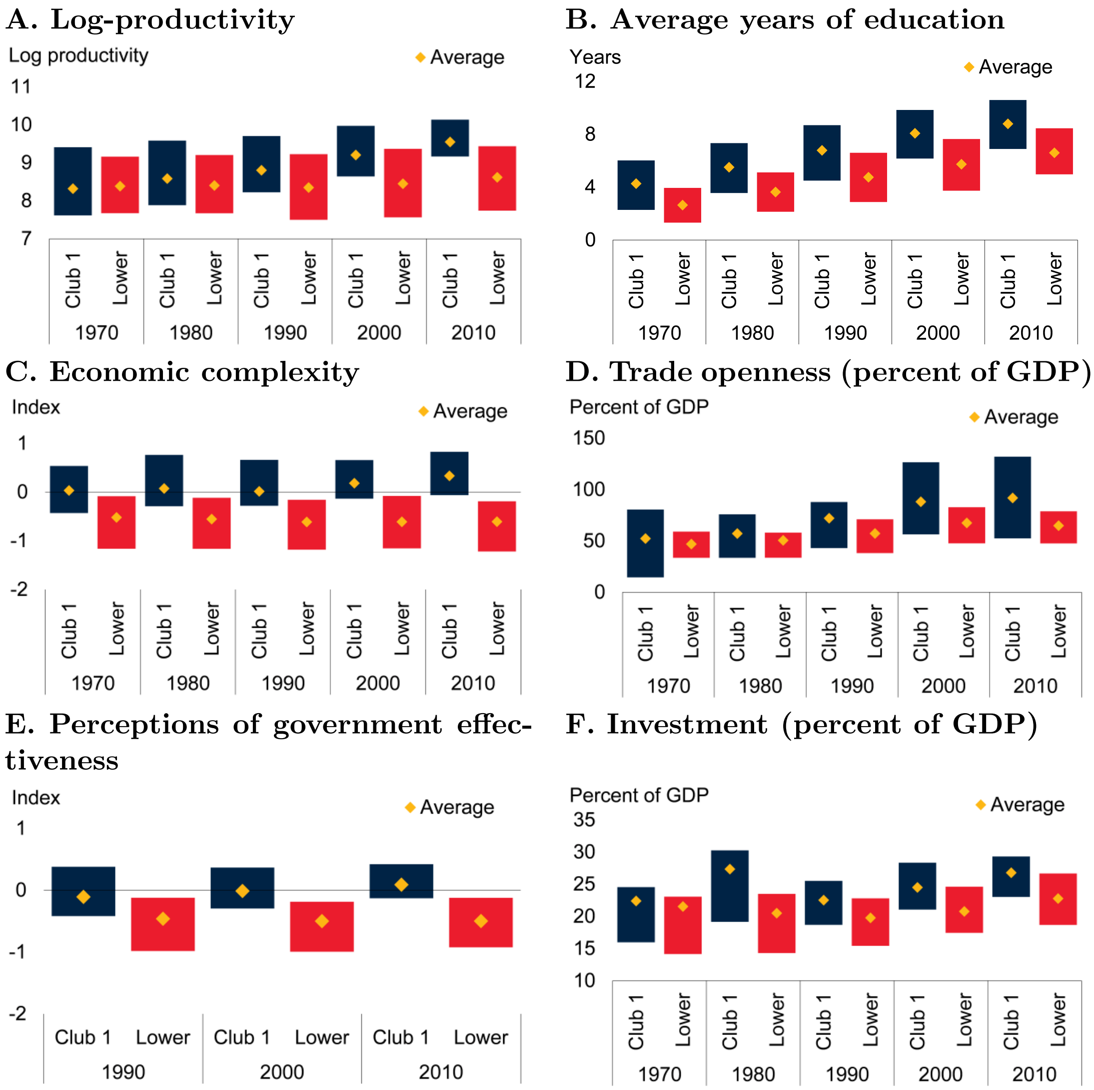
Group averages. EMDEs that switched into the higher-productivity convergence club were not initially more productive than other EMDEs, and their productivity levels only overtook other EMDEs only in the early 1990s on average (**Figure 8**). Their education levels were initially higher but did not accelerate at a faster pace than in other EMDEs. In contrast, economic complexity increased continuously among the EMDEs that transitioned into the high-productivity club, while it has stagnated in non-convergent EMDEs. Measures of institutional quality, such as perceptions of government effectiveness, were modestly higher in those countries that transitioned. Trade openness and levels of investment have significantly overlapped between the two groups for much of the sample—although trade openness did accelerate in transitioning economies from 2000 onwards.

Logit analysis. A logit model estimates the probability of transitioning into a higher-productivity club based on country characteristics (Annex E). The logit model was estimated over two separate time periods, 1980-90, just before the transitioning EMDEs overtook the non-transitioning EMDEs, and 1990-2000, just after the transitioning EMDEs began to display accelerating growth relative to other EMDEs. This allows an examination of the conditions in transitioning economies at key junctures in their development.

[15]This finding is consistent with the concept of the 'middle-income trap' (Aiyar et al., 2013; Eichengreen et al., 2013; Im and Rosenblatt, 2013). Economies that have progressed to productivity levels consistent with middle-income status risk stagnating if they do not continue to improve educational outcomes, expand to more complex industries, or improve governance.

[16]Examining the determinants of transitioning economies before or during the transition to faster productivity growth trajectories reduces the endogeneity problem between productivity growth and the drivers of productivity growth.

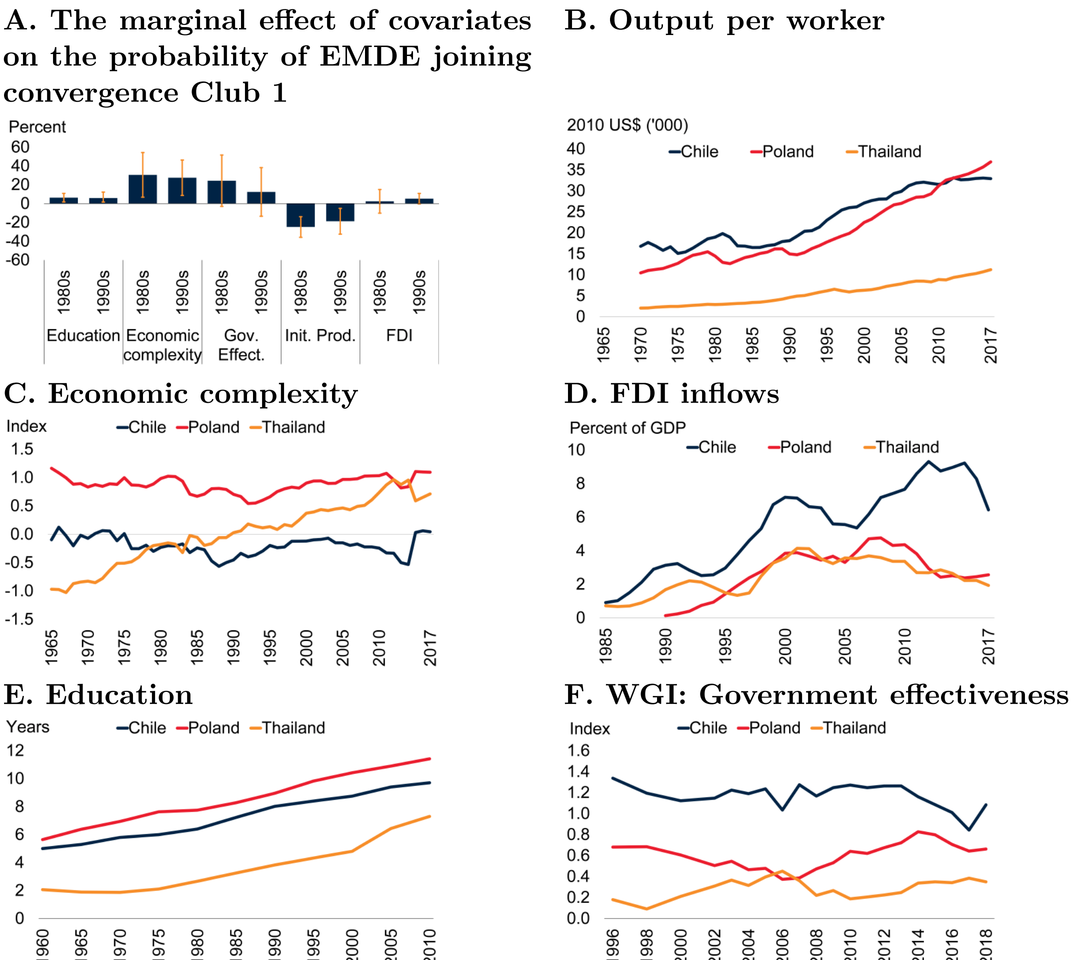
Figure 8: **Characteristics of EMDEs transitioning to the highest-productivity convergence club relative to economies in lower clubs**



Source: Barro and Lee (2015); Hidalgo and Hausmann (2009); World Bank (World Development Indicators, Worldwide Governance Indicators).
Notes: Bars show interquartile range of each group for average values in each decade. Club 1 are EMDEs who transitioned into the high-productivity convergence club after 2000 (16 economies), 'lower' indicates EMDEs who remained in a lower club (43).
B. Average years of schooling for males and females from Barro and Lee (2015).
C. Economic complexity index of Hidalgo and Hausmann (2009).
D. Exports and imports in percent of GDP.
E. Government effectiveness survey from the World Bank's Worldwide Governance indicators, defined as: perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.
F. Gross fixed capital formation in percent of GDP.

1980-90 covariates. Higher initial education, greater economic complexity, institutional quality (measured using the WGI government effectiveness index), and lower initial productivity levels are consistently associated with a higher probability of switching into a higher-productivity club between 1980-1990.[17] As with the results of the multinomial logit estimation on club membership, there is less evidence that the share of investment in GDP or openness to trade are key determinants of transitioning to higher convergence clubs. A one standard deviation increase in either the economic complexity index or WGI measure of government effectiveness results in an increase of around 30 percent in the probability of joining the highest convergence club.

Figure 9: **Covariates of EMDE joining top-tier convergence club**



Sources: Barro and Lee (2015); Hausmann and Hidalgo (2009); World Bank, World Development Indicators,.
A. Marginal effect of a one-unit increase in the covariates on the probability of an EMDE joining the fast productivity growth convergence Club 1. Derived using a logit model. Detailed results in Annex E.
B.C.D.E.F Average years of schooling for males and females from Barro and Lee (2015). Economic complexity index of Hidalgo and Hausmann (2009). FDI is measured in percent of GDP. Governement effectiveness survey from the World Bank's Worldwide Governance indicators, defined as: perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.
D. 5-year moving average

[17] The WGI indicators for government effectiveness and political stability are only available from 1995 onwards. Therefore, an average of their values between 1995-2000 are used. A range of other variables that proxy for governance (black market currency premium, inflation level, level of government debt) which extended to earlier time periods were tested. None were found to be statistically significant.

1990-2000 covariates. In the 1990s, institutional quality became less decisive in determining whether a country transitions to Club 1, becoming statistically insignificant in the logit results (**Figure 9**). Here, education, economic complexity, and FDI remain significant covariates, the latter only at the 10 percent significance level. One interpretation of this difference from the results for 1980-90 is that a foundation of high governance quality is required for EMDEs to transition to higher convergence clubs, but further success is often dependent on attracting FDI and introducing new and more complex production capabilities into an economy.

4.5 Transitions: Poland, Thailand, and Chile

These countries are among those that successfully transitioned from a lower-productivity club to the highest-productivity Club 1. Since the 1980s, labor productivity in Poland and Chile has increased from around one-quarter to 35 percent of the advanced-economy average. Thailand's labor productivity has increased from 5 to 10 percent of advanced economy levels over the same period. Poland and Thailand exemplify successful transitions to higher productivity trajectories through the attraction of FDI and engagement with global supply chains, maintaining or increasing economic complexity through these channels. Chile has taken another path, maintaining a concentration in the agricultural products and primary production sectors while pursuing quality upgrading within existing sectors and still attracting significant FDI inflows.

In Thailand, a sharp increase in economic complexity relative to the EMDE average was in part achieved by encouraging inward FDI and a focus on export promotion (Kohpaiboon (2003); **Figure 9**). Having previously been concentrated in agriculture, with over 70 percent of employment in this sector in 1980, Thailand was able to cultivate successful electronics and automobile exporting sectors through a concerted effort to integrate into regional and global supply chains (Hobday and Rush, 2007; Wad, 2009).[18] Tax exemptions and subsidized lending for export-focused manufacturers were also introduced in the 1980s and 1990s, while policies restricting foreign ownership and imports were gradually reduced (Herderschee, 1993; Urata and Yokota, 1994). These are thought to have reduced distortions that had previously been present. While there have been great strides in rapidly enhancing domestic production capabilities, there remain significant challenges to transitioning further to domestic, rather than FDI-led, innovation and increasing production at more advanced stages of the manufacturing supply chain (Busser, 2008; Ohno, 2009; World Bank, 2018c).

In Poland, industrial complexity was high even before joining the Club 1 convergence cluster. However, integration into European supply chains, particularly with Germany, enabled a larger export market and facilitated quality upgrading of Polish automobile and electronic goods production (Baldwin and Lopez-Gonzalez, 2015; Kaminski and Smarzynska, 2001). Polish firms that were foreign-owned or export-focused were found to be significantly more productive than their domestically-owned or focused counterparts as markets became more liberalized from the mid-1990s (Hagemejer and Kolasa, 2011). Poland and other former Warsaw Pact economies that received the largest inflows of FDI in the 1990s and 2000s saw the most rapid integration into European trade networks—these allowed a rapid transition from low-wage garment manufacturing

[18] This was in part driven by large Japanese FDI inflows, promoting agglomeration effects and encouraging further inflows (Milner et al., 2006). In addition, Thailand established domestic content requirements for automotive parts prior to WTO membership, restricting FDI that would have prevented the creation of sufficient value-added intermediate products domestically Natsuda and Thoburn (2013).

to advance significantly to higher stages of the supply chain (World Bank, 2005). As in Thailand and Chile, Poland has rapidly increased its stock of human capital, reflected by increasing average years of education of adults in each economy (**Figure 9**). In addition, Poland experienced a wave of progressive institutional reforms in the 1990s following the collapse of the Soviet Union, followed by a second wave on accession to the European Union, which would have supported domestic investment strength and aided in attracting FDI (Georgiev et al., 2018).

Both Poland and Thailand have expanded into industries more closely associated with more developed economies.[19] They illustrate how increasing industrial complexity and quality can improve productivity through a range of channels. For example, the existence of more complex industries can begin a chain-reaction of further development as the fixed costs associated with developing a domestic skill-base are spread more widely (Hausmann et al., 2007). A substantial literature explains the benefits of network and agglomeration effects which can foster the development of increasingly specialized, complex and productive industries (Fujita et al., 1999; Porter, 1989). In many convergence success stories, active government intervention has been used to establish production capabilities beyond an economy's immediate comparative advantage (Cherif and Hasanov, 2019). An important channel through which advanced technologies and production methodologies can be imported is through participation in global value chains (World Bank, 2020c). However, policies to encourage and promote new industries and workforce capabilities, including those to encourage new "hubs" of sophisticated industries in particular regions, have been met with mixed success (United Nations Conference on Trade and Development, 2019; World Bank, 2019c).

Not all strongly-performing EMDEs have achieved success by increasing the complexity of their industrial capabilities. Some economies, such as Chile, have displayed fast productivity growth relative to other EMDEs while remaining concentrated in the production of primary commodities. Copper alone accounts for 20 percent of total exports, while one-third consists of agricultural products in 2017. Therefore, Chile is an important, albeit rare, counterexample of a commodity-exporter which has experienced robust productivity growth. Expanded export markets and increasing value-added content have been accomplished through quality-upgrading of food exports (Herzer and Nowak-Lehnmann D., 2007; Agosin and Bravo-Ortega, 2009). Chile has also benefited from high levels of education, institutional quality and a macroeconomic policy framework that has provided stability and certainty for the private sector, boosting productivity growth (**Figure 9**; Kalter et al. (2004)). Therefore, with high levels of human capital and institutional certainty, productivity can still rapidly grow while remaining concentrated in a subset of traditionally-low productivity sectors and pursuing quality upgrading and diversity within existing sectors. Economies such as Chile that are less concentrated in manufacturing production have also been able to benefit from technology transfer and investment financing through high FDI inflows (**Figure 9**).

5 The future of convergence

Existing convergence models do not guarantee continued success in those economies who have made progress in reducing productivity gaps or provide a clear route for progress in those that have not.

[19] Imbs and Wacziarg (2003) find that industrial diversification occurs as part of the standard development process as income per capita increases. So when controlling for income per capita, the significance of the ECI variable in driving convergence suggests that transition-economies have expanded beyond their immediate comparative advantage for a given level of development.

A range of headwinds to EMDE productivity convergence should be considered.

Increasing barriers to manufacturing-led strategies. Adjustments to the traditional manufacturing-led model of productivity enhancement are particularly important in light of concerns over premature de-industrialization. A limited market for manufactured goods and falling global prices for them have, in recent years, led to declines in the share of manufacturing output in many low- and middle-income economies at lower per capita income levels than has occurred historically (European Bank for Reconstruction and Development, 2019; Rodrik, 2016). Increasingly, there are risks that further automation in the manufacturing sector will shrink opportunities to increase productivity growth by expanding into complex manufacturing production, as this will require an increasingly high-skilled labor force out of reach for many EMDEs, and provide fewer jobs (Hallward-Driemeier and Nayyar, 2017). Finally, the COVID-19 pandemic has severely disrupted some supply chains, particularly in the automobile sector (World Bank, 2020b). A key risk to manufacturing and value-chain led development will be if the pandemic leads to more inward-looking trade policies that seek to fragment current production processes and onshore activity.

Transitioning from foreign to domestically-led innovation. Early success in diversifying sectoral employment and increasing economic complexity can meet with later stagnation. Initially, low-wage and proximity advantages can provide a route to increasingly complex and higher value-added production processes through engagement in global supply chains and the attraction of FDI in the "flying geese" model of development (Kojima 2000). As productivity and wages grow, the comparative advantage of economies in attracting these forms of production, often reliant on foreign technology transfer and investment flows, may fade (Mahon, 1992). In the past, many economies have previously struggled to transition from the rapid-growth phase that has benefited from the adoption of technologies to the development of domestic-innovation (Im and Rosenblatt, 2013). Middle-income economies have been found to be vulnerable to growth slowdowns, particularly in economies with lower levels of tertiary education and where high-technology exports are low Eichengreen et al. (2013).

Commodity reliance and the outlook for commodity prices. Several upper-middle-income economies such as Argentina, Brazil, and South Africa have remained Club 2 members over the entire sample (1970-2018), and not transitioned to Club 1. In many cases, commodity-exporting upper-middle-income economies have fallen further away from the productivity frontier since the 1980s. In addition to risks facing economies taking a manufacturing-led approach to development, economies with a high degree of commodity reliance, even in those such as Chile where quality upgrading has been pursued, face a larger obstacle to growth as they contend with the challenge that the pre-crisis period of rapidly rising commodity prices has ended. The COVID-19 driven recession in 2020 may generate a prolonged reduction in demand for commodities. For example, changing consumer preferences for transportation, travel, and fuel may result, while industrial metals demand may be persistently weaker if the recovery is drawn out.

Slowing drivers of convergence. Furthermore, a range of additional headwinds to EMDE productivity growth could pose additional challenges to the development model of rapidly-growing economies. As educational systems mature in many fast-growing EMDEs, there will be fewer high-return gains to education. EMDEs in EAP and ECA currently have workforces where average years of education are within one-year of those of advanced economies (World Bank 2020). There is an additional danger of human capital development being set back in EMDEs due to COVID-19. The majority of schools and universities have been closed for some period during 2020 due to social distancing measures. EMDEs may be less well able to conduct remote learning, while large negative income shocks have also been found to increase school dropout rates in EMDEs (World Bank, 2020b). Finally, progress in improving institutional quality has stagnated in many EMDEs: measures of government effectiveness (Worldwide Governance Indicators) have not improved on average since the 1990s.

6 Conclusions and policy implications

This chapter is the first comprehensive study of long-term labor productivity convergence trends to take account of the EMDE productivity growth surge since 2000. It implements a range of methodologies, including newer techniques for estimating club convergence with a sample that reaches into the post-crisis period. In doing so, it highlights a shift in the pace of productivity convergence since 2000 among a subset of EMDEs. Specifically, the chapter documents the following findings:

Main findings. On average since 2010, labor productivity in EMDEs was just 16 percent of the advanced economy average and, in LICs, it was just 2 percent. While there was only limited evidence of broad-based productivity convergence until 2000, subsequently on average, EMDE economies are now closing the gap with advanced economies following a broad-based surge in EMDE productivity growth. However, the pickup in productivity growth in EMDEs is unlikely to reduce productivity disparities materially for EMDEs on average—productivity gaps were declining by just 0.5 percent annually in the post-crisis period, and the pace has recently begun to decline. Even at the peak rate of convergence, for the average EMDE, to reduce the productivity gap with advanced economies by half would take nearly 140 years.

The results in this chapter suggest that weak or non-existent average rates of convergence to the productivity frontier in EMDEs in part reflects the presence of multiple attraction points for different groups of EMDEs. Over the past five decades, multiple methodologies find that countries have fallen into distinct convergence clubs in which productivity moved towards a similar long-term productivity level. In contrast to previous studies, problems associated with PPP-adjusted output levels are avoided, using market-exchange rate adjusted productivity levels as an alternative.

Many EMDEs have separated from lower-productivity EMDE clubs and moved into higher-level productivity clubs since 2000. These countries have been characterized by systematically better initial education levels, greater political stability and governance, and greater or deepening economic complexity, producing in sectors beyond their immediate comparative advantage. EMDEs in lower productivity clubs have made little progress in catching up to advanced economy productivity levels over the past 50 years.

Policy implications. These findings highlight the critical importance of policies and institutions that are conducive to productivity growth. EMDEs that have made significant progress in rising to higher convergence trajectories have often had a strong foundation of high education levels with which to enhance production efficiency and incorporate new technologies. However, educational reforms should focus on learning outcomes rather than simply years of attainment (World Bank, 2018d). A highly educated and well-trained workforce will be better placed to adopt new technologies and attract FDI, which is also associated with faster rates of productivity convergence. Commitment to effective governance, including through the reduction of corruption and political violence and ensuring legal and institutional stability, has been found to be important in creating the optimal conditions for investment and innovation (World Bank, 2017)).

This chapter finds a key role for policies that can enhance the complexity of an economy beyond its immediate comparative advantage. Expanding the diversity of an economy to a broader set of increasingly complex industries to benefit from innovation spillovers and network effects is an attractive proposition, but one which is difficult to implement. New technologies that are likely to be introduced into the manufacturing sector will also mean that the bar for maintaining competitiveness with other economies in complex sectors will be increasingly difficult (Hallward-Driemeier and Nayyar, 2017). Countries should consider their proximity and connectedness to existing supply chains in more developed economies to judge how they can most readily benefit from technological spillovers. In addition, future risks from automation should be considered when expanding into new complex and higher-productivity sectors. Alternatively, a range of high-productivity service sectors, such as finance, offer alternatives to industrial-led development, but often require a costly investment in skillsets that are difficult to attain. Countries can also focus on quality-upgrading and diversity within existing sectors to enhance production capabilities and generate knowledge spillovers (Brenton et al., 2009).

Specific country examples show that a range of possible development approaches have been important in driving membership of the most rapidly growing productivity convergence club. These have included integration into regional supply chains, through the attraction of FDI and trade liberalization. Export-promotion policies have been used to increase engagement in value chains to promote knowledge transfer. Alternative strategies have consisted of maintaining a concentration in primary product production but pursuing quality upgrading and diversification among these products. However, both strategies face challenges as global trade volumes and commodity prices stagnate. And in many cases, the promotion of new industries or production capabilities by governments has failed or has not driven the same level of growth as observed in Club 1 economies. Notably, Club 1 economies have had a foundation of higher-than-average education levels and institutional quality than other economies, which may have increased the likelihood of success for policies that have aimed to promote certain industries. These features are likely to have been associated with high levels of government capacity, which is key to delivering successful industrial policies (Maloney and Nayyar, 2018).

Future research. Understanding the drivers of transitions of economies onto higher convergence trajectories can provide useful insights for policymakers about the conditions necessary for faster productivity growth. However, methodologies to isolate the period of transition are currently under-developed and generally rely on comparing results over different estimation samples. Future research should place more focus on estimating transition points. Further work should also be performed to understand the importance of developing capabilities in more advanced and complex sectors, while ensuring broad-based spillovers of new technologies to existing industries and sectors.

A Solow-Swan growth model

One of the implications of the Solow-Swan growth model (Solow, 1956; Swan, 1956) is that countries with low levels of productivity should catch-up to those at the frontier. In an economy characterized by the standard production function, consisting of technology (A_t), capital (K_t) and labor (L_t):[20]

$$Y_t = F\left(K_t, A_t L_t\right) = K_t^{\alpha}\left(A_t L_t\right)^{1-\alpha}$$

the rate of growth in the capital stock per worker (g_k), and therefore output per worker, is decreasing in $k_t = K_t/L_t$ (capital per worker). Formally:

$$g_k = \frac{s}{k_t^{1-\alpha}} - \left(\delta + n + g\right),$$

where s is the fraction of output that is saved, δ denotes the depreciation rate of capital, n is the growth rate of population, and g is the growth rate of technology.[21] Countries with lower initial capital should, therefore, grow faster, converging to the productivity level of high-income economies. However, this is contingent on several assumptions: that there are decreasing returns to capital intensity, saving rates (s) are homogenous across economies (Mankiw et al., 1992); and, that technology (A) is costless to replicate across borders regardless of country-characteristics.

B Data

Throughout the document, productivity is measured as output per worker, measured at 2010 prices and exchange rates to the US dollar. Labor productivity measured as output per worker can mismeasure output per unit of labor input when workers or employers adjust their working hours. Total hours worked is a more accurate measure of labor input than the number of workers, but data is available for only 30 EMDEs. As a result, sizable changes in hours worked over the business cycle can generate cyclical swings in measured labor productivity per worker.[22] Data on other macroeconomic aggregates such as GDP are from the World Bank's World Development Indicators (WDI) database, with data on employment from the Conference Board's Total Economy Database (TED), complemented by data from the International Labour Organization (ILO) where TED data is incomplete. Data are available on a consistent basis since 1970 for a sample consisting of 29 advanced economies and 74 EMDEs. Six oil-exporting EMDEs which had productivity levels above those of the United States in the 1970s are excluded from the statistical analysis of beta and club convergence. For the initial overview of the current distribution of productivity levels, the sample is expanded to 126 EMDEs and 35 advanced economies.

[20] See Romer (2011) and Barro and Sala-i Martin (2004) for a textbook treatment of the Solow-Swan model of growth.

[21] A zero-saving rate ($s = 0$) implies that the capital stock per worker declines at the effective rate ($\delta + n$), reflecting both capital depreciation and population increase.

[22] Hours worked per employee can fluctuate over time. For example, in the average OECD country since 1990, average hours per worker has fallen by 6 percent. Within the OECD, average hours per worker ranged from 1,363 in Germany to 2,148 in Mexico in 2015.

C β-convergence testing

This annex shows the results of the conditional and unconditional β-convergence tests described in section 3 of the main text in more detail.

The simple unconditional β-convergence regression includes no covariates of productivity growth except the initial level of productivity. Productivity growth is calculated as log-difference between the average level of productivity in one decade relative to the preceding decade. The coefficient on initial productivity levels only becomes statistically significant in the post-2000 period. Converting the coefficient to the rate at which the productivity gap declines annual, as in Barro and Sala-i Martin (1992), shows a decline of 0.5 percent per year in this final period (**Table 1**). Performing the same exercise on a sample containing only advanced economies shows a statistically significant rate of convergence in each decade. In EMDEs, the coefficient is only statistically significant in the final decade of the sample.

Tests for conditional convergence are also performed by including controls for average years of schooling, economic complexity (index of Hidalgo and Hausmann (2009)), commodity exporter status, trade openness, the ratio of investment to GDP and an index of law and order. The regression uses lagged values of each control variable to reduce endogeneity concerns. The coefficient on initial productivity level is negative and statistically significant in each decade and in the panel specification (which includes decade fixed effects). The peak annual rate of convergence implied by the conditional convergence regression is 1.5 percent (**Table 2**).

Results are also provided using labor productivity measured at purchasing power parity for comparison (**Tables 1 and 7**). The issues related to measuring productivity at market exchange rates or in PPP-adjusted terms are explored further in Annex F.

Table 1: Unconditional convergence 1970-2010, PPP and and market-exchange rate measured productivity

	Dependent variable:				
	10-year log change in labor productivity				
	1970-80s	1980-90s	1990-2000s	2000-2010s	Panel
	(1)	(2)	(3)	(4)	(5)
All economies					
Initial productivity (MER)	0.028*	0.034**	−0.013	−0.052***	−0.003
Initial productivity (PPP)	0.022	0.078**	-0.028	-0.066***	-0.005
Convergence rate (MER, annual)	*-0.28%**	*-0.33%***	*0.13%*	*0.53%****	*0.03%*
Convergence rate (PPP, annual)	*-0.22%***	*-0.75%*	*0.28%*	*0.68%****	*0.05%*
EMDEs					
Initial productivity (MER)	0.002	-0.030	-0.032	-0.045**	-0.026**
Initial productivity (PPP)	-0.026	-0.003	-0.067	-0.019	-0.030
Convergence rate (MER, annual)	*-0.02%*	*0.30%*	*0.33%*	*0.46%***	*0.27%***
Convergence rate (PPP, annual)	*0.26%*	*0.03%*	*0.69%*	*0.19%*	*0.30%*
Advanced economies					
Initial productivity (MER)	-0.191***	-0.185***	-0.125***	-0.079*	-0.101***
Initial productivity (PPP)	-0.310***	-0.420***	-0.237**	0.092	-0.294***
Convergence rate (MER, annual)	*2.12%****	*2.04%****	*1.34%****	*0.82%**	*1.74%****
Convergence rate (PPP, annual)	*3.71%****	*5.45%****	*2.71%****	*-0.88%*	*3.48%****
Observations (All)	98	98	98	98	392
Observations (EMDE)	69	69	69	69	276
Observations (AE)	29	29	29	29	116
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: Decade dummies are used in the panel specification but country fixed effects are not. Initial productivity is the average of log productivity over the 10-years in the preceding decade, measured in US dollars at 2010 prices and exchange rates. Productivity growth is calculated as the change in average log-productivity between the two decades (10-year average growth). Productivity is assumed to grow at its average rate between 2010-8 for the final year of the decade, 2019.

Table 2: Conditional convergence 1970-2010, Market exchange rates

	Dependent variable:				
	10-year log change in labor productivity				
	1970-80s	1980-90s	1990-2000s	2000-2010s	Panel
	(1)	(2)	(3)	(4)	(5)
All economies					
Initial productivity	-0.101***	-0.121***	-0.116***	-0.136***	-0.124***
Convergence rate (annual)	*1.06%****	*1.29%****	*1.24%*	*1.46%****	*1.33%****
Schooling (years)	0.004	0.011	0.013	0.011	0.008
Economic complexity	0.081**	0.087*	0.066*	0.043	0.065***
Commodity exporter	-0.129*	-0.109**	-0.089	-0.020	-0.089***
Trade (% GDP)	0.076	0041	-0.024	-0.006	0.019
Investment (% GDP)	0.012	0.404*	0.682**	0.720**	0.077*
Law and Order	0.035*	0.036*	0.033	0.026	0.042***
Observations (All)	62	68	78	79	287
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: Time-effects are used in the panel specification but country-fixed effects are not. Initial productivity is the average of log productivity over the 10-years in the preceding decade, measured in US dollars at 2010 prices and exchange rates. Productivity growth calculated as the change in average log-productivity between the two decades (10-year average growth). Productivity is assumed to grow at its average rate between 2010-8 for the final year of the decade, 2019. All conditioning variables are lagged decadal averages. Data availability of these covariates affects the sample size in each decade.

D Estimating convergence clubs: Commonalities in productivity levels

The mixture model analysis allows the detection of convergence clubs using snapshots of the cross-country distribution of productivity levels (Battisti and Parmeter, 2013; Henderson et al., 2008; Grün and Leisch, 2008). Countries fall into the same convergence club when their productivity levels gravitate toward the same long-term productivity level. In contrast, countries fall into distinct convergence clubs when their productivity levels are pulled toward different attraction points.

A finite mixture model with K components takes the form:

$$h\left(Y|Z,\psi\right)=\sum_{k=1}^{K}\pi_k\left(Z,\gamma\right)f_k\left(Y|\theta_k\right)$$

$$\pi_k\left(Z,\gamma\right)\geq 0,\quad \sum_{k=1}^{K}\pi_k\left(Z,\gamma\right)=1$$

Where Y is a (possibly multivariate) dependent variable with conditional density h, π_k is the prior probability of membership component k, θ_k is the component-specific parameter vector for the component-specific density function f_k, $\psi=(\pi_k,\theta_k)_{k=1,\ldots,K}$ denotes the vector of all parameters for the mixture density h. In the Gaussian case, the component-specific parameter vector contains the mean and the standard deviation, $\theta_k=(\mu_k,\sigma_k)$.

The prior probability (weight) of each component $\pi_k\left(Z,\gamma\right)$ can be fixed ($Z=\mathbb{1}$, a vector of ones) or depend on associated (exogenous) variables Z. In the latter case, one can incorporate a multinomial logit model to map the exogenous variables to the prior probability of inclusion in each sub-distribution:[23]

$$\pi_k\left(Z,\gamma\right)=\frac{e^{Z\gamma_k}}{\sum_{j=1}^{K}e^{Z\gamma_j}}\quad\forall\ j,\ with\ \gamma_1=0.$$

Mixture models are commonly estimated using an expectation-maximization (EM) approach. The EM algorithm (Dempster et al., 1977) is the most common method for maximum likelihood estimation of finite mixture models where the number of components K is fixed. In practice, the number of components K is unknown and can be determined using information criteria. The EM algorithm relies on a missing data augmentation scheme. It is assumed that a latent variable $\varepsilon_n\in\{0,1\}^K$ exists for each observation $n=1,\ 2,\ \ldots,\ N$ which indicates the component membership, i.e. $\varepsilon_{nk}=1$ if the n^{th} observation comes from component k and 0 otherwise. In the EM algorithm these unobserved component memberships ε_{nk} of the observations are treated as missing values and the data is augmented by estimates of the component membership, i.e. the estimated a-posteriori probabilities $\hat{\lambda}_{nk}$. For a sample of N observations $(Y_n,Z_n)_{n=1,\ldots,N}$ the two-step EM algorithm is as follows Dempster et al. (1977); Grün and Leisch (2008).

The Expectation steps. Given the current parameter estimates $\hat{\psi}^{(i)}$ in the i^{th} iteration, estimate the posterior class probability of each observation n (which amounts to replace the missing data ε_{nk}):

$$\Pr\left(k|Y_n,Z_n,\hat{\psi}^{(i)}\right):\ =\hat{\lambda}_{nk}=\frac{\pi_k\left(Z_n,\hat{\gamma}^{(i)}\right)f_k\left(Y_n|\hat{\theta}_k^{(i)}\right)}{\sum_{j=1}^{K}\pi_j\left(Z_n,\hat{\gamma}^{(i)}\right)f_j\left(Y_n|\hat{\theta}_j^{(i)}\right)}$$

and back-out the prior class probabilities as $\hat{\pi}_k=\frac{1}{N}\sum_{n=1}^{N}\hat{\lambda}_{nk}$.

The Maximization steps. Maximize the log-likelihood for each component separately using the

[23] Alternative specifications can be used to model component weights as a function of concomitant variables (Dayton and Macready, 1988)

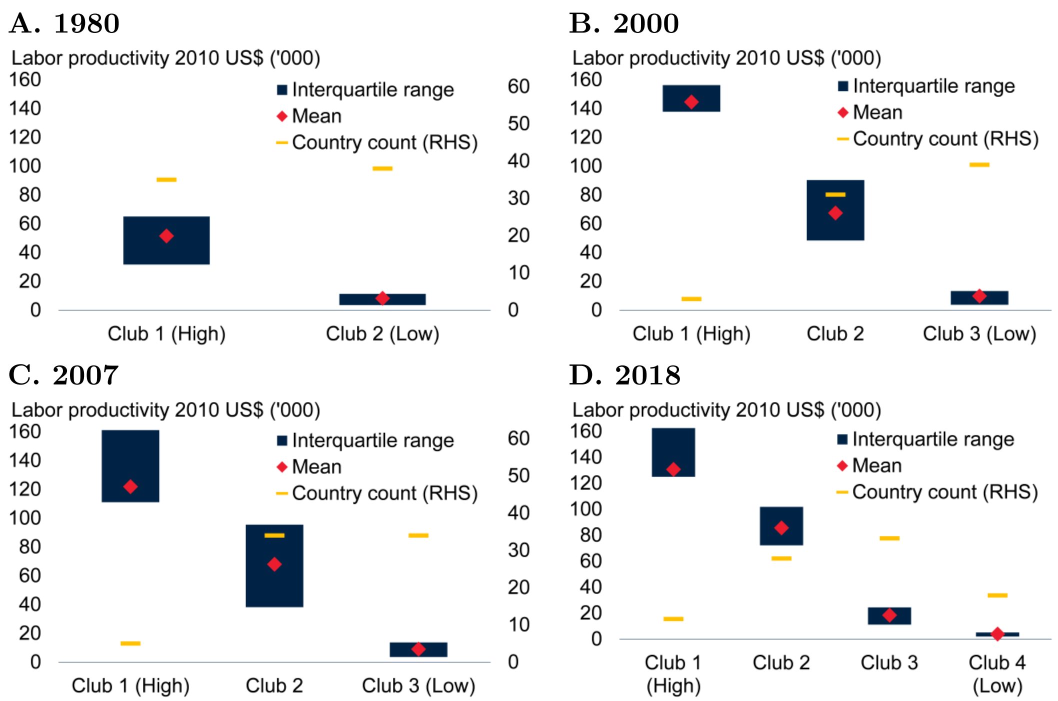
posterior probabilities as weights

$$\max \theta_k \sum_{n=1}^{N} \hat{\lambda}_{nk} \log f_k \left(Y_n | \theta_k\right).$$

The procedure iterates between these steps until the improvement in the overall likelihood becomes marginal (falls under a fixed threshold).[24]

Economies are divided into clubs based on snapshots of (the log of) labor productivity at ten-year intervals, as described above (Battisti and Parmeter, 2013). The sample includes data for 29 advanced economies and 68 EMDEs and for the period 1970-2018. Therefore, this approach extends earlier studies to include data from the 2000s onwards, the period of fastest EMDE productivity growth during the past five decades.

Figure 10: **Convergence clubs at specific points in time**



Sources: World Bank.
Convergence clubs estimated using mixture model clustering of labor productivity. Red diamonds are average labor productivity expressed in thousands of 2010 US$ for high and low-productivity clubs. Blue bars show corresponding interquartile ranges. Orange dashes are the number of countries in each club. The number of clubs and membership of clubs varies over time.

Results. Since 1980, countries have fallen into 2-4 distinct productivity clusters that have pulled apart over time (**Figure 10**). This finding is consistent with previous studies in some respects, but also demonstrates the existence of a new "breakout" cluster of EMDE economies away

[24] For cases where the weighted likelihood estimation is not feasible due to analytical or computational challenges, variants of the EM procedure use hard (Celeux and Govaert, 1992) or random Diebolt and Ip (1996) assignment of the observations to disjoint classes.

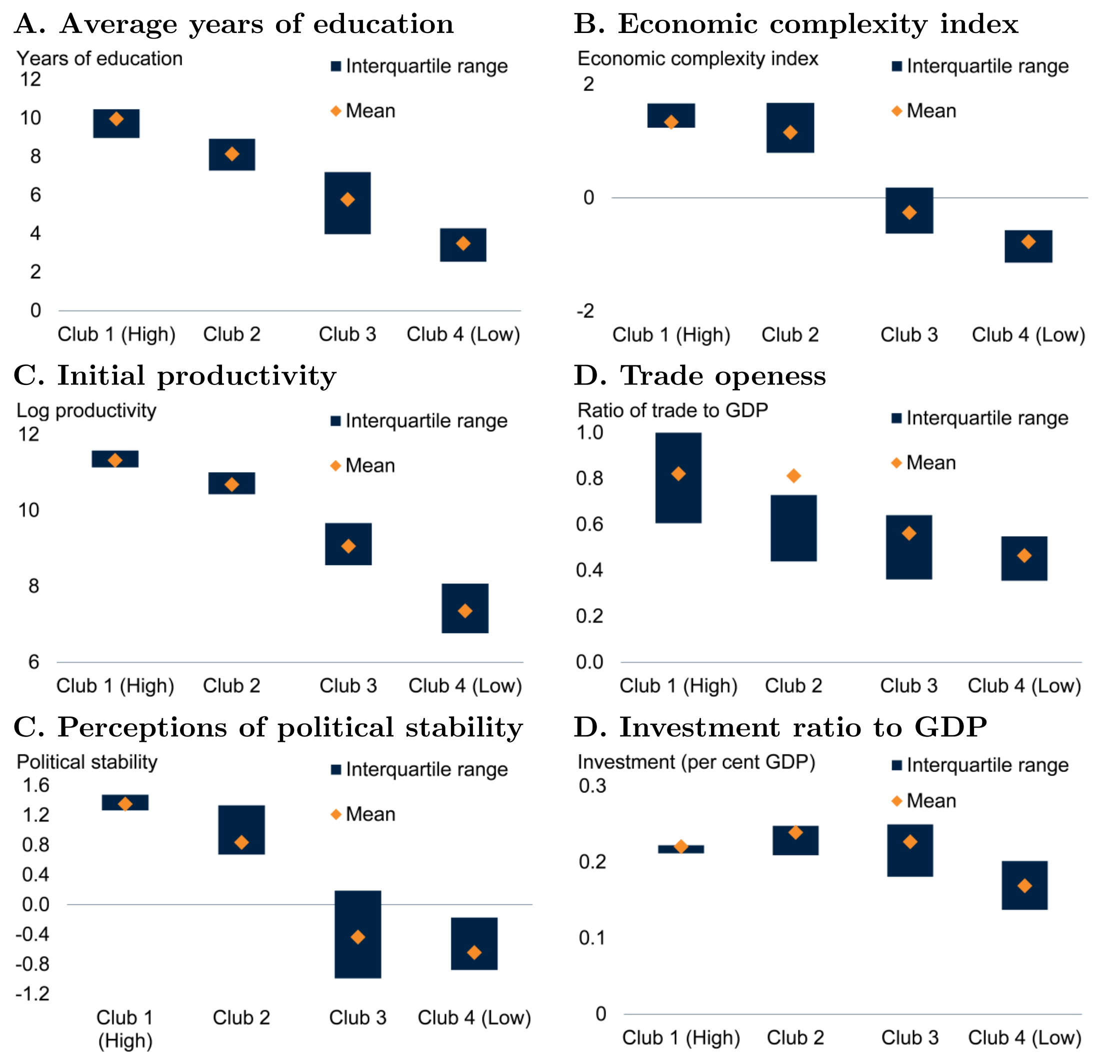
from the lowest productivity club in recent decades. Since the early 2000s, when EMDE productivity growth picked up sharply, 10 economies have transitioned to the intermediate-productivity cluster. This "breakout" cluster of EMDEs left behind mostly LIC economies primarily based on agricultural activities with widespread informal activity. Except for the lowest-productivity club, the countries in each cluster are geographically diverse but similar in per capita income and productivity levels.

- In the 1980s, labor productivity fell into two clusters: a high-productivity cluster and a low-productivity cluster. The low productivity cluster included most of today's EMDEs, but also several more productive Latin American and Central European EMDEs and South Africa. All of today's advanced economies fell into the high-productivity cluster.
- By 2000, a third cluster had emerged, reflecting a new frontier cluster, comprised of a few advanced economies (including Norway, Luxembourg, Switzerland).
- Post-crisis, a fourth cluster emerged with many EMDEs previously in the lowest income cluster moved into an intermediate Club 3, between the low-income cluster and the advanced economy cluster. This occurred shortly after the surge in EMDE growth that began in 2000.

By using productivity levels to identify convergence clubs, a subset of EMDEs has been identified as making progress in separating from the lowest productivity groups—at the same time, it is clear that a low-income grouping has made little progress and remains at very low levels of productivity.

Characteristics of club membership. On average, frontier economies (Club 1 and Club 2) in the mixture model analysis tend to have a significantly higher economic complexity index and higher average years of education relative to lagging economies (Clubs 3-4). Initial productivity, trade openness, political stability, and investment share seem to play a secondary role in explaining the different groupings in the mixture model approach (**Figure 11**).

Figure 11: **Key characteristics of convergence clubs 1970-1990 (Mixture Model)**



Sources: Barro and Lee (2015), World Bank (World Development Indicators, World Governance Indicators), National Accounts, Center for International Development at Harvard University.
Note: Average of data available between 1970 and 1990, with the exception E. which is only available as of 1995 (1995-200 average used instead)
A. Average years of schooling for males and females from Barro and Lee (2015).
B. Economic complexity index.
D. The ratio of exports and imports to GDP.
E. Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.
F. The ratio of gross fixed capital formation to GDP.

E Estimating convergence clubs and their determinants: Commonalities in productivity trajectories

Our time series analysis follows Phillips and Sul (2007, 2009) in proposing a simple factor model structure for log labor productivity developments in which each economy is attracted to a common steady-state $\log_i^*$, but also can follow an idiosyncratic transition path to that attractor.

$$\log y_{it} = \underbrace{\log y_i^* + \log A_{i0} + \left[\log_{i0} - \log {y_i}^*\right] e^{-\beta_0 t}}_{a_{it}} + x_{it} t$$

Initial conditions, such as the distance to the steady-state ($\log_{i0} - \log {y_i}^*$), affect the pace of growth. In addition, the rate of technological progress can vary across countries (x_{it}). This growth path of productivity for each economy can be considered in relative terms to a common growth path, μ_t.

$$\log y_{it} = \left(\frac{a_{it} + x_{it} t}{\mu_t}\right) \mu_t = b_{it} \mu_t$$

For b_{it} to converge across economies, the contribution of a_{it} will decline to 0, were μ_t to be a simple linear trend. The dynamics of y_{it} subsequently determined by x_{it}. As such, convergence in productivity levels requires that x_{it} converges across countries.

$$b_{it} = x_{it} + \frac{a_{it}}{t} \to x_{it}, \text{ as } t \ \to \infty$$

Estimation

Phillips and Sul advocate modeling the transition parameter b_{it} using a relative scaling of the data:

$$h_{it} = \frac{\log_{it}}{N^{-1} \sum_{i=1}^{N} \log y_{it}} = \frac{b_{it}}{N^{-1} \sum_{i=1}^{N} b_{it}}$$

Here, divergences from the common growth path (μ_t) are reflected by h_{it}. Effectively, the mean productivity level is assumed to be the common growth path, with deviations from that growth path reflected by each economies' divergence from that path their relative productivity level to the mean. b_{it} will converge to 1 if the convergence hypothesis holds. In order to test the hypothesis that $b_{it} = h_{it} = h$, or that $b_{it} = h_{it}$ are on a trajectory to steady-state values, Phillips and Sul propose a form for a test statistic of convergence:

$$H_t = N^{-1} \sum_{i=1}^{N} \left(h_{it} - 1\right)^2$$

and a functional form for b_{it} if it were, in fact, a declining function of time.

$$b_{it} = b_i + \frac{\sigma_i \xi_{it}}{L\left(t\right) t^{\alpha}}$$

Where ξ is iid but may be weakly time-dependent. $L\left(t\right)$ is a slowly increasing function of t, while $\alpha > 0$ ensures that $b_{it} \to b_i$ over time. In conjunction with this requirement, if $b_i = b$ across countries, the convergence hypothesis holds. There may also be multiple points of homogeneity $b = b_1, b_2, \ldots$ serving as attractors for groups of countries. Phillips and Sul (2007) show that under this specification, for b_{it}, the hypothesis statistic H has the limiting form $H \sim \frac{A}{L(t)^2 t^{2\alpha}}$ For some constant A. By letting $L\left(t\right) = \log t$, the following log-regression model can be specified

$$\log \frac{H_1}{H_t} - 2 \log\left(\log t\right) = a + \gamma \log\ t + u_t$$

Here, γ is equivalent to 2α, and must be positive for convergence to hold. Under the hypothesis of convergence, γ is more than 0, so the dispersion of productivity levels falls as a function of time. Because of the penalty term $2\log(\log t)$, the t-statistic will convergence to $-\infty$ where the hypothesis of convergence is rejected. A one-sided t-test of $\alpha \geq 0$ will assess the hypothesis for a given sample. In addition to the significance of the coefficient, the magnitude of γ shows the degree of convergence in effect. For $0 < \gamma < 2$, convergence in growth rates but not levels will occur. For $\gamma > 2$, convergence in levels will hold. The above convergence test is appropriate to test for convergence within a particular group but must be combined with an additional algorithm to test for club convergence among multiple potential clubs of economies. Phillips Sul propose the following procedure to establish the presence of "club" convergence

- Order economies according to income in the final period (or average in last half).
- Choose a core group G_k of k economies and compute the test statistic $t_k = t(G_k)$. Choose group size k to maximize the test statistic t_k $s.t. \min t_k > -1.65$ (the 5% critical value for the t-test). Where the minimum test statistic is not met with $k = 2$, drop the first economy and proceed to maximize t_k.
- Add one country at a time to group k and include in the group if the t-statistic exceeds the criterion c^*.
- Form a new group for those countries not included in the initial three steps. If the remaining countries have $t_k > 1.65$ then there are two groups. Otherwise, repeat steps 1-3. It may be the case that the remaining economies are divergent and that there is no additional club.
- If $c* = 0$, then the requirement to be added to an existing group will be very conservative (relative to -1.655% critical value).

Converging in levels vs growth rates

Applying the PS routine to our market-exchange rate adjusted data produces 5 convergence clubs (**Table 3**). The parameter $\gamma = 2\beta$ is between 0 and 1 in the majority of cases. This suggests that the convergence clubs uncovered show a tendency for relative convergence, or the reduction of the size of the gap in relative productivity levels over time, but not necessarily full convergence to the same level of output per worker. However, this does not rule out a substantial closure of productivity gaps over time—instead, it implies that over time productivity growth rates will align, alongside smaller productivity gaps between members of clubs. Full convergence in levels is a very strict condition not met even by advanced economies, where productivity gaps have declined considerably over the past 50 years, but persistent smaller gaps remain. Applying the PS log-t test to advanced economies yields a γ of just 0.15, in line with the results for many of the convergence clubs identified for in Table 3. Estimated over the period 1970-2000, there are considerably fewer members of the two highest convergence clubs, which as noted in the main text is a result of fewer EMDEs displaying fast-convergence characteristics.

Determinants of club membership

As noted in the main text, initial productivity, governance quality, education, and economic complexity are all statistically significant drivers of club membership in a multinomial logit regression. Further details of these regressors are provided in **Table 4**. To preserve degrees of freedom,

Table 3: Phillips and Sul convergence results

Club 1970-2018 [members]	Convergence rate (γ)	Club 1970-2000 [members]	Convergence rate (γ)
Club 1 [45]	0.18	Club 1 [26]	0.19
Club 2 [31]	0.16	Club 2 [21]	0.08
Club 3 [10]	0.09	Club 3 [18]	0.12
Club 4 [6]	0.06	Club 4 [25]	-0.03
Club 5 [5]	0.06	Club 5 [7]	0.74

clubs 3-5 are considered to be a single group. The coefficients in **Table 4** are directionally informative around the probability of being a member of either Club 2 or clubs 3-5 relative to the fast-converging Club 1. A positive coefficient implies an increased probability of being in either club relative to Club 1. These are converted to odds-ratios in main text **Figure 7**— this converts the coefficients into the change in probability of membership of clubs 2-5 relative to Club 1 for a one-unit increase in the variable under consideration.

Table 4: Determinants of club membership – multinomial logit, probability of membership of Club 2 relative to Club 1, and Clubs 3-5 relative to Club 1

	Dependent variable:			
	Club membership (2 and 3-5) relative to Club 1			
	(1)	(2)	(3)	(4)
2: Years of education	-0.80***	-0.92***	-0.82***	-0.88***
3-5: Years of education	-0.94***	-1.07***	-0.90 ***	-1.10***
2: Economic complexity index	-2.59***	-2.93***	-2.34***	-3.07***
3-5: Economic complexity index	-2.9***	-3.20***	-2.18***	-3.52***
2: Initial productivity	1.24***	1.45**	2.30***	1.64***
3-5: Initial productivity	0.80	0.56	1.89**	1.31*
2: Trade openness		2.08		
3-5: Trade openness		0.11		
2: WGI – government effectiveness			-2.45**	
3-5: WGI – government effectiveness			-3.58***	
2: Investment (% of GDP)				-5.56**
3-5: Investment (% of GDP)				-10.00
Observations (All)	78	73	78	76
Pseudo R^2	0.42	0.44	0.47	0.43

Note:
*p<0.1; **p<0.05; ***p<0.01

Note: Unadjusted coefficients from multinomial logit. Intercept included in estimation but omitted in results. Each variable reflects averages during 1970-90, except for WGI measures of government effectiveness, which is calculated as the average 1990s value due to data availability.

Determinants of transitioning to Club 1

Tables 5 & 6 show additional covariate regressors to the ones shows in assessing the determinants of an EMDE joining the fast-growing Club 1 economies (**Figure 9**). As in the main text, the averages of each covariate are taken separately for the period 1980-89 and for 1990-99 given the uncertainty of the period in which these economies transitioned to Club 1.

Table 5: Determinants of probability of transition into the high-productivity convergence Club 1: Logit model marginal effects – covariates average value, 1980-1990

	Dependent variable:			
	EMDE membership of convergence club 1			
	(1)	(2)	(3)	(4)
(5)				
Years of education	0.10***	0.09**	0.06***	0.09***
Economic complexity index	0.20**	0.33***	0.30**	0.32**
Initial productivity	-0.17***	-0.22***	-0.24***	-0.22***
Trade openness		0.15		
WGI: Government effectiveness			0.24*	
Investment in percent of GDP				-0.68
FDI in percent of GDP			0.02	0.06
Observations (All)	54	47	53	48
Pseudo R^2	0.32	0.39	0.46	0.54
0.49				

Note: *p<0.1; **p<0.05; ***p<0.01

Note: Marginal effects of a one unit increase in each variable on the probability of an EMDE joining convergence 'Club 1' relative to other EMDEs. Derived from a logit model, with standard errors calculated using the delta-method. Average years of schooling for males and females from Barro and Lee (2015). Economic complexity index of Hidalgo and Hausmann (2009). Exports and imports as a percent of GDP. Government effectiveness survey from the World Bank's Worldwide Governance indicators, defined as: perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. A higher index value indicates greater political stability. Gross fixed capital formation and FDI are measured in percent of GDP.

Table 6: Determinants of probability of transition into the high-productivity convergence Club 1: Logit model marginal effects – covariates average value, 1990-2000

	Dependent variable:				
	EMDE membership of convergence club 1				
	(1)	(2)	(3)	(4)	(5)
Years of education	0.07**	0.06**	0.05*	0.05*	0.05**
Economic complexity index	0.29***	0.29***	0.27***	0.26***	0.25***
Initial productivity	-0.18***	-0.18***	-0.19***	-0.16***	-0.17***
Trade openness			-0.10		
WGI: Government effectiveness			0.12***		0.06
Investment in percent of GDP				1.87**	1.76*
FDI in percent of GDP			0.05*	0.06**	0.05*
Observations (All)	54	54	54	54	54
Pseudo R^2	0.32	0.33	0.41	0.42	0.46
Note:			*p<0.1; **p<0.05; ***p<0.01		

Note: Marginal effects of a one unit increase in each variable on the probability of an EMDE joining convergence 'Club 1' relative to other EMDEs. Derived from a logit model, with standard errors calculated using the delta-method. Average years of schooling for males and females from Barro and Lee (2015). Economic complexity index of Hidalgo and Hausmann (2009). Exports and imports as a percent of GDP. Government effectiveness survey from the World Bank's Worldwide Governance indicators, defined as: perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Gross fixed capital formation and FDI are measured in percent of GDP.

F Productivity measurement: PPP versus market exchange rates

In the analysis of productivity growth and differentials in this chapter, cross-country comparisons are made using productivity measured in dollars at 2010 prices and exchange rates. Often, studies of convergence have used cross-country comparisons of income per capita calculated at purchasing-power parity (PPP). This box addresses the question of how PPP and market-exchange rate measurement of productivity differs conceptually, and how the different measurements affect statistical tests of convergence.

Purchasing power parity calculates the rate at which the currency of one country would have to be converted into another to buy the same assortment of goods and services. Market exchange rates are the rates at which goods and services are actually traded in international markets. Since PPP reflects that goods and services that are not traded internationally tend to be cheaper in lower-income countries, the purchasing power of lower-income country currencies tends to be higher at PPP exchange rates than at market exchange rates.

Transactions in global trade, financial markets, and commodity markets are all conducted at market exchange rates; hence, for aggregating output, market exchange rates (as used by the

World Bank) are the appropriate weighting scheme. In contrast, for measuring living standards and aggregating welfare, PPP weights would be appropriate since they capture the consumption affordable to households for comparable consumption baskets.

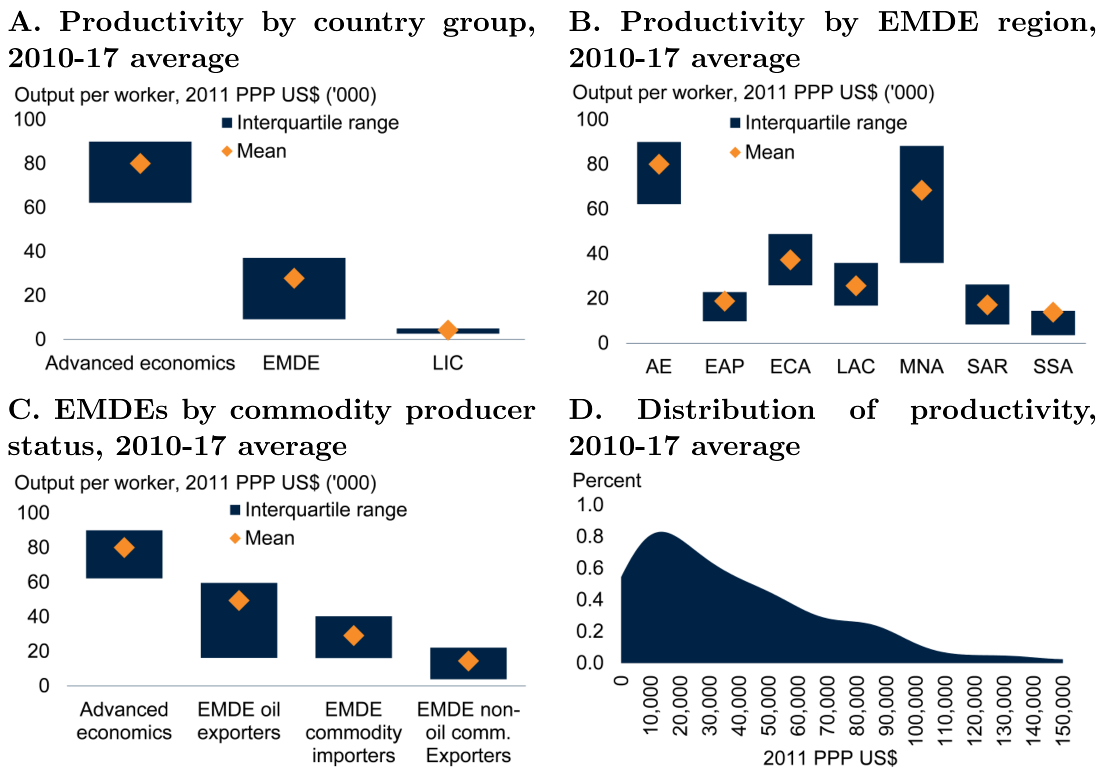
While the theoretical purposes of the weighting schemes are clearly distinct, they also have different features in practice. First, PPP exchange rates are subject to greater measurement challenges. Since they are constructed from prices of the same baskets of goods and services, they rely on price surveys by the World Bank's International Comparison Program (ICP; Callen (2007)). These are conducted infrequently and not available for all countries, hence subject to considerable measurement error and extrapolation to countries and years with missing data. PPP exchange rates tend to be more stable than market exchange rates (Schnatz, 2007). Hence, for weighting purposes, market exchange rates are typically fixed at the value of a specific year or period by the World Bank, and can therefore be influenced by short-term fluctuations that occurred in the chosen period.

The large majority of convergence studies have used versions of the Penn World Table (PWT) as a data source of PPP-adjusted income per capita due to its large coverage both the time and country coverage dimensions (Feenstra et al., 2015; Johnson et al., 2013). In recent iterations, the PPP-adjustment is estimated on a time-varying basis, rather than simply using survey-based evidence from a particular year. The PWT version 9.1 is used in this box as a source of PPP-adjusted labor productivity levels and growth rates.

The productivity gap between advanced economies and EMDEs is substantially smaller once productivity is measured at PPP-adjusted exchange rates (**Figure 12**). The average EMDE worker produces 34 percent (16 percent at market exchange rates) of the output of the average advanced economy worker, while LICs produce 4 percent (2 percent when measured at market exchange rates). While the scale of productivity differentials relative to advanced economies is smaller under PPP-measurement, the relative ordering of productivity levels between EMDE commodity exporters and importers, and EMDE regions, is largely unchanged. Oil-exporting EMDEs continue to have the smallest gap with advanced economies, followed by EMDE commodity importers and MENA has the highest output per worker among EMDE regions (**Figure 12**). In addition, the distribution of productivity retains its polarized structure, although the advanced economy and EMDE regions are significantly closer together.

To the extent that PPP-adjustments can accurately account for non-tradable pricing differentials between economies, productivity gaps are significantly lower. However, EMDEs still face a substantial productivity gap with advanced economies, requiring sustained high productivity growth to close.

Figure 12: **PPP-adjusted productivity gaps**



Source: Penn World Table, World Bank
Note: Output-measured real GDP at PPP-adjusted 2011 US dollars ("rgdpo" in the PWT dataset) per worker

Unconditional and conditional β-convergence results using PPP-measures of labor productivity Measuring labor productivity at PPP-adjusted levels suggests a modest increase in the pace of unconditional convergence relative to market-exchange rate based measures. Consistent with the market-exchange rate results, tests of unconditional convergence are insignificant before 2000 (**Table 1**). The pace of convergence is higher however, rising from 0.5 percent per annum at market exchange rates, to 0.7 percent at PPP-adjusted rates. At this rate, it would still take around 90 years to close half of the productivity gap. Conditional convergence results also show higher rates of convergence than when using market-exchange rate-based estimates. As with the market-exchange rate estimates, most decades show evidence of conditional convergence (**Table 7**). In each decade, convergence rates are higher when productivity is measured using PPP-adjusted dollars relative to those estimated in dollars converted at market exchange rates. The PPP panel specification, covering all decades since 1970, shows a convergence rate of 1.7 percent per year, close to the 'rule of 2' established in the literature, compared to 1.3 in the market exchange rate panel specification. In part, the faster convergence rates using the PPP-measurement reflect smaller estimated productivity gaps. However, productivity growth also differs in the PPP-estimates of productivity relative to those implied by the market-exchange rates—as the exchange rates applied in this chapter are fixed at 2010 levels, the growth of the MER series is equivalent to growth rates implied by the national accounts for each economy.

Table 7: Conditional convergence 1970-2010, PPP-measures productivity

	Dependent variable:				
	10-year log change in labor productivity				
	1970-80s	1980-90s	1990-2000s	2000-2010s	Panel
	(1)	(2)	(3)	(4)	(5)
All economies					
Initial productivity	-0.129**	-0.134**	-0.170***	-0.150***	-0.169***
Convergence rate PPP (annual)	*1.38%*	*1.43%***	*1.86%****	*1.62%****	*1.79%****
Convergence rate MER (annual)	*1.06%****	*1.29%****	*1.24%*	*1.46%****	*1.33%****
Schooling (years)	0.007	0.025	0.022	0.014	0.016*
Economic complexity	0.093*	0.135*	-0.024	-0.021	0.034
Commodity exporter	0.030	-0.065	-0.124	-0.052	-0.077*
Trade (% GDP)	0.134*	0.123	-0.033	-0.009	0.055
Investment (% GDP)	-0.208	-1.109**	2.133***	1.010***	-0.153
Law and Order	0.033	0.010	0.052	0.011	0.046***
Observations (All)	61	69	78	79	287
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: Decade dummies are used in the panel specification, but no fixed effects are included. Initial productivity is the average of log productivity over the 10-years in the preceding decade. Productivity growth calculated as the change in average log-productivity between the two decades (10-year average growth). For the decade beginning in 2010, productivity is assumed to grow at its average rate between 2010-7 for the final two years of the decade, 2018 and 2019. All conditioning variables are lagged decadal averages. Market exchange rate results are also provided for comparison.

PPP-effects on productivity growth

To establish the effects of differences in relative prices on the level of output across economies, the Penn World Tables draw on multiple years of data from the World Bank's ICP, with data beginning in 1970. Because their PPP-adjustments are updated across multiple years, their impact is not just on the level of output per worker but the growth rate of output per worker. The PPP-adjusted growth rate of output in each economy often differs substantially from the national-accounts growth rate used in the market-exchange rate approach (where exchange rates are fixed in one year). This occurs for two reasons, both of which cause the prices recorded by the ICP to differ from the price deflator recorded in national accounts (Feenstra et al., 2015):

- The basket of goods under consideration by the ICP can differ from the goods produced by an economy.
- Measurement error in the ICP or national accounts could cause them to diverge.

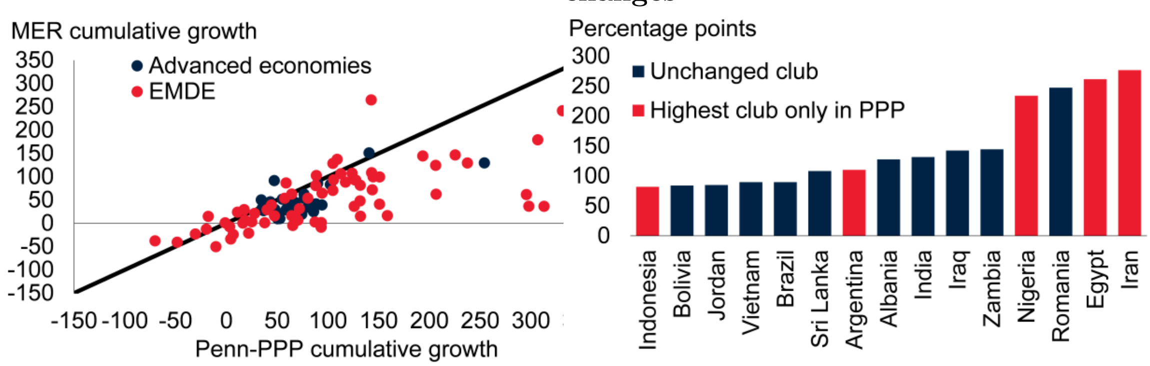
Since 1990, the cumulative growth of output per worker in PPP-terms has systematically exceeded the growth registered in the national accounts across nearly all economies under consideration (**Figure 13**). That could suggest that the ICP measure of prices has fallen more than the national accounts measure of prices. The faster rates of growth contribute to the faster rates of estimated convergence listed above and may provide a modest exaggeration of the pace of productivity convergence.

Secondly, certain economies are affected more than others by the discrepancy in the evolution of national-accounts-based growth and PPP-adjusted productivity growth. This also leads to different results in the club convergence clustering algorithms. For the Phillips and Sul approach, 5 EMDEs join the highest convergence club (1) than when the algorithm is applied to the market exchange rate measure of productivity (**Figure 13**). The size of the discrepancy between PPP and national accounts measures of growth in these economies suggests a degree of caution in interpreting these results. For example, the cumulative growth rates of Iran and Nigeria since 1990 are over 200 percentage points higher in the PPP-measure. In Argentina and Brazil, cumulative growth rates are over 75 percent higher.

Figure 13: **PPP-adjusted growth differentials**

A. Cumulative growth 1990-2017, PPP vs market exchange rate adjusted (MER)

B. Cumulative growth rate differences for PPP vs. market-exchange rates (1990-2017): convergence club changes



Source: Penn World Table, World Bank
Note: Output-measured real GDP at PPP-adjusted 2011 US dollars ("rgdpo" in the PWT dataset) per worker relative to output measured at 2010 US dollars at 2010 exchange rates.
A. Percent productivity growth between 1990 and 2017 under the PPP and market exchange rate measures of productivity.
B. Percentage point difference in cumulative productivity growth in the 15 countries with the largest growth differential between both measures of productivity. Five of these economies are found to be in the highest productivity club under the Phillips and Sul convergence algorithm (in red) when labor productivity is measured in PPP-adjusted US dollars but are found to be in lower clubs when labor productivity is measured at 2010 market exchange rates.

Several studies have found flaws in the price-surveying methodologies used prior to the 2011

ICP exercise. These flaws may be an important driver of the discrepancy between the price deflator in the ICP and the deflator used in the national accounts. Methodological changes in the 2011 ICP survey have resulted in substantial re-estimations of the size of many economies relative to the 2005 ICP (Deaton and Aten, 2017; Inklaar and Rao, 2011). Some of the discrepancies between national-accounts based measures of labor productivity and PPP-based estimates may also be due to inconsistent sampling methodologies for prices over time.

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