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Dynamic Development Accounting and Relative Income Traps

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Dynamic Development Accounting and Relative Income Traps

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ABSTRACT: Previous research suggests that economy-wide poverty traps are rarely observed in the data. In this paper, we explore a related hypothesis: low-income countries rarely improve their position relative to the US. Using finite state Markov chains, we show that upwards mobility is indeed limited. Since capital-output ratios are similar across countries, and human capital is also converging, the persistence of low relative income seems to originate in the persistence of low relative TFP. We study the dynamics of relative TFP and how they interact with absolute levels of human capital, casting new light on the future of convergence.

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WORKING PAPERS

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Contents

Executive Summary

Previous research suggests that economy-wide poverty traps are rarely observed in the data. In this paper, we explore a related hypothesis: low-income countries rarely improve their position relative to the US. Using finite state Markov chains, we show that upwards mobility is indeed limited. Since capital-output ratios are similar across countries, and human capital is also converging, the persistence of low relative income seems to originate in the persistence of low relative TFP. We study the dynamics of relative TFP and how they interact with absolute levels of human capital, casting new light on the future of convergence.

I. Introduction

One of the oldest ideas in development economics is that poor countries may find themselves in an economy-wide poverty trap. Perhaps it is hard to escape a low level of income, especially if some aspects of poverty reinforce themselves in a vicious circle: as Nurkse (1953) formulated this idea, a country is poor because it is poor. Among the candidate mechanisms, some models assume a lack of collateral for borrowing by the poor or imply that saving will be low because of a subsistence consumption constraint. Versions of such ideas have been used to motivate foreign aid, and the desirability of a concerted 'big push' that could advance a country to higher living standards (Sachs 2005).

As research has progressed, however, the concept of an economy-wide poverty trap has been more or less discarded. Bauer (1971) had already pointed out problems with the concept, not least that many developing countries were growing quickly. Easterly (2006, p. 299) noted that, between 1950 and 2001, the initially poorest one-fifth of countries grew almost as fast as the richer four-fifths. Later work by Kraay and Raddatz (2007) and Kraay and McKenzie (2014) gave further reasons for skepticism about aggregate poverty trap narratives. Like Bauer and Easterly, they point out that many countries that were once poor have successfully grown and developed, challenging the general relevance of a trap.

The empirical case for an absolute trap has few supporters, but the persistence of low *relative* levels of income has been less discussed and investigated. Canova and Marcet (1995, revised 2000) found a lack of mobility and concluded the 'poor stay poor'. Using a very different approach, Ho (2006) found that convergence effects are weak for the poorest countries. In a more recent analysis, Mountford (2024) also finds that relatively poor countries stay relatively poor. In a brief note, Arias and Wen (2015) discuss the difficulty of climbing the development 'ladder' and find that countries with income per head less than 15% of the US level often fail to breach that threshold in subsequent decades: low relative income is persistent. And if poor countries do not improve their relative positions, their living standards are likely to remain below — perhaps far below — their potential. The persistent failure to catch up with rich countries will contribute to various worldwide pressures, through migration and geopolitics; it also suggests a continued need for foreign aid and donor engagement.

In this paper, we study the persistence of low relative income using an approach we call 'dynamic development accounting'. This was effectively initiated by the pre-publication version of Feyrer (2008) and taken further by Johnson (2005) and Barseghyan and DiCecio (2011). Building on Quah (1993), the key idea in Feyrer's work was to move beyond the snapshots of development accounting at a single point in time and use Markov chains to consider the evolution of the proximate determinants of GDP per head: the capital-output ratio, human capital, and TFP.

We take a version of Feyrer's approach to more recent data and study the persistence of low relative income in particular.[1] We show that mobility within the cross-country income distribution is limited. Low mobility in relative TFP seems to be the main culprit. Our study of changes over time confirms and extends the conventional view that TFP differences have been central to underdevelopment and remain so.

One advantage of having more years of data than Quah (1993) and Feyrer (2008) is that we can compare transition matrices across subperiods. We find that upwards mobility within the distributions of relative income

[1] Note that, as in much of the literature, we use 'income' and 'output' more or less interchangeably; with some loss of precision, 'income' is here a shorthand for GDP.

and relative TFP has increased somewhat in recent decades. Similarly, Kane (2016) finds a change in estimates of a transition matrix for income; he predicts fast long-run convergence by assuming that the matrix will continue to change in the same way, which seems a strong assumption. Here we take a more structural approach, based on the idea that TFP growth may depend on the absolute level of human capital. This was first suggested by Nelson and Phelps (1966) and analyzed further by Benhabib and Spiegel (1994, 2005), among others.

In adapting this idea to transition matrices, we start with a two-dimensional state space, where the dimensions are relative TFP and absolute human capital. We exploit the fact that we can redefine this as a one-dimensional problem with more states and an extended set of state definitions. When we do this, we find that the countries with high absolute human capital indeed show greater upwards mobility from low categories of relative TFP, but this effect is quite modest. The analysis complements Feyrer (2008) and our earlier work on a middle-income trap (Imam and Temple 2024b).

The middle-income trap is sometimes defined not as a literal trap, but in terms of a slow escape from middle-income status (for example, Cherif and Hasanov 2019). We extend that idea to low relative income, and examine the average time taken to exit a low-income state. Taking our two papers together, it may seem awkward to identify both persistence in low income and a middle-income trap. But it remains meaningful to posit both, since we also find evidence of greater upwards mobility for intermediate income categories. This suggests that some productivity and growth challenges are distinct to particular development levels, as work on both poverty traps and middle-income traps has repeatedly argued.

Our work indicates that low relative TFP continues to hold back development. Verhoogen (2023) reviews the firm-level literature on technological upgrading in developing countries. But low aggregate TFP may not be a question solely of firm decisions, since one reason for a lack of convergence in relative TFP may be variation in the provision and quality of infrastructure and institutions. With this in mind, in our final analysis, we consider the evolution of two other variables, one a recently-introduced proxy for state capacity, and the other the extent of checks and balances in domestic political institutions.

The paper has the following structure. The next section provides some background. Section 3 describes the methods and section 4 the data. Section 5 sets out the results on relative income transitions, while section 6 looks at convergence in relative TFP. Section 7 examines the joint evolution of relative TFP and absolute human capital. Section 8 looks at convergence in state capacity and political institutions, before section 9 concludes. An appendix covers some technical issues in more detail than the main text.

II. Background

The recent idea that 'the world is converging' overlooks some awkward facts. Using data from version 8 of the Penn World Table, Jones (2016, figure 24) finds that countries in the lower part of the distribution in 1960 often failed to keep pace with the US between 1960 and 2011. For a set of 100 countries, Jones (2016, figure 27) finds that the standard deviation of log GDP per person rose by about 30% over the same time period.[2] Kremer et al. (2022, figure 3) find that growth for the countries below the first quartile has often been slower than for countries above it. They also find (their figure 2) sigma divergence between 1960 and 2010, before some convergence in the 2010s associated with faster growth in the developing world and slower growth in the rich countries.

[2] In this respect his analysis updates a similar finding in Jones (2003).

These patterns and trends suggest that we need to go beyond neoclassical growth models and β-convergence regressions. For example, using recent trade theory, Atkin et al. (2022) model a development ladder in which some countries may fall behind under globalization. In the older literature, there are many theoretical models of aggregate poverty traps; for extended discussions see Azariadis and Stachurski (2005), Kraay and Raddatz (2007) and Kraay and McKenzie (2014). These models could sometimes be adapted to deliver either a relative or an absolute trap.

Especially when the focus is a relative trap, perhaps the most natural empirical approach is to study transitions between income classes as in Quah (1993). This can be done using a first-order, finite state Markov chain. The use of a Markov chain allows considerable flexibility in the dynamics and patterns of mobility, rather than modelling the conditional mean as in a linear regression. We can quantify the extent of various forms of mobility within the distribution, see how the shape of the distribution is changing, and make projections for the future evolution of the marginal distribution over the states. For some questions, this approach has significant advantages, avoiding the need for more complex methods such as those used in Ho (2006).

Drawing on Quah's pioneering work, Feyrer (2008) used Markov chains to study transitions for the proximate determinants of GDP per head: relative TFP, the capital-output ratio, and human capital. In a companion paper to the current one, Imam and Temple (2024b) updated that analysis, taking advantage of another thirty years of data and making some refinements. Capital intensity and human capital were found to be converging, but this has disguised a lack of improvement in relative TFP. This is related to the earlier findings of Gallardo-Albarrán and Inklaar (2021), who found that differences in TFP are accounting for an increasingly large share of the international variation in output per head.

In the current paper, we take this further and focus on upwards mobility from low relative TFP in particular. We find persistence in low relative TFP, which suggests that the lack of TFP convergence will begin to dominate the outcomes for relative income per head. More positively, there are signs that upwards mobility in the relative TFP distribution has improved over time. Then, by studying relative TFP and absolute human capital jointly, we examine whether existing, worldwide gains in educational attainment will lead to faster TFP convergence in the years to come.

As we discuss more formally later, Quah's approach typically yields an estimate of the stationary distribution that will arise if the process remains stable and runs for long enough. The properties of this distribution can be related to formal definitions of convergence.[3] Loosely speaking, absolute convergence occurs where differences are being eliminated, as different units converge to similar levels. In our case, that means we would expect to see the stationary distribution placing most weight on one category. For example, we will show that capital-output ratios are increasingly similar across countries, and this is reflected in a concentrated stationary distribution for that variable. But since the stationary distribution can take a long time to reach, we also look at 25-year and 100-year projections.

The relation between our analysis and conditional convergence is less immediate. Conditional convergence asks whether countries are converging (in terms of log output per head) to parallel growth paths, the heights of which are a function of explanatory variables such as investment rates and population growth rates. This has often been examined using growth regressions in which log output per head is regressed on controls and lagged log output per head. That approach provides indirect evidence on the validity of neoclassical growth models but is less interesting if a conditional convergence regime is just one regime among several, and nor

[3] For a more detailed review and discussion of convergence concepts, see Galor (1996); for a time-series perspective see Silva Lopes (2024).

does it have to say much about the dynamics of relative TFP.[4]

In our case, conditional convergence could lead the stationary distribution for output per head to place most weight on one category, if the parallel growth paths are sufficiently close together. But if the steady-state determinants are further apart, so will be the balanced growth paths, and hence the stationary distribution for output per head could see probability mass spread across several categories. For some questions of interest, this takes us further than growth regressions, since we may be interested in the extent of dispersion of balanced growth paths as well as evidence for convergence towards them.[5] A further and perhaps more significant advantage of the distribution dynamics approach of Quah (1993) is that it provides information about movements within the distribution, such as the extent of upwards mobility from low relative income or low relative TFP.

In going down this route, some of our findings overlap with those of Schelkle (2014) and Koopman and Wacker (2023), although neither of those papers uses transition matrices. Schelkle finds that, when countries fall further behind the US, this is typically explained by declining relative efficiency rather than declines in relative factor supplies. Relatedly, Koopman and Wacker (2023) find that growth accelerations often arise through changes in TFP rather than faster accumulation of human capital and physical capital.
Our paper is also related to recent work analyzing changes in aggregate convergence, notably Dieppe (2020), Kindberg-Hanlon and Okou (2020), Kremer et al. (2022), Patel et al. (2021) and Roy et al. (2016).[6] Our paper adds information on mobility within cross-country distributions of outcomes, revealing the persistence of low levels of relative development. As we have already noted, consistent with some recent papers, we do find evidence for faster convergence in recent decades. This is manifested here in greater upwards mobility within the distributions of relative income and relative TFP. Even then, however, the average time taken to exit the lowest category of relative income — we will define this more precisely later — turns out to be surprisingly long. This finding works to qualify the recent idea that the world is converging.

In other work that followed Quah's contributions, Fiaschi and Lavezzi (2003, 2007) defined states by growth as well as income, while Im and Rosenblatt (2015) looked for a middle-income trap.[7] Perhaps the main drawback of the Markov chain approach is that translating a continuous variable into discrete categories can distort the findings (Bulli 2001). An alternative approach is to use stochastic kernels, as in Quah (1997), Johnson (2005), and Barseghyan and DiCecio (2011). But for the economic questions of most interest here, the results are much easier to report and interpret if we use discrete categories.

Another issue has been the choice of benchmark. Quah (1993) and Feyrer (2008) defined their classes relative to the world mean. As Pearlman (2003) pointed out, this creates scope for an internal inconsistency, since the unconditional distribution over states may tend towards one in which all countries would — impossibly — be above the world mean. Kremer et al. (2001) also discussed this problem. We avoid the issue by measuring outcomes relative to the US, the natural choice for the frontier country, as in Jones (1997, 2016) and Arias and Wen (2016).

[4] The former objection has been addressed by several influential papers; see Imam and Temple (2024a, especially section 9.1) for references.

[5] In principle a researcher could build on growth regression results to investigate this, but in practice that has rarely been done beyond brief examinations of sigma convergence (declining cross-section dispersion).

[6] For a recent review of the convergence literature, see Johnson and Papageorgiou (2020).

[7] For some other extensions and applications, see Quah (1996a, 1996b, 1997), while Durlauf and Quah (1999) discussed the approach and how it relates to the goals of a researcher.

III. Methods

The use of Markov chains to study 'distribution dynamics' is an alternative to modelling growth using linear regressions, which have well-known problems, including restrictive parametric assumptions and sensitivity to outliers and measurement error (Durlauf et al. 2005, Temple 2021). As in Quah (1993), we study income mobility using a finite state Markov chain. Since the basics of Markov chains are well known, we describe them only briefly, drawing heavily on the expositions in Imam and Temple (2024a,b), which in turn are based on Stachurski (2009).

Consider a series $\{X_n, n \geq 0\}$ in discrete time, with a discrete state space S with states $P = [p_{ij}]$ where $p_{ij} = P\{X_n = j | X_{n-1} = i\}$ for all $i, j \in S$. The elements of P are non-negative and each row sums to one; the individual elements are probabilities of transitions between states. The maintained assumption in a first-order Markov chain, known as the Markov property, is that the transition probabilities depend only on the current state and not on the earlier history of the process. Imam and Temple (2024b) investigated this property as part of their analysis; for a brief summary, see the appendix to this paper.

Denote the marginal or unconditional distribution over the states at time t by a row vector ψ_t.[8] Over time the evolution of this marginal distribution can be described by

$$\psi_{t+1} = \psi_t P$$

It can be shown (for example, Stachurski, 2009, theorem 4.3.5) that every Markov chain on a finite state space has at least one stationary distribution. Each stationary distribution will satisfy $\psi^* = \psi^* P$. When ψ^* is unique, this will be the long-run outcome. The individual elements of the row vector ψ^* indicate the proportions of time the process will spend in each state if the process runs for a long time. But depending on the elements of the transition matrix P, the process will converge slowly or quickly to the long-run equilibrium, and the nature of the stationary distribution will be more or less sensitive to the individual transition probabilities.

We use five-year intervals as in Kremer et al. (2001). Their analyses suggested that the Markov property did not hold in annual data, but they found no reason to reject it for five-year intervals. Relative to the early studies, we now have a lot more data, which means that five-year intervals are a natural choice. Quah's data ended almost forty years ago, in 1985; Feyrer's data ended in 1989; and the data of Kremer et al. (2001) ended in 1996. In our case, even though we use five-year intervals rather than annual data, our results draw on more than 300 transitions, and sometimes more than a thousand. This means that the probabilities of even quite rare transitions can be estimated with some precision, if a given state is observed in the data often enough.

To allow straightforward interpretation of the results, we translate GDP per head (and other outcomes, such as TFP) into discrete categories, usually measured relative to the US. This requires us to choose threshold levels that define the categories. As Imam and Temple (2024b) argue, a natural stipulation is that a country growing at a constant relative rate should take the same amount of time to traverse the intermediate income categories (not the highest or lowest). Imam and Temple (2024b) call these 'constant growth thresholds' and we use them in most of the analyses that we present; for more discussion, see the appendix to this paper.

The literature that followed Quah (1993) sometimes indicated that small changes in the transition probabilities

[8] For a more rigorous treatment, see Stachurski (2009,pp.74-76).

matter for predictions over long horizons (notably, when deriving the stationary distribution). Hence, we think it is good practice to report the absolute numbers of transitions. This is not redundant information: the transition probabilities can be derived from the transition counts but not vice versa.

That said, we should dispel some potential misconceptions about transition counts, and low counts in particular. As discussed in Imam and Temple (2024a,b), these are not always a problem. If a state *x* is observed many times in the data but is followed by state y only a handful of times, this should be reliable evidence that the probability of moving from state *x* to state *y* is low. A more serious problem arises when a given state is observed only rarely in the data, and so we select our thresholds so that each state does arise quite frequently.

To understand which transition probabilities can be precisely estimated, we report asymptotic standard errors based on Anderson and Goodman (1957). They derived the asymptotic variances of estimated transition probabilities p_{ij} for a Markov chain; for a transition from state *i* to *j*, they showed that

$$\sqrt{n_i}(\hat{p}_{ij} - p_{ij}) \longrightarrow N(0, p_{ij}(1 - p_{ij}))$$

where n_i is the number of observations of state *i* prior to the final period. In the growth literature, this result was previously used by Proudman et al. (1998) and also noted in Kremer et al. (2001). In our setting, our primary interest is in whether specific transition probabilities underlying our main findings are well determined; put differently, we are interested in the width of the confidence intervals for a subset of the matrix entries, and the question of whether all or most intervals exclude zero is otherwise largely irrelevant.

Quah (1993) identified an emerging tendency towards ‘twin peaks’ in the stationary distribution of relative GDP per head. For that variable, upwards and downwards mobility was found to be limited, and convergence to a stationary distribution rather slow (Kremer et al. 2001). As Imam and Temple (2024a) discuss, slow convergence tends to go together with a sensitivity of the stationary distribution to small changes in transition probabilities. These could arise through alternative state definitions, measurement errors, or changes in the sample of countries.[9]

Similarly to Kremer et al. (2001), we find that convergence to the stationary distribution of GDP per head is rather slow. But it is typically faster for some of the proximate determinants of GDP per head, and also — perhaps surprisingly — for measures of state capacity and political institutions that we use later. Hence, the stationary distributions for those variables should be more robust. As well as reporting stationary distributions, we report 25-year and 100-year projections, which will typically be less sensitive to individual transition probabilities (Kremer et al. 2001).

In each case, we report an asymptotic measure of convergence speed, also following Kremer et al. (2001, p. 290). The measure is defined as:

$$\gamma \equiv -\frac{\log(2)}{\log|\lambda_2|}$$

[9] The problem was noted by Ben-David in his discussion of Proudman et al. (1998) and discussed further in Kremer et al. (2001). Müller et al. (2022, Table 1) briefly present a long-run transition matrix using data for 1960-2017 and confirm that transitions across income quartiles are rarely seen.

where λ_2 is the second largest eigenvalue (after 1) of the transition matrix. This gives the number of periods needed to halve the norm of the difference between the current distribution and the stationary distribution. Note that, as an asymptotic rate, this does not take the initial distribution into account, and so actual convergence will sometimes be faster than this. We adjust γ for the fact that our intervals are five years apart.

In this paper, given our interest in the persistence of low relative income, a natural question is the expected time taken to exit a state, and especially the lowest state. We define the time to exit from state *i* as:

$$\tau_i = \inf(n > 0 : X_n \neq i | X_0 = i)$$

We denote the expectation of this by MET_i and it can be shown that

$$MET_i \equiv E[\tau_i] = \frac{1}{1 - p_{ii}}$$

where we will be especially interested in MET_1, the expected time taken to exit the lowest state. We could derive its asymptotic standard error using the delta method, but in our setting it is simpler to use the bootstrap. Since the distribution of MET_1 is likely to be skewed, we will report a bootstrapped 90% confidence interval rather than a standard error. Again, we adjust the statistic for the fact that these are five-year transition probabilities, so that we can measure MET_1 in years.

IV. The Data

We draw on two sources for our data on GDP per head (or more loosely, income per head). The first source is the Maddison Project Database 2023, released in 2024. The Maddison Project measures are designed to allow long-term comparisons across both time and space. The 2023 version uses the 1990 ICP benchmark, but also integrates information from the 2011 benchmark, with a number of departures from the original Maddison approach; for more details, see Bolt and van Zanden (2024). The use of data up to 2020 means that the sample includes the first year of the Covid-19 pandemic. Given our focus on relative income, the results for that year will be influenced to the extent that poor and middle-income countries were differently affected relative to the US.

The second source is version 10.01 of the Penn World Table (PWT; Feenstra et al. 2015). As with the Maddison data, the panels we use are balanced. When studying outcomes in the PWT data, rather than using real GDP per head, we use real GDP per adult of working age (15-64), where the data on the working-age population are taken from the World Development Indicators. This approach was used in Mankiw et al. (1992) and Imam and Temple (2024b) and may provide a better measure of productivity for our purposes than using either GDP per head or GDP per worker.[10]

Our samples for the various analyses include most of the world's countries. The balanced panel we will use for the Maddison dataset covers countries representing more than 97.7% of the world population in 2020. As in Imam and Temple (2024b), to avoid double-counting territories that overlap, we exclude the Russian Federation but include the former USSR; the 2023 version of the Maddison data includes a series that has been constructed for the latter territory for the whole period.

[10] Although data on GDP per worker are available, the way to define a 'worker' appropriately is often unclear in developing economies with a large informal sector.

V. Results

In our first exercise, we look at transitions within the Maddison data on real GDP per head. We first look at these between 1950 and 1995, and then between 1995 and 2020, for a common sample of countries. For the first time period, this leads to data on a total of $NT = 145 \times (10 - 1) = 1305$ transitions. Before we report the results, we note a qualification: since output fluctuates at short horizons, the matrices we present will typically overstate the true extent of mobility, and we would expect the mobility of *potential* output to be lower than this. But since we find that mobility is in any case limited, smoothing out short-run fluctuations would only reinforce our conclusion in this regard.

As in our companion paper on the middle-income trap, Imam and Temple (2024b), we often work with particular constant growth thresholds, namely (0.08, 0.16, 0.32, 0.64) where the numbers are relative to the US level. The first results are shown in Table 1. The entry in a row and column indicates the probability of moving from the row state to the column state. The individual transition probabilities are derived by asking what proportion of countries in a given row state at time t are found in a given column state at time $t + 1$. By a standard argument, these are the maximum likelihood estimates, as used in Quah (1993), Kremer et al. (2001), and Imam and Temple (2024a, 2024b) among others.

Table 1 and later tables also report the final observed distribution (that is, the one in the final period of the sample) and the marginal distributions to be expected 25 years and 100 years later, based on iterating the transition matrix. As noted earlier, the latter projections have the advantage that they will be less sensitive than the stationary distribution to individual transition probabilities; see Kremer et al. (2001). But the stationary distribution remains one way to reveal tendencies hidden in the data, at least if interpretation is cautious, and so we report that too, along with bootstrapped standard errors for the individual entries of the stationary distribution.

Looking at Table 1, we can see that upwards mobility is slow, and there are also downwards transitions, as countries fail to keep pace with the US. In addition, convergence as measured by γ is slow. This lack of mobility is consistent with Quah (1993) and Kremer et al. (2001), among others. There are clear limits to the extent to which countries are converging, but how persistent is low relative income? The five-year transition probability for exiting the lowest category is just 0.04 (from 1 − 0.96). In principle this may be an artifact of the 'depth' of this category, but we can see that even in the stationary distribution, the probability mass on the lowest category exceeds 25%; in other words, even in the long run, countries will spend more than a quarter of their time with income per head below 8% of the US level. There is also some evidence in the stationary distribution for the bimodality or 'twin peaks' that Quah (1993) identified as a long-run feature of the distribution.

This analysis is for the years 1950-95, and there have been suggestions in the literature that convergence forces have strengthened in recent decades (Roy et al. 2016; Patel et al. 2021; Kremer et al. 2022). In Table 2, we look at five-year transitions over a shorter and more recent period, 1995-2020. Now the highest category (above 64% of US income per head) is close to absorbing, and this means the stationary distribution places high mass on the highest category. The extent of mobility is greater than in the earlier period. This casual impression is confirmed by comparison of the asymptotic convergence measure (γ). But there is strong evidence for the persistence of low relative income even in this more recent data: the mean time to exit the lowest state is more than 80 years, with a 90% confidence interval of [55.0, 143.8].

Table 1: Five-year transitions, Maddison data, 1950-1995

Transition matrix	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.960	0.035	0.005		
	(0.010)	(0.009)	(0.004)		
<0.16	0.087	0.821	0.093		
	(0.017)	(0.023)	(0.017)		
<0.32		0.092	0.805	0.099	0.003
		(0.017)	(0.023)	(0.017)	(0.003)
<0.64			0.102	0.796	0.102
			(0.023)	(0.031)	(0.023)
< ∞				0.048	0.952
				(0.017)	(0.017)
Summary	γ = 162.2	MET_1 =	125.3	90%CI	[86.8, 207.0]
Last period	0.352	0.186	0.179	0.131	0.152
25 years ψ_{T+25}	0.358	0.169	0.167	0.126	0.180
100 years ψ_{T+100}	0.348	0.148	0.148	0.126	0.230
Stationary ψ^*	0.274	0.127	0.143	0.144	0.312
(s.e.)	(0.102)	(0.038)	(0.039)	(0.041)	(0.134)
Transition counts					
<0.08	385	14	2	0	0
<0.16	24	229	26	0	0
<0.32	0	27	236	29	1
<0.64	0	0	17	133	17
<∞	0	0	0	8	157
NT = 1305	N = 145	T = 9			

Transitions for GDP per head relative to US, using Maddison project data. Transitions from row state to column state. Anderson-Goodman asymptotic standard errors shown in parentheses below transition probabilities. Bootstrapped standard errors for the stationary distribution also shown. For more details see the text.

Table 2: Five year transitions, Maddison data, 1995-2020

Transition matrix	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.940	0.060			
	(0.016)	(0.016)			
<0.16	0.034	0.805	0.161		
	(0.017)	(0.036)	(0.034)		
<0.32		0.049	0.825	0.119	0.007
		(0.018)	(0.032)	(0.027)	(0.007)
<0.64			0.074	0.821	0.105
			(0.027)	(0.039)	(0.031)
$< \infty$				0.036	0.964
				(0.016)	(0.016)
Summary	$\gamma = 86.6$	$MET_1 =$	82.9	$90\%CI$	[55.0, 143.8]
Last period	0.283	0.172	0.186	0.166	0.193
25 years ψ_{T+25}	0.231	0.144	0.204	0.172	0.248
100 years ψ_{T+100}	0.131	0.098	0.184	0.197	0.390
Stationary ψ^*	0.021	0.037	0.120	0.206	0.617
(s.e.)	(0.026)	(0.028)	(0.067)	(0.088)	(0.180)
Transition counts					
<0.08	218	14	0	0	0
<0.16	4	95	19	0	0
<0.32	0	7	118	17	1
<0.64	0	0	7	78	10
$< \infty$	0	0	0	5	132
$NT = 725$	$N = 145$	$T = 5$			

Transitions from row state to column state. For other notes see Table 1.

VI. Relative TFP

In our companion paper, Imam and Temple (2024b), we followed Feyrer (2008) and examined the convergence of proximate determinants of output per head. Using data from version 10.01 of the Penn World Table, we found substantial upwards mobility for the capital-output ratio between 1974 and 2019, and only limited downwards mobility. Convergence is fast, and the stationary distribution places most mass on the highest category. Hence the persistence of low relative income that we documented above is unlikely to be driven by differences in equilibrium capital intensity.

Imam and Temple (2024b) also examined transitions for human capital. The variable of interest is human capital relative to the US, again computed from version 10.01 of the Penn World Table. There is very little downwards mobility in relative human capital, but some upwards mobility, albeit slow for the transition to the highest category. The stationary distribution has most of its mass in the highest category. Although the process still has further to run, it currently implies that absolute convergence in human capital will ultimately be achieved.

These findings suggest that, as with the middle-income trap, the lack of upwards mobility from the lowest relative incomes must reflect the rarity of sustained gains in relative TFP. We examine that conjecture in this section, before considering the interaction of TFP and human capital in the next section.

In Table 3 we report five-year transitions for relative TFP, initially for 1974-1999. This uses the measure of TFP that is provided in version 10.01 of the Penn World Table. That measure is computed from a measure of real output deflated by a Törnqvist quantity index of factor endowments; for more details see Feenstra et al. (2015, Section V). Hence, it is a more sophisticated measure than has been the norm in the development accounting literature, the majority of which assumes a Cobb-Douglas aggregate production function.

Looking at Table 3, it is clear that upwards mobility is quite limited; it takes an average of 85 years to exit the lowest category of relative TFP. The stationary distribution is imprecisely estimated, but in the 25-year projection more than 40% of the world's countries are below the highest category of relative TFP. Convergence as measured by γ is also quite slow, at 65.6 years. We should not place too much weight on these results, since the number of transitions underlying them is small. But the extent of downwards mobility suggests that failing to keep pace with the TFP of the US is quite common. This is perhaps because the institutional environment is not conducive to TFP growth, or because periodic dislocation and crisis lead to output collapses and lower measured TFP.[11]

One concern that might be raised is that our samples include some countries which specialize in exporting natural resources. But as noted in Imam and Temple (2024b), natural resource revenues are unlikely to explain our finding of persistent dispersion in relative TFP. In the presence of natural resource revenues, a standard calculation of aggregate TFP will overstate the relative TFP of the non-resource sector; see for example Hall and Jones (1999, p. 89), or the detailed and more rigorous treatment of Freeman et al. (2021), which treats natural resources as an input missing from conventional TFP calculations. Hence we conjecture that explicitly incorporating natural resources would only reinforce our finding of persistent dispersion in relative TFP. It is also worth noting that, among the 116 countries studied in Freeman et al. (2021), resource rents exceed 20% of GDP in just 11 (Freeman et al. 2021, p.3).

[11] For more analysis of output collapses, see Imam and Temple (2024a).

Table 3: Five-year transitions, TFP from PWT, 1974-1999

Transition matrix	<0.36	<0.48	<0.64	<∞
<0.36	0.941	0.059		
	(0.057)	(0.057)		
<0.48	0.237	0.553	0.184	0.026
	(0.069)	(0.081)	(0.063)	(0.026)
<0.64	0.031	0.246	0.492	0.231
	(0.021)	(0.053)	(0.062)	(0.052)
$< \infty$		0.006	0.079	0.915
		(0.004)	(0.015)	(0.015)
Summary	$\gamma = 65.6$	$MET_1 =$	85.0	[25.0, ∞)
Last period	0.111	0.133	0.122	0.633
25 years ψ_{T+25}	0.219	0.106	0.128	0.547
100 years ψ_{T+100}	0.388	0.113	0.104	0.395
Stationary ψ^*	0.527	0.120	0.085	0.269
(s.e.)	(0.325)	(0.081)	(0.057)	(0.188)
Transition counts				
<0.36	16	1	0	0
<0.48	9	21	7	1
<0.64	2	16	32	15
$< \infty$	0	2	26	302
$NT = 450$	$N = 90$	$T = 5$		

Transitions in relative TFP, using PWT data, reported from row state to column state. Anderson-Goodman asymptotic standard errors shown in parentheses below transition probabilities. Bootstrapped standard errors for the stationary distribution also shown. For more details see the text.

In Table 4 we report five-year transitions for relative TFP for the more recent period 1999-2019. This shows less downwards mobility than before, and more upwards mobility. Convergence is substantially faster, with γ falling from the 65.6 of the earlier subperiod to 28.0 years in this subperiod. The final observed distribution and the stationary distribution place most mass on the highest category, TFP greater than 64% of the US level. When contrasted with Table 3, these results for the later period are quite supportive of the idea that the convergence process has changed, as argued in Kremer et al. (2022) and Patel et al. (2021), but here using a different method and focusing on relative TFP. In the next section, we investigate one possible source for this change, namely the global changes in educational attainment already discussed.

Table 4: Five-year transitions, TFP from PWT, 1999-2019

Transition matrix	<0.36	<0.48	<0.64	<∞
<0.36	0.742	0.258		
	(0.079)	(0.079)		
<0.48	0.039	0.745	0.196	0.020
	(0.027)	(0.061)	(0.056)	(0.019)
<0.64	0.038	0.115	0.654	0.192
	(0.027)	(0.044)	(0.066)	(0.055)
$< \infty$		0.004	0.058	0.938
		(0.004)	(0.015)	(0.016)
Summary	$\gamma = 28.0$	$MET_1 =$	19.375	[11.4, 41.7]
Last period	0.067	0.156	0.178	0.600
25 years ψ_{T+25}	0.055	0.154	0.187	0.605
100 years ψ_{T+100}	0.050	0.146	0.186	0.618
Stationary ψ^*	0.050	0.145	0.185	0.621
(s.e.)	(0.060)	(0.082)	(0.062)	(0.160)
Transition counts				
<0.36	23	8	0	0
<0.48	2	38	10	1
<0.64	2	6	34	10
∞	0	1	13	212
$NT = 360$	$N = 90$	$T = 4$		

Transitions in relative TFP, using PWT data, reported from row state to column state. Anderson-Goodman asymptotic standard errors shown in parentheses below transition probabilities. Bootstrapped standard errors for the stationary distribution also shown. For more details see the text.

VII. Human capital and TFP

If the convergence process has changed over time, it would be useful to have a structural explanation. In this section, we pursue one possible candidate: rising educational attainment. It has long been thought that human capital may be important to the diffusion of technology and the convergence of aggregate TFP: Nelson and Phelps (1966) and Benhabib and Spiegel (1994, 2005) pursue this idea in different ways, as do Klenow and Rodríguez-Clare (2005) and Córdoba and Ripoll (2008), but with more emphasis on theory.

Our approach starts from a two-dimensional state space, in relative TFP and absolute human capital. We allow four states for relative TFP and two (low/high) for human capital, making eight in total. As in Imam and Temple (2024a), we can greatly simplify the analysis by transforming the two-dimensional state space into a single dimension, with extended state definitions, of eight possible states. For reasons that we explain later, we will omit OECD member countries from this part of the analysis. Feyrer (2008) uses a related approach, in which he estimates separate transition matrices for productivity for each quartile of human capital; the main drawback of that alternative is that, given smaller samples, the estimates will be less precise.

The PWT measure of TFP is available for relatively few countries, so in this section we construct our own 'basic' measure of TFP, as in Imam and Temple (2023a). As in many prior contributions, we use a Cobb-Douglas production function:

$$Y = AK^{\beta}(hL)^{1-\beta}$$

where A is aggregate TFP, K is the capital stock, h is human capital and L is the working- age population. To construct this measure, we need an assumption about the output-capital elasticity β. Feenstra et al. (2015, p. 3178) report an average labor share of 0.52, implying an output-capital elasticity of $\beta = 0.48$ under perfect competition.[12]

The human capital measure we use is taken from version 10.01 of the Penn World Table, which in turn relies on the approach used in Hall and Jones (1999) and Caselli (2005), who built on Klenow and Rodriguez-Clare (1997) and Bils and Klenow (2000). If s is the average years of schooling, the human capital index is equal to exp($\phi(s)$) where $\phi(s)$ is piecewise linear:

$$\begin{aligned} \phi(s) &= 0.134 \cdot s && \text{if } s \leq 4 \\ &= 0.134 \cdot 4 + 0.101(s-4) && \text{if } 4 < s \leq 8 \\ &= 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068(s-8) && \text{if } s > 8 \end{aligned}$$

For now, we classify countries as having low or high human capital depending on whether their average years of schooling exceeds five years. We report the first set of results in Table 5. Once a country attains the high human capital state, we treat that state as absorbing, so the lower-left quadrant of the transition matrix will contain only zeroes (shown here as blank entries; we return to this shortly). Looking at the transition counts at the foot of the table, in total there are 57 transitions from low human capital to high, represented by entries in the upper-right quadrant of the transition matrix and the transition counts.

To highlight the lack of mobility from the lowest relative TFP category, we highlight the relevant transition probabilities in bold. If we look at the upper part of the reported matrix, a low human capital country that starts out with TFP below 36% of the US level will move upwards, in a five-year period, with probability 0.146, from 0.110 + 0.024 + 0.012 = 0.146. For the countries with high human capital, the probability of an upwards transition from the lowest relative TFP category is around twice as high, at 0.289 (from 0.263 + 0.026). There are also differences, but less pronounced, for other upwards movements in relative TFP. The results suggest Nelson and Phelps (1966) were right — the absolute level of human capital does help to determine whether or not a country experiences catch-up in relative TFP — but the benefits of human capital may be less striking than expected.

[12] It might be suggested that we should allow the labor share to vary across countries. In the Cobb-Douglas case, however, this would be problematic, because TFP is an index number defined relative to a particular technology and would therefore cease to be comparable across Cobb-Douglas technologies. See Temple (2012) for more discussion.

Table 5: Five-year transitions, TFP and HC, 1974-2019

Matrix	<.36,L	<.48,L	<.64,L	$<\infty$,L	<.36,H	<.48,H	<.64,H	$<\infty$,H
<.36,L	0.805	**0.110**	**0.024**		0.049	**0.012**		
	(0.044)	(0.035)	(0.017)		(0.024)	(0.012)		
<.48,L	0.190	0.562	0.124		0.038	0.086		
	(0.038)	(0.048)	(0.032)		(0.019)	(0.027)		
<.64,L	0.051	0.265	0.496	0.077		0.034	0.068	0.009
	(0.020)	(0.041)	(0.046)	(0.025)		(0.017)	(0.023)	(0.009)
$<\infty$,L	0.006	0.035	0.182	0.624			0.029	0.124
	(0.006)	(0.014)	(0.030)	(0.037)			(0.013)	(0.025)
<.36,H					0.711	**0.263**	**0.026**	
					(0.074)	(0.071)	(0.026)	
<.48,H					0.203	0.594	0.203	
					0.050	(0.061)	(0.050)	
<.64,H					0.018	0.229	0.642	0.110
					(0.013)	(0.040)	(0.046)	(0.030)
$<\infty$,H						0.011	0.149	0.840
						(0.007)	(0.026)	(0.027)
Convergence	$\gamma = 37.6$							
Last period	0.124	0.072	0.041	0.000	0.124	0.268	0.186	0.186
25y ψ_{T+25}	0.083	0.042	0.020	0.005	0.198	0.260	0.227	0.166
100y ψ_{T+100}	0.021	0.010	0.005	0.001	0.230	0.300	0.258	0.174
ψ^*	0.000	0.000	0.000	0.000	0.234	0.309	0.270	0.187
(s.e.)	(0.000)	(0.000)	(0.000)	(0.000)	(0.078)	(0.055)	(0.051)	(0.066)
Counts								
<.36,L	66	9	2	0	4	1	0	0
<.48,L	20	59	13	0	4	9	0	0
<.64,L	6	31	58	9	0	4	8	1
$<\infty$,L	1	6	31	106	0	0	5	21
<.36,H	0	0	0	0	27	10	1	0
<.48,H	0	0	0	0	13	38	13	0
<.64,H	0	0	0	0	2	25	70	12
$<\infty$,H	0	0	0	0	0	2	28	158

$NT = 873$ $N = 97$ $T = 9$

Given that the high human capital states are treated as (collectively) absorbing, the stationary distribution places no probability mass on the four low human capital states. Over shorter horizons, there will be significant numbers of countries with low human capital after another 25 years, but not after a century. This is not enough to ensure the elimination of low relative TFP, however. In the stationary distribution, countries will spend 23% of the time with TFP less than 36% of the US level, so even a forward-looking assessment suggests that considerable inequality in the distribution of income per head will persist. The challenge for policymakers seems likely to go beyond investing in human capital. To shed light on this, it would be useful to compare the usefulness of other candidate explanations. That would take another paper in itself, but we will consider institutional convergence in the next section.

There are two other qualifications we should make. First, in the analysis we report, the threshold for ‘high’ human capital is average years of schooling of five years or more. When we vary this threshold — results not reported — we find broadly similar results, but the stationary distribution changes somewhat. This points to heterogeneity across countries in transition probabilities: as the threshold is varied, the composition of countries that begin in the high group is altered, and this affects the estimated probabilities and hence the implied stationary distributions. We have excluded OECD member countries to limit the extent of variation via this mechanism.

Second, in the results of Table 5, interpretation is made much easier by the absence of reverse transitions, from high to low absolute levels of human capital. This finding is not universal: given the advantages for interpretation, we have chosen to require the high human capital states to be collectively absorbing. This is done by effectively suppressing a handful of cases where countries have moved from the high to low human capital category (in other words, for a very small number of cases, we treat the relevant transition probabilities as zero rather than close to zero). The decreases in human capital in those cases are minor and perhaps arise through measurement error or net migration, so that suppressing them as anomalous may be a reasonable choice when drawing conclusions for the sample as a whole.

VIII. Institutions

If there is little upwards mobility in relative TFP, it seems natural to attribute this partly to differences in institutions and governance. These have been the subject of a vast literature by development economists, economic historians, and growth economists. Grier and Grier (2007) found that political institutions, measured using the constraints on the executive from the Polity IV database, converged across countries between 1965 and the early 2000s. But it seems likely that much of the upwards mobility in constraints on the executive has been driven by democratizations, and hence will be vulnerable to a reversal of that process.

More recent empirical work, such as Kremer et al. (2022), also investigates whether aspects of institutions are converging across countries. The Kremer et al. (2022) analysis of this question is based mainly on the Polity IV score for the extent of democracy and finds evidence of convergence. This progress may not be sustained: see the political science literature on ’illiberal democracy’, the ‘democratic recession’ and ‘autocratization’ (respectively, Zakaria 1997; Diamond 2008, 2015; Lührmann and Lindberg 2019). The Markov chain study of political institutions and output collapses by Imam and Temple (2024a) reports the incidence of reversals as well as democratizations.

In this section, we first look at state capacity and then at institutional checks and balances. For state capacity, we can take advantage of the recent work by O’Reilly and Murphy (2022), which (in its updated form) applies principal components analysis to version 12 of the V-Dem dataset to generate measures of state capacity with unusually comprehensive coverage across time and countries. We use their baseline measure to maximize the country coverage for the time period we consider. But to maintain comparability with our earlier analyses, we use the intersection of their country coverage with that of the Maddison dataset used earlier.

Since the measure of state capacity has no natural units, and it seems sensible to consider its evolution in absolute rather than relative terms, we need a simple way to determine categories. As in our study of TFP dynamics, we use four states. We take the observed levels of state capacity in 1974 and use the quartiles of that year to set the thresholds that determine the four states from then on. This means the countries are evenly distributed across the states in 1974 but places no restrictions on how they are distributed across the states in later years. An alternative approach would be to look at transitions across quantiles, by updating the thresholds at each date. Our appendix discusses some limitations of that approach.

Table 6: Five-year transitions, state capacity, 1974-2019

Transition matrix	Q1	Q2	Q3	Q4
Q1	0.846	0.111	0.034	0.009
	(0.024)	(0.021)	(0.012)	(0.006)
Q2	0.104	0.701	0.170	0.025
	(0.020)	(0.029)	(0.024)	(0.010)
Q3	0.009	0.079	0.822	0.091
	(0.005)	(0.015)	(0.021)	(0.016)
Q4		0.003	0.060	0.937
		(0.003)	(0.012)	(0.012)
Summary	$\gamma = 37.4$	$MET_1 = 32.5$	90% CI	[25.6,42.8]
Last period	0.189	0.106	0.348	0.356
25 years ψ_{T+25}	0.143	0.140	0.309	0.408
100 years ψ_{T+100}	0.108	0.125	0.299	0.468
Stationary ψ^*	0.097	0.118	0.296	0.488
(s.e.)	(0.037)	(0.037)	(0.080)	(0.133)
Transition counts				
Q1	198	26	8	2
Q2	25	169	41	6
Q3	3	26	272	30
Q4	0	1	23	358
$NT = 1188$	$N = 132$	$T = 9$		

State capacity transitions, category thresholds use quartiles in 1974. Transitions from row state to column state. For more details see the text.

Table 6 shows an estimated transition matrix for state capacity, for 132 countries observed between 1974 and 2019. There is some upwards mobility, but it is quite slow. Even after projecting forwards by a century, more than 50% of the countries will be outside the top category for state capacity, the level achieved by the top quarter of countries in 1974. The asymptotic convergence measure, at 37.4 years, and the mean time to exit the lowest category, 32.5 years, confirm the impression of limited mobility.

Next we look at transitions in 'horizontal' accountability or checks and balances for domestic political institutions. This uses the measure called v2x_horacc (Lührmann et al. 2020) from the V-Dem 14 dataset (Coppedge et al. 2024); again, the period we study is 1974-2019. Once again we find evidence of convergence, this time a little faster. As with the convergence in state capacity, perhaps this has contributed to greater upwards mobility for relative TFP, but it is worth noting that Acemoglu et al. (2019) find no evidence that democratization raises TFP. And given current trends towards 'autocratization', it would be optimistic to extrapolate from these findings, since the risk of downwards mobility for the quality of political institutions seems to be increasing.

Table 7: Five-year transitions, horizontal accountability, 1974-2019

Transition matrix	Q1	Q2	Q3	Q4
Q1	0.726	0.155	0.065	0.054
	(0.034)	(0.028)	(0.019)	(0.017)
Q2	0.076	0.722	0.131	0.072
	(0.017)	(0.029)	(0.022)	(0.017)
Q3	0.008	0.059	0.822	0.110
	(0.005)	(0.013)	(0.020)	(0.017)
Q4		0.008	0.041	0.951
		(0.004)	(0.009)	(0.010)
Summary	$\gamma = 24.2$	$MET_1 = 18.3$	90% CI	[14.9,23.0]
Last period	0.071	0.142	0.248	0.539
25 years ψ_{T+25}	0.047	0.109	0.245	0.599
100 years ψ_{T+100}	0.032	0.086	0.228	0.654
Stationary ψ^*	0.030	0.083	0.225	0.662
(s.e.)	(0.012)	(0.027)	(0.061)	(0.149)
Transition counts				
Q1	122	26	11	9
Q2	18	171	31	17
Q3	3	21	290	39
Q4	0	4	21	486
$NT = 1269$	$N = 141$	$T = 9$		

Horizontal accountability, category thresholds use quartiles in 1974. Transitions from row state to column state. For more details see the text.

IX. Conclusions

In many important respects, the world is converging: as Deaton (2013) documents, poverty rates are falling in many countries. Some of the most populous developing countries — China, India, Indonesia — have grown rapidly. But the broader picture is not quite so encouraging. Earlier work has suggested that growth at the lowest quartile has barely kept pace with the US, and the dispersion of log income per head has increased over time. In different ways, Arias and Wen (2015), Kindberg-Hanlon and Okou (2020), and Mountford (2024) all point to the persistence of low relative income.

This persistence is likely to be less of a concern than a poverty trap at an absolute level. If a country keeps pace with the US, its average living standards are improving, and poverty will typically decline. Nevertheless, if poor countries do not improve their relative positions, their living standards will remain below — perhaps far below — their potential. This suggests that there will continue to be important roles for foreign aid and donor engagement, as means to spur relative development.

In this paper, we have confirmed that the poorest countries are taking a long time to improve their position. By using transition matrices to examine the distributions of relative income and TFP, we are using a framework that is more flexible than a conventional linear regression. We call this approach ‘dynamic development accounting’ since, as in Feyrer (2008), it provides a natural way to extend the snapshots previously found in the literature. In describing movements within the distributions of proximate growth determinants, we can better understand the recent data. This can also be used to make projections for future years, if we assume that the transition probabilities will remain stable over time.

Overall, our results suggest that some of the recent optimism about convergence has been misplaced. The persistence of low relative TFP has been disguised by the ongoing convergence of capital-output ratios and (more slowly) human capital. If these patterns are maintained, as seems likely, the convergence process will ultimately be dominated by the dynamics of relative TFP. Our work suggests that convergence of relative TFP has been slow, although the most recent decades have seen a noticeable improvement.

We have found some tentative evidence that higher educational attainment is already helping TFP convergence; once a high absolute level of human capital has been achieved, the prospects for upwards mobility in relative TFP improve. This effect is quite modest, however, and seems unlikely to be the whole story. Perhaps TFP mobility is also influenced by state capacity and aspects of institutional quality. We show that a proxy for state capacity, and a measure of institutional checks and balances, have been converging across countries, but this may not continue. Given the current ‘democratic recession’, political institutions now seem likely to diverge again.

What can governments of low-income countries do to improve the relative positions of their economies? Part of the standard advice is to invest in human and physical capital, but since these are already converging, a broader approach seems needed. Improvements in relative TFP may rely on policies to generate economic dynamism, perhaps through structural reforms or strategies to overcome barriers to technology adoption. But the details of such policies are likely to matter greatly and would require different forms of analysis from those we use here.

In this paper, we have not undertaken the difficult task of comparing candidate explanations for changes in the TFP process, such as higher absolute human capital versus better governance, say, or improved macroeconomic stability versus greater integration with the world economy. Their relative merits remain open and important questions. Even in the most recent two decades, moving out of the lowest category for relative GDP per head takes a long time: more than eighty years on average. For many of the world's poorest countries, low relative income remains, perhaps surprisingly, a highly persistent state.

Annex I.

I.I Quantiles and mobility

One alternative to our approach would be the use of income quantiles, such as the use of quartiles to divide the sample. At first sight, a quantile-based approach might seem less arbitrary and would ensure that each state is well represented in the data. But in our setting, there is no guarantee that quantiles will line up with reasonable interpretations of 'low income'. In an analysis where the categories are based on continually updating quantiles, the implicit income thresholds will be varying over time; a country where relative income is growing at a constant rate will traverse the categories at varying speeds; and the stationary distribution will be uninformative by construction. These are all good reasons to avoid quantile-based studies of mobility when the subject of interest is the persistence of relative income.

1.2 Unique stationary distributions

The stationary distribution is hard to interpret unless it is unique. Once a transition matrix has been estimated, uniqueness can be verified using the Dobrushin coefficient, $\alpha(p)$, introduced in Dobrushin (1956). Our presentation follows Stachurski (2009, section 4.3.2) and repeats material in Imam and Temple (2024 a, b). Consider a right stochastic matrix P defined over the set of states S, and denote the transition probability from state x to state y by $p(x, y)$. The Dobrushin coefficient is defined as:

$$\alpha(p) := \min_{(x,x')\in\mathcal{S}\times\mathcal{S}} \sum_{y\in\mathcal{S}} p(x,y) \wedge p(x',y)$$

where the notation $a \wedge b := min\{a, b\}$ and the index $\alpha(p) \in [0, 1]$. It can be shown that the process is globally stable if and only if there exists a strictly positive integer t such that $\alpha(p^t) > 0$. If this is true, the process will converge to a unique stationary distribution regardless of the initial conditions.[13]

This means we can take a transition matrix M and check whether it implies a unique stationary distribution. If the Dobrushin coefficient $\alpha(p)$ for P is non-zero, the process is globally stable. If the coefficient is zero, we should compute the Dobrushin coefficient for an iterate of the transition matrix, P^2, and try again. As long as we can find a strictly positive integer t such that the coefficient associated with P^t is non-zero, the process is globally stable. That turns out to be the case for each of the transition matrices we report.

1.3 The Markov property

One of the maintained assumptions of our analysis is that the various series can be well described by a stochastic process that satisfies the first-order Markov property. Kremer et al. 2001) found that output at five-year intervals can be so described, but not output at annual intervals. We have used five-year intervals. To examine the first-order assumption, Imam and Temple (2024b) adopt a comparison similar to Kremer et al. (2001). Using the Maddison data set, which extends furthest back in time, they compute 10-year transitions and then compare them with the square of a transition matrix for the same time span based on 5-year transitions. The two matrices are remarkably similar, which supports the use of a first-order process for 5-year

[13] For a formal statement, see Stachurski (2009, theorem 4.3.18); a related result appears in Stokey et al. (1989, theorem 11.4).

intervals applied to the Maddison data. Imam and Temple (2024b) reached similar conclusions when looking at 10-year transitions in the Penn World Table data.

1.4 Constant growth thresholds

We briefly discuss constant growth thresholds, drawing on Imam and Temple (2024b). Note that, in using these, we are not making any assumption about whether countries grow at constant rates in practice (they clearly do not). Rather, we want to define the spans of our income classes so that the times taken to traverse them can be compared across classes, without spurious effects driven by the class definitions. Otherwise, the comparisons of upwards mobility between different points in the distribution would be undermined: some classes would be harder to traverse than others because of their wider span, and not because they were intrinsically harder to escape.

Quah (1993) used five states and chose thresholds (0.25, 0.5, 1, 2) where the numbers measure income relative to the world mean. These are an example of constant growth thresholds if growth is measured using the growth of income relative to the world mean. Kremer et al. (2001) initially used the same thresholds, but then adopted (1/16, 1/8, 1/4, 1/2) where the numbers now measure income relative to the five richest countries. Jones (1997) had earlier used income relative to that in the US, but with six states and thresholds of (0.05, 0.1, 0.2, 0.4, 0.8); see Jones (2016) for an update of this analysis. Again, these are constant growth thresholds.

Some papers on the middle-income trap, including Bulman et al. (2017), use just three income categories. In that case, there is only one intermediate state, and the question of constant growth thresholds becomes moot. But for present purposes, three income categories will be too few: it will be hard to distinguish between the persistence of low income and a middle-income trap. Using at least four or five categories, as in this paper, helps to ensure that the different possibilities are not conflated. Given the use of at least four categories, there is nothing in our approach which rules out persistence in low relative income at the same time as a middle-income trap.

1.5 Bootstrap

We use a parametric bootstrap with 2001 replications. The bootstrapped standard errors for the transition probabilities are typically very similar to the Anderson-Goodman asymptotic standard errors we report, except in a few cases where a state is relatively rarely observed. In those cases, the bootstrapped standard errors tend to be somewhat higher. In the case of the MET_1 statistic, its form means that its sampling distribution is likely to be skewed, and so we report a bootstrapped 90% confidence interval rather than a standard error.

Country samples

Sample for Tables 1 and 2

Afghanistan, Albania, Algeria, Angola, Argentina, Australia, Austria, Bahrain, Bangladesh, Barbados, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, China Hong Kong SAR, Colombia, Comoros, Congo, Costa Rica, Côte d'Ivoire, Cuba, Cyprus, Czechoslovakia, D.R. of the Congo, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Ethiopia, Finland, Former USSR, Former Yugoslavia, France, Gabon, Gambia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kuwait, Lao People's DR, Lebanon, Lesotho, Liberia, Libya, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Republic of Korea, Romania, Rwanda, Saint Lucia, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, State of Palestine, Sudan (Former), Swaziland, Sweden, Switzerland, Syrian Arab Republic, Taiwan, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, U.R. of Tanzania: Mainland, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Viet Nam, Yemen, Zambia, Zimbabwe.

Sample for Tables 3 and 4

Angola, Argentina, Australia, Austria, Bahrain, Barbados, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Cameroon, Canada, Chile, China, China Hong Kong SAR, Colombia, Costa Rica, Côte d'Ivoire, Cyprus, Denmark, Dominican Republic, Ecuador, Egypt, Finland, France, Gabon, Germany, Greece, Guatemala, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kuwait, Luxembourg, Malaysia, Malta, Mauritius, Mexico, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Niger, Nigeria, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Korea, Romania, Rwanda, Saudi Arabia, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sudan (Former), Sweden, Switzerland, Taiwan, Thailand, Trinidad and Tobago, Tunisia, Turkey, U.R. of Tanzania: Mainland, United Kingdom, United States, Uruguay, Venezuela, Zambia, Zimbabwe.

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