At the Threshold: The Increasing Relevance of the Middle-Income Trap

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ABSTRACT

We investigate the existence of a middle-income trap using finite state Markov chains, constant growth thresholds, and mean first passage times. As well as studying output per head, we examine the dynamics of its proximate determinants: TFP, the capital-output ratio, and human capital. We find upwards mobility for the relative capital-output ratio and human capital, but not for relative TFP. The lack of upwards mobility in relative TFP, at least from an intermediate level, suggests that escaping middle-income status can take many years. A middle-income trap may become increasingly apparent in the years to come.

JEL Classifications: O40

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1 Introduction

Over the last sixty years, the ranks of high-income countries have expanded more slowly than might once have been expected. Many countries in Latin America and the Middle East have spent several decades at an intermediate level of development. But since Gill and Kharas (2007) introduced the idea of a middle-income trap, wide-ranging discussions of its policy relevance have far outweighed formal statistical evidence. Their working paper and report have been cited more than 1,500 times in total.[1] In their original formulation, middle-income countries find themselves caught between the rapidly-advancing technology of rich countries, and competition in mature products from poor countries with low wages (Gill and Kharas 2007, p. 5). More recently, the trap is the subject of the 2024 *World Development Report*, which argues that, as countries develop, their growth strategies should evolve through investment, 'infusion' (technology transfer) and then innovation (World Bank 2024).

In the policy literature, the existence of a trap has often been investigated using informal methods such as charts, with plenty of room for disagreement over each approach and its interpretation, and few claims that are precise enough to be falsifiable. This has not stopped some policy discussions from taking the existence of a trap as more or less given, and exploring what this implies for growth strategies. For Wade (2016), drawing on informal evidence, the trap seemed 'real enough' to form one basis for reconsidering industrial policy. Ideally we would have a more rigorous assessment of its extent and origins, and that is what we seek to provide in this paper.

In neoclassical growth models, the growth rate will typically decline for a country converging to a balanced growth path from below, unless the determinants of the height of that path (like the investment rate) are themselves moving in a favourable direction. But this conditional convergence effect would often be modest, and the intimations that not all is well in the 'middle world' seem to extend further. The finding of 'premature deindustrialization', due to Rodrik (2016), diagnoses a tendency for manufacturing in late convergence to peak at lower levels of activity, and earlier in the development process, than formerly. Slower growth appears to be one force in emerging discontent, as seen in Eastern Europe (Dijkstra et al. 2020).

But is there a genuine trap? As in much of the literature, we are reluctant to regard a trap as literal in the sense that a given income category can never be escaped. We also want to avoid the idea that a trap either exists, or does not. Rather, as explicitly argued in Cherif and Hasanov (2019), the issue is the length of time taken to emerge from middle income status. In our view, there is a trap if emerging from middle income is a lengthy and uncertain process which compares unfavourably with some historical precedents. Later, we introduce a summary statistic which quantifies the extent of any such trap, using a continuous measure of its relevance rather than a binary outcome or the testing of a point null hypothesis.

In some accounts, as a country moves to more advanced technologies, this will increas-

[1] Citations as listed by Google Scholar, 6 May 2025.

ingly require complementary investments and policies — more advanced education, support for particular industries and skills, better business services — that are hard to implement effectively. This does not preclude continued growth, but the task may be harder than a country's past experience might suggest, and make greater demands on state capacity. The middle-income trap has been used to characterize growth in Latin America and, as in Arezki et al. (2021), the Middle East and North Africa. And given the rising share of world population that lives in middle-income countries, in a global environment rather different from that experienced by their precursors, these questions have become more urgent.

The concept's policy relevance helps to explain its appeal, but so does the view that it is 'just sufficiently nebulous that it could not be disproved' (Yusuf, 2017, p. 20). The answer to this problem is to define the concept precisely and examine it in the data. We study the existence and origins of a middle-income trap using finite state Markov chains, drawing on ideas in Quah (1993), Feyrer (2008), and Im and Rosenblatt (2015), and other work that we discuss below. When the transition probability from middle-income to high-income is low compared to other upward transitions, this suggests that achieving high income status will be harder than earlier growth might suggest.

That is far from the whole story, however. There may be a significant risk of downwards mobility at earlier stages. A country may take an especially long time, on average, to escape middle-income status if the transition to a high-income category is sometimes delayed by falling back. As in Im and Rosenblatt (2015), we can study this formally using transition matrices to derive mean first passage times: that is, the expected time it will take to reach one state from another, given that both upwards and downwards mobility can arise. (These are also known in the Markov chain literature as 'expected first passage times' or 'hitting times'.)

We complement the use of mean first passage times with the systematic use of 'constant growth thresholds' to define the income categories. By choosing the categories appropriately, we can make comparisons of mean first passage times more informative about the questions of interest. Although such thresholds have been used in some of the prior work in the literature, we explain why they should be the default choice when the subject is the middle-income trap. We also introduce a simple summary statistic, derived by comparing mean first passage times under constant growth thresholds. The proposed statistic is a continuous measure of the extent of a trap, rather than treating this as a binary question about 'existence'. Put differently, we are interested in economic significance rather than statistical significance (although we look at that too).

We first use these tools to investigate a middle-income trap. We start with GDP data in PPP terms for seventy years, from 1950 to 2020. The long time span means that, even when using five-year intervals, we can draw on more than 2000 transitions between income categories, and obtain precise estimates of transition probabilities. The sample of countries represents more than 97% of the world population in 2020. We then use version 10 of the Penn World Table to look at transitions over forty-five years, between 1974 and 2019. In either case, mobility within the distribution of output per head is low. There is no long-run tendency for income differences to disappear, but nor is there much evidence that upward transitions from a middle-income category are uniquely difficult.

We then extend the analysis to the proximate determinants of GDP per head, such as TFP and the capital-output ratio. This 'dynamic development accounting' goes beyond the snapshots used in much of the development accounting literature, to study patterns of mobility in the variables that directly affect GDP. We find that relative capital intensity and human capital both show upwards mobility. Indeed, the two have been converging across countries, and this has disguised the lack of convergence in relative TFP. If these patterns continue, the future outcomes for output will be driven mainly by the TFP process.[2] A middle-income trap may become increasingly apparent in the years to come, unless higher human capital helps to close the gaps in relative TFP, or unless — as Patel et al. (2021) and Kremer et al. (2022) argue — the convergence process has changed over the last twenty years.

If income classifications are made sufficiently fine, the persistence of middle income can coexist with the persistence of low income, or even a poverty trap. In a companion paper, Imam and Temple (2025a), we use some of the ideas developed here to examine the persistence of low relative income and TFP for the poorest countries. We also ask whether the worldwide increase in educational attainment is changing the dynamics of relative TFP, as an endogenous growth perspective might predict. To some extent, policymakers may need to know about both forms of trap, especially if particular investments — such as those in human capital or state capacity — can help both in escaping low income and in lessening the risk of later stagnation at intermediate levels of income.

Overall, the paper makes four main contributions. We explain why constant growth thresholds should be the default choice for Markov chains applied to this question; we make the concept of a trap operational by developing a continuous summary measure of its extent; we study potential traps not only in output dynamics but in the proximate determinants of output per head; and we take advantage of the longer time spans of data now available. Several steps in our analysis mirror those in Feyrer (2008), but his data ended in 1989. Since our samples typically end in 2019 or 2020, we bring another thirty years of new data to bear on these questions.[3] The longer span of the data means that we can estimate transition probabilities and mean first passage times more precisely than was possible in the earlier literature. It also means we can look at how income dynamics differ between subgroups of countries and between subperiods, and use formal tests of homogeneity, to an extent that would not have been possible at the time of Quah (1993).

The paper has the following structure. The next section provides background. Section 3 describes the methods and section 4 the data. Section 5 sets out the first results, for output dynamics. To understand what might be driving these dynamics, section 6 looks

[2]Note that here we are extrapolating from the final period of data using estimated transition matrices, given that the long-run equilibrium has not been reached; we assume that transition probabilities remain constant over time. We discuss this later in the paper.

[3]Compared to Quah (1993), for example, this is a doubling of the size of the data set even before improving the country coverage.

in detail at the proximate GDP determinants. Section 7 does the same, but now using a common sample of countries, with better country coverage; these results are the ones most important to our overall message. Section 8 explores robustness, before section 9 concludes. An appendix covers some technical issues in more detail than the main text.

2 Background

The literature on the middle-income trap distinguishes between an absolute trap (a region of income above which growth becomes more difficult) and a relative trap (a range of income relative to the frontier that is hard to move beyond).[4] Both seem of potential interest, but are likely to require different methods. Our empirical work will address only the relative trap, which has arguably been the one more commonly discussed. For reviews of the literature that discuss both types, see Agénor (2017), Glawe and Wagner (2016), and Im and Rosenblatt (2015), while Gill and Kharas (2015) review the broader debate.

Ideally there would be more guidance from theory, and some argue that middle-income traps have no theoretical foundations. But there are many different models of multiple equilibria in development levels, which could sometimes be adapted to deliver either a relative or an absolute trap. Indeed, there are arguably too many models to choose from relative to the scope for testing them against the data; it would then be a mistake to tether an empirical analysis too closely to a single theoretical model.[5]

Before the concept of a middle-income trap was introduced by Gill and Kharas (2007), Acemoglu et al. (2006) had developed a related model. They studied growth strategies or regimes when firms choose whether to innovate or adopt technologies from the world technology frontier. Countries may become trapped in an investment-based regime rather than one which promotes convergence. In retrospect, this can be seen as anticipating the idea of a middle-income trap, and it is among the models discussed in Agénor (2017).

Aghion and Bircan (2017) emphasize the Schumpeterian foundations of middle-income traps. For an economy undergoing structural transformation, the process may require complementary investments and policies, to improve the quality of institutions, upgrade skills, and stimulate technology transfer or even innovation. Ideas along these lines could be used to justify either an absolute or a relative middle-income trap. In contrast, Doner and Schneider (2016) argue that the origins of a trap should ultimately be sought in political economy rather than economics: what matters is whether there are political coalitions that favour institutional development and reform.

For an absolute trap, a natural approach is to look at whether growth slows down once a particular income range has been approached. Work in this vein includes Aiyar et al. (2018), Eichengreen et al. (2014), Felipe et al. (2017) and Spence (2011). These studies typically examine whether middle-income countries experience growth slowdowns. One drawback of

[4] Note that, in line with much of the literature, we often use 'income' as a convenient shorthand for GDP per head, albeit with some loss of precision.

[5] As Temple (2010, p. 4442) noted, growth economics has often been regarded as theory-rich and data-poor.

this approach is that medium-run global and regional growth varies over time, as when the debt and financial crises of the 1980s and 1990s saw many countries experience slow growth or even output collapses. Moreover, distinguishing between an absolute middle-income trap and other forms of slowdown, such as those associated with conditional convergence from below, may not be straightforward. And what ultimately matters is not just whether growth slows down, but the extent and persistence of the slowdown.

A different version of a middle-income trap considers 'middle income' to be a relative concept. Then, perhaps the most natural approach is to model transitions between income classes, building on Quah (1993).[6] This has been undertaken before, but we extend that work in several ways. When specifying the thresholds for the income categories in the Markov chain, our choices imply that a country growing at a constant rate (relative to the US, say) would take a constant length of time to traverse each of the intermediate states. This allows meaningful comparisons of mean first passage times between different states, which can then be combined into a useful continuous measure of the extent of a trap. Further, we look beyond GDP per head and study the evolving distributions of proximate GDP determinants: relative capital intensity, human capital, and TFP. This allows us to consider not only what has happened to date, but also, by extrapolating from recent trends, to make predictions about the possible future incidence of middle-income traps.

Our paper will conclude that capital intensity and human capital are converging, but this has disguised a lack of upwards mobility in relative TFP. If these patterns continue, the lack of TFP convergence will begin to dominate the outcomes for relative output per head. The findings tally with some earlier contributions to the growth literature, notably Krugman (1994). Drawing on a pre-publication version of the classic study by Young (1995), he argued that growth in the East Asian miracle economies was primarily due to factor accumulation rather than TFP growth. The likely outcome would be a growth slowdown and the end of the 'miracle age' (Yusuf and Evenett 2002; see also Cherif and Hasanov, 2019). The scope for catch-up through factor accumulation would exhaust itself before rich-country status had been reached.

This perspective is consistent with some other work on proximate GDP determinants, including work that was not directed at the middle-income trap. Feyrer (2008) uses Markov chains to study transitions for proximate growth determinants. Our analysis is influenced by his, but we make some changes for the current setting. The states in his paper are defined relative to the world mean (for example, TFP relative to the world mean) and this makes it harder to draw inferences about convergence to the frontier or the persistence of an intermediate level of development. In addition, his dataset ended in 1989, whereas we can now take advantage of another thirty years of data.

Another paper which overlaps with some of our findings is that of Schelkle (2014). He does not use transition matrices, but finds that, when countries fall further behind the US, the explanation is typically declining relative efficiency rather than declines in relative factor supplies. This is consistent with our findings, but reached via a different route.

[6] For an alternative approach to a relative trap using time series tests, see Ye and Robertson (2016).

Our paper is more distantly related to recent work analyzing aggregate convergence, such as Roy et al. (2016), Patel et al. (2021) and Kremer et al. (2022).[7] Our paper complements theirs by adding information on mobility within cross-country distributions of outcomes, especially the proximate determinants of GDP. Recent experience then sheds new light on the prospects for a continuing middle-income trap. At first sight, our findings on those prospects greatly differ from those of Patel et al. (2021). However, their middle-income category — GDP per head between 7.85% and 33.55% of the US level, in PPP terms — is less demanding than ours (Patel et al. 2021, fn. 5). In much of our analysis, the middle-income category extends between 32% and 64% of US GDP per head. We discuss this choice later, along with some alternative choices.

3 Methods

The use of Markov chains to study 'distribution dynamics' has been one alternative to modelling growth using linear regressions, which have well-known problems.[8] To clarify, we are not making a case that one method is somehow 'better' than another, since that will depend on the context and the research question, among other considerations. Instead our claim is that middle-income traps are often best examined in terms of differences in mobility between relative income classes, and that we can study this using a finite state Markov chain as in Quah (1993). We are not the first authors to propose this approach to middle-income traps — see Im and Rosenblatt (2015) in particular — but we argue that it can be taken further, and may help to resolve some of the problems of the existing literature.

Since the basics of Markov chains are well known, we describe them only briefly, following Imam and Temple (2024a), which in turn draws heavily on Stachurski (2009).[9] Consider a series $\{X_n, n \geq 0\}$ in discrete time, with a discrete state space $\mathcal{S}$ with states $1, .., S$. We consider a transition matrix $P = [p_{ij}]$ where $p_{ij} = P\{X_n = j | X_{n-1} = i\}$ for all $i, j \in \mathcal{S}$. The elements of this matrix 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. We will investigate this property as part of our later analysis.

Denote the marginal or unconditional distribution over the states at time t by a row vector ψ_t.[10] 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

[7] For wider reviews of the convergence literature see Johnson and Papageorgiou (2020) and the first part of Johnson et al. (2025).

[8] For extended discussions see, for example, Durlauf et al. (2005) and Temple (2021).

[9] See also the presentation in the classic textbook by Norris (1997).

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

on a finite state space has at least one stationary distribution, satisfying $\psi^* = \psi^* P$. 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 that equilibrium 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 evidence to reject it for five-year intervals. To investigate this, they compared a matrix estimated from ten-year intervals with the square of a matrix estimated from five-year intervals. If the Markov property holds for five-year transitions, the two matrices should be similar, and that is what they found. Using more recent data, we will make use of a similar comparison below, also with supportive results.

It is worth reiterating that, relative to the early studies, we now have far more data. Quah's data ended more than thirty-five 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 typically draw on more than a thousand transitions from which to estimate transition probabilities. This means that the probabilities of even quite rare transitions can be estimated with some precision, if the relevant origin state is observed in the data often enough.

To allow straightforward interpretation of the results, we translate GDP per head into discrete categories for income, relative to that of a benchmark country or group of countries. This requires us to choose threshold relative income levels that define the categories.[11] We think a natural stipulation here is to choose the thresholds so that, if a country is growing at a constant relative rate, it will take the same amount of time to traverse the intermediate income categories (not the highest or lowest). If relative GDP per head grows exponentially at a constant rate, it has a constant doubling time — indeed, there will be a fixed time specific to any other given proportionate change. Hence, we can meet our stipulation if (and only if) the income thresholds for the categories increase geometrically. We call these *constant growth thresholds* and use them in all the analyses that we present.

Note that 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.

This choice helps to bring approaches based on transition matrices closer to studies which examine within-country growth slowdowns. With constant growth thresholds, if a

[11] Note that, because we work in terms of *relative* income, the thresholds are constant; but these correspond to absolute levels of income that change over time, and that depend on the choice of benchmark countries.

country's relative growth slows down, the country will take longer to move upwards through the higher income classes. If other middle-income countries behave similarly, at least on average, then slowing relative growth will be reflected in probabilities for upward transitions that are lower for middle-income countries than for countries that are poorer.

Writing well before the concept of a middle-income trap was introduced, 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 relative to the growth of 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 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.

Although most of this work preceded research interest in a middle-income trap, the results of Quah (1993) and Kremer et al. (2001) do shed some light on the phenomenon.[12] In Table 1 of Quah (1993), the 23-year transition probability of moving upwards from the $(1, 2)$ income category (relative to the world mean) is 0.24, compared to 0.26 for the next lowest category. In Table 5 of Kremer et al. (2001), the 5-year transition probability of moving upwards from the $(1/4, 1/2)$ category is 0.083, while the probability of moving up from the next lowest category, $(1/8, 1/4)$, is slightly higher, at 0.113. These differences are clearly only modest, and do not provide much support for a middle-income trap.

In any case, an approach based purely on upwards mobility will miss part of the story. The risk of downwards mobility also influences the expected length of specific transitions: some middle-income countries may take a long time to 'graduate' because they happen to fall back for a time. The risk of detours means that we should assess the middle-income trap using mean first passage times as well as examining upward transitions. The passage or hitting time of matrix P for a subset J of the outcomes — the time taken to reach one of those outcomes — is the random variable H_J given by

$$H_J(\omega) = \inf\{n \geq 0 : X_n(\omega) \in J\}$$

The mean first passage time from state i to a state in J is then just the expectation of H_J given we start from a particular state i, and can be computed from the elements of the transition matrix (see the appendix). These mean passage times reflect the range of possible routes through the various states, taking into account that some routes are more likely than others.

Given a set of constant growth thresholds and a matrix of mean first passage times, we can define a middle-income trap in more precise terms than has been the norm in the literature. For there to be a genuine trap, the mean first passage time from middle to high income should be long, and greater than the mean first passage time from low to middle income. In addition, we wish to avoid reducing the complexity of an evolving

[12] Jones (1997, 2016) presents his findings in a way that makes our present comparisons more difficult.

income distribution to an over-simple dichotomy between the existence or non-existence of a trap. We propose using the difference in mean first passage times between the upwards transition to the highest category from the next highest, and upwards transitions from the third-highest category. We call this statistic ΔMPT and use it to summarize some of the later results.

More formally, if there are $n \geq 3$ states, we are interested in the following statistic:

$$\Delta MPT = MPT[n-1, n] - MPT[n-2, (n-1, n)] \tag{1}$$

where $MPT[i, j]$ is the mean first passage time from state i to state j, and the final term in the above expression is the mean time taken from state $n-2$ to hit first either state $n-1$ or state n. As with the mean first passage times from which it is constructed, an estimate of this statistic will be a complicated nonlinear function of the estimated transition probabilities, but our simulations suggest that it is approximately median unbiased.[13] Also note that if there are more than three states, and state $n-2$ corresponds to lower-middle income and state $n-1$ to upper-middle income, this statistic will reveal whether an upper-middle income trap is more severe than a lower-middle income trap; we return to this point later in the paper.

Since we can bootstrap the mean first passage times and hence the ΔMPT statistic, it might seem natural to test for the existence of a middle-income trap, perhaps based on whether the statistic is significantly greater than zero. But, as already mentioned, we want to avoid treating the existence of a trap as a binary question, and instead focus on its extent and practical significance. With this in mind, a confidence interval is our preferred form of presentation. For example, if the 90% interval for ΔMPT were, say, $[1, 3]$, we would reject the null of no trap, but there is clearly no trap of any real significance; the mean first passage times in (1) are different by only a few years. Conversely, if the interval were $[-1, 60]$, we would fail to reject the null of no trap, but clearly the data are potentially consistent with a trap of some importance. These conclusions can be reached directly from the reported intervals, whereas the testing of a point null hypothesis might obscure more than it reveals.

In more recent work directed at the middle-income trap, papers have used constant growth thresholds only sometimes. Han and Wei (2017) come close, with thresholds (0.16, 0.36, 0.75) in their first analysis. Im and Rosenblatt (2015) work with two sets of thresholds, one of which is (0.15, 0.30, 0.45, 0.60). A country growing at a constant relative rate will move upwards through these categories increasingly quickly, which seems problematic; for example, going from 0.15 to 0.30 requires a doubling of relative GDP per head, while going from 0.30 to 0.45 is an increase of only 50%. In another part of their analysis, the thresholds are based on Kremer et al. (2001) and do increase geometrically in the way we recommend.

Milanovic (2005, Table 7.3) reports transition matrices for 1960-78 and 1978-2000 with

[13] In a working paper version, Imam and Temple (2024b), we used a simpler statistic, but one which becomes harder to interpret when there is some leapfrogging from state $n-2$ to state n.

four income categories, but the income thresholds do not increase geometrically. Some other papers on the 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 existence of a middle-income trap versus the existence of a low-income (or poverty) trap. In practice both forms of trap, just one, or neither, may be empirically relevant. Using at least four or five income 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 the coexistence of a low-income trap and a middle-income trap. In a companion paper, Imam and Temple (2025a), we investigate the persistence of low relative income for the poorest countries.

Given the literature that followed Quah (1993), which demonstrated that small changes in transition probabilities can greatly alter long-run predictions, we think it is good practice to report the transition counts (the absolute numbers of transitions). This information is not redundant: 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), 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, and there is no reason for that probability to be estimated imprecisely. A more serious problem arises when a state is observed only rarely in the data, so that small numbers of transitions can have large effects on the estimated probabilities. But some results will be robust even then: a state which is observed only rarely will have little effect on the long-run properties of the process, such as the long-run distribution and the asymptotic rate of convergence. These points imply that low transition counts should be interpreted carefully, and do not preclude useful findings.

To understand which transition probabilities can be precisely estimated from our data, we will 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. This is also true of our estimated long-run distributions, mean first passage times, and the ΔMPT statistic, where we estimate the effects of sampling variability using a parametric bootstrap;

Feyrer (2008) used this approach for long-run distributions, but did not consider mean first passage times.

Quah (1993) identified an emerging tendency towards 'twin peaks' in the long-run distribution of relative GDP per head. For that variable, upwards and downwards mobility were both limited, and convergence to a long-run distribution rather slow. As Imam and Temple (2024a) discuss, slow convergence tends to go together with a sensitivity of the long-run distribution to small changes in transition probabilities. These could arise through alternative state definitions, measurement errors, or changes in the sample of countries.[14]

Similarly to Kremer et al. (2001), we find that convergence to the long-run distribution of GDP per head is slow. But it is typically much faster for the proximate growth determinants that we study, and hence the long-run distributions for those variables should be more robust. In each case, we report an asymptotic measure of convergence speed, following Kremer et al. (2001, p. 290). The measure is defined as:

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

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 long-run 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.

As always with convergence, definitions matter and there is a risk of conflating different economic ideas.[15] The γ statistic tells us how fast the unconditional distribution is converging (asymptotically) to the long-run distribution. But in the case of output, the world is converging towards a long-run distribution dispersed across several relative income categories: we hence find against absolute convergence (the long-run elimination of differences in levels). A similar conclusion obtains for relative TFP. In the long-run distribution, almost half the world's countries are below the highest category. It is this finding which prompts our suggestion that a middle-income trap will become increasingly apparent in the years to come.

In other work that followed Quah's contributions, Fiaschi and Lavezzi (2003, 2007) defined states by growth as well as income; Im and Rosenblatt (2015) looked for a middle-income trap; and Feyrer (2008), Johnson (2005) and Barseghyan and DiCecio (2011) showed what could be learnt from combining Quah's ideas with those of development accounting.[16] Perhaps the main drawback of the Markov chain approach is that translating the continuous variable of GDP per head into discrete categories can distort the findings (Bulli 2001). An

[14] 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.

[15] For a review and discussion of convergence concepts, see Galor (1996).

[16] 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.

alternative approach is to use stochastic kernels, as in Quah (1997), Johnson (2005), and Barseghyan and DiCecio (2011). But for the questions of most interest here, the results are much easier to report and interpret if we use discrete income categories. Later sections will report on what happens when we choose different thresholds.

Another issue has been the choice of benchmark. Quah (1993) defined his income classes at each date relative to the world mean at that date. 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, as in Jones (1997, 2016); in the robustness section, we will consider what happens when we instead study outcomes relative to the median of the G7 economies.

4 The data

Our samples for the various analyses include most of the world's countries and, in our largest sample, represent more than 7.6 billion people in 2020, or more than 97.7% of that year's world population. In the smaller samples, the countries missing are mainly the transition economies of Europe and central Asia, including successor states of the USSR such as Azerbaijan and Kazakhstan. The latter states would be especially hard to include in a balanced panel without reliable subnational data for the USSR, since this rules out a continuous time series for successor states.

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. This allows us to start the analysis in 1950 and consider more than two thousand transitions, based on 145 countries.[17] The Maddison Project measures are designed to allow comparisons across 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. Since we are focused on relative income, the results will be influenced to the extent that, say, middle-income and poor countries were differently affected. But our results are in line with our working paper, Imam and Temple (2024b), in which most of the samples ended in 2015.

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. Our typical sample based on PWT data starts in 1974 and ends in 2019, although we sometimes consider an earlier start date of 1964, which reduces the country coverage. The PWT output measure we use is that known in version 10 as 'rgdpo', which is output-side real GDP at chained

[17] 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.

PPPs, to compare relative productive capacity across countries and over time.

When analyzing the PWT data, rather than use 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 may provide a better measure of productivity for our purposes than using either GDP per head or GDP per worker. 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.

4.1 Category thresholds

We need a benchmark for middle income, relative to the frontier as defined by either the US or the median of the G7 economies. The frontier paths themselves are plotted in Figure 1, which uses the Maddison data. The paths run broadly in parallel until the most recent decade, when the US pulls ahead. This suggests that the results could vary depending on the choice of frontier economy, and we return to this in section 7 below.

How close does an economy need to approach these frontiers to be considered high income? The best-known thresholds are those of the World Bank, but they are defined using comparisons at market exchange rates (smoothed using the Bank's Atlas method) rather than in PPP terms. Given our focus on comparative productivity and living standards, we want to make comparisons in PPP terms, and to use thresholds that increase geometrically.[18]

Our chosen benchmark for high income draws on the historical positions of OECD member countries. In Table 1, we report relative GDP per head at ten-year intervals, and in PPP terms, for the countries that belonged to the OECD as of 1975, using the Maddison data. There are a few outliers, notably Greece, Portugal and Turkey, but more generally it is clear that the GDP per head of OECD members typically exceeds 64% of the US level. We convert this observation into a particular set of constant growth thresholds, namely $(0.08, 0.16, 0.32, 0.64)$. Hence an intermediate level (such as middle-income for a GDP series) will be defined as between 32% and 64% of the US level. By making this explicit, we can refine the 'nebulous' concept of a middle-income trap into one that can be studied more formally. In section 7, we will consider alternative definitions of the middle-income range.[19]

The 2024 *World Development Report*, in line with the World Bank's historical practice, uses a much less demanding (and absolute) income threshold for achieving middle income. On that definition, as of 2022, three-quarters of the world's population was found to live in middle-income countries (World Bank 2024, p. 31). Here, we define middle income as a narrow range of relative income. Our results could be seen as relating to an upper-middle

[18] Felipe et al. (2017) introduce a way to map between thresholds defined in PPP terms and those based on comparisons at market exchange rates, but their method would not lead to constant growth thresholds.

[19] In an early working paper version, we used slightly more demanding benchmarks for middle and high income, of 36% and 72% respectively; the qualitative conclusions were similar.

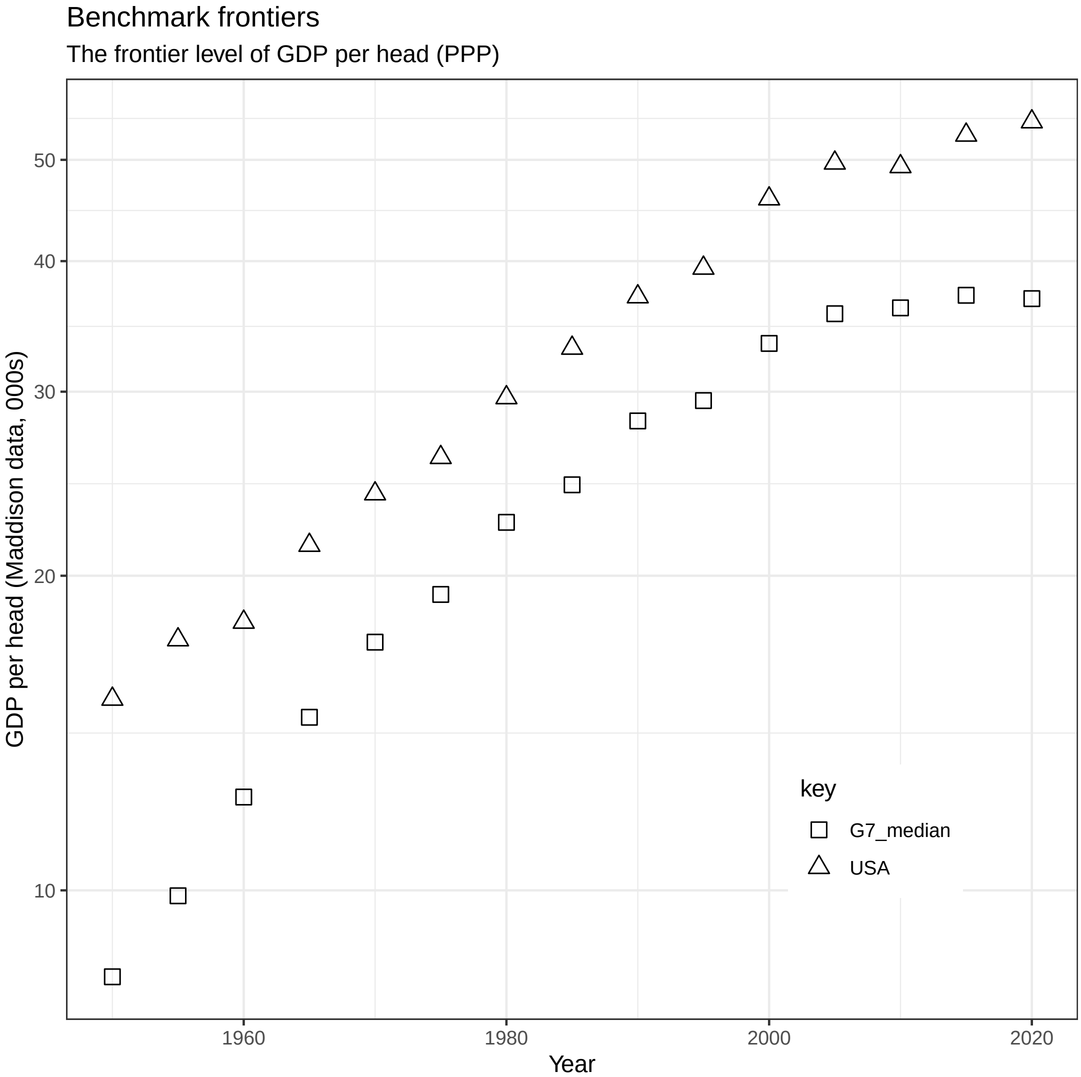

Figure 1: The income paths of the frontiers

income trap, a concept used in the prepublication version of Felipe et al. (2017) and taken up in Glawe and Wagner (2016) and Islam et al. (2023), among others. Indeed, our ΔMPT statistic, at least as implemented here, will in effect examine whether an upper-middle income trap is more severe than a lower-middle income trap. Such a distinction may be especially useful for policy purposes, and we return to this point in the conclusions.

5 Output dynamics

First of all, we look at transitions within the Maddison data on real GDP per head, between 1950 and 2020. This will be the largest sample used in the paper: a balanced panel of 145 countries observed at 15 points that are each five years apart. This leads to data on a total of $NT = 145 \times (15 - 1) = 2030$ transitions. The countries are listed in the Appendix. Before we report the results, we note a qualification to our findings: since output

Table 1: Relative GDP per head, 1950-2020, for 1975 OECD members

	1950	1960	1970	1980	1990	2000	2010	2020	Median
Australia	0.78	0.78	0.80	0.78	0.74	0.80	0.92	0.89	0.79
Austria	0.39	0.58	0.65	0.74	0.73	0.76	0.82	0.74	0.73
Belgium	0.57	0.61	0.71	0.78	0.74	0.73	0.77	0.71	0.72
Canada	0.76	0.77	0.80	0.87	0.81	0.81	0.84	0.78	0.80
Denmark	0.73	0.78	0.84	0.82	0.80	0.85	0.87	0.87	0.83
Finland	0.44	0.55	0.64	0.70	0.73	0.71	0.76	0.71	0.70
France	0.54	0.65	0.76	0.79	0.76	0.73	0.73	0.66	0.73
Germany	0.41	0.68	0.72	0.76	0.69	0.73	0.83	0.83	0.72
Greece	0.20	0.28	0.41	0.48	0.43	0.46	0.54	0.40	0.42
Iceland	0.56	0.61	0.62	0.83	0.78	0.72	0.74	0.72	0.72
Ireland	0.36	0.38	0.41	0.46	0.51	0.85	0.99	1.01	0.48
Italy	0.37	0.52	0.65	0.71	0.70	0.71	0.71	0.60	0.68
Japan	0.20	0.35	0.65	0.72	0.81	0.72	0.71	0.68	0.70
Luxembourg	0.88	0.88	0.87	0.84	0.99	1.09	1.10	0.98	0.93
Netherlands	0.63	0.73	0.80	0.79	0.74	0.83	0.89	0.85	0.80
New Zealand	0.88	0.84	0.74	0.66	0.59	0.58	0.64	0.66	0.66
Norway	0.57	0.64	0.67	0.81	0.80	1.18	1.59	1.54	0.80
Portugal	0.22	0.26	0.36	0.43	0.47	0.51	0.52	0.47	0.45
Spain	0.23	0.28	0.40	0.47	0.52	0.59	0.65	0.57	0.49
Sweden	0.70	0.77	0.85	0.80	0.76	0.75	0.87	0.81	0.78
Switzerland	0.76	0.91	0.98	0.93	0.93	0.94	1.16	1.11	0.94
Turkey	0.14	0.17	0.18	0.20	0.23	0.26	0.34	0.44	0.22
United Kingdom	0.73	0.76	0.72	0.70	0.71	0.70	0.71	0.64	0.71
United States	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table shows GDP per head relative to US, Maddison data

is subject to short-run fluctuations and measurement error, the matrices we present will tend to overstate mobility compared to the true extent of mobility within the distribution of potential output. It is likely that smoothing out short-run fluctuations would reinforce our conclusion that mobility is limited.

When reporting the transition matrices and mean first passage times, we show key entries in bold. These often relate to the transitions between, first, $[0.16, 0.32)$ and $[0.32, 0.64)$, and second, between $[0.32, 0.64)$ and $[0.64, \infty)$; the numbers here are for data relative to the US. If there is an upper-middle income trap, we would expect the second of these transition probabilities to be lower than the first. Similarly, and more importantly, we would expect the second mean first passage time to be higher than the first, indicating that upwards mobility takes longer to achieve as a country moves upwards through the categories. But we also need to take into account leapfrogging from the $[0.16, 0.32)$ state to the highest, which our ΔMPT statistic does, as explained earlier.

The results are shown in Tables 2 and 3. In Table 2, 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) and Kremer et al. (2001) among many others.

Table 2 and later tables also report the final observed distribution (that is, the one in the final period of data) and the distributions to be expected 25 and 100 years later, based on iterating the transition matrix. The 25-year and 100-year projections will be less sensitive than the long-run distribution to individual transition probabilities; see Kremer et al. (2001). The long-run distribution can be interpreted as a meaningful long-run forecast only if transition probabilities are assumed to remain constant indefinitely. That would clearly be a very strong assumption, but as in Quah (1993, fn. 4), we can see the long-run distribution as an interesting way to reveal tendencies hidden in the data, at least if interpretation is cautious. We also report bootstrapped standard errors for the long-run distribution, as in Feyrer (2008).

Table 3 shows the mean first passage times and the mean first recurrence times. In reading the former, the initial state sets the row, and the destination state the column. The entry in a row and column indicates the number of years that will elapse, on average, in moving from the row state to first reaching the column state. These mean passage times take into account all possible routes through the states over time, using calculations that are matrix-based as in Grinstead and Snell (2006); see our appendix for details.

We can see that upwards mobility is slow, while there are also some downwards transitions. The combination explains why, although the long-run distribution places the greatest mass on the highest output category (relative GDP per head at least 64% of the US level), countries will spend more than half the time below this category, so there will be major differences in productivity even in the long run. In addition, the asymptotic rate of convergence is slow. All this suggests there are limits to the speed and extent to which countries are converging. But is there a middle-income trap? At first glance, perhaps yes: the middle-income category, running from 32% to 64% of relative GDP per capita, is the second most important in the long-run distribution. Looking at the individual transitions, however, there is little evidence of a distinct middle-income trap, as opposed to limited mobility more generally. This lack of mobility is consistent with Quah (1993) and Kremer et al. (2001), among others.

A more systematic approach would use our ΔMPT statistic, and we report this in the last row of Table 3, together with a bootstrapped 90% confidence interval. The statistic is 29.6, indicating that the average time to move from the penultimate income category to the high income one is almost 30 years longer than the average time to move upwards from the category two below the highest. We cannot rule out much higher values, but the statistic is imprecisely estimated, as is clear from the 90% confidence interval. In some of our later results, the ΔMPT statistic will be estimated more precisely than this.

Table 2: Five-year transitions, Maddison data, 1950-2020

Transition matrix	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.953	0.044	0.003		
	(0.008)	(0.008)	(0.002)		
<0.16	0.071	0.816	0.113		
	(0.013)	(0.019)	(0.016)		
<0.32		0.078	0.812	**0.106**	**0.005**
		(0.013)	(0.019)	(0.015)	(0.003)
<0.64			0.092	0.805	**0.103**
			(0.018)	(0.024)	(0.019)
$< \infty$				0.043	0.957
				(0.012)	(0.012)
Convergence	$\gamma = 144$				
Last period	0.283	0.172	0.186	0.166	0.193
25 years ψ_{T+25}	0.274	0.155	0.182	0.154	0.234
100 years ψ_{T+100}	0.242	0.133	0.163	0.155	0.307
Stationary ψ^*	0.144	0.097	0.146	0.176	0.437
(s.e.)	(0.054)	(0.026)	(0.032)	(0.034)	(0.103)
Transition counts					
<0.08	603	28	2	0	0
<0.16	28	324	45	0	0
<0.32	0	34	354	46	2
<0.64	0	0	24	211	27
<∞	0	0	0	13	289
$NT = 2030$	$N = 145$	$T = 14$			

Transitions are always from the row state to the column state. For more details see the text.

Table 3: Mean first passage times, Maddison GDP per head

MPT/MFR	<0.08	<0.16	<0.32	<0.64	$<\infty$
<0.08		127.7	203.9	328.8	467.4
<0.16	605.2		105.4	230.3	368.9
<0.32	937.7	332.5		**124.9**	263.5
<0.64	1123.0	517.7	185.3		**149.7**
$<\infty$	1239.1	633.9	301.4	116.2	
MFR	34.7	51.7	34.1	28.4	11.4
$\Delta MPT = 29.6$	$90\% CI$	$[-23.5$	$103.1]$		

From row state to column state, mean passage times (MPT) and mean first recurrence (MFR) times in years, rounded to one decimal place. For more details see the text.

Next, we look at transitions using data from the Penn World Table, for the shorter time period of 1974 to 2019, and a set of countries that represents 92.7% of 2019 global population. The results are shown in Tables 4 and 5, based on data for 133 countries and 9 transitions per country. The results are quite similar to those from the Maddison data, despite the shorter time span. The long-run distribution is spread across a range of outcomes, as Feyrer (2008) also found, which means that relative income dispersion is expected to persist. Again there is a general lack of mobility, but the ΔMPT statistic is imprecisely estimated. At least on this metric, these data do not resolve whether there is a genuine middle-income trap, but do leave the possibility open.

6 Proximate determinants

What might explain the lack of long-run convergence? To investigate this, we next examine transitions for the proximate determinants of GDP per head. This allows us to consider the various different forces underlying the observed output dynamics, and ask how they might play out across future decades.

The first step draws on the literature on development accounting that began with Hall and Jones (1999) and Klenow and Rodriguez-Clare (1997), who in turn built on Mankiw et al. (1992). We start with 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. We then rewrite this in terms of output per working-age adult and the capital-output ratio, as:

$$\frac{Y}{L} = A^{\frac{1}{1-\beta}} \left(\frac{K}{Y}\right)^{\frac{\beta}{1-\beta}} h \tag{2}$$

Table 4: Five-year transitions, PWT output, 1974-2019

Transition matrix	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.923	0.074	0.003		
	(0.015)	(0.014)	(0.003)		
<0.16	0.132	0.745	0.123		
	(0.022)	(0.028)	(0.021)		
<0.32	0.004	0.117	0.771	**0.108**	
	(0.004)	(0.021)	(0.027)	(0.020)	
<0.64			0.126	0.753	**0.121**
			(0.025)	(0.032)	(0.024)
<∞				0.097	0.903
				(0.021)	(0.021)
Convergence	$\gamma = 92.3$				
Last period	0.271	0.165	0.203	0.173	0.188
25 years ψ_{T+25}	0.279	0.169	0.191	0.164	0.197
100 years ψ_{T+100}	0.291	0.168	0.183	0.155	0.194
Stationary ψ^*	0.299	0.170	0.181	0.155	0.194
(s.e.)	(0.082)	(0.034)	(0.034)	(0.038)	(0.067)
Transition counts					
<0.08	310	25	1	0	0
<0.16	32	181	30	0	0
<0.32	1	28	185	26	0
<0.64	0	0	23	137	22
<∞	0	0	0	19	177
$NT = 1197$	$N = 133$	$T = 9$			

Transitions from row to column. For more details see the text.

This reformulation has often been adopted because the capital-output ratio will be constant along a balanced growth path.[20] The capital-output ratio can be seen as indexing an economy's level of capital intensity even when A and (K/L) are both growing, as usually considered likely in the long run. The output contribution assigned to TFP is amplified when the capital-output ratio is held constant. This perspective is especially appropriate when motivated by neoclassical growth models: whenever TFP rises, capital will rise as

[20]In growth accounting, this form of decomposition may have originated with David (1977).

Table 5: Mean first passage times, PWT

MPT/MFR	<0.08	<0.16	<0.32	<0.64	$< \infty$
<0.08		69.4	165.7	331.4	546.0
<0.16	146.7		105.1	270.8	485.5
<0.32	262.8	123.5		**165.7**	380.3
<0.64	351.7	212.4	88.9		**214.6**
$< \infty$	403.2	264.0	140.5	51.6	
MFR	16.7	29.4	27.6	32.2	25.8
$\Delta MPT = 48.9$	$90\% CI$	$[-38.1$	$203.5]$		

Transitions from row to column. Times in years, rounded to one decimal place. For more details see the text.

well as output until an equilibrium capital-output ratio has been restored. It is this indirect effect of TFP on output which, together with the direct effect, leads output per head to be a convex function of TFP; see, for example, Hsieh and Klenow (2010, p. 209).

The expression suggests that we consider mobility within the distributions of relative K/Y, human capital h, and one or more measures of A, as in Feyrer (2008). Feyrer was primarily interested in whether the long-run distributions were single-peaked, or twin-peaked in ways that could explain a bimodal long-run distribution for output per head. Here, we are more interested in the extent of upwards mobility in the proximate determinants of GDP per head, and the long-run distributions associated with their dynamics.

In what follows, the category thresholds for the proximate determinants are typically less dispersed than those for output per head. This is because the outcome for output per head can be affected by shortfalls in several proximate determinants, which then compound into very low relative output. With this in mind, in this section we work with a new set of constant growth thresholds. We retain 0.64 as the benchmark for an advanced economy, and define the thresholds as (0.36, 0.48, 0.64) which increase geometrically by the factor 4/3. An alternative approach would be to use the quartiles in the first period. This would be likely to mean each state is well represented, but it would not lead to constant growth thresholds, a major drawback here; see the appendix for more discussion.

We start with the capital-output ratio, which on standard assumptions will converge across countries to the extent that investment rates and population growth rates are similar. The results are shown in Tables 6 and 7. We use data on the ratio relative to the US, computed from the Penn World Table using current-price series 'cn' and 'cgdpo', between 1974 and 2019.[21] There is substantial upwards mobility in this proximate growth determinant, but only limited downwards mobility. There is no evidence for a mid-level trap, which can

[21] In principle we could instead have considered convergence of the capital-output ratio in absolute terms; see Imam and Temple (2025b) for analysis.

be seen more clearly in the mean passage times in Table 7; the ΔMPT statistic is close to zero and precisely estimated. This is consistent with neoclassical growth models, in which a country with constant efficiency growth and converging to a balanced growth path from below will see slowly declining growth in its capital-output ratio.

Given these patterns, it is not surprising that the asymptotic rate of convergence is fast, and it can be seen that the distribution in the last period (2014-2019) is already close to the long-run distribution. If there is to be a middle-income trap, now or in the future, the explanation is unlikely to be found in equilibrium differences in capital intensity. This is consistent with the finding of Caselli and Feyrer (2007) that the marginal product of capital is similar across countries, but our results consider a larger set of countries, especially low-income countries not well represented in the Caselli and Feyrer dataset. The results suggest that rates of investment and population growth are broadly similar across countries, so that countries will spend most of their time in the highest category.

Next, we look at transitions for human capital. The variable of interest is human capital relative to the US, computed from version 10.01 of the Penn World Table. It is the exponential of a piecewise linear function of years of schooling, using the approach which became common in the wake of Hall and Jones (1999) and Caselli (2005), and which appeals to the large empirical literature on Mincerian wage regressions.[22] If s is the average years of schooling, the human capital index is equal to $\exp(\phi(s))$ where $\phi(s)$ is piecewise linear:

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

We present results in Tables 8 and 9, for 1974-2019. A clear pattern is discernible: there is very little downwards mobility in relative human capital, but some upwards mobility, albeit slow for the transition to the highest category. Given these patterns of mobility, it is not surprising that the long-run distribution has most of its mass in the highest category, nor that the process still has further to run: compare the 'last period' and 'stationary' rows in Table 8. Even after another 25 years, about a fifth of countries will be outside the highest category of relative human capital, but eventually countries will spend most of their time above the threshold for the highest category: as with the capital-output ratio, these results suggest long-run convergence rather than a mid-level trap.

Next, we look at the patterns in relative TFP, again for 1974-2019. This first analysis uses the TFP measure 'ctfp' from version 10.01 of the Penn World Table, which 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).

The results can be found in Tables 10 and 11. We find upwards mobility in relative TFP, but there is also some downwards mobility, not least from the highest category. This

[22] Bils and Klenow (2000) used the connection with these regressions to motivate an aggregate human capital measure based on an exponential in years of schooling.

Table 6: Five-year transitions, K/Y, 1974-2019

Transition matrix	<0.36	<0.48	<0.64	$<\infty$
<0.36	0.679	0.258	0.053	0.010
	(0.032)	(0.030)	(0.015)	(0.007)
<0.48	0.075	0.412	**0.356**	**0.156**
	(0.021)	(0.039)	(0.038)	(0.029)
<0.64	0.020	0.080	0.437	**0.462**
	(0.010)	(0.019)	(0.035)	(0.035)
$<\infty$	0.002	0.005	0.042	0.950
	(0.002)	(0.002)	(0.007)	(0.008)
Convergence	$\gamma = 12.4$			
Last period	0.013	0.026	0.090	0.871
25 years ψ_{T+25}	0.017	0.026	0.084	0.873
100 years ψ_{T+100}	0.018	0.027	0.084	0.871
Stationary ψ^*	0.018	0.027	0.084	0.871
(s.e.)	(0.007)	(0.007)	(0.013)	(0.022)
Transition counts				
<0.36	142	54	11	2
<0.48	12	66	57	25
<0.64	4	16	87	92
$<\infty$	2	4	35	786
$NT = 1395$	$N = 155$	$T = 9$		

Transitions from row to column. For more details see the text.

explains why the long-run distribution places significant mass on the lower categories. The analysis predicts that, even in the very long run, around half the world's countries will have TFP less than 64% of the US level. This statistic suggests that TFP differences will be a feature of the data for a long time to come, and hence one source of a middle-income trap. One drawback is that the sample covers only 90 countries, representing about 78% of the 2019 world population. Later in the paper, we will present some evidence for a larger sample that strengthens the finding of a mid-level trap for relative TFP. For now, note that our combined results tally with the earlier findings of Gallardo-Albarrán and Inklaar (2021), based on long-term development accounting: they found that differences in TFP account for an increasing share of the international variation in output per worker.

Taken together, what do these results on proximate GDP determinants imply? We find

Table 7: Mean first passage times, K/Y

MPT/MFR	<0.36	<0.48	<0.64	$< \infty$
<0.36		80.8	54.4	34.6
<0.48	827.2		**44.1**	20.9
<0.64	924.4	327.5		**13.1**
∞	970.7	384.4	107.8	
MFR	276.7	187.8	59.5	5.7
$\Delta MPT = 1.4$	$90\% CI$	$[-1.3$	$4.0]$	

Transitions from row to column. Times in years, rounded to one decimal place. For more details see the text.

that relative TFP will continue to show major dispersion even in the long run: it has been converging to a long-run distribution in which around half the world's countries will remain below the highest category (64% of the US level). This contrasts with the cases of the relative capital-output ratio and relative human capital, where cross-country differences are narrowing quickly (the capital-output ratio) or slowly (human capital). Indeed, the cross-country distribution for the relative capital-output ratio is already close to the long-run distribution.

These results suggest that a middle-income trap may become more visible. Thus far, the continued dispersion of relative TFP has been offset or hidden by convergence in capital intensity and human capital, where the highest category is becoming a near-universal norm. If we combine and extrapolate these trends, the dynamics of relative TFP will come to dominate, and a middle-income trap may become more, rather than less, prominent over time. The failure to eliminate cross-country differences in relative TFP will leave many countries short of the frontier. This is one of our central findings, as the next section will confirm for a larger sample and with more precise estimates of the ΔMPT statistic.

7 Common sample

Thus far, we have used the largest available sample for each series. This helps in obtaining precise estimates of the transition probabilities, but also means that countries move in and out of the sample as we vary the outcome variable of interest. This would not be a major problem if countries were missing at random, but in practice the likelihood of omission may vary with economic conditions. Moreover, given our central research questions and (especially) that we examine proximate GDP determinants, it might seem more natural and rigorous to base the analysis on a consistent sample. That is the task of this section, and its results are the most important to our overall message.

We make two relevant changes to this end. First, we replace the TFP measure from

Table 8: Five-year transitions, human capital, 1974-2019

Transition matrix	<0.36	<0.48	<0.64	<∞
<0.36	0.814	0.186		
	(0.039)	(0.039)		
<0.48	0.004	0.820	**0.176**	
	(0.004)	(0.024)	(0.023)	
<0.64		0.016	0.816	**0.168**
		(0.007)	(0.022)	(0.021)
<∞			0.006	0.994
			(0.004)	(0.004)
Convergence	$\gamma = 25.8$			
Last period	0.023	0.132	0.202	0.643
25 years ψ_{T+25}	0.010	0.069	0.148	0.774
100 years ψ_{T+100}	0.001	0.012	0.056	0.931
long-run ψ^*	0.000	0.003	0.035	0.961
Transition counts				
<0.36	83	19	0	0
<0.48	1	219	47	0
<0.64	0	5	252	52
<∞	0	0	3	480
$NT = 1161$	$N = 129$	$T = 9$		

Transitions from row to column. For more details see the text.

Table 9: Mean first passage times, human capital

MPT/MFR	< 0.36	< 0.48	< 0.64	$< \infty$
<0.36		26.8	55.8	88.3
<0.48	409342.0		**29.0**	61.5
<0.64	418023.0	8681.0		**32.5**
$< \infty$	418828.0	9486.0	805.0	
MFR	76255.0	1533.2	140.9	5.2

Transitions from row to column. Times in years, rounded to one decimal place. We do not bootstrap mean passage times in this case; for more details see the text.

Table 10: Five-year transitions, TFP from PWT, 1974-2019

Transition matrix	<0.36	<0.48	<0.64	<∞
<0.36	0.812	0.188		
	(0.056)	(0.056)		
<0.48	0.124	0.663	**0.191**	**0.022**
	(0.035)	(0.050)	(0.042)	(0.016)
<0.64	0.034	0.188	0.564	**0.214**
	(0.017)	(0.036)	(0.046)	(0.038)
<∞		0.005	0.070	0.924
		(0.003)	(0.011)	(0.011)
Convergence	$\gamma = 36.2$			
Last period	0.067	0.156	0.178	0.600
25 years ψ_{T+25}	0.108	0.155	0.162	0.575
100 years ψ_{T+100}	0.140	0.174	0.161	0.526
Stationary ψ^*	0.148	0.181	0.161	0.510
(s.e.)	(0.089)	(0.044)	(0.028)	(0.090)
Transition counts				
<0.36	39	9	0	0
<0.48	11	59	17	2
<0.64	4	22	66	25
<∞	0	3	39	514
$NT = 810$	$N = 90$	$T = 9$		

Transitions from row to column. For more details see the text.

version 10.01 of the Penn World Table with a simpler or 'basic' one, computed from equation (2) and hence available for a much larger number of countries. 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.[23] This is higher than usually adopted, and we will later consider a lower value for β.

Second, we now look at outcomes for output per working-age adult and its proximate determinants, including basic TFP, for a common sample of countries that represent 92%

[23]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 11: Mean first passage times, PWT TFP

MPT/MFR	<0.36	<0.48	<0.64	$< \infty$
<0.36		26.7	72.8	120.4
<0.48	152.9		**46.2**	93.8
<0.64	211.5	84.4		**61.4**
$< \infty$	273.5	144.6	69.5	
MFR	33.7	27.7	31.0	9.8
$\Delta MPT = 22.5$	$90\% CI$	$[1.6$	$56.9]$	

Transitions from row to column. Times in years, rounded to one decimal place. For more details see the text.

of the world population in 2019. The time period will be 1974 to 2019. This approach again indicates that there is a mid-level trap for basic TFP, but since this has been offset by upwards mobility in relative capital intensity and human capital, there has been less evidence to date for a middle-income trap in relative output per head.

For each series, we work with four states. Before we proceed, since we are looking at both output and its determinants, we should also discuss the extent to which the various long-run distributions can be expected to tally with one another. In particular, given convergence in human capital and the capital-output ratio, one might expect the long-run distribution of relative output per head to mirror the long-run distribution of relative TFP.

This is more complicated than it looks, however, and to see why, we return to equation (2) from earlier in the paper:

$$\frac{Y}{L} = A^{\frac{1}{1-\beta}} \left(\frac{K}{Y}\right)^{\frac{\beta}{1-\beta}} h$$

As explained previously, conditional on the capital-output ratio, the effect of TFP is amplified, because increases in TFP will induce an increase in capital under standard assumptions. Indeed, since $0 < \beta < 1$, output per head will be a convex function of TFP. This means that the long-run distribution of relative output per head will not simply mirror the distribution of relative TFP, even when we apply (as we now do) the same set of thresholds to both.

Rather than present a large number of transition matrices, we summarize the results using long-run distributions and our statistic for gauging the extent of a middle-income trap, ΔMPT, together with a bootstrapped 90% confidence interval. As described earlier, ΔMPT is the difference in mean first passage times between moving into the highest category from the one below, and moving upwards from the one two below. The larger this difference, the greater the challenge of moving upwards, and the stronger the evidence for a serious mid-level trap. We do not report the statistic for the human capital variable, since the highest category is so close to absorbing that bootstrapping becomes hard to implement effectively.

The results are shown in Table 12. We can see that relative capital-output ratios and human capital are expected to converge, spending most of the time in the highest state. But the long-run distribution of relative output per working-age adult appears to be twin-peaked, as in Quah's work, while even in the long run many countries will be some way behind the frontier in relative (basic) TFP.

These results tally with Feyrer (2008), but with more years of data and a greater focus on catching up to the frontier, rather than comparisons with the world mean. The lack of upwards mobility in TFP is glaring: the ΔMPT statistic for this series and sample is 153.8 years, and even the lower endpoint of the 90% confidence interval is 91.1 years. At least on average, moving into the highest relative TFP category may be the work of many decades.

Next, we carry out the same exercise, but with a start date that is ten years earlier (1964 rather than 1974). This reduces the country coverage, but the longer time span means we have more transitions overall. The results are shown in Table 13. The ΔMPT statistic for TFP is lower, but still as high as 86.9 years, while the lower endpoint of the confidence interval is 49.6 years. Hence, there is again strong evidence of a mid-level trap in TFP.

One risk of benchmarking outcomes against the US is that the findings become sensitive to particular developments in the US, such as the New Economy boom of the 1990s (see Temple 2002). So, we now consider the same common-sample exercise, but this time with outcomes benchmarked against the median of the G7 economies, rather than just the US.[24] We prefer this approach to using, say, the richest five economies at each date, because the latter will sometimes include oil producers whose incomes fluctuate sharply.

We benchmark against the median of the G7 and, since the median of the G7 has been a lower target than the US — see Figure 1 — we use a higher threshold (72% rather than 64%) for the highest category. The results are shown in Table 14. This does show some interesting differences: stronger evidence of a middle-income trap for output, but imprecisely estimated; and somewhat less evidence of a mid-level trap for basic TFP, as the ΔMPT statistic for the latter has fallen to 31.8 years. But it remains the case that, even in the long run, more than 60% of countries will be outside the highest relative TFP category.

It might be objected that we are using discrete categories, so the results could be sensitive to alternative choices of thresholds.[25] In Table 15, we repeat the common sample exercise, but make the highest threshold less demanding: 64% of the median of the G7, which is the least demanding threshold we have considered thus far. The results are similar, although now the ΔMPT statistic for relative TFP is lower, at 18.6 years. This change, when combined with our earlier results, suggests that many countries show upwards mobility into the range between 64% of the G7 median and 64% of the (higher) US level; that is not inconsistent with our overall finding that relative TFP is failing to converge.

In an earlier working paper version, we used a higher threshold (72%) and found results

[24] The G7 countries are Canada, France, Germany, Italy, Japan, the UK, and the USA. Although most of these economies were badly affected by the Second World War, those effects are likely to have dissipated before the start of our sample in 1974.

[25] For an approach which groups countries without predefined thresholds, see Anderson et al. (2016).

similar to those reported here (Imam and Temple 2024b). We have also generated results (not reported) with a more conventional value for the output-capital elasticity β, of $1/3$, reflecting a common choice in the literature, albeit one that is probably too low. We continue to find a mid-level trap for relative TFP in that case, reflecting a lack of upwards mobility into the top category.

What do these findings imply? Over time, a middle-income trap for output per head may become more apparent rather than less. This will happen once the convergence of capital intensity and human capital have worked themselves out, and no longer offset the lack of mobility to higher relative TFP. But perhaps the higher absolute levels of human capital already achieved will be important to increasing relative TFP in the years to come. In that case, the dynamics of TFP could yet change over time, even without further changes in the economic environment. This hypothesis is explored further as part of a companion paper on the persistence of low income, Imam and Temple (2025a).

Table 12: Findings, common sample, 1974-2019

	<0.36	<0.48	<0.64	$< \infty$	Δ MPT	90% CI
Output per w/a adult	0.637	0.049	0.072	0.242	-3.4	[-137.7, 160.5]
Basic TFP	0.377	0.302	0.182	0.140	153.8	[91.1, 295.4]
K/Y ratio	0.014	0.024	0.085	0.877	1.7	[-1.4, 4.8]
Human capital	0.000	0.003	0.039	0.958	3.1	(n/a)
NT	$= 1089$	$N = 121$	$T = 9$			

The table shows long-run distributions for relative output per working-age adult and its proximate determinants. For more details see the text.

Table 13: Findings, common sample, 1964-2019

	<0.36	<0.48	<0.64	$< \infty$	Δ MPT	90% CI
Output per w/a adult	0.438	0.049	0.097	0.417	-20.9	[-119.3, 69.3]
Basic TFP	0.318	0.260	0.200	0.221	86.9	[49.6, 157.7]
K/Y ratio	0.020	0.036	0.107	0.837	3	[-1.0, 7.0]
Human capital	0.003	0.010	0.069	0.918	-11.9	(n/a)
NT	$= 1155$	$N = 105$	$T = 11$			

The table shows long-run distributions for relative output per working-age adult and its proximate determinants, now for fewer countries but a longer time period. For more details see the text.

Table 14: Findings, common sample, benchmarked to G7

	<0.32	<0.48	<0.72	$< \infty$	Δ MPT	90% CI
Output per w/a adult	0.643	0.111	0.06	0.186	150.2	[-42.5, 692.5]
Basic TFP	0.070	0.225	0.307	0.398	31.8	[19.2, 51.3]
K/Y ratio	0.027	0.075	0.221	0.678	6.3	[2.04, 10.9]
Human capital	0.000	0.004	0.077	0.919	5.3	(n/a)
NT	$= 1089$	$N = 121$	$T = 9$			

The table shows long-run distributions for relative output per working-age adult and its proximate determinants, this time benchmarked against the median of the G7 rather than the US. For more details see the text.

Table 15: Common sample, G7, less demanding upper threshold

	<0.36	<0.48	<0.64	$< \infty$	Δ MPT	90% CI
Output per w/a adult	0.672	0.076	0.045	0.208	142.2	[-30.1, 591.8]
Basic TFP	0.118	0.188	0.207	0.487	18.6	[8.61, 32.1]
K/Y ratio	0.040	0.056	0.138	0.766	4.2	[0.1, 8.3]
Human capital	0.000	0.002	0.029	0.969	-7.7	(n/a)
NT	$= 1089$	$N = 121$	$T = 9$			

The table shows long-run distributions for relative output per working-age adult and its proximate determinants, benchmarked against the median of the G7, with a less demanding threshold for the highest category. For more details see the text.

8 Robustness

In this section, we consider some further dimensions of robustness. One of the maintained assumptions of the analysis is that the various series can be well described by a first-order Markov process, in which transition probabilities depend only on the current state and not on earlier states. Kremer et al. (2001) found that output transitions at five-year intervals can be so described, but not transitions at annual intervals. We have used five-year intervals thus far. To examine the first-order assumption, we adopt a comparison similar to Kremer et al. (2001). Using the Maddison data set, which extends furthest back in time, we 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 results are shown in Table 16. The two matrices are remarkably similar, as are the implied long-run distributions.[26] We see these results as supporting the use of a first-order process for 5-year intervals applied to the Maddison data. We reach similar conclusions

[26] We do not attempt to test the equality of the matrices formally; this would not be straightforward, because the underlying estimates overlap in their use of the data.

when looking at 10-year transitions in the Penn World Table data for 1969-2019 (results not reported, but available on request).

Table 16: 5-year squared, and 10-year transitions, Maddison data, 1950-2020

5-year, squared	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.911	0.078	0.011		
<0.16	0.125	0.678	0.185	0.012	0.001
<0.32	0.005	0.127	0.678	0.171	0.019
<0.64		0.007	0.148	0.663	0.182
<∞			0.004	0.076	0.920
10-year	<0.08	<0.16	<0.32	<0.64	<∞
<0.08	0.917	0.073	0.010		
<0.16	0.119	0.698	0.178	0.005	
<0.32		0.113	0.698	0.176	0.014
<0.64		0.016	0.117	0.672	0.195
<∞			0.014	0.068	0.919
long-run (5-year) ψ^*	0.144	0.097	0.146	0.176	0.437
long-run (10-year) ψ^*	0.142	0.099	0.149	0.172	0.438
$N = 145$	$T = 7$	(10-year)	$T = 14$	(5-year)	

Transitions from row to column. Comparing the matrices casts some light on whether the Markov property holds; for more details see the text.

Another concern that might be raised is that our samples include some countries which specialize in exporting natural resources. It is worth noting that natural resource revenues are unlikely to explain our finding of persistent dispersion in TFP relative to the US or the median of the G7. If we take the example of oil, this would often be produced in an enclave sector using relatively few factor inputs. The oil revenues add to GDP, and so a standard calculation of aggregate TFP will overstate the relative TFP of the non-oil sector; see for example Hall and Jones (1999, p. 89) or, for a more detailed treatment, Freeman et al. (2021). Hence we conjecture that stripping resource revenues or mining value added from GDP would only reinforce our finding of persistent dispersion in relative TFP.

That said, resource exporters may follow output dynamics that differ from those of other countries. We now examine whether the results for GDP per head change when we exclude exporters of oil and minerals. Kremer et al. (2001) excluded 20 countries with high shares of the mining and quarrying sector in GDP, based on sectoral data from the United Nations. They argued that these countries may follow different dynamics, not least because oil exporters will be heavily affected by the oil price. We have computed a transition matrix for the Maddison data, excluding the countries omitted by Kremer et al. (2001), and Equatorial Guinea, which discovered oil in 1996. The long-run distributions with and without these countries are compared in Table 17. Excluding the resource-dependent countries increases the amount of time that the remaining countries are expected to spend in the highest category, perhaps indirect evidence of a 'resource curse'. But the long-run distribution is otherwise quite similar, as is the underlying transition matrix (not reported).

Thus far, we have assumed that each Markov process is homogeneous in time. Since transition probabilities might evolve, we now split the time span in two: we look at 1950-85 and 1985-2020 separately, again for the Maddison data. Examining subperiods involves a trade-off between robustness and efficiency: allowing the probabilities to change increases robustness in one respect, but means we typically have fewer observations from which to estimate each transition probability. But as can be seen in Table 17, the long-run distributions are fairly similar between the two subperiods. A Pearson goodness-of-fit test does not reject the hypothesis that the two transition matrices are the same.[27] Interestingly, however, the long-run distribution for the 1985-2020 time period puts more mass on the highest category than obtained for 1950-85. This is tentative support for a favourable change in the convergence process; see Imam and Temple (2025b) for further analysis and references.

Finally, we look at long-run distributions associated with twenty-year subperiods, the final panel in Table 17. These results are striking in that the lowest income category predominates in 1980-2000: these were the 'lost decades' of the developing world, associated with the debt crises in Latin America and sub-Saharan Africa, and considerable downwards mobility. Either side of those two decades, the long-run distributions show much higher concentrations in the highest category, but with high bootstrapped standard errors. Since the underlying transition matrices are estimated from around 600 transitions over just twenty years, the estimates of the long-run distributions are rather noisier than in the upper panel; these results should not be over-interpreted. But they do perhaps indicate that the convergence experience of the 2000s and 2010s has more in common with that of the 1960s and 1970s than with the lost decades of the 1980s and 1990s. This is discussed in more detail in Imam and Temple (2025b), which examines the extent to which global convergence has been delayed by major crises.

9 Conclusions

The idea of a middle-income trap has been much discussed, sometimes with more controversy than precision. We revisit this question using transitions between relative income categories, and introducing a new summary statistic based on mean first passage times. We also use a dynamic version of traditional development accounting, considering the dynamics of the proximate determinants of output per head separately. We can thereby come to a better understanding of the prospects for upwards mobility and ultimate convergence in output per head, if each underlying process remains stable over time.

[27]For the relevant test statistic, see Bickenbach and Bode (2003).

Table 17: Robustness tests

Oil/mineral producers	<0.08	<0.16	<0.32	<0.64	$< \infty$
With	0.144	0.097	0.146	0.176	0.437
(s.e.)	(0.053)	(0.027)	(0.032)	(0.034)	(0.100)
Without	0.120	0.070	0.099	0.152	0.559
(s.e.)	(0.063)	(0.028)	(0.036)	(0.046)	(0.137)
Thirty-five year spans					
1950-1985	0.182	0.109	0.157	0.169	0.382
(s.e.)	(0.095)	(0.043)	(0.054)	(0.053)	(0.169)
1985-2020	0.107	0.083	0.137	0.184	0.489
(s.e.)	(0.066)	(0.036)	(0.046)	(0.053)	(0.142)
Twenty-year spans					
1960-1980	0.078	0.030	0.065	0.134	0.692
(s.e.)	(0.105)	(0.029)	(0.052)	(0.088)	(0.218)
1980-2000	0.595	0.191	0.120	0.047	0.046
(s.e.)	(0.183)	(0.083)	(0.068)	(0.035)	(0.077)
2000-2020	0.011	0.025	0.125	0.256	0.583
(s.e.)	(0.018)	(0.023)	(0.079)	(0.111)	(0.182)

Robustness tests: we compare long-run distributions and bootstrapped standard errors for the Maddison data when excluding the Kremer et al. (2001) oil and mineral producers, and Equatorial Guinea. We also compare long-run distributions for subperiods, again using the Maddison data.

When we turn to the data, we find that the long-run distribution for output per head implies long-run dispersion across a range of relative income categories. This is consistent with the usual finding that cross-country differences in income are likely to persist. But the evidence for a middle-income trap is weaker, not least because the mean first passage times are estimated imprecisely.

The findings extend beyond this, however. We have examined mobility not only within the distribution of relative output per head, but also within its proximate determinants — relative TFP, capital intensity, and human capital. Our results suggest that cross-country differences in capital-output ratios and human capital are narrowing, which has disguised the lack of upwards mobility in relative TFP. If these patterns continue, the dynamics of relative TFP will come to dominate the future path of output per head, and middle-income traps may become increasingly apparent.

One qualification is that we have applied a higher income threshold for middle income than has sometimes been applied elsewhere. World Bank (2024) uses a much less demanding threshold. We could interpret our paper as looking for an upper-middle income trap; indeed, our use of the ΔMPT statistic here can be interpreted as testing whether an upper-middle income trap is more severe than a lower-middle income trap. The results tend to point in that direction. Such a distinction, implicit in Felipe et al. (2017), may be especially useful for policy purposes. World Bank (2024) discusses how growth strategies might change as countries move from lower-middle to upper-middle income.

Another qualification is that we are extrapolating from experience since the mid-1970s, and the convergence process may have changed in the most recent twenty years (Kremer et al. 2022, Patel et al. 2021). It is also possible that higher absolute levels of human capital might unlock the upwards mobility in relative TFP that has been rare in the data thus far; see Imam and Temple (2025a), although they find such an effect to be modest.

Are there implications for policy-makers? One interpretation of a middle-income trap runs as follows: developing countries can reach an intermediate level of development through conventional economic reforms — macroeconomic stability, opening up the economy, and building institutions and human capital — but reaching an advanced level requires further changes, such as complementary investments that may be harder to carry out well than sometimes assumed.

Our own emphasis on the long-run role of TFP dynamics may help to sharpen the focus of policy discussions. Yusuf (2017, p. 27) contended that 'If escape from the MIT requires elaborating current growth theories and augmenting the list of policies specific to middle-income countries, that challenge has still to be met.' The current findings confirm the need to understand firm-level learning and technological upgrading in developing countries: for a review mainly focused on manufacturing, see Verhoogen (2023). But low TFP may not be a question solely of firm decisions, since it could also arise through underprovision of infrastructure. Agénor and Canuto (2015) discuss how advanced infrastructure might allow a trap to be escaped, and also consider other policy implications.

The results do raise the question of whether governments in middle-income countries will sometimes need to intervene to promote innovation and industrial diversification. Such measures could include funding for research and development (R&D), establishing technology parks, and offering tax incentives for startups. As an example, Taiwan's establishment of the Hsinchu Science and Industrial Park has been effective in creating a hub for technology companies, driving innovation and economic growth. Such measures, if well implemented, may help middle-income countries to catch up with advanced economies.

Naturally in a paper of this kind, there are many other relevant considerations that we have barely touched upon. For example, the ongoing advances in artificial intelligence may disproportionately benefit advanced economies, while proving harder to apply in middle-income countries (Alonso et al. 2020). The impact of a green transition may complicate the picture further (World Bank 2024). These broader considerations, as well as the statistical evidence we have put forward, suggest that policymakers may yet need a better understanding of the middle-income trap in the years to come.

10 Appendix

10.1 Quantiles and mobility

Given the concern that specific threshold choices are inevitably somewhat arbitrary, one alternative to our approach would be the use of income quantiles. At first sight, the quantile-based approach might seem less arbitrary and would ensure that each state is well represented in the data. It corresponds to an interest in country rankings, as in Park and Mercado (2020). But for our questions of interest, this approach seems less attractive. There is no guarantee that quantiles will line up with reasonable interpretations of 'middle income'. In an analysis where the income categories are based on continually updating quantiles, the implicit thresholds will be varying over time, a country growing at a constant relative rate will traverse the categories at varying speeds — which makes mean first passage times much harder to compare and interpret — and the long-run distribution will be uninformative by construction. These are all good reasons to avoid quantile-based studies of mobility when the main focus is the middle-income trap.

10.2 Unique long-run distributions

The long-run 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 (2024a). Consider a right stochastic matrix P defined over the set of states $\mathcal{S}$, and denote the transition probability from state x to state y by $p(x, y)$. The Dobrushin coefficient is defined as:

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

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 long-run distribution regardless of the initial conditions.[28]

This means we can take a transition matrix P and check whether it implies a unique long-run 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.

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

10.3 Mean first passage times

We can calculate the mean first passage times following Grinstead and Snell (2006), pp. 456-460. Let P be the transition matrix of an ergodic chain, and let W be the matrix whose rows are all equal to the long-run distribution for P. Then the 'fundamental matrix' is given by $Z \equiv (I - P + W)^{-1}$ where the inverse always exists given the structure of the problem. The mean first passage times for an ergodic chain, from state i to state j where $i \neq j$, are then determined from the individual entries in the fundamental matrix Z and the long-run distribution w by:

$$m_{ij} = \frac{z_{jj} - z_{ij}}{w_j}$$

For a detailed derivation, see Grinstead and Snell (2006). In this calculation, the entries on the main diagonal will be zeroes; with a modified formula, as in Hunter (2018), the entries on the main diagonal will be mean first recurrence times.

The analysis in the paper is complicated by the need, for ΔMPT, to measure the mean passage time to hit first *either* state n *or* state $n-1$. To carry out these calculations we use the R software of Spedicato et al.; see Spedicato (2017) for an introduction. For an analysis of bootstrapping mean first passage times, see Kulperger and Prakasa Rao (1989). Based on simulations, they note (p. 187) that the bootstrap distributions of mean first passage times are highly skewed, and hence we will report confidence intervals rather than standard errors when presenting ΔMPT statistics.

10.4 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. We do not bootstrap mean first passage times for the human capital results; the rarity of downwards mobility from the highest state means that, in many of the bootstrap samples, the highest state is absorbing and hence most of the mean first passage times are no longer defined.

10.5 Countries used

Country names are those used in the Maddison Project Database 2023.

Maddison sample: 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 Province of China, 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.

PWT sample: 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, Cyprus, D.R. of the Congo, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Ethiopia, Finland, 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, Lao People's DR, Lebanon, Lesotho, Liberia, 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, Qatar, Republic of Korea, Romania, Rwanda, Saint Lucia, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sudan (Former), Swaziland, Sweden, Switzerland, Syrian Arab Republic, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, U.R. of Tanzania: Mainland, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Viet Nam, Zambia, Zimbabwe.

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

References

[1] Acemoglu, D., Aghion, P. and Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, 4(1), 37–74.

[2] Agénor, P.-R. (2017). Caught in the middle? The economics of middle-income traps. *Journal of Economic Surveys*, 31(3), 771-791.

[3] Agénor, P.-R. and Canuto, O. (2015). Middle-income growth traps. *Research in Economics*, 69(4), 641-660.

[4] Aghion, P. and Bircan, C. (2017). The middle-income trap from a Schumpeterian perspective. EBRD Working Paper No. 205.

[5] Aiyar, S., Duval, R., Puy, D., Wu, Y. and Zhang, L. (2018). Growth slowdowns and the middle-income trap. *Japan and the World Economy*, 48, 22-37.

[6] Alonso, C., Berg, A., Kothari, S., Papageorgiou, C. and Rehman, S. (2020). Will the AI revolution cause a Great Divergence? IMF Working Paper No. 184.

[7] Anderson, T. W. and Goodman, L. A. (1957). Statistical inference about Markov chains. *Annals of Mathematical Statistics*, 28(1), 89-110.

[8] Anderson, G., Pittau, M. G., and Zelli, R. (2016). Assessing the convergence and mobility of nations without artificially specified class boundaries. *Journal of Economic Growth*, 21(3), 283-304.

[9] Arezki, R., Fan, R. Y. and Nguyen H. (2021). Technology adoption and the middle-income trap: Lessons from the Middle East and East Asia. *Review of Development Economics*, 25, 1711–1740.

[10] Barseghyan, L. and DiCecio, R. (2011). Cross-country income convergence revisited. *Economics Letters*, 113(3), 244-247.

[11] Bickenbach, F. and Bode, E. (2003). Evaluating the Markov property in studies of economic convergence. *International Regional Science Review*, 26(3), 363-392.

[12] Bils, M. and Klenow, P. J. (2000). Does schooling cause growth? *American Economic Review*, 90(5), 1160–1183.

[13] Bolt, J. and van Zanden, J. L. (2024). Maddison-style estimates of the evolution of the world economy: A new 2023 update. *Journal of Economic Surveys*, 1-41.

[14] Bulman, D, M. Eden and H. Nguyen, (2017). Transitioning from low-income growth to high-income growth: is there a middle-income trap? *Journal of the Asia Pacific Economy*, 22(1), 5-28

[15] Bulli, S. (2001). Distribution dynamics and cross-country convergence: A new approach. *Scottish Journal of Political Economy*, 48(2), 226-243.

[16] Caselli, F. (2005). Accounting for cross-country income differences. In Aghion, P. and Durlauf, S. N. (eds.) *Handbook of Economic Growth*, Volume 1, Part A. Elsevier, Amsterdam.

[17] Caselli, F. and Feyrer, J. (2007). The marginal product of capital. *Quarterly Journal of Economics*, 122(2), 535-568.

[18] Cherif, R. and F. Hasanov (2019). The leap of the tiger: Escaping the middle-income trap to the technological frontier. *Global Policy*, 10(4), 497-511.

[19] David, P. A. (1977). Invention and accumulation in America's economic growth: A nineteenth-century parable. *Carnegie-Rochester Conference Series on Public Policy*, 6(1), 179-228.

[20] Dijkstra, L., Poelman, H. and Rodríguez-Pose,A. (2020). The geography of EU discontent. *Regional Studies*, 54(6), 737-753.

[21] Dobrushin, R. L. (1956). Central limit theorem for nonlong-run Markov chains. *Theory of Probability and its Applications*, 1, 65-80.

[22] Doner, R. and Schneider, B. (2016). The middle-income trap: More politics than economics. *World Politics*, 68(4), 608-644.

[23] Durlauf, S. N., Johnson, P. A., and Temple, J. R. W. (2005). Growth econometrics. In P. Aghion and S. N. Durlauf (eds.) *Handbook of Economic Growth*, Volume 1A, North-Holland: Amsterdam, 2005, pp. 555-677.

[24] Durlauf, S. N. and Quah, D. T. (1999). The new empirics of economic growth. In J. B. Taylor and M. Woodford (eds.) *Handbook of Macroeconomics*, Volume 1, North-Holland: Amsterdam, 1999, pp. 235-308.

[25] Eichengreen, B., Park, D. and Shin, K. (2014). Growth slowdowns redux. *Japan and the World Economy*, 32, 65-84.

[26] Feenstra, R. C., Inklaar, R. and Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105, 3150-3182.

[27] Felipe, J., Kumar, U. and Galope, R. (2017). Middle-income transitions: trap or myth? *Journal of the Asia Pacific Economy*, 22(3), 429-453.

[28] Feyrer, J. D. (2008). Convergence by parts. *The B.E. Journal of Macroeconomics*, 8(1), 1-35.

[29] Fiaschi, D. and Lavezzi, A. M. (2003). Distribution dynamics and nonlinear growth. *Journal of Economic Growth*, 8(4), 379-401.

[30] Fiaschi, D. and Lavezzi, A. M. (2007). Nonlinear economic growth: Some theory and cross-country evidence. *Journal of Development Economics*, 84(1), 271-290.

[31] Freeman, D., Inklaar, R. and Diewert, W.E. (2021). Natural Resources and Missing Inputs in International Productivity Comparisons. *Review of Income and Wealth*, 67, 1-17.

[32] Gallardo-Albarrán, D. and Inklaar, R. (2021). The role of capital and productivity in accounting for income differences since 1913. *Journal of Economic Surveys*, 35, 952-974.

[33] Galor, O. (1996). Convergence? Inferences from theoretical models. *Economic Journal*, 106(437), 1056-1069.

[34] Gill, I. and Kharas, H. (2007). *An East Asian Renaissance: Ideas for Economic Growth*. World Bank, Washington DC.

[35] Gill, I. S. and Kharas, M. (2015). The middle-income trap turns ten. World Bank Policy Research Working paper no. 7403.

[36] Glawe, L. and Wagner, H. (2016). The middle-income trap: Definitions, theories and countries concerned — a literature survey. *Comparative Economic Studies*, 58, 507-538.

[37] Grinstead, C. M. and Snell, J. L. (2006). *Grinstead and Snell's Introduction to Probability*. Manuscript, Dartmouth.

[38] Hall, R. E. and Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics*, 114(1), 83-116.

[39] Han, X. and Wei, S.-J. (2017). Re-examining the middle-income trap hypothesis (MITH): What to reject and what to revive? *Journal of International Money and Finance*, 73, 41-61.

[40] Hsieh, C.-T. and Klenow, P. J. (2010). Development accounting. *American Economic Journal: Macroeconomics*, 2(1), 207-23.

[41] Hunter, J. J. (2018). The computation of the mean first passage times for Markov chains. *Linear Algebra and its Applications*, 549, 100-122.

[42] Im, F. G. and Rosenblatt, D. (2015). Middle-income traps: A conceptual and empirical survey. *Journal of International Commerce, Economics and Policy*, 6(3), 1550013.

[43] Imam, P. and Temple, J. R. W. (2024a). Political institutions and output collapses. *European Journal of Political Economy*, 85, 102573.

[44] Imam, P. and Temple, J. R. W. (2024b). At the threshold: The increasing relevance of the middle-income trap. IMF working paper no. 2024/091.

[45] Imam, P. and Temple, J. R. W. (2025a). Dynamic development accounting and the persistence of low income. CEPR discussion paper 20152.

[46] Imam, P. and Temple, J. R. W. (2025b). Growth, interrupted: how crises delay global convergence. IMF working paper, forthcoming.

[47] Islam, Md. J. A., Mahmud, I., Islam, A., Sobhani, F. A., Hassan, Md. S., and Ahsan, A. (2023). Escaping the middle-income trap: A study on a developing economy. *Cogent Social Sciences*, 9(2).

[48] Johnson, P. A. (2005). A continuous state space approach to 'Convergence by Parts'. *Economics Letters*, 86(3), 317-321.

[49] Johnson, P. and Papageorgiou, C. (2020). What remains of cross-country convergence? *Journal of Economic Literature*, 58(1), 129-75.

[50] Johnson, P. A., Papageorgiou, C., Pittau, M. G. and Zelli, R. (2025). Lessons from 40 years of cross-country convergence empirics. In Anderson, G. and Bandyopadhyay, S. (eds.) *Oxford Handbook of Income Distribution and Economic Growth*. OUP, forthcoming.

[51] Jones, C. I. (1997). On the evolution of the world income distribution. *Journal of Economic Perspectives*, 11(3), 19-36.

[52] Jones, C. I. (2016). The facts of economic growth. In J. B. Taylor and H. Uhlig (eds.). *Handbook of Macroeconomics*, Volume 2A, Elsevier, Amsterdam.

[53] Klenow, P. J. and Rodríguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER Macroeconomics Annual*, 12, 73-114.

[54] Kremer, M., Onatski, A. and Stock, J. (2001). Searching for prosperity. *Carnegie-Rochester Conference Series on Public Policy*, 55(1), 275-303.

[55] Kremer, M., Willis, J. and You, Y. (2022). Converging to convergence. *NBER Macroeconomics Annual*, 337-412.

[56] Krugman, P. (1994). The myth of Asia's miracle. *Foreign Affairs*, 73(6), 62-78.

[57] Kulperger, R. J. and Prakasa Rao, B. L. S. (1989). Bootstrapping a finite state Markov Chain. *Sankhyā: The Indian Journal of Statistics*, Series A (1961-2002), 51(2), 178-191.

[58] Mankiw, N. G., Romer, D. and Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107(2), 407-437.

[59] Milanovic, B. (2005). *Worlds Apart: Measuring International and Global Inequality*. Princeton University Press, Princeton.

[60] Müller, U. K., Stock, J. H. and Watson, M. W. (2022). An econometric model of international growth dynamics for long-horizon forecasting. *Review of Economics and Statistics*, 104(5), 857–876.

[61] Norris, J. R. (1997). *Markov Chains*. Cambridge University Press, Cambridge.

[62] Park, C.-Y. and Mercado, R. V., Jr. (2020). Economic Convergence, Capital Accumulation, and Income Traps: Empirical Evidence. *Review of Income and Wealth*, 66, 26-58.

[63] Patel, D., Sandefur, J. and Subramanian, A. (2021). The new era of unconditional convergence. *Journal of Development Economics*, 152, 102687.

[64] Pearlman, J. (2003). Twin Peaks - a reassessment. *The Manchester School*, 71(1), 78-88.

[65] Proudman, J., Redding, S. and Bianchi, M. (1998). Is international openness associated with faster economic growth? In Proudman, J. and Redding, S. (eds.) (1998). *Openness and Growth*. Bank of England, London.

[66] Quah, D. (1993). Empirical cross-section dynamics in economic growth. *European Economic Review*, 37(2-3), 426-434.

[67] Quah, D. T. (1996a). Twin Peaks: Growth and convergence in models of distribution dynamics. *Economic Journal*, 106(437), 1045-1055.

[68] Quah, D. T. (1996b). Convergence empirics across economies with (some) capital mobility. *Journal of Economic Growth*, 1, 95–124.

[69] Quah, D. T. (1997). Empirics for growth and distribution: Stratification, polarization, and convergence clubs. *Journal of Economic Growth*, 2, 27–59.

[70] Rodrik, D. (2016). Premature deindustrialization. *Journal of Economic Growth*, 21, 1-33.

[71] Roy, S., Kessler, M. and Subramanian, A. (2016). Glimpsing the end of economic history? Unconditional convergence and the missing middle income trap. CGD working paper no. 438, October.

[72] Schelkle, T. (2014). Accounting for convergence between countries. Manuscript, University of Cologne.

[73] Spedicato, G. A. (2017). Discrete time Markov chains with R. *The R Journal*, 7. https://journal.r-project.org/archive/2017/RJ-2017-036/index.html

[74] Spence, M. (2011). *The next convergence: the future of economic growth in a multi-speed world*. Farrar, Straus and Giroux, New York.

[75] Stachurski, J. (2009). *Economic Dynamics: Theory and Computation*. MIT Press, Cambridge, MA.

[76] Stokey, N., Lucas, R. E., Jnr., with Prescott, E. C. (1989). *Recursive Methods in Economic Dynamics*. Harvard University Press, Cambridge, MA.

[77] Temple, J. (2002). The Assessment: The New Economy. *Oxford Review of Economic Policy*, 18(3), 241-264.

[78] Temple, J. R. W. (2010). Aid and conditionality. In D. Rodrik and M. Rosenzweig (eds.). *Handbook of Development Economics*, Volume 5. Elsevier, Amsterdam.

[79] Temple, J. (2012). The calibration of CES production functions. *Journal of Macroeconomics*, 34(2), 294–303.

[80] Temple, J. R. W. (2021). Growth econometrics. *Oxford Research Encyclopedia of Economics and Finance*, Oxford University Press online, April 2021.

[81] Verhoogen, E. (2023). Firm-level upgrading in developing countries. *Journal of Economic Literature*, 61(4), 1410-64.

[82] Wade, R. H. (2016) Industrial policy in response to the middle-income trap and the Third Wave of the digital revolution. *Global Policy*, 7(4), 469-480.

[83] World Bank (2024). *World Development Report 2024: The middle-income trap*. World Bank, Washington DC.

[84] Ye, L. and Robertson, P. E. (2016). On the existence of a middle-income trap. *Economic Record*, 92(297), 173-189.

[85] Young, A. (1995). The tyranny of numbers: Confronting the statistical realities of the East Asian growth experience. *Quarterly Journal of Economics*, 110(3), 641–80.

[86] Yusuf, S. (2017). Middle-income countries: trapped or merely slowing? *Asia Pacific Economic Literature*, 31, 19-29.

[87] Yusuf, S. and Evenett, S. J. (2002). *Can East Asia Compete? Innovation for Global Markets*. World Bank, Washington DC.