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# Relative Development and the Intelligence Divide: Human Capital, Technology Diffusion, and AI

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ABSTRACT: Will artificial intelligence (AI) help poorer countries catch up? The answer depends less on access to AI than on the capacity to turn cheaper intelligence into productivity. Combining development accounting with distribution dynamics for 1,097 five-year country transitions, we show that capital and measured human capital move through their relative distributions more readily than total factor productivity (TFP), whose lower tail is persistent. On a common sample and harmonized state construction, mean exit from the lowest state is 16 years for capital intensity, 32 for human capital, and 44 for TFP. Workforce composition explains only a modest share of productivity gaps, yet measured human capital is informative about mobility. A fixed within-year median split implies mean exit times from the lowest-productivity state of 79 years below the median and 28 above it, while smooth human-capital terms improve held-out transition predictions. The evidence supports capability-related mobility heterogeneity, not a causal schooling threshold. AI may therefore move the frontier without promoting catch-up if it mainly augments existing skills. It promotes convergence only to the extent that it lowers learning, validation, adaptation, and implementation costs where productive capability is weakest. The Intelligence Divide is a conversion gap, not merely an access gap.

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WORKING PAPERS

# Relative Development and the Intelligence Divide:
## Human Capital, Technology Diffusion, and AI

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# I. Introduction

Will artificial intelligence (AI) help poorer countries catch up, or widen existing gaps? AI can lower the cost of using knowledge across an unusually broad range of tasks. Expertise may become cheaper, some tacit knowledge easier to codify, and frontier ideas easier to adapt. Yet the same technology may favor economies that already possess skilled workers, reliable data, capable firms, and effective institutions. Its effect on relative development therefore depends on the complements with which it is combined.

Access can spread quickly, but productive capability is slower to build. Importing hardware or licensing software does not by itself raise productivity. Gains require firms to redesign workflows, managers to change decisions, workers to acquire complementary skills, and public institutions to provide reliable infrastructure and rules. The ICT experience shows why: productivity gains lagged adoption while firms accumulated organizational and other intangible capital (David 1990; Brynjolfsson, Rock, and Syverson 2021). AI may diffuse faster, but cheap access does not eliminate the costly work of becoming productive.

The resulting gap is the Intelligence Divide: not simply unequal access to AI, but unequal capacity to convert increasingly cheap cognitive services into sustained productivity gains. Its empirical counterpart is productivity mobility—whether economies leave low-productivity states and move toward the frontier.

This framing connects the literatures on appropriate technology, absorptive capacity, and technology diffusion. Frontier techniques may be poorly matched to the factor endowments, managerial systems, infrastructure, and institutions of poorer economies (Atkinson and Stiglitz 1969; Lall 1992; Acemoglu and Zilibotti 2001). Recent work brings these mechanisms together: distance from the frontier creates scope for catch-up, but weak education and management, institutional distortions, inappropriate technology, and credit frictions can make that advantage largely notional (Acemoglu, Akcigit, and Johnson 2026). Evidence on adoption intensity points in the same direction: technologies can arrive widely while their productive use remains uneven (Comin and Mestieri 2018).

Early tractorization in sub-Saharan Africa illustrates the distinction. Machinery designed for different factor prices and farm structures often remained uneconomic or idle when credit, fuel, repair facilities, and complementary infrastructure were scarce (Binswanger and Donovan 1986). The machine could be imported more readily than the system that made it productive. This is a problem of appropriate technology, not technological backwardness (Basu and Weil 1998). AI changes the technology, not the economic logic. Frontier models can be available almost instantly while the skills, data, management, finance, infrastructure, and institutions needed to use them productively remain local. Postwar experience gives the same warning. Schooling, capital, and digital access spread more readily than the efficiency with which they were combined.

AI can therefore raise world productivity without producing convergence. A frontier shift expands what is possible; a diffusion shift changes who moves toward what is possible. The paper asks whether human capital helps explain this second margin and what AI would need to change for the lower tail of the productivity distribution to become less persistent.

Human capital sits at the center of this question. Development accounting finds that measured human capital explains only a limited share of international income and productivity gaps (Hall and Jones 1999; Caselli 2005;

Caselli and Ciccone 2013). Equalizing schooling would raise output in poorer countries but would leave much of the distance from the frontier unexplained.

The technology-diffusion tradition reaches a different-looking conclusion. Beginning with Nelson and Phelps (1966), human capital matters because it helps economies understand, adapt, and implement technologies developed elsewhere (Benhabib and Spiegel 1994, 2005; Howitt and Mayer-Foulkes 2005). More schooling may improve the performance of existing tasks, but sustained catch-up requires a broader capability to operate modern firms, maintain complex capital, reorganize production, and continue adapting as technology changes. The two views therefore answer different questions. Development accounting is mainly about levels: why one country is more productive than another at a point in time. Diffusion theory is about mobility: why some countries move toward the frontier while others remain behind. Schooling raises the stock of effective labor; absorptive capacity affects the rate at which machines, blueprints, software, and other forms of knowledge are turned into reliable production. The distinction matters because this second margin compounds through repeated transitions. Human capital may therefore account for only a modest part of the contemporaneous productivity gap while remaining informative about whether an economy subsequently moves toward the frontier.

This reconciliation also changes how the AI question should be posed. If AI mainly augments skilled labor, its gains may accrue disproportionately where skilled workers, capable firms, reliable infrastructure, and effective organizations are already abundant. AI can then raise global productivity without necessarily narrowing relative productivity gaps. For AI to promote convergence, it must operate on a different margin: it must lower the costs of acquiring, interpreting, codifying, adapting, validating, and implementing knowledge in economies where complementary capabilities remain limited. A frontier-expanding technology is therefore not necessarily a convergence technology.

We study these issues using a finite-state Markov framework, in the tradition of Quah (1993, 1996), Durlauf and Johnson (1995), Feyrer (2008), Johnson and Papageorgiou (2020), and Imam and Temple (2026a, 2026b). Transition probabilities are useful because convergence need not be linear or homogeneous. A country can grow substantially in absolute terms and still remain in the lower part of the relative productivity distribution if the frontier moves as well. The Markov framework therefore asks a direct question: how often do economies move out of low-productivity states and toward the frontier? We combine this with a Caselli–Coleman decomposition of relative productivity (Caselli and Coleman 2006). The decomposition asks whether differences in workforce composition are large enough to account for observed productivity gaps. The transition analysis asks whether measured human capital is associated with a different mobility process. Together, the two exercises distinguish a direct level effect from a broader capability channel.

The results reveal a consistent asymmetry between the accumulation of observable inputs and the movement of productivity toward the frontier. On the same 1,097 country-period transitions, and using fixed 1975 non-U.S. quartiles for each variable, the mean time required to leave the lowest state is 16.1 years for capital intensity, 31.5 years for measured human capital, and 44.0 years for TFP. Countries therefore appear able to accumulate capital and measured human capital more readily than they are able to translate those inputs into sustained improvements in relative productivity. The accounting evidence points in the same direction: workforce composition explains only a modest share of observed productivity gaps, suggesting that the main constraint is not simply the quantity of educated labor available, but the broader capacity to deploy skills, technologies, and complementary inputs productively.

Human capital nevertheless contains substantial information about productivity mobility. A fixed within-year median split, which avoids searching for an estimated threshold, implies a mean exit time from the lowest-productivity state of 79.1 years for observations below the median, compared with 28.0 years above it. Specifications using human capital continuously also improve the prediction of subsequent transitions in held-out observations. The exact location of a data-selected absolute cutoff is unstable and should not be interpreted as a structural threshold. What is more robust is the underlying mobility contrast: economies with higher measured human capital display systematically greater mobility out of low-productivity states. The evidence is therefore more consistent with a broad capability gradient than with a universal tipping point.

The contribution is a dynamic reconciliation of two literatures that are usually read separately. Development accounting asks how much measured human capital explains differences in productivity levels; the Nelson–Phelps tradition asks how human capital and related capabilities shape the process of moving toward the frontier. Combining the two shows how both propositions can hold simultaneously. Human capital can account for relatively little of the contemporaneous productivity gap while remaining informative about the transition process that governs catch-up. Put differently, the stock of observable inputs and the rate at which economies convert those inputs into productivity are distinct margins of development. This level–mobility distinction is not an artifact of a particular state definition or specification: the broad pattern survives fixed-rank, continuous, residualized, and out-of-sample exercises.

The distinction also gives the Intelligence Divide a precise economic meaning. Skill-augmenting AI raises the productivity and returns of capabilities that are already present. Diffusion-enhancing AI promotes convergence only if it changes the process by which economies acquire, adapt, and use productive knowledge—ultimately raising the probability of moving out of low-productivity states. In this sense, access to AI is not the same as the capacity to benefit from it. The policy-relevant question is not simply whether increasingly powerful cognitive technologies become widely available, but whether they relax the capability constraints that have historically limited productivity mobility.

The empirical design is deliberately more modest than a causal interpretation of these patterns would require. It documents systematic heterogeneity in productivity mobility; it does not identify a causal return to schooling, establish that human capital itself generates the observed transitions, or forecast the cross-country diffusion of AI. Measured human capital should instead be viewed as an informative but incomplete marker of a broader capability bundle that includes education quality, management and organizational capacity, infrastructure, finance, state capability, and institutions supporting technological adaptation. This qualification is important for policy. Expanding access to education, capital, digital infrastructure, or AI may be necessary for convergence without being sufficient. The central development problem is whether economies can combine these inputs in ways that generate sustained productivity improvements. The Intelligence Divide is therefore best understood as a conversion gap: a difference not merely in access to increasingly powerful technologies, but in the capacity to turn widely available knowledge into movement toward the productivity frontier.

# II. Background

The argument rests on a distinction between human capital as a production input and human capital as absorptive capacity. Development accounting decomposes output per worker into physical capital, measured human capital, and TFP. Its central result is familiar: measured human capital explains part of cross-country income differences, but most of the gap remains in productivity (Hall and Jones 1999; Caselli 2005; Caselli and Ciccone 2013). This limits a purely schooling-based account of convergence.

In the static channel, a larger skilled share or a higher productivity premium for skilled labor raises effective labor. Under plausible calibrations, however, changes in workforce composition alone cannot explain most of the productivity gap.

This is the narrow channel through which skill-biased AI enters the accounting. If AI raises A_H, its immediate gains depend on the existing supply of skilled workers and on the production systems in which they are employed. The technology may therefore raise the return to capabilities that are already scarce without changing the process by which economies acquire or deploy those capabilities.

A different tradition gives human capital a dynamic role. In Nelson and Phelps (1966), human capital accelerates the adoption and implementation of frontier technologies. Benhabib and Spiegel (1994, 2005) and Howitt and Mayer-Foulkes (2005) develop related mechanisms. Recent work shows how absorptive capacity interacts with management, institutions, technology mismatch, and credit constraints in determining a country's distance from the frontier (Acemoglu, Akcigit, and Johnson 2026). Human capital is therefore not only an input; it is part of the capacity to learn.

The agricultural literature makes the absorptive-capacity mechanism unusually visible. During the Green Revolution, access to high-yielding seeds did not remove the need to learn when and how to use them. Imperfect knowledge slowed adoption, while farmers learned from their own experience and from neighboring farmers; technical change also raised the return to schooling (Foster and Rosenzweig 1995, 1996). The technology was embodied in a seed, but its productivity depended on the knowledge surrounding the seed. AI is more general, but the distinction between access and effective use is similar.

For low-income countries, this broader interpretation is essential. Schooling may improve the execution of existing tasks, but sustained convergence also requires firms that can maintain complex capital, managers who can reorganize production, finance for complementary investment, and public institutions that can implement policy. Measured schooling is best read as one observable component of a wider capability bundle, not as the mechanism itself. State capacity is one part of that bundle because adoption often requires reliable public administration as well as capable firms (Imam and Temple 2026d).

The advantage of backwardness is therefore conditional. A large technology gap creates more to imitate, but not necessarily more capacity to imitate well. Historical and contemporary evidence shows that blueprints travel more readily than the productive systems in which they are embedded (Clark and Feenstra 2001; Acemoglu and Zilibotti 2001; Comin and Mestieri 2018). Inappropriate technologies, weak complementarities, and barriers to firm selection can therefore leave economies far from the frontier even when techniques are observable (Acemoglu, Akcigit, and Johnson 2026). Productivity policy must connect frontier innovation to diffusion and to the intangible investments that support both (van Ark 2026).

The contrast need not always be pessimistic. Mobile phones spread rapidly through the fishing industry in Kerala because they relaxed a specific information constraint: fishermen could compare markets before deciding where to land their catch (Jensen 2007). Little frontier research was required locally; the technology worked because it fit a concrete bottleneck. This is a useful benchmark for AI. The greatest development gains may come not from replicating the frontier, but from adapting relatively inexpensive tools to problems where scarce information or expertise is itself the binding constraint.

Artificial intelligence gives this old problem a new form. Potential task exposure, adoption, intensive use, and productivity are distinct margins. If AI primarily augments skilled labor, it works through the level channel and may favor economies with stronger complements. If it reduces the cost of codifying knowledge, diagnosing problems, and adapting frontier practices, it may alter the mobility process itself.

This is why the paper turns to distribution dynamics. Statistical convergence in average growth rates need not imply economic convergence toward a common frontier, especially when countries occupy different regimes (Durlauf and Johnson 1995; Quah 1996). A country can grow and remain in the same part of the relative distribution if the frontier moves as well. Development is therefore not only a question of growth rates; it is a question of mobility.

Feyrer (2008), Johnson and Papageorgiou (2020), and Imam and Temple (2026a, 2026b) show that the proximate determinants of income have different transition dynamics. Capital intensity and measured human capital tend to move more readily than relative TFP. The present paper uses that asymmetry to ask whether human capital is small as an accounting term but important as a marker of the regime governing productivity mobility.

These arguments motivate a sharper empirical question: does human capital mainly explain productivity levels, or does it distinguish the process by which countries move toward the frontier?

# III. Methods

The empirical strategy separates a level margin from a mobility margin. The Caselli–Coleman decomposition asks how much of the productivity gap is mechanically associated with workforce composition. The transition framework asks whether economies with different levels of measured human capital face different probabilities of moving through the productivity distribution. A variable can explain little of a cross-country level gap and still be closely associated with catch-up.

The framework is reduced-form by design. It does not identify a structural model of technology adoption, institutional change, or AI diffusion. Its purpose is to characterize the transition process governing relative productivity and to isolate the margin on which AI would have to operate to change relative development. The results should therefore be read as descriptive evidence and conditional counterfactuals, not as causal estimates.

**3.1 Distribution dynamics**

Following Quah (1993, 1996), let $\{X_t\}$denote a discrete-time stochastic process taking values in a finite state space $S = \{1, \dots, K\}$, where each state corresponds to a category of relative productivity. The transition matrix is

$$P = [p_{ij}], \text{with}$$
$$p_{ij} = Pr(X_{t+\tau} = j | X_t = i).$$

Thus p_ij is the probability that an economy in state i moves to state j over interval tau. The first-order Markov assumption is a parsimonious approximation, not a claim that history is irrelevant. It summarizes mobility conditional on the current state. Directly estimated ten-year transitions are also compared with the matrix implied by two five-year steps as an internal consistency check, not a structural test.

One way to read the transition matrix is as a summary of development momentum. Two economies can occupy the same relative-productivity state today yet face very different odds of moving upward over the next five years. The matrix records those odds rather than assuming that every gap closes at a common speed. This is why the framework is useful here. Capabilities may matter primarily by changing the probability of transition, not by shifting current productivity mechanically.

All variables are expressed relative to the United States:

$$\tilde{x} = \frac{x}{x_{US,t}}.$$

The United States is used as a stable benchmark frontier economy. This gives upward movement a clear interpretation: closing part of the productivity gap with a fixed reference. The normalization does not imply that the United States leads in every sector or that successful economies must reproduce its sectoral structure. Comparative advantage can support high income away from particular technological frontiers; the object here is broad productive efficiency relative to a transparent benchmark.

Transitions are measured over five-year intervals. Annual movements are dominated by business cycles, temporary shocks, and measurement error, while longer intervals sharply reduce the number of observations. Five years is a compromise and is better matched to technology adoption, organizational change, and capability formation than annual data.

Let $\psi_t$ denote the distribution of countries across states at time $t$. Its evolution is

$$\psi_{t+\tau} = \psi_t P.$$

Under standard regularity conditions, the process admits a stationary distribution $\psi$ satisfying

$$\psi = \psi P.$$

The stationary distribution is not a forecast. It summarizes the persistence embedded in an estimated transition matrix if that matrix were repeated indefinitely. Concentration near the frontier indicates a mobility process favorable to convergence; dispersion indicates persistent relative differences. The long-run exercises below use stationary distributions only in this conditional sense.

We report transition probabilities, mean exit times, mean first-passage times, and a convergence statistic based on the second-largest eigenvalue of P. Exit times translate persistence into the expected time required to leave a state; first-passage times report the expected time to reach another state for the first time. These translations are economically useful because a seemingly small five-year probability can imply persistence over generations.

Following Kremer et al. (2001), we summarize convergence toward the stationary distribution using

$$\gamma = \frac{-log\, 2}{log\, |\lambda_2|},$$

where $\lambda_2$ is the second-largest eigenvalue of $P$ in absolute value. Since $\gamma$ is measured in transition periods, we multiply it by the interval length when reporting years. Lower values correspond to faster convergence toward the stationary distribution.

Discretizing a continuous distribution inevitably loses information. The baseline uses fixed thresholds so that moving upward closes a fixed part of the frontier gap rather than merely improving rank in a moving cross-section. Robustness checks use absolute thresholds, time-varying quartiles, terciles, quintiles, and a longer transition horizon. Transition probabilities are sample-frequency maximum-likelihood estimates under the Markov approximation; standard errors follow Anderson and Goodman (1957), with country-block bootstrap inference where appropriate (see also Imam and Temple 2026a, 2026b).

**3.2 Decomposing relative productivity**

To study the sources of relative productivity differences, we use the Caselli–Coleman framework. Output per worker in country $i$ is written as

$$Y_i = K_i^{\alpha}(A_i E_i)^{1-\alpha},$$

where $K_i$ is physical capital, $A_i$ total factor productivity, and $E_i$ effective labor. We set the capital share $\alpha$ equal to one-third throughout.

Effective labor is constructed from skilled and unskilled labor using a CES aggregator:

$$E_i = \left[(A_{u,i}L_{u,i})^{(\sigma-1)/\sigma} + (A_{s,i}L_{s,i})^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)},$$

where $L_{u,i}$ and $L_{s,i}$ denote unskilled and skilled labor, and $\sigma$ is the elasticity of substitution between the two groups.

The decomposition can then be written as

$$log\left(\frac{TFP_i}{TFP_{US}}\right) = log\left(\frac{A_{u,i}}{A_{u,US}}\right) + log\left(\frac{B_i}{B_{US}}\right) + \varepsilon_i.$$

Here B is the effective-labor term implied by workforce composition under the maintained common skill-premium assumptions. The first term is a relative-efficiency component; it should not be interpreted as a pure technology measure. The residual collects what the two-part accounting representation does not explain. The exercise asks a narrow question: how much of the observed productivity gap can workforce composition account for before broader efficiency, organization, and implementation margins must enter?

A small composition term would not show that human capital is unimportant. It would show that the direct static channel is insufficient. Human capital may instead matter through the transition process by helping economies absorb, adapt, and implement technologies. The decomposition is therefore a diagnostic bridge to the mobility analysis, not a structural allocation of TFP to named mechanisms.

Two assumptions are especially important. Following Caselli and Coleman (2006), the baseline imposes a common skill premium across countries. We also report alternative elasticities of substitution between skilled and unskilled labor, including the preferred Caselli–Coleman calibration, a Cobb-Douglas benchmark, and higher-substitution cases. The robustness question is whether any plausible calibration makes workforce composition large enough to overturn the mobility interpretation.

**3.3 Human capital and mobility**

The transition analysis then asks whether human capital is associated with the mobility process rather than only with current productivity levels.

We first estimate separate transition matrices for human-capital regimes. We then let the data select the split. For each candidate threshold tau, observations below and above tau are assigned separate transition matrices, and the likelihood gain relative to a pooled matrix is recorded. Candidate cutoffs must leave adequate observations in each regime. The selected threshold maximizes the likelihood-ratio statistic. This is a test for heterogeneous mobility regimes, not an attempt to impose convergence clubs by construction.

The threshold is not a precise law of development. Measured human capital proxies for education quality, cognitive skills, management, organizational depth, state capacity, and the ability to adapt technology. The estimated split is therefore best interpreted as a diagnostic of where the transition process changes most sharply, not as a causal treatment effect or a mechanical tipping point. We use the term capability regime to make that limitation explicit.

A useful complementary check is regression-adjusted mobility. The transition matrices condition on the initial state by construction, but one may still ask whether human capital predicts upward mobility after controlling for initial productivity, income, region, and period effects. We therefore estimate specifications of the form

$$Pr(s_{i,t+\tau} > s \quad ) = F\left(\alpha_{s(i,t)} + \beta h \quad + \Gamma Z \quad + \rho_r + \delta_t\right),$$

where $s_{it}$ is the productivity state, $h_{it}$ is measured human capital, $Z_{it}$ is a vector of controls including log income per capita, and $\rho_r$ and $\delta_t$ denote region and period fixed effects, respectively. These regressions are supporting checks, not a separate identification strategy. They ask whether the transition-matrix pattern remains visible after familiar conditioning; they do not identify the causal effect of schooling.

**3.4 AI counterfactuals**

The AI exercises are comparative statics under two interpretations. In the first, AI is skill-augmenting technological change and raises the productivity parameter attached to skilled labor:

$$A'_{s,i} = (1+\theta)A_{s,i}, \theta > 0.$$

Under this channel, gains depend on the existing supply of skilled labor and the production systems in which it is used. Economies with larger skilled workforces benefit more immediately. The exercise captures the possibility that AI raises the return to existing capabilities without changing the process through which countries acquire productive capability.

In the second interpretation, AI is a diffusion technology. By lowering the cost of codifying, translating, diagnosing, adapting, and applying knowledge, it may raise the probability that low-productivity economies move upward. This channel operates through the transition matrix rather than the workforce-composition term.

Neither exercise is a forecast. They show what would have to be true for AI to narrow rather than reinforce relative development gaps. The framework deliberately abstracts from labor displacement, capital ownership, changes in factor shares, and cross-border rents. Those outcomes matter for welfare and distribution, but they are distinct from the productivity-mobility margin studied here.

# IV. Data

The analysis combines three standard sources, each used for the task it is best suited to perform. The Maddison Project describes the long-run evolution of relative income. Penn World Table 11.0 supplies internally consistent measures of output, capital, employment, human capital, and TFP. Barro-Lee educational-attainment data provide the skilled and unskilled labor shares used in the Caselli–Coleman decomposition.

The main production sample uses Penn World Table 11.0 (Feenstra, Inklaar, and Timmer 2015) over 1960–2015 in non-overlapping five-year intervals. The endpoint aligns the production data with the educational-attainment series and avoids treating the exceptional 2020 observation as an ordinary medium-run transition. A separate 2020 PWT cross-section is used only to illustrate the accounting decomposition and does not enter the baseline mobility estimates.

The Maddison Project Database (Bolt and van Zanden 2020) documents long-run relative-income persistence. The production-function and mobility exercises use PWT 11.0 because they require mutually consistent measures of output, capital, employment, human capital, and TFP. The two sources answer different empirical questions rather than provide competing estimates of the same object.

Educational attainment comes from Barro and Lee (2013), updated through 2015. Skilled labor is the share of the population aged 25 and over with completed secondary education or more. The auxiliary 2020 decomposition matches PWT outcomes to the latest available attainment observation. This is a coarse measure; it does not capture school quality, cognitive skill, management, or technological adaptability. A separate mobility comparison therefore uses Hanushek and Woessmann’s (2012) cognitive-skill data.

All principal variables are expressed relative to the United States. The mobility analysis uses the PWT human-capital index, rescaled so that the United States equals one in each year; the decomposition uses Barro-Lee attainment shares. The distinction is intentional. The first measure classifies time-varying human-capital regimes, while the second enters the skilled-unskilled effective-labor calculation.

Coverage differs across exercises because the required variables differ. The pooled decomposition uses 120 countries and 1,186 country-period observations. The baseline relative-TFP transition matrix uses 1,097 five-year transitions; the capital-output and human-capital matrices use larger samples. Each observed country-period transition receives equal weight, so countries with longer usable histories contribute more transitions. The matrices therefore describe mobility across national economies rather than population-weighted global mobility.

The baseline classifies relative TFP into four states using thresholds from the 1975 cross-section, held fixed thereafter. The early benchmark avoids the thinner coverage of 1960 while preserving a stable state space. Upward movement therefore means closing a fixed portion of the productivity gap, not merely improving rank. Alternative absolute and rank-based state definitions test the sensitivity of this choice.

Transition probabilities are estimated from observed frequencies. Anderson-Goodman standard errors are reported where appropriate, and country-block bootstrap procedures are used for threshold inference and nonlinear functions of the estimated matrices. The threshold exercise uses 300 bootstrap replications. These procedures acknowledge that repeated observations for the same country are not independent.

Three limitations deserve emphasis. Educational attainment is an imperfect proxy for capability. International productivity comparisons are sensitive to PPP adjustments, national-accounts quality, and the construction of TFP, especially in lower-income economies. Finally, the United States is a benchmark rather than a universal sectoral frontier. These concerns motivate the alternative skill measure, state definitions, and restrained interpretation of the threshold.

The sample retains economies with complex transition histories, including successor states of the former Soviet Union and Yugoslavia, when the required observations are usable. Excluding such cases would select the sample toward stable national histories and successful development paths. The results should therefore be read as describing the postwar cross-country distribution, with the usual caution around institutional and statistical breaks.

The long-run benchmark is stark. Countries' positions in the relative income distribution are highly persistent even when absolute incomes rise.

# V. Relative Income Dynamics: A First Look

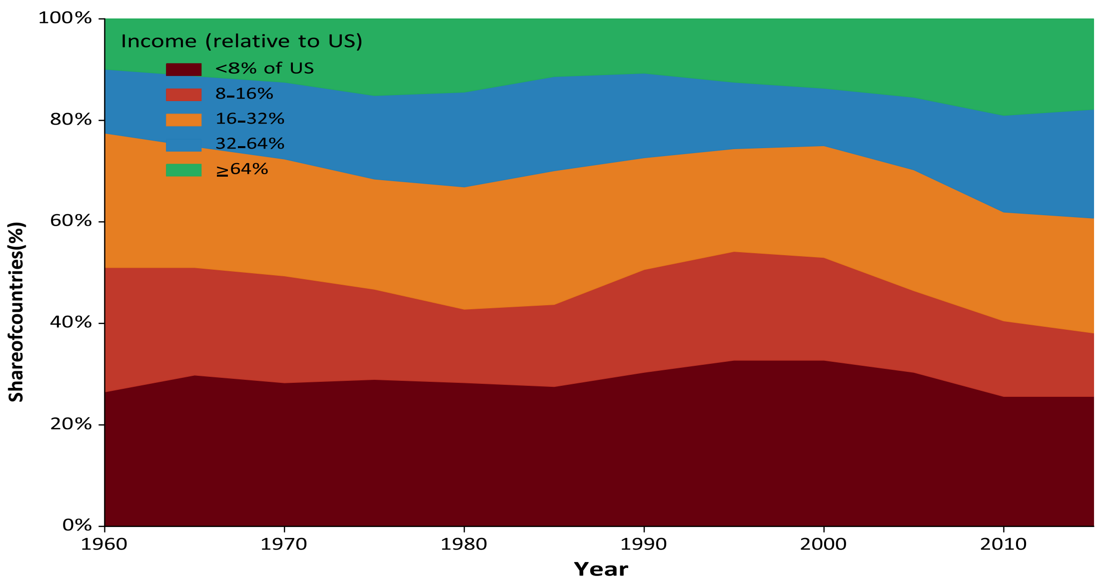
The first empirical fact is the persistence of relative income positions. Convergence cannot be inferred from the spread of inputs or from positive growth alone; it requires countries to move toward the frontier relative to others.

Income is measured relative to the United States. The question is not whether poorer economies grow, many do, but whether they grow enough, and persistently enough, to enter a different part of the relative distribution. Average convergence and lower-tail immobility can therefore coexist. Relative persistence should not be confused with absolute stagnation. An economy can grow, reduce poverty, and improve living standards while still failing to close the gap with the frontier. The concern here is the foregone gain from catch-up, not a claim that relative persistence implies no development.

A narrowing distribution also does not reveal which countries moved. Convergence can reflect catch-up from below, relative decline from above, or both. Imam (2026) shows that economies above their predicted long-run trajectories subsequently grow more slowly and are more likely to move down the world income distribution. Distribution dynamics are useful precisely because they distinguish these movements rather than treating every compression of income gaps as catch-up.

Figure 1 tracks the share of countries in fixed relative-income states using Maddison Project data for 1960–2015. The distribution changes, but slowly. The lower tail remains large and the upper tail stable. The world distribution is neither frozen nor fluid: mobility is limited, especially at the extremes. This is why distribution dynamics reveal something that average growth regressions can miss (Pritchett 1997; Quah 1993, 1996).

**Figure 1. Evolution of the relative income distribution, 1960–2015.**




Share of countries in fixed relative-income states, measured as GDP per capita relative to the United States. State thresholds are fixed over time, so movements reflect changes in relative position rather than redefinition of the state space. Source: Authors' calculations from the Maddison Project Database 2020.

Table 1 reports the corresponding five-year transition matrix. States are defined from the 1975 distribution and held fixed, so upward movement closes a fixed part of the income gap rather than merely improves rank. The persistence pattern also survives alternative state definitions.

Persistence is high at both ends. Economies in the lowest state remain there with probability 0.943 over five years; economies in the highest state remain there with probability 0.931. Movements are mostly local, and jumps from the bottom to the top are absent. The lower tail is therefore not simply a set of countries observed to be poor at one date. It is a durable part of the world distribution.

Table 1: Relative income transition matrix, 1960–2015 (five-year intervals).

| *From / To* | Q1 | Q2 | Q3 | Q4 | N_transitions |
|---|---|---|---|---|---|
| Q1 | **0.943** | 0.057 | 0.000 | 0.000 | 980 |
| | *(0.007)* | *(0.007)* | *(0.000)* | *(0.000)* | |
| Q2 | 0.097 | **0.798** | 0.102 | 0.002 | 401 |
| | *(0.015)* | *(0.020)* | *(0.015)* | *(0.002)* | |
| Q3 | 0.005 | 0.087 | **0.764** | 0.144 | 195 |
| | *(0.005)* | *(0.020)* | *(0.030)* | *(0.025)* | |
| Q4 | 0.000 | 0.005 | 0.064 | **0.931** | 203 |
| | *(0.000)* | *(0.005)* | *(0.017)* | *(0.018)* | |
| Stationary | 0.300 | 0.167 | 0.171 | 0.361 | |

Five-year transition probabilities from the row state to the column state. Quartile thresholds fixed at the 1975 cross-section. N_transitions reports the number of country-period observations used to estimate each row. Standard errors in parentheses below each point estimate; diagonal (persistence) entries shown in bold. 90% confidence intervals where reported are country-block bootstrap with 300 replications. Source: Authors' calculations from the Maddison Project Database 2020.

Appendix A translates these probabilities into development time. The mean exit time from the lowest income state is 87.7 years, and the mean first-passage time from the bottom to the top is 330.8 years. These are not forecasts. They express the persistence embedded in the estimated process in units that are easier to interpret.

Expressed in years, the persistence is easier to see. An 87.7-year mean exit time is not a calendar forecast for a particular country. It says that a five-year persistence probability of 0.943, when repeated as a statistical process, describes a state that can last across generations. What looks like a small difference in a transition probability can therefore represent a large difference in development experience.

Nor are transition probabilities invariant to shocks. Imam and Temple (2026c) show that conflict and debt crises help explain the persistence of low relative income by changing upward and downward mobility. The matrices here average over such episodes. They summarize the realized postwar transition process rather than a structural law that applies unchanged in crises and tranquil periods.

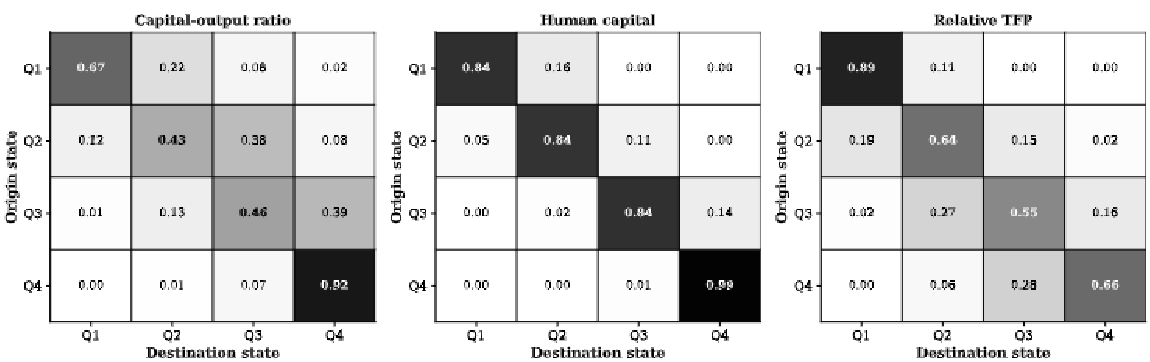
Over the same period, schooling expanded, investment increased, and access to modern technologies broadened, yet relative income positions changed only gradually (Quah 1996; Feyrer 2008; Imam and Temple 2026a, 2026b; Patel, Sandefur, and Subramanian 2021). Persistence could reflect slow input accumulation or the harder problem of slow productivity mobility.

# VI. Proximate Determinants: Capital, Human Capital, and Productivity

Relative-income persistence can originate in observable inputs or in productivity itself. If capital, human capital, and TFP all move slowly, the evidence points to a broad failure of accumulation. If inputs move more readily than TFP, economies may acquire machines and schooling without comparable improvements in how those inputs are combined and used.

We apply the transition framework to the capital-output ratio, measured human capital, and relative TFP. The result is a clear asymmetry. Capital and human capital display more directional mobility; relative TFP is more persistent, especially in the lower tail. The world economy has narrowed gaps in measurable inputs more readily than gaps in productive efficiency.

**Figure 2. Transition Matrices: Proximate Determinants**




Note: Five-year transition probabilities from row state to column state; darker cells indicate higher probabilities. Diagonal entries measure persistence. Panels show the capital-output ratio, the human-capital index, and relative TFP. The full capital-output and human-capital transition matrices underlying the first two panels are reported in Appendix B. The relative-TFP matrix underlying the third panel is reported in Table 3. Source: Authors' calculations from Penn World Table 11.0.

Figure 2 shows the contrast. Capital-output ratios display substantial upward mobility: countries in the bottom state leave it with probability 0.327 over five years, and movement from the middle states is often toward higher states. Capital deepening is not frictionless, but its direction is clear. Human capital moves more slowly but more monotonically. The bottom state has an upward-mobility probability of 0.156, downward movements are rare, and the top state is highly persistent. This pattern is consistent with the postwar expansion of schooling: measured human capital behaves like an accumulating stock rather than a volatile residual.

Relative TFP is different. The lowest state has five-year persistence of 0.886, so upward movement from Q1 is only 0.114. In the middle of the distribution, movement is not uniformly progressive.

From Q3, downward movement to Q2 is more common than upward movement to Q4. The top state also exhibits churn, but weak upward mobility from below prevents this from becoming convergence. The implied stationary mass in Q4 is only 8.9 percent, compared with 77.1 percent for capital-output and 90.3 percent for human capital.

**Table 2. Mobility Statistics Across Proximate Determinants.**

| Variable | P(Q1,Q1) | Mean exit Q1 (years) | P(Q1→Q2,Q3,Q4) | P(Q4,Q4) | Stationary Q4 mass | Number of transitions (NT) |
|---|---|---|---|---|---|---|
| Capital-output ratio (K/Y) | 0.673 | 15.3 | 0.327 | 0.921 | 0.771 | 1208 |
| Human capital (PWT hc) | 0.844 | 32.1 | 0.156 | 0.988 | 0.903 | 1441 |
| Relative TFP (PWT ctfp) | 0.886 | 44.0 | 0.114 | 0.660 | 0.089 | 1097 |

Note: Summary statistics derived from the three transition matrices visualized in Figure 2. P(Q1,Q1) is five-year persistence in the bottom state. Mean exit Q1 is the expected number of years required to leave the bottom state. P(Q1→Q2,Q3,Q4) is the probability of upward movement from Q1 within five years. P(Q4,Q4) is persistence in the top state. The stationary Q4 mass is the long-run share implied by the estimated transition matrix and should not be interpreted as a forecast. States are defined using the same fixed thresholds as in Figure 2: K/Y and human capital use {0.36, 0.48, 0.64} of the U.S. level; relative TFP uses 1975 cross-sectional quartile thresholds. Source: Authors’ calculations from Penn World Table 11.0.

Table 2 summarizes the economically relevant contrasts. Mean exit time from Q1 is 15.3 years for capital-output, 32.1 years for human capital, and 44.0 years for relative TFP; upward mobility from Q1 is 0.327, 0.156, and 0.114, respectively. The ordering is unambiguous. Because capital and schooling are cumulative stocks, their stationary distributions should not be read as comparable welfare forecasts; they are reported only as summaries of directionality and persistence.

A stricter comparison places all three variables on the same 1,097 transitions and defines each state by its fixed 1975 non-U.S. quartiles. Mean exit from Q1 is then 16.1 years for capital intensity, 31.5 for human capital, and 44.0 for TFP; upward mobility is 0.310, 0.159, and 0.114. The ordering therefore does not arise from different samples or state boundaries.

The result does not imply that inputs converge quickly or that productivity never changes. It is narrower. When observable inputs move, they tend to move upward, while productivity mobility is more local, reversible, and unlikely to carry countries into the near-frontier state. This asymmetry changes the diagnosis of slow convergence. If countries can accumulate capital and schooling without comparable movement in TFP, the bottleneck cannot be accumulation alone; the harder problem is converting accumulated inputs into higher productivity. Machines and schooling travel more easily than the production systems that use them well. As gaps in capital and schooling narrow, the dynamics of productivity become increasingly important for relative income.

The distinction is familiar at the micro level. A machine can be purchased in a single transaction; the routines needed to maintain it, finance complementary inputs, train workers, manage inventories, and reach customers accumulate more slowly. Schooling is similar: years of education can rise without firms simultaneously acquiring the management and organizational capital needed to use more educated workers effectively. The aggregate transition matrices appear to capture this difference between acquiring inputs and learning to use them.

Table 3. Relative TFP transition matrix, 1960–2015.

| *From / To* | <0.65 | <0.88 | <1.04 | >=1.04 | N_transitions |
|---|---|---|---|---|---|
| <0.65 | **0.886** | 0.111 | 0.002 | 0.000 | 449 |
| | *(0.015)* | *(0.015)* | *(0.002)* | *(0.000)* | |
| <0.88 | 0.185 | **0.640** | 0.155 | 0.020 | 297 |
| | *(0.023)* | *(0.028)* | *(0.021)* | *(0.008)* | |
| <1.04 | 0.019 | 0.271 | **0.551** | 0.159 | 207 |
| | *(0.010)* | *(0.031)* | *(0.035)* | *(0.025)* | |
| >=1.04 | 0.000 | 0.056 | 0.285 | **0.660** | 144 |
| | *(0.000)* | *(0.019)* | *(0.038)* | *(0.039)* | |
| Stationary | 0.479 | 0.278 | 0.154 | 0.089 | |

Note: Five-year transition probabilities for relative total factor productivity. State boundaries are the 1975 cross-sectional quartiles of relative TFP, held fixed thereafter; this is the same construction used in the right panel of Figure 2. Standard errors are in parentheses below each point estimate; diagonal entries are shown in bold. Source: Authors' calculations from Penn World Table 11.0.

Table 3 reports the relative-TFP transition matrix. The lower tail is sticky, transitions out of Q1 are overwhelmingly local, and jumps from the bottom to the frontier state are absent. The middle is not a smooth ladder: from Q3, downward movement to Q2 is more common than upward movement to Q4. Productivity mobility is therefore constrained rather than a common escalator toward the frontier.

TFP is not a primitive force independent of capital and human capital. It is a residual that also reflects management, sectoral allocation, institutions, technology use, and measurement error. Its persistence does not mean that technology never crosses borders. It means that broad productive systems change more slowly than observable inputs.

Many developing economies have expanded schooling, accumulated capital, and gained access to modern technologies, yet sustained movement toward frontier productivity remains rare. The finding adds a dynamic dimension to development accounting: productivity accounts for much of the cross-country variation in income levels, and the differences are themselves persistent.

Workforce composition is the most immediate candidate explanation for the productivity gap. If it is quantitatively small, measured human capital may matter more as a marker of the capabilities governing movement through the productivity distribution.

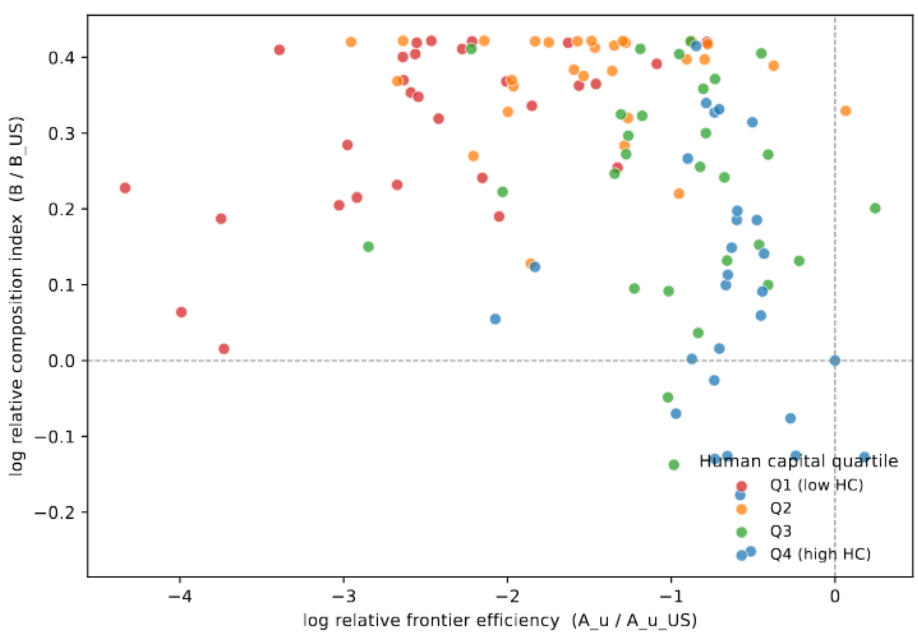
# VII. Decomposing Relative Productivity: Efficiency versus Workforce Composition

Relative TFP combines technology use, workforce composition, management, allocation, institutions, and measurement error. The transition matrices show that it moves slowly, but not which component is responsible. The immediate question is whether persistence is mainly a disguised skill-composition problem. If so, expanding skills should close most of the gap. If not, the harder issue is how skills and technologies are used inside firms and production systems.

The Caselli–Coleman decomposition provides a disciplined accounting check. It separates a workforce-composition term from a relative-efficiency term and a residual. None of these terms should be given a structural interpretation. The exercise asks only whether the static composition channel is quantitatively large enough to carry the convergence story.

It is not. The direct workforce-composition term is too small to account for most observed productivity differences. Human capital may still matter, but mainly through a broader channel: by supporting the absorption, adaptation, and implementation of technologies over time.

**Figure 3. Relative-Efficiency and Workforce-Composition Components of Relative Productivity, 2020**




Note: Each point is a country in the auxiliary 2020 cross-section. The horizontal axis reports the relative-efficiency component, log(A_u/A_u,US), and the vertical axis the workforce-composition component, log(B/B_US). Colors distinguish human-capital quartiles. The figure is an accounting illustration; it is not used to estimate the 1960–2015 transition matrices. Source: Authors' calculations from Penn World Table 11.0 and the educational-attainment data described in Section IV.

Figure 3 makes the point visually. Cross-country variation is much greater along the relative-efficiency axis than along the workforce-composition axis. High-human-capital economies tend to lie farther to the right, but the relationship is not one in which workforce composition mechanically maps into productivity.

The visual pattern rules out a simple composition story. Countries with similar measured human capital can be embedded in very different production systems. Schooling may become more equal while the productive use of skills remains uneven—the accounting counterpart of asymmetric productivity mobility.

Put differently, counting skilled workers is not the same as measuring what skilled workers can accomplish. Engineers and technicians with similar formal education can generate very different output depending on the equipment they use, the quality of management, the information available to them, and whether firms have the finance and incentives to reorganize production. The decomposition is useful precisely because it shows how much remains after the readily measured composition effect has been taken out.

Table 4 quantifies the same point. Mean relative TFP rises across human-capital quartiles, but the movement is much larger in the relative-efficiency term than in workforce composition. The sign and level of the composition term depend on the common skill-premium calibration and normalization. The robust conclusion is limited but important: workforce composition contributes to productivity differences, but does not dominate them.

**Table 4. Caselli–Coleman Decomposition of Relative TFP by Human-Capital Quartile, Auxiliary 2020 Cross-Section**

| HC group (cross-section) | N | Mean rel. TFP | log(TFP/TFP_US) obs. | log(A_u / A_u_US) | log(B / B_US) | log residual |
|---|---|---|---|---|---|---|
| Q1 (low HC) | 29 | 0.486 | -0.782 | -2.469 | 0.312 | 1.375 |
| Q2 | 29 | 0.657 | -0.484 | -1.52 | 0.371 | 0.665 |
| Q3 | 28 | 0.727 | -0.368 | -0.991 | 0.23 | 0.393 |
| Q4 (high HC) | 29 | 0.759 | -0.304 | -0.671 | 0.079 | 0.288 |

Note: The auxiliary cross-section uses 2020 PWT outcomes and the educational-attainment inputs described in Section IV. The relative-efficiency component is log(A_u/A_u,US); the workforce-composition component is log(B/B_US). The residual includes cross-country skill-premium differences, measurement error, and all other omitted elements. This is an accounting decomposition of log relative TFP, not a variance decomposition. Pooled results and elasticity sensitivity are reported in Appendix E. Source: Authors' calculations from Penn World Table 11.0 and Barro-Lee educational-attainment data.

The residual is largest in the lowest human-capital quartile. This is not evidence for a particular omitted mechanism; it is a warning against reading the decomposition structurally. The exercise cannot separately identify technology, management, institutions, allocation, unobserved labor quality, and measurement error. It supports only the narrow conclusion that workforce composition alone is insufficient.

The pooled 1960–2015 decomposition and alternative elasticities in Appendix E lead to the same qualitative result. Greater substitutability between skilled and unskilled labor enlarges the composition term, as it should, but no plausible calibration makes it the dominant source of the productivity gap. The static result therefore points toward a dynamic role for human capital.

This helps interpret Pritchett's (2001) finding that schooling expansions need not translate mechanically into growth. Measured human capital can rise while firms, management, institutions, and organizational capital remain unable to use skills effectively. The remaining issue is whether broader capability is associated with movement toward the frontier.

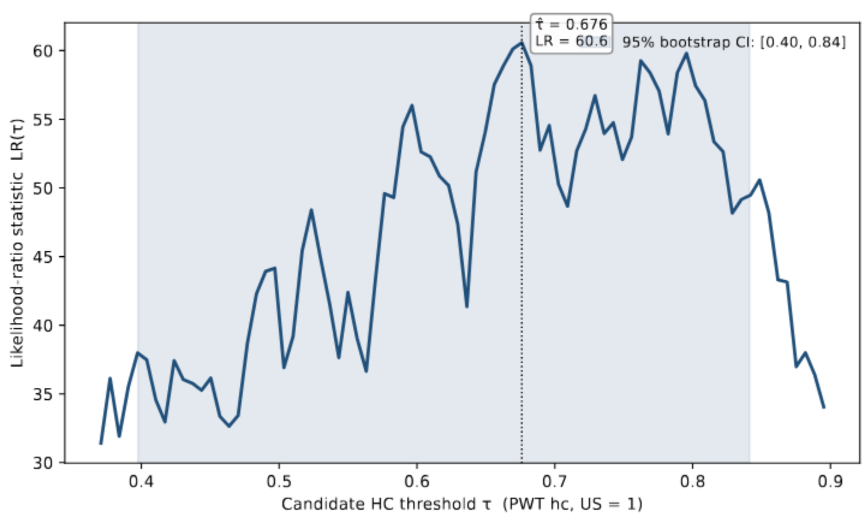
# VIII. Human Capital and Productivity Mobility: An Estimated Capability Threshold

Stronger measured human capital may be associated with a different transition process even when workforce composition explains little of the productivity gap—specifically, with faster exit from low-productivity states.

The intuition is Nelson–Phelps with complementarities. An engineer is more useful when the firm can finance new equipment, managers can reorganize workflows, data are reliable, and infrastructure works; better management has less value if skilled workers or finance are missing. When these inputs are complements, the payoff to any one of them can rise sharply once enough of the others are in place. A threshold in measured human capital can therefore be a reduced-form marker of a broader change in the returns to adaptation, without being a literal schooling threshold (Acemoglu, Akcigit, and Johnson 2026).

We estimate an endogenous sample split in the statistical sense: the cutoff is selected from the data rather than imposed. For each candidate tau, observations below and above the cutoff receive separate transition matrices, and the likelihood gain over a pooled matrix is recorded. Candidate cutoffs must leave adequate cell sizes. The selected value maximizes the likelihood-ratio statistic and tests whether one common mobility process is an adequate description.

**Figure 4. Likelihood-Ratio Profile and the Estimated Capability Threshold**




*Note: Profile of the two-regime Markov log-likelihood as a function of the candidate human-capital threshold. The vertical dashed line marks the maximum-likelihood estimate. Source: Authors' calculations from Penn World Table 11.0.*

The estimated threshold is a diagnostic device, not a level at which development begins. Measured human capital proxies for cognitive skill, management, organizational depth, technological familiarity, and state capacity. The exercise tests for heterogeneous mobility regimes; it does not identify a causal schooling effect or a mechanical tipping point. We therefore place more weight on the regime contrast than on the numerical cutoff.

Figure 4 shows a broad interior region of elevated fit rather than a sharply localized breakpoint. Allowing the transition process to differ across regimes improves the fit, but does not establish a mechanical tipping point. The estimated cutoff is 0.676 of the U.S. human-capital index, with a 95 percent bootstrap interval from 0.398 to 0.841. Because the interval spans much of the middle of the distribution, the evidence is stronger for mobility heterogeneity than for a precise numerical threshold. Under the estimated split, mean time to leave the lowest productivity state is 64.8 years below the cutoff and 25.4 years above it.

For transparent comparisons elsewhere in the paper, Table 6 uses an operational cutoff of 0.64, close to the point estimate and identical to the upper human-capital state boundary used in the transition analysis. The purpose is comparability, not a claim that 0.64 is a structural constant.

**Table 5. Estimated Capability Threshold**

| Statistic | Value |
|---|---|
| Endogenous HC threshold $\hat{\tau}$ | 0.676 |
| 95% bootstrap CI lower | 0.398 |
| 95% bootstrap CI upper | 0.841 |
| LR at $\hat{\tau}$ | 60.57 |
| Bootstrap replications | 300 |
| Mean exit time from Q1 \| HC < $\hat{\tau}$ (years) | 64.8 |
| Mean exit time from Q1 \| HC ≥ $\hat{\tau}$ (years) | 25.4 |
| Exit-time ratio (Low/High) | 2.55× |
| N transitions, HC < $\hat{\tau}$ | 632 |
| N transitions, HC ≥ $\hat{\tau}$ | 476 |

Note: Threshold $\hat{\tau}$ = 0.676, estimated by adapting Hansen's (2000) sample-splitting approach to a two-regime Markov likelihood. The 95 percent confidence interval is obtained by country-block bootstrap with 300 replications. Mean exit times report the expected years required to leave the lowest relative-TFP state under the estimated transition process. The effective threshold-search sample differs slightly from the baseline transition-matrix sample; the replication files report the exact observations used in each exercise. Source: Authors' calculations from Penn World Table 11.0.

The contrast is large. In the low-capability regime, Q1 persistence is 0.922 and only 7.8 percent of observations move upward over five years; the stationary distribution assigns 68.8 percent of mass to Q1 and 5.2 percent to Q4. Above the operational cutoff, Q1 persistence falls to 0.826, upward mobility rises to 17.4 percent, and stationary Q4 mass reaches 12.8 percent. Higher-capability economies do not converge instantly; low productivity is simply less persistent.

**Table 6. Mobility Statistics by Capability Regime**

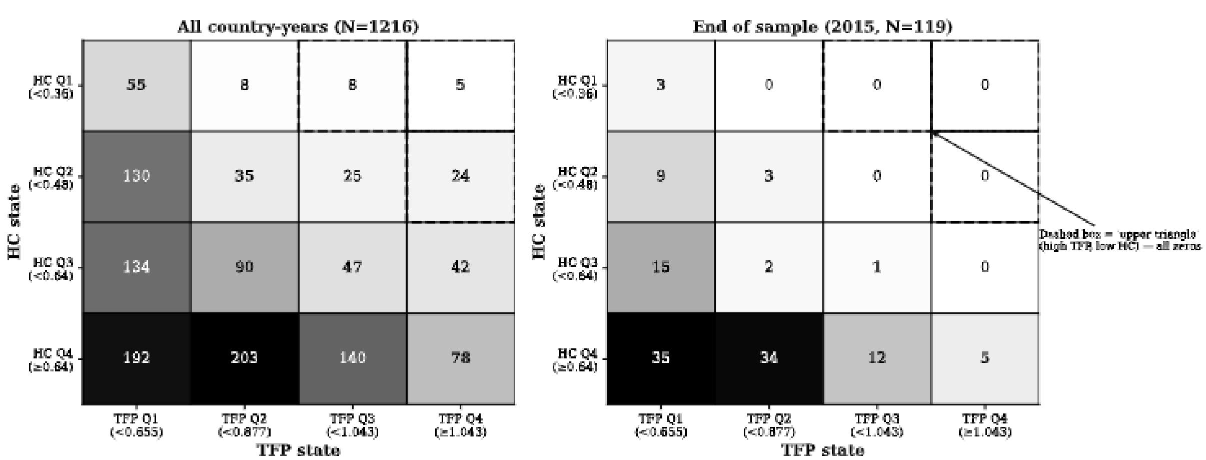
| Group | Q1 persistence | $\gamma$ (years) | $\text{MET}_1$ (years) | 90% CI | Passage Q1→Q4 (yrs) | 90% CI | Stationary Q1 | Stationary Q4 | NT |
|---|---|---|---|---|---|---|---|---|---|
| Low HC (rel_hc $<$ 0.64) | 0.922 | 17.8 | 64.3 | [48.3, 92.8] | 368.5 | [278.3, 616.3] | 0.688 | 0.052 | 526 |
| High HC (rel_hc $\geq$ 0.64) | 0.826 | 20.6 | 28.7 | [22.5, 36.1] | 177.0 | [142.7, 226.2] | 0.254 | 0.128 | 522 |
| Unconditional | 0.886 | 21.2 | 44.0 | [35.1, 55.4] | 241.8 | [198.3, 302.2] | 0.479 | 0.089 | 1097 |

Mean exit time from Q1, passage time Q1–Q4, and stationary shares are computed analytically from the Low-HC and High-HC transition matrices reported in Appendix D. Source: Authors' calculations from Penn World Table 11.0.

Note: Summary statistics from separate relative-TFP transition matrices estimated for observations below and above the operational human-capital cutoff of 0.64. The conditional rows use observations with the required human-capital classification; the unconditional row uses the full baseline relative-TFP sample. Mean exit time is the expected number of years required to leave the lowest productivity state. Mean first-passage time reports the expected years required to move from the lowest to the highest productivity state under the estimated transition process. Stationary masses summarize the estimated Markov chains and should not be interpreted as forecasts. Full transition matrices and supporting counts are reported in Appendix D. Source: Authors' calculations from Penn World Table 11.0.

The difference is most intuitive in development time. Under the operational split, mean exit time from Q1 falls from 64.3 to 28.7 years, and expected passage from Q1 to Q4 from 368.5 to 177.0 years. These conditional waiting times show how small differences in five-year mobility cumulate into differences measured in generations rather than percentage points.

**Figure 5. Joint Distribution of Human-Capital and TFP States**




Note: Left panel reports pooled country-year counts in each human-capital state and TFP state. Right panel reports the 2015 cross-section. In the 2015 cross-section, the high-TFP/low-HC region is empty; in the pooled panel such observations exist but are rare. Supporting counts are reported in the appendix. Source: Authors' calculations from Penn World Table 11.0.

Figure 5 is a cross-sectional check, not the main evidence. In 2015, no country combines the lowest human-capital state with frontier-level TFP; in the pooled panel, such observations exist but are rare. This does not prove a threshold mechanism. It establishes an asymmetry: schooling without frontier productivity is common, while sustained frontier productivity with very low measured human capital is difficult to find.

Regression-adjusted mobility provides a stricter test by conditioning on the initial productivity state and familiar controls. These estimates complement rather than replace the full transition matrices.

**Table 7. Regression-Adjusted Mobility in Relative TFP**

| Spec. | Outcome | Sample | Human-capital term / control | HC association (SE) | Estimator | N | Countries |
|---|---|---|---|---|---|---|---|
| *Panel A. Theory-consistent: distance-to-frontier (origin-state FE) + period FE* | | | | | | | |
| (1) | Upward move | Q1–Q3 | High HC (≥0.64) | 0.063** (0.024) | Logit AME | 950 | 118 |
| (2) | Upward move | Q1–Q3 | Continuous HC | 0.184*** (0.062) | Logit AME | 950 | 118 |
| (3) | Exit from Q1 | Q1 | High HC (≥0.64) | 0.128*** (0.036) | LPM (logit fallback) | 442 | 84 |
| (4) | Upward move | Q1–Q2 | High HC (≥0.64) | 0.071*** (0.025) | Logit AME | 748 | 115 |
| (5) | Upward move | Q1–Q3 | High HC (≥0.64) | 0.565** (0.227) | GEE logit (pop.-avg. coef.) | 950 | 118 |
| *Panel B. Saturated controls (income and/or region FE) — over-controls / limits* | | | | | | | |
| (1) | Upward move | Q1–Q3 | + region FE | 0.020 (0.032) | Logit AME | 950 | 118 |
| (2) | Upward move | Q1–Q3 | + log GDP p.c. | -0.045 (0.027) | Logit AME | 950 | 118 |
| (3) | Upward move | Q1–Q3 | + income + region | -0.044 (0.034) | Logit AME | 950 | 118 |

Note: Dependent variable is an indicator for upward movement in the relative-TFP state over the next five years; one specification focuses on leaving Q1, and another restricts the sample to the lower tail. Upward-mobility samples exclude origins in the top state, which cannot move upward. Baseline specifications condition on the initial productivity state and period effects. Additional specifications add log GDP per capita and/or region fixed effects. Logit rows report average marginal effects; linear probability model rows report coefficients; GEE logit specifications report log-odds coefficients. Country-clustered standard errors are in parentheses. Estimates are associations, not causal effects. Source: Authors' calculations from Penn World Table 11.0. Asterisks denote statistical significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

The discrete specifications show that the regime contrast is concentrated among economies that begin in the lowest-productivity state, Q1. This is economically intuitive. The distinction matters most where the productivity gap is largest and where upward mobility is rare. At the same time, the estimated relationship becomes substantially weaker once we control more flexibly for where countries start within Q1. When exact initial productivity is included as a flexible control, the coefficient on continuous human capital falls from 0.417 to 0.150 ($p = 0.068$). Adding initial income reduces it further to 0.028 ($p = 0.790$). This matters for interpretation. Crossing the Q1 boundary is partly a function of how close an economy already is to that boundary and of its broader level of development. The threshold result should therefore not be read as an independent causal effect of human capital or as evidence of a sharp structural tipping point.

A less discontinuous measure of mobility produces a more robust pattern. Instead of asking whether a country crosses a particular state boundary, we examine five-year growth in log relative TFP. Conditional on a cubic in exact initial productivity, a one-unit increase in human capital relative to the United States is associated with 0.222 higher five-year growth in log relative TFP. The coefficient remains 0.200 after controlling additionally for income and capital intensity ($p < 0.001$). Similar estimates are obtained for welfare-relevant TFP, national-price

TFP growth, and labor-productivity growth. Country fixed effects weaken the precision of the ctfp estimate, although the coefficient remains positive, while the national-price TFP estimate remains positive and statistically significant. These regressions are descriptive rather than causal. Their value is that they show that the human-capital relationship is not confined to crossing an arbitrarily defined state boundary.

The broader mobility relation also does not depend on a searched absolute cutoff. A fixed within-year median split, which avoids selecting a threshold from the data, implies a mean exit time from Q1 of 79.1 years for observations below the median and 28.0 years for those above it. Equality of the full transition matrices is rejected in a 1,000-replication country-block permutation test ($p = 0.001$). The predictive evidence points in the same direction. The fixed-rank specification improves both early-to-late and late-to-early prediction and performs better in eight of ten country folds. When human capital enters smoothly rather than through a discrete split, it improves held-out transition prediction in all fifty repeated country-fold assignments. Moreover, human capital residualized on income, period effects, and initial productivity state continues to contain information about the transition matrix ($p = 0.022$). The precise numerical cutoff therefore moves across samples and specifications, but the broader information contained in measured human capital about productivity mobility is considerably more stable.

Taken together, these results help reconcile the human-capital literatures and sharpen Pritchett's puzzle. Measured human capital contributes only modestly to the static decomposition of productivity differences, yet it is informative about the expected duration of low-productivity states and about subsequent productivity growth. The distinction is between a stock and a conversion process. Schooling increases the stock of effective labor, but the wider capability bundle influences how quickly skills, capital, and knowledge are converted into reliable production. This helps explain why substantial increases in schooling need not translate mechanically into productivity convergence. Catch-up is more likely when education is connected to firms that use skills productively, managers able to reorganize production, finance for complementary investment, and institutions that support experimentation, learning, and technological adaptation.

For AI, the implication is direct. Skill-augmenting AI can raise output by increasing the productivity of workers and firms that already possess the relevant capabilities, without necessarily changing a country's position in the relative productivity distribution. Diffusion-enhancing AI operates on a different margin. To promote convergence, it must reduce the costs of learning, validation, adaptation, and implementation precisely where productive capability is weakest. The relevant question is therefore not only whether AI becomes widely available, but whether it changes the process by which low-productivity economies convert increasingly accessible knowledge into sustained productivity gains.

# IX. AI as Skill Augmentation and Diffusion

Artificial intelligence sharpens the distinction between a frontier shift and a diffusion shift. It can raise output in every country without changing relative positions, and its aggregate gains can be distributed unevenly (Aghion, Jones, and Jones 2018; Korinek and Stiglitz 2018). Convergence requires AI to change the transition process, not merely the frontier. Skill augmentation and diffusion are therefore economically distinct channels.

Technical capability, task exposure, access, adoption, adaptation, intensive use, productivity gains, and relative mobility are separate margins. Technical capability describes what an AI system can do; productive capability describes whether firms and institutions can use it reliably at scale. A system may perform a task in principle while users lack data, suitable workflows, managerial capacity, or incentives to act on its output. Exposure is therefore not adoption, and adoption is not economic transformation.

This distinguishes productivity mobility from AI exposure and preparedness. Exposure measures tasks that AI could affect, while preparedness indexes observable conditions for adoption (Cazzaniga et al. 2024). Capability regimes are outcome-based: they classify historical movement through the productivity distribution. Preparedness asks whether conditions for adoption are present; mobility asks whether productive capability is associated with escape from low productivity.

Recent IMF work on Asia provides a useful complement. Che, Xin, and Yoshida (2026) show in a structural model that better-prepared economies adopt AI earlier, while weaker human capital and infrastructure delay adoption; reforms that strengthen these fundamentals bring adoption forward. Our historical evidence asks a related question on the other side of the adoption decision: once technologies are available, do stronger capabilities coincide with a greater probability of escaping low productivity? The transition evidence points in that direction, without identifying a causal effect.

The narrower channel is skill-biased technological change. In the CES decomposition, AI raises the productivity of skilled labor, so identical access can generate different aggregate gains. Task-level substitution can coexist with firm- and economy-level complementarity: AI may automate drafting, coding, translation, or diagnosis while raising the value of judgment, validation, coordination, and organizational redesign. Knowledge can become abundant without productive capability becoming abundant. Economies able to act on cheaper codified knowledge gain first; the transition process changes only if AI also lowers the costs of experimentation, adaptation, training, and implementation.

Table 8 is an accounting sensitivity exercise, not an estimate of aggregate AI effects. It raises the skill premium over a deliberately wide range and traces the workforce-composition term under stagnant and rising human-capital paths. No probability is attached to the calibrations, and the broader mobility process is held fixed.

**Table 8. AI as a Skill-Biased Premium Shock: Composition-Channel Gap by Human-Capital Path**

| AI scenario | HC path | log B (High HC) | log B (Low HC) | Composition gap $\Delta_B$ |
|---|---|---|---|---|
| Baseline ($\pi$ =1.80) | Stagnant HC | 1.476 | 1.563 | -0.088 |
| Baseline ($\pi$ =1.80) | Rising HC | 1.476 | 1.653 | -0.177 |
| Moderate AI ($\pi$ =2.50) | Stagnant HC | 1.706 | 1.732 | -0.025 |
| Moderate AI ($\pi$ =2.50) | Rising HC | 1.706 | 1.85 | -0.143 |
| Strong AI ($\pi$ =3.00) | Stagnant HC | 1.838 | 1.829 | 0.009 |
| Strong AI ($\pi$ =3.00) | Rising HC | 1.838 | 1.963 | -0.125 |

Note: Composition-channel gap under three calibrated AI premia , evaluated under stagnant and rising low-HC paths. Negative values indicate that the low-HC path attains a higher composition index than the high-HC benchmark under the maintained calibration; the purpose of the exercise is to trace how the composition channel changes as the AI premium rises, not to forecast aggregate AI effects. Source: Authors' calculations.

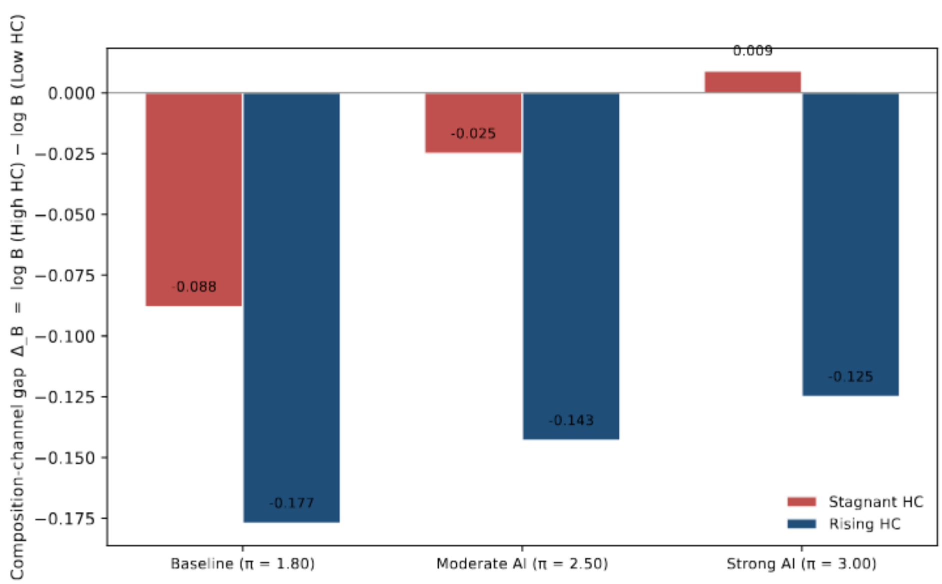
As the AI premium rises, the composition gap narrows and can change sign under stagnant human capital; continued skill accumulation offsets part of the premium effect. Skill-biased AI therefore does not mechanically cause either convergence or divergence. The outcome depends on the initial distribution of skills and on subsequent capability formation.

Figure 6 traces the same mechanism continuously. Higher AI premia favor economies with larger skilled-labor shares, while human-capital accumulation in initially weaker economies can offset part of the difference. Cheaper intelligence does not imply more equal productivity.

The more optimistic channel is diffusion. AI can reduce the cost of codifying tacit knowledge, translating technical information, diagnosing production problems, and adapting frontier practices. Rapid adoption or large task-level gains need not appear immediately in aggregate productivity: data, training, workflow redesign, and organizational capital must be accumulated, and measured productivity may initially fall during installation (Brynjolfsson, Rock, and Syverson 2021). AI promotes convergence only if these changes raise mobility in low-productivity economies.

Within the diffusion channel, adoption and adaptation are distinct. Adoption puts a tool into use; adaptation fits it to local data, workflows, production constraints, and institutional settings. For follower economies, this adaptation margin is central: AI at the frontier can improve rapidly while users far from the frontier remain unable to reorganize production around it.

**Figure 6. Composition-Channel Gap ΔB as a Function of the AI Premium π**




For follower economies, adaptation is pivotal. They need not build frontier foundation models; they do need to fit available tools to local languages, data, regulations, production processes, and service-delivery systems. Electrification offers the useful parallel: large gains arrived when factories reorganized around distributed power, not when an electric motor merely replaced steam (David 1990). The relevant object is the production system into which AI is introduced, not the model in isolation.

The implication is not to wait until every complement is in place, but to pair adoption with the investments that make adaptation productive—data, management, cognitive skills, infrastructure, competition, finance, and implementation capacity (van Ark 2026). These complements determine whether initial use becomes intensive use and whether intensive use raises productivity.

The most valuable application need not use the largest model. A task-specific tool may matter more if it relaxes a binding local constraint and is embedded in a workflow that can act on its output. Data quality, human validation, electricity, connectivity, and institutional follow-through are therefore part of the technology's effective productivity, not peripheral conditions (Acemoglu, Akcigit, and Johnson 2026; Schindler et al. 2026).

The distinction is especially relevant for sub-Saharan Africa. Schindler et al. (2026) emphasize that the immediate challenge is not unusually high exposure to displacement, but the ability to adopt, adapt, and scale AI amid constraints in electricity, digital infrastructure, technical skills, and regulatory and institutional capacity. Those constraints map closely to the capability bundle considered here. The present paper adds a dynamic question: whether stronger capability is associated with movement toward frontier productivity.

Three AI effects can coexist: frontier expansion, skill augmentation, and lower diffusion costs. Only the third can directly improve relative mobility, and even then the effect depends on local complements. AI may also alter labor demand, capital intensity, factor shares, trade, and the location of rents (Korinek and Stiglitz 2018); those channels are distinct from the question isolated here—whether AI shortens the duration of low-productivity states.

# X. Long-Run Projections: Convergence under Alternative Mobility Regimes

Alternative mobility regimes compare how the distribution evolves when AI augments existing capabilities or changes the transition process. They are conditional illustrations, not forecasts.

Four regimes are considered. The baseline uses the unconditional relative-TFP matrix. The high-capability case applies the matrix estimated above the operational human-capital cutoff. Broad AI diffusion raises upward mobility across the distribution, while unequal AI diffusion concentrates the improvement among economies already in the stronger-capability regime. The exact matrices, perturbations, and row normalization are documented in the replication files.

Applying the high-capability transition matrix substantially shortens persistence. After 100 years, the Q1 share is 0.262 rather than 0.482 and the Q4 share is 0.124 rather than 0.088. Mean exit time from Q1 falls from 44.0 to 28.7 years, and passage time from Q1 to Q4 from 241.8 to 177.0 years. The result is not rapid convergence; it is a materially shorter duration in the lower tail.

Broad AI diffusion also improves mobility without eliminating persistence. After 100 years, Q1 is 0.340 and Q4 is 0.105. This regime has the fastest convergence statistic and a mean exit time similar to the high-capability case. The exercise shows that AI affects relative development only when it changes the transition probabilities themselves.

**Table 9. Implied State Distributions under Alternative Mobility Regimes.**

| Scenario | Horizon | Q1 | Q2 | Q3 | Q4 | $\gamma$ (years) | $MET_1$ (years) | Passage Q1→Q4 (years) |
|---|---|---|---|---|---|---|---|---|
| Baseline (unconditional TFP) | 25 years | 0.510 | 0.276 | 0.140 | 0.074 | 21.2 | 44.0 | 241.8 |
| Baseline (unconditional TFP) | 100 years | 0.482 | 0.277 | 0.153 | 0.088 | 21.2 | 44.0 | 241.8 |
| Baseline (unconditional TFP) | Stationary | 0.479 | 0.278 | 0.154 | 0.089 | 21.2 | 44.0 | 241.8 |
| High-HC transition matrix | 25 years | 0.356 | 0.360 | 0.206 | 0.077 | 20.6 | 28.7 | 177.0 |
| High-HC transition matrix | 100 years | 0.262 | 0.353 | 0.262 | 0.124 | 20.6 | 28.7 | 177.0 |
| High-HC transition matrix | Stationary | 0.254 | 0.352 | 0.267 | 0.128 | 20.6 | 28.7 | 177.0 |
| Broad AI diffusion (scale $=1.0$) | 25 years | 0.398 | 0.353 | 0.171 | 0.077 | 17.2 | 28.6 | 187.6 |
| Broad AI diffusion (scale $=1.0$) | 100 years | 0.340 | 0.355 | 0.200 | 0.105 | 17.2 | 28.6 | 187.6 |
| Broad AI diffusion (scale $=1.0$) | Stationary | 0.337 | 0.355 | 0.202 | 0.106 | 17.2 | 28.6 | 187.6 |
| Unequal AI diffusion (scale $=1.0$) | 25 years | 0.555 | 0.239 | 0.128 | 0.078 | 25.2 | 58.8 | 285.9 |
| Unequal AI diffusion (scale $=1.0$) | 100 years | 0.545 | 0.235 | 0.133 | 0.087 | 25.2 | 58.8 | 285.9 |
| Unequal AI diffusion (scale $=1.0$) | Stationary | 0.543 | 0.235 | 0.134 | 0.088 | 25.2 | 58.8 | 285.9 |

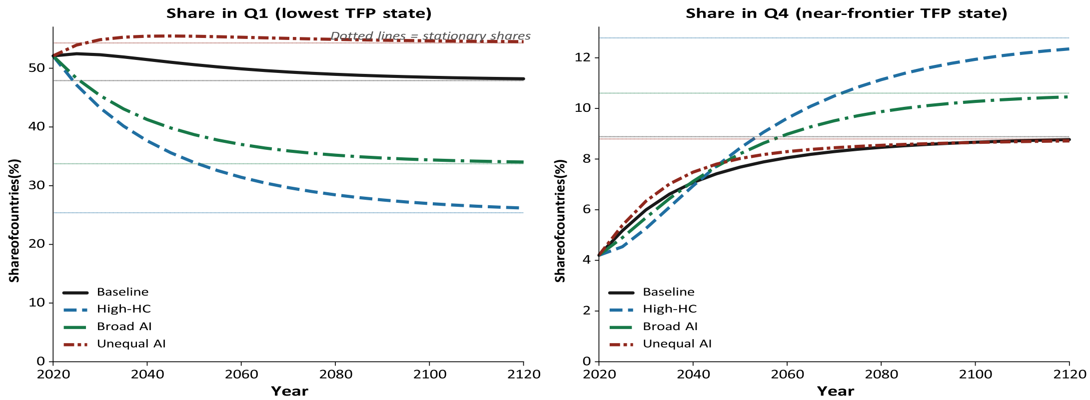
Note: Finite-horizon distributions start from the common 2015 unconditional relative-TFP distribution and are reported at 25-year and 100-year horizons, together with the stationary distribution implied by each transition process. γ is the convergence statistic defined in Section III. MET1 is the mean exit time from the lowest productivity state. Passage Q1→Q4 is the mean first-passage time from the lowest to the highest productivity state. Scenarios are conditional on the estimated transition matrices and should be interpreted as illustrative dynamics, not forecasts. Source: Authors' calculations.

Unequal AI diffusion is the cautionary case. Q1 remains above one half after a century and converges to a stationary share of 0.543; mean exit time rises to 58.8 years and passage time to Q4 to 285.9 years. AI is present, but its mobility benefits accrue where complementary capabilities already exist. Widespread use of AI need not imply widespread productivity mobility.

The contrast between broad and unequal diffusion is therefore not about access but about where implementation capability is strong enough to change mobility. Figure 7 shows these paths directly: broad diffusion and the high-capability regime steadily reduce Q1 and raise Q4, whereas unequal diffusion leaves the lower tail large.

Improvements are gradual because countries move state by state and persistence operates at every step. That gradualism is itself the point. Development gaps are rarely transformed by one spectacular jump; they are compounded from small differences in the probability of moving up, remaining in place, or slipping back. A technology that raises the chance of upward movement by only a few percentage points at each five-year step can have a large effect over a generation, even when no single period looks dramatic.

**Figure 7. TFP State-Share Trajectories under Alternative Mobility Regimes, 0–200 Years.**




Note: Left panel reports the projected share of countries in the lowest TFP state, Q1. Right panel reports the projected share in the near-frontier TFP state, Q4. All paths start from the same 2015 unconditional relative-TFP distribution; dotted lines indicate stationary shares. The unequal-diffusion scenario leaves the lower tail most persistent, while broad diffusion and high-HC mobility reduce Q1 and raise Q4. Source: Authors' calculations.

The scenarios are therefore a mechanism test, not a forecast. AI compresses the lower tail only if lower implementation costs raise upward mobility in low-productivity economies; if gains depend mainly on capabilities already concentrated near the frontier, existing regimes persist.

Cheaper translation, coding, diagnosis, or administrative support matters for convergence only if firms reorganize, workers use the tools effectively, and institutions support implementation. Widespread AI can coexist with stratified productivity mobility.

# XI. Robustness, Stability, and Interpretation

The results depend on choices about state definitions, transition horizons, human-capital measurement, threshold estimation, and the decomposition calibration. None is innocuous. The relevant robustness question is not whether every number is invariant, but whether lower-tail productivity persistence and the capability-regime contrast survive reasonable alternatives.

The qualitative findings survive these alternatives. Magnitudes vary, as they should, but relative TFP remains slow-moving, lower-tail persistence remains large, and stronger capability is associated with greater upward mobility. The result is therefore not an artifact of one discretization, one horizon, or one measure of human capital.

The first concern is the transition horizon and the first-order Markov approximation. Table 10 compares the directly estimated ten-year matrix with the matrix implied by two five-year steps. This is a descriptive Chapman-Kolmogorov consistency check: it asks whether the broad mobility pattern survives a longer interval, not whether the Markov model is a structural law.

**Table 10. Robustness to Transition Horizon**

| Statistic | 5-year baseline | 10-year direct | Difference |
|---|---|---|---|
| $\gamma$ (years) | 21.186 | 12.102 | -9.084 |
| MET Q1 (years) | 44.020 | 29.923 | -14.097 |
| Passage Q1→Q4 (years) | 241.825 | 149.076 | -92.749 |
| Stationary Q1 | 0.479 | 0.478 | -0.001 |
| Stationary Q4 | 0.089 | 0.085 | -0.004 |
| $\lVert P_{10} - P_5^2 \rVert F$ | | 0.098 | Max \|entry\|: 0.041 |
| N transitions (10-year) | 978 | | |

Note: The table compares a directly estimated ten-year transition matrix, $P_{10}$, with the two-step matrix $P_5^2$ implied by the baseline five-year process. $\lVert P_{10} - P_5^2 \rVert F$ is the Frobenius norm of the difference. Source: Authors' calculations from Penn World Table 11.0.

The direct ten-year matrix implies faster movement than the five-year specification, but almost the same long-run distribution. Stationary Q1 mass is 0.479 under the baseline and 0.478 under the direct ten-year matrix; stationary Q4 mass is 0.089 and 0.085. Timing estimates are horizon-sensitive, but the lower-tail conclusion is not.

A second concern is temporal stability. Table 11 divides the sample before and after 1995, a period over which global value chains, digital technologies, and international integration expanded substantially. If these changes transformed productivity mobility, the two transition processes should differ.

**Table 11. Temporal Stability: TFP Mobility Statistics by Subperiod**

| Statistic | Early period (<1995) | Late period (≥1995) |
|---|---|---|
| Q1 persistence | 0.870 | 0.911 |
| Upward mobility from Q1 | 0.130 | 0.089 |
| Mean exit time Q1 (years) | 38.409 | 56.190 |
| Passage time Q1→Q4 (years) | 152.481 | 452.799 |
| Stationary Q1 mass | 0.350 | 0.612 |
| Stationary Q4 mass | 0.154 | 0.036 |
| N transitions | 517 | 476 |
| $\chi^2$ homogeneity test (p-value) | 0.4500 | |

Note: The relative-TFP transition matrix is re-estimated for the early period (before 1995) and the late period (1995 onward). The chi-squared homogeneity test does not reject equality of the transition matrices at conventional levels. Source: Authors' calculations from Penn World Table 11.0.

The homogeneity test does not reject equality of the transition matrices at conventional levels. The point estimates nevertheless show, if anything, greater lower-tail persistence after 1995: Q1 persistence rises from 0.870 to 0.911 and upward mobility falls from 0.130 to 0.089. Wider access to global technology and markets did not automatically make the lower tail more mobile.

The post-1995 comparison is informative for interpretation. This was a period of much wider access to digital technologies, global value chains, and codified knowledge, yet the lower tail did not become visibly more fluid. The pattern is consistent with the paper's central distinction. Diffusion of tools can coexist with persistent differences in the capability to turn them into productivity. The homogeneity test is important precisely because it prevents reading the point estimates as evidence of a structural break.

This is compatible with evidence of stronger average convergence after 1990. Average convergence can improve in the middle of the distribution while the lower tail remains persistent. The two statistics answer different questions: whether poorer economies grow faster on average and whether countries leave low-productivity states.

A third concern is discretization. The baseline fixed 1975 quartiles preserve an economic meaning over time, but any partition of a continuous distribution is contestable. Table 12 therefore reports alternative absolute thresholds, time-varying quartiles, terciles, and quintiles.

Exact values change, but the qualitative result survives. Mobility remains slow under fixed quartiles, time-varying quartiles, terciles, and quintiles. Absolute thresholds produce more apparent convergence because they ask a different question: whether countries cross fixed low levels, rather than whether they move through the historical distribution toward the frontier.

**Table 12. Robustness to State Definitions**

| Specification | States | P(Q1,Q1) | Upward Q1 | Exit Q1 | Passage B→T | Stat. bottom | Stat. top | N |
|---|---|---|---|---|---|---|---|---|
| 1975 quartile thresholds (main) | 4 | 0.886 | 0.114 | 44.0 | 241.8 | 0.479 | 0.089 | 1097 |
| Absolute thresholds [0.20,0.40,0.70] | 4 | 0.400 | 0.600 | 8.3 | 71.0 | 0.009 | 0.509 | 1097 |
| Time-varying quartiles | 4 | 0.829 | 0.171 | 29.2 | 159.2 | 0.264 | 0.194 | 1097 |
| Terciles | 3 | 0.863 | 0.137 | 36.5 | 103.4 | 0.358 | 0.293 | 1097 |
| Quintiles | 5 | 0.820 | 0.180 | 27.8 | 205.9 | 0.214 | 0.154 | 1097 |

Note: Mobility statistics under alternative discretizations of the productivity distribution: fixed 1975 quartiles, absolute thresholds, time-varying quartiles, terciles, and quintiles. Exit and passage times are in years; B and T denote the bottom and top productivity states. Source: Authors' calculations from Penn World Table 11.0.

A fourth concern is that schooling quantity may be a weak proxy for the capability relevant to diffusion. Table 13 repeats the comparison using Hanushek–Woessmann cognitive skills for 69 countries. This replaces attainment with a measure closer to learning quality, though at the cost of a smaller and more selected sample.

The contrast is at least as pronounced with cognitive skills, consistent with evidence linking cognitive skill to technology diffusion (Jones 2012). Low-skill economies have higher Q1 persistence, longer exit and passage times, and a stationary Q4 mass of 0.087, compared with 0.235 for the high-skill group. The restricted sample is not globally representative, so these values should not be generalized mechanically. They show that the capability-regime result is not an artifact of schooling quantity alone.

**Table 13. Cognitive-Skills Robustness: Mobility by Hanushek–Woessmann Skill Group**

| Group | Threshold | | P[Q1,Q1] | SE | MET Q1 (yr) | 90% CI | Passage Q1→Q4 (yr) | Stationary Q1 | Stationary Q4 | N transitions | N countries |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Low cognitive skills | HW score ≤ 4.69 (median) | | 0.881 | (0.028) | 41.9 | [29.5, 61.7] | 196.6 | 0.467 | 0.087 | 334 | 34 |
| High cognitive skills | HW score > 4.69 (median) | | 0.818 | (0.047) | 27.5 | [17.1, 45.8] | 111.0 | 0.098 | 0.235 | 321 | 35 |
| All countries | | All | 0.860 | (0.025) | 35.7 | [27.2, 48.2] | 147.3 | 0.279 | 0.150 | 655 | 69 |

Note: Sample restricted to the 69 countries with Hanushek–Woessmann cognitive-skills coverage. Countries are split at the median Hanushek–Woessmann score of 4.69. Mobility statistics are computed using the same relative-TFP state definitions as in the baseline. Source: Authors' calculations using the Hanushek–Woessmann cognitive-skills measure merged with Penn World Table 11.0.

The cognitive-skill evidence also disciplines the AI interpretation. Access to advanced tools may diffuse quickly, but their productive use depends on learning quality, management, and organizational depth. The paper does not claim that cognitive skills are the sole mechanism; it shows that the accumulation-capability distinction survives a stricter measure.

Appendix E varies the elasticity of substitution between skilled and unskilled labor. The workforce-composition term changes, as it should, but does not dominate the productivity gap under the reported calibrations. The human-capital argument therefore does not rest on one production-function parameter.

The mobility ordering is not tied to the U.S. frontier. Replacing it with the 90th percentile, 95th percentile, or geometric mean of the five leaders changes the waiting times but preserves the low- versus high-capability ordering. Population weighting lengthens lower-tail persistence mainly because China and India receive large weight; excluding them restores estimates close to the unweighted results. Leave-one-country-out threshold searches preserve a higher-capability exit advantage in every case. The pattern is therefore not driven by a particular frontier or a single influential country.

The remaining concerns are interpretive. Measured human capital is correlated with institutions, infrastructure, management, sectoral structure, culture, embodied skills, migration, and state capacity. It is best read as one observable marker of an inherited capability bundle, not as a deep historical determinant or a structural threshold. The fixed-rank and held-out exercises also clarify what is novel relative to convergence clubs and deep-history accounts. Historical forces help explain how capabilities were formed; the postwar evidence asks whether the inherited bundle predicts subsequent movement through the productivity distribution. It is a statement about mobility conditional on history, not a new stage theory of development.

Across horizons, subperiods, state definitions, capability measures, frontiers, weighting schemes, and influence checks, the same empirical object remains visible: relative productivity has a persistent lower tail, and mobility is greater in stronger-capability regimes. The evidence identifies the transition process that AI would have to change, not every structural source of persistence.

# XII. Conclusion

Will artificial intelligence help poorer countries catch up? The answer is conditional. Access to technology is not enough; convergence depends on whether economies can turn increasingly accessible knowledge into sustained productivity gains and movement toward the frontier. The postwar record reveals a striking asymmetry between the accumulation of observable inputs and the mobility of productivity. On an identical sample and a harmonized state construction, the mean time to leave the lowest quartile is 16.1 years for capital intensity, 31.5 years for measured human capital, and 44.0 years for TFP. Countries therefore appear able to accumulate capital and measured human capital more readily than they are able to translate those inputs into sustained improvements in relative productivity. Technology can diffuse without producing productivity convergence. As machines, information, and formal skills become easier to acquire, the capacity to combine and use them productively becomes a more important margin of relative development.

Workforce composition accounts for only a modest share of productivity gaps, yet measured human capital remains informative about mobility. The fixed within-year median split—chosen without threshold search—implies mean exit times from the lowest-productivity state of 79.1 years below the median and 28.0 years above it. The broader relationship is not confined to crossing a discrete state boundary: smooth human-capital terms improve held-out transition predictions, and human capital remains positively associated with subsequent five-year relative-productivity growth across alternative productivity measures. Because flexibly controlling for exact initial productivity and income substantially weakens the discrete exit coefficient, the evidence supports a broad capability-related mobility gradient, not a causal schooling threshold or a universal tipping point.

These results help reconcile two influential views of human capital. Development accounting concerns the stock of effective labor and the extent to which it accounts for today's productivity gap. The Nelson–Phelps tradition concerns the process by which economies absorb, adapt, and implement available technologies. The distinction is therefore between an observable stock and a broader conversion process. Schooling raises effective labor, whereas absorptive capacity affects the rate at which skills, capital, and knowledge become reliable production. Small differences in that conversion rate, repeated across successive transitions, can translate into decades of expected time at the bottom. Human capital may therefore explain relatively little about where an economy is at a point in time while remaining informative about whether, and how rapidly, it moves.

That distinction changes how AI should be evaluated. AI can expand the frontier, augment skills already in place, or lower the costs of technological diffusion. The first two channels can raise world productivity while preserving or widening relative gaps. Task-level substitution can coexist with firm- and economy-level complementarity when AI raises the value of judgment, validation, coordination, and reorganization. For convergence, however, the relevant margin is different. AI becomes a convergence technology only when it lowers the costs of learning, validation, adaptation, and implementation sufficiently to change the mobility process of economies initially far from the frontier. Put differently, a technology that shifts the frontier outward need not help countries move toward it.

Historical experience supplies the intuition. Tractors, electrification, high-yielding seeds, and mobile phones generated their largest gains when they fit local constraints and were embedded in systems able to act on them. The comparison is not that these technologies are technologically equivalent to AI, but that access and productive use are economically distinct margins. A technology may cross borders in a shipment or a download; the productive system surrounding it cannot be imported as readily.

Policy should therefore start with the bottleneck, not the model. The objective is not AI adoption per se, but productive adaptation: identify tasks where AI can relax a binding information or expertise constraint, then pair adoption with the capabilities needed to act on its output—skills, reliable data and infrastructure, management, finance, competition, and institutions able to experiment and learn (Cazzaniga et al. 2024; Cerutti et al. 2025; Schindler et al. 2026). Which complement binds will differ across countries and sectors. These complements are not a mechanical readiness checklist, nor does every country need to reproduce the institutional or production structure of the frontier. But when a critical complement is missing, cheaper technology can leave productivity mobility unchanged even while measured access or adoption rises.

Exposure, access, adoption, adaptation, intensive use, productivity, and relative mobility should therefore be treated as distinct empirical and policy margins. Exposure can rise without adoption; adoption can rise without organizational change; organizational change can raise productivity without materially altering a country's relative position; and productivity gains can occur without convergence. This distinction is particularly important when interpreting indicators of AI preparedness or exposure across countries. The policy objective is not adoption for its own sake, but to increase the capacity of economies to convert technological opportunities into durable productivity gains and, where catch-up is the objective, a higher probability of moving out of low-productivity states.

For IMF surveillance and capacity development, this distinction also disciplines scenario design. Technological exposure should not be translated mechanically into productivity assumptions. An increase in observed AI use can have very different macroeconomic implications depending on the mechanism through which it operates. Scenarios should state explicitly which margin AI is assumed to change: frontier productivity, the return to existing skills, or the probability that low-productivity economies move upward. A frontier shift primarily changes potential output; skill augmentation can alter productivity, wages, and distribution conditional on existing capabilities; a diffusion shift changes the speed of catch-up. The macroeconomic implications differ across these channels even when observed AI use is similar. For capacity development, the same logic argues for diagnosing the constraints that prevent knowledge and technology from being used productively rather than treating technology acquisition itself as the objective.

The limits are substantive. Markov matrices characterize rather than identify transition mechanisms; the decomposition is accounting rather than structural; and the AI exercises are conditional comparisons rather than forecasts. The results therefore establish neither that additional schooling causally raises transition probabilities nor that the historical human-capital relationship will remain unchanged in an AI-intensive economy. Human capital is an observable marker of a broader capability bundle, not a stand-alone treatment. Labor displacement, capital ownership, factor shares, trade, and the international allocation of AI rents remain outside the productivity-mobility question. These margins will matter for welfare and distribution even if AI ultimately accelerates aggregate productivity growth.

AI does not overturn the old economics of development; it makes the underlying constraint more visible. As access to cognitive capability becomes cheaper, productive capability may become the more binding constraint. The central question for convergence is therefore not how widely AI spreads, but whether it changes the capacity of economies to use knowledge well enough to alter the persistence of relative productivity. Convergence depends on whether AI weakens the forces that keep low-productivity economies from moving toward the frontier. The Intelligence Divide is therefore not simply a gap in access to artificial intelligence. It is the gap between increasingly accessible intelligence and the capacity to make it productive.

# References


Acemoglu, Daron, Ufuk Akcigit, and Simon Johnson. 2026. "Technology and Economic Development." NBER Working Paper No. 34730. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w34730.

Acemoglu, Daron, and Fabrizio Zilibotti. 2001. "Productivity Differences." *Quarterly Journal of Economics* 116 (2): 563–606.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2018. "Artificial Intelligence and Economic Growth." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 237–282. Chicago: University of Chicago Press.

Anderson, T. W., and Leo A. Goodman. 1957. "Statistical Inference about Markov Chains." *Annals of Mathematical Statistics* 28 (1): 89–110.

Atkinson, Anthony B., and Joseph E. Stiglitz. 1969. "A New View of Technological Change." *Economic Journal* 79 (315): 573–578.

Barro, Robert J., and Jong-Wha Lee. 2013. "A New Data Set of Educational Attainment in the World, 1950–2010." *Journal of Development Economics* 104: 184–198.

Basu, Susanto, and David N. Weil. 1998. "Appropriate Technology and Growth." *Quarterly Journal of Economics* 113 (4): 1025–1054.

Benhabib, Jess, and Mark M. Spiegel. 1994. "The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data." *Journal of Monetary Economics* 34 (2): 143–173.

Benhabib, Jess, and Mark M. Spiegel. 2005. "Human Capital and Technology Diffusion." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven N. Durlauf, Vol. 1A, 935–966. Amsterdam: Elsevier.

Binswanger, Hans P., and Graeme Donovan. 1986. *Agricultural Mechanization: Issues and Policies*. World Bank Report No. 6470. Washington, DC: World Bank.

Bolt, Jutta, and Jan Luiten van Zanden. 2020. "Maddison Style Estimates of the Evolution of the World Economy: A New 2020 Update." Maddison Project Database, version 2020.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2021. "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies." *American Economic Journal: Macroeconomics* 13 (1): 333–372.

Caselli, Francesco. 2005. "Accounting for Cross-Country Income Differences." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven N. Durlauf, Vol. 1A, 679–741. Amsterdam: Elsevier.

Caselli, Francesco, and Antonio Ciccone. 2013. "The Contribution of Schooling in Development Accounting: Results from a Nonparametric Upper Bound." *Journal of Development Economics* 104: 199–211.

Caselli, Francesco, and Wilbur John Coleman II. 2006. "The World Technology Frontier." *American Economic Review* 96 (3): 499–522.

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma J. Rockall, and Marina Mendes Tavares. 2024. "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note 2024/001. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798400262548.006.

Cerutti, Eugenio M., Antonio I. Garcia Pascual, Yosuke Kido, Longji Li, Giovanni Melina, Marina Mendes Tavares, and Philippe Wingender. 2025. "The Global Impact of AI: Mind the Gap." IMF Working Paper No. 2025/076. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798229008570.001.

Che, Natasha X., Weining Xin, and Taichi Yoshida. 2026. “AI and Economic Divergence in Asia.” IMF Working Paper No. 2026/166. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798229054348.001.

Clark, Gregory, and Robert C. Feenstra. 2001. “Technology in the Great Divergence.” NBER Working Paper No. 8596. Cambridge, MA: National Bureau of Economic Research.

Comin, Diego, and Martí Mestieri. 2018. “If Technology Has Arrived Everywhere, Why Has Income Diverged?” American Economic Journal: Macroeconomics 10 (3): 137–178.

David, Paul A. 1990. “The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox.” *American Economic Review* 80 (2): 355–361.

Durlauf, Steven N., and Paul A. Johnson. 1995. “Multiple Regimes and Cross-Country Growth Behaviour.” *Journal of Applied Econometrics* 10 (4): 365–384.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. “The Next Generation of the Penn World Table.” *American Economic Review* 105 (10): 3150–3182.

Feyrer, James D. 2008. “Convergence by Parts.” B.E. Journal of Macroeconomics 8 (1): 1–35. https://doi.org/10.2202/1935-1690.1646.

Foster, Andrew D., and Mark R. Rosenzweig. 1995. “Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture.” *Journal of Political Economy* 103 (6): 1176–1209.

Foster, Andrew D., and Mark R. Rosenzweig. 1996. “Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution.” *American Economic Review* 86 (4): 931–953.

Hall, Robert E., and Charles I. Jones. 1999. “Why Do Some Countries Produce So Much More Output per Worker than Others?” *Quarterly Journal of Economics* 114 (1): 83–116.

Hansen, Bruce E. 2000. “Sample Splitting and Threshold Estimation.” *Econometrica* 68 (3): 575–603.

Hanushek, Eric A., and Ludger Woessmann. 2012. “Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation.” *Journal of Economic Growth* 17 (4): 267–321.

Howitt, Peter, and David Mayer-Foulkes. 2005. “R&D, Implementation, and Stagnation: A Schumpeterian Theory of Convergence Clubs.” *Journal of Money, Credit and Banking* 37 (1): 147–177.

Imam, Patrick A. 2026. “Convergence from Above: When Global Catch-Up Reflects Falling Back.” IMF Working Paper No. 2026/159. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798229056878.001.

Imam, Patrick A., and Jonathan R. W. Temple. 2026a. “At the Threshold: The Increasing Relevance of the Middle-Income Trap.” *Scandinavian Journal of Economics*. https://doi.org/10.1111/sjoe.70036.

Imam, Patrick A., and Jonathan R. W. Temple. 2026b. “Dynamic Development Accounting and Relative Income Traps.” Economic Inquiry 64 (2): 591–613. https://doi.org/10.1111/ecin.70028.

Imam, Patrick A., and Jonathan R. W. Temple. 2026c. “Growth, Interrupted: How Crises Delay Global Convergence.” *Journal of International Money and Finance* 163: 103534. https://doi.org/10.1016/j.jimonfin.2026.103534.

Imam, Patrick A., and Jonathan R. W. Temple. 2026d. “State Capacity and Growth Regimes.” *Empirical Economics* 70: Article 74. https://doi.org/10.1007/s00181-026-02908-3.

International Monetary Fund, Institute for Capacity Development. 2024. Review of the Fund’s Capacity Development Strategy—Towards a More Flexible, Integrated, and Tailored Model. IMF Policy Paper 2024/014. Washington, DC: International Monetary Fund.

Jensen, Robert. 2007. “The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector.” *Quarterly Journal of Economics* 122 (3): 879–924. https://doi.org/10.1162/qjec.122.3.879.

Johnson, Paul, and Chris Papageorgiou. 2020. “What Remains of Cross-Country Convergence?” *Journal of Economic Literature* 58 (1): 129–175.

Jones, Garett. 2012. “Cognitive Skill and Technology Diffusion: An Empirical Test.” *Economic Systems* 36 (3): 444–460.

Korinek, Anton, and Joseph E. Stiglitz. 2018. “Artificial Intelligence and Its Implications for Income Distribution and Unemployment.” In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 349–390. Chicago: University of Chicago Press.

Kremer, Michael, Alexei Onatski, and James Stock. 2001. “Searching for Prosperity.” *Carnegie-Rochester Conference Series on Public Policy* 55 (1): 275–303.

Lall, Sanjaya. 1992. “Technological Capabilities and Industrialization.” *World Development* 20 (2): 165–186.

Nelson, Richard R., and Edmund S. Phelps. 1966. “Investment in Humans, Technological Diffusion, and Economic Growth.” *American Economic Review* 56 (1/2): 69–75.

Patel, Dev, Justin Sandefur, and Arvind Subramanian. 2021. “The New Era of Unconditional Convergence.” *Journal of Development Economics* 152: 102687.

Pritchett, Lant. 1997. “Divergence, Big Time.” *Journal of Economic Perspectives* 11 (3): 3–17.

Pritchett, Lant. 2001. “Where Has All the Education Gone?” *World Bank Economic Review* 15 (3): 367–391.

Quah, Danny. 1993. “Empirical Cross-Section Dynamics in Economic Growth.” *European Economic Review* 37 (2–3): 426–434.

Quah, Danny. 1996. “Twin Peaks: Growth and Convergence in Models of Distribution Dynamics.” *Economic Journal* 106 (437): 1045–1055.

Schindler, Martin, Andrew J. Tiffin, Andrea Richter Hume, Kamil Dybczak, Marwa Ibrahim, Youssouf Kiendrebeogo, Jacinta Bernadette Shirakawa, Nikola Spatafora, and Solo Zerbo. 2026. “Unlocking the Potential: AI in Sub-Saharan Africa.” IMF Departmental Paper 2026/013. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798229047821.087.

van Ark, Bart. 2026. “Rewiring Europe’s Productivity Framework: Aligning Investment, Innovation, and Diffusion.” Productivity Insights Paper No. 096. Manchester: The Productivity Institute.

# Appendix A: Relative Income Dynamics

Table A.1: Implied mobility statistics for relative income.

| Statistic | Point estimate |
|---|---|
| Persistence in Q1 P(Q1,Q1) | 0.943 |
| Mean exit time from Q1 (years) | 87.7 |
| Mean passage time Q1 -> top state (years) | 330.8 |
| Upward mobility probability from Q1 | 0.057 |
| Convergence speed gamma (years to halve distance) | 88.9 |
| Stationary mass in Q1 | 0.299 |
| Stationary mass in top state | 0.363 |
| Number of transitions (NT) | 1779 |

Note: Mobility statistics implied by the relative-income transition matrix in Table 1. Exit and passage times are reported in years; the convergence statistic is defined in Section III. Source: Authors' calculations from the Maddison Project Database 2020.

Table A.2: Relative income: mean first-passage times (years).

| From / To | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| Q1 | | 87.7 | 217.9 | 330.8 |
| Q2 | 201.7 | | 130.2 | 243.1 |
| Q3 | 342.6 | 155.0 | | 117.8 |
| Q4 | 404.8 | 216.2 | 81.9 | |
| MFR | 16.7 | 30.0 | 29.3 | 13.8 |

Off-diagonal cells report mean first-passage times from the row state to the column state, computed from the preceding income transition matrix. The MFR row reports mean first-recurrence times, 1/pi_i, in years. The implied Q1-to-Q4 passage time is 330.8 years. Source: Authors' calculations from the Maddison Project Database 2020.

# Appendix B: Mobility of Inputs

Table B.1: Relative capital-output ratio: transition matrix.

| *From / To* | <0.36 | <0.48 | <0.64 | >=0.64 | N_transitions |
|---|---|---|---|---|---|
| <0.36 | **0.673** | 0.222 | 0.082 | 0.023 | 171 |
| | *(0.036)* | *(0.032)* | *(0.021)* | *(0.012)* | |
| <0.48 | 0.118 | **0.429** | 0.376 | 0.076 | 170 |
| | *(0.025)* | *(0.038)* | *(0.037)* | *(0.020)* | |
| <0.64 | 0.013 | 0.135 | **0.462** | 0.390 | 223 |
| | *(0.008)* | *(0.023)* | *(0.033)* | *(0.033)* | |
| >=0.64 | 0.002 | 0.008 | 0.070 | **0.921** | 644 |
| | *(0.002)* | *(0.003)* | *(0.010)* | *(0.011)* | |
| Stationary | 0.030 | 0.056 | 0.144 | 0.771 | |

Five-year transition probabilities for the relative capital-output ratio, using fixed thresholds of 0.36, 0.48, and 0.64 of the U.S. level and the state assignment used in the left panel of Figure 2. Diagonal entries are in bold; the bottom row reports the stationary distribution. Standard errors are in parentheses. Source: Authors' calculations from Penn World Table 11.0.

Table B.2: Relative capital-output ratio: mean first-passage times (years).

| From / To | <0.36 | <0.48 | <0.64 | >=0.64 |
|---|---|---|---|---|
| <0.36 | | 70.1 | 37.2 | 38.7 |
| <0.48 | 463.8 | | 25.3 | 28.2 |
| <0.64 | 566.2 | 160.5 | | 17.3 |
| >=0.64 | 608.2 | 206.1 | 66.3 | |
| MFR | 168.7 | 89.4 | 34.8 | 6.5 |

Off-diagonal cells report mean first-passage times from the row state to the column state, computed from the preceding capital-output transition matrix. The MFR row reports mean first-recurrence times, 1/pi_i, in years. Source: Authors' calculations from Penn World Table 11.0.

Table B.3: Relative human capital: transition matrix.

| *From / To* | <0.36 | <0.48 | <0.64 | >=0.64 | N_transitions |
|---|---|---|---|---|---|
| <0.36 | **0.844** | 0.156 | 0.000 | 0.000 | 122 |
| | *(0.033)* | *(0.033)* | *(0.000)* | *(0.000)* | |
| <0.48 | 0.050 | **0.836** | 0.115 | 0.000 | 383 |
| | *(0.011)* | *(0.019)* | *(0.016)* | *(0.000)* | |
| <0.64 | 0.000 | 0.019 | **0.842** | 0.139 | 360 |
| | *(0.000)* | *(0.007)* | *(0.019)* | *(0.018)* | |
| >=0.64 | 0.000 | 0.000 | 0.012 | **0.988** | 576 |
| | *(0.000)* | *(0.000)* | *(0.005)* | *(0.005)* | |
| Stationary | 0.004 | 0.013 | 0.079 | 0.903 | |

Five-year transition probabilities for the relative human-capital index, using fixed thresholds of 0.36, 0.48, and 0.64 of the U.S. level. Diagonal entries are in bold and standard errors are in parentheses. Source: Authors' calculations from Penn World Table 11.0.

Table B.4: Relative human capital: mean first-passage times (years).

| From / To | <0.36 | <0.48 | <0.64 | >=0.64 |
|---|---|---|---|---|
| <0.36 | | 32.1 | 89.5 | 133.5 |
| <0.48 | 7501.9 | | 57.4 | 101.4 |
| <0.64 | 10697.8 | 3195.9 | | 44.0 |
| >=0.64 | 11109.2 | 3607.3 | 411.4 | |
| MFR | 1173.3 | 373.7 | 63.3 | 5.5 |

Off-diagonal cells report mean first-passage times from the row state to the column state, computed from the preceding human-capital transition matrix. The MFR row reports mean first-recurrence times, 1/pi_i, in years. Very large lower-left entries reflect the near-absence of downward transitions from high human-capital states to the lowest states. Source: Authors' calculations from Penn World Table 11.0.

# Appendix C: Productivity Mobility

Table C.1: Relative TFP: mean first-passage times (years).

| From / To | <0.65 | <0.88 | <1.04 | >=1.04 |
|---|---|---|---|---|
| <0.65 | | 44.5 | 119.2 | 241.8 |
| <0.88 | 47.5 | | 76.7 | 198.9 |
| <1.04 | 67.8 | 26.0 | | 141.3 |
| >=1.04 | 79.2 | 36.4 | 27.2 | |
| MFR | 10.4 | 18.0 | 32.4 | 56.3 |

Mean first-passage times implied by the baseline relative-TFP transition matrix in Table 3, which also underlies the right panel of Figure 2 and the baseline state-definition results. The MFR row reports mean first-recurrence times, 1/pi_i, in years. Source: Authors' calculations from Penn World Table 11.0.

Table C.2: Relative TFP transition matrix, early subperiod (< 1995).

| *From / To* | Q1 | Q2 | Q3 | Q4 | N_transitions |
|---|---|---|---|---|---|
| Q1 | **0.870** | 0.130 | 0.000 | 0.000 | 169 |
| | *(0.026)* | *(0.026)* | *(0.000)* | *(0.000)* | |
| Q2 | 0.156 | **0.617** | 0.199 | 0.028 | 141 |
| | *(0.031)* | *(0.041)* | *(0.034)* | *(0.014)* | |
| Q3 | 0.008 | 0.246 | **0.542** | 0.203 | 118 |
| | *(0.008)* | *(0.040)* | *(0.046)* | *(0.037)* | |
| Q4 | 0.000 | 0.056 | 0.281 | **0.663** | 89 |
| | *(0.000)* | *(0.024)* | *(0.048)* | *(0.050)* | |

Early-subperiod pooled estimates of the relative TFP transition matrix. Standard errors are reported in parentheses below each point estimate; diagonal (persistence) entries are shown in bold. Source: Authors' calculations from Penn World Table 11.0.

Table C.3: Relative TFP transition matrix, late subperiod (≥ 1995).

| *From / To* | Q1 | Q2 | Q3 | Q4 | N_transitions |
|---|---|---|---|---|---|
| Q1 | **0.911** | 0.085 | 0.004 | 0.000 | 236 |
| | *(0.019)* | *(0.018)* | *(0.004)* | *(0.000)* | |
| Q2 | 0.206 | **0.667** | 0.111 | 0.016 | 126 |
| | *(0.036)* | *(0.042)* | *(0.028)* | *(0.011)* | |
| Q3 | 0.014 | 0.333 | **0.542** | 0.111 | 72 |
| | *(0.014)* | *(0.056)* | *(0.059)* | *(0.037)* | |
| Q4 | 0.000 | 0.071 | 0.333 | **0.595** | 42 |
| | *(0.000)* | *(0.040)* | *(0.073)* | *(0.076)* | |

Late-subperiod pooled estimates of the relative TFP transition matrix. Standard errors are reported in parentheses below each point estimate; diagonal (persistence) entries are shown in bold. Source: Authors' calculations from Penn World Table 11.0.

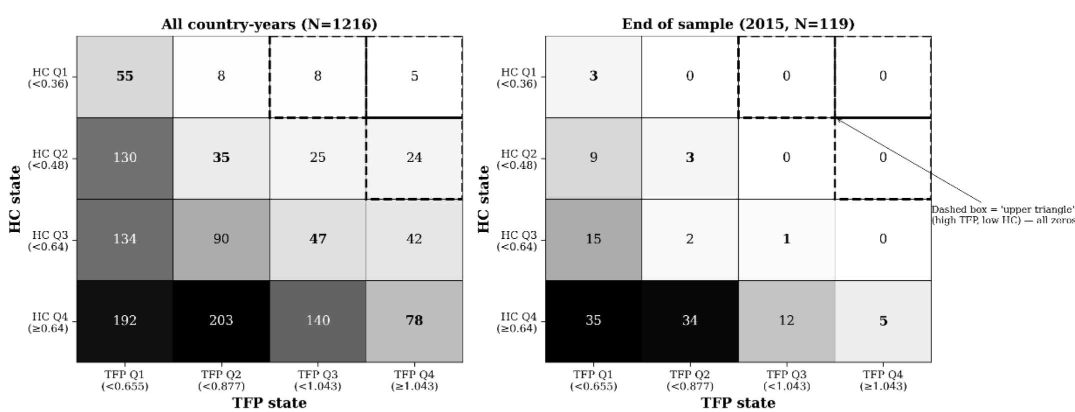
# Appendix D: Human Capital and Productivity Mobility

Table D.1: Joint distribution of human-capital and TFP quartiles, 2015 cross-section.

| | TFP Q1 | TFP Q2 | TFP Q3 | TFP Q4 |
|---|---|---|---|---|
| HC Q1(<.36) | 3 | 0 | 0 | 0 |
| HC Q2(<.48) | 9 | 3 | 0 | 0 |
| HC Q3(<.64) | 15 | 2 | 1 | 0 |
| HC Q4(≥.64) | 35 | 34 | 12 | 5 |

*Country counts in each (HC quartile) × (TFP quartile) cell. In the 2015 cross-section the upper-right region (low HC, high TFP) is empty; in the pooled country-year panel such observations exist but are rare (see Figure 5). This pattern is consistent with, but does not by itself prove, the threshold mechanism estimated in Table 5. Source: Authors' calculations from Penn World Table 11.0.*

Figure D.1. Joint Distribution of Human-Capital and TFP States




Left panel: pooled country-year counts (all years) in each (HC state) × (TFP state) cell. Right panel: 2015 cross-section. Source: Authors' calculations from Penn World Table 11.0.

Table D.2: Relative TFP transition matrix: Low-human-capital regime (operational cutoff).

| Transition matrix | <0.65 | <0.88 | <1.04 | ≥1.04 |
|---|---|---|---|---|
| <0.65 | **0.922** | 0.078 | | |
| | (0.016) | (0.016) | | |
| <0.88 | **0.263** | **0.551** | **0.144** | 0.042 |
| | (0.041) | (0.046) | (0.032) | (0.019) |
| <1.04 | 0.057 | **0.357** | **0.443** | **0.143** |
| | (0.028) | (0.057) | (0.059) | (0.042) |
| ≥1.04 | | **0.103** | **0.250** | **0.647** |
| | | (0.037) | (0.053) | (0.058) |
| $\gamma = 17.8$ | | | | |
| Last period | 0.818 | 0.152 | 0.030 | 0.000 |
| 20 years $\psi_{T+20}$ | 0.749 | 0.170 | 0.051 | 0.030 |
| 100 years $\psi_{T+100}$ | 0.691 | 0.187 | 0.071 | 0.051 |
| Stationary $\psi^*$ | 0.688 | 0.188 | 0.072 | 0.052 |
| (s.e.) | (0.043) | (0.025) | (0.014) | (0.012) |
| $N_T = 526$ $N = 73$ $T = 7$ | | | | |
| *Transition counts* | | | | |
| <0.65 | 249 | 21 | | |
| <0.88 | 31 | 65 | 17 | 5 |
| <1.04 | 4 | 25 | 31 | 10 |
| ≥1.04 | | 7 | 17 | 44 |
| *Mobility summary* | | | | |
| | $\downarrow 2$ | $\downarrow 3$ | $\downarrow 4$ | $\uparrow 1$ |
| | 0.263 | 0.414 | 0.353 | 0.078 |

Conditional transition matrix estimated on country-year observations with relative human capital below the operational cutoff of 0.64. Diagonal entries are in bold. Source: Authors' calculations from Penn World Table 11.0.

Table D.3: Relative TFP transition matrix: High-human-capital regime (operational cutoff).

| Transition matrix | <0.65 | <0.88 | <1.04 | ≥1.04 |
|---|---|---|---|---|
| <0.65 | **0.826** | **0.168** | 0.006 | |
| | (0.030) | (0.030) | (0.006) | |
| <0.88 | **0.126** | **0.701** | **0.174** | |
| | (0.026) | (0.035) | (0.029) | |
| <1.04 | | **0.228** | **0.614** | **0.157** |
| | | (0.037) | (0.043) | (0.032) |
| ≥1.04 | | 0.014 | **0.315** | **0.671** |
| | | (0.014) | (0.054) | (0.055) |
| $\gamma = 20.6$ | | | | |
| Last period | 0.407 | 0.395 | 0.140 | 0.058 |
| 20 years $\psi_{T+20}$ | 0.334 | 0.364 | 0.218 | 0.084 |
| 100 years $\psi_{T+100}$ | 0.259 | 0.352 | 0.264 | 0.125 |
| Stationary $\psi^*$ | 0.254 | 0.352 | 0.267 | 0.128 |
| (s.e.) | (0.039) | (0.034) | (0.033) | (0.027) |
| $N_T = 522$ $N = 81$ $T = 6$ | | | | |
| *Transition counts* | | | | |
| <0.65 | 128 | 26 | 1 | |
| <0.88 | 21 | 117 | 29 | |
| <1.04 | | 29 | 78 | 20 |
| ≥1.04 | | 1 | 23 | 49 |
| *Mobility summary* | | | | |
| | $\downarrow 2$ | $\downarrow 3$ | $\downarrow 4$ | $\uparrow 1$ |
| | 0.126 | 0.228 | 0.329 | 0.174 |

Conditional transition matrix estimated on country-year observations with relative human capital at or above the operational cutoff of 0.64. Diagonal entries are in bold. Source: Authors' calculations from Penn World Table 11.0.

# Appendix E: Development Accounting

In Table E.1, the column labeled "frontier share" is the relative-efficiency component defined in Section III; the label is inherited from the original Caselli–Coleman accounting convention and is not intended to identify a structural technology frontier.

Table E.1: Detailed Caselli-Coleman decomposition by HC group (pooled, 1960-2015).

| HC group (pooled) | N_obs | N_countries | Mean rel. TFP | log(TFP/TFP_US) obs. | log(A_u / A_u_US) | log(B / B_US) | log residual | Frontier share (%) | Composition share (%) | Residual share (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| High HC (≥0.64) | 615 | 86 | 0.797 | -0.293 | -0.939 | 0.245 | 0.401 | 320.5 | -83.6 | -136.9 |
| Low HC (<0.64) | 571 | 72 | 0.694 | -0.477 | -1.607 | 0.079 | 1.051 | 336.9 | -16.6 | -220.3 |

Pooled decomposition across all five-year cross-sections. Operational High-HC vs Low-HC split at rel_hc = 0.64. The frontier component is $\log(A_u/A_{u,\mathrm{US}})$; the composition component is $\log(B/B_{\mathrm{US}})$. Source: Authors' calculations from Penn World Table 11.0.

Table E.2 reports the sensitivity of the pooled decomposition to alternative elasticities of substitution between skilled and unskilled labor.

Table E.2. Caselli–Coleman decomposition: sensitivity to elasticity of substitution σ.

| σ | HC group | log(TFP/US) | $\log(A_u/A_{u},US)$ | log(B/BUS) | log residual | Composition (%) | Efficiency (%) | Residual (%) |
|---|---|---|---|---|---|---|---|---|
| 0.34 | High HC (≥0.64) | -0.293 | -0.939 | 0.245 | 0.401 | -83.7 | 320.5 | -136.8 |
| 0.34 | Low HC (<0.64) | -0.477 | -1.607 | 0.079 | 1.052 | -16.6 | 337.3 | -220.7 |
| 1.00 | High HC (≥0.64) | -0.293 | -0.564 | -0.130 | 0.401 | 44.5 | 192.3 | -136.8 |
| 1.00 | Low HC (<0.64) | -0.477 | -1.158 | -0.370 | 1.052 | 77.6 | 243.1 | -220.7 |
| 1.40 | High HC (≥0.64) | -0.293 | -0.479 | -0.215 | 0.401 | 73.5 | 163.3 | -136.8 |
| 1.40 | Low HC (<0.64) | -0.477 | -1.041 | -0.487 | 1.052 | 102.2 | 218.5 | -220.7 |

The entries labeled shares are contributions to the observed log productivity gap; because components offset one another, they can be negative or exceed 100 percent and should not be read as variance shares. Across the reported calibrations, the relative-efficiency component remains larger in absolute magnitude than the workforce-composition component. Source: Authors' calculations from Penn World Table 11.0 and Barro-Lee educational-attainment data.

# Appendix F: Artificial Intelligence Counterfactuals

This appendix reports one additional translation of the mobility scenarios. It is deliberately illustrative and does not add a welfare interpretation to the productivity counterfactuals.

Table F.1. Illustrative mean-relative-income implications by scenario and horizon.

| Scenario | Horizon | Q1 share | Q4 share | Implied mean income (rel. US) | Gain vs baseline |
|---|---|---|---|---|---|
| Baseline (unconditional TFP) | 25 years | 0.510 | 0.074 | 0.302 | +0.000 |
| Baseline (unconditional TFP) | 100 years | 0.482 | 0.088 | 0.313 | +0.000 |
| High-HC transition matrix | 25 years | 0.356 | 0.077 | 0.352 | +0.050 |
| High-HC transition matrix | 100 years | 0.262 | 0.124 | 0.389 | +0.076 |
| Broad AI diffusion | 25 years | 0.398 | 0.077 | 0.336 | +0.034 |
| Broad AI diffusion | 100 years | 0.340 | 0.105 | 0.358 | +0.045 |
| Unequal AI diffusion | 25 years | 0.555 | 0.078 | 0.289 | -0.013 |
| Unequal AI diffusion | 100 years | 0.545 | 0.087 | 0.293 | -0.020 |

Note: The table translates the state-share counterfactuals in Table 9 into an illustrative mean-relative-income metric using empirical mean relative income within each productivity state in the 2015 cross-section. It is not a welfare calculation or a forecast. Source: Authors' calculations.