Capability Thresholds and the Middle-Income Trap

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3/1/2026

Abstract

Why do some middle-income economies sustain convergence toward the technological frontier while others remain trapped in imitation-based growth despite continued investment and openness? This paper proposes a structural interpretation of the middle-income trap as a regime failure in productivity growth. We develop a dynamic model in which an endogenous stock of capabilities governs both implementation efficiency in production and absorptive capacity in technology diffusion. Capabilities accumulate gradually through policy effort scaled by relative income, generating feedback between productivity growth and capability formation. When capabilities remain below a threshold, productivity growth relies primarily on technology diffusion. Once the threshold is crossed, innovation becomes an additional source of productivity growth, allowing economies to sustain convergence toward the global frontier.

The model is disciplined quantitatively using data for Indonesia over 2000–2020. Baseline projections indicate that under continuation of recent conditions Indonesia remains in the imitation regime for more than a century, corresponding to a middle-income trap. Escaping this trajectory requires sustained capability investment of roughly two to three percent of GDP annually for about twenty-five years. Comparisons with China and Korea illustrate how sustained capability accumulation enables transition to innovation-driven growth and the dynamics of economies operating near the technological frontier.

Keywords: Middle-income trap; technology diffusion; innovation; productivity; capabilities; regime transition; development policy.
JEL Codes: O11, O14, O30, O40, E23.

*The theoretical model was developed while the author was a visiting professor at Grand Valley State University, Michigan. This is a working paper. Comments are welcome.

1 Introduction

A central puzzle in economic development is why some middle-income economies sustain long-run convergence toward the global technological frontier while others experience persistent stagnation despite continued investment, industrialization, and integration into the global economy. Over the past several decades, a small number of economies—including Korea, Taiwan, Hong Kong, and Singapore—have successfully transitioned from technology adoption to innovation-driven growth, while many others have experienced persistent slowdowns in productivity convergence. Standard neoclassical growth theory predicts conditional convergence driven by capital accumulation and diminishing returns (Solow, 1956). However, development accounting shows that persistent income gaps across countries primarily reflect differences in productivity rather than factor accumulation alone (Hall and Jones, 1999; Caselli, 2005).

At the same time, a large literature also emphasizes that the sources of productivity growth evolve across stages of development. Far from the technological frontier, growth relies primarily on technology adoption and diffusion, while economies closer to the frontier increasingly depend on domestic innovation (Nelson and Phelps, 1966; Acemoglu, Aghion, and Zilibotti, 2006). These insights suggest that successful development requires a structural transition from an imitation-based growth regime to an innovation-driven regime.

A large empirical literature documents the persistence of middle-income status and growth slowdowns across many emerging economies (Gill and Kharas, 2007; Eichengreen, Park, and Shin, 2012; Felipe, Abdon, and Kumar, 2012). However, the concept of the middle-income trap is often used descriptively, with less emphasis on the structural mechanisms governing transitions from imitation-based growth to innovation-driven development.

This paper proposes a structural interpretation of the middle-income trap as a regime failure in productivity growth. In the framework developed here, economies remain trapped not because capital accumulation mechanically stops, but because an endogenous stock of capabilities fails to reach a threshold required for innovation-oriented development. Capabilities summarize the institutional, organizational, and knowledge-producing capacity of an economy, encompassing advanced human capital, research systems, and the broader innovation ecosystem that supports technological adoption and creation.

To formalize this mechanism, the paper develops a tractable dynamic model linking capability accumulation, technology diffusion, and innovation-driven productivity growth. Capabilities influence economic performance through two channels. First, they determine the efficiency with which frontier technologies are implemented in production through a capability-dependent implementation-efficiency wedge. Second, they govern absorptive capacity, determining the speed at which frontier technologies diffuse into the economy. Once capabilities exceed a threshold level, the economy acquires the institutional and scientific capacity necessary to generate innovation directly.

Capabilities themselves evolve as a slow-moving stock accumulated through policy effort scaled by relative income. This formulation captures the idea that building universities, research institutions, and innovation systems requires substantial real resources. As a result, productivity growth and capability accumulation interact through a feedback loop: higher capabilities increase productivity and income, which expand the resource base available for further capability investment. Depending on initial conditions and policy effort, this feedback can generate either persistent low-capability stagnation or finite-time transition to an innovation-driven regime.

The paper makes three main contributions. First, it provides a structural definition of the middle-income trap. Rather than classifying countries based on income levels or observed growth slowdowns, the model defines the trap as a persistent failure of the capability stock to cross an innovation threshold. This definition transforms the MIT from a descriptive label into a formally defined dynamic outcome.

Second, the framework delivers analytical characterization of the development regimes implied by capability dynamics. The paper derives conditions under which economies remain confined to imitation-driven growth and conditions under which capability accumulation eventually crosses the innovation threshold. These results clarify how diffusion, implementation efficiency, and capability investment interact to shape long-run productivity dynamics.

Third, the paper introduces a quantitatively disciplined framework for mapping capability-building policies into development trajectories. The model is calibrated using macroeconomic benchmarks and empirical identification of diffusion and capability formation parameters. Counterfactual policy analysis is formulated as a minimal cross-by-horizon problem: for a given time horizon, we compute the minimum policy effort required to accumulate sufficient capability to enter the innovation regime.

The quantitative analysis focuses on Indonesia as a development laboratory. Indonesia represents a large emerging economy that has achieved sustained growth through capital accumulation and technology adoption but remains well below the capability threshold associated with innovation-driven development. Using data for the period 2000–2020, the model is validated against the medium-run evolution of capabilities and productivity before being used to generate long-run projections.

The baseline results deliver a stark implication. Under continuation of recent policy conditions, Indonesia's capability stock grows gradually but remains below the innovation threshold even over a century-long horizon. In this scenario the economy remains permanently in the imitation regime, relying primarily on technology diffusion rather than innovation-driven productivity growth. As a result, relative productivity and income converge only partially toward the global frontier.

In the baseline projection, Indonesia's capability stock grows gradually but remains below the innovation threshold even over a century-long horizon. In this scenario the economy remains permanently in the imitation regime, relying primarily on technology diffusion rather than innovation-driven productivity growth. In the framework of this paper, this outcome corresponds directly to a middle-income trap, in which the economy converges only partially in productivity and income toward the global technological frontier despite continued capital accumulation.

Escaping this trajectory requires a substantial and sustained increase in capability investment. The model indicates that Indonesia would need to devote roughly two to three percent of GDP annually to capability-building investments—such as tertiary education expansion, research systems, and innovation infrastructure—for approximately twenty-five consecutive years in order to accumulate sufficient capability to enter the innovation regime. Our baseline results imply that without sustained capability investment, Indonesia risks remaining in an imitation-based development regime for the next century.

These results are directly relevant to Indonesia's national development strategy. The government's long-term roadmap, "Golden Indonesia 2045," aims to transform the country into a high-income economy by the centenary of independence in 2045—approximately twenty-five years after the end of the baseline period used in our analysis. The model suggests that achieving this objective requires not only continued economic growth but also a sustained and coordinated expansion of capability investment sufficient to push the economy across the innovation threshold within this policy horizon.

To provide comparative perspective, the paper also examines China and Korea. China illustrates the dynamics of capability accumulation approaching the innovation threshold. Under continuation of recent conditions, the calibrated model predicts that China crosses the threshold within the next decade as sustained capability investment activates reinforcing feedback between productivity growth and capability formation. Korea serves as a benchmark innovation-regime economy, illustrating the productivity dynamics that arise once capabilities exceed the threshold and domestic innovation becomes the primary driver of growth.

Taken together, the results highlight a central implication: the timing and persistence of capability-building policies are first-order determinants of long-run development trajectories. Economies that accumulate sufficient capabilities can transition from imitation-driven growth to innovation-oriented development, while those that fail to do so remain confined to partial convergence below the technological frontier. The framework developed in this paper draws on several strands of research in growth and development economics, including the development accounting literature on productivity differences, the diffusion literature on absorptive capacity, and the empirical literature on the middle-income trap.

This paper develops a capability-driven growth framework in which the accumulation of technological and organizational capabilities governs the transition from imitation-driven development to innovation-led growth. The model shows that capital accumulation alone cannot sustain convergence toward the technological frontier. Instead, economies must accumulate capabilities sufficient to activate a self-reinforcing process linking productivity growth and capability formation. Applying the model to Indonesia, China, and Korea illustrates how sustained capability investment and institutional effectiveness determine whether economies remain trapped in imitation-based growth or transition toward innovation-driven development.

The remainder of the paper proceeds as follows. Section 2 reviews the conceptual foundations and related literature. Section 3 develops the model. Section 4 derives the theoretical implications of the capability dynamics. Section 5 describes the empirical implementation and calibration strategy. Section 6 presents the quantitative analysis. Section 7 evaluates the Indonesian case through validation, projections, and policy experiments. Section 8 examines cross-country comparisons with China and Korea. Section 9 concludes.

2 Conceptual foundations and related literature

This section situates the paper within three strands of research that jointly motivate the framework developed here. Rather than providing an exhaustive survey, we focus on the specific conceptual foundations that inform the model and clarify how the present framework contributes to the literature.

2.1 TFP differences, productivity wedges, and development accounting

A central finding of development accounting is that persistent income differences across countries are primarily explained by productivity rather than by factor accumulation alone (Hall and Jones, 1999; Caselli, 2005). Cross-country income gaps therefore reflect differences in the efficiency with which economies transform capital, labor, and technology into output.

One influential approach interprets these productivity differences through the lens of wedges or distortions that prevent economies from efficiently allocating resources or implementing available technologies (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Empirical evidence further shows that managerial quality, organizational capability, and institutional effectiveness play a central role in determining productivity outcomes (Bloom and Van Reenen, 2007; Bloom, Sadun, and Van Reenen, 2013).

Our framework incorporates these insights through a capability-dependent implementation-efficiency wedge. The key difference from existing wedge interpretations is that the wedge is tied to an endogenous state variable—the capability stock—which evolves through investment and policy effort. This structure allows the model to move beyond static accounting decompositions and instead analyze how institutional and organizational capacity evolves over time and affects long-run development trajectories.

2.2 Technology diffusion, absorptive capacity, and distance to the frontier

A second foundational literature studies the process through which technologies diffuse from global leaders to follower economies. The classic insight of Nelson and Phelps (1966) is that the speed of technology adoption depends on a country's stock of human capital and its ability to absorb new knowledge. Subsequent empirical research documents substantial heterogeneity in the timing and intensity of technology diffusion across countries and sectors (Keller, 2004; Comin and Hobijn, 2010).

Related work in Schumpeterian growth theory emphasizes that the nature of productivity growth changes as economies approach the technological frontier. Far from the frontier, growth is largely driven by imitation and technology adoption. Near the frontier, innovation and technological experimentation become increasingly important (Aghion and Howitt, 1992; Acemoglu, Aghion, and Zilibotti, 2006).

Our model formalizes these ideas by linking diffusion dynamics directly to the capability stock. In the imitation regime, relative productivity evolves through capability-conditioned diffusion from the frontier. Capabilities determine the economy's absorptive capacity and therefore the speed at which frontier technologies are adopted and implemented. Once capabilities exceed a threshold level, innovation becomes an additional source of productivity growth.

2.3 Middle-income traps and development transitions

A large empirical literature documents the persistence of middle-income status and growth slowdowns in many emerging economies (Gill and Kharas, 2007; Eichengreen, Park, and

Shin, 2012; Felipe, Abdon, and Kumar, 2012). These studies highlight that many economies experience rapid growth during early stages of industrialization but fail to sustain convergence toward advanced-economy income levels.

While the empirical regularities associated with the middle-income trap are well documented, the concept is often used descriptively rather than as a structural diagnosis. Countries are typically classified as "trapped" based on income thresholds or observed growth slowdowns, but the mechanisms generating these outcomes remain less clearly defined.

This paper proposes a structural interpretation of the middle-income trap as a regime failure in productivity growth. In the model, economies remain trapped when the capability stock fails to reach the threshold required for innovation-driven development. As a result, productivity growth remains limited to technology diffusion and the economy converges only partially toward the global technological frontier.

2.4 Contribution of the paper

Relative to these literatures, the framework developed in this paper contributes in three main ways. First, it provides a tractable dynamic model in which the middle-income trap corresponds to a formally defined failure of capability accumulation to cross an innovation threshold. This framework converts the middle-income trap from a descriptive classification into a structural object determined by capability dynamics.

Second, the model integrates several mechanisms typically studied separately in the development literature—implementation efficiency, technology diffusion, and innovation capacity—into a unified dynamic framework governed by the evolution of the capability stock.

Third, the paper imposes quantitative discipline on the framework by mapping capability-building policies into development trajectories. Using calibrated simulations, the model provides a transparent mapping from sustained capability investment to the timing of regime transition. This mapping allows the policy problem of escaping the middle-income trap to be expressed in concrete quantitative terms: the level and duration of capability investment required for an economy to cross the innovation threshold.

3 Model

This section develops a dynamic framework linking capability accumulation, technology diffusion, and innovation-driven productivity growth. The economy is modeled as a follower evolving relative to an exogenous global technological frontier. The key state variable is a stock of productive capabilities that determines both the efficiency with which technologies are implemented in production and the economy's ability to absorb and generate new technologies.

Capabilities accumulate gradually through policy effort scaled by the economy's resource base. As a result, productivity growth and capability formation interact dynamically: economies that accumulate sufficient capability eventually transition from imitation-driven growth to innovation-driven development, while those that do not remain trapped in imitation-driven growth

Time is continuous. Variables without a superscript refer to the follower economy, while variables with superscript * denote the frontier economy. Labor is normalized to one in both economies so that all variables are expressed in per–worker terms.

3.1 Production and implementation efficiency

Output in the follower economy is produced using physical capital and technology, but the effectiveness with which these inputs are deployed depends on the economy's implementation capabilities. Production therefore takes the form

$$Y_t = E(C_t) A_t K_t^{\alpha}, \quad \alpha \in (0,1), \tag{1}$$

where A_t denotes total factor productivity (TFP), K_t is the capital stock, and $E(C_t)$ represents implementation efficiency determined by the capability stock C_t.

The function $E(C_t)$ captures organizational, institutional, and managerial factors that affect how effectively technologies are implemented in production. Development accounting studies show that differences in measured productivity across countries reflect not only technological gaps but also differences in implementation efficiency and resource allocation (Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2009). Micro-level evidence further emphasizes the importance of managerial quality and organizational capability in determining productivity outcomes (Bloom and Van Reenen, 2007; Bloom, Sadun and Van Reenen, 2013).

Implementation efficiency is assumed to increase with capability but remain bounded above by the frontier level:

$$E(C_t) = \begin{cases} \left(\dfrac{C_t}{\bar{C}}\right)^{\eta}, & C_t < \bar{C} \\ 1, & C_t \geq \bar{C} \end{cases} \qquad \eta \in (0,1). \tag{2}$$

This specification captures two features of the development process. When capability is low, improvements in organizational capacity and institutional quality substantially increase implementation efficiency. As capability approaches the threshold $\bar{C}$, efficiency gains diminish and production approaches frontier efficiency.

The frontier economy operates at full implementation efficiency:

$$Y_t^* = A_t^* (K_t^*)^{\alpha}. \tag{3}$$

Define relative variables:

$$y_t^r = \frac{Y_t}{Y_t^*}, \quad k_t^r = \frac{K_t}{K_t^*}, \quad a_t = \frac{A_t}{A_t^*}. \tag{4}$$

Combining the production functions yields the decomposition

$$y_t^r = E(C_t) a_t (k_t^r)^{\alpha}. \tag{5}$$

Relative income therefore depends on three components: implementation efficiency governed by capability, relative productivity, and relative capital intensity.

3.2 Capital accumulation

Capital evolves according to a standard accumulation equation:

$$\dot{K}_t = sY_t - \delta_K K_t \tag{6}$$
$$\dot{K}_t^* = s^* Y_t^* - \delta_K K_t^* \tag{7}$$

where s and s^* denote saving rates and δ_K is the depreciation rate of capital.

Capital accumulation contributes to income convergence but does not eliminate cross-country income differences on its own. Development accounting studies consistently find that productivity differences explain the majority of income gaps across countries (Hall and Jones, 1999; Caselli, 2005). Accordingly, the central mechanisms of the model operate through productivity and capability dynamics rather than capital accumulation alone.

This section develops a dynamic framework linking capability accumulation, technology diffusion, and long-run productivity growth. The model describes a follower economy evolving relative to an exogenous technological frontier. The central mechanism is the accumulation of a stock of productive capabilities that governs both the effectiveness of technology implementation and the ability of the economy to absorb and generate new technologies.

Capabilities are interpreted broadly as the institutional, organizational, and human-capital foundations that allow societies to transform technological knowledge into productive outcomes. These capabilities include the quality of universities and research institutions, the depth of engineering and scientific skills, the efficiency of public administration, and the broader innovation ecosystem that supports knowledge creation and diffusion.

A key feature of the framework is that capabilities evolve gradually as a stock variable that requires sustained investment. Because capability formation depends on both policy effort and the resources available to the economy, the model generates endogenous development dynamics in which productivity growth and capability accumulation reinforce one another over time.

3.3 Capability accumulation

Capability evolves according to[1]

$$\dot{C}_t = \kappa\big(\tau_t\, y_t^r\big)^{\nu} - \delta_C C_t, \qquad \kappa > 0,\ \nu \in (0,1),\ \delta_C > 0, \tag{8}$$

where $\tau_t \geq 0$ denotes policy effort devoted to capability formation and y_t^r represents relative income.

[1] A more general specification could allow capability formation to depend on distance to the technological frontier. For example,

$$\dot{C}_t = \kappa(\tau_t y_t^r)^{\nu}(1 - a_t)^{\psi} - \delta_C C_t,$$

where $a_t = A_t/A_t^*$ denotes relative productivity and $\psi \geq 0$ governs the sensitivity of capability formation to frontier distance. When $\psi > 0$, capability accumulation becomes progressively more difficult as the economy approaches the technological frontier. For parsimony and identification, the quantitative analysis focuses on the baseline case $\psi = 0$.

Capability C_t is interpreted as a stock of productive knowledge and institutional capacity that enables an economy to implement, adapt, and eventually create advanced technologies. In this sense, capability functions as a form of intangible capital. Just as physical capital accumulates through investment and depreciates over time, the capability stock grows through deliberate investment in knowledge-producing institutions and erodes in the absence of sustained effort.

The accumulation equation therefore treats capability as the outcome of a continuous investment process supported by public policy and economic resources. Examples of capability-building investments include the expansion of tertiary education, the establishment of research universities and laboratories, the development of national innovation systems, and institutional reforms that improve the effectiveness of public administration and regulatory frameworks.

The flow of capability investment depends on the product $\tau_t y_t^r$. This formulation reflects the idea that capability formation requires resources measured in absolute terms rather than purely as a share of output. Building advanced research systems, universities, and technological infrastructure involves globally priced inputs such as highly trained researchers, specialized equipment, and international collaboration networks.

As a result, identical policy effort expressed as a share of GDP can translate into very different effective investments across countries. Economies with higher income levels possess larger resource envelopes that allow them to invest more heavily in capability formation, even when policy effort is comparable. Conversely, lower-income economies face tighter resource constraints that limit the scale of capability investment.

This formulation captures a central challenge of development: countries that begin with low productivity also possess fewer resources with which to build the institutional and knowledge foundations necessary for sustained technological progress.

The parameter $\kappa > 0$ governs the efficiency with which policy effort and economic resources are transformed into capability accumulation. Economically, κ captures the effectiveness of the national capability-building system.

Higher values of κ correspond to environments in which investments in education, research infrastructure, and innovation systems are translated efficiently into productive knowledge and institutional capacity. In such settings, universities produce high-quality graduates, research funding is allocated effectively, and innovation systems successfully connect research institutions with firms and entrepreneurs.

Conversely, when institutional quality is weak or policy implementation is ineffective, a significant portion of capability investment may fail to translate into lasting productive capacity. In this case, the same level of policy effort generates smaller increases in national capability. The parameter κ therefore summarizes a broad set of institutional and organizational factors that determine how effectively societies convert knowledge investments into productive capabilities.

The curvature parameter $\nu \in (0, 1)$ introduces diminishing returns in the conversion of effective investment into capability accumulation. This feature reflects the empirical observation that early stages of capability formation often yield rapid improvements, whereas further expansion becomes progressively more costly as systems mature. For example, establishing basic tertiary education programs or foundational research institutions may initially produce large gains in national capability. However, achieving frontier-level research capacity requires increasingly sophisticated infrastructure, highly specialized human capital, and complex institutional coordination. Empirical research on human capital accumulation and institutional development provides support for such diminishing returns in capability formation (Benhabib and Spiegel, 1994, 2005; Acemoglu, Johnson and Robinson, 2005). The parameter ν captures this feature by ensuring that marginal increases in capability become progressively more difficult as the scale of investment expands.

The parameter $\delta_C > 0$ represents the depreciation or erosion of the capability stock. Capabilities can deteriorate over time due to institutional decay, technological obsolescence, or the loss of skilled workers through migration or retirement. For example, research infrastructure may become outdated, educational institutions may decline in quality, or highly trained scientists may relocate to countries offering better research opportunities. Without sustained investment, the capability stock therefore declines over time. This feature highlights the importance of maintaining long-term commitment to capability-building policies.

Equation (8) also introduces an important feedback mechanism in the model. Because capability investment depends on relative income y_t^r, improvements in productivity expand the resource base available for capability formation. Higher productivity therefore generates additional resources that can be devoted to education, research infrastructure, and innovation systems. In turn, stronger capabilities enhance the economy's ability to implement technologies, absorb frontier knowledge, and eventually generate innovation. This feedback creates a dynamic complementarity between productivity growth and capability accumulation. Economies that successfully begin to build capabilities can experience reinforcing growth dynamics, while those with insufficient capability investment may struggle to generate the resources required to sustain further development. Such feedback mechanisms between knowledge accumulation and economic performance have long been emphasized in the development and growth literature, which highlights the role of human capital, institutions, and innovation systems as key drivers of long-run productivity growth.

3.4 Frontier benchmark

The frontier economy represents the global technology leader. Frontier productivity grows exogenously at rate g^*:

$$A_t^* = A_0^* e^{g^* t}. \tag{9}$$

This assumption reflects the idea that global technological progress is driven by frontier innovation dynamics beyond the control of any individual follower economy.

3.5 Productivity dynamics and development regimes

The central mechanism of the model lies in the evolution of relative productivity. Let

$$a_t = \frac{A_t}{A_t^*} \tag{10}$$

denote relative TFP. Productivity dynamics depend on whether the capability stock is below or above the innovation threshold $\bar{C}$.

Imitation regime: capability-conditioned diffusion

When $C_t < \bar{C}$, productivity growth occurs through technology diffusion from the frontier:

$$\dot{a}_t = \phi_I m(C_t)(1 - a_t) - g^* a_t. \tag{11}$$

The term $(1 - a_t)$ represents the remaining technology gap relative to the frontier. As the follower economy approaches the frontier, the scope for further technology adoption diminishes, so diffusion-driven productivity growth naturally slows. The parameter $\phi_I > 0$ governs the baseline intensity of international technology diffusion. It measures the speed at which frontier technologies become available for adoption by follower economies, conditional on absorptive capacity. In this sense, ϕ_I captures global forces that facilitate knowledge transmission across countries, including trade in intermediate goods, multinational production networks, international research collaboration, and the diffusion of technical knowledge embodied in capital goods and managerial practices.

The specification separates two distinct components of the diffusion process. The parameter ϕ_I represents the exogenous global diffusion environment that determines the potential rate of technology transfer from the frontier. The function $m(C_t)$, in contrast, captures country-specific absorptive capacity. While frontier technologies may be widely available through global markets and knowledge networks, the speed at which they translate into productivity improvements depends critically on domestic capabilities such as human capital, managerial expertise, and institutional quality.

This decomposition follows the classic insight of Nelson and Phelps (1966), who argue that the ability to absorb frontier knowledge depends on a country's stock of human capital. Subsequent empirical work has documented substantial cross-country heterogeneity in diffusion speeds and has emphasized the role of human capital, institutions, and innovation systems in shaping technology adoption (Benhabib and Spiegel, 2005; Keller, 2004; Comin and Hobijn, 2010). In the present framework, these factors are summarized by the capability stock C_t, while ϕ_I captures the global diffusion environment common across countries.

The function

$$m(C_t) = \min\left\{\left(\frac{C_t}{\bar{C}}\right)^{\mu}, 1\right\} \tag{12}$$

represents absorptive capacity. Higher capability increases the speed at which frontier technologies are adopted and implemented.

This formulation reflects the Nelson–Phelps hypothesis that human capital and institutional capacity determine the speed of technology adoption (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005).

Innovation regime with frontier headwinds

Once capability exceeds the threshold $\bar{C}$, the economy acquires the institutional and scientific capacity required for frontier-directed innovation. Productivity growth then reflects both continued diffusion and domestic innovation:

$$\dot{a}_t = \left[\phi_I + \phi_N \left(\left(\frac{C_t}{\bar{C}} \right)^{\beta} - 1 \right) \right] (1 - a_t) - (g^* + \chi) a_t, \quad C_t \geq \bar{C}. \tag{13}$$

The innovation premium governed by ϕ_N and β captures the increasing ability of high-capability economies to generate frontier technologies. At the threshold $C_t = \bar{C}$, the innovation term vanishes and the productivity dynamics reduce to the diffusion equation. This ensures continuity of productivity growth at the regime boundary.

The parameter χ introduces a headwind associated with frontier proximity. Sustaining productivity growth near the technological frontier typically requires increasingly complex institutional, scientific, and organizational systems. These requirements generate adjustment costs and diminishing returns to innovation activity, which appear as an additional drift term reducing relative productivity growth.

This specification therefore combines two opposing forces in the innovation regime. Capability deepening strengthens innovation-driven productivity growth, while frontier proximity introduces structural headwinds that slow relative convergence. The interaction between capability accumulation and productivity dynamics therefore generates endogenous development regimes in which economies may remain confined to imitation-based growth or transition to innovation-driven convergence.

3.6 Definition of the middle-income trap

The model implies that long-run development depends critically on whether the economy accumulates sufficient capability to transition from imitation-driven growth to innovation-driven growth. When capability remains below the threshold $\bar{C}$, productivity growth occurs exclusively through the adoption and diffusion of existing technologies from the frontier. In this regime the economy can continue to grow and may even experience substantial income gains through capital accumulation and technology adoption. However, it lacks the institutional and scientific capacity required to sustain frontier-oriented innovation.

This mechanism captures a central insight in the middle-income trap (MIT) literature. Many economies achieve rapid growth during early stages of development by reallocating labor, accumulating capital, and adopting foreign technologies. Yet some of these economies fail to transition to innovation-based growth once the scope for imitation diminishes (Gill and Kharas, 2007; Eichengreen, Park and Shin, 2012; Felipe, Abdon and Kumar, 2012). In such cases growth does not necessarily cease, but it becomes insufficient to close the gap with the global technological frontier.

The present framework provides a structural interpretation of this phenomenon. In the model, the middle-income trap corresponds to a regime failure in capability accumulation: the economy fails to reach the capability threshold required to sustain innovation-driven productivity growth.

Definition 1 (Middle-income trap)**.** *Given initial conditions and a policy path $\{\tau_t\}_{t \geq 0}$, the economy is in a* middle-income trap *if*

$$C_t < \bar{C} \quad \textit{for all } t \geq 0. \tag{14}$$

Equivalently, the economy remains permanently in the imitation regime (**??**)*, so productivity growth relies solely on technology diffusion and the transition to innovation-driven growth never occurs.*

A middle-income trap in this framework does not imply that economic growth stops. The follower economy may continue to grow through capital deepening and gradual technology adoption. However, because the capability threshold for innovation is never reached, productivity growth remains bounded by the limits of imitation. As a result, relative productivity converges to a level strictly below the technological frontier.

Because relative income satisfies

$$y_t^r = E(C_t)a_t(k_t^r)^\alpha,$$

this productivity bound implies incomplete convergence in income as well. The economy therefore remains persistently below frontier income levels despite continued growth, which corresponds to the empirical pattern often described as the middle-income trap. This definition converts the middle-income trap from a descriptive classification based on income levels into a structural object determined by capability dynamics.

4 Theoretical implications

We now analyze the dynamic properties of the model. The system consists of the capital accumulation equations (6)–(7), the capability accumulation equation (8), and the regime-dependent productivity laws (11)–(13), with relative income determined by (5). The state variables are (K_t, K_t^*, C_t, a_t).

We begin by establishing basic properties of the productivity dynamics when the economy remains in the imitation regime. These results clarify the limits of convergence when innovation capabilities are absent and provide the analytical foundation for the middle-income trap mechanism developed in the model.

4.1 Imitation steady state in relative TFP

Consider first the case in which capability remains below the innovation threshold, so that productivity growth occurs exclusively through technology diffusion from the frontier.

Proposition 1 (Imitation-regime steady state of relative TFP)**.** *Fix any constant capability level $C \in (0, \bar{C})$. Under the imitation dynamics* (11)*, there exists a unique steady state level of relative TFP $a^I(C) \in (0,1)$ given by*

$$a^I(C) = \frac{\phi_I(C/\bar{C})^\mu}{\phi_I(C/\bar{C})^\mu + g^*}. \tag{15}$$

Moreover, for any initial condition $a_0 \in [0,1]$, the trajectory a_t converges monotonically to $a^I(C)$.

Proof. With capability fixed at C, equation (**??**) becomes

$$\dot{a}_t = \phi_I (C/\bar{C})^{\mu}(1 - a_t) - g^* a_t.$$

Rearranging yields the linear differential equation

$$\dot{a}_t = \phi_I (C/\bar{C})^{\mu} - \big(\phi_I (C/\bar{C})^{\mu} + g^*\big) a_t.$$

Let

$$\lambda \equiv \phi_I (C/\bar{C})^{\mu} + g^* > 0.$$

The equation can then be written as

$$\dot{a}_t = \phi_I (C/\bar{C})^{\mu} - \lambda a_t.$$

Setting $\dot{a}_t = 0$ yields the unique steady state

$$a^I(C) = \frac{\phi_I (C/\bar{C})^{\mu}}{\lambda} = \frac{\phi_I (C/\bar{C})^{\mu}}{\phi_I (C/\bar{C})^{\mu} + g^*}.$$

The differential equation is linear with slope $-\lambda < 0$. Hence the steady state is globally asymptotically stable on $[0, 1]$. The solution path satisfies

$$a_t = a^I(C) + (a_0 - a^I(C))e^{-\lambda t},$$

which converges monotonically to $a^I(C)$ for any $a_0 \in [0, 1]$. □

Proposition 1 highlights a central implication of the imitation regime. Relative productivity converges to a level strictly below the technological frontier whenever capability remains below the threshold $\bar{C}$. From (15), the steady-state level of relative TFP is increasing in capability:

$$\frac{\partial a^I(C)}{\partial C} > 0.$$

Thus improvements in capability allow economies to approach the frontier more closely even when productivity growth is driven solely by technology diffusion.

However, for any $C < \bar{C}$,

$$a^I(C) < 1.$$

Hence the frontier level of productivity cannot be reached within the imitation regime. Even with sustained diffusion from the frontier, countries that fail to accumulate sufficient capability remain permanently below the frontier productivity level. This result provides the core analytical mechanism underlying the middle-income trap in the model.

Corollary 1 (Upper bound of imitation-driven convergence)**.** *Let $a^I(C)$ denote the steady-state relative TFP in the imitation regime given by* (15)*. Then*

$$\lim_{C \to \bar{C}^-} a^I(C) = \frac{\phi_I}{\phi_I + g^*}. \tag{16}$$

Proof. Taking the limit of (15) as $C \to \bar{C}^-$ yields

$$\lim_{C\to\bar{C}^-} a^I(C) = \lim_{C\to\bar{C}^-} \frac{\phi_I (C/\bar{C})^\mu}{\phi_I (C/\bar{C})^\mu + g^*} = \frac{\phi_I}{\phi_I + g^*}.$$

□

Corollary 1 shows that imitation-driven growth alone can close only part of the technology gap with the frontier. Even as capability approaches the innovation threshold $\bar{C}$, the maximum attainable level of relative productivity remains strictly below one as long as innovation does not occur. The upper bound (16) depends on the relative strength of diffusion forces ϕ_I and frontier technological progress g^*. Faster frontier growth increases the steady-state technology gap, while stronger diffusion forces allow follower economies to approach the frontier more closely.

This result illustrates a key insight of the model: diffusion-driven development alone cannot deliver full convergence to the technological frontier. Sustained convergence ultimately requires the transition to innovation-driven productivity growth.

Proposition 2 (Imitation regime implies incomplete convergence)**.** *Suppose capability remains permanently below the innovation threshold, i.e.,*

$$C_t < \bar{C} \quad \textit{for all } t \geq 0.$$

Then relative productivity remains strictly below the frontier level in the long run:

$$\limsup_{t\to\infty} a_t < 1.$$

Consequently, relative income y_t^r also remains strictly below the frontier level.

Proof. If $C_t < \bar{C}$ for all t, the economy remains permanently in the imitation regime and relative productivity evolves according to (11). For any fixed $C < \bar{C}$, Proposition 1 shows that a_t converges to the steady-state value

$$a^I(C) = \frac{\phi_I (C/\bar{C})^\mu}{\phi_I (C/\bar{C})^\mu + g^*}.$$

Because $(C/\bar{C})^\mu < 1$ whenever $C < \bar{C}$, it follows that

$$a^I(C) < 1.$$

Hence relative productivity converges to a level strictly below the frontier. In particular,

$$\limsup_{t\to\infty} a_t = a^I(C) < 1.$$

Relative income satisfies

$$y_t^r = E(C_t) a_t (k_t^r)^\alpha.$$

Since $E(C_t) \leq 1$ and $a_t < 1$ in the limit, it follows that relative income also remains strictly below the frontier level. Therefore full convergence in income cannot occur. □

This proposition formalizes the central mechanism of the middle-income trap in the model. If capability fails to reach the threshold required for innovation, the economy remains confined to imitation-driven growth. Although technology diffusion allows partial convergence in productivity and income, the frontier productivity level cannot be attained. The technology gap therefore persists indefinitely.

4.2 Capability threshold crossing

We now characterize conditions under which the economy accumulates sufficient capability to transition into the innovation regime.

Proposition 3 (Capability threshold crossing)**.** *Suppose policy effort is constant,* $\tau_t \equiv \tau$*. If there exists a constant* $\underline{y} > 0$ *such that* $y_t^r \geq \underline{y}$ *whenever* $C_t \leq \bar{C}$*, and*

$$\kappa(\tau \underline{y})^\nu > \delta_C \bar{C}, \tag{17}$$

then capability eventually reaches the innovation threshold in finite time. That is, there exists $T < \infty$ *such that*

$$C_T = \bar{C}.$$

Proof. While $C_t \leq \bar{C}$, capability evolves according to

$$\dot{C}_t = \kappa(\tau y_t^r)^\nu - \delta_C C_t.$$

If $y_t^r \geq \underline{y}$, then

$$\dot{C}_t \geq \kappa(\tau \underline{y})^\nu - \delta_C C_t.$$

Consider the comparison equation

$$\dot{\tilde{C}}_t = \kappa(\tau \underline{y})^\nu - \delta_C \tilde{C}_t,$$

with $\tilde{C}_0 = C_0$. Its solution is

$$\tilde{C}_t = e^{-\delta_C t} C_0 + \frac{\kappa(\tau \underline{y})^\nu}{\delta_C} \left(1 - e^{-\delta_C t}\right).$$

Condition (17) implies

$$\frac{\kappa(\tau \underline{y})^\nu}{\delta_C} > \bar{C}.$$

Hence the solution $\tilde{C}_t$ eventually exceeds $\bar{C}$ in finite time. Because $C_t \geq \tilde{C}_t$ while $C_t \leq \bar{C}$, the actual capability path must also reach $\bar{C}$ in finite time. □

Condition (17) characterizes the boundary between two development regimes in the model. When effective capability investment remains below the critical level implied by $\delta_C \bar{C}$, the capability stock converges to a level strictly below the innovation threshold and the economy remains permanently in the imitation regime. Conversely, when capability investment exceeds this critical level, capability accumulates sufficiently fast to cross the threshold in finite time, triggering the transition to innovation-driven growth.

Condition (17) provides a transparent characterization of when an economy accumulates sufficient capability to transition into the innovation regime. Capability grows when the effective flow of capability investment exceeds the depreciation of the existing capability stock. From (8), this flow equals $\kappa(\tau y_t^r)^\nu$, which depends on both policy effort and the economy's resource base.

Economically, higher policy effort τ corresponds to stronger investment in tertiary education, research systems, and innovation infrastructure. The parameter κ captures the efficiency with which these investments are translated into productive capabilities. At the same time, capability depreciates at rate δ_C, reflecting institutional decay, knowledge obsolescence, or loss of skilled human capital.

Condition (17) therefore requires that capability investment, evaluated at a minimal income level $\underline{y}$, exceeds the depreciation flow associated with the threshold capability level $\bar{C}$. When this inequality holds, the economy accumulates capability faster than it depreciates, ensuring that the innovation threshold is eventually reached.

Taken together, the previous propositions characterize the fundamental development regimes of the model. When effective capability investment remains insufficient relative to capability depreciation, the economy remains trapped in the imitation regime and converges only partially toward the frontier. Conversely, when capability investment exceeds the critical threshold, capability eventually reaches $\bar{C}$ and the economy transitions to innovation-driven growth.

The crossing condition (17) can also be expressed as a threshold requirement for policy effort. Rearranging the inequality yields

$$\tau > \tau^{crit} = \frac{1}{\underline{y}}\left(\frac{\delta_C \bar{C}}{\kappa}\right)^{1/\nu}.$$

The parameter τ^{crit} represents the minimum level of capability-building policy effort required for the economy to accumulate sufficient capability to reach the innovation threshold. When policy effort remains below this level, capability investment is insufficient to overcome capability depreciation and the economy remains trapped in the imitation regime. Conversely, when policy effort exceeds this critical level, capability accumulation becomes strong enough to push the economy across the innovation threshold in finite time. Condition (17) guarantees that the innovation threshold is reached in finite time but does not determine the exact crossing date. The timing of the transition depends on the joint dynamics of capability, productivity, and income, which are analyzed quantitatively in later sections. The crossing condition in Proposition 3 can also be interpreted through the steady-state behavior of the capability dynamics. Consider the comparison equation

$$\dot{C}_t = \kappa(\tau \underline{y})^\nu - \delta_C C_t.$$

This equation admits a unique steady state

$$C^* = \frac{\kappa(\tau \underline{y})^\nu}{\delta_C}.$$

The position of this steady state relative to the innovation threshold $\bar{C}$ determines the long-run development regime. If $C^* < \bar{C}$, capability converges to a level below the innovation threshold and the economy remains permanently in the imitation regime. Conversely, if $C^* > \bar{C}$, capability eventually crosses the threshold and the economy transitions to innovation-driven growth.

4.3 Phase diagram and development regimes

The joint dynamics of capability and relative productivity can be illustrated using a phase diagram in the (C, a) space. The horizontal axis measures the capability stock C, while the vertical axis represents relative productivity $a = A/A^*$. Figure 1 illustrates the phase diagram implied by the model. The two state variables interact through the capability accumulation equation (8) and the productivity dynamics (11) and (13). The phase diagram provides a convenient graphical representation of how these variables evolve jointly over time.

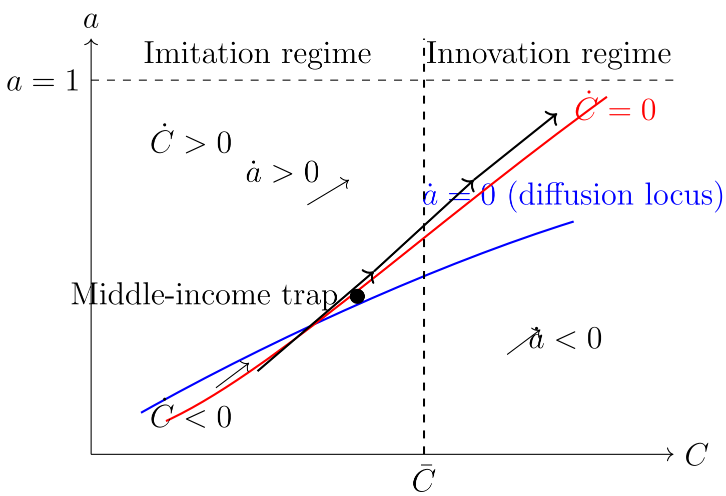

Figure 1: Phase diagram of capability and productivity dynamics. The blue curve represents the productivity locus ($\dot{a} = 0$) implied by technology diffusion, while the red curve represents the capability accumulation locus ($\dot{C} = 0$). The dashed vertical line marks the innovation capability threshold $\bar{C}$. Economies that remain to the left of the threshold converge to an imitation steady state below the frontier productivity level $a = 1$, corresponding to a middle-income trap. Economies that accumulate capability sufficiently fast cross the threshold and transition into innovation-driven growth.

The vertical dashed line at $C = \bar{C}$ separates the imitation and innovation regimes, highlighting that sufficiently strong capability accumulation is required for the economy to transition toward innovation-driven productivity growth. To the left of the threshold the economy operates in the imitation regime, where productivity growth is driven by technology diffusion. Once capabilities exceed $\bar{C}$, domestic innovation becomes an additional source of productivity growth.

The horizontal dashed line at $a = 1$ represents the frontier productivity level. In the imitation regime productivity evolves through technology diffusion from the frontier. Because diffusion depends on absorptive capacity and the remaining technology gap, the diffusion locus lies strictly below the frontier when capabilities are limited. Technology adoption therefore narrows the productivity gap but cannot eliminate it in the absence of sufficiently strong capabilities.

The $\dot{C} = 0$ locus describes the combinations of capability and productivity for which the capability stock remains constant. Along this locus the flow of capability investment exactly offsets the depreciation of existing capabilities. Using the capability accumulation equation together with the expression for relative income implied by the production structure, the locus satisfies

$$\delta_C C = \kappa(\tau y^r)^\nu.$$

Because higher productivity raises relative income, and therefore the effective resources available for capability investment, higher values of a are associated with higher steady-state levels of capability. The $\dot{C} = 0$ locus is therefore upward sloping in (C, a) space.

The interaction between the diffusion and capability loci determines the evolution of the economy. When capability levels are low, absorptive capacity is limited and productivity converges slowly toward the frontier. At the same time, low income restricts the scale of capability investment, slowing the accumulation of capabilities themselves. As capabilities increase, however, two reinforcing channels become stronger. Implementation efficiency improves and absorptive capacity rises, accelerating productivity convergence. Higher productivity in turn raises income and expands the effective scale of capability investment.

This feedback mechanism generates the regime transition emphasized in the model. Once capability accumulates sufficiently, the economy moves toward the innovation threshold $\bar{C}$, beyond which domestic innovation becomes an additional source of productivity growth. In this sense, the phase diagram illustrates how gradual capability accumulation can transform the economy's growth regime from imitation-driven convergence to innovation-led productivity growth.

4.4 Comparative statics

We now examine how the model's parameters affect the likelihood that an economy escapes the middle-income trap and transitions into innovation-driven growth. The comparative statics can be organized around three economic forces that govern development in the model: capability investment, diffusion capacity, and innovation strength.

Capability accumulation depends on the balance between effective capability investment and capability depreciation. From equation (8), increases in policy effort τ or in the efficiency of capability formation κ raise the flow of capability investment, thereby accelerating the growth of the capability stock C_t. Higher values of these parameters therefore increase the likelihood that the economy eventually crosses the innovation threshold $\bar{C}$. Conversely, a higher depreciation rate δ_C reduces the net accumulation of capability by increasing the rate at which existing capabilities erode. Economies with weak capability investment or high capability depreciation may therefore converge to capability levels below the threshold required for innovation, remaining permanently in the imitation regime. These parameters thus determine whether capability accumulation is strong enough to sustain the transition to innovation-driven growth.

The parameters governing technology diffusion determine how closely an economy can approach the technological frontier while remaining in the imitation regime. From equation (15), higher diffusion intensity ϕ_I increases the steady-state level of relative productivity $a^I(C)$, allowing economies to achieve greater convergence through imitation alone. Similarly, a larger absorptive-capacity elasticity μ strengthens the responsiveness of diffusion to capability accumulation, making productivity growth more sensitive to improvements in capability. However, diffusion-driven convergence remains inherently limited. As long as capability remains below the threshold $\bar{C}$, relative productivity remains strictly below the frontier level. Even when diffusion forces are strong, imitation alone cannot eliminate the technology gap.

Once the capability threshold $\bar{C}$ is reached, productivity growth reflects both diffusion and domestic innovation. The parameters ϕ_N and β govern the strength of innovation forces in this regime. Higher values of these parameters increase the contribution of innovation to productivity growth and strengthen the responsiveness of innovation to further capability accumulation. Stronger innovation forces accelerate productivity growth after the transition to the innovation regime, allowing the economy to converge more rapidly toward the technological frontier. Economies with more effective innovation systems therefore experience larger long-run gains from successfully escaping the imitation regime. These comparative statics results guide the quantitative analysis that follows, which evaluates how differences in capability investment, diffusion capacity, and innovation strength shape development trajectories across economies.

5 Quantitative implementation and calibration

This section describes how the theoretical framework developed above is mapped to observable data and implemented quantitatively. The goal of the empirical implementation is not to estimate a fully structural model but to discipline the capability-driven mechanism using macroeconomic and innovation indicators.

The quantitative framework links four observable components of the data: relative income, relative productivity, capital intensity, and a proxy for the economy's capability stock. These variables allow the dynamic system governing capability accumulation and productivity diffusion to be simulated and compared with historical data.

The empirical implementation proceeds in five steps. First, we construct a proxy for the capability stock using indicators of human capital, research investment, and innovation activity. Second, we describe the data sources used to construct relative variables. Third, we present the baseline structural parameters governing the model. Fourth, we outline the calibration strategy linking model parameters to empirical moments. Finally, we describe the construction of relative variables used in the quantitative simulations.

5.1 Empirical implementation: Indonesia as a development laboratory

The theoretical framework developed above highlights capability accumulation as the central mechanism governing the transition from imitation-driven growth to innovation-driven development. To examine the empirical relevance of this mechanism, the quantitative analysis focuses on a specific country case.

Rather than estimating the model in a cross-country panel, the empirical implementation treats a single economy as a *development laboratory* in which the dynamics of capability accumulation, productivity growth, and policy effort can be studied in a concrete institutional context. This approach allows the model's mechanisms to be mapped directly to observable policy choices and structural conditions while preserving the theoretical structure developed above.

Indonesia provides a particularly informative setting for examining the capability-driven development mechanism. As one of the largest emerging economies in the world, Indonesia has achieved sustained growth through capital accumulation, structural transformation, and technology adoption. However, the country remains substantially below the global technological frontier in terms of productivity and innovation capacity.

Indicators of research intensity, patenting activity, and advanced human capital remain significantly lower than those observed in frontier innovation economies. Indonesia therefore represents a typical middle-income economy operating within the imitation regime, where productivity growth depends primarily on technology diffusion rather than domestic innovation.

At the same time, Indonesia has articulated an explicit long-run development objective through the national strategy *Golden Indonesia 2045*. This roadmap aims to transform the country into a high-income economy by the centenary of its independence in 2045. Achieving this objective requires a substantial acceleration of productivity growth and a structural transition toward innovation-driven development. Policy priorities within the roadmap include expanding tertiary education, strengthening research institutions, increasing research and development expenditure, and fostering domestic innovation ecosystems (Bappenas, 2019; World Bank, 2020).

These policy priorities correspond closely to the capability-building mechanisms emphasized in the theoretical model. Indonesia therefore provides a natural empirical setting for evaluating whether sustained capability accumulation can generate a transition from imitation-driven development to innovation-based growth.

Indonesia therefore offers a useful empirical setting for evaluating the model's predictions. The economy is large enough to exhibit meaningful innovation potential, yet its current development stage remains consistent with the imitation regime described in the model. This combination makes Indonesia a particularly informative case for examining the conditions under which economies accumulate sufficient capability to transition toward innovation-driven growth.

5.2 Measuring capability

The capability stock C_t represents the institutional, organizational, and knowledge-producing capacity of an economy. Because this concept is not directly observable, it must be proxied using measurable indicators that capture the ability of an economy to absorb and generate technological knowledge.

Following the literature on national innovative capacity (Nelson and Phelps, 1966; Furman, Porter, and Stern, 2002; Benhabib and Spiegel, 2005), capability is constructed as a composite index combining three observable components:

1. advanced human capital,
2. research and development intensity, and
3. innovation output.

Specifically, the capability index is defined as

$$C_{it} = 0.2\, HC_{it} + 0.4\, RD_{it} + 0.4\, PAT_{it},$$

where HC denotes the share of tertiary-educated workers in the labor force, RD represents research and development expenditure as a share of GDP, and PAT measures patent stock per million population. Each component is normalized relative to the United States, which serves as the global technological frontier in the empirical implementation. The resulting index therefore measures each country's capability relative to the frontier innovation system.

The weighting scheme reflects the distinct roles played by human capital, research investment, and innovation output in the development process. Tertiary education provides the foundational supply of advanced human capital required for technology adoption and scientific training. However, tertiary education systems are largely domestically oriented and often exhibit substantial cross-country variation in quality and research intensity. For this reason, human capital is assigned a smaller weight in the index.

In contrast, research and development activity and patenting outcomes are more directly associated with the operation of innovation systems and are more closely linked to globally comparable measures of knowledge creation. R&D expenditure represents the primary input into scientific discovery and technological development, while patenting activity captures observable innovation output. Together these indicators reflect both the scale of research investment and the ability of an economy to generate new technological knowledge. Assigning greater weight to these components therefore emphasizes the role of organized research activity and innovation performance in driving the transition from imitation to innovation.

This construction is consistent with empirical research on national innovative capacity, which highlights the central importance of research investment, scientific institutions, and knowledge production in determining long-run technological leadership (Furman, Porter, and Stern, 2002; Aghion and Howitt, 2009).

5.3 Data sources

The theoretical variables in the model are mapped to observable economic indicators using macroeconomic and innovation data for the follower economy and the global technological frontier. Output and income are measured using real GDP per capita from the Penn World Table, with the United States serving as the frontier benchmark. Relative income is therefore defined as the ratio of domestic GDP per capita to that of the United States.

Capital stocks are obtained from the Penn World Table capital series, allowing relative capital intensity to be constructed as the ratio of capital per worker in the follower economy to that of the frontier. Total factor productivity is also taken from the Penn World Table, so relative productivity is measured as $a_t = A_t/A_t^*$.

The capability stock is not directly observable and must therefore be proxied using indicators capturing the economy's innovation capacity. Following the innovation and growth literature, capability is constructed as a composite index combining measures of tertiary education, research intensity, and patenting activity. These indicators capture the key dimensions of the capability concept emphasized in the model: advanced human capital, organized research systems, and the ability to generate and absorb technological knowledge.

Macroeconomic variables are obtained from the Penn World Table version 10.0 (Feenstra, Inklaar, and Timmer, 2015). Real GDP per capita, capital stock, and total factor productivity are used to construct the relative variables required by the model.

The frontier economy is defined as the United States, consistent with the standard practice in the growth and development accounting literature. Relative income is therefore measured as the ratio of country-level GDP per capita to U.S. GDP per capita.

Capital stocks are taken from the Penn World Table capital series and converted to per-worker terms. Relative capital intensity is then constructed as the ratio of domestic capital per worker to that of the frontier economy.

Indicators used to construct the capability index are obtained from multiple sources. Tertiary education attainment is taken from the World Bank's World Development Indicators. Research and development expenditure data are obtained from UNESCO and OECD innovation statistics. Patent counts are drawn from the World Intellectual Property Organization (WIPO) patent database.

Combining these sources yields a balanced dataset covering the period 2000–2020 for the countries analyzed in the quantitative exercises.

Relative variables used in the quantitative simulations follow directly from the definitions introduced in the model section. Relative productivity is measured as $a_t = A_t/A_t^*$, where A_t denotes domestic total factor productivity and A_t^* represents frontier productivity in the United States. Relative capital intensity is constructed as $k_t^r = K_t/K_t^*$ using capital stock data from the Penn World Table. Relative income is measured as the ratio of real GDP per capita to the frontier level, $y_t^r = Y_t/Y_t^*$. These variables provide empirical counterparts to the model's state variables governing productivity convergence and capability accumulation.

5.4 Baseline parameter values

Several parameters governing standard production and accumulation mechanisms are fixed using widely accepted values from the macroeconomic and development literature.

The capital share in production is set to $\alpha = 0.33$, consistent with development accounting estimates of factor income shares (Gollin, 2002; Caselli, 2005). The depreciation rate of physical capital is set to $\delta_K = 0.06$ per year, a value widely used in quantitative macroeconomic models (King and Rebelo, 1993).

Frontier productivity growth is assumed to follow an exogenous process with growth rate $g^* = 0.02$, corresponding to the long-run average growth rate of total factor productivity in the United States.

The frontier saving rate is set to $s^* = 0.17$, consistent with the average investment share observed in advanced economies in the Penn World Table data.

Parameters governing capability dynamics are chosen to reflect empirical regularities in human capital and institutional accumulation. The curvature parameter governing diminishing returns in capability formation is set to $\nu = 0.75$, while the depreciation rate of the capability stock is set to $\delta_C = 0.10$. These values are broadly consistent with empirical evidence on the persistence and depreciation of human capital and institutional capacity (Benhabib and Spiegel, 1994; Acemoglu, Johnson, and Robinson, 2005).

The capability threshold separating imitation and innovation regimes is identified from the data as the 33^{th} percentile of the capability index among OECD innovation economies. This procedure yields a threshold value of

$$\bar{C} = 0.68.$$

Parameters governing diffusion and innovation dynamics are discussed in Appendix A.

The quantitative implementation separates parameters that are fixed externally from those disciplined by empirical moments. Standard macroeconomic parameters governing production and capital accumulation (α, δ_K, g^*, and s^*) are taken directly from the growth and development literature. The capability threshold $\bar{C}$ and the implementation elasticity η are calibrated using observed capability distributions and empirical evidence on productivity wedges.

Implementation efficiency is modeled as a capability-dependent wedge that limits the effectiveness with which capital and technology are translated into output. The idea is that economies with weak institutional and technological capabilities may be able to access advanced technologies but may not be able to implement them efficiently in production. As specified in equation (2), efficiency increases with capability below the innovation threshold and reaches its maximum once the threshold is crossed.

The elasticity parameter η determines how strongly implementation efficiency responds to capability accumulation below the threshold. In the baseline calibration we set $\eta = 0.30$. This value implies diminishing marginal improvements in implementation efficiency as capability increases, consistent with empirical evidence on management practices and resource misallocation (Hsieh and Klenow, 2009; Bloom et al., 2013). Because implementation efficiency enters both the production function and the feedback from income into capability formation, η directly influences the strength of development traps in the quantitative model.

Capability evolves according to the accumulation equation introduced in the model section (equation (8)). This law of motion reflects two forces: depreciation of existing capability and new capability formation generated by effective investment effort. Existing capabilities gradually erode due to institutional decay, skill obsolescence, and technological change, while new capability is accumulated through investments in education, research systems, and innovation infrastructure. The term $\tau_t y_t^r$ captures the idea that capability formation requires real resources, so the effectiveness of policy effort depends on the economy's income level.

The curvature parameter $\nu \in (0, 1)$ governs diminishing returns in the conversion of effective effort into capability increments, while δ_C captures the depreciation or obsolescence of the capability stock. In the baseline specification we set $\nu = 0.75$ and $\delta_C = 0.10$. These values are consistent with empirical evidence on the accumulation of human capital and institutional capacity, which typically exhibit strong diminishing returns and gradual depreciation over time (Benhabib and Spiegel, 1994; Acemoglu, Johnson, and Robinson, 2005).

The remaining parameters govern the central mechanisms of the model: capability accumulation, technology diffusion, and innovation dynamics. The capability formation parameter κ is calibrated separately for each country to match the observed evolution of the capability index over the sample period. The diffusion parameter ϕ_I is identified using observations in the imitation regime where capability remains below the innovation threshold. Finally, the innovation parameter ϕ_N governs the additional contribution of domestic innovation to productivity growth once the capability threshold is crossed.

This structure ensures that the quantitative dynamics of the model are disciplined primarily by observed capability accumulation and productivity convergence rather than by extensive parameter tuning.

5.5 Calibration strategy

The quantitative implementation combines externally fixed parameters with a small number of calibrated parameters governing capability formation, technology diffusion, and innovation dynamics. The objective of the calibration strategy is to discipline the model using empirical moments implied by the structure of the capability accumulation and productivity equations.

Standard macroeconomic parameters are fixed using widely accepted values from the literature. These parameters include the capital share α, the depreciation rate of physical capital δ_K, the frontier productivity growth rate g^*, and the frontier saving rate s^*. Fixing these parameters ensures that the production and capital accumulation blocks of the model remain consistent with empirical benchmarks widely used in growth accounting and quantitative macroeconomic studies.

The remaining parameters govern the key mechanisms emphasized in the model: capability accumulation, technology diffusion, and innovation dynamics. These parameters are disciplined using empirical information on productivity convergence and the observed evolution of capability indicators.

Three parameters play a central role in the quantitative dynamics of the model:

1. the capability formation parameter κ,
2. the diffusion parameter ϕ_I, and
3. the innovation parameter ϕ_N.

The parameter κ determines the efficiency with which effective effort $(\tau_t y_t^r)^\nu$ is transformed into capability accumulation. Because institutional environments differ across countries, κ is calibrated separately for each country using the observed trajectory of the capability index over the sample period.

The diffusion parameter ϕ_I governs the speed at which follower economies close the productivity gap with the frontier through technology adoption. Identification uses observations in which the capability stock remains below the innovation threshold, corresponding to the imitation regime of the model.

Finally, the innovation parameter ϕ_N captures the contribution of domestic innovation to productivity growth once the capability threshold is exceeded and the economy enters the innovation regime.

Detailed calibration procedures for these parameters are provided in Appendix A.

The diffusion parameter ϕ_I measures the speed at which follower economies adopt frontier technologies. We identify ϕ_I using observations in the imitation regime where capability remains below the innovation threshold ($C_{i,t} < \bar{C}$).

Define

$$\mathrm{LHS}_{i,t} = (a_{i,t+1} - a_{i,t}) + g^* a_{i,t}, \qquad X_{i,t} = m(C_{i,t})(1 - a_{i,t}).$$

Aggregating across all imitation-regime observations yields the ratio-of-sums estimator

$$\widehat{\phi}_I = \frac{\sum_{(i,t):\, C_{i,t}<\bar{C}} \mathrm{LHS}_{i,t}}{\sum_{(i,t):\, C_{i,t}<\bar{C}} X_{i,t}}. \tag{18}$$

This estimator matches average adjusted productivity growth to average effective diffusion exposure and avoids the instability associated with year-by-year inversion of the diffusion equation.

Applying this estimator to the data yields

$$\phi_I = 0.10,$$

which implies that approximately ten percent of the productivity gap with the frontier is closed annually through diffusion, conditional on absorptive capacity. This magnitude is consistent with empirical estimates of international technology diffusion (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005; Comin and Hobijn, 2010).

The innovation parameter ϕ_N captures the additional contribution of domestic innovation to productivity growth in economies with sufficiently high capability levels. In the baseline calibration we set

$$\phi_N = 0.03.$$

This value implies that innovation strengthens productivity growth beyond the diffusion mechanism while remaining smaller in magnitude than the diffusion parameter ϕ_I. Empirically, even frontier innovation economies continue to rely heavily on global knowledge diffusion alongside domestic innovation. Setting $\phi_N < \phi_I$ therefore reflects the empirical observation that innovation complements rather than replaces international technology diffusion (Aghion and Howitt, 2009; Bloom et al., 2020).

5.6 Baseline structural parameters

Table 1 summarizes the structural parameters governing the core mechanisms of the model. Standard macroeconomic parameters such as the capital share, capital depreciation rate, frontier growth rate, and frontier saving rate are taken directly from the literature and discussed earlier in the text. The table therefore reports only parameters that directly determine the dynamics of capability accumulation, technology diffusion, and innovation.

Table 1: **Baseline structural parameters**

Parameter	Value	Description
$\bar{C}$	0.68	Capability threshold separating imitation and innovation regimes.
η	0.30	Elasticity governing the implementation efficiency wedge below the capability threshold.
ν	0.75	Curvature parameter governing diminishing returns in capability accumulation.
δ_C	0.10	Annual depreciation (obsolescence) rate of the capability stock.
μ	1.00	Elasticity mapping capability into absorptive capacity in technology diffusion.
β	1.00	Elasticity of innovation intensity with respect to capability above the threshold.
ϕ_I	0.10	Diffusion parameter determining the speed of technology adoption in the imitation regime.
ϕ_N	0.03	Innovation parameter governing the additional contribution of domestic innovation to productivity growth above the capability threshold.

The parameters governing the key dynamic mechanisms of the model are disciplined using empirical moments implied by the model structure. The capability formation parameter κ is identified using the observed evolution of the capability index between 2000 and 2020 through the endpoint-matching estimator described in Appendix A.1. The diffusion parameter ϕ_I is identified from productivity dynamics observed in the imitation regime where capability remains below the innovation threshold, as described in Appendix A.2. Finally, the innovation parameter ϕ_N governs the contribution of domestic innovation to productivity growth once capability exceeds the threshold; its calibration is discussed in Appendix A.3.

6 Quantitative analysis

This section evaluates the quantitative implications of the model for capability accumulation, productivity convergence, and the possibility of escaping the middle-income trap. Using the calibrated framework described in the previous section, the analysis examines how sustained capability investment and institutional effectiveness jointly shape long-run development trajectories.

The quantitative exercises proceed in three steps.

First, the model is validated using historical data for Indonesia over the period 2000–2020. This exercise evaluates whether the capability accumulation mechanism embedded in the model can reproduce the observed medium-run evolution of capabilities, productivity, and relative income.

Second, the model is used to generate baseline projections under continuation of recent policy conditions. These projections illustrate the long-run implications of Indonesia's current capability accumulation path and quantify the risk that the economy remains trapped in the imitation regime.

Third, the framework is used to conduct policy experiments that evaluate the scale and timing of capability investment required for Indonesia to cross the innovation threshold within a policy-relevant horizon. These experiments provide quantitative benchmarks for the capability investment needed to transition from imitation-driven growth to innovation-driven development.

Taken together, these exercises provide a quantitative assessment of the central mechanism emphasized in the paper: whether sustained capability accumulation can generate a self-reinforcing transition toward innovation-led growth, or whether the economy remains confined to partial convergence below the technological frontier. In this sense, the quantitative analysis provides a structural interpretation of the middle-income trap as a failure of capability accumulation rather than a failure of capital accumulation alone.

6.1 Model validation: capability dynamics in Indonesia

We begin by evaluating whether the calibrated model can reproduce the medium-run dynamics of capability accumulation and productivity convergence observed in Indonesia over the period 2000–2020. This exercise provides an empirical validation of the model's central mechanism linking capability investment, productivity diffusion, and relative income dynamics.

The simulation is initialized using observed values of capabilities, productivity, and relative income in 2000. The model is then simulated forward at annual frequency using the observed path of policy effort $\{\tau_t\}$ and relative capital intensity k_t^r during the validation period.

Relative income is constructed using the model identity

$$y_t^r = E(C_t)\, a_t\, (k_t^r)^{\alpha}, \tag{19}$$

where $E(C_t)$ denotes the implementation-efficiency mapping, a_t is relative productivity, and k_t^r is relative capital per worker. For the validation exercise k_t^r is taken directly from the data rather than generated from a closed capital accumulation block. This choice isolates the capability and diffusion mechanisms from measurement issues in international capital series such as PPP adjustments and capital stock construction.

The parameter κ governs the efficiency with which effective effort $(\tau_t y_t^r)^{\nu}$ translates into capability accumulation. For the validation exercise we estimate a trajectory-fit parameter κ_{IDN}^{val} that minimizes the distance between the model and the observed capability path over 2000–2020 using centered five-year moving averages (MA(5)). The resulting estimate is

$$\kappa_{IDN}^{val} = 2.001.$$

The estimation procedure is described in detail in Appendix A.1. Economically, this parameter summarizes the institutional effectiveness with which investments in education, research, and technological upgrading translate into durable capabilities.

Validation focuses on medium-run dynamics rather than annual fluctuations. Specifically, we compare the average level and the linear time trend of the centered five-year moving average (MA(5)) series over the period 2000–2020. The reported trend corresponds to the OLS slope obtained from regressing the smoothed series on a linear time index.

Table 2: **Indonesia validation (2000–2020): mean and trend (MA(5)).**

	Mean (MA(5))		Trend (MA(5))	
Variable	Data	Model	Data	Model
Capability C_t	0.0718	0.0742	0.0021	0.0015
Relative TFP a_t	0.4277	0.3999	0.0029	-0.0016
Relative income y_t^r	0.1437	0.1322	0.0065	0.0014

The validation yields three main insights.

First, the model performs well on the variable that is quantitatively most important for regime dynamics: the level and medium-run trend of capabilities C_t. Because capabilities determine both implementation efficiency $E(C_t)$ and absorptive capacity $m(C_t)$, accurately reproducing their evolution directly disciplines the regime-transition mechanism.

Second, conditional on the fitted capability path, the model under-predicts the level and trend of relative productivity a_t during 2000–2020. While the data show modest productivity convergence, the baseline diffusion specification produces a slightly flatter trajectory. This discrepancy indicates that the productivity block is the primary margin for improving medium-run fit.

Third, relative income y_t^r reflects the interaction between implementation efficiency, productivity, and capital intensity. Because validation conditions on the observed path of relative capital k_t^r, the model's under-prediction of productivity mechanically translates into a flatter income trajectory.

Figure 2 compares the model simulations with the smoothed data for capabilities, relative productivity, and relative income. The model closely reproduces the medium-run trajectory of capabilities, the key state variable governing regime transition.

This result is non-trivial because the capability accumulation equation embeds a feedback mechanism: when capabilities are low, the implementation wedge $E(C_t)$ depresses income levels, which in turn limits effective capability investment $(\tau_t y_t^r)^\nu$. The model's ability to replicate the observed capability path therefore provides empirical support for the mechanism linking policy effort, income, and capability accumulation.

Because capabilities remain well below the innovation threshold throughout the sample period, the implementation wedge remains binding. As a result, improvements in relative productivity translate only partially into income convergence relative to the global technological frontier.

The validation results support the use of the model for medium- and long-run projections.

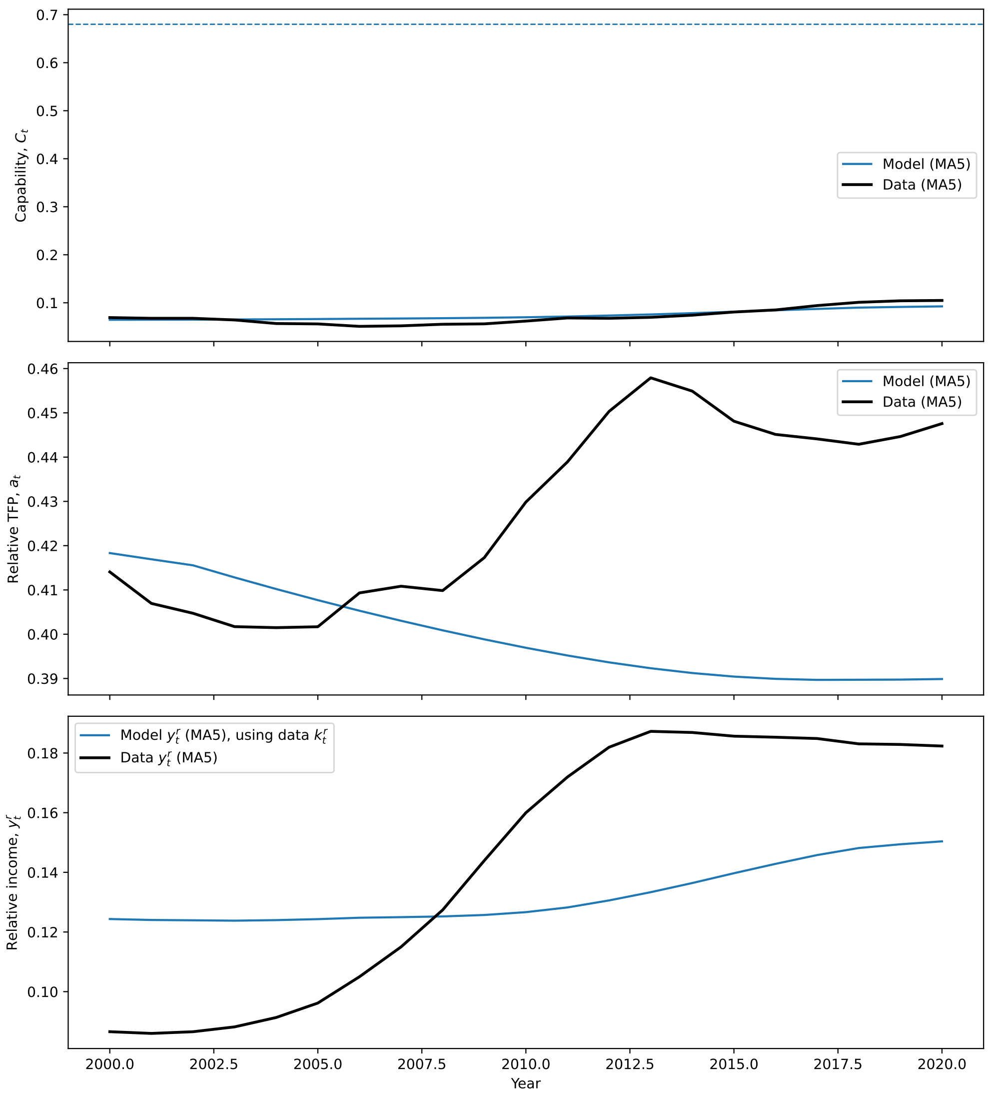

Figure 2: **Indonesia: baseline validation (2000–2020).**

Because the model accurately captures the evolution of capabilities—the central slow-moving state variable—it provides a credible basis for evaluating future regime dynamics.

A central question in the projections is whether the capability stock C_t eventually crosses the innovation threshold $\bar{C}$ under baseline policy conditions. If the baseline path does not generate threshold crossing within 25–50 years, the counterfactual policy experiments examine the policy adjustments required to achieve $C_t \geq \bar{C}$ within specified horizons.

Finally, it is useful to distinguish between the model-implied income ratio and empirical income measures. In the validation exercise we report a model-consistent accounting measure constructed using observed relative capital. In projection and counterfactual exercises we instead report the internally consistent model variable generated jointly with endogenous capital accumulation.

6.2 Baseline projections: long-run capability dynamics

We next examine the long-run implications of Indonesia's current capability accumulation trajectory. Using the validated model structure, the system is simulated forward beginning from the observed 2020 state under continuation of recent policy conditions. Specifically, policy effort and capital intensity are held constant at their late-sample values so that $\tau_t = \tau_{2020}$ and $k_t^r = k_{2020}^r$ for $t > 2020$. This assumption isolates the intrinsic dynamics of the capability accumulation mechanism without imposing additional policy changes.

The projections begin from the observed state of the economy in 2020, including the empirically measured levels of capability, relative productivity, and relative capital. To ensure consistency with the historical capability trajectory, we use the endpoint-anchored capability formation parameter κ^{proj} described in Section **??**, which guarantees that the simulated economy starts from the observed capability level C_{2020}.

The baseline projection assumes that policy effort devoted to capability formation remains constant at its 2020 level, $\tau_t = \tau_{2020}$ for all $t \geq 2021$. To keep the projections interpretable as regime dynamics driven by capabilities and productivity diffusion, relative capital k_t^r is held fixed at its 2020 level when constructing relative income using equation (5). This isolates the mechanism of interest—capability accumulation and productivity diffusion—while avoiding additional uncertainty associated with long-horizon capital accumulation forecasts.

The continuation assumption reflects the relatively stable trajectory of Indonesia's capability investment over the past two decades. Despite sustained economic growth, investment in research and development and advanced human capital has remained modest by international standards. Indonesia's R&D expenditure has consistently remained below one percent of GDP—indeed closer to 0.3 percent—far below the levels observed in innovation-driven economies where R&D spending typically exceeds two percent of GDP.

A large body of empirical research documents the structural constraints underlying this pattern. Indonesia's innovation system remains characterized by limited research intensity, fragmented institutional coordination, and weak linkages between universities and industry (World Bank, 2020; Asian Development Bank, 2019). Studies of technological upgrading similarly emphasize the relatively slow expansion of advanced human capital and research capacity as important barriers to productivity growth (Kim, Lee, and Park, 2012; Hill and Negara, 2019).

International comparisons highlight the magnitude of this gap. China has increased R&D spending to more than two percent of GDP, while Korea invests over four percent of GDP in research and development. These differences reflect the substantially stronger innovation systems observed in economies that have successfully transitioned toward innovation-driven growth.

In this context, the continuation scenario provides an informative benchmark. It evaluates whether Indonesia could achieve its development ambitions under the current trajectory of capability investment without assuming policy changes that have not yet materialized.

To evaluate Indonesia's long-run development prospects, we generate projections over two horizons: a 25-year horizon (2021–2045) and a 50-year horizon (2021–2070). The shorter horizon coincides with Indonesia's national development objective of achieving high-income status by 2045 under the government's "Golden Indonesia 2045" vision. The longer horizon extends the analysis beyond this policy target to examine whether the economy eventually crosses the innovation threshold even if the transition is delayed. Together, these horizons allow the model to assess both the feasibility of Indonesia's stated development goals and the long-run consequences of maintaining current policy conditions.

Figure **??** reports the resulting projections for capabilities, relative productivity, and relative income over the next century. The most striking result concerns the evolution of the capability stock C_t. Despite continued capability investment, the projected capability trajectory increases only gradually and remains well below the innovation threshold $\bar{C}$ throughout the simulation horizon.

Even after one hundred years, the capability stock does not reach the threshold required for the activation of the innovation regime.[2] In this scenario Indonesia remains permanently in the imitation regime, where productivity growth depends primarily on the diffusion of existing technologies rather than on domestic innovation.

This outcome reflects the interaction of three structural forces embedded in the model. First, the effective scale of capability investment $(\tau_t y_t^r)^\nu$ remains limited because relative income levels are still modest compared with the technological frontier. Second, capability accumulation is gradual due to the concave formation process governed by the parameter ν together with the depreciation rate δ_C. Third, because capabilities remain below the threshold, the implementation wedge $E(C_t)$ continues to depress income levels, which further limits effective capability investment.

The projections indicate that capabilities continue to increase gradually over time but remain below the innovation threshold throughout the 25-year horizon ending in 2045. As a consequence, Indonesia remains in the imitation regime during the period corresponding to the government's high-income development target. Extending the projection to the 50-year horizon yields a similar conclusion. Although the capability stock continues to grow, diminishing returns in capability accumulation and the income feedback embedded in the accumulation equation slow the pace of convergence. As a result, the trajectory of C_t approaches the innovation threshold only gradually and does not reach $\bar{C}$ within the projection window. This dynamic produces a development pattern consistent with the middle-income trap mechanism analyzed in the theoretical section. The economy continues to grow and

[2] Extending the simulation horizon to 250 years yields the same qualitative result: the capability stock remains below the innovation threshold.

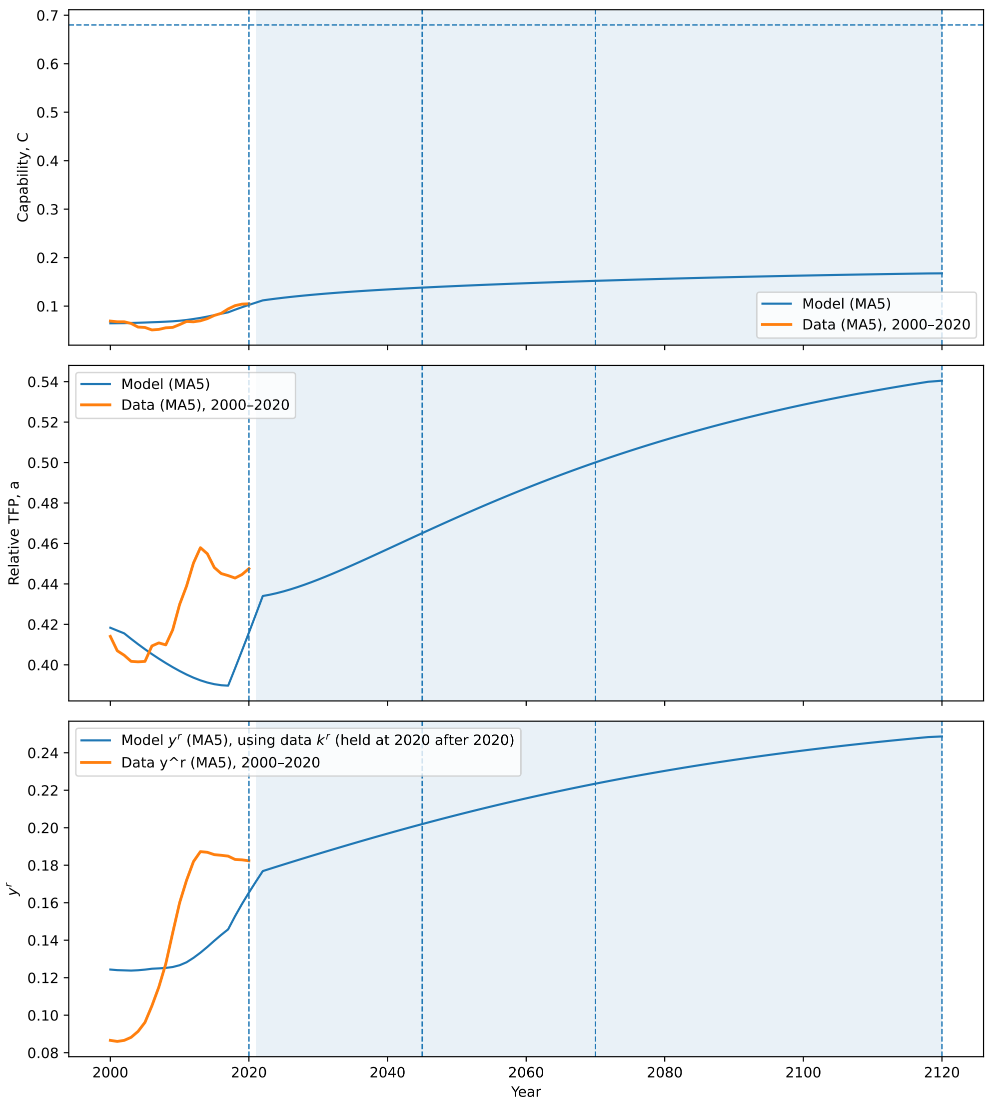

Figure 3: **Indonesia baseline: MA(5) history fit (2000–2020) and projection (2021–2120).**

accumulate capabilities, but the pace of capability formation remains insufficient to trigger the transition to innovation-driven growth. Under the continuation scenario, Indonesia's development trajectory therefore falls short of the capability transformation required for sustained convergence toward the technological frontier.

Taken together, these mechanisms generate a slow-moving capability trajectory that fails to activate the self-reinforcing amplification mechanism linking capability accumulation, productivity diffusion, and income growth. In the framework of this paper, this outcome corresponds directly to a *middle-income trap*. The economy continues to accumulate capital and gradually improves productivity through technology diffusion, but the capability stock never reaches the level required to sustain innovation-driven productivity growth. As a result, income converges only partially toward the global technological frontier.

This baseline scenario provides a useful benchmark for evaluating the policy experiments conducted in the following subsection. If escaping the imitation regime requires crossing the capability threshold within a policy-relevant horizon, the key policy question becomes how much additional capability investment is required to accelerate the transition toward the innovation regime.

6.3 Policy experiments: pathways to crossing the capability threshold

The baseline projections indicate that under continuation of current policy effort Indonesia remains below the capability threshold $\bar{C}$ and therefore continues to operate in the imitation regime. This raises a central policy question: what magnitude and timing of capability investment would allow the economy to transition into the innovation regime within a relevant development horizon?

This question is particularly important in the Indonesian context. National development strategy emphasizes the objective of reaching high-income status by 2045, the centennial of Indonesia's independence. Achieving this objective requires sustained productivity growth and structural upgrading beyond the gradual convergence implied by the baseline projection.

To evaluate the scale of policy effort required to accelerate the transition toward the innovation regime, we conduct counterfactual policy experiments that examine alternative paths of capability investment τ_t. The objective is to determine the minimal policy magnitudes required for the economy to reach the capability threshold within finite horizons that are economically meaningful. We consider two horizons: a 25-year horizon corresponding approximately to the 2045 development target, and a longer 50-year horizon capturing a slower structural transition.

Crossing the innovation threshold requires that the capability stock reaches $\bar{C}$ within the policy horizon. Because capabilities accumulate as a stock and depreciate gradually over time, the future capability level depends on the cumulative contribution of past investments after accounting for depreciation. Earlier investments therefore receive greater weight in determining the speed of transition.

The analytical condition linking the required capability investment to the initial capability gap and the transition horizon is derived in Appendix B. This condition provides a benchmark for evaluating the magnitude of policy effort required to close the capability gap within a given time horizon.

While the analytical benchmark identifies the total capability investment required to reach the threshold, different temporal profiles of investment may generate different transition dynamics. To evaluate these possibilities, we consider three policy classes.

i. Constant-Commitment Policy (CCP). Capability investment increases permanently beginning in 2021,

$$\tau_t = \begin{cases} \tau_t^{data}, & t \leq 2020, \\ \tau^{\uparrow}(H), & t \geq 2021. \end{cases}$$

The parameter $\tau^{\uparrow}(H)$ represents the constant level of capability investment required to ensure that the capability stock reaches the threshold within the horizon H.

ii. Gradual-Scaling Policy (GSP). Capability investment increases gradually over time,

$$\tau_t = \min\{\tau_{\max}, \tau_{2020} + \Delta_\tau(H)(t - 2020)\}.$$

This specification captures a realistic policy environment in which capability investment expands progressively as fiscal capacity and institutional capabilities improve.

iii. Front-Loading Policy (FLP). This policy allocates a larger share of capability investment to the early years of the transition. Because capability accumulation generates persistent gains in productivity and implementation efficiency, early investment can accelerate the transition toward the innovation regime.

For each policy class we compute the minimal policy parameter that satisfies the threshold-crossing condition

$$C_{2020+H} \geq \bar{C},$$

where $H \in \{25, 50\}$ denotes the policy horizon.

Across policy strategies, the quantitative simulations yield a clear benchmark for the magnitude of capability investment required to escape the imitation regime. For a 25-year transition horizon corresponding to Indonesia's 2045 development target, the model implies that capability investment must rise from roughly 0.5 percent of GDP at present to approximately 2–3 percent of GDP per year in order to reach the innovation threshold. Extending the transition horizon to fifty years reduces the required annual effort to roughly 1.5–2 percent of GDP. These magnitudes reflect the scale of sustained capability accumulation required to close the initial capability gap relative to the innovation threshold.

For each policy class we compute the minimal policy parameter required to satisfy the threshold-crossing condition and simulate the resulting transition dynamics of capability, relative productivity, and relative income. Table 3 reports the corresponding policy magnitudes required to reach the innovation threshold within 25- and 50-year horizons.

The table translates the model's capability threshold into concrete policy magnitudes. Three patterns emerge.

First, achieving innovation-driven growth within the 25-year horizon requires a substantial increase in capability investment. Under the constant-commitment benchmark,

Table 3: **Indonesia: minimal capability investment required to reach the innovation threshold.** Policy parameters are solved numerically as the smallest values that ensure $C_{2020+H} \geq \bar{C}$. All values are annual shares of GDP.

Policy design	Policy parameter	Early τ	Peak τ	Avg. $\bar{\tau}$
Panel A: 25-year horizon (crossing by 2045)				
Current policy (2020)	–	0.0055	0.0055	0.0055
Constant Commitment (CCP)	$\tau^{\uparrow} = 0.0262$	0.0262	0.0262	0.0262
Gradual Scaling (GSP)	$\Delta_\tau = 0.0014$	$\approx \tau_{2020}$	0.0414	0.0244
Front-Loading (FLP)	$(\tau^{high}, \tau^{low})$	0.0348	0.0348	0.0278
Panel B: 50-year horizon (crossing by 2070)				
Current policy (2020)	–	0.0055	0.0055	0.0055
Constant Commitment (CCP)	$\tau^{\uparrow} = 0.0185$	0.0185	0.0185	0.0185
Gradual Scaling (GSP)	$\Delta_\tau = 0.0004$	$\approx \tau_{2020}$	0.0252	0.0158
Front-Loading (FLP)	$(\tau^{high}, \tau^{low})$	0.0257	0.0257	0.0206

Notes. Current policy corresponds to Indonesia's observed capability investment share in 2020. CCP sets a constant policy effort $\tau_t = \tau^{\uparrow}(H)$ for $t \geq 2021$. GSP increases effort linearly with slope $\Delta_\tau(H)$. FLP allocates half of cumulative effort to the early transition window.

Indonesia would need to sustain capability investment of approximately 2.6 percent of GDP annually—nearly five times the current level of roughly 0.55 percent of GDP.

Second, gradual scaling postpones capability accumulation and therefore requires significantly higher effort toward the end of the transition horizon. In the cross-by-25 scenario the peak investment rate exceeds four percent of GDP, reflecting the economic logic of delayed investment in a stock accumulation problem.

Third, front-loaded investment accelerates capability accumulation early in the transition. Because capabilities affect both implementation efficiency $E(C_t)$ and absorptive capacity $m(C_t)$, earlier investment generates persistent productivity gains and strengthens the feedback between capabilities, diffusion, and income growth.

6.4 Transition dynamics under alternative policy paths

While Table 3 reports the required policy magnitudes, the simulated transition paths illustrate how different policy designs shape the trajectory of development. Figures 4 and 5 show the evolution of capability C_t, relative productivity a_t, and relative income y_t^r under the three policy strategies.

Although all three policies are calibrated to satisfy the same terminal condition $C_{2045} \geq \bar{C}$, they generate markedly different transition paths. Front-loaded investment produces the fastest early improvements in capabilities and productivity, while gradual scaling delays these gains and requires stronger late-horizon effort. Constant commitment generates a smoother transition path between these two extremes.

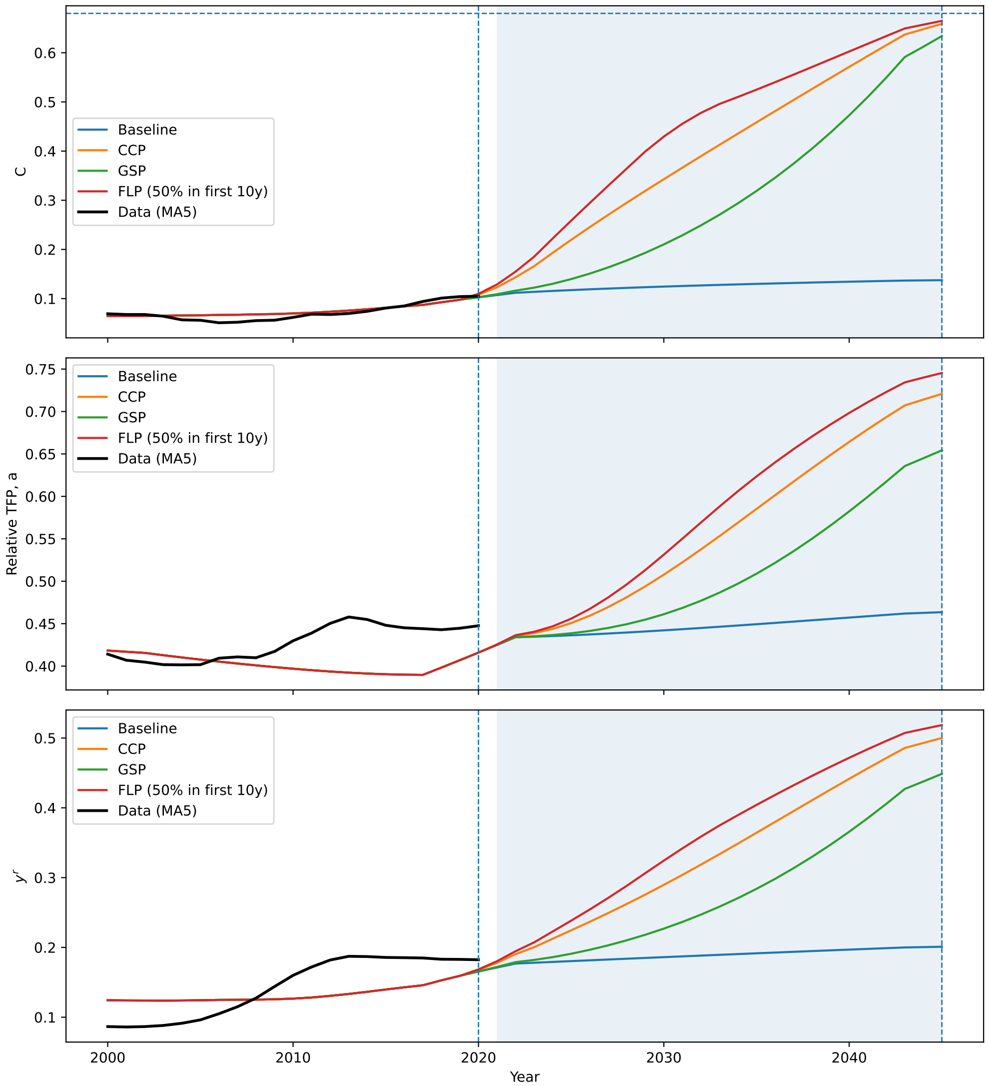

Figure 4: **Indonesia: minimal cross-by-25 policies (CCP, GSP, FLP).** MA(5) trajectories for capability C_t, relative productivity a_t, and relative income y_t^r. The shaded region denotes projections (2021–2045).

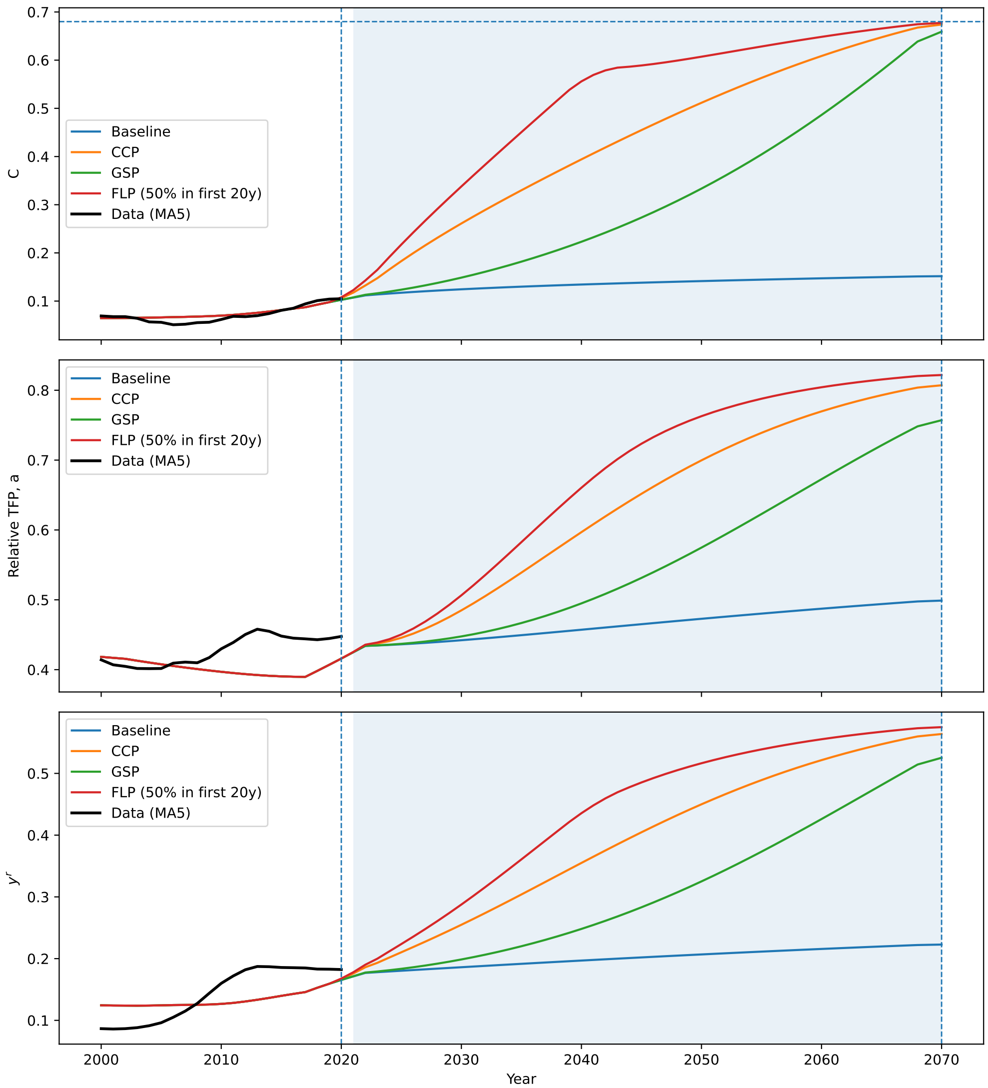

Figure 5: **Indonesia: minimal cross-by-50 policies (CCP, GSP, FLP).** MA(5) trajectories for capability C_t, relative productivity a_t, and relative income y_t^r. The shaded region denotes projections (2021–2070).

Extending the horizon to fifty years reduces the required policy effort but does not change the qualitative ranking across policies. Early investment continues to accelerate capability accumulation and productivity growth, while delayed investment shifts the adjustment burden toward later periods.

An important implication of the transition dynamics is that crossing the innovation threshold at the same date does not imply identical development outcomes. Because capability accumulation affects productivity and income throughout the transition period, policies that raise capabilities earlier generate higher productivity and income levels along the entire adjustment path.

This result highlights that the middle-income trap should be interpreted as a dynamic transition problem rather than a purely static threshold condition. The capability threshold defines the boundary between imitation- and innovation-driven growth regimes, but the path through which economies approach this boundary critically shapes development outcomes. Policies that accelerate capability accumulation earlier in the development process therefore generate stronger productivity growth and faster income convergence even when the innovation threshold is reached at the same horizon.

6.5 Sensitivity analysis: policy requirements under parameter uncertainty

The quantitative policy results depend on structural parameters governing capability accumulation, production efficiency, and technology diffusion. To assess the robustness of the policy conclusions, we recompute the *minimal policy effort* required to reach the capability threshold $\bar{C}$ under alternative parameter values.

Rather than evaluating arbitrary policy experiments, the exercise focuses directly on the policy-relevant object of the model: the capability investment required for regime transition. For each perturbation, holding all other parameters at their baseline values, we solve for the minimal policy effort satisfying $C_{2020+H} \geq \bar{C}$ under the three policy designs introduced earlier: constant commitment (CCP), gradual scaling (GSP), and front-loading (FLP).

Table 4 reports the resulting ranges of minimal policy parameters across the sensitivity grid. The parameters varied fall into three categories reflecting the core mechanisms of the model: (i) capability formation parameters (ν, δ_C), (ii) the elasticity of the implementation wedge (η), and (iii) diffusion parameters (ϕ_I, μ).

Two patterns emerge from the sensitivity analysis. First, the policy requirement is most sensitive to the parameters governing capability accumulation. Higher curvature in the capability formation function (ν) reduces the effort required to reach the threshold, while faster capability depreciation (δ_C) increases the policy burden by eroding previously accumulated capabilities.

Second, the implementation wedge and diffusion parameters influence policy requirements more indirectly. A stronger implementation wedge lowers income when capability is low, weakening the endogenous amplification mechanism embedded in $(\tau_t y_t^r)^\nu$. Slower technology diffusion similarly reduces the productivity gains associated with rising capabilities, thereby dampening income growth and effective capability investment.

Despite parameter uncertainty, the central policy implication remains stable. Across

Table 4: **Sensitivity of minimal policy requirements to structural parameters (Indonesia).** Each entry reports the range (min–max) of the minimal policy parameter required to achieve $C_{2020+H} \geq \bar{C}$ when varying parameters within the indicated category while holding others at baseline values.

Parameter category	CCP	GSP	FLP
Panel A: Cross-by-25 horizon (2045)			
Capability formation (ν, δ_C)	0.0198–0.0380	0.0010–0.0025	0.0208–0.0406
Implementation wedge (η)	0.0224–0.0308	0.0012–0.0017	0.0236–0.0329
Diffusion/TFP (ϕ_I, μ)	0.0254–0.0303	0.0014–0.0016	0.0264–0.0328
Panel B: Cross-by-50 horizon (2070)			
Capability formation (ν, δ_C)	0.0141–0.0264	0.0003–0.0006	0.0156–0.0297
Implementation wedge (η)	0.0155–0.0222	0.0003–0.0005	0.0171–0.0249
Diffusion/TFP (ϕ_I, μ)	0.0176–0.0224	0.0004–0.0005	0.0190–0.0256

Notes. Parameter ranges used in the sensitivity grid are: $\nu \in \{0.65, 0.75, 0.85\}$, $\delta_C \in \{0.06, 0.10, 0.14\}$, $\eta \in \{0.20, 0.30, 0.40\}$, $\phi_I \in \{0.07, 0.10, 0.13\}$, and $\mu \in \{0.5, 1.0, 1.5\}$. CCP reports the minimal constant effort $\tau^{\dagger}(H)$, GSP the minimal ramp slope $\Delta_\tau(H)$, and FLP the minimal horizon-average effort $\bar{\tau}(H)$ under the 50% early-mass allocation rule.

all sensitivity exercises, the capability investment required to reach the innovation regime remains on the order of two to four percent of GDP for a 25-year transition and roughly one to two percent for a 50-year horizon. Parameter variation therefore affects the precise magnitude of the policy requirement but does not alter the qualitative conclusion that escaping the imitation regime requires a substantial and sustained increase in capability investment relative to current levels.

7 Cross-country comparison: capability accumulation and development transitions

The Indonesia analysis highlights the central mechanism of the model: long-run development depends on whether capability accumulation is sufficient to move an economy across the innovation threshold $\bar{C}$. Under continuation of recent policy conditions, Indonesia's capability stock grows gradually but remains below the threshold, implying that productivity growth continues to rely primarily on technology diffusion rather than domestic innovation.

To better understand the forces governing this transition, this section extends the analysis to two additional economies that occupy different positions along the capability accumulation path. China provides an example of an economy that has experienced rapid capability expansion and is approaching the innovation threshold, while Korea represents an economy that has already crossed the threshold and operates within the innovation regime.

The purpose of this cross-country comparison is therefore not to use the model to classify economies into development regimes. Instead, the goal is to illustrate how sustained capability investment and the efficiency with which that investment is translated into productive capabilities jointly determine whether an economy is able to transition from imitation-driven growth to innovation-led development.

China provides a particularly informative case because its capability stock has expanded rapidly over the past two decades. This trajectory allows the model to illustrate the transition mechanism through which sustained capability accumulation can eventually push an economy across the innovation threshold. Korea, by contrast, provides a benchmark for the dynamics of an economy operating within the innovation regime, where productivity growth increasingly reflects frontier-directed innovation rather than technology diffusion alone.

Examining these economies under a common structural framework provides a useful test of the capability-driven mechanism developed in this paper. All structural parameters governing production, diffusion, and innovation are held fixed across countries. Cross-country differences in development trajectories therefore arise only from initial conditions, observed policy effort paths, and the institutional effectiveness with which capability investment is converted into durable technological and organizational capacity.

Taken together, Indonesia, China, and Korea illustrate three stages of capability-driven development: an economy that remains below the innovation threshold, an economy approaching the threshold through sustained capability accumulation, and an economy operating within the innovation regime. Studying these cases under a common framework helps clarify the mechanisms through which capability investment shapes long- run development trajectories.

7.1 Cross-country validation

Before examining the long-run projections, it is useful to evaluate whether the model can reproduce the medium-run evolution of capability accumulation, productivity convergence, and relative income across the three economies. Because the capability stock C_t is the central state variable governing regime dynamics in the model, validation focuses primarily on whether the model can match the observed evolution of capabilities during the period 2000–2020.

Table 5 compares the mean levels and linear trends of the smoothed MA(5) series for capability, relative productivity, and relative income over the validation period. The model is simulated using observed policy effort paths $\{\tau_t\}$ and relative capital levels k_t^r, while the capability formation parameter κ is calibrated using the procedure described in Section **??**.

Two observations emerge from the validation exercise. First, the model reproduces the medium-run trajectory of the capability stock remarkably well across all three economies. This result is particularly important because capabilities are the key state variable governing the regime transition mechanism. Since both implementation efficiency $E(C_t)$ and absorptive capacity $m(C_t)$ depend directly on the capability stock, matching the evolution of C_t ensures that the model captures the central mechanism through which capability accumulation influences productivity and income dynamics.

Second, conditional on the fitted capability trajectories, the model generates productivity and income dynamics broadly consistent with the data. Some discrepancies in productivity trends appear for individual countries, reflecting the parsimonious diffusion specification used in the model. These differences are not surprising because productivity growth in the data

Table 5: **Cross-country validation (2000–2020): mean and trend (MA(5)).**

Country	Variable	Data Mean	Model Mean	Trend (Data / Model)
Indonesia	C_t	0.0718	0.0742	0.0021 / 0.0015
	a_t	0.4277	0.3999	0.0029 / -0.0016
	y_t^r	0.1437	0.1322	0.0065 / 0.0014
China	C_t	0.4334	0.4292	0.0250 / 0.0254
	a_t	0.6145	0.5434	0.0030 / 0.0008
	y_t^r	0.1549	0.1440	0.0042 / 0.0034
Korea	C_t	0.8995	0.9137	0.0170 / 0.0133
	a_t	0.6794	0.7876	-0.0026 / 0.0064
	y_t^r	0.6398	0.7470	0.0042 / 0.0111

reflects a wide range of short-run disturbances, structural changes, and measurement issues that lie outside the scope of the model.

These discrepancies do not undermine the central capability-driven mechanism. The evolution of the capability stock is well captured across countries, and the model therefore provides a credible framework for examining how differences in capability accumulation translate into divergent long-run development trajectories. Hence, the validation exercise provides empirical discipline for the cross-country projections examined in the following sections. Because the model reproduces the medium-run evolution of capabilities, it can be used to analyze how continued capability investment may shape future transitions toward innovation-driven growth (in China's case) and toward frontier (in Korea's case).

7.2 China: capability-driven transition toward innovation

China provides a particularly informative case for understanding the mechanism emphasized in this paper. It represents an economy that has undergone rapid capability accumulation while remaining below the innovation threshold during most of the historical sample. The China exercise therefore illustrates how sustained capability investment, combined with effective institutional conversion of that investment into productive capabilities, can move an economy toward crossing the innovation threshold.

The model is applied to China using the same structural parameters governing production, diffusion, and innovation dynamics as in the Indonesia exercise. Cross-country differences therefore arise only from observed initial conditions, policy effort paths, and the efficiency with which capability investment translates into durable capability formation.

The calibrated capability formation parameter for China is

$$\kappa_{\mathrm{CHN}} \approx 3.33,$$

substantially higher than the corresponding value for Indonesia ($\kappa_{\mathrm{IDN}} \approx 2.0$). Economically, this parameter summarizes the institutional effectiveness of the national innovation system in converting investments in education, research, and industrial innovation into durable technological capabilities.

Figure 6 shows that China experienced rapid capability accumulation over the period 2000–2020. Although capability remains below the innovation threshold throughout most of the historical sample, the economy approaches the threshold rapidly. Under continuation of recent policy effort and saving behavior, the model predicts that China crosses the innovation threshold during the projection horizon.

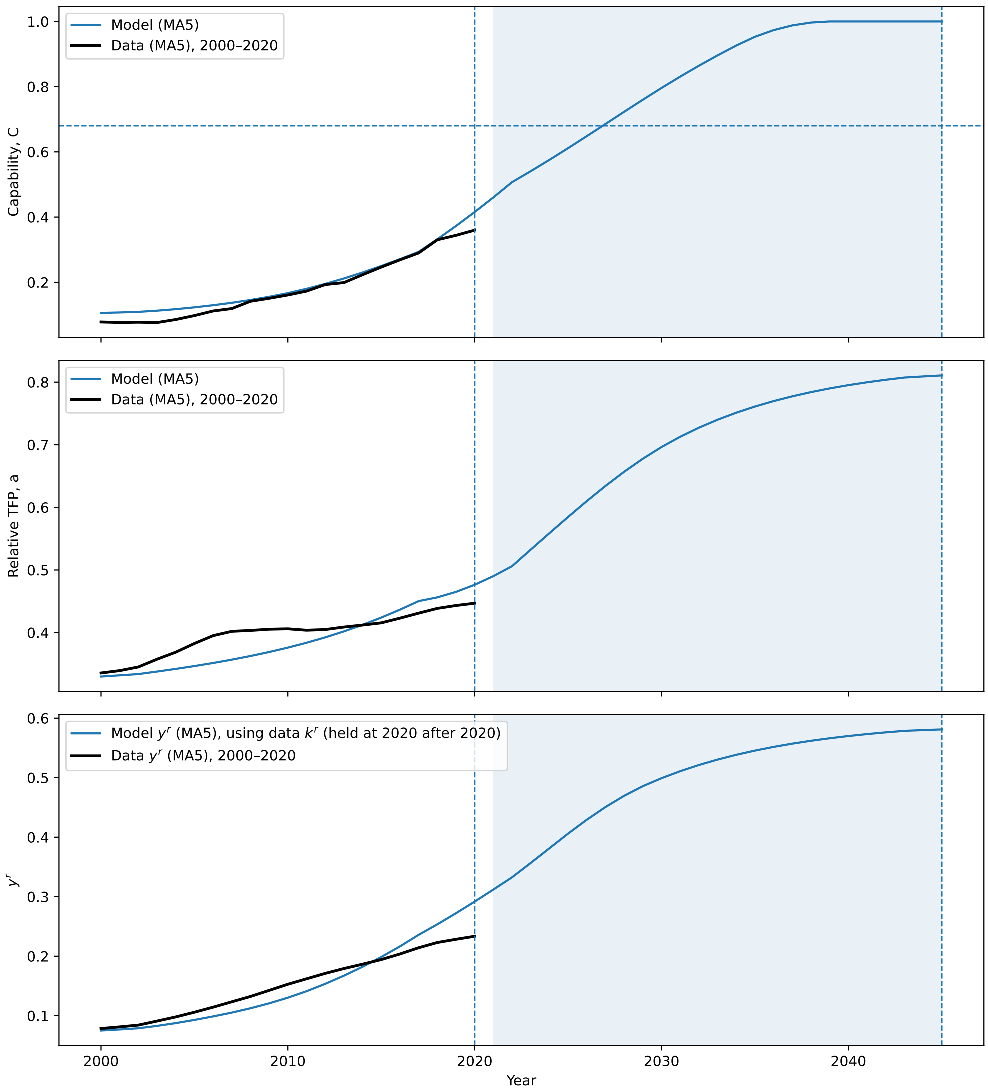

Figure 6: **China: validation (2000–2020) and 25-year projection (2021–2045) under standardized κ protocol.** Panels show MA(5) series for capabilities C_t (top), relative TFP a_t (middle), and relative income y_t^r (bottom). Black lines report data through 2020. Colored lines report the model using a trajectory-fit κ^{val} for 2000–2020 and an endpoint-anchored κ^{proj} for post-2020 projections. Shading denotes the projection period (2021 onward). Vertical dashed lines mark 2020 and 2045 (25 years after 2020). The horizontal dashed line marks the innovation threshold $\bar{C} = 0.68$. For projections, we hold $\tau_t = \tau_{2020}$ and $k_t^r = k_{2020}^r$ (for the construction of y_t^r). The model-implied threshold crossing year under continuation is **2027**.

Within the framework of the model, this transition reflects three reinforcing forces.

First, effective capability investment is large. Capability accumulation depends on the scaled effort term $(\tau_t y_t^r)^\nu$. Because China's relative income is substantially higher than that of most middle-income economies, a given policy effort share τ_t translates into a larger absolute resource base devoted to capability formation.

Second, capability investment is translated efficiently into durable capabilities. The higher calibrated value of κ_{CHN} implies that China's investments in education, research systems, and technological infrastructure generate stronger improvements in the capability stock. This parameter captures the effectiveness of China's national innovation system, including the rapid expansion of research universities, large public investments in R&D, and strong linkages between industrial policy and technological upgrading.

Third, rising capabilities activate the model's endogenous amplification mechanisms. As C_t increases, implementation efficiency improves through $E(C_t)$ and absorptive capacity strengthens through $m(C_t)$. These changes accelerate productivity convergence toward the frontier. Higher productivity raises relative income, which further increases the effective scale of capability investment through the term $(\tau_t y_t^r)^\nu$. The result is a self-reinforcing process in which capability accumulation and productivity growth reinforce one another.

A substantial empirical literature supports this interpretation of China's development trajectory. Early studies documented the rapid expansion of China's research system and its growing technological capacity (Hu and Jefferson, 2009; Fu, 2011). Subsequent work highlights the interaction between industrial policy, competition, and innovation in driving productivity growth (Aghion et al., 2015). More recent evidence links the expansion of patenting activity and R&D investment to firm-level productivity gains (Fang, He, and Li, 2020). International comparisons similarly show that China has become one of the world's largest investors in scientific research and technological development, with R&D expenditure exceeding two percent of GDP.

Taken together, these developments are consistent with the capability accumulation mechanism emphasized in this paper. Sustained investments in human capital, research infrastructure, and industrial upgrading have gradually expanded China's national innovation capacity, placing the economy on a trajectory toward crossing the innovation threshold.

China's experience provides an important benchmark for countries seeking to escape the imitation regime. The model suggests that the key determinant of transition is not simply the level of investment in capability formation, but the interaction between the scale of investment and the institutional effectiveness with which that investment is translated into durable capabilities.

For economies such as Indonesia, the challenge is therefore twofold. First, capability investment must reach a scale sufficient to expand the capability stock over time. Second, the institutional environment must allow these investments to translate effectively into technological and organizational capacity. When these conditions are satisfied, capability accumulation can gradually activate the endogenous amplification mechanisms embedded in the model, allowing the economy to approach and eventually cross the innovation threshold.

7.3 Korea: dynamics of the innovation regime

While the China exercise illustrates the dynamics of capability accumulation approaching the innovation threshold, the Korea case provides a benchmark for the post-threshold regime.

Korea is widely recognized as one of the world's leading innovation economies, characterized by sustained high levels of research investment, advanced technological specialization, and strong institutional support for innovation.

In the framework of the model, Korea represents an economy operating within the innovation regime, where capability levels exceed the threshold $\bar{C}$ and productivity dynamics increasingly reflect domestic innovation activity rather than technology diffusion alone. The purpose of the Korea exercise is therefore twofold. First, it evaluates whether the model remains quantitatively credible in an economy operating near the technological frontier. Second, it illustrates the structural advantages associated with operating above the capability threshold.

As in the previous exercises, the structural parameters governing production, diffusion, and capability accumulation are held fixed across countries. Differences arise only from country-specific initial conditions and the efficiency with which capability investment translates into durable capabilities. The calibrated capability formation parameter for Korea is

$$\kappa_{\mathrm{KOR}} \approx 3.6,$$

the highest among the three economies examined in this paper. This value reflects the high institutional effectiveness of Korea's innovation system in converting investments in education, research, and technological development into durable technological capabilities.

Because Korea operates above the innovation threshold for most of the sample period, productivity dynamics include the innovation component of the model governed by the parameters ϕ_N and χ. These parameters capture the contribution of domestic innovation activity to productivity growth once the economy operates within the innovation regime.

Korea provides a natural empirical benchmark for the innovation regime. Over the past several decades the country has developed one of the world's most intensive innovation systems, with gross domestic expenditure on research and development exceeding four percent of GDP and a strong concentration of industrial activity in technology- intensive sectors such as semiconductors, electronics, and advanced manufacturing. International assessments consistently classify Korea among the global innovation leaders. OECD innovation policy reviews emphasize Korea as one of the most R&D-intensive economies in the world and highlight the strength of its national innovation system (OECD, 2023). Similarly, the Global Innovation Index ranks Korea among the frontier group in terms of research capability, technological output, and knowledge diffusion (WIPO, 2023).

Figure 7 illustrates Korea's capability, productivity, and income dynamics over the period 2000–2020 together with the model's projections for the subsequent 25 years. Several patterns are immediately apparent.

First, Korea's capability stock remains well above the innovation threshold throughout the historical sample, confirming that the economy operates firmly within the innovation regime. The model closely reproduces the medium-run evolution of capabilities, indicating that the capability accumulation mechanism remains consistent even in a near-frontier economy.

Second, relative productivity remains close to the global frontier but does not exhibit sustained convergence beyond it. This pattern reflects the inherent difficulty of maintaining frontier proximity. In the model, this behavior arises from the frontier-maintenance headwind embedded in innovation-regime productivity dynamics, which captures the increasing

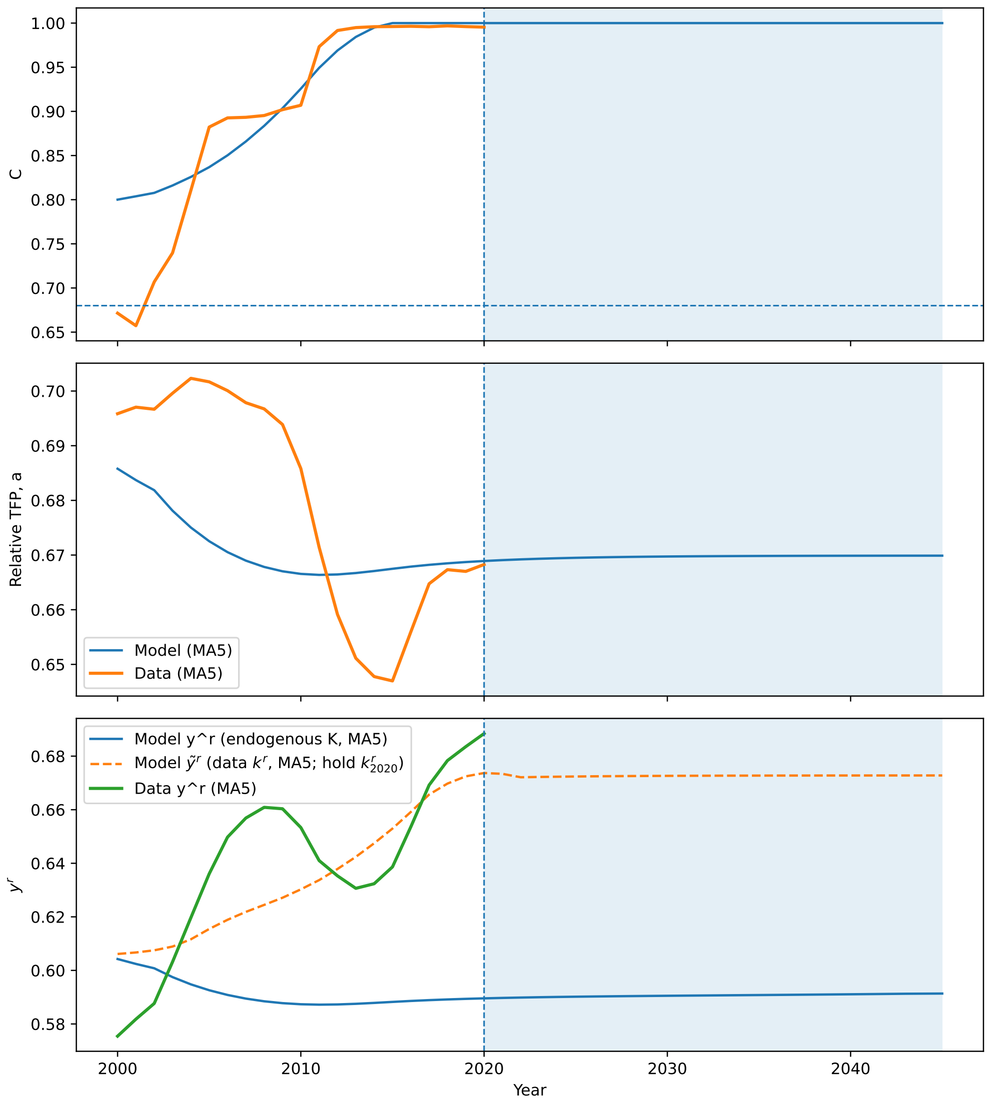

Figure 7: **Korea: MA(5) history fit (2000–2020) and 25-year projection (2021–2045).** Panels report (top) capability C_t, (middle) relative TFP a_t, and (bottom) relative income y_t^r. Thick lines show data for 2000–2020; the shaded region indicates projections beyond 2020. The model uses the baseline production and frontier parameters $\alpha = 0.33$, $\delta_K = 0.06$, $g^* = 0.02$, and $s^* = 0.17$, as well as $\nu = 0.75$, $\delta_C = 0.10$, $\eta = 0.30$, $\mu = 1$, $\phi_I = 0.10$, $\phi_N = 0.02$, and $\beta = 1$. For the in-sample validation window, the capability accumulation parameter is disciplined via the trajectory-matching criterion (minimum-distance on MA(5) C_t), yielding $\hat{\kappa}^{\text{val}}$. For the projection window, policy effort and savings are held constant at their 2020 values ($\tau_t = \tau_{2020}$, $s_t = s_{2020}$). In the income panel, the dashed series reports $\tilde{y}_t^r \equiv E(C_t)a_t(k^r_{t,\text{data}})^\alpha$, which validates the capability/TFP mechanism conditional on observed relative capital $k^r_{t,\text{data}}$ constructed from constant-price capital per worker (Korea relative to the US).

complexity and scale of frontier innovation activities.

Third, relative income remains high but grows more gradually than in catch-up economies. This outcome reflects the structural transition in the sources of growth once economies approach the technological frontier: productivity improvements increasingly depend on domestic innovation rather than diffusion-based convergence.

Taken together, these dynamics illustrate the distinctive features of innovation-regime growth, where capability levels remain high and innovation capacity becomes the central driver of productivity performance.

Operating within the innovation regime fundamentally changes the structure of productivity growth. In economies below the innovation threshold, productivity growth is driven primarily by technology diffusion from the global frontier. Once capability exceeds the threshold, however, domestic innovation becomes an additional source of productivity improvement.

In the model, this transition appears through the activation of the innovation component of productivity growth. Higher capability levels support research activity, technological experimentation, and the generation of new knowledge, allowing domestic innovation to contribute directly to productivity improvements.

At the same time, sustaining productivity growth near the technological frontier becomes increasingly challenging. As technologies become more complex and innovation systems expand in scale, maintaining frontier proximity requires continuous investment in advanced human capital, research infrastructure, and institutional capacity. The frontier- maintenance headwind incorporated in the model ensures that economies operating near the frontier do not mechanically outpace frontier productivity growth.

The Korea benchmark therefore highlights the structural advantages of operating above the innovation threshold. The implementation-efficiency wedge effectively disappears ($E(C_t) \approx 1$), meaning that organizational and institutional frictions no longer reduce the effective productivity of inputs. At the same time, stronger capability levels support domestic innovation activity, allowing productivity growth to be driven increasingly by knowledge creation rather than imitation.

For middle-income economies such as Indonesia, the Korea experience illustrates the long-run payoff from sustained capability accumulation. Crossing the innovation threshold not only removes implementation constraints but also fundamentally changes the composition of growth, shifting the economy from imitation-driven development toward innovation-led technological upgrading.

Together with the China transition case, the Korea benchmark therefore illustrates the broader development trajectory emphasized in the model: sustained capability accumulation allows economies to approach and eventually cross the innovation threshold, after which innovation capacity becomes the primary driver of long-run productivity growth.

7.4 Interpretation: capability accumulation and development transitions

The quantitative exercises for Indonesia, China, and Korea reveal several general mechanisms governing capability-driven development. Although the countries differ in initial conditions and policy effort, their trajectories illustrate how the interaction between capability investment, institutional effectiveness, and productivity dynamics determines whether economies remain confined to imitation-based growth or transition toward innovation-driven development.

First, the results highlight the complementarity between capability investment and institutional effectiveness. In the model, capability accumulation depends on both policy effort τ_t and the efficiency with which this effort is converted into durable capabilities, summarized by the parameter κ. High investment alone does not guarantee rapid capability accumulation if institutional mechanisms translating investment into productive knowledge are weak. Conversely, strong institutional effectiveness can significantly amplify the impact of sustained investment. The comparison between Indonesia and China illustrates this mechanism clearly: China's higher capability-formation efficiency allows similar policy effort to generate substantially faster capability accumulation.

Second, the results illustrate the importance of sustained capability investment for enabling development transitions. Because capability is a stock variable that accumulates gradually over time, the transition from imitation to innovation requires persistent investment rather than temporary policy surges. The China exercise shows how sustained capability investment combined with rising income generates a self-reinforcing feedback mechanism. As capabilities increase, implementation efficiency improves and absorptive capacity strengthens technology diffusion. These channels raise productivity and income, which in turn expand the resource base available for further capability investment. Once this feedback loop becomes sufficiently strong, the economy eventually crosses the innovation threshold.

Third, the Korea benchmark highlights the dynamics of economies operating within the innovation regime. When capability exceeds the threshold, implementation inefficiencies largely disappear and domestic innovation becomes an additional driver of productivity growth. At the same time, operating near the technological frontier introduces new challenges. Maintaining frontier proximity requires sustained investment in advanced human capital, research infrastructure, and innovation systems. As a result, innovation-led economies must continue investing in capability accumulation even after the transition to the innovation regime.

Fourth, capability dynamics generate strong path dependence in development trajectories. Because capability accumulation interacts with productivity growth and income dynamics, small differences in initial capability levels or institutional effectiveness can lead to large differences in long-run outcomes. Economies that accumulate capabilities slightly faster activate stronger diffusion and implementation channels, which raise income and further accelerate capability accumulation. Conversely, economies with slower capability formation experience weaker amplification and may remain confined to imitation-driven growth for extended periods.

A further implication of the framework is that capability dynamics can generate multiple development trajectories. Because capability accumulation interacts with productivity growth and income dynamics, small differences in policy effort or institutional effectiveness can lead to large differences in long-run outcomes.

When capability investment remains insufficient relative to capability depreciation, the economy converges to a low-capability equilibrium in which productivity growth is driven solely by technology diffusion. Relative productivity and income converge only partially toward the global frontier, corresponding to a persistent middle-income trap.

In contrast, when capability accumulation is sufficiently strong to push the economy across the innovation threshold, the feedback between capability accumulation and productivity growth becomes self-reinforcing. Higher capability improves implementation efficiency and absorptive capacity, raising productivity and income and thereby expanding the resources available for further capability investment. The economy therefore transitions to an innovation-driven development path.

This mechanism implies that development trajectories exhibit strong path dependence. Economies with similar initial conditions may diverge substantially depending on the scale and persistence of capability investment and the institutional effectiveness with which that investment is translated into productive capabilities. In this sense, the model generates multiple development paths consistent with the threshold-based dynamics emphasized in the development literature (Azariadis and Drazen, 1990; Murphy, Shleifer, and Vishny, 1989; Acemoglu and Zilibotti, 1997).

Finally, these mechanisms provide a structural interpretation of the middle-income trap. In the framework developed in this paper, the trap arises when capability accumulation remains insufficient to reach the innovation threshold. In such cases the economy continues to grow through capital accumulation and technology diffusion but converges only partially toward the global technological frontier. Escaping the trap therefore requires sustained capability investment and institutional effectiveness sufficient to push the economy across the innovation threshold and activate innovation-driven productivity growth. These results therefore suggest that development transitions are governed not only by the scale of investment but also by the institutional capacity to transform that investment into productive capabilities.

Taken together, these results provide a unified interpretation of development transitions driven by capability accumulation. The model shows that long-run convergence toward the technological frontier is not determined solely by capital accumulation or access to foreign technology, but by the gradual buildup of technological and organizational capabilities that allow economies to absorb, implement, and ultimately generate advanced technologies. Because capability accumulation is a slow-moving stock process subject to threshold effects, development trajectories exhibit strong path dependence. Economies that accumulate sufficient capabilities activate a self-reinforcing process linking productivity growth and capability formation, allowing them to transition from imitation-based growth to innovation-driven development. In contrast, economies that fail to reach this capability threshold remain confined to diffusion-based productivity growth and converge only partially toward the global frontier. In this sense, the middle-income trap emerges not as a temporary growth slowdown but as a structural outcome of insufficient capability accumulation.

8 Conclusion

This paper develops a structural framework linking capability accumulation, technology diffusion, and innovation-driven productivity growth. The central idea is that long-run development depends on whether an economy accumulates sufficient technological and organizational capabilities to transition from an imitation-based growth regime to an innovation-oriented regime.

In the model, capabilities influence economic performance through implementation efficiency and absorptive capacity. When capability remains below a critical threshold, productivity growth is driven primarily by the diffusion of frontier technologies. Once this threshold is crossed, domestic innovation becomes an additional source of productivity growth. Because capability accumulates gradually through policy effort scaled by the economy's resource base, productivity growth and capability formation interact through a self-reinforcing feedback mechanism.

The framework provides a structural interpretation of the middle-income trap. Rather than representing a temporary slowdown in growth, the trap corresponds to a persistent failure of the capability stock to reach the level required for innovation-driven development. In this regime, economies continue to grow through capital accumulation and technology adoption but converge only partially toward the technological frontier.

Using Indonesia as a development laboratory, the quantitative analysis shows that under continuation of current conditions the economy remains below the innovation threshold even over very long horizons. Escaping this regime would require sustained capability investment on the order of two to three percent of GDP per year—several times higher than current levels. Policies that front-load capability investment further accelerate the transition by activating the feedback mechanism linking capability accumulation, productivity growth, and income earlier in the development process.

Cross-country comparisons provide additional perspective on these mechanisms. China illustrates how sustained capability investment and effective institutional conversion can generate rapid capability accumulation and eventually push an economy across the innovation threshold. Korea provides a benchmark for the innovation regime, where productivity growth depends increasingly on frontier innovation and the continuous upgrading of advanced technological capabilities.

Taken together, these results emphasize that long-run convergence toward the technological frontier depends not only on capital accumulation but on the gradual development of the institutional and technological capabilities that support innovation. Economies that accumulate such capabilities can transition from imitation-driven growth to sustained technological upgrading, while those that fail to do so remain confined to partial convergence below the frontier.

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A Calibration of Model Parameters

This appendix describes the calibration procedures used to discipline the key parameters governing capability accumulation and productivity dynamics. The calibration strategy aims to match the medium-run evolution of observable variables while maintaining transparency and parsimony in parameter selection.

A.1 Capability formation parameter κ

The parameter κ governs the efficiency with which effective capability investment translates into the accumulation of durable capabilities. From the capability accumulation equation,

$$C_{t+1} = (1 - \delta_C)C_t + \kappa(\tau_t y_t^r)^\nu, \tag{20}$$

κ scales the contribution of effective effort $(\tau_t y_t^r)^\nu$ to the growth of the capability stock.

For each country, κ is calibrated using an endpoint-matching procedure over the validation period 2000–2020. Let C_{2000} denote the observed initial capability level and C_{2020}^{data} the observed terminal level. Given the observed series for policy effort $\{\tau_t\}$ and relative income $\{y_t^r\}$, the simulated capability path satisfies

$$C_{2020}^{model}(\kappa) = (1 - \delta_C)^{20} C_{2000} + \sum_{t=2000}^{2019} (1 - \delta_C)^{2019-t} \kappa(\tau_t y_t^r)^\nu. \tag{21}$$

The calibrated value κ^{proj} is chosen such that

$$C_{2020}^{model}(\kappa^{proj}) = C_{2020}^{data}. \tag{22}$$

This procedure ensures that the model reproduces the observed level of capabilities at the end of the validation window before generating forward projections. Differences in calibrated values of κ across countries capture differences in the institutional efficiency with which capability investment is translated into technological and organizational capabilities.

A.2 Diffusion parameter ϕ_I

The diffusion parameter ϕ_I determines the strength of technology diffusion from the global frontier in the imitation regime. Relative productivity evolves according to

$$a_{t+1} - a_t = \phi_I m(C_t)(1 - a_t) - g^* a_t, \tag{23}$$

where $m(C_t)$ represents absorptive capacity and g^* is frontier productivity growth.

The calibration exploits observations in which economies operate below the innovation threshold. Rearranging the diffusion equation yields

$$\phi_I = \frac{(a_{t+1} - a_t) + g^* a_t}{m(C_t)(1 - a_t)}. \tag{24}$$

The baseline value of ϕ_I is obtained by matching the average adjusted productivity growth rate implied by the model to the observed rate of relative productivity convergence in the imitation regime.

A.3 Innovation parameter ϕ_N

The parameter ϕ_N governs the additional contribution of domestic innovation to productivity growth once capability exceeds the innovation threshold. In the innovation regime productivity dynamics take the form

$$a_{t+1} - a_t = \phi_I m(C_t)(1 - a_t) + \phi_N n(C_t) - g^* a_t, \tag{25}$$

where $n(C_t)$ captures the strength of innovation capacity.

Identifying innovation dynamics requires observations from economies operating near the technological frontier. Rather than estimating ϕ_N directly from the limited sample available, the baseline calibration selects a value consistent with observed productivity dynamics in advanced innovation economies. The baseline value $\phi_N = 0.02$ ensures that domestic innovation contributes positively to productivity growth without generating persistent productivity growth rates exceeding frontier growth.

Taken together, these calibration procedures ensure that the model reproduces the observed evolution of capabilities and productivity while maintaining a transparent mapping between model parameters and empirical moments.

B Finite-horizon condition for threshold crossing

Capability accumulation follows the law of motion

$$C_{t+1} = (1 - \delta_C)C_t + \kappa(\tau_t y_t^r)^\nu. \tag{26}$$

Iterating this equation forward T periods yields

$$C_T = (1 - \delta_C)^T C_0 + \sum_{t=0}^{T-1} (1 - \delta_C)^{T-1-t} \kappa(\tau_t y_t^r)^\nu. \tag{27}$$

The first term represents the surviving portion of the initial capability stock, while the second term captures the cumulative contribution of capability investment over the transition horizon. Because capabilities are a stock variable, earlier investments persist longer and therefore receive greater weight in determining the future capability level.

Crossing the innovation threshold requires

$$C_T \geq \bar{C}. \tag{28}$$

Substituting equation (27) yields the cumulative investment requirement

$$\sum_{t=0}^{T-1} (1 - \delta_C)^{T-1-t} \kappa(\tau_t y_t^r)^\nu \geq \bar{C} - (1 - \delta_C)^T C_0. \tag{29}$$

This condition highlights two key determinants of regime transition. First, the total investment required depends on the initial capability gap $\bar{C} - C_0$. Second, the timing of investment matters: because capabilities accumulate as a stock, earlier investments accelerate the transition by generating persistent gains.

For analytical transparency, consider the benchmark case of constant policy effort $\tau_t = \tau$. Approximating relative income as evolving slowly over the transition horizon ($y_t^r \approx y_0^r$) yields

$$C_T = (1-\delta_C)^T C_0 + \frac{\kappa(\tau y_0^r)^\nu}{\delta_C}\left[1-(1-\delta_C)^T\right]. \tag{30}$$

Solving for the policy effort required to reach the threshold gives

$$\tau \geq \frac{1}{y_0^r}\left[\frac{\delta_C\left(\bar{C}-(1-\delta_C)^T C_0\right)}{\kappa\left[1-(1-\delta_C)^T\right]}\right]^{1/\nu}. \tag{31}$$

The right-hand side defines the minimum capability investment required to close the capability gap within T periods. Denote this value by

$$\tau^{req}(T) = \frac{1}{y_0^r}\left[\frac{\delta_C\left(\bar{C}-(1-\delta_C)^T C_0\right)}{\kappa\left[1-(1-\delta_C)^T\right]}\right]^{1/\nu}. \tag{32}$$

The quantity $\tau^{req}(T)$ can be interpreted as the *regime-transition price* of capability investment: the minimum annual effort required to move the economy from the imitation regime to the innovation regime within T periods.

Table 6: **Capability and Relative TFP (China, Indonesia, Korea), 2000–2020**

	Capability			TFP relative to US		
Year	China	Indonesia	Korea	China	Indonesia	Korea
2000	0.104	0.064	0.793	0.326	0.421	0.691
2001	0.063	0.099	0.608	0.338	0.415	0.686
2002	0.068	0.044	0.614	0.342	0.406	0.711
2003	0.072	0.063	0.615	0.351	0.386	0.701
2004	0.081	0.068	0.905	0.369	0.396	0.695
2005	0.098	0.047	0.957	0.388	0.406	0.705
2006	0.109	0.062	0.962	0.394	0.414	0.700
2007	0.129	0.040	0.972	0.412	0.407	0.708
2008	0.143	0.038	0.667	0.413	0.424	0.693
2009	0.118	0.073	0.908	0.403	0.403	0.684
2010	0.210	0.063	0.967	0.395	0.401	0.700
2011	0.155	0.066	0.995	0.404	0.451	0.685
2012	0.180	0.069	0.997	0.415	0.470	0.667
2013	0.202	0.070	0.999	0.402	0.469	0.621
2014	0.219	0.069	1.000	0.409	0.460	0.623
2015	0.240	0.074	0.984	0.415	0.439	0.660
2016	0.276	0.088	1.000	0.420	0.436	0.669
2017	0.296	0.102	0.998	0.432	0.436	0.663
2018	0.313	0.092	1.000	0.439	0.454	0.665
2019	0.324	0.115	0.998	0.448	0.455	0.667
2020	0.443	0.108	0.989	0.453	0.433	0.673