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From assimilation to innovation: A Bayesian Nelson–Phelps model of China's technological catch-up with the United States

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ABSTRACT

Over the past half-century, China has been evolving into the second-largest economic system, which creates endogenous innovation as a key driver of growth. Yet, a scientific inquiry into whether or not this nation can technologically keep pace with the United States (U.S.) remains unexplored. The purpose of this research is to explore China's possibilities for technological convergence with the frontier, evaluating the logistic against exponential variants within the neo-Schumpeterian diffusion paradigm. The study also assesses how education and other structural capacities—including governance quality, financial capacity, openness policies, and digital infrastructure—condition China's standing vis-à-vis the frontier. To this end, Bayesian mixed regressions are applied to the Chinese and U.S. time-series data spanning 1996–2022. The research findings indicate that this country's technological convergence predominantly occurs through implementation rather than innovation. An increasing contribution from innovation-oriented human capital and R&D activities signals China's steady evolution toward innovation-driven expansion. Policy implications include enhancing the quality of education, strengthening institutional, innovation, and financial capacities, and promoting a balanced combination of technology absorption and generation for China and other emerging economies.

Contribution/Originality: The study contributes to the literature by evaluating a neo-Schumpeterian diffusion framework through a Bayesian mixed approach. The findings show that China has technologically caught up with the United States, progressively shifting from implementation to innovation. The results provide strategic implications for economies striving for technological modernization.

1. INTRODUCTION

Since the initiation of post-socialist transformation in 1978, the Chinese economy has undertaken one of the most successful reforms in contemporary economic history. From 1978 to 2019, before the impact of the coronavirus pandemic, China experienced an extraordinary pace of development. Its GDP growth exceeded 10% in fifteen separate years, and only twice fell below 5% (Kroeber & Marek, 2025; Peschel & Liu, 2022). Neither the 1997 Asian financial crisis, the 2007–2009 Great Recession, nor China's policy modifications obstructed this trajectory. Consequently, China has dramatically narrowed the income disparity with the U.S., reducing it from 24.3 times in 1990 to just 3.2 times (2024) (World Bank, 2025). This unprecedented advancement, which has transformed China into the world's second-largest economy, is primarily due to an investment-driven growth strategy that focuses on manufactured exports and extensive industrialization. This strategic approach has not only propelled the Chinese economy forward but has also reshaped global supply chains, as companies worldwide have relocated manufacturing operations to China to capitalize on its cost advantages (Dieppe, Gilhooly, Han, Korhonen, & Lodge, 2018; Dorrucci, Pula, & Santabárbara, 2013; Zhang et al., 2018).

Nonetheless, China's industrialization model is now challenged by diminishing returns due to structural drags. Industrial overcapacity, falling marginal efficiency of capital, a declining workforce, and shrinking productivity have all begun to erode its potential (Al-Haschimi & Spital, 2024). Perceiving these obstacles, the Chinese government has repositioned its development strategy toward innovation. China's 14th Five-Year Plan Outline (2021–2025) and Vision 2035 highlight its focus on technological self-reliance, "high-quality development," and a leading role in a range of "strategic emerging industries" an evident shift from factor accumulation to knowledge-intensive expansion (State Council of the People's Republic of China, 2015). This strategy sets 2035 as a benchmark for achieving breakthroughs in cutting-edge technologies, enhancing research and development capabilities, and building an advanced innovation ecosystem (National Development and Reform Commission (NDRC), 2021). Within this paradigm, the signature initiative is "Made in China 2025," aimed at enhancing global competitiveness and promoting import substitution in ten core industries, including aerospace, advanced machinery and equipment, new energy vehicles, next-generation information technology, and biotechnology. This policy is designed to elevate Chinese corporations along the global value chain and narrow the technological gap with affluent economies, particularly the United States (Wübbeke, Meissner, Zenglein, Ives, & Conrad, 2016). That strategic reorientation raises an essential question: Can China successfully achieve technological and economic equivalence with or even overtake the United States in the near future?

China's astonishing growth story has attracted significant scholarly attention. However, despite the extensive literature on China's development trajectory, there are still areas that require further exploration and analysis (Boulter, 2018; Di Sano, Pongetti, Schuler, & Toh, 2023; Dieppe, Frankovic, & Liu, 2024; Dorrucci et al., 2013; Fernández-Villaverde, Ohanian, & Yao, 2023; García-Herrero & Schindowski, 2024; Jean, 2023; L. Zhang et al., 2018) very little work has modeled this country's technological catch-up process within a flexible but rigorous theoretical framework. Notably, no empirical research to date has applied (Nelson & Phelps, 1966) cross-national technological catch-up model to China. This gap prevents policymakers from making use of a robust modeling framework that can explore the interactions between education, openness, innovation, digital infrastructure, and institutional capacity in China's technological ascent. Furthermore, while the Nelson–Phelps framework provides a fruitful perspective for examining technological convergence (Benhabib & Spiegel, 1994; Benhabib & Spiegel, 2005; Thach, 2025a), its original version centers exclusively on human capital as a catalyst for adopting foreign technologies, without incorporating domestic innovation and multiple structural barriers that may hamper the catch-up process. Moreover, adding more explanatory variables exacerbates the risk of model complexity, reverse causality, and multicollinearity. These potential issues can be addressed using a Bayesian mixed approach, which incorporates well-specified prior information to handle parameter uncertainty.

To fill the aforementioned gaps, this research examines whether and how China has been technologically catching up with the U.S. To this end, an exponential specification is empirically evaluated against the logistic model within the Nelson–Phelps paradigm of technology diffusion, combined with Schumpeterian innovation ideas. Bayesian hierarchical inferences are conducted utilizing the series-time data of China and the U.S. over 1996-2022 to accommodate structural heterogeneity. The study contributes to the catch-up literature in three ways. First, our results suggest reliable and strong evidence favoring China's convergence with the U.S., though chiefly through assimilation rather than indigenous innovation. Second, despite being a major adopter of technology, China is steadily advancing toward an innovation-based model of economic growth, which is mainly directed by expanding R&D capabilities and high-skilled resources. Third, beyond cognitive skills, a range of structural enablers—including openness policies, governance effectiveness, financial capacity, digital infrastructure, and high-tech trade—

enormously influence China's technological progress. Our results offer a robust empirical foundation for strategic policymaking aimed at accelerating technological progress for emerging economies that strive to emulate China's path.

The remaining work is organized into the following sections. Section 2 reviews the theoretical and empirical literature. Section 3 details the Bayesian mixed methods, model specifications, and data. Preliminary and main empirical results, along with robustness checks, are presented in Section 4. Section 5 concludes with core policy implications and directions for future research.

2. LITERATURE REVIEW

2.1. The Nelson–Phelps Catch-Up Framework

In assessing international income differentials, the concept of catch-up is central to understanding why growth rates and levels of national income tend to converge (Abramovitz, 1986; Thach, 2025a). The catch-up hypothesis postulates that economies functioning far below the technological frontier can build on the world's existing knowledge pool to achieve faster productivity gains, whereas countries already near the frontier experience fewer opportunities for rapid expansion. Consequently, economies starting from lower initial technological levels tend to exhibit higher growth rates, leading to a convergence in per capita income. Foundational theoretical accounts of this process were offered by Ames and Rosenberg (1963) and Gomulka (1971).

In its essence, the catch-up hypothesis is grounded in the assumption that innovation serves partly as a non-rival, cross-border good, available to countries beyond the original innovator. Through international relationships of trade, FDI, and R&D, laggard economies can gain from cutting-edge technologies yielded abroad, thereby boosting their productivity. Empirical studies (Abramovitz, 1986; Baumol, 1986; Dollar & Wolff, 1997; Dowrick & Nguyen, 1989) uncovered a strong negative relationship between the initial level and subsequent growth of income, providing evidence of conditional convergence. Nevertheless, convergence is not automatic. Baumol (1986) famously documented that "rather than sharing in convergence, some of the poorest countries have also been growing most slowly" (p. 1079), stressing that convergence is critically dependent on the quality of education, institutions, and broader structural determinants. Under these circumstances, Nelson and Phelps (1966) introduced an analytical framework of catch-up to explain these divergences by connecting the diffusion of technology directly to educational level and national absorptive capabilities.

Nelson and Phelps (1966) framework of catch-up models the technology growth of a follower economy as a function of its own educational level and its technology gap relative to the frontier. Widely tested in the convergence empirical literature (Ang, Madsen, & Islam, 2011; AtiqurRahman & Zaman, 2016; Benhabib & Spiegel, 1994; Kim & Terada-Hagiwara, 2010; Thach, 2025a) it formalizes technology diffusion as an exponential process. By contrast, in the logistic formulation (Benhabib & Spiegel, 2005; Griliches, 1957; Sharif & Ramanathan, 1981; Thach, 2025b; Verspagen, 1991) diffusion slows down as a follower economy near the frontier owing to absorptive capacity limitations. Highlighting human capital as the key engine for technology adoption and convergence, both models imply diverse growth trajectories.

Exponential technology growth depends on the gap between an economy's current technological level and the leader, with human capital functioning as a catalyst for catch-up:

$$\frac{\dot{A}_{it}}{A_{it}} = g(H_{it}) + c(H_{it})(\frac{A_{mt}}{A_{it}} - 1) \qquad (1)$$

Where A_{it} is the current technological level of an economy (e.g., TFP), $\frac{\dot{A}_{it}}{A_{it}}$ is the rate of technological progress or the growth rate of technology, H_{it} is human capital stock in an economy, A_{mt} is TFP of the technology leader, $g(H_{it})$ and $g(H_{mt})$ are innovation rates depending on human capital H_{it} for country i and the technology leader, $c(H_i(t))$ is the technology diffusion rate, increasing with H_{it}. g (innovation parameter) represents the autonomous innovation intensity associated with a country's human-capital-driven R&D capacity, while c (diffusion coefficient) measures the rate of technology transfer from abroad i.e., how effectively a country absorbs and implements foreign technologies. $g(.)$ and $c(.)$ are increasing functions.

The logistic model modifies (1) by assuming that diffusion slows as a follower approaches the frontier.

$$\frac{\dot{A}_{it}}{A_{it}} = g(H_{it}) + c(H_{it})(1 - \frac{A_{it}}{A_{mt}}) \qquad (2)$$

Here, the diffusion term declines as the technological gap narrows, introducing diminishing returns to adoption. This implies that some countries may never fully converge if structural barriers persist.

Define the relative productivity gap as.

$$D_t = \frac{A_{it}}{A_{mt}(0)} e^{-gmt} \qquad (3)$$

Normalizing productivity relative to the frontier, the logistic model yields.

$$\frac{\dot{D}}{D} = c(H_{it})(1 - D) + g(H_{it}) - g(H_{mt}) \qquad (4)$$

Expanding further gives.

$$\dot{D} = [c(H_{it}) + g(H_{it}) - g(H_{mt})]D - c(H_{it})D^2 \qquad (5)$$

Where $\dot{D}$ denotes the time derivative of D. Mathematically, this means: $\dot{D} = \frac{dD}{dt}$. The D^2 term presents non-linearity, describing the S-shaped logistic diffusion curve.

To unify both model specifications, a generalized Bernoulli-type diffusion equation is formulated:

$$\frac{\dot{D}}{D} = \frac{c(H_{it})}{s}(1 - D^s) + g(H_{it}) - g(H_{mt}). \qquad (6)$$

(6) nests both exponential and logistic patterns, with elasticity parameter s determining the diffusion type: if s = 1, the model is logistic; if s = −1, it is exponential. The growth differential form can be expressed as:

$$\dot{D} = \frac{c(H_{it}) + sg(H_{it}) - sg(H_{mt})}{s} D + \frac{c(H_{it})}{s} D^{s+1} . \qquad (7)$$

Further simplifying gives the reduced-form expression for the catch-up process.

$$\dot{D} = \frac{c(H_it) + sg(H_{it}) - sg(H_{mt})}{s} D(1 - \frac{D^s}{1 + s(g_i - g_m)/c_i}) \qquad (8)$$

Where $g_i = g(H_{it})$ and $g_m = g(H_{mt})$. The fraction inside the parentheses adjusts the diffusion rate based on the technology gap and human capital.

Finally, the empirical specification is formulated as.

$$\Delta A_{it} = \left(g + \frac{c}{s}\right) H_{it} - \frac{c}{s} H_{it} (\frac{A_{it}}{A_{mt}})^s \qquad (9)$$

Where ΔA_{it} represents the TFP growth for country *i*, H_{it} denotes its initial or average human capital, and $\frac{A_{it}}{A_{mt}}$ is the ratio of the country's TFP to that of the technology leader. This specification encompasses both the logistic (s = 1) and exponential (s = −1) models. The estimates of c, g, and s determine whether a country will converge to the growth rate of the leader or whether growth rates will diverge.

2.2. Empirical Evidence

Since the mid-19th century, the global income distribution has been marked more by divergence than convergence, with widening discrepancies between the richest and poorest countries (Lucas Jr, 1988) even as some groups such as the OECD have converged toward the global frontier (Mayer-Foulkes, 2002; Perilla, 2024). Against this backdrop, China and a small handful of other emerging economies have posted striking growth (Kroeber & Marek, 2025; Peschel & Liu, 2022). China's catch-up experience has attracted significant theoretical and policy interest. Having become the world's second-largest economy, with rapidly developing industries in next-generation information technology, advanced machinery, aerospace, new-energy vehicles, and biomedicine, China now poses increasing strategic challenges to the United States. This situation raises two essential questions: Can China catch up or even surpass the United States? And through what mechanisms can this be achieved?

Contemporary empirical catch-up literature has broadly adopted a technology-centric view, arguing that international differentials in productivity and income are fundamentally determined by technology (Caselli, Esquivel, & Lefort, 1996; Hall & Jones, 1999; Islam, 1995; Klenow & Rodriguez-Clare, 1997; Knight, Loayza, & Villanueva, 1993). This technology-centered perspective is primarily divided into the diffusion literature and the Schumpeterian conception of innovation. Throughout the 1990s, research on technological capability and economic growth developed along two relatively separate paths: diffusion and development. Over time, these paths gradually converged as the diffusion literature expanded, leading to a more integrated understanding of technological progress and its impact on economic growth. Early contributions highlighted powerful spillover channels: Griliches (1992) emphasized R&D spillovers as core mechanisms for transmitting innovation; Coe and Helpman (1995) showed that foreign R&D boosts domestic productivity via trade linkages; Branstetter (2001), using micro data, documented sizable spillovers among technologically proximate firms. Nadiri and Kim (1996) discovered heterogeneous spillover effects across advanced countries where national technologies considerably contribute to U.S. productivity, whereas Canada and Italy rely on foreign knowledge. Eaton and Kortum (1996) underscored the paramount importance of technology diffusion, uncovering that, except for the U.S., much of OECD productivity growth is of foreign origin. The U.S. and Japan constitute at least two-thirds of global improvements in productivity, with trade acting as a key channel for embodied technological achievements. Similarly, Keller (2004) considered trade and investment as the two principal channels of knowledge diffusion. While these studies establish technology dissemination as a driver of convergence, a shared limitation is their limited treatment of human capital, a gap that complicates purely technological explanations of convergence and divergence.

Subsequent research placed the human-capital–technology nexus at center stage. Early work by Welch (1975); Bartel and Lichtenberg (1987) and Foster and Rosenzweig (1995) suggested that education enhances the adoption and profitability of new technologies: highly educated workers have a comparative advantage in implementing innovations (Bartel & Lichtenberg, 1987) and learning-by-doing raises returns to high-yield seeds in rural India (Foster & Rosenzweig, 1995). Building on these insights, Klenow and Rodriguez-Clare (1997) incorporated multiple human-capital measures into growth models and concluded that productivity differentials explain most growth disparities; Hall and Jones (1999) similarly found that knowledge capital explains a large share of international income variation. Human-capital quality matters as well: Hanushek and Kimko (2000) showed that international math and science scores predict growth, and Hanushek, Ruhose, and Woessmann (2017) found that knowledge-capital differences explain 20–30% of U.S. state-level per-capita GDP variation. Nonetheless, despite recognizing cognitive skills' vital role, most studies do not amount to a unified mechanism relating education's specific channels to technological development.

A more explicit mechanism evolves in Nelson and Phelps (1966) lineage and its Schumpeterian elaborations (Benhabib & Spiegel, 1994; Benhabib & Spiegel, 2005; Howitt & Mayer-Foulkes, 2002; Mayer-Foulkes, 2002; Verspagen, 1991) which advocate for a twofold function of cognitive skills. On the one hand, human capital leverages national capabilities to create its own technologies tailored to production; on the other, it fastens know-how diffusion, thereby accelerating catch-up. Nelson and Phelps (1966) set up an exponential model in which human capital determines the speed of diffusion. In a different vein, Romer (1990) posited that a highly qualified workforce advances the boundaries of innovation. Empirically, Benhabib and Spiegel (1994) validated an extended Nelson–Phelps hypothesis using cross-country data, suggesting that technology transfer depends critically on education level. Correa-Lopez (2008) incorporated quality-improving innovations into an exponential framework and showed that higher human-capital stocks interpreted as the skill composition of non-research labor raise steady-state growth and heighten sensitivity to interest rates when adoption lags are long. Complementary evidence in Griffith, Redding, and Reenen (2004) and Madsen, Islam, and Ang (2010) links human capital to both innovation and adoption. Importantly, effects are heterogeneous across human-capital types: Vandenbussche, Aghion, and Meghir (2006) and Ang et al. (2011) argued that skilled and unskilled labor impact innovation and imitation differently. Consistent with this, Kim and Terada-Hagiwara (2010) reported that primary education interacted with the technology gap yields a negative but insignificant coefficient, suggesting that low schooling alone cannot absorb foreign technology. Reassessing Benhabib and Spiegel (1994) and AtiqurRahman and Zaman (2016) used a 75-country panel and found no catch-up when the U.S. or single countries are treated as technological leaders, but strong catch-up when OECD or major high-income trading partners collectively serve as leaders. Most recently, using 1996–2019 data, Thach (2025a) found that five advanced ASEAN economies (Malaysia, Thailand, Indonesia, the Philippines, Singapore) tend to converge to the U.S.

At the same time, the unqualified exponential view of universal convergence is often overly optimistic because real-world diffusion barriers are substantial. Intellectual property protection and blueprint ownership can constrain imitation and require market structures that sustain innovation and limit free-riding (Aghion, Harris, & Vickers, 1997; Barro & Sala-i-Martin, 1997; Eeckhout & Jovanovic, 2002; Grossman & Helpman, 1991; Helpman, 1993; Segerstrom, 1991). Basu and Weil (1998) argued that large differences in factor proportions can create "convergence clubs," as imitation becomes less appropriate and fails to steer technical change toward cost-efficient directions (Acemoglu, 2003). Social capability constraints (Abramovitz, 1986) low intrinsic learning capacity (Verspagen, 1991), and weak human capital (Benhabib & Spiegel, 2005; Howitt & Mayer-Foulkes, 2002; Thach, 2025b) further impede diffusion. Against this backdrop, a more pragmatic extension of Nelson–Phelps is the logistic model of diffusion: it preserves the leading role of human capital and cross-border knowledge flows but embeds saturation and structural frictions. Benhabib and Spiegel (2005) assessed exponential vs. logistic specifications on a cross-section of 84 countries spanning 1960–1995, discovered that the logistic model outperforms the exponential alternative. In line with these structured barriers, Das and Drine (2020) identified a weak business environment, infrastructure shortfalls, and low educational level as pronounced impediments to technology convergence.

In spite of substantial literature on technological convergence, several research gaps have been identified. First, to the best of our knowledge, no studies have employed the Nelson–Phelps paradigm in conjunction with Schumpeterian innovation ideas to analyze China's catch-up process, despite its applicability for modeling innovation-driven technological development. Second, although education remains a decisive factor, the original framework insufficiently accounts for structural barriers such as policy limitations, institutional fragility, underdeveloped finance, and poor infrastructure. Third, frequentist analyses of catching up are challenged by econometric issues particularly multicollinearity and reverse causality. Our work employs a Bayesian mixed-effects approach to address these issues, enabling flexible and efficient inference on China's technological convergence trajectory within a unified exponential logistic framework.

3. METHODOLOGY

3.1. Bayesian Mixed Method

Bayesian statistics, originally used in macroeconomic theory, has been widely applied across various social and behavioral sciences over the past few decades. A growing body of methodological research (Briggs, 2023; Muthén & Asparouhov, 2012; Smid, McNeish, Miočević, & van de Schoot, 2020; Wagenmakers, Lee, Lodewyckx, & Iverson, 2008) highlights several advantages of Bayesian methodologies over conventional frequentist methods. First, Bayesian inference has a very broad applicability: Bayes' theorem can be used for any parametric model, whereas each frequentist method is suitable for only a certain class of models. Second, Bayesian approaches straightforwardly interpret probabilities. Third, Bayesian inference produces an entire posterior distribution of a parameter, thereby explicitly quantifying the uncertainty level and facilitating out-of-sample evaluation. Fourth, in the case of correctly defined priors, the Bayesian approach can encode genuine information (e.g., a range of plausible parameter values or interactions between coefficients), which guides estimation in complex models like non-linear models, efficiently handling econometric issues such as multicollinearity and reverse causality. Finally, Bayesian estimators perform better in small-sample research. By combining two information sources the likelihood conveyed by the data and well-specified prior knowledge about parameters, Bayesian estimation offers robust and trustworthy inferences. Several simulation studies have concluded that Bayesian inference, using thoughtful prior settings, outperforms both frequentist procedures and naïve (non-informative prior) Bayesian methods (McNeish, 2016; Miočević, MacKinnon, & Levy, 2017; Natesan, 2015; Price, 2012; Serang, Zhang, Helm, Steele, & Grimm, 2015; Yuan & MacKinnon, 2009; Zondervan-Zwijnenburg, Depaoli, Peeters, & Van De Schoot, 2018). In particular, combining random and fixed effects to account for cross-country variations, Bayesian mixed-effects models are well purpose-built for statistical complexities including multicollinearity and reverse causation via shrinkage and hierarchical regularization effects (Block, Jaskiewicz, & Miller, 2011; Bucur, Claassen, & Heskes, 2019; Howey, Shin, Relton, Davey Smith, & Cordell, 2020; Pesaran & Smith, 2019; Winship & Western, 2016). The work initiates this process by yielding posterior estimates that amalgamate two information sources: prior beliefs and data distribution.

$$\text{Posterior} \propto \text{prior} \times \text{likelihood} \qquad (10)$$

(10) depicts Bayes' theorem, which is expressed as follows.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad (11)$$

Where *P(A|B)* is the conditional probability that event *A* occurs given the occurrence of event *B*, (*P(B|A)* is also the conditional probability, but the positions of *A* and *B* are reversed, *P(A)* and *P(B)* denote the marginal probabilities of occurrence of event *A* and event *B*, respectively.

3.2. Model

Based on (9), our Bayesian baseline catch-up model is specified as follows.

$$Grow\_tech_{it} = \left(g + \frac{c}{s}\right) lnHC_{it} - \frac{c}{s} lnHC_{it}(Gap_{it})^{s} + Z_{it} + v_i + \varepsilon_{it} \qquad (12)$$

Where technology growth ($Growth\_tech$) is represented by the annual growth rate of TFP, innovative human capital ($lnHC$) is proxied by the logarithm of the Mincerian human capital index over the estimation period (1996–2022), technology gap (Gap) refers to the ratio of the TFP level of country *i* to that of the U.S. in the corresponding years, and Z_{it} are control variables (Openness, Tacit knowledge spillovers, Governance capacity, Financial development, Digital infrastructure, ICT technology transfer, High-tech transfer, Education policy, Innovation policy, FDI policy). The definitions of all primary and control variables are provided in Table 1. The unknown parameters g, c, and s require estimation. As previously discussed, g and c must be positive, while s is constrained to the interval $[-1,1]$. The subscripts *i* and *t* represent country and year, respectively. Additionally, v_i captures country specifics, and ε_{it} is the random error term.

Table 1. Variable, acronym, measurement.

Variable meaning	Symbol	Definition	Timeframe	Source
Technology growth	*Growth_tech*	Growth rate of TFP	1996–2022	PWT 11.00
Technology gap	*Gap*	Ratio of country's TFP level to that of the U.S.	1996–2022	PWT 11.00
Mincerian human capital	*lnHC*	Natural logarithm of Mincerian human capital index	1996–2022	PWT 11.00
Tertiary education	*lnTER*	Natural logarithm of tertiary school enrollment ratio	1996–2022	WDI 2025
Secondary education	*lnSEC*	Natural logarithm of secondary school enrollment ratio	1996–2022	WDI 2025

Variable meaning	Symbol	Definition	Timeframe	Source
Primary education	*lnPRI*	Natural logarithm of primary school enrollment ratio	1996–2022	WDI 2025
Openness	*Open*	KOF economic globalization index	1996–2022	KOF Swiss economic institute
Tacit knowledge spillovers	*Tacit*	KOF social globalization index	1996–2022	KOF Swiss economic institute
Governance capacity	*Rule*	Rule of law	1996–2022	WDI 2025
Financial development	*FI*	Domestic credit to private sector (% of GDP)	1996–2022	WDI 2025
Digital infrastructure	*Digital*	Mobile subscriptions per 100 people	1996–2022	WDI 2025
ICT technology transfer	*ICT*	Share of ICT goods in total imports (% of total)	1996–2022	WDI 2025
High-tech transfer	*High_tech*	Share of manufactured goods in total imports (% of total)	1996–2022	WDI 2025
Education policy	*Edu*	Government expenditure on education (% of GDP)	1996–2022	WDI 2025
Innovation policy	*RD*	R&D expenditure (% of GDP)	1996–2022	WDI 2025
FDI policy	*FDI*	FDI inflows (% of GDP)	1996–2022	WDI 2025

3.3. Data and Prior Specifications

Annual data are compiled for the years 1996–2022 from three primary sources: the Penn World Table (PWT, version 11.00; coverage from 1950 to 2023), the World Development Indicators (WDI, 2025; covering 1960 to 2023), and the KOF Globalisation Index (covering 1970 to 2022). The PWT offers annual data on national TFP levels and the TFP ratio for each country relative to the United States, serving as a proxy for technological gap or backwardness. Due to its strong representation of innovative human capacity, the Mincerian human capital indicator is used as the primary measure of human capital.

To ensure robustness, alternative flow-based human capital measures such as primary, secondary, and tertiary enrollment rates are also included. Since the WDI series for two key variables, research and development (R&D) expenditure and the rule of law begins in 1996, the China time-series data are limited to the period from 1996 to 2022. Data for secondary enrollment (lnSEC) and government education spending (Edu) contain some missing observations, which reduces the effective sample size for estimation. To address small-sample concerns, Bayesian inference methods are employed, as they generally perform well under such conditions (Muthén & Asparouhov, 2012; Smid et al., 2020; Wagenmakers et al., 2008).

Priors, which accommodate prior knowledge about parameters before observing data, are essential in Bayesian inferences.

To constrain the values of s within the range $[-1,1]$, the study sets a Truncated Normal $(0, \sigma^2)$ prior on [-1, 1]. For sensitivity analysis, we additionally consider Truncated Laplace (Double Exponential) Lap (0, b) on [-1, 1], Truncated Cauchy (0, τ) on [-1, 1], Triangular on [-1, 1], mode $m \in [-1, 1]$, and Uniform (-1,1). Since parameters c and g are always positive, we assign them a Gamma (1,1) prior. For further sensitivity analysis, we also consider Gamma (2,2), Gamma (3,3), Gamma (4,4), and Gamma (5,5) priors. This approach to sensitivity analysis is proposed by Giannone, Lenza, and Primiceri (2015). For more details, see Table 2, which presents prior specifications for the key parameters in the Nelson–Phelps model. Densities are given with their support; indicator $1\{|\cdot|\leq 1\}$ denotes truncation to $[-1,1]$.

Table 2. Prior distributions for the key parameters c, g, s.

Prior	Density (support)	For parameter
Uniform (−1, 1)	$p(s) = 1/2 \cdot 1\{\|s\| \le 1\}$	s
Truncated normal (0, σ^2) on [−1, 1]	$p(s) = \varphi(s/\sigma) / (\sigma\cdot[\Phi(1/\sigma) - \Phi(-1/\sigma)]) \cdot 1\{\|s\| \le 1\}$	s
Truncated laplace lap (0, b) on [−1, 1]	$p(s) = \exp(-\|s\|/b) / (2b [1 - \exp(-1/b)]) \cdot 1\{\|s\| \le 1\}$	s
Truncated cauchy (0, τ) on [−1, 1]	$p(s) = [(1/\tau)/(1 + (s/\tau)^2)] / (\arctan(1/\tau) - \arctan(-1/\tau)) \cdot 1\{\|s\| \le 1\}$	s
Triangular on [−1,1], mode m ∈ [−1,1]	If m = 0 (symmetric): $p(s) = 1 - \|s\|$ for $s \in [-1,1]$. General m: $p(s) = (s+1)/(m+1)$ for $s \le m$; $p(s) = (1-s)/(1-m)$ for $s \ge m$; 0 otherwise.	s
Gamma (k, k) with k ∈ {1,2,3,4,5} (Shape=rate=k)	$p(x) = k^k / \Gamma(k) \cdot x^{k-1} \cdot \exp(-k x)$, $x>0$ (mean = 1, var = 1/k)	c, g

Note: • φ(·) and Φ(·) denote the standard normal pdf and cdf, respectively. • Truncated densities include their normalizing constants on [−1,1]. • Triangular density integrates to 1 on [−1,1] for any m ∈ [−1,1]. • Gamma(k,k) is placed on positive parameters such as c and g.

4. RESULTS AND DISCUSSION

4.1. Preliminary Analysis

Descriptive and correlation statistics are provided in this subsection.

First, as Table 3 reports, Growth_tech has a mean of approximately 2.87 (sd ~ 2.12), ranging from −0.46 to 10.58, implying considerable variation over time. Gap obtains a mean of approximately 0.39 (sd ~ 0.05), reflecting a significant distance to the frontier. lnHC has moderate dispersion on the log scale (mean ~ 0.90, sd ~ 0.07). Open and Tacit show moderate variation; RD centers around ~ 1.57 (% of GDP; sd ~ 0.61). Digital displays very wide dispersion (mean ~ 59, sd ~ 44, min near 0.56 and max ~ 124), which likely reflects early-period penetration and later saturation. High_tech averages ~ 66 (sd ~ 9.7). Note that coverage differs by variable (e.g., lnSEC has 14 observations; Edu 18; ICT 23), so multivariate models that include many variables simultaneously may shrink the usable sample substantially.

Table 3. Descriptive statistics.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Growth_tech	27	2.874	2.122	-0.461	10.577
lnHC	27	0.902	0.068	0.776	1.008
Gap	27	0.391	0.0497	0.309	0.474
Open	27	44.182	4.306	34.166	52.157
Tacit	27	50.592	8.602	30.046	59.721
FI	27	128.437	26.191	88.964	181.785
FDI	27	3.062	1.154	1.038	4.695
Edu	18	11.856	1.747	8.415	14.407
ICT	23	22.398	2.062	18	26.07
High_tech	27	66.233	9.689	51.486	80.623
Digital	27	59.096	44.296	0.558	124.195
RD	27	1.573	0.608	0.563	2.555
lnPRI	21	4.639	0.051	4.576	4.753
lnSEC	14	4.263	0.212	3.949	4.536
lnTER	27	3.116	0.823	1.667	4.276
Rule	24	-0.419	0.190	-0.670	0.010

Second, according to Table 4, a clear "capability cluster" emerges: lnHC, lnTER, lnSEC, Gap, Tacit, Digital, RD, Rule, and FI are all very highly correlated with each other (many pairwise correlations ≥ 0.90). For example, RD–Digital ≈ 0.99; RD–lnTER ≈ 0.99; Digital–lnSEC ≈ 0.98; Gap–(lnHC, lnTER, lnSEC) ≈ 0.94–0.97. Primary enrollment (lnPRI) moves inversely with this cluster (often ≤ −0.80), consistent with development-stage differences. High_tech import share is likewise strongly negative with the capability cluster (≈ −0.87 to −0.93), which is plausible if more capable economies internalize more high-tech production (lowering the import share). FDI is negatively associated with several capability measures (e.g., FI), potentially reflecting composition effects or differing growth/development strategies. Growth_tech shows only modest pairwise associations: the largest positive links are with Open (~ 0.47), ICT (~ 0.38), and FDI (~ 0.32); other correlations are small in magnitude and sometimes sensitive to limited coverage (e.g., Edu shows a negative correlation but has only 18 observations). The extremely high correlations among human-capital proxies, capability measures (RD, Digital, Rule, FI), and Gap indicate severe multicollinearity if included jointly. Consequences include inflated standard errors, unstable coefficients and signs, and sensitivity to variable inclusion. As recommended by several authors (Block et al., 2011; Bucur et al., 2019; Howey et al., 2020; Pesaran & Smith, 2019; Winship & Western, 2016) the Bayesian hierarchical method is one of the practical remedies.

Table 4. Correlation statistics.

Variables	Growth_tech	lnHC	lnTER	lnSEC	lnPRI	Gap	Open
Growth_tech	1.000						
lnHC	-0.115	1.000					
lnTER	-0.029	0.981	1.000				
lnSEC	0.139	0.945	0.966	1.000			
lnPRI	0.177	-0.885	-0.899	-0.790	1.000		
Gap	0.071	0.945	0.971	0.946	-0.797	1.000	
Open	0.468	0.510	0.617	0.788	-0.384	0.666	1.000
Tacit	-0.001	0.949	0.970	0.933	-0.823	0.936	0.709
FI	-0.311	0.937	0.877	0.638	-0.838	0.816	0.258
FDI	0.320	-0.890	-0.826	-0.464	0.821	-0.756	-0.185
Edu	-0.462	-0.097	-0.074	0.810	0.105	-0.231	-0.538
ICT	0.384	0.072	0.095	-0.379	-0.186	0.122	0.380
High_tech	0.114	-0.870	-0.893	-0.935	0.778	-0.898	-0.509
Digital	-0.153	0.979	0.970	0.980	-0.914	0.937	0.442
RD	-0.128	0.983	0.988	0.989	-0.881	0.960	0.542
Rule	-0.352	0.800	0.716	0.297	-0.672	0.699	-0.129
	Tacit	**FI**	**FDI**	**Edu**	**ICT**	**High_tech**	**Digital**
Tacit	1.000						
FI	0.805	1.000					
FDI	-0.780	-0.922	1.000				
Edu	0.063	-0.126	-0.111	1.000			
ICT	0.017	0.131	0.025	-0.797	1.000		
High_tech	-0.871	-0.723	0.703	-0.477	0.369	1.000	
Digital	0.916	0.910	-0.869	0.064	-0.054	-0.922	1.000
RD	0.952	0.901	-0.848	0.060	-0.033	-0.928	0.986
Rule	0.594	0.893	-0.832	-0.066	-0.004	-0.602	0.800
	RD	**Rule**					
RD	1.000						
Rule	0.754	1.000					

4.2. Main Analysis

Bayesian mixed regressions, utilizing well-specified informative priors on the key parameters (c, g, s) within a Nelson–Phelps catch-up framework, augmented by a neo-Schumpeterian growth perspective, yield three principal implications (Table 5).

First, the posterior estimates of c ≈ 3.9, g ≈ 0.1 and s ≈ -0.95 suggest that the empirical results are in full agreement with the theoretical structure of the Nelson–Phelps model: both c and g are positive as expected, and the estimated value of s lies within the theoretical range [-1,1], thereby confirming the correct nesting of the exponential and logistic diffusion properties. Theoretically, if s = 1, technology diffusion slows near the frontier economy (logistic case), while if s = −1, diffusion remains constant relative to the technological gap (exponential). We clarify the implied mechanism suggested by s ≈ -0.95: A posterior probability of 1.00 for the coefficient lends support for a strong exponential formulation where China's diffusion is fast, smooth, and mostly unconstrained by absorptive barriers. To put it differently, its productivity converges toward the U.S. level without the slowdown effect of logistic diffusion. This outcome agrees with Nelson and Phelps (1966) exponential catch-up mechanism and is in line with empirical studies (Ang et al., 2011; AtiqurRahman & Zaman, 2016; Benhabib & Spiegel, 1994; Correa-Lopez, 2008; Griffith et al., 2004; Kim & Terada-Hagiwara, 2010; Madsen et al., 2010; Thach, 2025b; Vandenbussche et al., 2006)

Second, this part interprets the mechanisms implied by c and g. A positive and relatively large estimated value of c (approximately 3.9) indicates the predominant adoptive capacity of human capital, demonstrating that China effectively absorbs cutting-edge technologies from the world. The smaller yet positive estimate of g (approximately 0.1) reflects an emerging innovation-driven mechanism: national R&D increasingly contributes to China's technological advancement. The strong evidence that c exceeds g indicates that China decisively shifts toward an innovation-driven model of development (Boeing, Mueller, & Sandner, 2016; Fang, He, & Li, 2020; Gunter, Zenglein, Meick, & Ohlberg, 2025; Lewis & Segal, 2022; Liu, 2011; Liu & White, 2001; Naughton, 2021; OECD, 2008; State Council, 2006; Sun & Cao, 2023; Wübbeke et al., 2016; Xi, 2020; Zhang, Sun, Delgado, & Kumbhakar, 2012; Zhou & Dahal, 2024; Zhou, Lazonick, & Sun, 2016).

This country's technological and economic evolution progressed in three main phases: (i) Implementation and accumulation of technological capacity (late-1970s – early-2000s), propelled by importing capital goods, OEM/ODM participation, licensing, and FDI spillovers (Albert, Jefferson, & Jinchang, 2005); (ii) Indigenous innovation (mid-2000s – mid-2010s), prompted by the 2006 Medium- and Long-Term S&T Plan, with mega-projects, IP improvements, talent programs, and procurement preferences; and (iii) A breakthrough push in advanced manufacturing and digital technologies alongside a marked increase in R&D intensity and patenting fillings (mid-2010s – present), directed by the Chinese government through large-scale programs such as "Made in China 2025," extensive applied/industrial R&D, and a recent pivot toward fundamental research. This result aligns with many earlier analyses, which attributed a prominent role to human capital in implementation and innovation (Ang et al., 2011; AtiqurRahman & Zaman, 2016; Benhabib & Spiegel, 1994; Benhabib & Spiegel, 2005; Correa-Lopez, 2008; Griffith et al., 2004; Howitt & Mayer-Foulkes, 2002; Kim & Terada-Hagiwara, 2010; Madsen et al., 2010; Mayer-Foulkes, 2002; Thach, 2025a; Thach, 2025b; Vandenbussche et al., 2006; Verspagen, 1991).

Third, beyond innovation-effective human capital, a suite of structural facilitators, including openness policies, FDI attraction policies, innovation-education policies, institutional quality, financial development, ICT diffusion, high-tech transfer, digital infrastructure, and overall technological capacity exert pronounced positive effects on technological growth in China, with posterior effect probabilities exceeding 0.70. These strong effects reflect a broadly favorable structural environment for technological progress, underscoring the effectiveness of China's integration, education, and innovation policies.

This finding aligns with prior literature that identifies human capital (Baumol, 1986; Bénabou, 1996; Benhabib & Spiegel, 2005; Durlauf, 1993; Galor & Tsiddon, 1997; Galor & Zeira, 1993; Howitt & Mayer-Foulkes, 2002; Perilla, 2024; Thach, 2025a; Tsiddon, 1992; Verspagen, 1991) international openness (Branstetter, 2001; Coe & Helpman, 1995; Eaton & Kortum, 1996; Griliches, 1992; Keller, 2004; Nadiri & Kim, 1996) governance quality (Benhabib & Spiegel, 1994; Benhabib & Spiegel, 2005; Parente & Prescott, 1999) financial development (Aghion, Howitt, & Mayer-Foulkes, 2005; Das & Drine, 2020) digital infrastructure (Aker & Mbiti, 2010) ICT and high-tech transfer (Das & Drine, 2020; Thach, 2025b; Zhu & Fu, 2013) and education and innovation investments (Howitt & Mayer-Foulkes, 2002; Thach, 2025a; Verspagen, 1991) as central drivers of technological progress and catch-up. By contrast with some prior work (e.g., (Howitt & Mayer-Foulkes, 2002; Keller, 2004; Thach, 2025b), our estimates suggest that tacit-knowledge spillovers have an ambiguous effect.

Table 5. Posterior estimates using Gamma (1,1) priors for c and g, and Truncated Normal N(0, σ^2) on [-1, 1] for s.

Parameter	Mean	Std. dev.	MCSE	Probability of effect	95% credible interval
b	7.725	7.019	1.826	0.70	[-4.815, 22.157]
c	3.916	0.377	0.046	1	[3.205, 4.615]
g	0.077	0.058	0.012	1	[0.003, 0.219]
s	-0.954	0.042	0.006	1	[-0.998, -0.843]
Open	0.148	0.413	0.038	0.95	[-0.720, 0.967]
Tacit	0.614	0.275	0.042	0.52	[0.057, 1.110]
Rule	1.742	0.262	0.022	1	[1.217, 2.264]
FI	0.085	0.144	0.027	0.71	[-0.199, 0.352]
ICT	1.797	0.589	0.153	0.99	[0.779, 2.883]
Hi-tech	-1.020	0.180	0.032	1	[-1.371, -0.654]
Digital	-0.417	0.086	0.014	0.99	[-0.591, -0.260]
RD	0.715	0.477	0.049	0.99	[-0.203, 1.566]
FDI	-2.995	0.536	0.073	0.99	[-3.996, -1.894]
Edu	0.184	0.086	0.009	0.99	[0.024, 0.354]
Random-effect variance	11.777	7.123	0.199	1	[4.270, 29.591]
Overall variance	14.356	7.513	0.568	1	[5.747, 33.056]

Finally, Table 5 demonstrates that the control variables ICT diffusion, digital infrastructure, high-tech transfer, and institutional quality exhibit high correlations conceptually and economically. Although the Bayesian mixed-effects approach specifying informative priors mitigates the most severe consequences of multicollinearity (through shrinkage of parameter uncertainty), it may not eliminate the issue.

Posterior standard deviations and credible intervals reflect shared explanatory power. Even though most variables show high posterior effect probabilities (e.g., ICT = 0.99, rule of law = 1.00, digital infrastructure = 0.99), their overlapping conceptual domains imply that individual coefficient magnitudes should not be interpreted as entirely independent structural effects.

4.3. Robustness Checks

For robustness analyses, some alternative indicators—namely primary, secondary, and tertiary enrollment ratios—are substituted for the Mincer human-capital measurement. The estimates of c, g, and s preserve their expected signs across these alternatives, ensuring the robustness of the results (Table 6, Appendix A).

Furthermore, to evaluate robustness, we vary the prior specifications for c and g to Gamma (2,2), Gamma (3,3), Gamma (4,4), and Gamma (5,5) (Table 7), and for s to Uniform [−1,1], truncated Laplace, truncated Cauchy, and triangular distributions (Table 8). The results hold consistently across prior choices: c and g take positive signs, while s approaches −1. Moreover, we typically find c > g in most cases, favoring the predominance of adoption-driven growth mechanisms.

Finally, when inspecting MCMC convergence, we detect no signs of non-convergence. For illustrative purposes, we present kernel density plots for the key parameters (Figure 1). Similarly, CUSUM and histogram plots perform well (Figures 2-3, Appendix B).

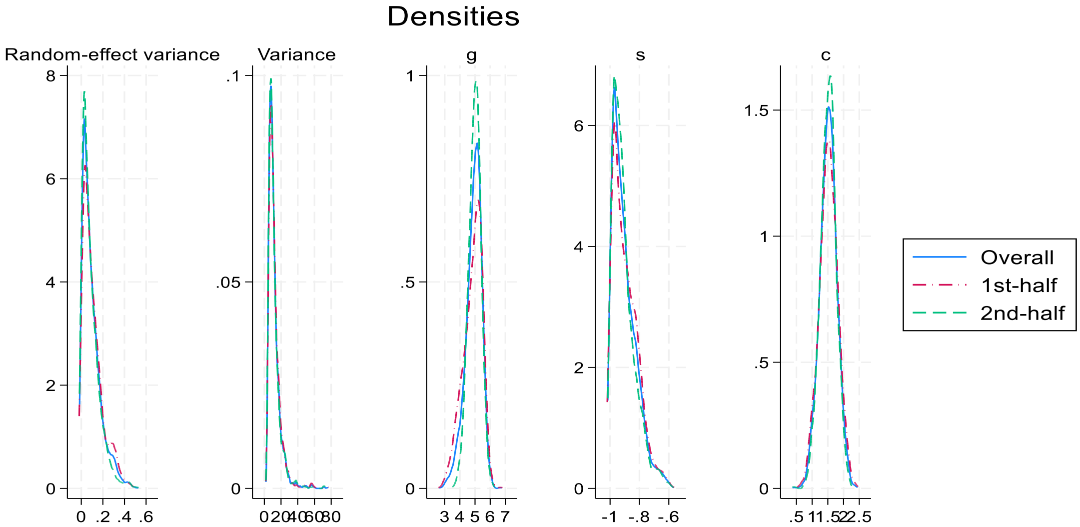

Figure 1. Graphical diagnostics.

5. CONCLUSION, LIMITATION, AND FUTURE RESEARCH

China's remarkable development from an investment-driven manufacturing base to a powerful nation of innovation represents one of the most significant structural transformations in the modern era. Empirical outcomes based on Bayesian analysis and neo-Schumpeterian diffusion insights confirm that China has been technologically converging with the United States during the period from 1996 to 2022. This catch-up pattern indicates that, while China is approaching the technological frontier, its innovation ecosystem still primarily depends on technology diffusion and policy-led industrial modernization. However, when interacting with a range of absorptive capabilities, including governance effectiveness, financial capacity, liberalization, R&D employment, and digital infrastructure, human capital that fosters innovation increasingly contributes to China's steady transition from imitation to original innovation. Therefore, the effective interaction between human absorptive capacity and these structural facilitators remains crucial for strengthening convergence momentum.

Policy implications for China: China should decisively shift from increasing the volume of R&D toward fostering positive changes, prioritizing creativity, multidisciplinary scholarship, and supporting intellectual property protection to translate R&D expenditure into genuine cutting-edge innovation. Such a reorientation should be based on inclusive institutions. Indeed, more transparent governance and more efficient public–private coordination are ultimately crucial to convert policy-enhanced programs into market-sustained technological achievements. In parallel, to further assimilate frontier technologies, China should continue expanding global relations trade, investment, and R&D cooperation while systematically bolstering resilience against external negative influences. Finally, reinforcing innovation-effective human capital for state-of-the-art technologies is instrumental. Advanced STEM-oriented education, AI literacy across the labor force, and well-structured international mobility programs will accelerate the transition from implementation to original creation.

Policy implications for other developing countries: First, let us emphasize that the Nelson–Phelps model of technology diffusion employed is structurally general, but our estimated parameters are specific to the China–US technology gap and to China's contemporary institutional and developmental characteristics. The catch-up framework is constructed to account for how high skills, governance quality, and other absorptive capabilities shape the pace of catch-up to the technological leader. This mechanism is not unique to China; however, the quantitative magnitudes and the specific frictions we uncover are, by construction, China-specific. Therefore, we explicitly describe our analysis as a detailed case study of China's catch-up vis-à-vis the U.S., rather than a universal template. Second, the policy implications for China are presented as a direct interpretation of the estimated adjustment dynamics for this particular follower–leader pair. Our recommendations that China move from quantitative expansion of R&D toward qualitative upgrading, strengthen institutions and public–private coordination, deepen but also de-risk its global linkages, and invest heavily in frontier-oriented human capital are grounded in the empirical finding that China's catch-up potential is increasingly constrained by the quality of its innovation system rather than by sheer scale. We now stress that these China-specific lessons are conditional on China's current stage of development, the size and complexity of its economy, and its relatively advanced position close to the frontier.

Third, concerning "policy implications for other developing countries," we emphasize that these are not mechanical extrapolations of the China–US estimates. Instead, they are framed as structured hypotheses and stylized lessons derived from the general Nelson–Phelps logic, informed by China's experience but requiring careful adaptation to local conditions. Specifically: (i) the suggested dual-path strategy combining disciplined technology absorption with gradually rising domestic R&D follows directly from the model's emphasis on absorptive capacity and the transition from imitation to innovation, but we now explicitly state that the relative weights of absorption versus indigenous R&D will differ across countries depending on income level, human capital, institutional quality, and fiscal capacity; (ii) recommendations on industrial policy are presented as contingent on each country's constraints and comparative advantages. We explicitly warn against "copying China" by attempting large-scale high-tech pushes in settings where human capital, financial depth, or state capacity are insufficient, and we highlight staged upgrading and cumulative capability-building as the core transferable principles; (iii) the discussion of global linkages and South–South cooperation is now explicitly positioned as a way to diversify learning channels and reduce dependence on a narrow set of advanced economies, rather than as evidence derived uniquely from the China–US dyad.The study faces two primary limitations. First, while the Bayesian hierarchical framework effectively addresses many statistical challenges, further improvements could be achieved by employing Bayesian instrumental-variables and latent-variable models. These alternatives would facilitate a more in-depth examination of temporal heterogeneity and allow for additional refinements to the empirical specifications, resulting in clearer explanations of technology convergence in China and other emerging economies. Second, it is important to acknowledge the constraints associated with Bayesian prior sensitivity. The parameter s determines whether the empirical dynamics resemble an exponential or logistic form within the Nelson–Phelps framework. Theory stipulates that s must lie within the closed interval $[-1, 1]$ to ensure the model encompasses relevant diffusion cases and avoids implausible or unstable adjustment dynamics. Although the empirical results for s are qualitatively stable across different priors, there are inherent practical limitations to prior sensitivity analysis in complex hierarchical Bayesian models. The high-dimensional nature of the parameter space, which includes s and other structural and hierarchical parameters, makes exploring all possible prior configurations computationally infeasible. Our mixed-effects model already involves intensive MCMC sampling and using diffuse or heavy-tailed priors for multiple parameters can impair mixing, increase Monte Carlo error, and reduce the reliability of posterior estimates. Consequently, our sensitivity analysis concentrates on a structured, theoretically motivated subset of priors for the key parameter s, rather than attempting an exhaustive exploration of all potential prior configurations.

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Appendix A.

Table 6. Alternative human capital proxies: Specification comparison.

Parameter	HC	TER	SEC	PRI
c	3.916	2.302	0.614	1.298
g	0.077	0.346	0.283	0.249
s	-0.954	-0.129	-0.886	-0.339

Table 7. Comparison of prior specifications for *c* and *g*.

Parameter	Gamma (1,1)	Gamma (2,2)	Gamma (3,3)	Gamma (4,4)	Gamma (5,5)
c	3.916	1.574	1.663	1.070	2.389
g	0.077	1.799	0.829	0.588	3.484
s	-0.954	-0.988	-0.235	-0.799	-0.341

Table 8. Comparison of prior specifications for *s*.

Parameter	Truncated normal	Truncated laplace	Truncated cauchy	Triangular	Uniform (-1.1)
c	3.916	0.143	0.068	0.626	0.245
g	0.077	0.254	2.987	0.281	0.272
s	-0.954	-0.971	-0.785	-0.968	-0.866

Appendix B.

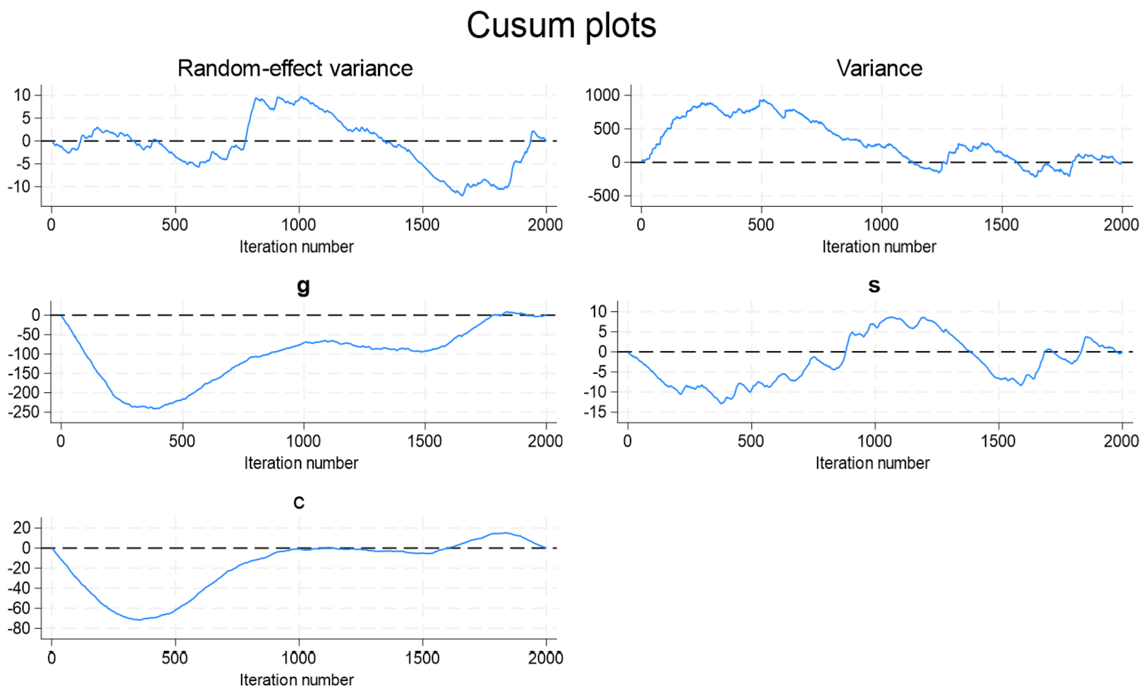

Figure 2. Graphical diagnostics (CUSUMs).

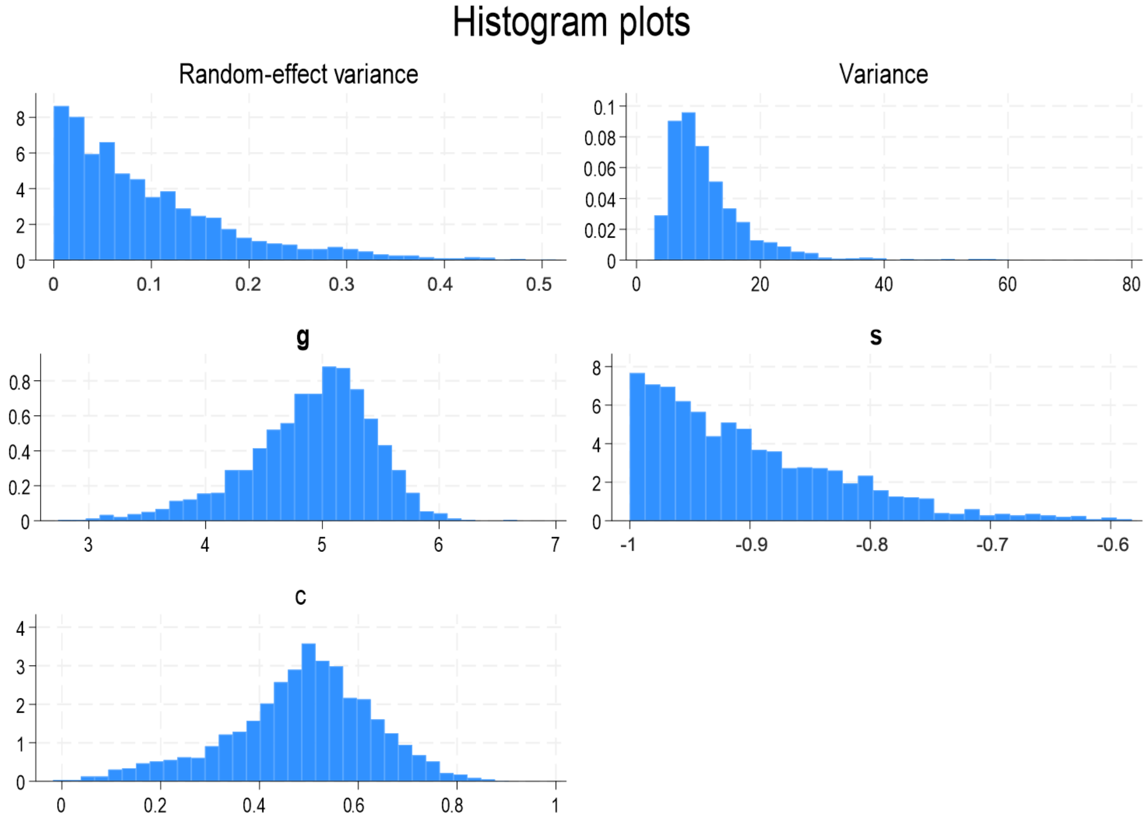

Figure 3. Graphical diagnostics (Histograms).