The Neoclassical Growth of China

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Abstract

This paper examines how China's per capita GDP grew more than tenfold relative to the U.S. between 1978 and 2023. We show that China's growth trajectory closely mirrors the earlier East Asian miracles. A simple Ramsey–Cass–Koopmans model, extended to incorporate observed changes in relative TFP, captures real GDP growth in China and the other East Asian economies reasonably well. We then combine this framework with a parsimonious TFP catch-up process to assess China's prospects. If China's TFP convergence follows the pattern of its regional predecessors, the model predicts a substantial slowdown: U.S. growth would overtake China's by 2034, driven by faster American population growth and decelerating TFP catch-up. By 2100, China's income per capita is projected to settle at roughly 38% of the U.S. level.

Keywords: China, East Asia, economic growth, Ramsey-Cass-Koopmans model, TFP catch-up.

JEL codes: E10, E20, O4

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1 Introduction

China's real per capita GDP rose from about 2.6% of the U.S. level in 1978 (on the eve of economic reform) to 30% in 2023 (the last year of data in Penn World Tables 11.0, PWT 11.0), a more than tenfold catch-up in just 46 years.[1] This extraordinary rise is one of the most striking developments in economic history, and it has made China the world's largest economy in PPP terms.

Against this backdrop, this paper uses a neoclassical framework to study China's growth experience and assess what its past implies for its future. Two central findings emerge. First, China's aggregate growth path bears a clear family resemblance to the earlier East Asian miracles. Second, a simple Ramsey–Cass–Koopmans model, augmented with a parsimonious TFP catch-up process, accounts well for China's real GDP dynamics and those of its regional peers. Extending China's TFP trajectory beyond 2023, and assuming it follows the pattern of these neighboring economies, the model projects a sharp slowdown. U.S. output growth would overtake China's by 2034, as most of China's catch-up is then nearly complete and its demographic outlook is deteriorating.

We begin by comparing China's experience with that of Japan, Korea, Taiwan, Hong Kong, and Singapore.[2] At first glance, China's catch-up looks much like theirs: rapid early growth followed by a marked slowdown. Yet this similarity masks a key difference. China's TFP has traced the same broad convergence pattern as these economies, but starting from a much lower level, while its investment rate has been considerably higher.

This contrast motivates our use of a minimalist Ramsey–Cass–Koopmans one-sector model augmented with a parsimonious TFP catch-up process. We calibrate the model to standard aggregate targets, feed in observed TFP through 2023, and infer the post-2023 TFP path from the historical catch-up patterns of earlier East Asian miracles. We remain agnostic about the specific forces behind TFP catch-up in China or in these economies. Instead, we aim to provide a simple and transparent way to understand the broad contours of China's growth.

The result of this exercise is striking. The model matches China's income per capita growth from 1978 to 2023 *surprisingly* well. We stress *surprisingly* because the model is intentionally simple. It omits many mechanisms emphasized in the literature, such as sectoral reallocation, financial development, industrial policy, foreign direct investment, and trade

[1]Unless otherwise noted, all per capita measures are from PWT 11.0 and adjusted for purchasing power parity (PPP). We set the threshold for classifying a country as a middle-income nation at $3,000 in 2021 PPP-adjusted dollars, a commonly used benchmark.

[2]To conserve space, we refer to the Republic of Korea; China, Taiwan Region; and China, Hong Kong SAR as Korea, Taiwan, and Hong Kong throughout this article.

reforms. Yet despite these omissions, the model captures the main arc of China's growth and offers a tractable benchmark for thinking about what comes next. We do not dismiss the importance of these or other factors. Rather, the analysis suggests that many of their key effects are embodied within a straightforward productivity catch-up process operating in a standard one-sector framework.

Our model also matches the level of the investment rate in China. This success is noteworthy, as the literature on the neoclassical growth model has long struggled to replicate China's high investment rates (see the discussion in King and Rebelo, 1993, and Christiano, 1989). The model performs less well in explaining measured investment rates after 2008. Nonetheless, two considerations help reconcile the data with the model. First, several indicators suggest that China's official investment rates are mismeasured. Using the corrected series from Chen et al. (2019), the model aligns closely with observed investment. Second, we present evidence that investment efficiency in China is low after 2008, which creates a wedge between investment and output growth.

We apply the same minimalist model (with modest economy-specific recalibration) to Japan, Korea, Taiwan, Hong Kong, and Singapore, and we find that it also accounts well for these growth episodes. This result strengthens our interpretation, particularly because these other miracles unfolded in different institutional and policy environments and span many more years than the analysis for China. For example, the model must incorporate Japan's population decline, as documented by Fernández-Villaverde et al. (2025). The longer time horizon for these economies also sheds light on China's future, as TFP growth relative to the U.S. declined steadily in all cases after their growth-miracle stage.[3]

The common growth experiences of China and the other miracles, together with the model's quantitative success, allow us to assess China's prospects. Using the model and the fitted TFP catch-up process, we project that China's relative per capita GDP will reach about 38% of the U.S. level around 2100, a result driven by the sharp deceleration of China's TFP catch-up in recent years. Moreover, based on China's forecast demographics, which we take from the UN (a relatively optimistic scenario that assumes a significant rebound in fertility), the model predicts that U.S. output will grow faster than China's by 2034. Slowing TFP growth and a shrinking population point toward a Chinese economy whose future looks far less dynamic than its past.

This analysis builds on much previous research. Most importantly, given our neoclassical approach, Barro (2016) has argued that, from the perspective of conditional convergence,

[3]Even though this lies beyond the geographical scope of our paper, it is worth noting that Western European economies display a similar pattern. Their convergence toward the U.S. stalled in the late 1980s and, in several cases, reversed during the 2010s.

China's GDP growth rate since 1990 has been surprisingly high, and that consequently, China's growth is likely to fall back toward historical averages. We show that Barro's findings can be reconciled with neoclassical growth by introducing a process of TFP catch-up. Furthermore, our projection of China's future growth supports Barro's view that China's growth will decline and provides a quantitative assessment of China's economic future relative to that of the U.S.

Pritchett and Summers (2013) elaborate on the regression to the mean in terms of growth across many economies. Additionally, they argue that discontinuous drop-offs often follow rapid growth episodes. The authors conjecture that China's salient characteristics, such as high levels of state control and authoritarian rule, make a discontinuous decline in growth relatively likely. We reach a similar conclusion, reflecting a rapid decline in TFP catch-up, which in turn may be related to the institutional aspects emphasized by these authors.

Song et al. (2011) construct a growth model consistent with China's economic transition. The key behind their dynamics is that firms that use more productive technologies must finance investments through internal savings due to financial market imperfections. The most intriguing aspect of their model is that downsizing financially integrated firms forces domestic savings to be invested abroad, thereby generating a foreign surplus. Since we do not deal with an open economy, we do not explore this aspect of China's growth experience. Thus, we view our paper as complementary to Song et al. (2011). Chen and Zha (2023) highlight the importance of the gradualist approach to China's reforms and compare the path under gradualism with a laissez-faire counterfactual. The authors devote considerable attention to the trade-offs between active government interventions and long-term growth.

Our emphasis on the low investment efficiency in China is shared by Bai et al. (2020), who focus on the distortions created by loans from local authorities to unskilled labor-intensive firms after 2008. Similarly, Jiang et al. (2022) analyze the role of local governments in using land-sale revenue to fund infrastructure investment and how such a policy leads to declining capital returns. Song and Xiong (2023) studies the agency problem between the central and local governments, which may lead to overinvestment and unreliable economic statistics.

Our paper is also related to studies on China's business cycle fluctuations, such as Chang et al. (2019) and Yao and Zhu (2021). In particular, Chang et al. (2016) explore the policy implications of subsidized investments in capital-intensive industries facing a collateral constraint within a distorted banking system and find that these subsidies increased China's growth.

Finally, our paper connects to the literature on Japan's growth experience, the first East Asian growth miracle. Christiano (1989) argues that the neoclassical growth model cannot account for Japan's postwar saving experience. Interestingly, he obtains much better results when he slows convergence to the model's balanced growth path (BGP) by introducing a minimum consumption level. Our assumption of TFP catch-up with respect to the U.S. generates the same basic mechanism (slower convergence to the BGP, since there is a strong incentive to accumulate more capital only after TFP has caught up). This idea is supported by Chen et al. (2006), who show that using actual Japanese TFP growth rates in a standard growth model produces saving rates close to those in the Japanese data between 1956 and 2000. Parente and Prescott (1994) examine how barriers to technological adoption slow convergence to a BGP and account for large differences in income per capita.

The rest of the paper is organized as follows. Section 2 compares China's growth experience with that of other Asian growth miracles. Section 3 presents the model, and Section 4 calibrates it. Section 5 reports our quantitative results for China. Section 6 extends the model to the other East Asian growth miracles. Section 7 concludes. An Appendix provides additional details about the data and presents further quantitative exercises, including growth accounting.

2 Stylized Facts on China's Growth

This section compares China's GDP per capita growth and investment rate to those of other East Asian economies at similar stages of development, providing a benchmark for interpreting China's growth. Let us first define our data.

Data. Data for China, Japan, Korea, Taiwan, Hong Kong, and Singapore come from the Penn World Tables (PWT) 11.0 (see Feenstra et al., 2015).

The real GDP corresponds to $RGDP^O$ in PWT 11.0, which is the production-side real GDP based on prices that are constant across countries and over time. The population variable corresponds to *pop* in PWT 11.0. However, these data are slightly lower than those from the China Statistical Yearbook 2024, published by the National Bureau of Statistics (NBS).[4] The difference is not quantitatively significant.

The investment variable corresponds to v_{gfcf} (or $v_{gfcf} + v_x + v_m$) in PWT 11.0. We define the investment rate as nominal investment over nominal output, which avoids potential issues with relative price adjustments that arise when using real series (Whelan, 2002). Finally, the labor share corresponds to *labsh* in PWT 11.0.

China's GDP growth. We compare China with other East Asian economies starting from similar income per capita levels. We identify the year in which China, Korea, and Taiwan

[4] https://www.stats.gov.cn/sj/ndsj/2024/indexch.htm

each reached the per capita income level of Japan in 1950 — the earliest year available for Japan in PWT 11.0. Japan's income per capita in 1950 was \$3,138 (2021 PPP dollars), matching China in 1995, Korea in 1972, and Taiwan in 1961.[5] We then trace the evolution of GDP and investment for each economy from that point onward. While it would be interesting to compare the evolution of these economies from an earlier level of income per capita, we are limited by data availability in the PWT.

In Appendix B, we extend the analysis to include Hong Kong and Singapore, which also experienced rapid growth. We exclude them from the main text to avoid cluttering the graphs and because their dynamics may reflect factors specific to their status as city-economies.

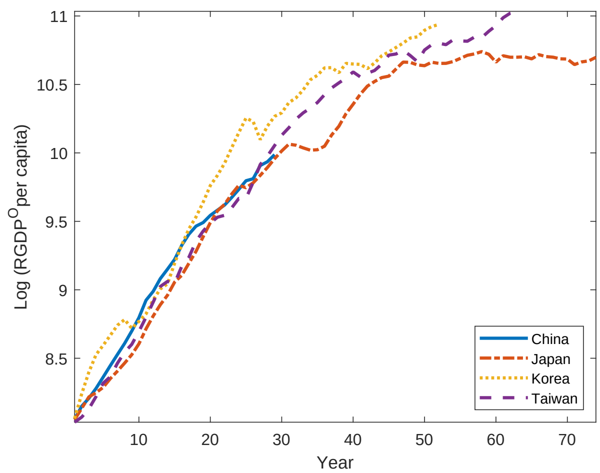

Figure 2.1: GDP per capita, normalized at China's GDP per capita in 1995

Figure 2.1 shows real GDP for China, Japan, Korea, and Taiwan, each starting at approximately the same per capita income level. The most striking aspect is how closely China's per capita GDP path mirrors those of the three other East Asian miracle economies. After almost 30 years of becoming middle-income economies, China, Japan, and Taiwan had nearly the same per capita real GDP. The one exception is Korea, which was somewhat ahead of the others. These data show nothing unusual about China's real GDP growth compared to these economies.

Figure 2.2 compares China's GDP per capita to the average of the other three economies (what we will call the "representative Asian economy"). China's real GDP path has been slightly below that of the representative Asian economy over the last 10 years.

Figure 2.3 shows a very similar pattern between China and the other East Asian economies when per capita real GDP is measured using two alternative definitions: the expenditure approach ($RGDP^E$) and the national accounts approach ($RGDP^{NA}$). Note that the right

[5] This initial per capita income of \$3,138 is close to the middle-income threshold (\$3,000) used by many international institutions and statistical agencies.

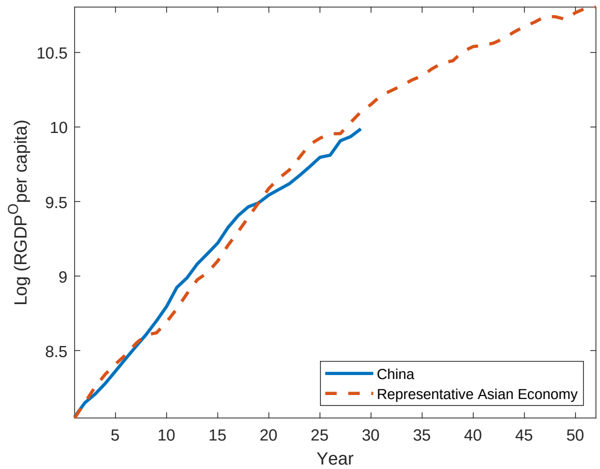

Figure 2.2: GDP per capita, normalized at China's GDP per capita in 1995

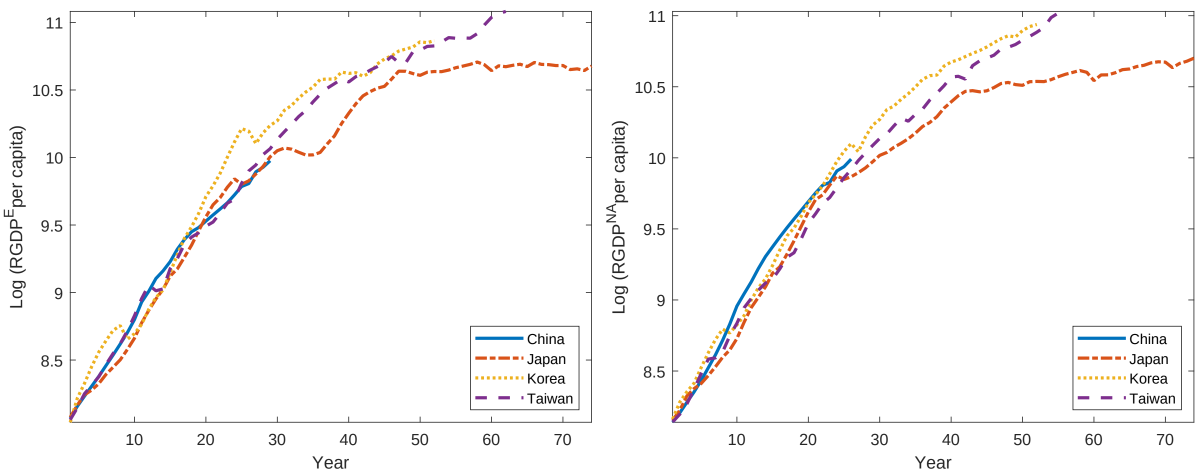

Figure 2.3: GDP per capita, alternative definitions with alternative base year

panel, which reports the national-accounts measure, begins at China's 1998 per capita income level rather than 1995, because China's $RGDP^{NA}$ per capita in 1998 (\$3,427) most closely matches Japan's level in 1950 (\$3,478).

A possible shortcoming of the previous figures is that the world technological frontier was at a different point when China had income levels similar to those of the other East Asian economies. To control for this, we examine the evolution of each economy's GDP per capita relative to the U.S. level. This assumes that U.S. GDP per capita is a reasonable proxy for what is achievable given the world technological frontier and prevailing social institutions.

The left panel of Figure 2.4 shows that China's performance is less impressive than that of the other economies. This is unsurprising: Figure 2.1 shows that China's growth was roughly similar to the others', but it started much later, when U.S. GDP per capita was significantly higher. This implies that China benefited from an even more advanced

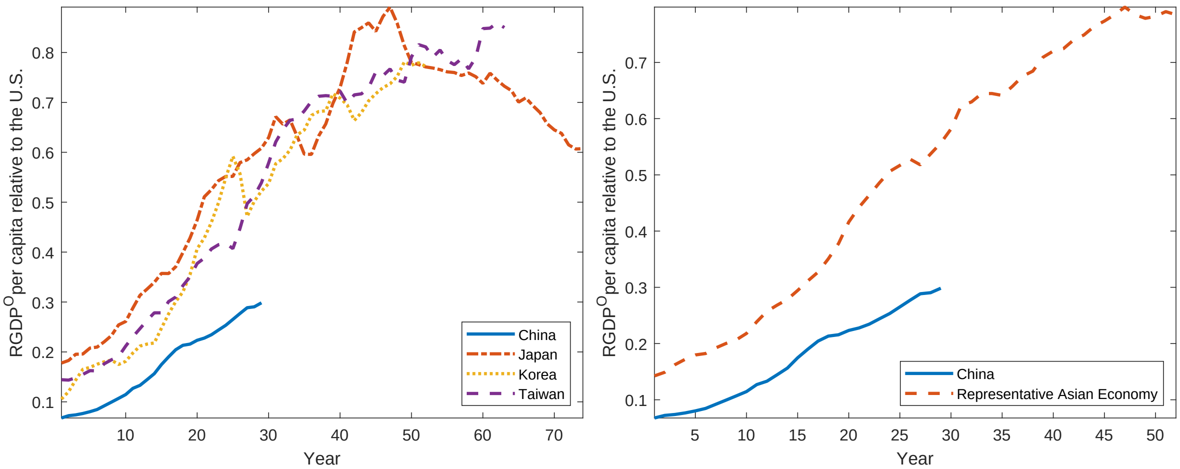

Figure 2.4: GDP per capita relative to the U.S., normalized at China's GDP per capita in 1995

technological frontier for its catch-up. This idea of distance to the frontier will play a key role in our model in Section 3. The right panel of Figure 2.4 replicates Figure 2.2, but now compares China's GDP per capita relative to the U.S. with the average relative GDP per capita of the "representative Asian economy" defined above.

China's investment rate. Figure 2.5 plots the investment rate for China, Japan, Korea, and Taiwan from the same initial year as in Figure 2.1. Figure 2.6 does the same but plotting China and the "representative Asian economy."

The left panel in both figures presents gross fixed capital formation (GFCF) as a share of GDP, while the right panel uses an alternative measure (the sum of GFCF and net exports over GDP). All variables are in nominal terms. The data show that China's nominal investment rate is qualitatively similar to that of the other Asian miracle economies, and somewhat higher in quantitative terms. This pattern also holds when the investment rate is expressed in real terms.

Figure 2.7 plots the return to capital across economies. Bai et al. (2006) construct the return to capital in China from 1978 to 2005, and Chen et al. (2019) extend their results to 2016. According to Chen et al. (2019), China's return to capital fell sharply after 2008 and became substantially lower than in the other economies, suggesting low investment efficiency.[6] This observation will play an important role when we discuss how our model matches the observed investment data.

[6] PWT 11.0 also reports rates of return to capital for China. We believe the data from Chen et al. (2019) are superior. In any case, results using PWT 11.0 data are very similar and available upon request.

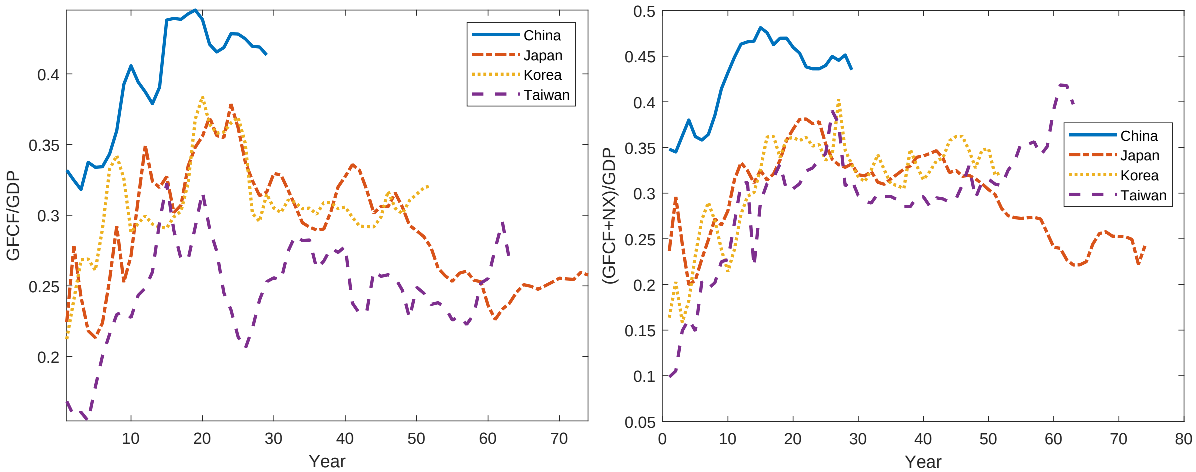

Figure 2.5: Investment rates

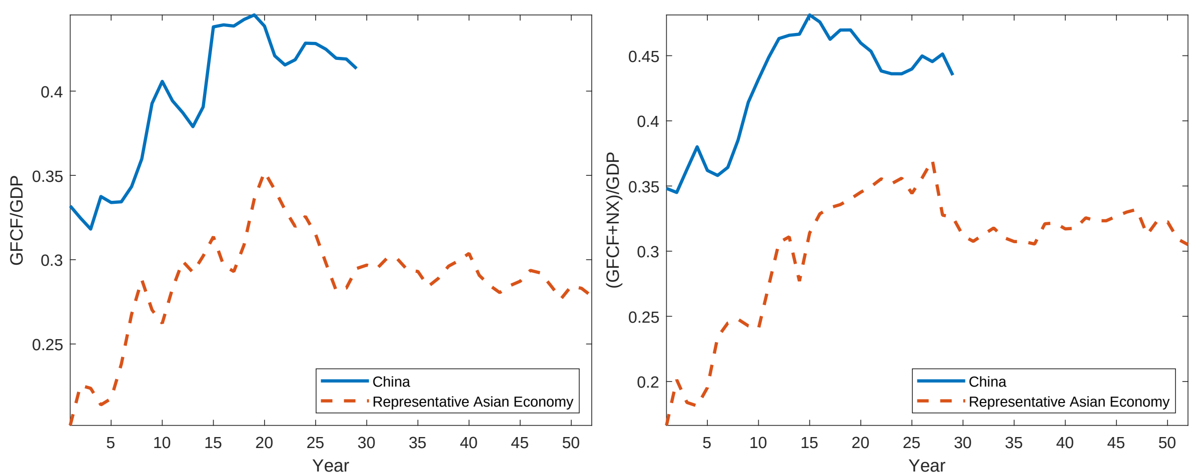

Figure 2.6: Investment rates

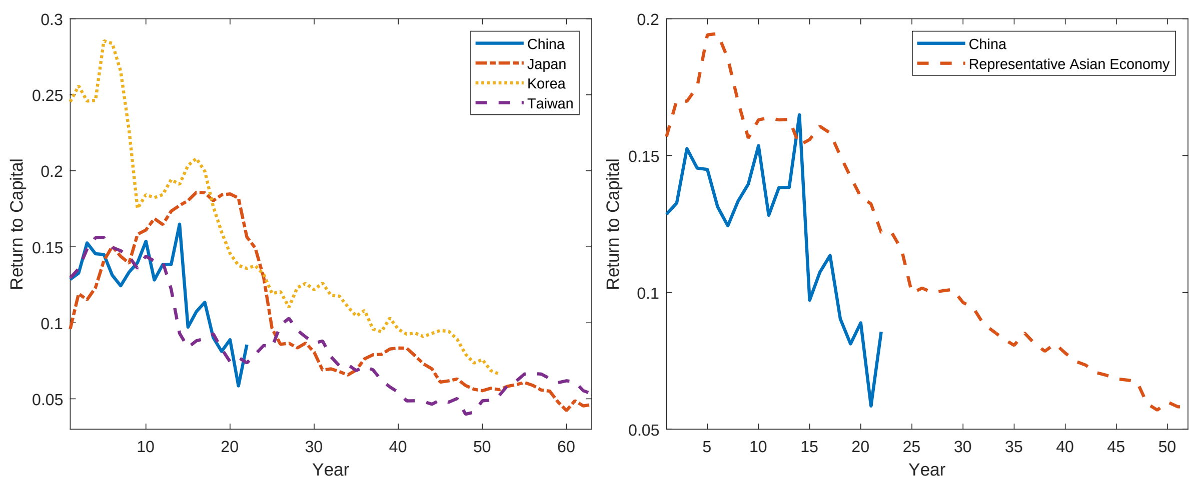

Figure 2.7: Return to capital

Taking stock. We have documented two central features that link China's growth experience to those of Japan, Korea, and Taiwan, while also highlighting key differences in the sources of growth:

1. China has expanded at roughly the same aggregate growth rate as the earlier East Asian economies. The difference is scale, since China's far larger population gives its growth a much greater global impact.

2. China's investment rate has been qualitatively similar and quantitatively somewhat higher, suggesting capital accumulation contributed more to growth in China. On the other hand, the return to capital in China is lower than in the other economies.

The next section uses a minimalist growth model to interpret these facts.

3 A Minimalist Neoclassical Growth Model

This section presents a deterministic, discrete-time Ramsey-Cass-Koopmans framework with two countries. One country is at the technological frontier, with technology growing at a constant rate. The other country starts at a lower level of technology but, deterministically, catches up to a fraction of the frontier. The only connection between the two countries is technological diffusion from the frontier to the catch-up country. These are the only elements needed to make our points, allowing us to abstract from complex features such as endogenous technology, uncertainty, multiple sectors, international trade, and other complications. More broadly, our results suggest that to the extent such complexities influenced China's growth, they may be reasonably captured by our TFP catch-up process.

Preferences and technology. The economy consists of two countries. The first country (China) is populated by an infinitely lived representative household of varying size N_t and whose preferences over per capita consumption are:

$$\max_{C_t/N_t} \sum_{t=0}^{\infty} \beta^t N_t \log\left(\frac{C_t}{N_t}\right),$$

where β is the discount factor and C_t is aggregate consumption.

China's output is given by $Y_t = K_t^{\theta}(A_t L_t)^{1-\theta}$ where K_t is capital, A_t is China's level of labor-augmenting technology, and L_t is employment (which we assume is time-varying and given exogenously). Recall, when we present results in the next sections, that TFP is equal to $A_t^{1-\theta}$.

Output is used for consumption or investment I_t, which induces a law of motion for capital $K_{t+1} = I_t + (1-\delta)K_t$, where δ is China's depreciation rate. China's resource constraint is given by $C_t + I_t = Y_t$. Finally, we assume that China's population N_t grows at a time-varying rate n_t, so that $N_t = \prod_{i=1}^{t}(1+n_i)$, given $N_0 = 1$.

The second country, which we will call the U.S., is also populated by an infinitely lived representative household of varying size N_t^* (when a variable or a parameter does not have a superscript star, it denotes either a parameter for China or a parameter common to the U.S. and China) with the same preferences:

$$\max_{C_t^*/N_t^*} \sum_{t=0}^{\infty} \beta^t N_t^* \log\left(\frac{C_t^*}{N_t^*}\right),$$

and technology $Y_t^* = (K_t^*)^{\theta^*}(A_t^* L_t^*)^{1-\theta^*}$.

This technology is the same as China's, except for four elements. First, the capital share in the U.S. is θ^*. Second, the depreciation rate in the U.S. is δ^*. Differences between China and the U.S. in the elasticity of output with respect to capital and in the depreciation rate might reflect variation in industry composition, production techniques, or maintenance decisions by firms, factors that we do not model.[7] Third, the U.S. population grows at a time-varying rate n_t^*, so that $N_t^* = \prod_{i=1}^{t}(1+n_i^*)$, given $N_0^* = 1$. Because we compare China and the U.S. only in terms of relative per capita income, population size does not affect our results, and the normalization $N_0 = N_0^* = 1$ is irrelevant. Fourth, the U.S. technology level A_t^* represents the world technological frontier and grows at the exogenously given rate g, that is, $A_t^* = (1+g)^t$.

China's labor-augmenting technology is a time-varying fraction of the U.S. level, $A_t = \lambda_t A_t^*$, where λ_t is China's technology level relative to the U.S. at time t. This time variation is key to our model because, as Appendix C documents using growth accounting, TFP growth accounts for 80% of China's income per capita growth from 1978 to 2023.

The stationary problem. Given the model has continuous growth, we follow standard practice and normalize the variables. We use the growth rates of U.S. technology and China's population to make the problem stationary in China. We use the U.S. growth rate of technology as a scaling factor because $A_t = \lambda_t A_t^*$.

[7] See, on maintenance and repair, McGrattan and Schmitz (1999). Below, we use data from PWT 11.0 to discipline our choices for θ and δ.

Specifically, let $c_t = \frac{C_t}{A_t^* N_t}$, $k_t = \frac{K_t}{A_t^* N_t}$, $i_t = \frac{I_t}{A_t^* N_t}$, and

$$y_t = \frac{Y_t}{A_t^* N_t} = \left(\frac{K_t}{A_t^* N_t}\right)^{\theta} \left(\frac{A_t L_t}{A_t^* N_t}\right)^{1-\theta} = k_t^{\theta} (\lambda_t l_t)^{1-\theta},$$

where l_t denotes the exogenously given employment-to-population ratio L_t/N_t.

Therefore, we rewrite the social planner's problem for China as follows:

$$\max_{c_t} \sum_{t=0}^{\infty} \beta^t N_t \log c_t$$

subject to:

$$y_t = k_t^{\theta} (\lambda_t l_t)^{1-\theta},$$
$$c_t + i_t = y_t,$$
$$i_t = (1+g)(1+n_{t+1})k_{t+1} - (1-\delta)k_t.$$

A standard Euler equation characterizes the solution to the optimization problem:

$$c_t^{-1}(1+g) = \beta c_{t+1}^{-1} \left(\theta k_{t+1}^{\theta-1} (\lambda_{t+1} l_{t+1})^{1-\theta} + 1 - \delta\right).$$

There is an equivalent stationary problem for the social planner in the U.S., in which we use the U.S. growth rates of technology and population to scale the variables, but we omit this for brevity. The Euler equation for this normalized problem is given by:

$$(c_t^*)^{-1}(1+g) = \beta (c_{t+1}^*)^{-1} \left(\theta^* \left(k_{t+1}^*\right)^{\theta^*-1} \left(l_{t+1}^*\right)^{1-\theta^*} + 1 - \delta^*\right).$$

4 Calibration

We calibrate the parameters of our model annually using data from 1978 to 2023. We begin in 1978, the eve of China's economic reforms. We end in 2023, the final year of our dataset. Our calibration, therefore, captures the full arc of China's reform-driven growth. For completeness, we also consider a calibration starting in 1995 to match the empirical analysis in Section 2. As shown in Appendix E, the results remain virtually unchanged. This reinforces our preference for the 1978 start date, which offers a broader perspective on China's growth.

4.1 Standard Parameters

First, population growth rates are calibrated to match observed annual data for both countries, using United Nations population projections through 2100, the most recent estimates available as of 2025.

Next, we set the discount factor $\beta = 0.94$ to match an 8.1% annual return to capital reported by PWT 11.0 for the U.S. between 1978 and 2023 (note that our model targets the return on all capital goods, not on bonds or other financial assets). The capital share for the United States is set to $\theta^* = 0.39$, matching the average value in PWT 11.0. For China, we adopt a higher capital share of $\theta = 0.5$ rather than the PWT value of 0.42. Bai et al. (2006) support this higher value using provincial capital income share data from China's National Bureau of Statistics. The value $\theta = 0.5$ is also widely used in the literature on China, including Song et al. (2011) and Brandt et al. (2008). Nevertheless, we conduct a robustness check using $\theta = 0.42$, and the corresponding results are reported in Appendix E.

Similarly, we use the average depreciation rates reported in PWT 11.0, setting $\delta = 0.053$ for China and $\delta^* = 0.039$ for the United States. We calibrate $g = 1.12\%$ to match the average TFP growth of 0.68% in the U.S. between 1978 and 2023. Under these parameters, the model implies a steady-state capital-to-output ratio of 3.29 for the United States, close to the average value of 3.28 (including government capital stocks) over the 1978-2023 period. The initial capital stock, K_{1978}, is set to match China's observed income per capita relative to that of the United States in 1978. Table 1 summarizes the calibration. In Subsection 5.2, we discuss the robustness of our quantitative results to changes in the calibrated values.

Table 1: Calibration

Parameter		Value
Discount factor	β	0.94
Capital income share, China	θ	0.5
Capital income share, U.S.	θ^*	0.39
Depreciation rate, China	δ	0.053
Depreciation rate, U.S.	δ^*	0.039
Technology growth rate, U.S.	g	1.12%

4.2 Calibration of Relative TFP

Historical Relative TFP. We now determine the path of the relative technology level, λ_t. For the period 1978–2023, λ_t can be measured directly using relative TFP for China and the United States. Relative TFP is constructed using three time series from PWT 11.0: the level of each economy's TFP relative to that of the United States in the base year ($CTFP$), together with the TFP growth rates for both China and the United States ($RTFP^{NA}$). Appendix A provides a detailed description of the TFP construction process.[8]

Since the choice of base year used to construct relative TFP affects the resulting time series, we choose the base year b that minimizes the distance between model-implied and observed relative income per capita over 1978–2023:[9]

$$\min_b \sum_{t=1}^{T} \left(\frac{Y_t/N_t}{Y_t^*/N_t^*} - \widehat{\frac{Y_t/N_t}{Y_t^*/N_t^*}} \right)^2$$

This procedure selects 1982 as the base year. The solid red line in Figure 4.1 shows the resulting relative TFP series for 1978–2023.

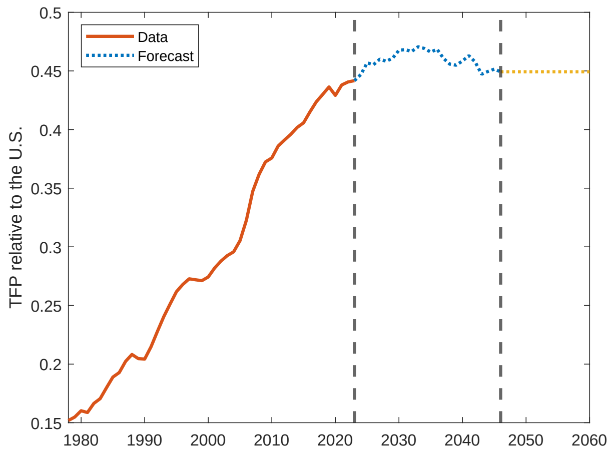

Figure 4.1: China's TFP relative to the U.S.

Future Relative TFP. For years beyond 2023, we infer China's TFP trajectory from the convergence experience of other East Asian economies. The left panel of Figure 4.2 plots log TFP relative to the United States for China and the representative Asian economy. As in Figure 2.1, the representative economy's series starts in its corresponding initial year, while China's extends back to 1978. China's relative TFP is measured on the left axis; the representative economy's on the right.

[8] PWT 11.0 computes TFP growth using constant national-price GDP ($RGDP^{NA}$) and constant national-price capital stock. Since capital stocks are not reported at constant prices across countries, TFP cannot be directly constructed from $RGDP^{O}$. However, given the close similarity between $RGDP^{O}$ and $RGDP^{NA}$ documented in Figure 2.3, the quantitative implications of this inconsistency are likely to be minimal.

[9] $CTFP$ (current-price TFP) is constructed with prices that are constant across countries within a given year, whereas $RTFP^{NA}$ (constant-national-price TFP) uses national prices that are fixed over time. By construction, the data underlying these two measures coincide in the base year but diverge elsewhere because they are evaluated at different prices.

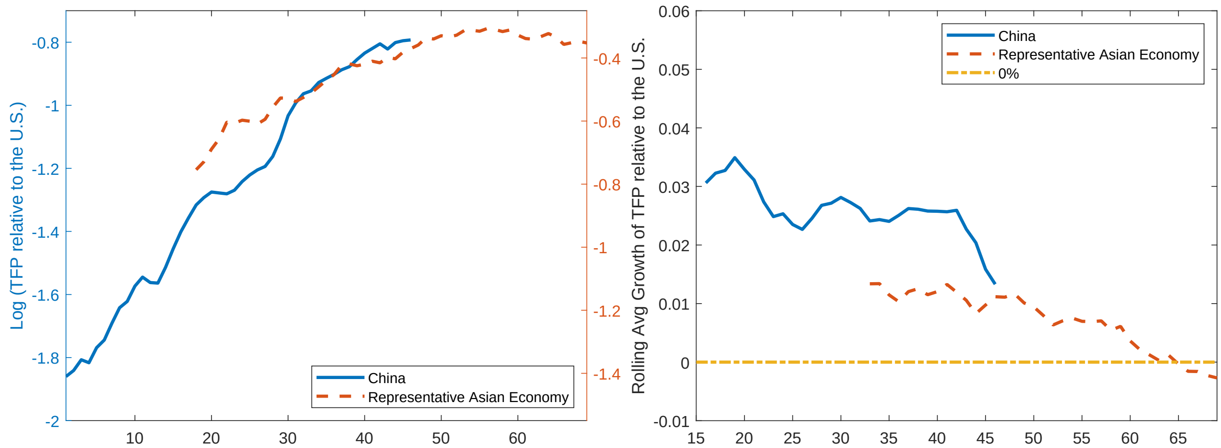

Figure 4.2: TFP relative to the U.S., normalized at China's GDP per capita in 1995

Two observations stand out. First, although China's TFP level remains below that of the representative Asian economy, its relative TFP growth over the past 15 years closely tracks its East Asian peers. Second, the representative economy's relative TFP growth has slowed to near zero toward the end of the sample, suggesting that these economies have essentially completed their catch-up. The fact that TFP convergence in the representative economy has been stagnant during the past two decades suggests China, too, has largely exhausted its relative TFP gains. The right panel reinforces this reading: it shows the growth rate of relative TFP as a 15-year rolling average, filtering out short- and medium-run fluctuations to reveal the long-run trend. By 2023, China's catch-up speed has declined to match that of the representative Asian economy.

Based on these observations, we assume that, after 2023, China's relative TFP follows the representative economy's trajectory for an additional 23 years, rising modestly from 0.44 to 0.45 (dotted blue line in Figure 4.1). Thereafter, convergence is assumed complete (dotted yellow line in Figure 4.1). This does not mean China's TFP stops growing; only that it stops growing *relative* to U.S. TFP. In Section 5.2, we assess the robustness of our results to a more optimistic projection of China's relative TFP growth.

5 Quantitative Results

This section presents the quantitative findings. First, we report our benchmark results and discuss how they compare with the data. Second, we examine the robustness of the results to alternative calibrations and to different assumptions about how investment is determined in the model.

5.1 Benchmark Results

Output. Figure 5.1 compares the model results to the data on both the level (left panel) and growth rate (right panel) of income per capita. The left panel illustrates that the model closely aligns with the evolution of China's income per capita relative to the U.S. from 1978 to 2023.

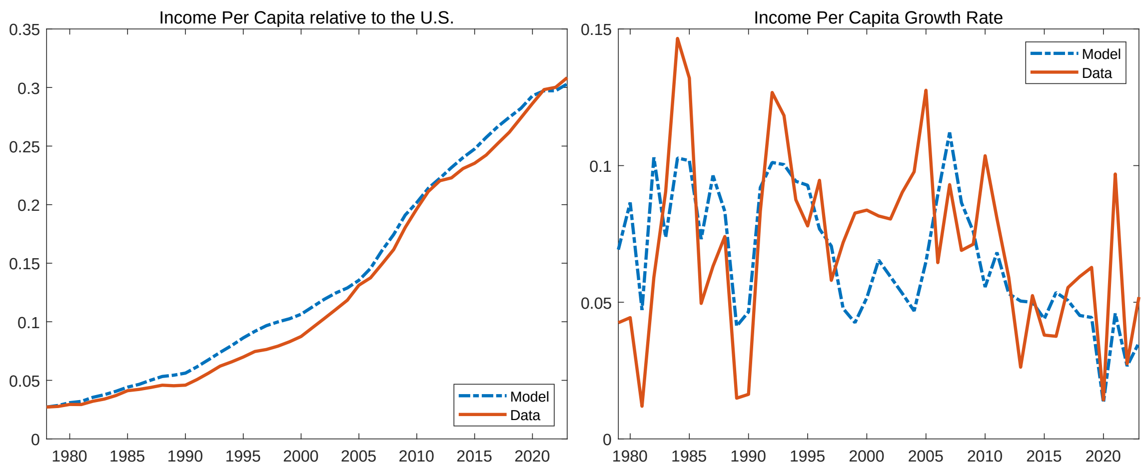

Figure 5.1: Transitional dynamics (model and data): Income per capita

The right panel shows a clear similarity between the model and the data in the movements of income per capita growth. This suggests that our minimalist neoclassical growth model captures the key patterns of China's growth experience, including its recent deceleration. Put differently, China's growth during this period is consistent with that generated by a simple, deterministic, one-sector optimal growth model with an exogenous TFP catching-up path. While one still needs a theory of TFP evolution, conditional on such a path, nothing about China's growth is puzzling.

Investment. The left panel of Figure 5.2 shows investment as forecasted by the model against the investment series in the data.[10] The right panel presents the rate of return on capital from Chen et al. (2019) and compares it with the model.

Our model matches roughly the level of investment observed in China between 1978 and 2008. As shown by King and Rebelo (1993) and Christiano (1989), applying the neoclassical growth model to low-income economies, such as China in 1978, typically yields counterfactual investment rates and returns to capital of about 500%. However, we show that once TFP catch-up is incorporated into the neoclassical framework, the model-implied investment rate and return to capital become consistent with empirically observed levels.

[10]We also compare the model with real investment rate from the data in Appendix E, and the results are similar.

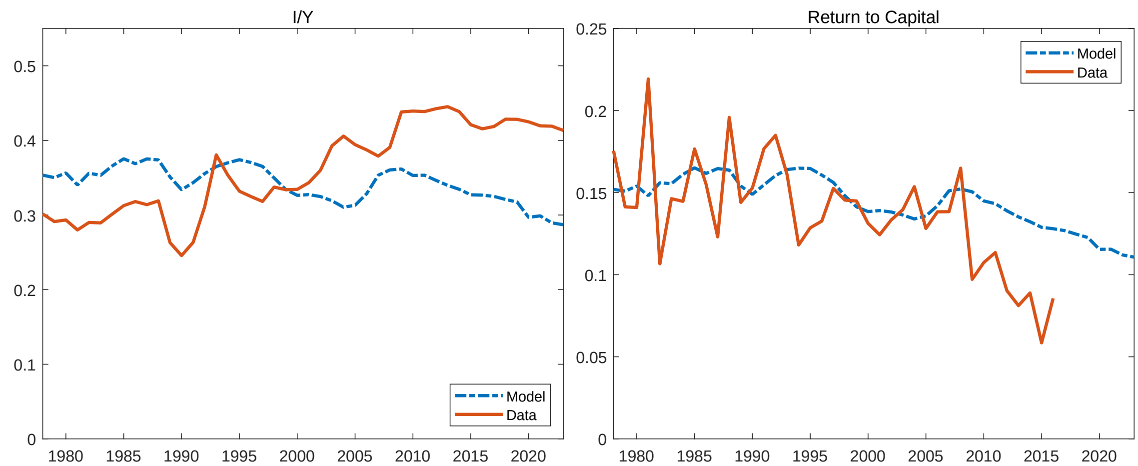

Figure 5.2: Transitional dynamics (model and data): Investment, and return to capital

The left panel of Figure 5.2 also shows how our model undershoots investment after 2008. This raises the question of why China has not grown more, given this higher investment. Four factors can help reconcile the model with the data. The first is that much of China's investment has had low marginal productivity due to distortions. For example, König et al. (2022) document that between 2007 and 2012 the return to R&D investment is lower in China than in Taiwan due to pervasive output wedges. This explanation fits well with the right panel of Figure 5.2: the model's rate of return to capital is higher than the data's. This argument also reconciles the data with the stylized facts from Section 2: while investment rates in China have been somewhat higher than in other East Asian economies, its output growth rate has been about the same, and the rate of return on capital has been lower.

The second factor is the mismeasurement of investment. Chen et al. (2019) have argued that the investment rate in 2016 was about seven percentage points lower than officially reported (see also Song and Xiong, 2023 for a model of how flawed statistics arise in China due to the agency problem between central and local governments). Figure 5.3 plots the results of our model against the nominal investment rate in Chen et al. (2019, p. 106, Figure 10).[11] With the series from Chen et al. (2019), the model does an excellent job of replicating investment. This explanation has the additional advantage that, by lowering the total amount of investment, it increases the rate of return on capital, helping with that aspect of the model as well.

The third factor is that much of the investment in China has reflected political priorities. Herd (2020) has shown that business investment follows the same hump shape we document. Compare Figure 6.B in his paper with our right panel in Figure 5.2, and the difference be-

[11] For this comparison to be precise, we would need to recalibrate China's TFP process to be consistent with the output data in Chen et al. (2019). Since our goal is to highlight that the official investment series may mismeasure the extent of capital formation, we skip this additional step.

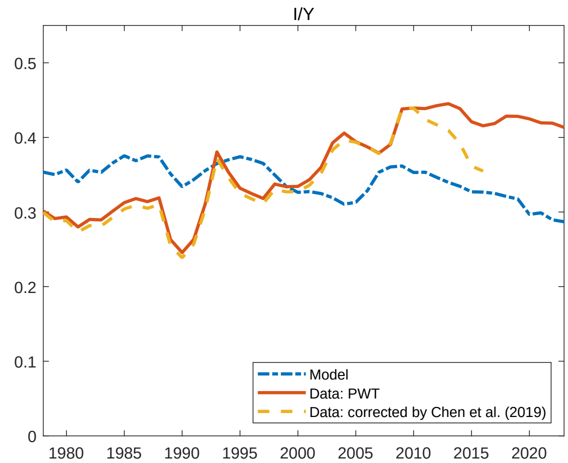

Figure 5.3: Corrected investment by Chen et al. (2019)

tween the model and the data can be attributed to increased investment in housing and infrastructure. Bai et al. (2020) and Jiang et al. (2022) make related points based on the behavior of local authorities, who have used local government financing vehicles to borrow and invest in low-return projects. However, investment in infrastructure in China has fluctuated between 7% and 10% of output since the early 2000s (Jiang et al., 2022). While this is a high rate compared to other middle-income economies, infrastructure investment accounts for only part of the difference in total investment.

To explore this third factor more thoroughly, in Subsection 5.3, we document that if investment is fixed exogenously, à la Solow, at a higher level, the model cannot match the data on per capita income and its growth. This factor fits particularly well with Figure 5.2: the rate of return on capital in the data is lower than in the model, while the investment rate is higher, especially after 2008, because many investment decisions during this period were made for reasons other than maximizing profits.

Finally, a fourth factor is that our calibration might yield too little investment. We revisit and dismiss this explanation in Subsection 5.2.

Future catch-up. Next, we examine the model's projection through the end of the century. As shown in Figure 4.1, China's catch-up in TFP gradually decelerates and converges to approximately 45% of the U.S. level by 2046. Figure 5.4 shows that due to differences in capital share, depreciation rate, population growth, and the employment-to-population ratio relative to the U.S., China's income per capita will reach 38% of the U.S. level in 2100. According to United Nations population projections, China's population in 2100 will be roughly 1.5 times that of the United States (633.4 million versus 421.2 million). Consequently, the model implies that by the end of the century, the U.S. economy will remain about 77% larger than China's in aggregate output.

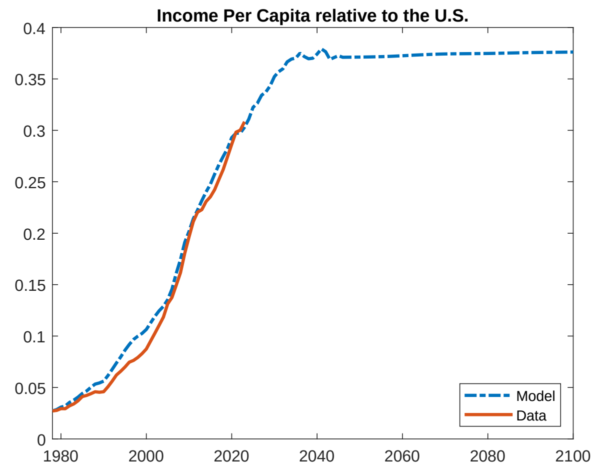

Figure 5.4: Transitional dynamics: Forecast

Yet this aggregate comparison masks an important shift in growth dynamics. According to our model, U.S. output will grow faster (1.6%) than China's (1.54%) by 2034. The left panel of Figure 5.5 shows this pattern by plotting total income growth rates for China and the U.S. Note that the projected output growth rate fluctuates after 2023 because the future income path is constructed using the realized relative TFP growth rates of other East Asian economies.

Three mechanisms drive this striking prediction. First, China's unfavorable demographics, with a falling population.[12] Second, the stabilization of the employment-to-population ratios (right panel of Figure 5.5). Third, the slowdown of technological catch-up (Figure 4.1).

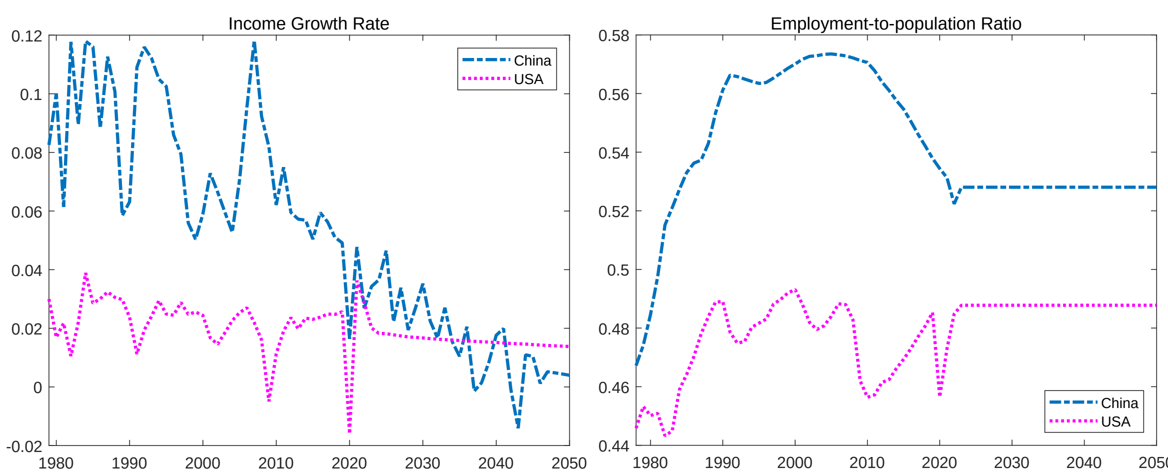

Figure 5.5: Transitional dynamics: Total income and employment-to-population ratio

[12]According to China's National Bureau of Statistics, China's total population started falling in 2022.

Gauging the model's forecast. The decomposition of the previous three mechanisms helps us gauge possible caveats to the model's forecast.

Let us start with mechanism one: demographics. This is the least uncertain of the three elements. Absent a particularly deadly epidemic or massive migration flows, the population in 2034, when the U.S.'s output growth overtakes China's, is already largely determined: around 95% of the Chinese people alive in 2034 have already been born. The same holds for nearly all workers, since a person born in 2025 will be only nine years old in 2034.

Demographic (and social norms) changes might have a greater impact on the second mechanism, the employment-to-population ratio, but by only a few percentage points up or down. If anything, the right panel of Figure 5.5 suggests that China's employment-to-population ratio will fall due to aging, accelerating the date at which the U.S. would overtake China's output growth rate.[13]

The main source of uncertainty in the model forecast lies in the third mechanism: the evolution of relative TFP shown in Figure 4.1. The evidence from other East Asian economies, presented in Section 2, suggests that sustaining convergence without a slowdown is a tall order. Even if TFP growth in the U.S. declines, thereby lowering total U.S. income growth, this could still hurt China through weaker international technological diffusion, or, at best, delay the U.S. overtaking China in income growth by a decade.

Ultimately, the logic of the neoclassical growth model is unforgiving. With the UN projecting a long-run population decline of -1.7% per year (even assuming an optimistic fertility rebound from 1.00 to 1.35 children per woman) for China, TFP must grow at 1.7% annually just to keep total income constant —holding employment-to-population and capital-to-worker ratios fixed. Sustaining a 3% growth rate in total income would require TFP growth of 4.7%, a very high bar for an economy that has already reached middle-high income status. While such a rate is not inconceivable, especially in light of advances in AI and automation, the historical record offers little comfort that it can be maintained over the long run. In this context, China's shrinking population and decelerating TFP convergence represent powerful structural headwinds.[14]

[13]Nonetheless, there might be a counterbalancing effect as the average human capital of Chinese workers increases as younger, more educated cohorts enter the job market. We will explore this possibility in future research. Still, the experience of southern European countries, such as Italy and Spain, that have experienced a similar increase in average human capital over the last 25 years, is not very optimistic. In the absence of rapid TFP growth, many highly educated workers are assigned to jobs for which they are overqualified, thereby substantially reducing the potential contribution of higher human capital.

[14]There are many other possible headwinds (financial crises, geopolitical tensions, etc.), but since those are outside our model, we remain silent on them. Suffice it to say that their inclusion would only strengthen our main conclusion.

5.2 Robustness

We conduct an extensive battery of robustness tests on our model by varying parameter values. In the interest of space, we will report the four most interesting experiments.

Alternative convergence level. We first experiment with different TFP convergence levels. Specifically, we assume that China's final TFP level converges to that of the representative Asian economy, corresponding to 70% of the U.S. level. To characterize the transition between 2023 and the final convergence level, we specify the evolution of λ_t as

$$\lambda_t = \lambda - (\lambda - \lambda_{2023})e^{-\eta t}, \tag{1}$$

where λ_{2023} denotes China's relative technology level in 2023, $\lambda \in (0, 1)$ represents the final convergence level of China, and η governs the speed of convergence. The term $e^{-\eta t}$ generates a path that asymptotically approaches zero, capturing the typical slowing of catch-up growth as the frontier is approached and further improvements become more difficult. The parameter η is calibrated such that the growth of λ_t between 2024 and 2033 does not exceed its growth between 2014 and 2023, consistent with the assumption of a gradual slowdown in the convergence process.

Figures 5.6 presents the calibrated TFP convergence path and the corresponding model outcomes. Assuming a higher TFP convergence level, China's TFP is projected to reach 63% of the U.S. level by 2100, while its income per capita reaches 72% of the U.S. level in the same year. This assumption also delays the year in which U.S. GDP overtakes China's to 2055. Meanwhile, this alternative convergence specification exerts only a negligible effect on China's historical growth trajectory over the period 1978-2023.

Alternative future TFP growth rate. Next, we assume that China's future relative TFP growth rate will resemble that of other economies when they were at similar levels of TFP relative to the U.S. As shown in the left panel of Figure 4.2, China's relative TFP level in 2023 reaches the level attained by the representative Asian economy at the beginning of the sample. Accordingly, we assume that China's future TFP growth follows the TFP growth rate experienced by the representative Asian economy from the start of the sample period, i.e., the average of Japan in 1950, Korea in 1972, and Taiwan in 1961. Figure 5.7 shows that, under this specification, China's TFP will continue to grow for another fifty years and eventually reach 63% of the U.S. level by 2100, while its income per capita rises to 75% of the U.S. level.

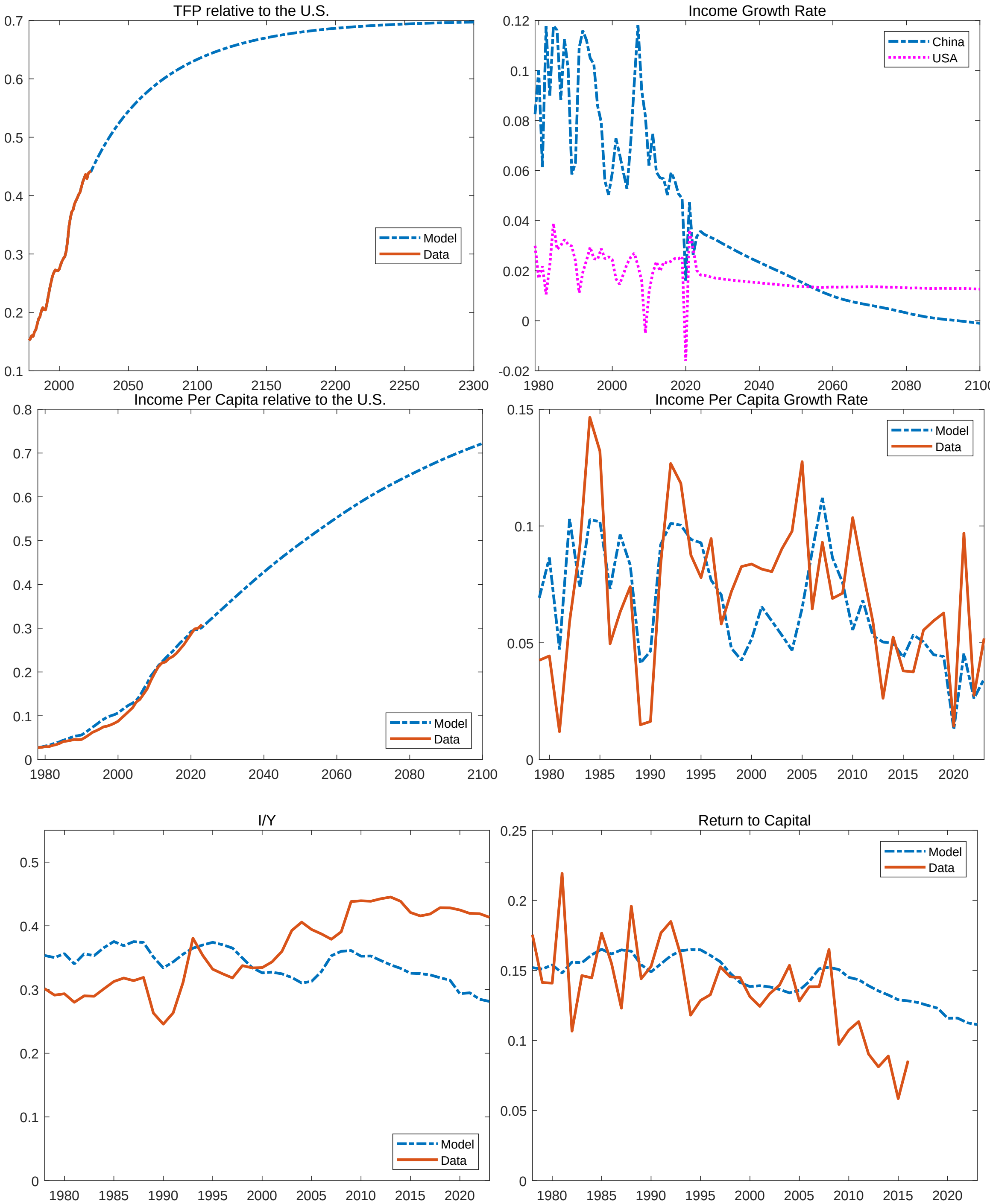

Figure 5.6: Transitional dynamics: converge to alternative TFP level

Changing the depreciation rate. In our third experiment, we examine the role of depreciation rates. In Figure 5.8, we set the depreciation rate to 0.1 for both China and the U.S. The simulation results show that the model's predictions are robust to this alternative

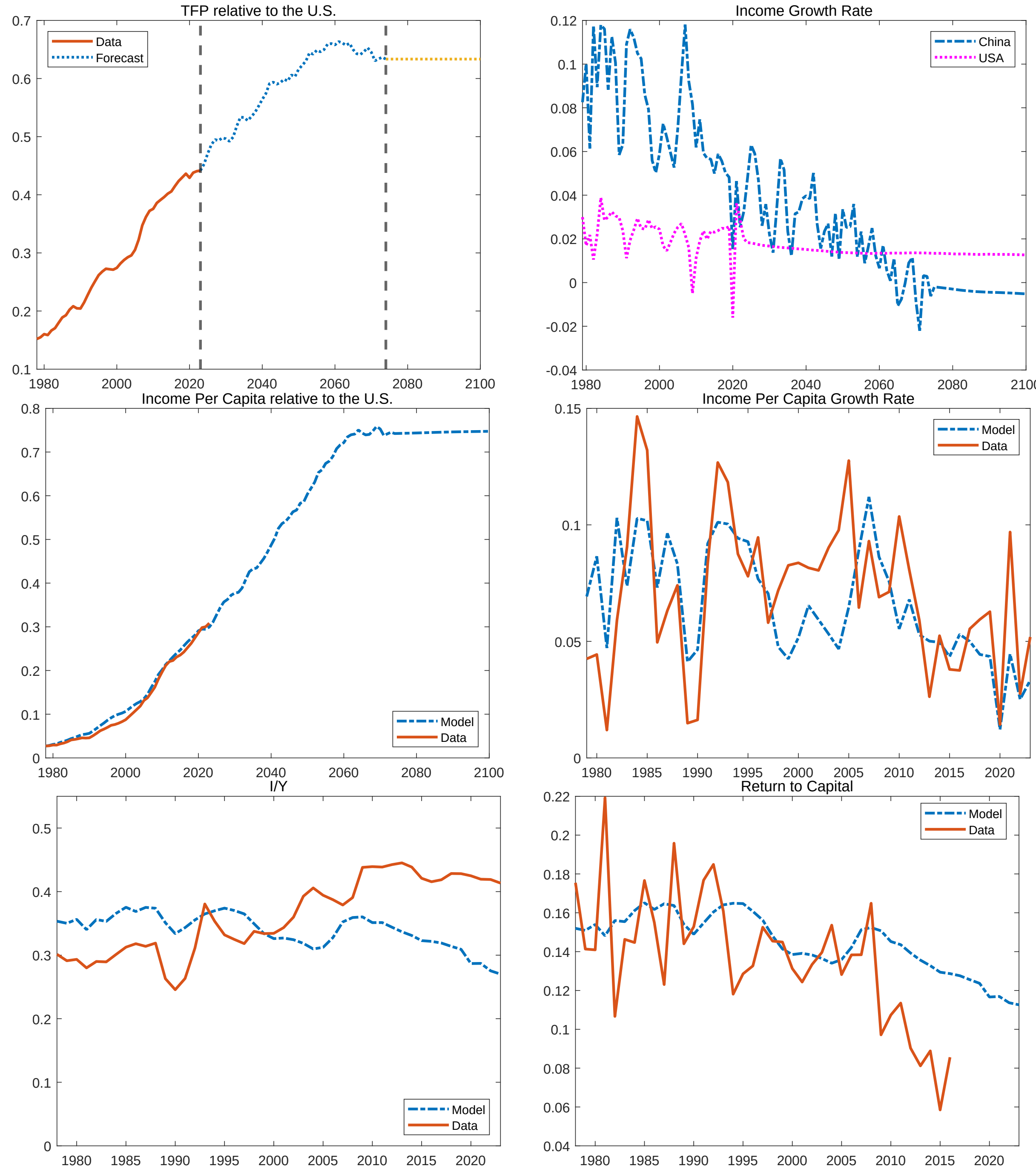

Figure 5.7: Transitional dynamics: alternative future TFP growth

calibration, although the difference at the end of the sample is somewhat larger. Recall that, in our benchmark calibration, the U.S. depreciation rate is 0.039, as reported in PWT 11.0. We therefore also consider an experiment in which both countries' depreciation rates are set to 0.039. Because the model's predictions remain very similar under this specification, we do not report these results.

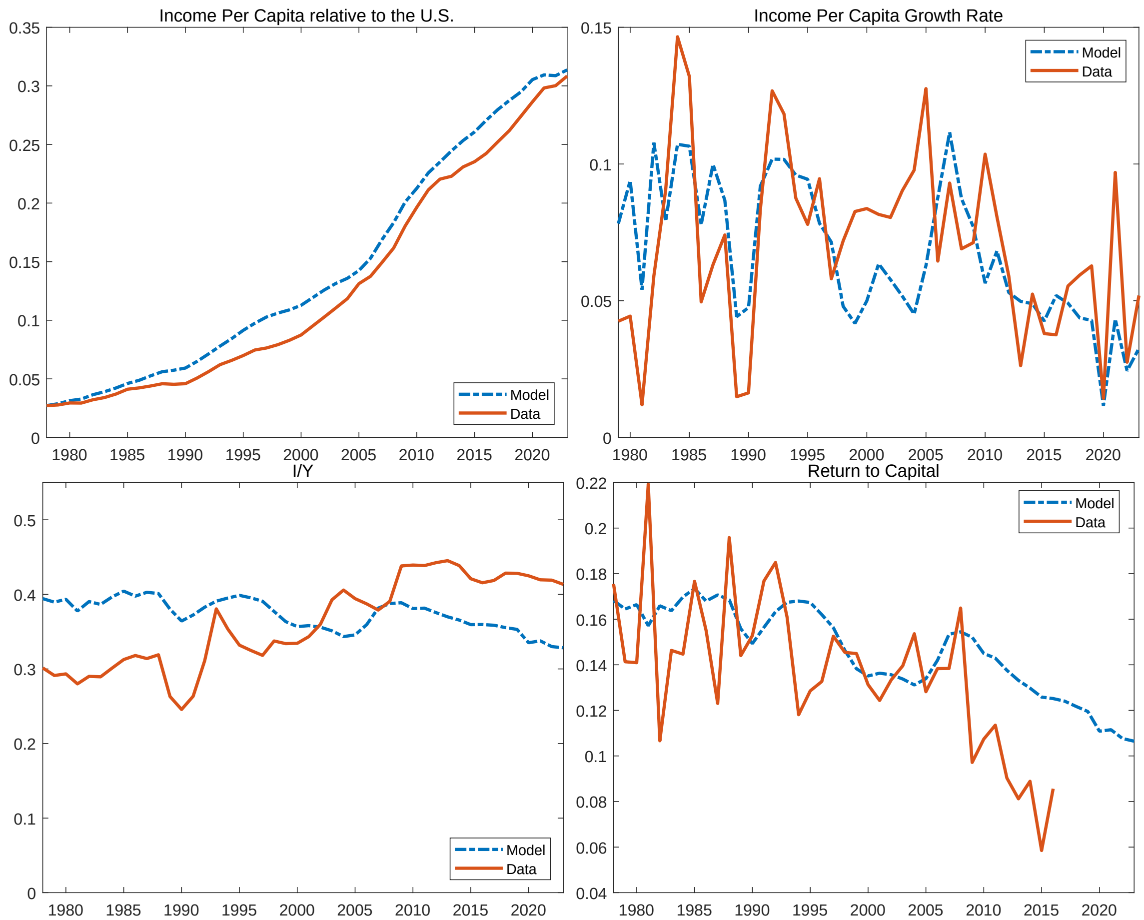

Figure 5.8: Transitional dynamics: $\delta = \delta^* = 0.10$

Changing the elasticity of intertemporal substitution. Finally, we experiment with lower elasticity of intertemporal substitution, replacing the log utility with a general CRRA function. Reducing the elasticity to 1/2 produces an investment rate that falls below the data (bottom-left panel of Figure 5.9). Consequently, it yields slower income-per-capita growth, bringing the model's predictions closer to the data. In contrast, increasing the elasticity of intertemporal substitution above one improves the fit of investment (which, as noted, may be mismeasured) but overstates income growth relative to the data.

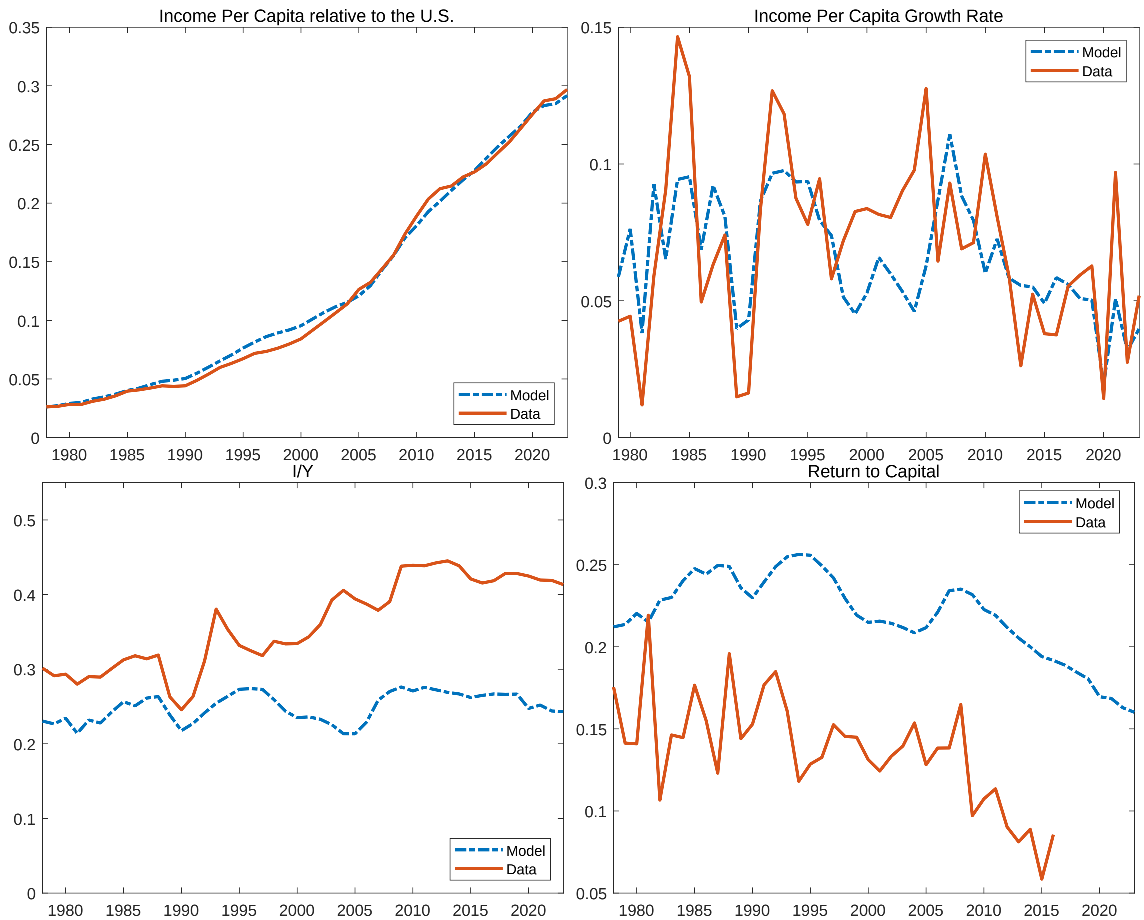

Figure 5.9: Transitional dynamics: IES = 1/2

5.3 From Ramsey–Cass–Koopmans to Solow

In this section, we fix the investment rate exogenously at its 2009 level (0.44) to capture the persistently high investment seen in the left panel of Figure 5.2. Conceptually, this shifts the model from a Ramsey-Cass-Koopmans framework (with endogenous consumption-saving decisions) to a Solow-type framework (with exogenously fixed savings). We interpret this experiment as exploring whether political or other forces outside the model drive investment.

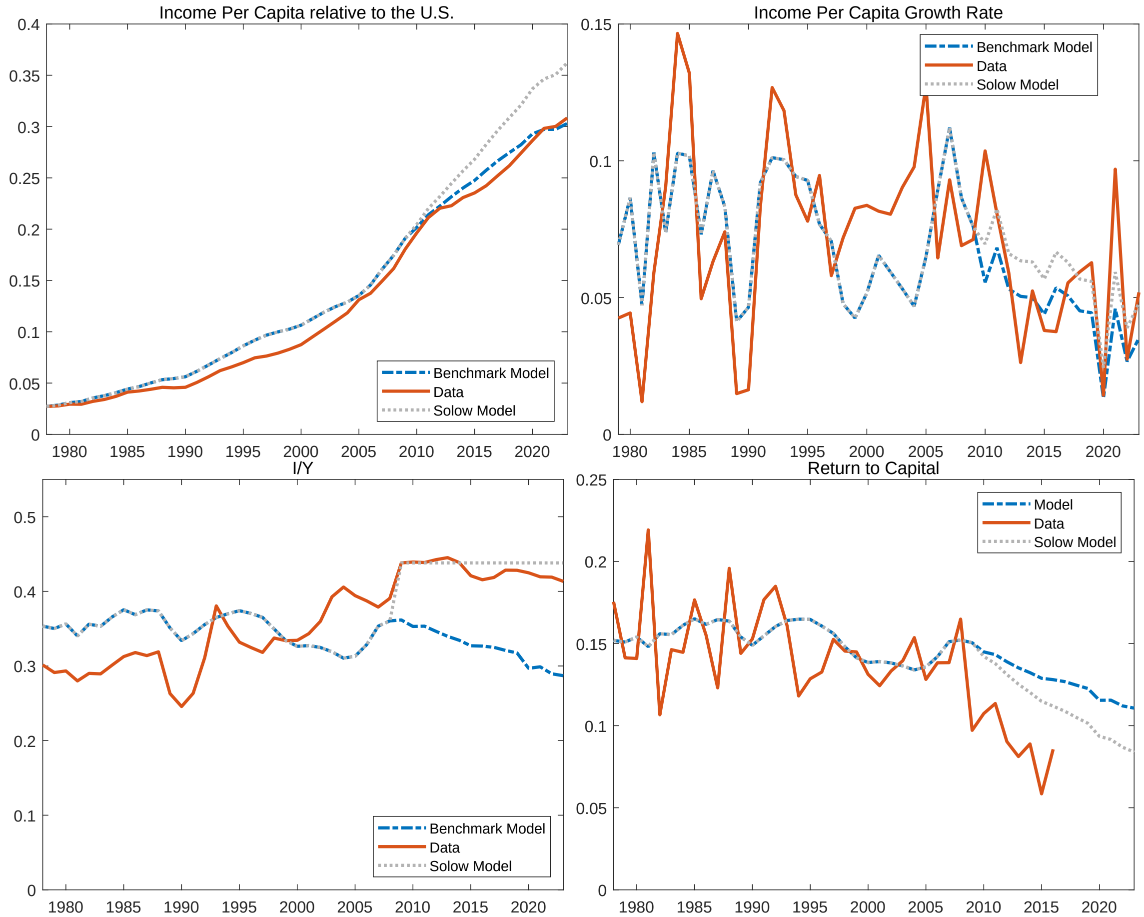

Figure 5.10: Transitional dynamics: investment rate fixed at 0.44

Figure 5.10 reports these results. In this experiment, China continues to experience rapid growth. However, the model no longer matches data on per capita income and income growth after 2009. While a simple Solow model can generate rapid growth from China's high investment rates, the data do not support the view that China is reaping substantial gains from these investments. Our earlier explanation, which combines low investment efficiency and mismeasurement, fits the data better.

6 The Asian Miracle Economies

We have shown that a minimalist Ramsey–Cass–Koopmans model can account for China's growth experience since 1978 and that it projects a slowdown in China's medium-run growth. But can this model also explain the experience of other Asian miracles?

In this section, we argue that the answer is yes and that these cases offer important support for our claim that the model captures key aspects of China's catch-up dynamics.

This validation is especially valuable because, as noted in the introduction, the model must match longer trajectories (e.g., Japan's since the 1950s), pushing it to its explanatory limits.

More concretely, we examine the experiences of Korea, Japan, and Taiwan.[15] In all cases, we calibrate the model as in Section 4. The U.S. parameters remain unchanged, except for the technology growth rate, calibrated to each economy's sample period. The TFP relative to the U.S. and population growth rates are derived from the data, and the initial level of capital for each economy matches its income per capita relative to the U.S. in that year. Because TFP data are missing for some economies in the early years, we restrict the calibration to the period for which TFP observations are available.

We use the capital income share and depreciation rates from PWT 11.0. We make an exception for Taiwan: PWT 11.0 imputes self-employed labor compensation assuming they earn the same wage as employees, which overstates labor income and yields $\theta = 0.28$. As we argue in Appendix D, this is not a plausible value. Instead, we adopt an alternative labor share from PWT 11.0 that only includes employee compensation, giving $\theta = 0.47$.[16] Finally, we assume these economies completed their TFP convergence by 2023 and that their relative TFP levels remain constant thereafter. Table 2 summarizes the calibration.

Table 2: Calibration: The Asian miracle economies

Economy	δ	θ	g	Initial Year	TFP Available From
Japan	0.036	0.44	1.40%	1950	1954
Korea	0.045	0.48	1.07%	1972	1972
Taiwan	0.050	0.47	1.34%	1961	1961
China	0.053	0.50	1.12%	1978	1978

Japan. We begin with Japan. As shown in the top-left panel of Figure 6.1, Japan's income per capita rises steadily from the 1950s through 1996 and declines thereafter. The model replicates the cumulative increase in per capita income from the beginning of the sample through 1991, consistent with the rapid growth of TFP during this period. As the relative TFP peaks in 1991, the model's income per capita also reaches its maximum and subsequently declines. As illustrated in the top-right panel of Figure 6.1, the model generates per capita income growth rates that closely track the data after the mid-1990s.

Finally, the evolution of TFP (middle left panel of Figure 6.1) suggests that Japan's relative TFP convergence with the U.S. has ended at 55% of the U.S. level. This is a crucial

[15] We also show the growth experience of Hong Kong and Singapore in Appendix F.

[16] See https://www.stlouisfed.org/on-the-economy/2018/january/measuring-labor-share-asian-tigers and Appendix D for more details on the challenges of measuring labor shares in East Asia.

observation for our main argument: TFP convergence in East Asia toward the U.S. tends to stall or even diverge when these economies reach approximately two-thirds of the U.S. level.

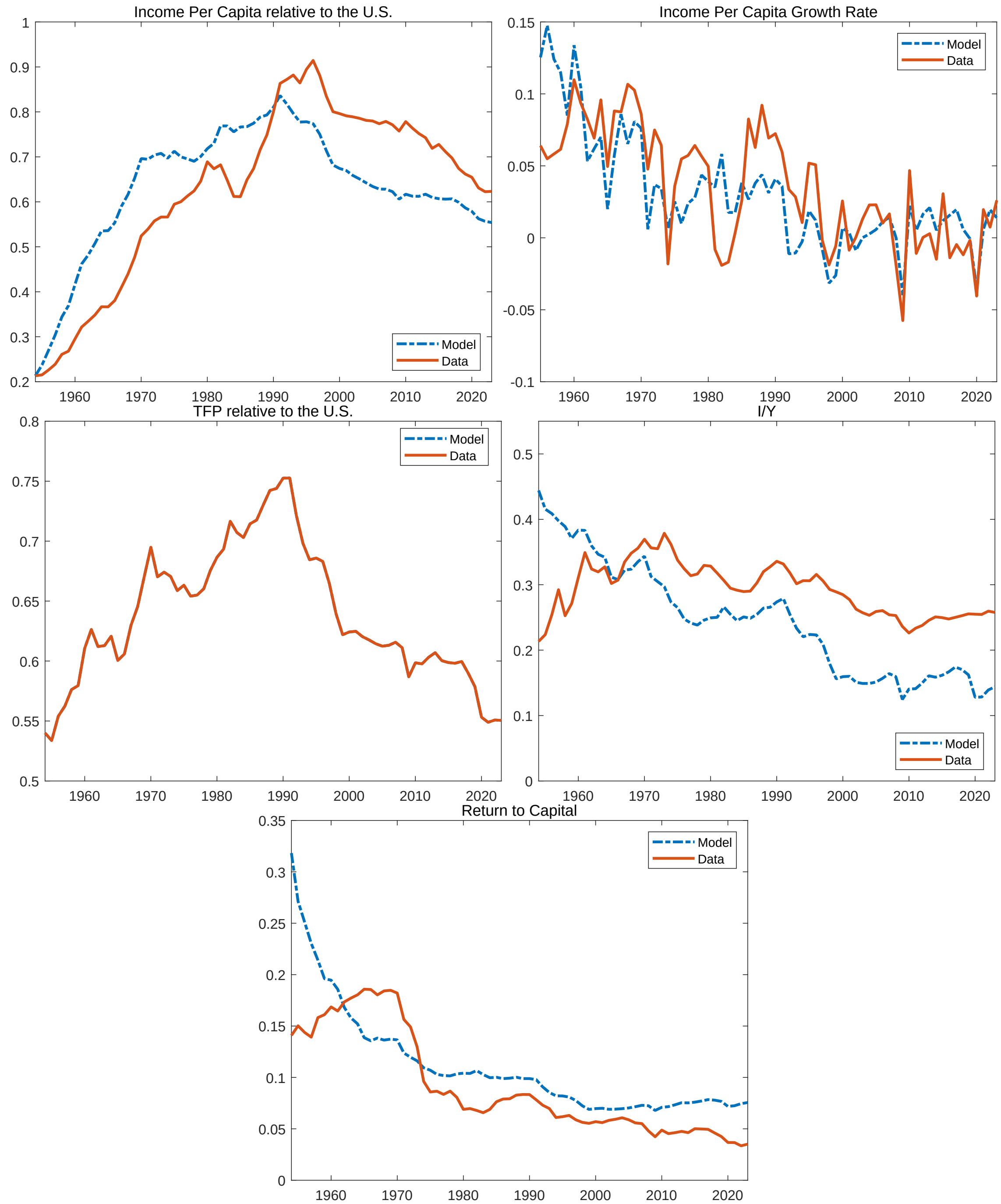

Figure 6.1: Japan: Transitional dynamics

Korea. Figure 6.2 presents the results for Korea. The top-left panel shows that the model tracks Korea's output growth reasonably well. There are, however, two exceptions associated

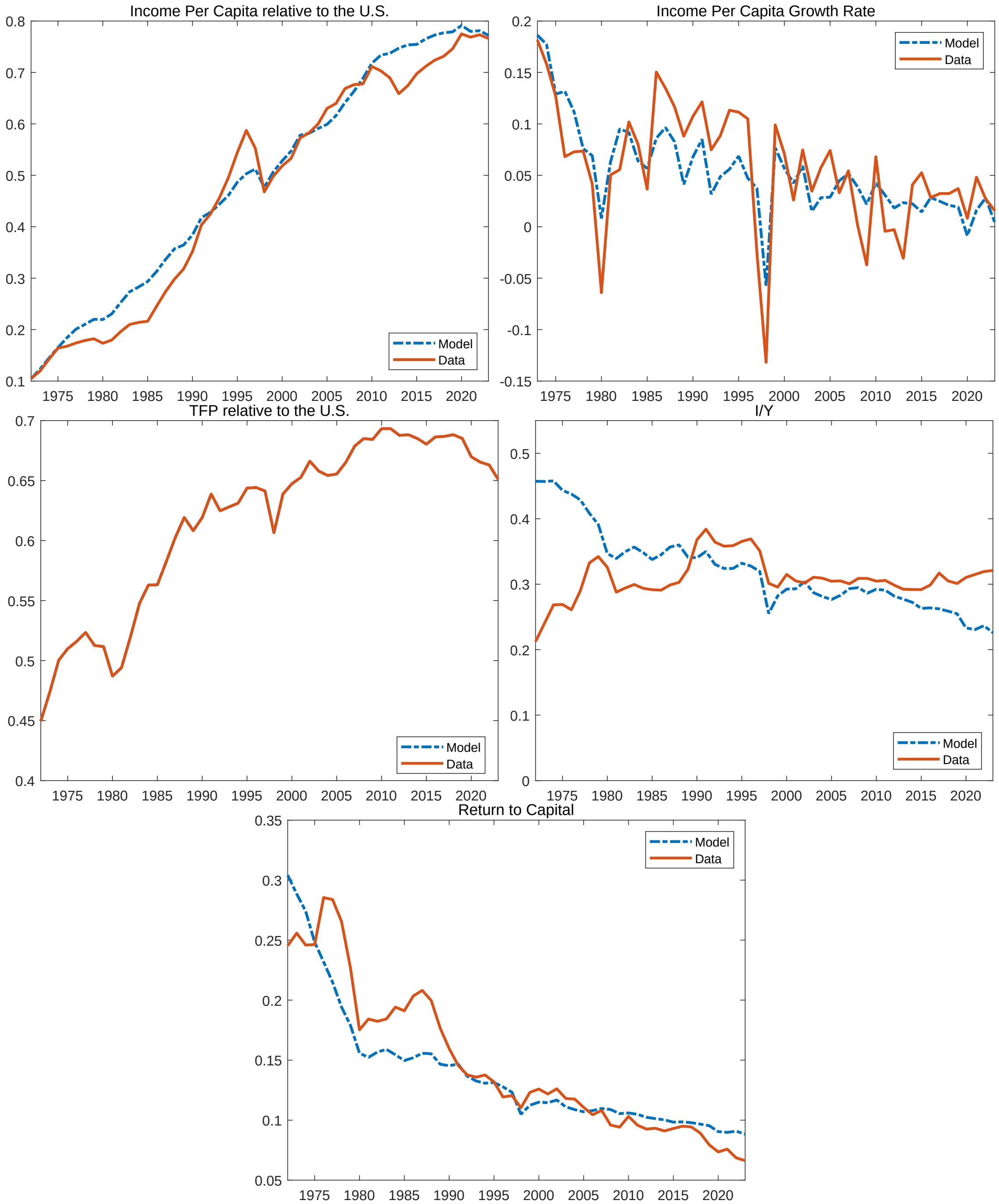

Figure 6.2: Korea: Transitional dynamics

with major financial crises. First, the model does not capture the exceptionally rapid growth from 1990 to 1996, which drove observed output substantially above the model-predicted path, and the subsequent sharp contraction during the 1997 Asian financial crisis. Second, the model misses the pronounced downturn after the global financial crisis, which pushes observed output well below the predicted trajectory. Interestingly, despite these deviations, the model and the data converge and coincide by the end of the sample period in 2023.

The central message of the model, namely that growth slows once an economy catches up, is vindicated by the data: Korea has recently grown in line with the Ramsey–Cass–Koopmans model's predictions (top-right panel of Figure 6.2). The model also captures the level of investment rate after the 1980s (middle-right panel) and the return on capital (bottom panel). Finally, it is worth noting once again that Korea's TFP convergence relative to the United States effectively stops once its TFP is slightly below two-thirds of the U.S. level.

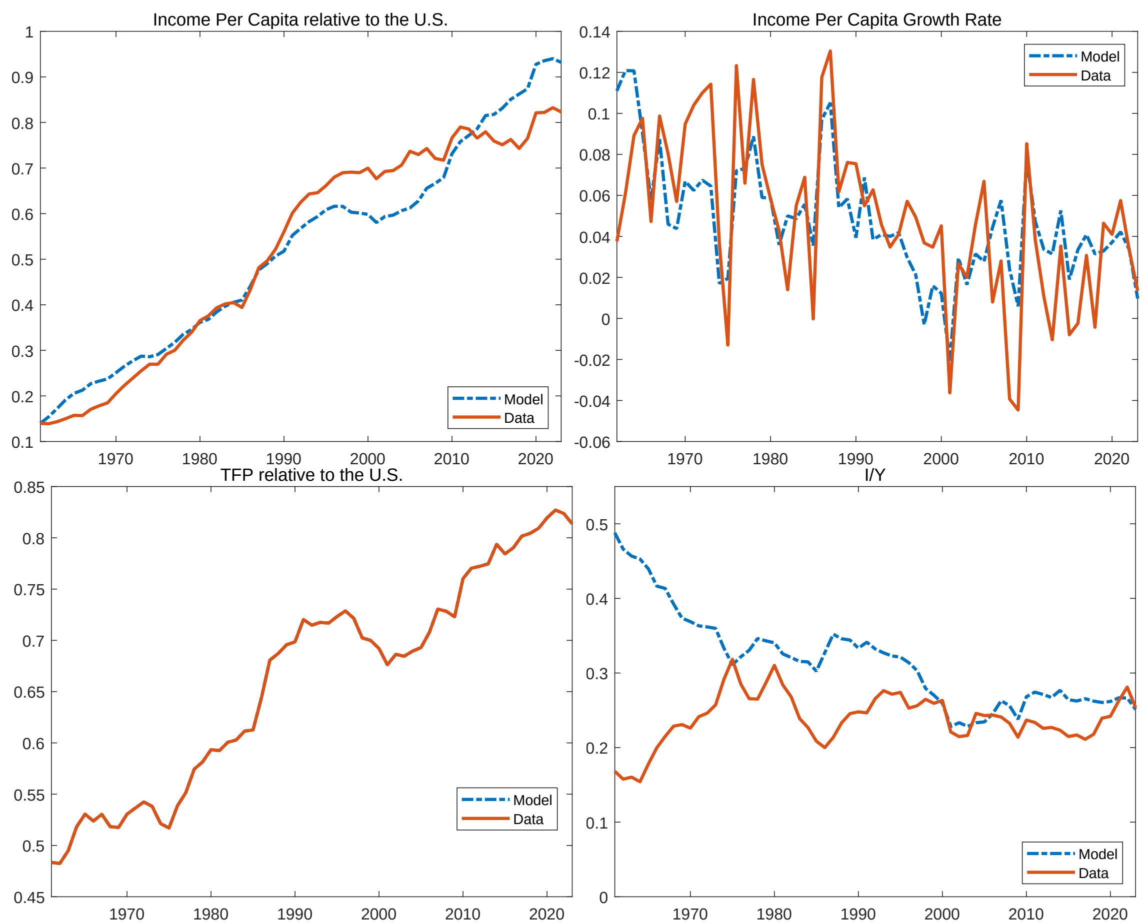

Figure 6.3: Taiwan: Transitional dynamics

Taiwan. Our final case study examines Taiwan. As shown in the top-left panel of Figure 6.3, the model matches the cumulative growth of per capita income till 2009. Thereafter, however, Taiwan's actual growth falls short of the model's forecast (top-right panel), and its convergence toward the U.S. level appears to have stalled.

Taiwan is the only of the three East Asian miracles in which TFP has approached the level of the U.S. (81%), but even in this case, convergence appears to have halted, although it may be too early to tell whether this halt will be long-lasting.

The model also predicts a slightly higher investment rate than observed during the early part of the sample. We do not report the return to capital here because the return to capital reported in PWT is constructed using a capital income share that differs from the value employed in our model; hence, the two measures are not directly comparable.

Taking stock. Our minimalist model accounts reasonably well for the historical experiences of Japan, Korea, and Taiwan. The core predictions of a Ramsey–Cass–Koopmans model augmented with exogenous TFP growth, namely, a gradual slowdown in output growth and a declining return to capital, are clearly vindicated in the data. These patterns provide strong grounds for expecting a broadly similar trajectory in China.

7 Summary and Conclusion

China's growth performance over recent decades has closely mirrored that of other East Asian growth miracles at comparable stages of development. A minimalistic neoclassical framework with a simple TFP catch-up mechanism accounts well for the growth patterns in these economies. More broadly, many factors often viewed as central to understanding these miracles, including industrial policies, financial market modernization, trade, and FDI policies, manifest in a one-sector model as a straightforward TFP catch-up process.

Our paper complements those that build detailed models of such mechanisms. The minimalism of our model is a fundamental strength: added complexity poses empirical challenges, notably the difficulty of projecting the future paths of these mechanisms, which are required for forecasting China's growth.

China has grown by accumulating capital and catching up with the global technological frontier. But this catch-up is slowing, as it did in the other East Asian cases. Combined with a shrinking population, this implies China's growth must slow, possibly sharply. Our forecast, which assumes sustained high savings and a stable employment-to-population ratio, may be overly optimistic if either assumption is violated. It may be too pessimistic if institutional reforms boost economic efficiency, reversing the TFP slowdown, or if human capital improves substantially.

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Appendix

The following appendices provide additional details on the data used in the paper, Hong Kong and Singapore, and robustness experiments.

A TFP Construction

We use two different TFP measurements from PWT 11.0 to construct relative TFP used in our paper:[17]

- "current price" TFP ($CTFP$):
  - $CTFP$ is the TFP level at current PPPs (USA=1), constructed using $CGDP^O$, where $CGDP^O$ is GDP constructed with prices that are constant across countries.
  - PWT computes each economy's $CTFP$ level and normalizes them using the U.S. $CTFP$. Hence, $CTFP$ represents a country's TFP level relative to the U.S.
- "constant-price" TFP ($RTFP^{NA}$):
  - $RTFP^{NA}$ is TFP at constant national prices (base year = 1), constructed using $RGDP^{NA}$, where $RGDP^{NA}$ is based on constant national prices GDP growth rate obtained from each country's national account data. $RGDP^{NA} = CGDP^O$ in the base year.
  - PWT normalizes $RTFP^{NA}$ to 1 in the base year for all economies, and backs out the $RTFP^{NA}$ level for other years for each economy.

We construct China's TFP relative to the U.S., denoted by $\frac{TFP_{CN,t}}{TFP_{US,t}}$, as follows:

- In the base year b, we assume $\frac{TFP_{CN,b}}{TFP_{US,b}} = CTFP_{CN,b}$.
- The relative TFP in any year t is

$$\frac{TFP_{CN,t}}{TFP_{US,t}} = CTFP_{CN,b}\frac{RTFP^{NA}_{CN,t}/RTFP^{NA}_{CN,b}}{RTFP^{NA}_{US,t}/RTFP^{NA}_{US,b}}$$

The constructed relative TFP is plotted in Figure 4.1.

[17] Note that PWT incorporates human capital and hours worked when constructing TFP. To maintain consistency with our model specification, we compute TFP ($CTFP$ and $RTFP^{NA}$) using the production function of the form $Y_t = TFP_t K_t^{\theta} L_t^{1-\theta}$ where K_t is capital stock, L_t is employment.

B Facts including Hong Kong and Singapore

We exclude Hong Kong and Singapore from our benchmark analysis because their populations are relatively small. We now add them for completeness. Hong Kong's first year in the data is 1960, with a GDP per capita of \$6093. China reached a comparable level (\$5994) in 2003. Hence, we begin with the figure for China in 2003 below.

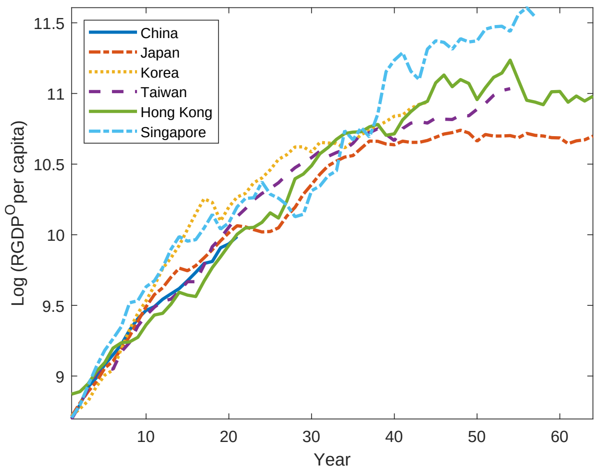

Figure B.1: GDP per capita, normalized at China's GDP per capita in 2003

Figure B.1 shows that our conclusions about output growth remain robust when including these two city-economies. Hong Kong and Singapore experienced strong performance in the early 2000s, temporarily outpacing the other East Asian economies. Still, their growth rates eventually slowed down, just as in the rest of the region. Similarly, alternative measures of GDP (Figure B.2) do not significantly alter the picture.

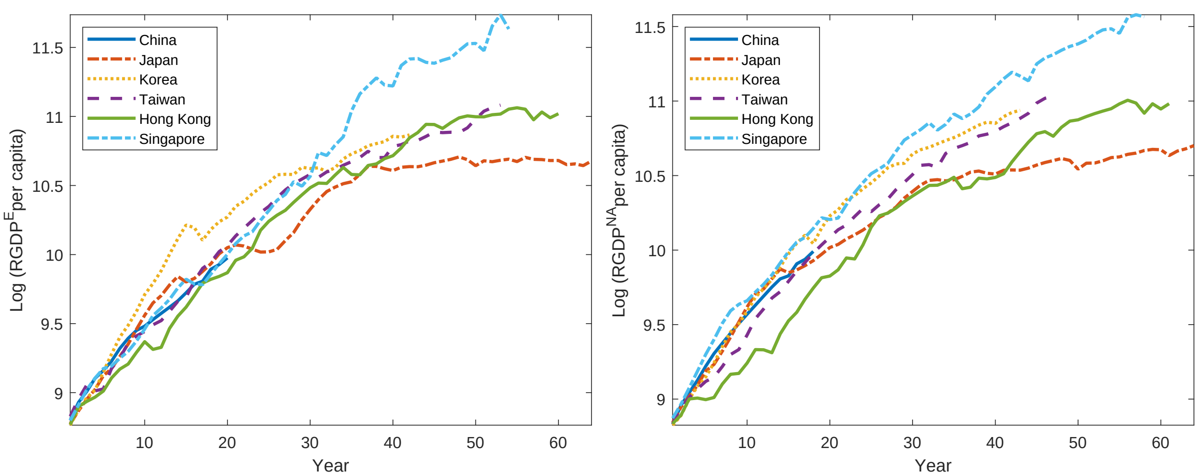

Figure B.2: GDP per capita, alternative definitions, normalized at China's GDP per capita in 2004

Figure B.3 plots the investment rates. The left panel (GFCF/GDP) shows that both economies follow the general pattern of East Asian economies, with Singapore in the high range and Hong Kong in the lower range.

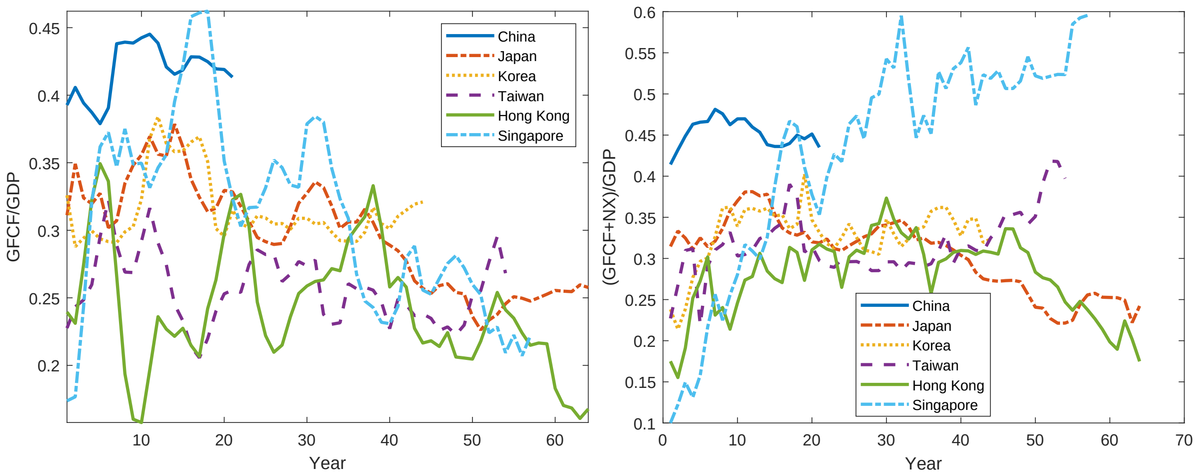

Figure B.3: Investment rates, normalized at China's GDP per capita in 2003

The right panel ((GFCF+NX)/GDP), however, shows a much higher level for Singapore. This result is not surprising. Singapore received large inflows of foreign direct investment (FDI). Given the small size of its economy earlier in the sample, a few large FDI projects could induce wild fluctuations in measured investment, as shown in Figure B.3. Recall, for instance, that Mobil began building a large oil refinery in Jurong (Pioneer Road) in 1966, while Esso started another one at Pulau Ayer Chawan (now part of Jurong Island) in 1970, turning Singapore into a regional refinery hub.

Thus, the sensitivity of these economies to such FDI projects reinforces our decision to exclude Hong Kong and Singapore from the main text's discussion.

C Growth Accounting

An interesting complement to our quantitative experiments is undertaking a standard growth accounting exercise for China. This exercise demonstrates that, indeed, TFP growth is a key driver of China's GDP growth, and therefore, as TFP growth is expected to slow down, so too is China's GDP growth.

Let us assume a production function of the form $Y_t = K_t^{\theta}(A_t L_t)^{1-\theta}$, where $TFP = A_t^{1-\theta}$. Following Hall and Jones (1999), we can decompose GDP per capita into:

$$\frac{Y_t}{pop_t} = A_t \left(\frac{K_t}{Y_t}\right)^{\frac{\theta}{1-\theta}} \frac{L_t}{pop_t}$$

where pop_t is the total population.

Hence, the growth of GDP per capita can be expressed as:

$$\begin{aligned}\Delta\left(\frac{Y_t}{pop_t}\right) &= \Delta A_t + \frac{\theta}{1-\theta}\Delta\left(\frac{K_t}{Y_t}\right) + \Delta\left(\frac{L_t}{pop_t}\right) \\ &= \frac{1}{1-\theta}\Delta TFP_t + \frac{\theta}{1-\theta}\Delta\left(\frac{K_t}{Y_t}\right) + \Delta\left(\frac{L_t}{pop_t}\right)\end{aligned}$$

where Δ denotes a growth rate.

Table 3 presents the growth-accounting exercises using the national accounts approach, including TFP, capital, and GDP ($RGDP^{NA}$). Since the contribution of TFP growth is weighted by $1/(1-\theta)$, the growth contribution of TFP is $2 \times 3.05/7.68 = 79.5\%$ of the growth in GDP per capita.

Table 3: Growth accounting in the data, national accounting approach

	Data			
	GDP per capita ($RGDP^{NA}$)	TFP	Capital/output ratio	Emp/pop ratio
Aver. annual growth rate	7.68	3.05	1.30	0.27
Cont. to per capita GDP growth	100.00	79.50	16.96	3.54

Unfortunately, data limitations preclude us from undertaking this growth accounting using production-based GDP (the concept that we use in our quantitative model) consistently.

D Discussion of Labor Income Shares

D.1 Labor Shares from the PWT 11.0

Computing the labor share from income data is challenging because we need to estimate the labor compensation of self-employed workers, whose income includes both labor and capital components. Gollin (2002) discusses several methods for handling this issue. PWT 11.0 estimates the labor share using five approaches, of which Adjustments 1-3 originate from Gollin (2002):[18]

- **Naive share**: Labor income includes only the compensation of employees and excludes self-employed income.

[18] See details in Feenstra et al. (2015, Appendix C).

- **Adjustment 1**: All self-employed income is treated as labor compensation.
- **Adjustment 2**: Self-employed workers are assumed to use labor and capital in the same proportion as the rest of the economy. Although Adjustment 2 is generally considered the best measure, only Japan in our sample reports mixed income.
- **Adjustment 3**: Self-employed workers are assumed to earn the same average wage as employees. This method tends to overstate labor shares in East Asian economies, where the majority of self-employed workers are low-skilled. PWT 11.0 considers Adjustment 3 the best measure for Taiwan.
- **Adjustment 4**: All self-employment is assumed to take place in agriculture. Accordingly, the entire value added in agriculture is added to labor compensation. PWT 11.0 considers Adjustment 4 the best measure for Korea, Hong Kong, and Singapore.

Table 4 shows the labor shares PWT 11.0 constructs for each economy. PWT 11.0 selects what it considers the best measure of labor income in each case from among five possible adjustments and uses it to construct TFP.

Table 4: Labor shares reported by PWT 11.0

Economy	Sample Period	Different Adjustment Methods					PWT Labor Share	
		Naive (1)	Adj 1 (2)	Adj 2 (3)	Adj 3 (4)	Adj 4 (5)	Method	Value
US	1978-2023	0.56	0.63	0.61	0.61	0.58	Adj 2	0.61
China	1978-2023	0.58			0.62	0.73	Naive	0.58
Japan	1950-2023	0.50	0.60	0.56	0.67	0.54	Adj 2	0.56
Korea	1972-2023	0.46	0.57	0.52		0.55	Adj 2	0.52
Taiwan	1961-2023	0.53			0.72		Adj 3	0.72
Hong Kong	1960-2023	0.48			0.54	0.48	Adj 4	0.48
Singapore	1960-2023	0.42			0.52	0.43	Adj 4	0.43

Figure D.1 plots the different labor shares from PWT 11.0. In a blog entry, Restrepo and Reinbold also report Adjustment 4 for Taiwan, which is very similar to the naive share.[19] However, we did not find such information in PWT 11.0 to replicate their computations in a model-consistent way.

[19] https://www.stlouisfed.org/on-the-economy/2018/january/measuring-labor-share-asian-tigers

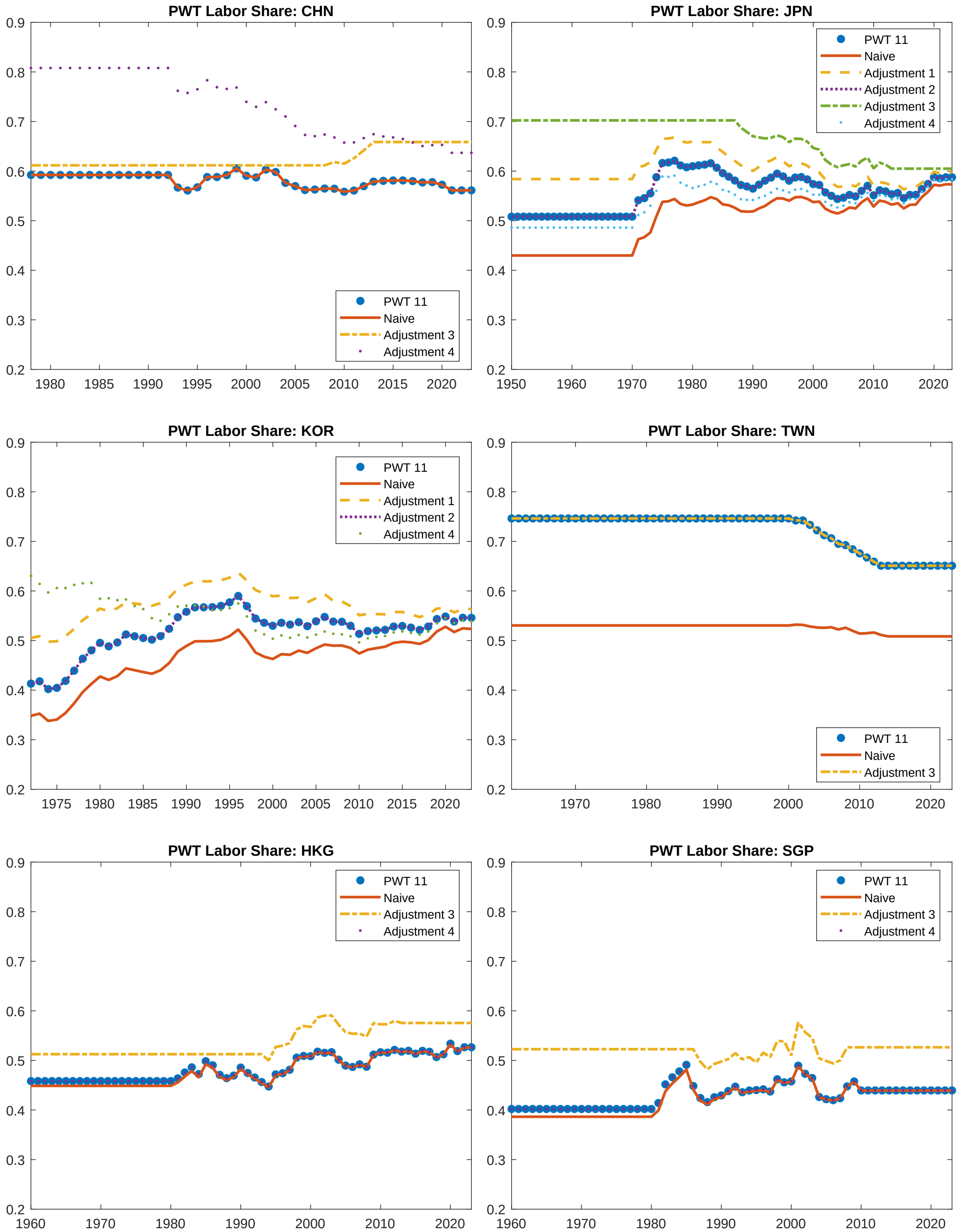

Figure D.1: Labor shares reported by PWT 11.0

D.2 Discussion of Adjustment of Labor Income Shares

China. China's National Bureau of Statistics provides annual data on the labor share for each province, but not for the aggregate economy. Bai et al. (2006) construct an aggregate labor share by taking the average of the provincial labor shares, weighted by each province's GDP share. This yields an average labor income share of 0.5.

Before 2004, the National Bureau of Statistics counted all self-employment income as labor income, consistent with Adjustment 1 in PWT 11.0. As a result, the 0.5 estimate from Bai et al. (2006) likely overstates the true labor share and understates the true capital share. In 2004, for the first time, the National Bureau of Statistics explicitly excluded the imputed capital income of self-employed workers from its definition of labor income. Unfortunately, the Bureau does not report the size of this adjustment, preventing us from correcting labor share estimates prior to 2004.

PWT 11.0 adopts the naive labor share (0.58) as the preferred estimate for China, a measure that includes only employee compensation and excludes all self-employed income. However, this value does not appear in China's official data, raising the possibility that it may be mislabeled or the result of an undocumented adjustment.

Taiwan. PWT 11.0 uses Adjustment 3 for Taiwan as the preferred estimate of the labor share, which yields a value of 0.72. The "same-wage" assumption underlying this adjustment may be reasonable in advanced economies, where employees account for 85–95% of the total number of persons engaged (employees plus self-employed). However, in many emerging economies, this share falls below 50% and can be as low as 4%. In such cases, relying on employee wage data to impute the labor income of the self-employed is likely to overstate their actual earnings. Therefore, Taiwan's labor share under this adjustment is likely to be too high, and we prefer not to use it.

Singapore. PWT 11.0 follows Adjustment 4 by adding the entire value added in agriculture to labor compensation, assuming that all self-employment in Singapore takes place in agriculture. This yields a labor share of 0.43, which remains too low, as the labor income of the self-employed outside agriculture is largely ignored. Moreover, the impact of this adjustment is minimal: the adjusted labor share is very close to the unadjusted share of 0.42. In a robustness exercise in the Appendix F, we adopt a more conventional value for the labor income share of 0.6, nearly identical to that used for the U.S.

E Additional Robustness

Starting from 1995. Now, we aim to match the period of the empirical facts in Section 2. We simulate the model from 1995. Figure E.1 shows the patterns of GDP growth, investment rate, and return to capital from the model. Clearly, the results are nearly identical to those in the benchmark calibration in the main text (when we start from 1978).

Figure E.1: China: Transitional dynamics 1995-2023

Alternative capital income share. Now, we set China's capital income share to 0.42, the value from PWT 11.0. Figure E.2 shows the new transitional dynamics. Under this calibration, the model delivers income growth slightly lower than the benchmark (top-left panel). At the same time, the model invests less, resulting in a large gap between the model's and observed investment rates. The explanation is transparent: with $\theta = 0.42$, the production function is more concave in capital. Thus, the social planner does not want to invest that much in capital, leading to weaker capital accumulation and slower growth.

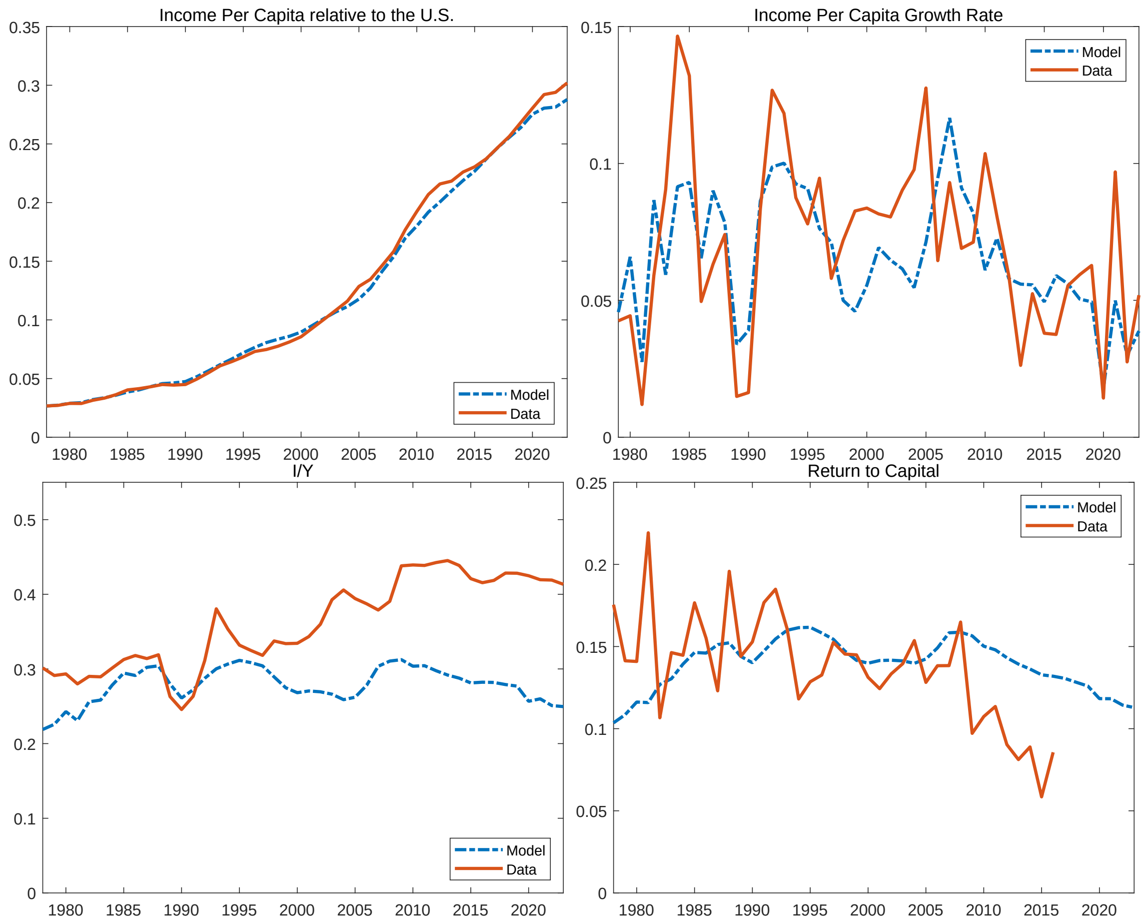

Figure E.2: China: Transitional dynamics with $\theta = 0.42$

Real investment rate. Our final robustness analysis shows that our result is robust when compared with the real investment rate. The solid line in the left panel of Figure E.3 compares the real investment rate with our benchmark model, while the solid line in the right panel compares the nominal investment rate with our benchmark model.

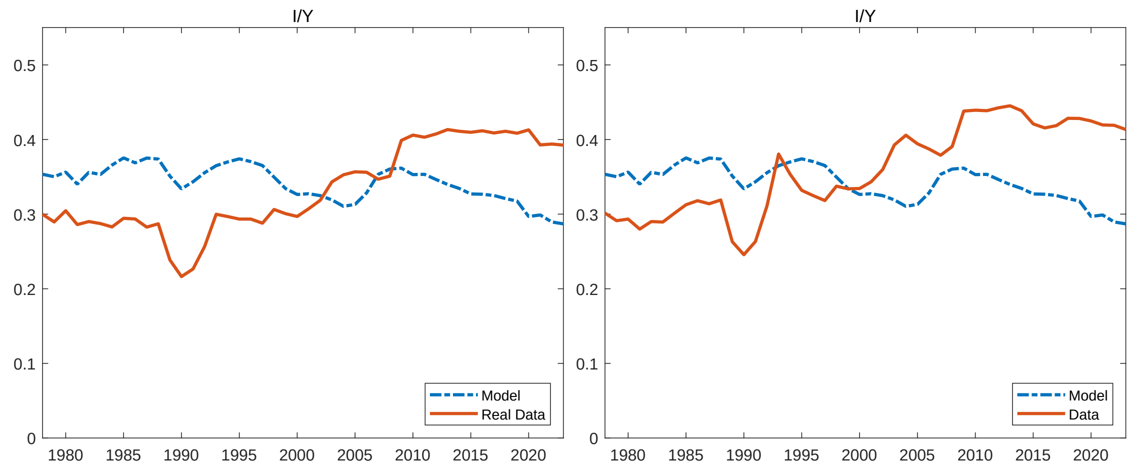

Figure E.3: Transitional dynamics (model and data): Investment rate

F Additional Transitional Dynamics

Table 5: Calibration: The Asian miracle economies

Economy	δ	θ	g	Initial Year	TFP Available From
Hong Kong	0.028	0.51	1.18%	1960	1964
Singapore	0.045	0.40	1.18%	1960	1964

Hong Kong. Our next set of results deals with Hong Kong, where we use the capital share, $\theta = 0.51$, directly from PWT 11.0. In the top left panel of Figure F.1, the model accurately forecasts Hong Kong's income per capita. However, a growing gap emerges toward the end of the sample, where the city's economy appears to lag behind expectations.

The main divergence between the data and the model is in investment, which appears much lower in the data than in the model. However, since Hong Kong is heavily dependent on trade and services, our model may need to be modified to capture the peculiarities of Hong Kong's investment data fully. For example, investments in factories located near but outside Hong Kong (i.e., in the Chinese hinterland of Hong Kong) might not be properly recorded in Hong Kong's official statistics.

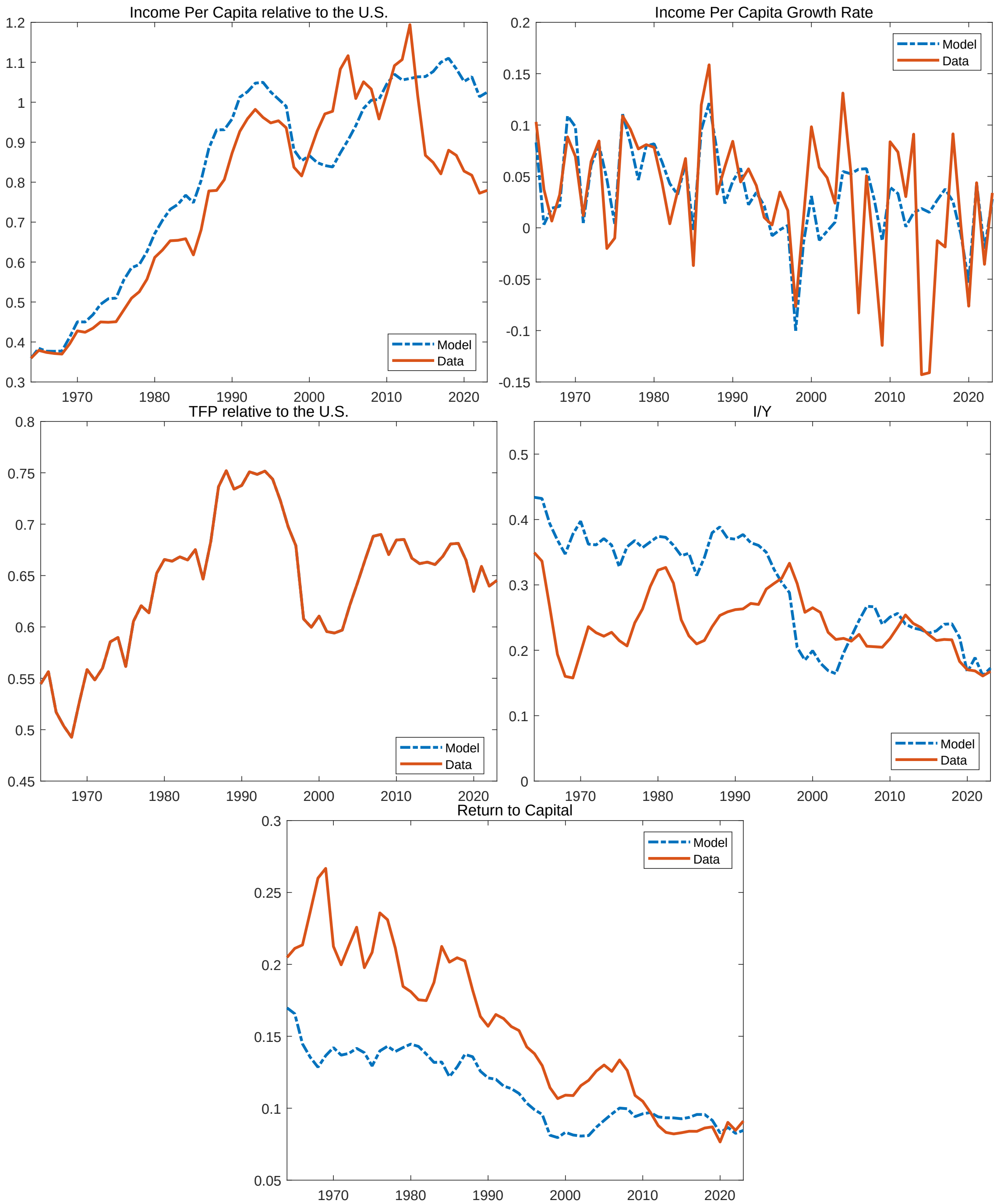

Figure F.1: Hong Kong: Transitional dynamics

Singapore. We conclude our analysis with Singapore, with results reported in Figure F.2. As in the previous cases, the model tracks income per capita reasonably well (top-left panel). However, after 2010, Singapore's growth relative to the United States effectively ceased. Strikingly, Singapore appears to have converged rapidly to a TFP level close to 80% of that of the United States, with this convergence essentially completed by the early 1990s. The model also performs notably well in matching the investment rate (bottom-right panel).

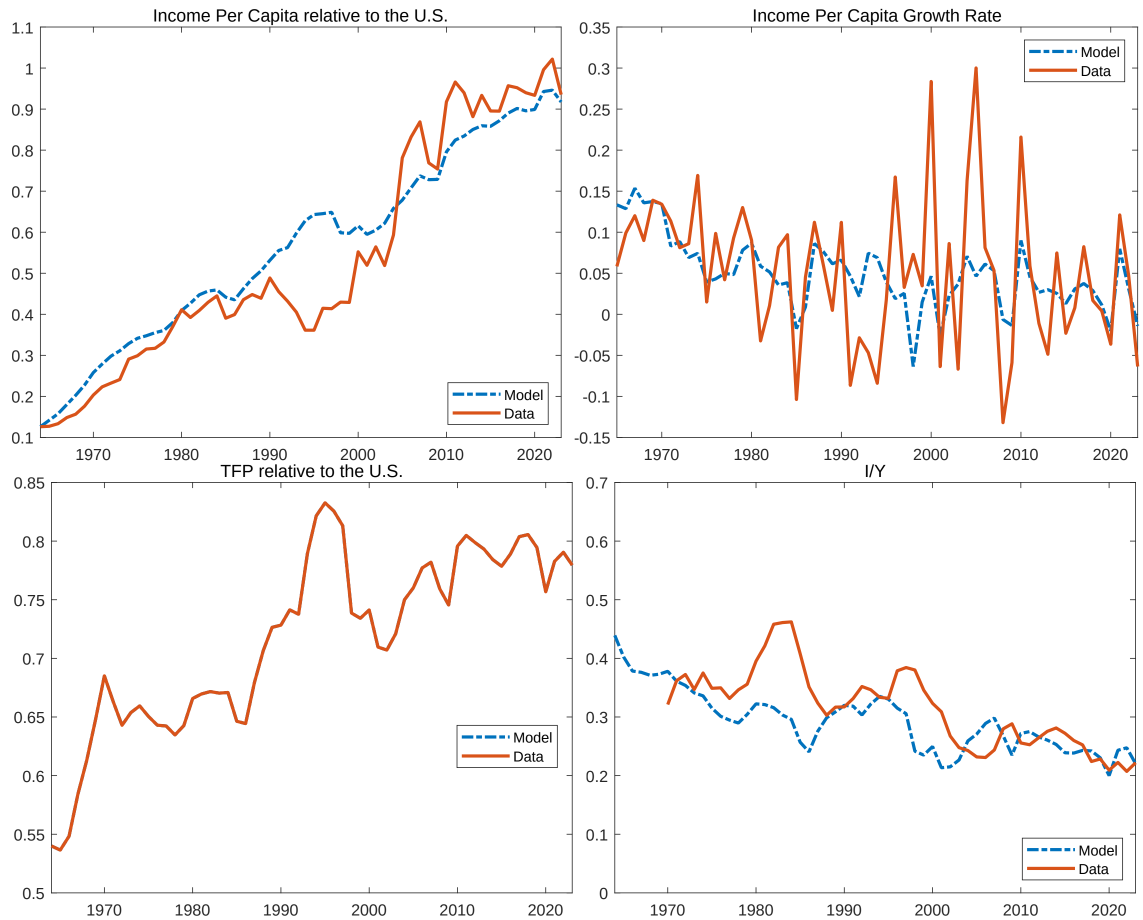

Figure F.2: Singapore: Transitional dynamics $\theta = 0.4$

Taking stock. To sum up, our minimalist model can also match the experience of Hong Kong and Singapore, including the recent slowdown in growth (a key forecast of our model regarding China's future).

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