

Demographic change and long-term economic growth path in Asia[☆]

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ABSTRACT

Asia faces significant demographic challenges with uncertain economic implications. This study projects the economic trajectories of major Asian economies over 50 years using a growth model focused on demographic change. It provides a practical, tractable growth projection framework that avoids complex dynamic optimization. Utilizing historical data, this framework consists physical and human capital accumulation, technological progress, and labor-capital substitution. While a slowing labor force poses challenges, it does not predetermine Asia's growth prospects. The simulation results highlight the importance of technological progress and physical and human capital investment in mitigating demographic impacts. Projections suggest China's Gross Domestic Product (GDP) growth rate will decline to 0.9–2.5% during 2051–2070. China will surpass Japan in Purchasing Power Parity (PPP)-adjusted GDP per capita by 2050 and approach about 90% of the US level by 2070. India is projected to outpace the US in GDP by 2050 and potentially surpass China by 2070.

1. Introduction

Asia has made dramatic economic progress over the past 50 years, making it the largest and most dynamic region in the world. Asian countries, including Japan, South Korea, China, India, and others, have achieved impressive growth, closing the gap with advanced economies and showing an increase in per capita Gross Domestic Product (GDP).

With 60% of the world population, Asia accounts for about 40% of the world's GDP measured in purchasing power parity (PPP) (Fig. 1). It is home to five of the world's 10 most populous countries: China, India, Indonesia, Pakistan, and Bangladesh.¹ Moreover, China, Japan, India,

and South Korea are the current major economic powers. China is the world's largest economy, surpassing the United States (US) in terms of the size of GDP based on PPP (Fig. 1).²

Asia's strong economic growth has narrowed the gap with advanced economies. The per capita GDP of Japan, Singapore, and South Korea have risen rapidly, approaching that of the US. China, India, and Indonesia have followed a similar trajectory. China has rapidly caught up with the US in terms of per capita GDP based on PPP, increasing from a mere 2.4% of that of the US in 1980 to 28.3% in 2022. Over the same period, India's per capita GDP increased from 4.2% of that of the US to 11.0%.³

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¹ Please refer to the latest UN Population Division estimates (<https://www.worldometers.info/world-population/population-by-country/>).

² In terms of market exchange rates, China is the second-largest country, accounting for 18% of the world's GDP in 2022, compared to the US GDP of 25%.

³ According to the IMF estimates, China's per capita GDP, measured by PPP-adjusted current international dollars, increased from 307 USD in 1980 to 18,093 USD in 2022, while India's per capita GDP increased from 532 USD to 7048 USD during the same period.

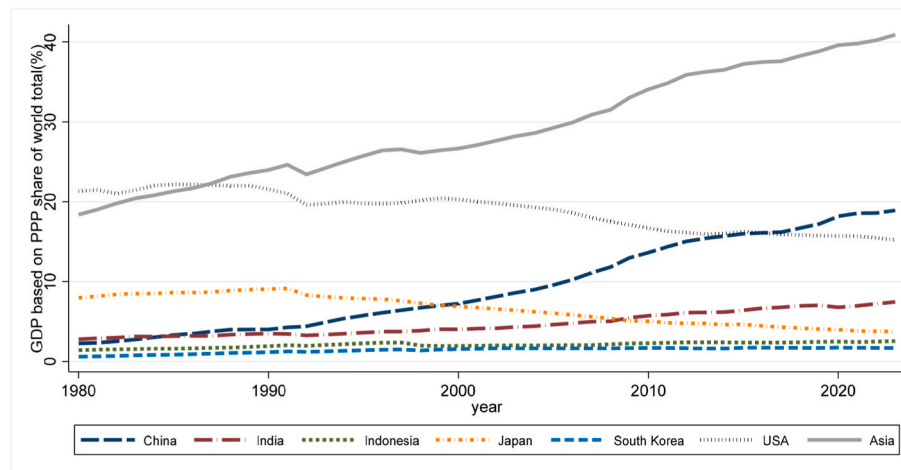


Fig. 1. Trend of GDP share in 1980–2022, Asia and selected economies (%).

Note: Asia comprises countries in the “emerging and developing Asia” group and six advanced economies, including Hong Kong SAR, Japan, South Korea, Macao SAR, Singapore, and Taiwan Province of China (<https://www.imf.org/external/pubs/ft/weo/2022/02/weodata/groups.htm>).

Source: International Monetary Fund’s (IMF) World Economic Outlook Database: October 2022 (<https://www.imf.org/en/Publications/WEO/weo-database/2022/October>)

However, the question is whether the Asian economies can continue this path of rapid growth. While many expect Asia’s growth to continue over the next few decades, a major challenge that could hamper the region’s economic growth potential is rapid demographic changes. Specifically, China, Japan, and South Korea are already experiencing the impact of population aging and declining birthrate, as both could reverse the demographic dividends that have supported strong regional growth over the past five decades.

This study aims to analyze Asia’s economic prospects over the next half-century, considering the impact of demographic change. According to the growth models (Barro and Sala-i-Martin, 2004; Weil, 2014), demographic shifts have a multi-faceted impact on an economy’s the growth potential. Population aging and declining birth rate have a direct impact on production due to a shrinking labor force. In addition, demographic changes influence physical capital accumulation and technological development. A reduced labor force lowers the productivity of physical capital, which in turn lead firms to decrease their physical capital investment. Investment in technological innovation might also decline if a shrinking population decreases the profitability of technological innovation (Romer, 1990). However, a declining labor force could also have positive effects on physical capital accumulation and technological development, and thereby output growth. In the neo-classical growth model, lower labor growth rate leads to a higher physical capital-labor ratio, resulting in a positive impact on output growth per worker (Barro and Sala-i-Martin, 2004). In addition, as the labor force declines, firms may consider increasing their investment in physical capital and technological development to replace labor shortage (Acemoglu, 2002; Acemoglu and Restrepo, 2017).

As in theory, the impact of population on economic growth is ambiguous even in empirical studies. Some studies indicate a positive relationship between population growth and economic growth (Kremer, 1993; Bloom and Williamson, 1998; Park et al., 2022), while others demonstrate the negative effect of population growth or fertility rate on economic growth (Mankiw et al., 1992; Barro and Lee, 2015).

To forecast the GDP and per capita GDP growth rates for major Asian countries up to 2070, this study employs a growth model in which population growth, physical capital accumulation, technological progress, and human capital accumulation play roles in determining long-term growth. In this model, physical capital accumulation is endogenously determined. We augment the model with the determination of investment (saving) and technological innovation and imitation, along with the projected trajectory of population growth. Additionally, in our

model, human capital accumulation is a crucial factor for enhancing labor quality that compensates for declining labor quantity.

Based on the growth model, we demonstrate how GDP and per capita GDP growth rates for major Asian countries including China, Japan, India, Indonesia, and South Korea will develop until 2070. As of 2021, these five economies account for about 84% of Asia’s GDP measured in PPP.

This study builds upon existing literature on macroeconomic projections using growth models, offering an approach that balances theoretical and empirical knowledge regarding the long-run drivers of economic growth. It advances the existing studies by proposing a practical, tractable growth projection model that avoids the need for complex dynamic optimization programming.⁴ Our study is consistent with existing research that constructs long-term growth projections based on various growth models, such as Solow-type, neoclassical, and endogenous growth models. The majority of these studies adopt a “conditional convergence” framework, using a neoclassical growth model as a foundation (Duval and de la Maisonneuve, 2010; Fontagné et al., 2022; Guillemette et al., 2017; Loayza and Pennings, 2022; McKibbin et al., 2007; Otsu and Shibayama, 2016). In this framework, output per worker of less developed economies tends to converge to that of a frontier economy when conditions such as population growth, investment rate, and technological progress are similar. As these economies accumulate capital, the returns diminish, leading to a slowdown in growth rates.

While our approach shares some similarities with previous studies based on the conditional convergence framework, we take a more integrated approach, incorporating labor, physical capital, human capital and technological change—along with their interactions—into growth projections. For instance, Duval and de la Maisonneuve (2010) and Fontagné et al. (2022) employing Solow-growth and growth accounting frameworks consider long-run drivers of economic growth – labor, physical capital, human capital and total factor productivity using historical trends, and under their framework, the demographic change is expected to have an impact on economic growth directly through labor force. However, our work further examines how each country’s labor dynamics impact output growth directly and indirectly. A key contribution of this study is its explicit consideration of the effects of demographic changes—such as labor force decline and population

⁴ The MATLAB and STATA codes for replicating the estimation and simulation are uploaded in the Mendeley repository [DOI: 10.17632/vtvcc9jgyb.1].

aging—on physical capital accumulation and technological change during the transitional dynamics of Asian economies. While the existing studies like Duval and de la Maisonneuve (2010), Loayza and Pennings (2022) and Fontagné et al. (2022) have considered the role of human capital in technological progress, our model explicitly considers the role of both human capital and population size (market size) in driving technological innovation. In addition, unlike other forecasting models based on the Cobb-Douglas production function, which assume a substitution elasticity of one, such as Duval and de la Maisonneuve (2010), Fontagné et al. (2022), and Loayza and Pennings (2022), our model uses the CES-type production function with country-specific estimates of labor-capital substitution elasticity that allows for more flexible impact of demographic change on physical capital accumulation.

Previous studies, such as Azarnert (2023), Buffie et al. (2024), McKibbin et al. (2007) and Otsu and Shibayama (2016), have constructed growth models based on dynamic optimization with rational expectations and forward-looking agents. These studies are valuable for examining how economic agents, such as households and firms, respond to various policies. In comparison, our approach might be more minimalistic, relying on a reduced-form estimation for saving rate and human capital investment. However, our framework offers significant advantages in other areas. Specifically, it offers a practical, tractable growth projection model that avoids the need for complex dynamic optimization. Without modelling household and firm policy responses through complex iterative projection methods, we focus on analyzing the influence of individual growth factors and their interactions on long-term economic growth. Despite its simple structure, our model enables the exploration of various scenarios, emphasizing the critical role of factors such as human capital investment, technological innovation, and its diffusion in driving growth, rather than focusing solely on demographic changes.

Many prior studies on long-term growth projections for Asian and global economies, including Fontagné et al. (2022), incorporate the concept of “technological diffusion”, where follower economies adapt and catch up with technologies from more advanced economies. Building on the growth literature, our model aims to take a careful approach to technological progress, assuming Asian countries acquire new technologies through both innovation and adaptation at the frontier of technological development. Specifically, unlike the US, where technological progress is primarily driven by innovation, technological growth in Asian economies depends on factors such as labor force size (market size), human capital, existing technology levels, and the technological gap with the US.

This study also contributes to the broader discussion on Asia’s growing role in the global economy and its geopolitical implications (Daly and Gedminas, 2022; Mahubani, 2022; International Monetary Fund [IMF], 2022). Over the past five decades, the rise in Asia’s economic power, particularly China, has reshaped the global economic and geopolitical landscape. A key question remains: Can China and the Asian region sustain strong economic growth and continue emerging as a major player on the global stage, potentially transforming the global governance structure in the coming decades. By providing growth projections for Asian economies and the US, this study sheds light on how shifts in economic power might influence global governance and international relations in the years ahead.

This study assesses the influences of demographic changes on Asian economies and provides estimates of their growth potential, based on a growth model. While demographic challenges might suggest a slowing growth trajectory for some Asian economies, our simulation results demonstrate that the equilibrium economic growth rate is not proportionally determined by population or labor force growth. Other key factors, such as physical and human capital accumulation, technological progress and the substitution between physical capital and labor play crucial roles in determining the growth rate.

However, it is crucial to note that our long-term projections until 2070 are subject to risks and uncertainties, including economic crises,

natural disasters, military conflicts, technological breakthroughs in artificial intelligence (AI), and major external shocks. Additionally, this study assumes that economic policies or institutions will remain unchanged, except for those explicitly considered in our analysis, although it is unlikely that this assumption will hold. Significant policy changes and unexpected shocks can deviate actual growth from the potential growth path projected by the model, either exceeding or dipping below the projection. Therefore, our findings must be interpreted with caution.

Section 2 briefly describes demographic changes and prospects in Asia. Section 3 explores the extent to which the demographic reversal in major Asian economies will directly affect growth potential, utilizing a growth accounting methodology. Section 4 introduces a long-term growth model to evaluate the role of demographic change and other key growth factors in economic growth. Section 5 presents the results of projections for major Asian economies and the US. Section 6 provides the conclusion.

2. Demographic change and prospects in Asia

Asia’s demographic changes have been dynamic and rapid. Following World War II (WWII), the region witnessed a rapid improvement in the birth rate, leading to an accelerated pace in population growth. When the baby boom generation that was born around WWII reached the age of 15 years and older, Asia experienced the advantageous expansion of its working-age population, commonly referred to as the population dividend. This abundant labor is one of the contributing factors supporting the region’s rapid growth.

However, alongside other structural challenges, the Asian economy now confronts significant demographic challenges arising from a rapidly aging population and a shrinking workforce coupled with a declining birth rate. These demographic shifts pose profound implications for the region’s social and economic landscape.

Nevertheless, the pattern and the pace of demographic change within Asia differ by country, as demonstrated in Fig. 2.⁵ Specifically, Fig. 2a, b and 2c present the trends and perspectives of total population size and the share and growth rate of the working-age population for the five selected Asian countries and the US from 1980 to 2070, based on the United Nations’ (UN) World Population Prospects 2022.

East Asian economies, including China and South Korea, seem to follow Japan in terms of the demographic trajectory. Japan is the world’s most rapidly aging society, where the elderly aged over 65 years currently account for 30% of the population, almost doubling from 15.0% in 1995. The country’s total population has been shrinking since 2012. It is expected to decrease from 124 million in 2022 to 89.1 million in 2070 (Fig. 2a). The share of the working-age population aged 15–64 years has been declining rapidly from 69.8% in 1992 to 58.5% in 2022 and is expected to reach 50.4% in 2070 (Fig. 2b). The working-age population growth rate is likely to continue negative over the period with an average of −0.17% in 2020–2030 to −1.14% in 2060–2070 (Fig. 2c).

South Korea’s total population began declining in 2020. According to UN estimates, South Korea’s total population is expected to decrease from 51.8 million in 2022 to 35.9 million in 2070. It is projected that the share of the population aged 65 years and over is expected to increase continuously from 17.5% of the population in 2022 to 46.5% in 2070. The share of the working-age population aged 15–64 years will shrink by 25.4 percentage points (p) between 2022 (70.9%) and 2070 (45.5%). The working-age population growth rate is expected to drop from an average of 0.53% in 2010–2020 to −1.02% in 2020–2030 and continue

⁵ We use data sourced from the UN World Population Prospects 2022 (UN, 2022). We use the medium scenario projection that assumes medium changes in future levels of fertility, mortality, and international migration. For further details, please refer to UN (2022) and Online Appendix Table 1. Appendix Table 1.

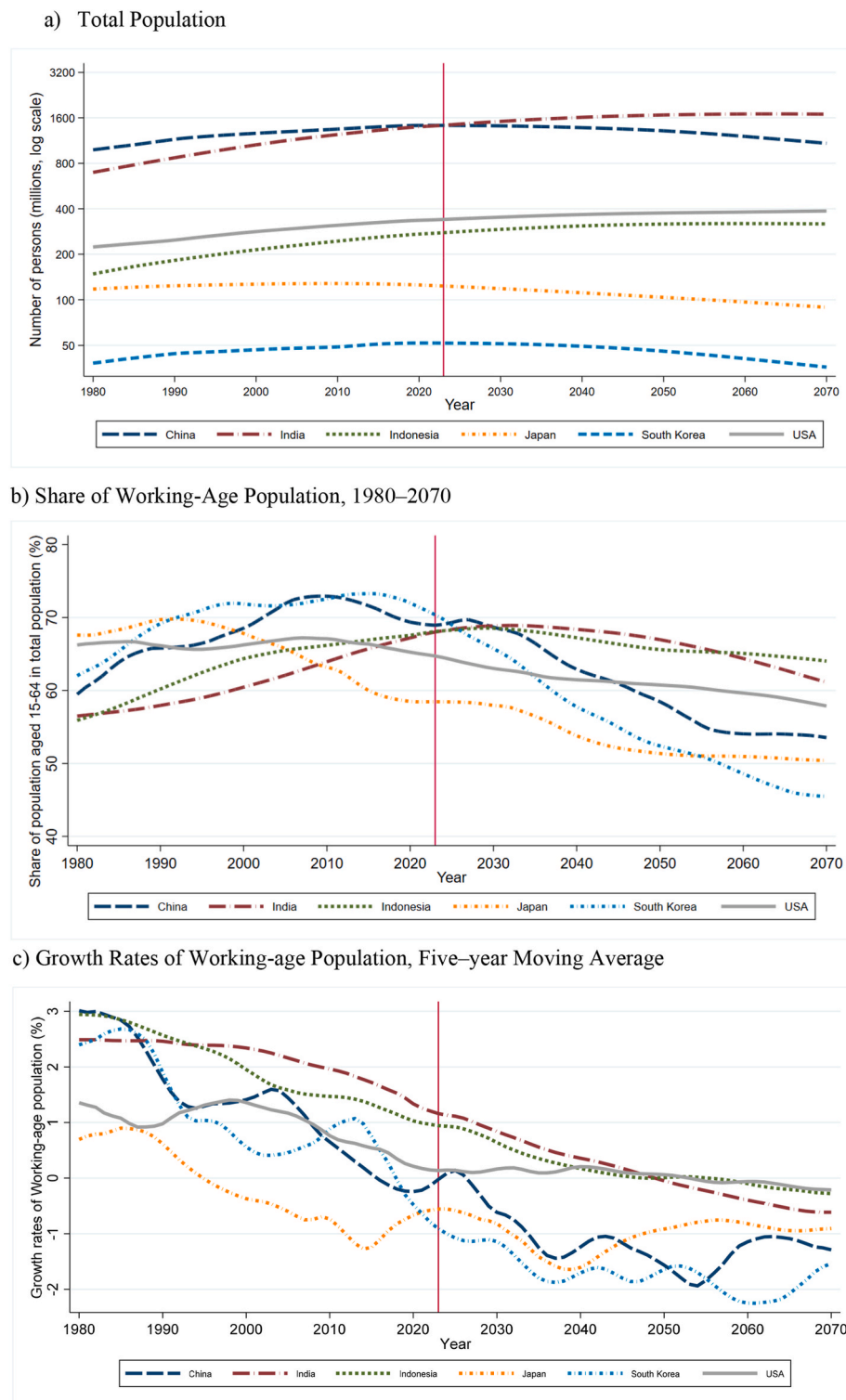


Fig. 2. Trend and projection of total population and working-age population in 1980–2070, selected economies.

Note: Forecasts are the UN's medium scenario projections.

Source: UN, World Population Prospects 2022 (<https://population.un.org/wpp/>)

to decline to -1.96% in 2060–2070.

Similar to Japan and South Korea, China is also facing an aging population and a simultaneous decline in birth rates amid its rapid catch-up. In terms of population size, China has reached its peak of around 1425.9 million in 2021 and reversed its increasing demographic path (Fig. 2a). The share of the working-age population aged 15–64 years has been declining from 72.8% in 2010 to 69.0% in 2022 and is

expected to further decline to 53.5% in 2070. The growth rate of the working-age population is expected to decline from an average of -0.64% in 2020–2030 to -0.92% in 2060–2070.

The population landscape in India and Indonesia is quite different, compared to the three East Asian countries mentioned earlier. Both countries are expected to experience an increasing population size. The population size in India is estimated around 1417.2 million in 2022 and

it is expected to reach around 1697.0 million in 2063 and decline to 1690.2 million in 2070. The share of the working-age population is expected to grow from 67.8% to around 68.9% over the next ten years and decline to 61.2% in 2070, which is still higher than the three East Asian countries. India's working-age population is expected to grow by an average of 0.86% in 2020–2030, as demonstrated in Fig. 2c. Yet, it will likely decline in the 2050s and will be -0.28% on average in 2060–2070.

The population growth rate for Indonesia would be modest. The current population of 273.8 million in 2021 is expected to peak in 2060 at around 319.4 million and begin decreasing to 317.7 million in 2070. The working-age population amounted to 67.7% in 2021 and is expected to increase until the late 2020s. However, its share will begin decreasing from 2030 onward around 68.5%–64.0%, which is higher than the three East Asian countries and India.

3. Demographic reversal and change in growth potential: what does growth accounting predict?

A shrinking labor force is a potential threat to the sustained growth of Asian economies that are already losing economic vitality. The shrinking workforce will likely reverse the demographic dividends that supported the region's strong growth. Applying Solow's growth accounting technique, we can assess the individual impact of the labor force on economic growth, independent of other growth factors. Growth accounting is a methodology that is used for decomposing the growth rate of the total output of an economy into the contribution of four productive components, including growth in physical capital stock, labor force, human capital per worker, and total factor productivity (TFP) growth, which reflects technological progress and economic efficiency.

This approach is applied to decompose output growth rates in the six selected economies, including China, Japan, India, Indonesia, South Korea, and the US during the period, 2010–2019. Data on GDP are gathered from the IMF's World Economic Outlook Database, October 2022 (IMF, 2022), while data on physical capital stock, human capital, and labor share are collected from the Penn-World Table (PWT) 10.1 (Feenstra et al., 2015). As for the number of workers, we use data on the working-age population sourced from the UN (2022), considering that sources available for cross-country labor force or employee data are less reliable than those for the working-age population.⁶

Table 1 presents a summary of the growth accounting estimates for six selected economies over the period, 2010–2019. China, India, and Indonesia exhibited higher GDP growth rates compared to Japan, South Korea, and the US. China achieved an annual average GDP growth rate of 7.67% during this period, with physical capital accumulation contributing most to GDP growth at 4.6%p (about 60%).⁷ Total factor productivity (TFP) growth contributed 2.4%p (31.7%) of GDP growth. Labor contribution to GDP was merely around 0.1%p (1.1%), and human capital contribution was about 0.6%p (7.7%).

⁶ If the working-age population declines, the labor force is expected to decrease accordingly. However, for a more accurate calculation of the labor force as the total number of employed persons, it is essential to consider changes in the demographic structure by age, sex, and education level, and variations in the employment rate for each group. For example, the total number of employed people may vary significantly, as demonstrated in South Korea by Han and Lee (2020), depending on factors such as women's labor force participation and the employment rate of older individuals.

⁷ The reliability of Chinese growth data is controversial. The PWT 10.1 provides much lower estimates than the IMF or the World Bank, suggesting an annual average GDP growth of only 4.9% during the period from 2010 to 2019. According to the growth accounting results reported in the PWT 10.1, physical capital accumulation contributed the most toward GDP growth, accounting for 4.6%p (about 93%). Conversely, TFP growth had a negative contribution of -0.5% (-9.5%) to GDP growth during this period.

Table 1

Growth accounting for selected economies, 2010–2019.

	GDP Growth Rate	Contribution from			
		Labor	Human Capital	Physical Capital	Total Factor Productivity
China	0.0767	0.0008	0.0059	0.0456	0.0243
	100%	1.1%	7.7%	59.5%	31.7%
India	0.0694	0.0090	0.0057	0.0339	0.0208
	100%	12.9%	8.2%	48.8%	30.0%
Indonesia	0.0543	0.0062	-0.0021	0.0328	0.0174
	100%	11.4%	-3.8%	60.3%	32.1%
Japan	0.0121	-0.0056	0.0018	0.0019	0.0140
	100%	-46.3%	14.9%	15.4%	116.0%
South Korea	0.0333	0.0034	0.0047	0.0179	0.0074
	100%	10.1%	14.0%	53.6%	22.3%
USA	0.0225	0.0033	0.0010	0.0054	0.0128
	100%	14.6%	4.4%	23.9%	57.1%

Note: Data on real GDP growth rates are sourced from the IMF's World Economic Outlook Database, October 2022. Data on physical capital stock, human capital, and labor share are collected from the PWT 10.1 (Feenstra et al., 2015). Data on the working-age population, obtained from the UN, are used as the labor input.

India and Indonesia maintained high investment rates throughout their catch-up process. During the sample period, India achieved an annual average GDP growth rate of 6.94%, while Indonesia achieved 5.43%. For both countries, physical capital and TFP were the two major factors that contributed towards their GDP growth in the recent decade, whereas growth in labor contributed positively—0.9%p (12.9%) in India and 0.6%p (11.4%) in Indonesia. Compared to the other factors, human capital made the smallest contribution to their GDP growth.

During the same sample period from 2010 to 2019, South Korea's annual GDP growth rate was 3.3%. The accumulation of physical capital contributed highest toward GDP growth, accounting for 1.8%p (54%), whereas TFP growth contributed 0.7%p (22.3%) to GDP growth. The contribution of human capital and labor to GDP growth were about 0.5%p (14%) and 0.3%p (10%), respectively.

Japan's annual GDP growth was at around 1.2%, which is the lowest among the six selected economies, whereby TFP contributed 1.4%p to GDP growth, while physical capital and human capital contributed about 0.2%p each to GDP growth. The decline in labor contributed negatively -0.6% to GDP growth.

The US economy achieved an annual average growth rate of 2.25% from 2010 to 2019. The largest contributor to GDP was TFP growth, accounting for 1.3%p (about 57%). Physical capital growth contributed 0.5%p (24%), while labor and human capital made smaller contributions of around 0.3%p (15%) and 0.1%p (4%), respectively.

Table 1 shows that labor force was not a major factor that affected economic growth directly in Asia over the past decade. In most countries, compared to labor force growth, physical and human capital accumulation and technological progress played a more significant role in economic growth.

We can also assess, based on the projected demographic changes, what the projected GDP growth rates of the six selected economies would be in the upcoming five decades between 2022 and 2070. Applying the growth accounting framework, we can estimate how much the change in working population growth will directly affect GDP growth rates. We estimate the contribution of labor force growth to GDP growth rates over two periods, 2023–2050 and 2051–2070, assuming that the average labor share during the 2010–2019 period would remain unchanged.

Table 2 presents the results of our estimation. The change in GDP growth rates due to the working population growth rate is calculated by multiplying the average forecasted growth rate in the working population and the average labor share. The results show that demographic change will undermine growth across all the major Asian economies and the US over the next five decades. As discussed in Section 2, the growth rate of the working-age population in China is projected to decline from

0.1% in 2010–2019 to −0.9% in 2023–2050 and −1.14% in 2051–2070. It is estimated that this demographic change alone will reduce China's average GDP growth rate by 0.6%p over the period 2023–2050 and by 0.9%p during 2051–2070 as compared to the growth rate over the period 2010–2019. This result, based on the growth accounting analysis, indicates that the decline in the labor force will not solely reduce China's future growth potential significantly.

For India, the working-age population growth rate will reverse from 1.7% in 2010–2019 to 0.5% in 2023–2050 and −0.4% in 2051–2070. Consequently, due to this negative demographic change, India's average GDP growth rate is expected to reduce by about 0.6%p in 2023–2050 and 1.1%p in 2051–2070 as compared to the growth rate observed during the period 2010–2019.

Similarly, Indonesia's working-age population growth rate is projected to decrease from 1.3% to 0.4% in 2023–2050 and further decline to −0.1% in 2051–2070. Consequently, demographic changes alone will have a negative impact on the average GDP growth rate, causing a decline of about 0.4%p in 2023–2050 and 0.7%p in 2051–2070, relative to the growth rate observed during 2010–2019.

Japan's working population growth will continue to decline from −1.0% in 2010–19 to −1.1% in 2023–2050, with a slight increase to −0.9% in 2051–2070. These demographic changes alone will result in an average GDP growth rate decrease of 0.1%p during the period 2023–2050 and an increase of 0.1%p in 2051–2070 versus the growth rate observed in 2010–2019.

South Korea will experience a sharp reversal in the working-age population growth, shifting from 0.7% in 2010–19 to −1.5% in 2023–2050 and −1.9% in 2051–2070. It is estimated that demographic change alone will reduce the average GDP growth rate by about 1.1%p in 2023–2050 and 1.3%p in 2051–2070 relative to the growth rate observed during the period 2010–2019.

In the US, the working-age population growth will decline from 0.6% in 2010–2019 to 0.1% in 2023–2050 and −0.1% in 2051–2070. Owing to this negative demographic change, The US' average GDP growth rate will be reduced by about 0.2%p in 2023–2050 and 0.4%p in 2051–2070 as compared to the growth rate observed from 2010 to 2019.

These estimates of labor contribution to GDP, derived from the growth accounting approach, offer valuable insights. However, it is important to note that the equilibrium economic growth rate will not change in proportion to the change in the contribution of labor force to the GDP growth rate calculated by the growth accounting technique. Changes in the labor force can also influence the GDP growth rate through other important factors, such as physical capital accumulation

and technological progress. Physical capital accumulation tends to slow down with a lower labor force growth rate because a smaller labor force reduces the average productivity of physical capital per labor. Conversely, physical capital accumulation can grow rapidly when labor force growth rate is lower, depending on the characteristic of the production function, that is, the extent to which physical capital substitutes for labor.⁸

Endogenous technological progress models suggest that a smaller population size or a lower rate of population growth can diminish the profitability of technological innovation, resulting in a lower rate of technological progress (Romer, 1990; Jones, 1995). Recent studies also suggest that the population (labor force) growth rate plays a pivotal role in shaping the market entry strategies of new firms (Hopenhayn et al., 2022). However, Acemoglu's (2002, 2008) theory of directed technological change proposes that a population decline can stimulate technological progress and capital accumulation. Faced with a shrinking labor force, firms may increase investments in physical and human capital and develop labor-saving technologies, to compensate. This shift can lead to the development of more capital- and technology-intensive industries.

4. A model of long-term growth

To assess the overall growth effect of demographic change, we present a long-term growth model in which physical capital accumulation is endogenously determined. The model considers the impact of labor force change on technological progress and the saving rate. Additionally, human capital accumulation, which improves labor quality, is endogenously determined.

The Solow-type neoclassical growth model, such as that described by Barro and Sala-i-Martin (2004) and Acemoglu (2008), suggests the “conditional convergence of income.” This implies that a country with a low initial income (GDP) per capita relative to its long-run or steady-state income per capita will grow faster, assuming constant population (labor force) growth, saving rate, and technological progress. Lower-income countries that are far away from their long-run levels would be able to catch up quickly through higher rates of physical and human capital accumulation due to higher returns on investment. Thus, India, with its lower per capita GDP, has the potential to grow faster than China or the US. However, as a low-income country increases its per capita income and approaches its long-run level, its growth rate will decline. The model indicates that a higher population growth reduces capital per worker, lowering the steady-state level of output per worker and the growth rate of output per worker during the transition to the steady-state. Technological progress, which is assumed to be exogenous, determines the long-run growth rate of output per worker in the steady state.

We have augmented the standard neoclassical growth model by elaborating the technological progress. Countries innovate modern technologies by investing in research and development (R&D) (Romer, 1990). Additionally, developing countries adopt technology imitation from technologically advanced economies to narrow their technology gap and accelerate technological diffusion (Nelson and Phelps, 1966).

We also consider that workers encompass diverse levels of human capital (quality of labor). Human capital accumulation happens through education, job experience and training. Human capital is a crucial factor contributing to economic growth (Lucas, 1988; Barro and Lee, 2013, 2015; Galor and Weil, 2000; Carillo, 2024). Improvement in human

Table 2

Decline in GDP growth due to the change in the working-age population growth.

	Growth rate in the working-age population			Change in the GDP growth rates due to the change in the working-age population growth rates	
	2010–19	2023–50	2051–70	Between 2023–50 and 2010–19	Between 2051–70 and 2010–19
China	0.001	−0.009	−0.014	−0.006	−0.009
India	0.017	0.005	−0.004	−0.006	−0.011
Indonesia	0.013	0.004	−0.001	−0.004	−0.007
Japan	−0.010	−0.011	−0.009	−0.001	0.001
South Korea	0.007	−0.015	−0.019	−0.011	−0.013
US	0.006	0.001	−0.001	−0.002	−0.004

Note: The change in GDP growth rates due to changes in the working population growth rates is calculated assuming that the labor share remains unchanged throughout the period. Therefore, figures in the last two columns are computed by multiplying the difference between the average forecasted growth rate in the working population over the period 2023–2050 (or 2050–2070), and its average growth rate over the period 2010–2019 with the average labor share over the period 2010–2019.

⁸ In the case of the constant elasticity of substitution (CES) production function with the elasticity of substitution between labor and physical capital greater than 1, if the labor force growth rate is lower, the growth rates of physical capital per labor and output per labor are higher. As capital accumulates, the average product of capital per labor converges to a positive value that decreases with the labor growth rate (Barro and Sala-i-Martin, 2004).

capital will affect the growth rate by changing the steady-state level of physical capital per worker or output per worker. Human capital growth can also directly change the growth rate of output per worker.

In the model economy, the production sector is represented by a firm which hires effective labor and rents physical capital to produce and sell a single good in a perfectly competitive market, taking the level of technology or stock of ideas A_t as exogenous. The production function of an economy is defined as follows:

$$Y_t = F(K_t, A_t h_t L_t), \quad (1)$$

where Y_t is total production, K_t and L_t represent physical capital and labor respectively, A_t represents the level of technology, and h_t denotes human capital per capita. The neoclassical production function follows the law of diminishing marginal product. We assume labor-augmenting technological progress.

We assume the following CES production function:

$$Y_t = [\alpha K_t^\rho + (1 - \alpha)((1 - u)h_t L_t A_t)^\rho]^{1/\rho}, \quad 0 < \alpha < 1, \rho < 1, \quad (2)$$

where α is a value between 0 and 1, and it indicates the degree to which physical capital contributes to the production of final goods. ρ is a substitution parameter between labor and physical capital and takes a value of $\rho < 1$. The elasticity of substitution between physical capital and effective labor, $\sigma = 1/(1 - \rho)$, represents the degree to which labor and capital are substituted for changes in the relative prices of capital and labor. If $\sigma > 1$, when the relative price of physical capital and labor changes, the input ratio of physical capital and labor experience a relatively large change compared to their price change. The model economy invests a certain fixed portion, $0 < u < 1$, of the total labor force (including human capital) in human capital accumulation, and the remaining $1 - u$ in production.

The population growth rate is assumed to equal the labor force growth rate. We assume that labor force, measured by the working age population (those aged 15–64 years), will grow based on UN (2022) population projections that assume medium changes in future levels of fertility, mortality, and international migration, as displayed in Fig. 2c. The population growth rate between t and $t + 1$, n_{t+1} , changes every period but is assumed to be constant in the long-run equilibrium.

$$L_{t+1} = (1 + n_{t+1})L_t, \lim_{t \rightarrow \infty} n_t = n^{ss} \quad (3)$$

Human capital grows by the investment in human capital accumulation and the efficiency parameters.

$$h_{t+1} - h_t = B u h_t^\varepsilon, B > 0, \varepsilon \leq 1 \quad (4)$$

The equation shows that human capital stock increases with the size of the accumulated human capital stock and the amount of human capital investment. The growth of human capital per capita between t and $t + 1$ ($g_{h,t+1}$) is determined by $B u h_t^{\varepsilon-1}$. B is an efficiency parameter transforming educational investment into human capital. The parameter ε represents the magnitude of spillovers from the accumulated human capital stock. If $\varepsilon = 1$, as in the specific case of Lucas (1988), human capital stock increases at a constant rate. Conversely, if $\varepsilon < 1$, human capital grows at a decreasing rate as the accumulated human capital stock increases. This can be supported by the observation that the human capital growth rate approaches zero when the maximum of average schooling years stops at 16 years.

The economy is composed of households that earn their income by providing their labor, embodied with human capital, to the production sector and by receiving interest on accumulated assets. In the neoclassical growth model with consumer optimization, households can choose their consumption and saving to maximize their lifetime utility. The representative consumer optimization model indicates that the saving rate is a complex function of preference parameters and lifetime income. Conversely, the life cycle model suggests that the demographic structure determines the saving rate. The old-age dependency ratio,

which is the ratio of the population aged 65 years or above to the working-age population, negatively impacts the saving rate, as the elderly only consume savings they have accumulated in the past. Similarly, the youth dependency ratio, which is the ratio of the population aged 14 years or younger to the workforce, also negatively impacts the saving rate, as children tend to consume without generating income.

We assume a reduced-form equation for the saving rate to fit actual data and apply it to projections. Specifically, we assume that aggregate saving is determined by income and the demographic structure.⁹ Several empirical studies show that the income variable and the old-age and youth dependency ratios determine the saving rate (Horioka and Terada-Hagiwara, 2012; Grigoli et al., 2018). Following the theory and empirical studies, we consider that saving rates depend on per capita GDP in the previous period and the old-age and youth dependency ratios.

$$s_t = s\left(\left(\frac{Y}{L}\right)_{t-1}, \text{old-age dependency}_t, \text{youth dependency}_t, \dots\right) \quad (5)$$

Physical capital accumulates over time, responding to the country-specific investment rate (s_t) and depreciation rate (δ). The law of motion of K is derived from

$$K_{t+1} = Y_t - C_t + (1 - \delta)K_t = s_t Y_t + (1 - \delta)K_t \quad (6)$$

We assume that the domestic investment rate is highly correlated with the domestic saving rate (Feldstein and Horioka, 1980). equation (6), combined with the production function, can be expressed for physical capital per capita, k_t , and the growth rate of physical capital per capita between t and $t + 1$, $g_{k,t+1}$, as follows.

$$k_{t+1}(1 + n_{t+1}) = (1 - \delta)k_t + s_t y_t$$

$$(1 + g_{k,t+1})(1 + n_{t+1}) = (1 - \delta) + s_t \left[\alpha + (1 - \alpha) \left(\frac{K_t}{A_t(1 - u)h_t L_t} \right)^{-\rho} \right]^{1/\rho} \quad (7)$$

Consider the case where the amount of per capita physical capital increases. The greater the elasticity of substitution (i.e., the closer the value of ρ is to zero), the higher the growth rate of physical capital per person. This is because the average productivity of physical capital $\left(\frac{Y_t}{K_t}\right)$ is higher with the higher value of substitution elasticity at the same physical capital-labor ratio. When the elasticity of substitution among factors of production is high, physical capital can substitute for scarce labor.

We consider countries that acquire new technologies through innovation and/or adaptation at the frontier of technological development. Technological innovation equation is assumed as follows:

$$A_{t+1} = A_t (1 + g_{A,t+1}) = A_t (1 + \psi (L_t h_t)^\lambda A_t^{\varphi-1}), \quad 0 \leq \lambda \leq 1, \varphi \leq 1 \quad (8)$$

In the above equation, advancement in technology (knowledge) is determined by the size of the total labor force including both labor quantity (L) and quality (h) and the stock of technology (knowledge). ψ is an efficiency parameter.

In the endogenous technological change model, technological progress is determined by the population of the economy (Romer, 1990). The size of the profit that a company can obtain from technological

⁹ In a two-period overlapping-generations (OLG) model, the young generation learns at schools, works, and saves, while the old generation retires. Assuming a log-utility form, young generation consumes a fixed fraction of their lifetime income in each period (Barro and Sala-i-Martin, 2004). Hence, our specification aligns with the implications of this model under some restrictive assumptions. Nevertheless, this reduced-form specification for consumption and saving has a serious limitation, as it cannot consider the effects of policy changes and shocks on consumer behavior.

innovation depends on the market size, and population size is a key factor that determines the market size. Also, the larger the population, with a higher level of human capital, the greater the pool of workers (researchers) who can improve their knowledge and generate ideas through learning-by-doing and externalities. The parameter λ determines the proliferation of new ideas associated with the increase in population through market size or learning-by-doing effects. If $\lambda = 1$, new ideas increase in proportion to the size of the population embodied with human capital. If $0 \leq \lambda < 1$, new ideas increase less proportionally.¹⁰

The parameter φ represents the influence of the technology stock on new technology development. If $\varphi > 0$, the accumulated technology supports new technology development, corroborating Isaac Newton's famous statement "... standing on the shoulders of giants". If $\varphi = 1$, as in [Romer \(1990\)](#) assumes, a scale effect occurs in which the equilibrium growth rate for technology increases in proportion to the size of the population. This is not supported by most evidence. Subsequent literature on endogenous technological change restricts or excludes scale effects by assuming $\varphi < 1$ ([Jones, 1995](#)). If $\varphi < 0$, it indicates that technologies are more developed, and the more difficult it is to develop new technologies. This is supported by [Bloom et al. \(2020\)](#) where the spillover effect of existing technologies on innovation is negative in advanced countries, implying that it is becoming difficult to find new ideas.

The technological innovation equation with $0 \leq \lambda < 1$, $\varphi < 1$ corresponds to the standard semi-endogenous growth model of [Jones \(1995\)](#). The technology level increases at the constant rate of $\lambda n^{ss} / (1 - \varphi)$ in the steady-state, with human capital stock converging to the steady state and $n^{ss} \geq 0$. With negative population growth, technology level converges to a steady-state value ([Jones, 2022](#)).

In developing countries, technological progress is also driven by technological imitation and adaptation. The key assumption is that it is less expensive for the follower country to imitate the technology than to reinvent it on its own. This cost of replicating technology is lower when the follower (country x)'s technology gap with the leading country (US) is wider. This technology imitation equation is assumed as follows:

$$g_{A,t+1}^{im} = \kappa^* \log \left(\frac{A_{us}}{A_x} \right), \kappa > 0. \quad (9)$$

This equation implies that as the ratio of $\frac{A_{us}}{A_x}$ approaches one, technological imitation becomes difficult as the cost of replicating technology in country x approaches that of technological innovation in the US. The parameter κ indicates the speed of convergence or catch-up, that is, the extent to which less technologically developed countries can narrow its gap with the US in the technology level. We assume that technology advances in the US according to technological innovation equation (8), but for Asian economies, we assume their technology levels change by combining both technological innovation, $g_{A,t+1}$, in equation (8), and imitation, $g_{A,t+1}^{im}$, in equation (9). Therefore, the growth rate for technology decreases when the labor force declines, the technology level increases, and the technological gap with the US decreases over time.

$$A_{t+1} = A_t \left(1 + g_{A,t+1} + g_{A,t+1}^{im} \right) = A_t \left(1 + \psi(L_t h_t)^\lambda A_t^{\varphi-1} + \kappa^* \log \left(\frac{A_{t,us}}{A_t} \right) \right) \quad (10)$$

According to the model, per capita GDP growth rate is determined by per capita physical capital and human capital growth rates and

¹⁰ This model does not explicitly incorporate R&D expenditure that might increase the rate of technological advancement. However, alternatively we may assume $A_{t+1} = A_t \left(1 + \psi((s_A) L_t h_t)^\lambda A_t^{\varphi-1} \right)$, assuming that technological innovation depends on the size of technological investment rather than market size or learning-by-doing effect. Here, s_A indicates the investment rate for technological innovation, such as research and development. The simulation results remain unchanged as long as s_A vary little over time.

technological progress.¹¹ Population change alters the growth of per capita physical capital and technological progress. The change in the rate of technological progress and the rate of human capital accumulation has a direct impact on the per capita GDP growth.

5. Growth projections of Asian economies

5.1. Parameter values and simulation strategies

Consider an economic system composed of the equations in Section 4. Consistent with the growth model's parameter values and the country-specific initial values of economic conditions such as population growth, human capital growth, investment rate, and technological growth, we conduct simulations of the growth model to determine the GDP and per capita GDP of the five major Asian economies and the US by 2070. We analyze the balanced growth path in the transition to the steady state.

[Table 3](#) reports the growth model's parameter values and initial values of economic conditions, most of which are country-specific. For the production function, we assume the depreciation rate for physical capital varies across the countries, ranging from 0.042 in Indonesia to 0.056 in India and is sourced from the PWT 10.1.

Regarding the elasticity of substitution between capital and labor, we rely on recent studies, including cross-country ([Mallick, 2012](#); [Knoblach and Stöckl, 2020](#)) and country-specific analysis, to determine the values for each country. Priority is given to estimate from country-specific analysis based on available micro-level data. According to [Knoblach and Stöckl \(2020\)](#), while most cross-country regressions indicate elasticity of substitution (σ) greater than one, values of σ vary widely among individual countries, with the majority estimates declining below one.

For the US, we set the substitution elasticity at 0.60, based on previous studies. [Knoblach and Stöckl \(2020\)](#) meta-analysis indicates that most estimates for the elasticity of substitution between capital and labor in the US economy are within the range of 0.45–0.87. This range is also consistent with [Herrendorf et al.'s \(2015\)](#) estimates of 0.84 and 0.80 for the US economy and manufacturing sector, respectively. [Karabarbounis and Neiman \(2014\)](#) estimate an elasticity of 1.25 using industry-level data. However, the most recent study ([Oberfield and Raval, 2021](#)) estimates that the aggregate elasticity for the US manufacturing sector falls within the range of 0.5–0.7, considering substitution within plants and reallocation across plants.

Unlike the US, previous studies focusing on Asian countries are limited for reference. For China, we set the elasticity of substitution to be around 1.17, based on recent studies ([Manu et al., 2022](#); [Berkowitz et al., 2017](#)), suggesting values above unity. [Manu et al. \(2022\)](#) provides an extensive discussion on the Chinese economy and obtain an estimate for the elasticity of substitution at around 1.17.

For India, we assume an elasticity of substitution of unity. Previous studies by [Mallick \(2012\)](#), [Upender \(2009\)](#), and [Pohit et al. \(2000\)](#) suggest a range of estimates between 0.52 and 1.4. Mallick's estimate at the aggregate level is around 0.52, while the industry-cross section analyzes the estimate at around 1.28. [Pohit et al. \(2000\)](#) also find that most industries have estimates around unity.

In the case of Indonesia, we rely on [Mallick \(2012\)](#) as it is the only reference available to the best of our knowledge. This work estimated

¹¹ Assuming continuous time, if the production function of (1) is differentiated by time (t), the growth accounting formula is obtained and expressed in per capita terms as follows.

$$\left(1 + g_{y,t+1} \right) = \alpha_{K,t} \left(1 + g_{k,t+1} \right) + \alpha_{H,t} \left(1 + g_{A,t+1} \right) \left(1 + g_{h,t+1} \right)$$

where $\alpha_{K,t}$ and $\alpha_{H,t}$ indicate the contribution of physical capital and technology-embodied labor ($A_t h_t L_t$) to total output, respectively that vary over time.

Table 3

Initial values and parameters for baseline simulation exercises.

	China	Indonesia	India	Japan	South Korea	US
λ	0.75	0.75	0.75	0.75	0.75	0.75
φ	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
δ	0.054	0.042	0.056	0.044	0.052	0.044
u	0.126	0.164	0.140	0.133	0.150	0.185
κ	0.015	0.015	0.015	0.015	0.015	N/A
B	0.123	0.009	0.116	0.043	0.121	0.015
ψ	0.07	0.48	0.20	0.66	0.06	1.65
σ	1.17	1.14	1.00	0.91	1.18	0.60
ρ	0.15	0.12	0.00	-0.10	0.15	-0.67
ε	0.5	0.5	0.5	0.5	0.5	0.5
α	0.418	0.537	0.481	0.436	0.482	0.404
A_0	42.21	46.24	45.04	65.78	62.05	103.39
A_x	0.41	0.45	0.44	0.64	0.60	1
A_{US}						
L_0	986.46	185.45	950.26	72.82	37.04	219.31
h_0	2.70	2.29	2.17	3.59	3.77	3.75
s_0	0.47	0.33	0.29	0.25	0.40	0.19
Old-age dependency	0.19	0.10	0.10	0.51	0.23	0.26
Youth dependency	0.26	0.38	0.38	0.20	0.17	0.28

the elasticity of substitution at around 1.14. For Japan, we use an estimate by Paul (2018) based on Japanese industry/sector-level data between 1970 and 2012. His estimation suggests that the elasticity substitution fluctuates around unity with an overall average of 0.91. Finally, for South Korea, we assume an elasticity of substitution around 1.18, based on the industry-level study done by Song (2021).

Note that the greater the elasticity of substitution, the higher the economic growth rate in the balanced growth path. As an economy has a high elasticity of substitution among production factors, it can maintain higher productivity of physical capital while substituting labor with physical capital. Therefore, it is possible to maintain a relatively high rate of increase in per capita physical capital and per capita production.

We estimate the reduced form of the saving equation (5) using the panel data of cross-country data for the six economies from 1980 to 2019.

$$\text{Savingrate}_{it} = \beta_0 + \beta_1 \log(\text{GDPPC}_{it-1}) + \beta_2 \log(\text{GDPPC}_{it-1})^2 + \beta_3 \text{Old} \\ - \text{age dependency}_{it} + \beta_4 \text{Youth dependency}_{it} + \varepsilon_t + \theta_t + \nu_{it}, \quad (5)$$

where Saving rate_{it} represents the real domestic saving rate in country i at time t ; $\log(\text{GDPPC}_{it-1})$ is the log of real GDP per capita and $\log(\text{GDPPC}_{it-1})^2$ is its squared term at time $t-1$. Table 4 shows our estimation results. We report country-fixed effects models with and without year dummies.¹²

The estimation results in Columns (1) and (2) of Table 4 are broadly consistent with those of previous studies. The coefficient of old-age dependency is negative and significant, as the life cycle model predicts. The coefficient of youth dependency is statistically insignificant. Turning to the GDP-related variables, the coefficient of Log (GDPPC) is positive and significant, with its square term being negative and significant, suggesting a nonlinear (concave) relationship with the domestic saving rate. Initially, the income level has a positive effect on the domestic saving rate, but the marginal effect of income on the saving rate decreases gradually.

In addition to Columns (1) and (2), we re-estimated equation (5') with different specifications, including the exclusion of the US and China from the sample, respectively, as in Column (3) and (4), and a different sample period as in Column (5), considering different economic conditions and structural changes that the countries in our sample encountered during the periods, 1980–2019. Broadly, the results in Columns

(3)–(5) demonstrate that the significance and sign of the coefficient remain unchanged across various specifications and consistent with the main results of Column (2) of Table 4.¹³

We calibrate the human capital equation (4) in order to obtain the parameter B for individual countries. To do so, we set the average growth rate over 2015–2019 as an initial value for human capital growth and the 2019 value of human capital as an initial value for human capital. The parameter ε is assumed to be 0.5, indicating that it becomes difficult for human capital to grow as the accumulated human capital stock increases. The parameter u is calculated as a proportion of the working-age population that attained upper secondary education and tertiary education in 2022, using UNESCO's UIS dataset and the UN (2022). Its value ranges from 0.126 for China to 0.185 for the US. Our estimates for B range from 0.009 in Indonesia to 0.116 in India. Following this specification, the average human capital growth rate will decline gradually from the level of the average growth rate over 2015–2019 at different rates for individual countries.

For technological progress, we set $\lambda = 0.75$ and $\varphi = -1$ as the values of the parameters in the technological innovation equation (8).¹⁴ These values were obtained based on US data by Bloom et al. (2020) and Jones (2022), suggesting that there is no scale effect and technological innovation becomes more challenging as technologies advance. In contrast, Asian economies can develop their technologies through technological imitation in addition to technological innovation, as shown in equation (10). We assume the parameter k to be 0.015, based on convergence literature, which suggests that less technologically developed countries, with their technological level being half that of the US, can increase their technology by about 1% ($0.015 \times \log 2$) per annum. The efficiency parameter ψ varies across individual countries and is obtained by calibrating the technological progress equations to the initial technological growth rates, initial labor force, human capital stock and technology gap.

The initial values for GDP and its growth rates are obtained from the

¹³ For the additional robustness check, we have also attempted an instrumental variable estimation using two-year lagged values for $\log(\text{GDPPC}_{it-2})$ and its squared term, and the estimation results remain consistent with the main results in Column (2) of Table 4. Estimation results will be available upon request.

¹⁴ As an alternative approach, we adopted a panel estimation using cross-country data as we did for saving rate. However, the estimation results did not perform well in explaining country-specific trends for some Asian economies. Therefore, we have opted for the current approach that distinguishes between the roles of innovation and adaptation in technological advancement, and calibrated parameters for individual countries using historical data.

¹² The Hausman (1978) test rejects the null hypothesis (Prob > chi2 = 0.0001), indicating that the random effects estimator is inconsistent.

Table 4
Equation for saving rate.

	(1)	(2)	(3)	(4)	(5)
	All	All	w/o US	w/o China	All
Variables	1980–2019	1980–2019	1980–2019	1980–2019	1990–2019
Log(GDPPC)	0.495** (0.133)	0.485** (0.130)	0.390*** (0.054)	0.892*** (0.151)	0.685*** (0.105)
Log(GDPPC) ²	−0.022** (0.008)	−0.022** (0.008)	−0.016** (0.004)	−0.038*** (0.005)	−0.032*** (0.006)
Old-age dependency ratio	−0.488*** (0.057)	−0.451*** (0.111)	−0.847** (0.284)	−0.279*** (0.055)	−0.503*** (0.052)
Youth dependency ratio	0.120 (0.278)	−0.012 (0.252)	0.515 (0.576)	0.481 (0.408)	0.228 (0.186)
Constant	−2.330** (0.586)	−2.231** (0.596)	−1.982*** (0.385)	−4.809** (1.155)	−3.310*** (0.503)
Observations	234	234	195	195	180
R-squared	0.870	0.896	0.900	0.900	0.878
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes

Note: Table 4 reports pooled-OLS estimates of Equation (5). The dataset contains six selected economies, including China, India, Indonesia, Japan, South Korea, and the United States from 1980 to 2019. The dependent variable is the real domestic saving rate. The independent variables include the log of real GDP per capita and its squared term, old-age dependency ratio (ratio of the population aged 65 years or older to the working-age population aged 15–64 years) and the youth dependency ratio (ratio of the population aged 14 years or younger to the working-age population aged 15–64 years). One-year lagged values for log (GDPPC_{it-1}) and its squared term are used. Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

IMF's World Economic Outlook Database, October 2022. The working-age population growth is obtained from the UN World Population Prospects 2022. The initial values of human capital growth, physical capital growth, saving rate (measured by real domestic investment rate), technological growth, and the output share of physical capital are obtained from PWT 10.1. Technological growth is measured by TFP growth divided by labor share. We take the average of these variables from 2015 to 2019 to construct their initial values for individual countries. Therefore, we assume that Asian countries will revert to their pre-pandemic equilibrium growth trajectory after recovering from the COVID-19 shock.

5.2. Baseline simulation results

A summary of our baseline projections for the selected countries—China, India, Indonesia, Japan, South Korea, and the US—is reported in Fig. 3 and Tables 5 and 6. Fig. 3 depicts the simulation results for the six economies, showing the population (working-age population) growth rate, human capital growth, technological progress, investment rate, output per capita growth, and total output growth along the transition path approaching the steady-state in this model. Table 5 provides our projections for GDP and per capita GDP growth rates across three different periods—2010–2019, 2023–2050, and 2051–2070. The projection results in terms of GDP and per capita GDP are reported in Table 6 and illustrated in Figs. 4 and 5.

The simulation results for China are presented in Fig. 3a). The rate of technological progress is forecasted to decrease from its initial value of 2.7% to 1.2% by 2070. The investment rate is likely to start declining from its initial value of 47% to 29% by 2070. Our projections imply that China is experiencing a significant slowdown in potential GDP growth, declining from 7.7% in 2010–2019 to 4.1% in 2023–2050 and 0.9% in 2051–2070 (Table 5). This slowdown, driven by declines in labor force growth, physical capital accumulation, and technological growth, could result in China's potential growth rate falling below that of India and Indonesia.

Despite the slower pace of the catch-up, the Chinese economy is projected to continue to narrow its per capita income gap with the US. By 2070, China's per capita income is expected to reach 110,791 USD and 90.0% of the US per capita income in the constant 2017 PPP price (Table 6). In terms of GDP, China is projected to surpass the US over the next 50 years. In terms of per capita income, China is expected to

overtake Japan by 2050 (Fig. 5).

India's simulation results are illustrated in Fig. 3b). India is expected to experience a gradual decline in the rate of technological progress from its initial value of 4.3% in 2015–2019 to 1.2% in 2070. In addition, the investment rate is expected to increase from 29%, the initial value during the 2015–2019 period, to 34.1% in 2045, but reverse course and decline to 29% in 2070. The GDP and GDP per capita growth rates are expected to decrease significantly, reaching 1.7% and 2.3% in 2070, respectively. The average annual GDP growth rate for the period 2051–2070 is expected at 2.7%, and the GDP per capita growth rate at 3.0% (Table 5).

According to our projections, the potential GDP growth of the Indian economy is forecasted to decline from 6.9% in 2010–2019 to 5.2% in 2023–2050, and further decline to 2.7% during the period 2051–2070 (Table 5). This is because both the rate of return to physical capital investment and the speed of technological catch-up are lower. Although the Indian economy is predicted to have high growth potential over the next 50 years, its actual growth path can deviate from this projected potential growth path depending on the country's policies and unexpected shocks. If India can achieve its potential growth rate, then the Indian economy is likely to continue to narrow its per capita income GDP to other Asian countries and the US. By 2070, India will reach 45,962 USD, equivalent to 37.3% of the US per capita income in constant 2017 PPP price (Table 6). India can surpass the US in terms of GDP by 2050, attributable to its more favorable demographics and higher per capita GDP growth (Fig. 4). India is also projected to narrow its gap with China in terms of GDP over the next 50 years.

Indonesia presents a similar growth trajectory, as demonstrated in Fig. 3c). The Indonesian economy is projected to demonstrate a declining growth potential over the next 50 years—4.6% in 2023–2050 and 2.7% in 2051–2070, relative to 5.4% in 2010–2019 (Table 4). With its higher potential growth rate, Indonesia is expected to undergo a process of catching up with China, Japan, and the US. By 2070, Indonesia's per capita income is expected to reach around 67,713 USD, accounting for about 55.0% of the US per capita income in constant 2017 PPP price (Table 5). By 2050, Indonesia's GDP is likely to be nearly twice that of Japan.

Fig. 3d) presents the simulation results for Japan. The rate of technological progress is expected to drop to 0.9% by 2070 from its initial value of 1.7%. The investment rate is expected to gradually decline to 14% by 2070. Japan's potential GDP growth is forecasted to decline

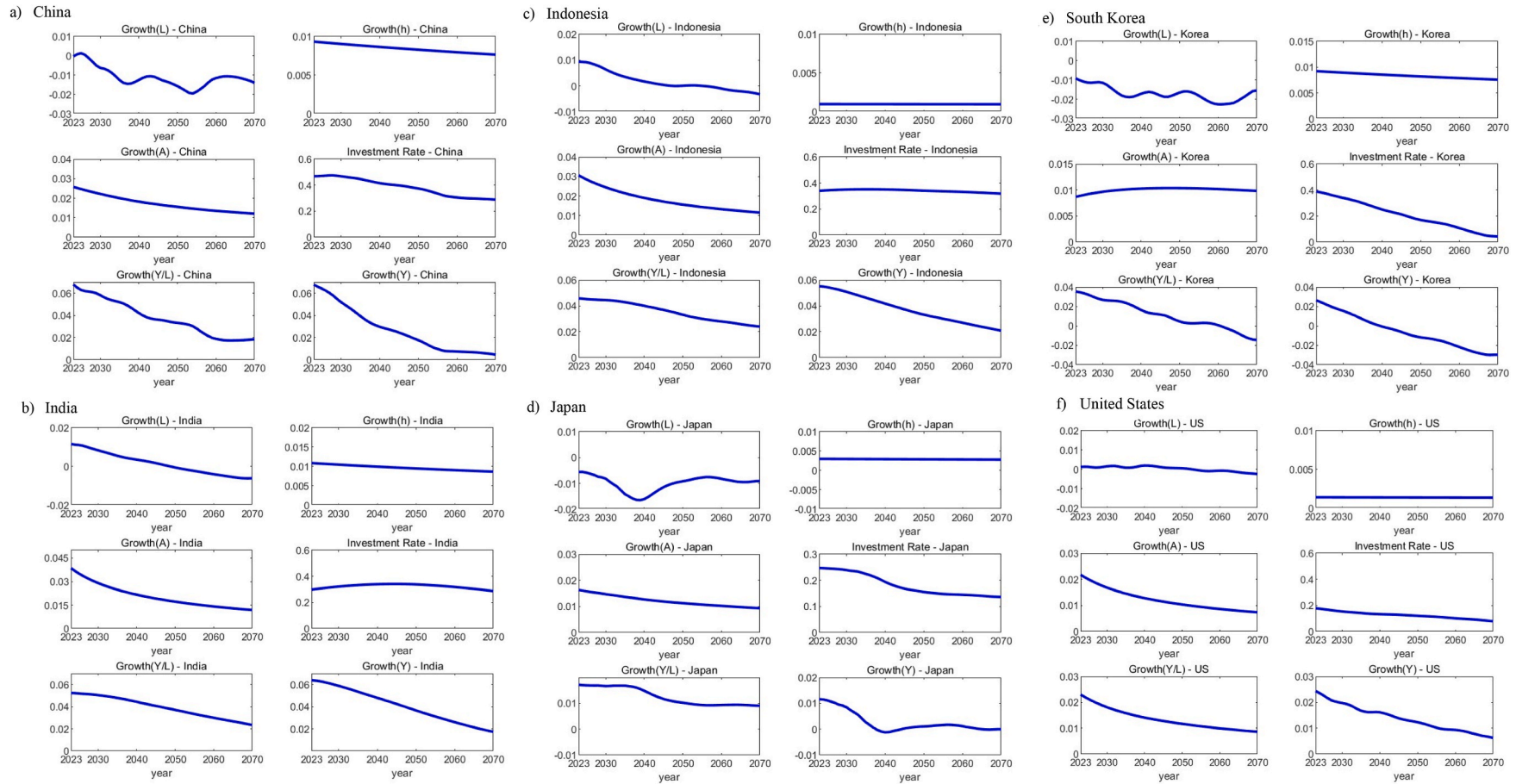


Fig. 3. Baseline simulation results from the growth model.

Note: The baseline simulation results are obtained assuming the initial values and parameters presented in Table 3.

Table 5

Baseline simulation result for average GDP and per capita GDP growth rates.

	2010–2019	2023–2050	2051–2070
	Actual data	Predicted	Predicted
A. GDP growth (%)			
China	7.669	4.144	0.880
India	6.939	5.248	2.680
Indonesia	5.431	4.560	2.724
Japan	1.207	0.432	0.087
South Korea	3.333	0.706	−2.120
United States	2.251	1.776	0.930
B. Per capita GDP growth (%)			
China	6.831	4.992	2.275
India	5.545	4.661	3.045
Indonesia	3.985	4.146	2.824
Japan	1.298	1.515	0.945
South Korea	2.785	2.197	−0.193
United States	1.559	1.641	1.008

Note: The baseline simulation results assume the initial values and parameters in Table 3.

Table 6

Baseline Simulation Result for GDP and per capita GDP.

	2022	2050	2070
	Actual data	Predicted	Predicted
A. GDP (billions; PPP; 2017 international \$)			
China	25,800	92,764	120,240
India	9988	42,149	77,686
Indonesia	3427	12,307	21,513
Japan	5142	6558	6798
South Korea	2359	3825	2887
United States	21,613	37,827	47,631
A. Per capita GDP (PPP; 2017 international \$)			
China	18,094	70,670	110,791
India	7048	25,231	45,962
Indonesia	12,440	38,796	67,713
Japan	41,483	63,189	76,263
South Korea	45,529	83,567	80,374
United States	63,890	100,766	123,140

Note: The baseline simulation results assume the initial values and parameters in Table 3.

from 1.2% in 2010–2019 to 0.4% in 2023–2050, and further to 0.09 in 2051–2070 (Table 5). Given these low growth rates, the Japanese economy will be unable to narrow its per capita income gap with that of the US. By 2070, Japan's per capita income will reach 76,263 USD, which is about 61.9% of the US's per capita income in constant 2017 PPP price (Table 6).

The simulation results for South Korea are demonstrated in Fig. 3e). The South Korean economy is expected to maintain about 1% technological growth over time until 2070. Additionally, it will experience a considerable decrease in the investment rate, down from its initial value of 39.9% to 4.3% in 2070, and this is attributable to rapid population aging and per capita income increase. The South Korean economy will experience a rapid decline in GDP growth rate, declining from 3.3% in 2010–2019 to 0.7% in 2023–2050 and further to −2.1 % in 2051–2070 (Table 5). Its per capita GDP growth rate is also projected to decrease, albeit less steeply, from 2.8% in 2010–2019 to 2.2% in 2023–2050 and further to −0.2% in 2051–2070. Given these low growth rates, it is forecasted that the South Korean economy will not be able to continuously narrow its per capita income gap with that of the US over the next 50 years. By 2070, South Korea will reach 80,374 USD, which is equivalent to 65.3% of the US's per capita income in constant 2017 PPP price (Table 6).

Lastly, Fig. 3f) presents the simulation results for the US. The rate of technological progress is projected to decline modestly from its initial value of 2.4% to 0.7% by 2070, and the investment rate shows a decline from its initial value of 18.6% to 8.0% by 2070. According to our

projections (Tables 5 and 6), the US economy is forecasted to experience a modest decline in its growth potential from 2.3% in 2010–2019, to 1.8% in 2023–2050 and 1.0% in 2051–2070. By 2070, the US is estimated to reach 123,140 USD in constant 2017 PPP price.

5.3. Simulation results with alternative scenarios

We present additional projections for the GDP and per capita GDP growth rates for the five major Asian countries and the US under three alternative scenarios, each based on different assumptions to enable meaningful comparisons with the baseline: 1) a higher rate of population growth with higher fertility rate and lower dependency ratio; 2) a higher rate of technological progress with increased efficiency parameters; 3) a higher rate of human capital growth.¹⁵ The simulation results for each of the three alternative scenarios are presented in Table 7, compared with the baseline simulation result.

For the first scenario, we assume higher population growth and a lower dependency ratio over the next 50 years, based on the UN high fertility scenario (see Appendix Table 1). According to Columns 2 and 7 of Table 7, this scenario outperforms the baseline in GDP growth rates across all the countries over the two different periods, 2051–2070 and 2051–2070. This is attributable to the direct positive impacts on GDP growth rates resulting from a higher labor growth rate as well as the increase in the saving rates resulting from a lower old dependency ratio. The increase in GDP growth rate would range from 0.59%p in Indonesia to 0.15%p in Japan over 2023–2050 and range from 0.41%p in Indonesia to 1.00%p in South Korea 2051–2070. In the case of China, the average annual GDP growth is estimated to be about 1.57%, which is higher than the 0.88% estimated under the baseline scenario over 2051–2070. The simulation indicates that changes in population structure have an important impact on GDP growth rates. Nevertheless, all Asian countries will continue to experience a declining trend in growth rates over the growth paths of an economy, highlighting the importance of other factors such as technological progress and human capital accumulation. This is consistent with the growth accounting results in Table 2 in Section 3.

The scenario with higher population growth shows slightly lower or similar growth rates in per capita GDP compared to the baseline (Columns 2 and 7 of Table 7). The change in the per capita GDP would be smaller than that in GDP, ranging from −0.101%p in South Korea to 0.005%p in the US over 2023–2050 and range from −0.14%p in Indonesia and 0.28%p in South Korea over 2051–2070.

For the second scenario, we assume a higher rate of technological progress over the next 50 years, achieved by augmenting the parameter for technology spillover ($\varphi = 0$) in the technological innovation

¹⁵ We can also consider an alternative scenario in which the value of substitution elasticity (σ) changes due to industry upgrading, improvements in labor quality, changes in production technology, and more. However, in an environment where technological innovations, such as artificial intelligence (AI), are occurring rapidly, predicting how the value of σ will change in the future becomes quite challenging. Nonetheless, to provide an example of assessing the impact of σ value changes for the Chinese economy, we have analyzed a scenario that assumes a gradual decline of σ to 0.9 (Japan's value) over the next ten years, followed by a further gradual decline to 0.6 (US value) from 2051 to 2060. The simulation results demonstrate that the annual GDP growth rates predicted in this alternative scenario are, on average, lower by about 0.7%p over the period from 2023 to 2050, and about 0.2%p over the period from 2050 to 2070 versus those in the benchmark scenario. Conversely, if the value of the substitution elasticity (σ) increases from its current value of 1.17–1.4, the growth rates are, on average, higher by about 0.7%p over the period from 2023 to 2050 and about 0.3%p over the period from 2050 to 2070 versus those in the benchmark scenario. The detailed estimation results will be available upon request.

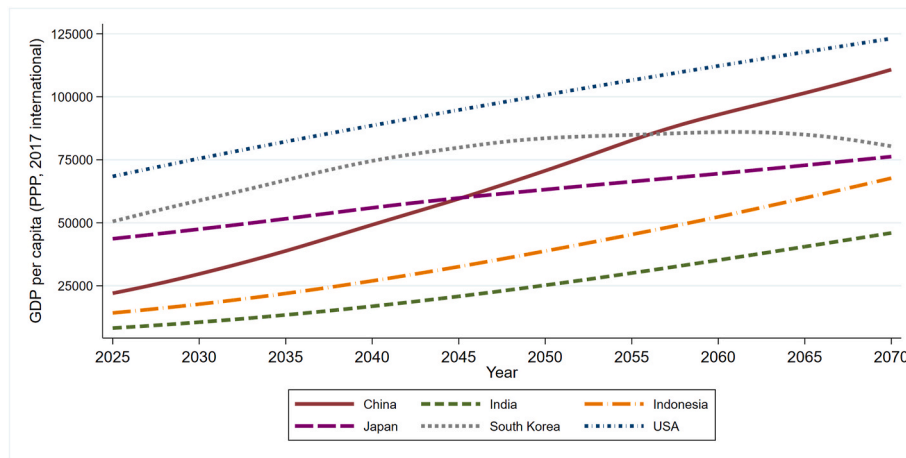


Fig. 4. Projections for GDP per capita of selected economies, 2025–2070.

Note: Fig. 4 provides projection results for PPP (Purchasing Power Parity)-adjusted real per capita GDP for the selected five Asian countries and the United States, subject to the baseline scenario.

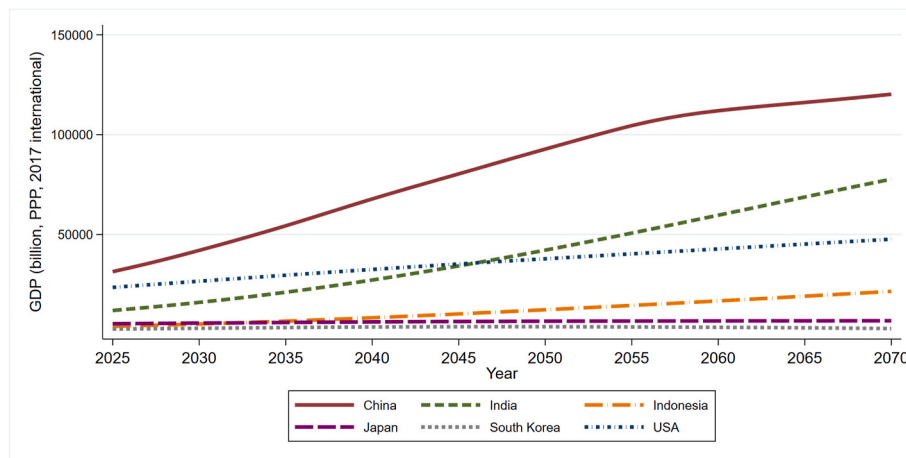


Fig. 5. Projections for real GDP for selected economies, 2025–2070.

Note: Fig. 5 provides the projection results for the purchasing power parity (PPP)-adjusted real GDP for the selected five Asian countries and the United States, subject to the baseline scenario.

(Equation (8)) and increasing the speed of convergence ($\kappa = 0.03$) in the technological imitation (Equation (9)).¹⁶ In Columns 3 and 8 of Table 7, this scenario outperforms the baseline in both GDP and per capita GDP growth rates. The increase in GDP growth rate would range from 0.12% p in South Korea to 0.46% p in India over 2023–2050 and range from 0.22% p in South Korea to 0.54% p in India over 2051–2070.

More specifically, in the US, improving the efficiency parameter of technological innovation would promote a higher rate of technological progress, resulting in higher economic growth rates. The average annual GDP growth over 2051–2070 is estimated to decrease to 1.4%, about 0.43% p higher than the baseline (Table 7). The US's per capita growth is projected at 1.4% during the same period, surpassing the 1.0% estimated under the baseline.

In Asian countries, in addition to an improvement in the efficiency of technological innovation, a higher catching-up effect to the US technology level would also play a role in increasing GDP and per capita GDP growth rates over the next 50 periods. The impacts are significant for China and India. China's average annual GDP growth is estimated to decline to 1.3%, about 0.40% p higher than the estimated baseline

scenario over 2051–2070 (Table 7). Similarly, per capita GDP growth is projected at 2.7% during the same period, compared to the 2.3% estimated under the baseline scenario. India's average annual GDP growth is estimated to decrease to 3.2%, about 0.5% p higher than the baseline scenario over 2051–2070. India's per capita GDP growth is projected at 3.6% during the same period, surpassing the 3.0% estimated under the baseline scenario.

For the third scenario, we assume higher human capital growth, with the efficiency parameter (B) doubling over the next 10 years and then remaining constant. Columns 4 and 9 of Table 7 report higher economic growth rates for all countries relative to the baseline scenario. The increase in GDP growth rate ranges from 0.12% p in the US to 0.63% p in India over 2023–2050 and from 0.15% p in the US to 0.74% p in India over 2051–2070. Significant impacts are observed in China, India and Indonesia, with GDP and per capita GDP growth rates over 2051–2070 being 0.5% p, 0.7% p and 0.5% p in China, India, and Indonesia higher than the baseline, respectively.

The combined scenario, incorporating all three assumptions, shows the most significant improvement in growth rates, as reported in Columns 5 and 10 of Table 7. This scenario outperforms the baseline in GDP and per capita GDP growth rates for all countries and closely matches the sum of the growth rates from the three previous scenarios. The combined scenario increases the average annual GDP growth rates over

¹⁶ The parameter ψ is adjusted to ensure it aligns with the initial values of the rate of technological progress.

Table 7
Average Annual GDP and per capita GDP growth rates over two different periods: Baseline vs Alternative Scenarios.

	Growth rates over 2023–2050					Growth rates over 2051–2070				
	Baseline		Simulation with alternative scenarios			Baseline		Simulation with alternative scenarios		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Population structure	Technological progress	Human capital	All		Population structure	Technological progress	Human capital	All
China	GDP	4.144	4.233	4.399	4.541	4.877	1.570	1.284	1.364	2.485
	Per capita GDP	4.992	4.918	5.248	5.389	5.562	2.299	2.759	3.214	3.214
India	GDP	5.248	5.354	5.711	5.874	6.447	3.236	3.217	3.415	4.548
	Per capita GDP	4.661	4.608	5.124	5.287	5.701	3.045	3.582	3.780	4.360
Indonesia	GDP	4.560	4.619	4.803	4.966	5.264	2.724	3.110	3.231	4.054
	Per capita GDP	4.146	4.048	4.390	4.553	4.694	2.824	3.210	3.331	3.609
Japan	GDP	0.432	0.577	0.704	0.620	1.034	0.087	0.763	0.325	1.468
	Per capita GDP	1.515	1.485	1.787	1.702	1.943	0.945	1.387	1.183	1.738
South Korea	GDP	0.706	0.802	0.828	0.957	1.172	−1.114	−1.900	−1.829	−0.520
	Per capita GDP	2.197	2.095	2.318	2.448	2.465	0.086	0.027	0.098	0.680
US	GDP	1.776	1.938	2.108	1.896	2.396	1.480	1.356	1.081	2.101
	Per capita GDP	1.641	1.646	1.973	1.761	2.104	1.008	1.434	1.159	1.680

Notes: The baseline simulation results in Columns (1) and (6) assume the initial values and parameters presented in Table 3. The simulation results for each of the three alternative scenarios across Columns (2)–(9) have different assumptions. Columns (2) and (7) assume a higher rate of population growth with a higher fertility rate and a lower dependency ratio. Columns (3) and (8) assume a higher rate of technological progress, with increased parameters for technology spillover and imitation. Columns (4) and (9) assume a higher rate of human capital growth with an increased efficiency parameter. Columns (5) and (10) report the simulation results of the combined scenario that incorporates all three alternative assumptions.

2051–2070 by 1.61%p for China, 1.87%p for India, 1.33% for Indonesia, 1.38%p in Japan, 1.60%p in South Korea and 1.17%p in the US relative to the baseline. Additionally, it lifts the average annual GDP per capita growth rates by 0.94%p for China, 1.32%p for India, 0.79% for Indonesia, 0.79%p in Japan, 0.87%p in South Korea and 0.67%p in the US over the same period.

Under this combined scenario, China's average annual GDP growth is estimated to become 2.5%, higher than the 0.9% estimated under the baseline over 2051–2070. Similarly, per capita GDP growth is projected at 3.2% during the same period, compared to the 2.3% estimated under the baseline. Given these higher growth rates, the Chinese economy will continue to narrow its per capita income gap with that of the US at an accelerated pace compared to the baseline scenario. By 2070, China will reach 154,854 USD, 40% higher than the baseline scenario (110,791 USD). If China can follow this higher growth path and the US remains at a lower growth path, it will surpass the US in per capita GDP in PPP terms by 2058.

India's average annual GDP growth is estimated to be 4.5%, about 1.9%p higher than the baseline over 2051–2070. India's per capita GDP growth is projected at 4.4% during the same period, compared to the 3.0% estimated under the baseline. By 2070, India's per capita GDP will reach 78,121 USD, 70% higher than the baseline scenario (45,962 USD). If India can follow this higher growth path and China remains at a lower growth path, India can overtake China in terms of GDP by 2067.

Under this alternative scenario, the US's average annual GDP growth is estimated to decrease to 2.1%, which is 1.2%p higher than the baseline scenario of 0.9% over 2051–2070. By 2070, the US will reach an income per capita of 159,689 US, 30% higher than the baseline (123,140 USD).

Our simulation results from both the baseline and alternative scenarios highlight that demographic change, specifically a declining working-age population, is not the only major factor influencing economic growth in the five Asian economies over the next 50 years. The significant decline in GDP growth rates will primarily be the result of slower accumulation of physical and human capital and declining TFP growth. Therefore, to mitigate the negative impact of a declining working-age population on economic growth, improving the pace of physical and human accumulation and technological progress is crucial.

In addition, both our simulation results indicate a significant slowdown in the growth rates of all five Asian economies, while the US is expected to maintain more consistent growth over the next 50 years. Consequently, the convergence of emerging Asian economies with the US in terms of per capita income is expected to continue. However, it is unlikely that the major Asian economies will reach the US level of per capita GDP under the plausible scenarios. Nevertheless, the overall Asian economy will sustain its significant expansion, primarily driven by China and India. China has already surpassed the US in terms of PPP-adjusted GDP and is projected to close the gap significantly with the US, even in terms of PPP-adjusted per capita GDP, over the next 50 years. India is also expected to surpass the US in terms of PPP-adjusted GDP by 2045.

6. Conclusion

This study presents an analysis of the economic prospects of the five major Asian countries and the US over the next 50 years, focusing on the impact of demographic changes. The simulation results of our growth model suggest that population growth will not solely determine the equilibrium economic growth rate. In determining the growth rate, factors such as the accumulation of physical and human capital and technological progress contribute substantially. The simulation results imply that the five Asian economies can improve their respective potential growth rates by replacing labor shortages with capital and technology, while simultaneously improving the quality of the labor force, promoting technological progress, and improving rates of return to investment in physical capital.

To mitigate the adverse impact of population aging and a shrinking workforce on economic growth, Asian countries should adopt proactive and effective strategies. Primarily, enhancing the quantity and quality of the workforce is essential. The labor market should encourage greater participation of females and the elderly, especially in countries experiencing a decline in the working-age population. Given the varying timing of changes in population structure among Asian countries, promoting active migration flows between nations can help address labor supply and demand issues, ultimately leading to a more efficient allocation of human resources in the region. More importantly, to accumulate human capital, Asian countries should improve the education system and implement training programs. The education system must address the challenges posed by rapidly changing industry structures and technologies. Strengthening lifelong education and skill training would be helpful in enhancing the productivity of workers, especially older employees. Additionally, efforts should be made to foster technological innovation by developing technological capabilities, infrastructure, and systems that match advanced countries. Asian countries also need to improve their returns on public and private investment and support more efficient capital allocation.

Asian economies, through effective policies and reforms, can experience higher economic growth and emerge as major global players, thus potentially transforming the global economic and geopolitical landscapes. This economic growth of these five Asian countries can foster increased cross-border exchanges and deepen trade and investment within the region, fueled by a growing middle class and industry upgrading. This increased interdependence within Asia serves as an opportunity.

However, Asia's ascent also heightens geopolitical risks, both within the region and on a global scale. The willingness of major players to prioritize global peace and prosperity over their own national interests remains uncertain. The world witnessed the US–China trade tensions and technology rivalry, as well as geo-economic fragmentation. These events have had significant repercussions on Asia and the global economy. As Asian countries begin to gain influence on the regional and global stages, it is crucial for the major economies, including China, India, and the US, to work together to reduce conflicts and hostilities while actively fostering cooperation and collaboration.

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Declaration of competing interest

The authors declare that we have no financial or proprietary interests that relate to the research described in the paper, “Demographic Change and Long-Term Economic Growth Path in Asia”.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.econmod.2025.107043>.

Data availability

We have shared the link to the replication folder at the Attach File step.

[Demographic Change and Long-Term Economic Growth Path in Asia \(Original data\)](#) (Mendeley Data)

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