HARNESSING THE SYNERGY OF ARTIFICIAL INTELLIGENCE (AI) AND HUMAN CAPITAL RESTRUCTURING IN AGEING ECONOMIES

Jong-Wha Lee and **Warwick McKibbin**

The SEACEN Centre

The South East Asian Central Banks (SEACEN) Research and Training Centre
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Jong-Wha Lee
(Project Team Lead)

and

Warwick McKibbin
(Project Team Co-Lead)

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Research and Training Centre, 198201000672 (80416-M)
(The SEACEN Centre)
Level 5, Sasana Kijang, Bank Negara Malaysia,
2, Jalan Dato' Onn, 50480 Kuala Lumpur, Malaysia
Tel. No.: +603 5891 2900
Email: enquiries@seacen.org; and rsu@seacen.org

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This SEACEN collaborative research project (RP2 2025), entitled: *"Harnessing the Synergy of Artificial Intelligence and Human Capital Restructuring in Ageing Economies"*, should not be reported as representing the views of SEACEN member central banks/monetary authorities. The views expressed in this report are those of The SEACEN Centre and do not necessarily represent those of its member central banks/monetary authorities.

Notes:
- The SEACEN Centre recognises "China" as the People's Republic of China," "Hong Kong, China" as the Hong Kong SAR, China, and "Korea" as the Republic of Korea.

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FOREWORD

Asia is undergoing a major demographic shift, with lower fertility rates and longer lifespans impacting economic growth, price stability, and fiscal sustainability. The shrinking workforce and reduced productivity pose significant challenges, but technologies such as artificial intelligence (AI) and robotics could help offset these effects. Many Asian economies are advancing technological adoption to address labour shortages and mitigate the consequences of an ageing population. However, the results are complex, as technology and demographics interact to create uneven impacts across sectors, widening disparities between groups. Yet, research on how ageing and technology drive structural change is still limited.

This SEACEN collaborative research project (RP2-2025) investigates the macroeconomic implications of population ageing within SEACEN member economies, focusing on the interplay between technology adoption and human capital development and how this combination can counteract a shrinking workforce. A key takeaway of this study is that demographic shifts are not inherently deflationary or restrictive to growth; rather, their ultimate impact is shaped by institutional frameworks, labour market flexibility, and the velocity of technological adoption. Economies that invest in human capital across all life stages are better equipped to sustain productivity and maintain growth momentum even as their populations age. By fostering inclusive AI adoption, economies can effectively shield their productivity and growth from demographic headwinds. This finding demonstrates that the link between age and productivity is dynamic, proving that strategic policy interventions can preserve economic vitality amidst demographic change.

Central banks and monetary authorities face a unique set of challenges as they navigate the complexities of an ageing population and the rise of AI. An ageing population generally exerts downward pressure on interest rates as increased savings, reduced consumption, and lower investment demand drive down the cost of borrowing. One pressing issue is that the decline in the natural rate of interest would complicate the transmission of monetary policy. AI may partially offset some of these pressures by improving productivity, but the net impact on inflation remains complex and uncertain. Failure to account for these demographic and technological trends may lead to policy stances that are either too tight or loose. Therefore, it is important for institutions to incorporate demographic factors into their assessments of potential output and the natural rate. Gaining a comprehensive understanding of these mechanisms and their overall effects will inform the development of more robust financial policy frameworks going forward.

I believe the major findings, key takeaways, and policy recommendations from this joint research will provide useful perspectives to policymakers both within the region and beyond on leveraging AI and developing human capital during demographic shifts. This collaboration also created a valuable opportunity for exchanging knowledge and experiences among SEACEN member participants. The report's various country chapters demonstrate how the G-Cubed model—a multi-country, multi-sectoral, intertemporal general equilibrium framework—can be used to assess the impact of demographic changes on macroeconomic outcomes.

We are very grateful to Prof. Jong-Wha Lee (Visiting Research Economist, RP2-2025) and Prof. Warwick McKibbin (Visiting Scholar, VS2-2025) for their guidance and support on this SEACEN collaborative research project. We also acknowledge the vital contribution of researchers from participating SEACEN member central banks, who provided country case studies and background papers, namely Reserve Bank of India (Soumya Suvra Bhadury, and Harendra Behera), Bank of Korea (Jae Won Lee, Woong Yong Park, Seolwoong Hwang, and Seung Jun Jung), Bank Negara Malaysia (Mikael Azwa, Akmal Zulkarnain, Christopher Ho Chun Wai, Zul-Fadzli Abu Bakar, and Helmi Ramlee), Bangko Sentral ng Pilipinas (Reynalyn Punzalan-Wong, Karen Annette Lazaro Enriquez, Clarisa Joy Flaminiano, and Dennis Bautista), Central Bank of Sri Lanka (Janaka D Maheepala, and Kasun D Pathirage), and State Bank of Vietnam (Nguyen Trung Anh, and Do Thi Thu).

Finally, I wish to express my sincere appreciation to the SEACEN team for their support and management of the research project. Dr. Rogelio Mercado, Senior Economist, took the lead for this collaborative research initiative and managed the publication process under the overall oversight of Dr. Ole Rummel and Dr. Donghyun Park as former and current Director of the Macroeconomics and Monetary Policy Management Pillar. Mr. Ahmad Aizudeen assisted with research and facilitated the production of this study. Ms. Yun Yee Seow edited the draft chapters, while Mr. Zamri Abu Bakar of Zabriz Enterprise handled the design, typesetting, and layout of this publication. Dr. Ole Rummel, Prof. Dr. Leef Dierks, Dr. Meltem Chadwick, Dr. Nur Ain Shahrier, and Prof. Dr. Eunbi Song provided valuable comments and suggestions during the interim workshop.

Dr. Cynyoung Park
Executive Director
The SEACEN Centre

ABSTRACT

Asia is undergoing one of the fastest demographic transitions in the world, characterised by rapidly declining fertility rates and rising life expectancy. Population ageing poses significant challenges to economic growth, price stability, fiscal sustainability, and financial stability. At the same time, rapid advances in artificial intelligence (AI) and digital technologies offer new opportunities to offset labour shortages, raise productivity, and reshape monetary and financial policy frameworks.

This report examines the macroeconomic and financial consequences of population ageing in Asia and explores how synergies between AI-driven technological innovation and human capital development can help mitigate its adverse effects. Drawing on theoretical insights, empirical evidence, and country case studies from SEACEN member economies, the analysis highlights how ageing affects growth, inflation, saving and investment behaviour, interest rates, and the transmission of monetary policy. The report emphasises that ageing is not mechanically deflationary or growth-reducing; its net effects depend critically on institutional settings, labour market adaptability, and the pace of technological adoption.

A central finding is that population ageing does not, in itself, lead to lower living standards or macroeconomic stagnation. Economies that invest in human capital across the life course and promote inclusive AI-driven technological adoption can substantially cushion the adverse growth effects of ageing.

The report also identifies key challenges for central banks, including a declining natural rate of interest, changes in the transmission of monetary policy, and rising financial stability risks related to pension systems and asset markets. As population ageing puts downward pressure on equilibrium real interest rates, monetary policy space becomes more constrained, increasing the risk of hitting the effective lower bound. Failure to adequately account for demographic trends may lead to persistently tight or overly accommodative policy stances, underscoring the importance of incorporating demographic factors into estimates of potential output and the natural rate of interest.

AI also has important implications for monetary policy. Productivity gains from AI may partially offset demographic pressures on the natural rate of interest, while AI-driven efficiency improvements could ease labour shortages and lower production costs. At the same time, stronger investment and demand effects may counteract these supply-side gains, leaving the net impact on inflation uncertain. Moreover, AI may alter price-setting behaviour, wage dynamics, and financial intermediation, complicating monetary policy transmission. Central banks, therefore, need to closely monitor AI's evolving effects on inflation dynamics, labour markets, and financial systems.

The findings point to several overarching policy priorities for SEACEN economies:

1. *Integrate demographic trends into macroeconomic frameworks*, including estimates of potential output, inflation, and the natural rate of interest.

2. *Strengthen human capital across the life course,* with particular emphasis on lifelong learning and digital skill formation for older workers.

3. *Promote inclusive AI adoption*, ensuring that productivity gains are broadly shared and that older workers are not left behind.

4. *Adapt monetary and macroprudential frameworks and policies* to a low-interest-rate environment shaped by demographic forces.

5. *Develop country-specific analytical and modelling frameworks* to assess alternative scenarios of the combined effects of population ageing and AI on macroeconomic outcomes and the effectiveness of monetary policy. The interaction between ageing and AI adds a further layer of complexity, requiring models that can disentangle key transmission channels and quantify their relative impacts, as illustrated by the country case studies in this volume.

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CHAPTER 1

INTEGRATIVE REPORT: HARNESSING THE SYNERGY OF ARTIFICIAL INTELLIGENCE (AI) AND HUMAN CAPITAL RESTRUCTURING IN AGEING ECONOMIES

Jong-Wha Lee[1,*] and **Warwick McKibbin**[2,*]

1. Introduction

1.1 Background

Asia is experiencing a significant demographic shift. The number of older people aged 65 years and over is projected to more than double, increasing from 422 million in 2020 to about 984 million by 2050 (United Nations, 2024). The share of the population aged 65 years and over will increase from 9.01% in 2020 to around 18.64% in 2050. Rapidly declining fertility rates and rising life expectancy are some of the known causes of Asia's ageing population structure.

This ongoing demographic trend will pose challenges to policymakers, including central banks and monetary authorities. An ageing population will have effects on the broader economy and the financial system. Key macroeconomic challenges include a potential decrease in the labour force participation rate, which could push wages higher and potentially trigger a wage-price spiral. Additionally, the elderly tend to have lower saving rates, potentially exerting upward pressure on real interest rates. Conversely, a smaller workforce can lower the marginal productivity of capital, leading to lower real interest rates, reduced domestic investment and slower economic growth. Population aging and reduced aggregate demand may generate disinflationary pressures.

Turning to financial stability, a growing proportion of retirees increases government spending on pensions, healthcare, and social security, which could lead to higher fiscal deficits. If investment returns decline, defined-benefit pension systems may lead to a shortfall in funds needed to pay out pensions to retirees. Moreover, the transmission and effects of monetary policy on the macroeconomy and financial markets can also be influenced by the demographic structure of the population, complicating policy implementation. These trends pose policy challenges in conducting effective monetary policy and safeguarding financial stability.

1. Distinguished Professor Emeritus at Korea University.

2. Distinguished Professor Emeritus at Australian National University and Nonresident Senior Fellow, The Peterson Institute for International Economics.

* The authors thank Dr. Eunbi Song for her dedicated support with data collection, as well as her helpful comments and discussions, which improved the quality of this work.

In addition, the advent of new technologies, particularly AI, offers a potential counterbalance by driving productivity growth and exerting disinflationary pressures. AI can increase efficiency, enhance automation, and reduce labour costs, which may help offset some of the adverse economic effects of an ageing population.

The interplay between the megatrends of population ageing and rapid technological advancement highlights the potential impacts and challenges of these structural changes. Key questions arise regarding how to create synergy between technology and talent during major demographic shifts, both for the conduct of monetary policy and the maintenance of financial stability. Analysing the macroeconomic and financial implications of population ageing, along with exploring synergies between AI and human capital development, can provide valuable policy insights for Asian countries, particularly SEACEN member economies, including India, Korea, Malaysia, the Philippines, Sri Lanka, and Vietnam.

1.2 Objective of the Study

This collaborative research study aims to identify and analyse the economic impacts and policy challenges posed by population ageing among SEACEN member economies. This study is guided by four main questions:

1. What are the causes and macroeconomic consequences of population ageing in Asia?
2. What policy challenges does population ageing present for Asian economies, particularly in conducting monetary policy and maintaining financial stability?
3. How can Asian economies foster synergies between technology and human capital to offset the adverse effects of an ageing population and a shrinking labour force?
4. How can monetary and financial policy be adapted to mitigate the economic and financial impacts of ageing, while also addressing emerging challenges associated with the rise of AI?

To achieve these objectives, the study builds on existing research, empirical frameworks, macro-financial models, and analytical methods. It specifically investigates how ageing and AI technological innovation can affect macroeconomic variables such as saving, investment, labour productivity and income growth drawing on recent studies (Lee, Song, and Kwak, 2020; Liu and McKibbin, 2022; Parteka and Kordalska, 2023; Lee and Song, 2025).

The study also assesses how an ageing population can impact price and financial stability and examines the role of monetary and financial policy in mitigating the negative effects of population ageing on the economy and the financial system. More importantly, it brings together a deeper analysis of economic impacts and policy challenges posed by population ageing and AI in individual SEACEN member economies.

This chapter serves as an integrative report and is structured as follows. The remainder of section 1 provides an overview of demographic structure changes in Asia and explores the causes of population ageing. It also presents recent trends in the use and adaptation of AI in the region. Section 2 reviews existing literature on the macroeconomic and financial consequences of population ageing. Section 3 assesses the role of human capital and AI-driven technological innovation in mitigating the negative economic impact of ageing. Section 4 examines the policy challenges posed by population ageing and discusses how monetary and financial policies can be adapted to mitigate the economic and financial impacts of ageing, while also addressing emerging challenges associated with the rise of AI. Section 5 synthesises key findings from the seven country case studies and presents policy recommendations.

1.3 Demographic Shifts and Population Ageing in Asia

Asia is undergoing significant demographic transformation, with East and Southeast Asia ageing faster than any other region. These regions are projected to experience the largest increase in the population aged 65 and above between 2020 and 2050 (UN DESA, 2019). By 2050, the share of those aged 65 and above in Asia is expected to be around 18.64%. Moreover, the older population itself is ageing, and by 2050, the “oldest-old” (80 years or older) will comprise more than one-fifth of all older people (about 28%).

Demographic profiles within Asia vary significantly. Korea, Japan, and China have already become or are approaching super-aged societies. Some Asian economies are ageing rapidly, while others are undergoing a more gradual transition. Singapore and Thailand are rapidly ageing, transitioning into super-aged societies, while Malaysia became an ageing society in 2020, experiencing accelerating demographic shifts. Conversely, Cambodia and Lao PDR currently have relatively youthful populations but are expected to undergo similar demographic transitions in the coming decades (World Bank, 2020).

Table 1.1 illustrates the increasing share of the population aged 65 years and above for 18 SEACEN member economies and four advanced countries (including Australia and the United States) for the years 2023, 2050, 2075 and 2100. As of 2023, Japan stands as the region’s most aged economy (29.6% aged 60+), while Papua New Guinea is the youngest (3.3%). Significant diversity exists: Australia, China, Chinese Taipei, the Republic of Korea, the U.S., and Vietnam all report over 15% in this age group, with Singapore and Sri Lanka just exceeding 10%.

By 2050, projections show that at least 10% of the population in every listed economy will be aged 60 or older. The Republic of Korea is forecast to have the highest portion (39.7%), followed by Chinese Taipei, 38.7%) and Japan (37.5%). While remaining the youngest, Papua New Guinea (7.4%), Lao PDR (9.9%), and Fiji (10.6%) will still see notable increases. The ageing pace is particularly swift in major emerging economies like China (doubling from 14.3% to 30.9%) and India (rising from 6.9 to 14.7%). Younger ASEAN nations like Brunei Darussalam, Indonesia, and the Philippines are expected to surpass the 15% mark by 2050. Comparatively, advanced economies like Australia and the U.S. exhibit a more gradual ageing process, adding about six percentage points but remaining less aged than the fastest-ageing Asian societies.

Table 1.1: Share of Population Aged 65 and Above, Across Different Years

	2023	2050	2075	2100
Australia	17.4	23.9	26.6	28.4
Brunei Darussalam	6.5	19.3	26.2	29.2
Cambodia	6.0	11.6	17.4	23.5
China	14.3	30.9	42.0	45.8
Chinese Taipei	18.3	38.7	42.9	41.8
Fiji	6.3	10.6	15.7	21.5
India	6.9	14.7	25.0	29.9
Indonesia	7.0	15.1	20.7	25.8
Japan	29.6	37.5	37.1	37.4
Lao People's Democratic Republic	4.5	9.9	18.5	25.2
Malaysia	7.5	16.8	27.3	30.2
Mongolia	4.9	12.6	15.8	23.6
Myanmar	7.1	13.5	19.0	23.6
Nepal	6.4	11.1	21.8	28.8
Papua New Guinea	3.3	7.4	11.3	15.6
Philippines	5.3	11.2	21.1	26.2
Republic of Korea	18.3	39.7	47.4	45.2
Singapore	13.1	26.8	44.0	40.6
Sri Lanka	11.7	20.3	27.4	32.8
Thailand	14.7	29.6	34.8	35.5
United States of America	17.4	23.1	26.7	28.4
Vietnam	8.6	20.0	26.1	31.4

Note: Medium Scenario; Shaded areas indicate ASEAN countries.
Source: UN DESA, Population Division. World Population Prospects 2024.

Long-term projections extending beyond 2050 also continue to highlight the divergence across the economies in the Asia Pacific region. Korea, Singapore, and Chinese Taipei are anticipated to become "super-aged" (over 50% elderly) by the early 2070s. Japan, despite starting as the oldest, is expected to stabilise around 37%. Several upper-middle-income ASEAN members, including Malaysia and Thailand, will continue to age rapidly, nearing or exceeding 30% by 2100. Conversely, many Pacific and Himalayan economies, such as Papua New Guinea (15.6%), Fiji (21.5%), and Nepal (28.8%), are projected to remain relatively young even by 2100. These divergent trajectories highlight the global trend of demographic transition but also underscore the need for country-specific policy responses.

As discussed above, the speed at which populations are ageing differs. Measured by the time taken for the share of older population aged 60 and above to double from 10% to 20%, the transition has been rapid in Singapore (17 years), Thailand (18 years), and the Republic of Korea (19 years) (ADB, 2024). Brunei Darussalam is forecast to achieve this doubling in just 16 years. By 2050, Vietnam, Sri Lanka, Malaysia, and Indonesia are also projected to cross the 20% threshold. ADB (2024) reports that some countries are ageing faster than anticipated.

Table 1.2: Life Expectancy Across SEACEN Member Economies

	2023	2050	2075	2100
Australia	83.9	87.2	90.0	92.6
Brunei Darussalam	75.3	79.6	83.3	86.5
Cambodia	70.7	74.5	77.9	81.1
China	78.0	83.4	86.9	89.8
Chinese Taipei	80.6	84.9	88.0	90.9
Fiji	67.3	70.9	74.0	77.2
India	72.0	77.5	81.8	85.3
Indonesia	71.1	74.9	78.4	81.9
Japan	84.7	88.4	91.5	94.4
Lao People’s Democratic Republic	69.0	74.2	77.9	81.3
Malaysia	76.7	81.1	84.8	87.9
Mongolia	71.7	77.7	82.1	85.7
Myanmar	66.9	71.6	75.4	79.1
Nepal	70.4	76.0	80.1	83.7
Papua New Guinea	66.1	69.2	71.9	74.8
Philippines	69.8	73.2	76.7	80.4
Republic of Korea	84.3	87.3	90.2	93.1
Singapore	83.7	87.1	89.9	92.7
Sri Lanka	77.5	82.1	85.6	88.7
Thailand	76.4	81.7	85.4	88.4
United States of America	79.3	83.2	86.4	89.2
Vietnam	74.6	78.9	82.7	86.1

Note: Shaded areas indicate ASEAN countries.
Source: UN DESA, Population Division. World Population Prospects 2024.

Population ageing in Asia is mainly driven by increasing life expectancy and declining fertility rates. Over the last few decades, remarkable improvements in longevity and significant reductions in birth rates have combined to expedite the shift toward older demographic structures in Asia.

Life expectancy at birth in Asia has risen dramatically, climbing from approximately 64.1 years in 1990 to around 74.7 years in 2024 (ESCAP, 2024). Key factors contributing to this improvement include lower mortality rates (particularly infant and maternal), enhanced control over infectious diseases, and better access to nutrition and healthcare services. The gap in life expectancy between advanced and developing countries has narrowed significantly due to the widespread adoption of essential health measures, benefiting many countries in Asia.

Further increases in longevity are anticipated. Average life expectancy in Asia is projected to reach 79.2 years by 2050 (ESCAP, 2024). By the year 2100, forecasts suggest it could rise to nearly 84.8 years in Southeast Asia and 91.5 years in East Asia (UN DESA), Population Division, 2024. Forecasted life expectancy trends for individual SEACEN member economies are detailed in Table 1.2.

Table 1.3: Total Fertility Rate Across SEACEN Member Economies

	2023	2050	2075	2100
Australia	1.64	1.64	1.63	1.63
Brunei Darussalam	1.75	1.61	1.62	1.64
Cambodia	2.58	2.03	1.87	1.80
China	1.00	1.18	1.28	1.35
Chinese Taipei	0.87	1.08	1.22	1.33
Fiji	2.28	1.93	1.81	1.76
India	1.98	1.76	1.71	1.69
Indonesia	2.13	1.85	1.77	1.73
Japan	1.21	1.35	1.43	1.47
Lao People’s Democratic Republic	2.42	1.88	1.76	1.71
Malaysia	1.55	1.53	1.55	1.56
Mongolia	2.68	1.99	1.84	1.79
Myanmar	2.12	1.83	1.75	1.73
Nepal	1.98	1.73	1.69	1.67
Papua New Guinea	3.10	2.36	2.04	1.88
Philippines	1.92	1.73	1.70	1.67
Republic of Korea	0.72	1.03	1.19	1.30
Singapore	0.94	1.15	1.28	1.36
Sri Lanka	1.97	1.77	1.72	1.69
Thailand	1.21	1.29	1.38	1.44
United States of America	1.62	1.64	1.64	1.65
Vietnam	1.91	1.74	1.72	1.70

Note: Shaded areas indicate ASEAN countries.
Source: World Population Prospects 2024.

Parallel to rising life expectancy, Asia has witnessed a dramatic fall in fertility rates. The majority of the population in Asia lives in countries where the total fertility rate (TFR) is below 2.1 births per woman, the requirement for population replacement. In 1990, only 12.1% of the population in Asia and the Pacific lived in low-fertility nations; this figure rose to 81.6% by 2024 and is expected to reach 88.7% by 2050 (ESCAP, 2024). Correspondingly, the number of countries with replacement-level fertility or higher, dropped from 50 in 1990 to 28 in 2024, with a projected further decrease to 18 by 2050 (ESCAP, 2024).

The decline in fertility rates is attributed to a complex interaction among socio-economic developments. These include delayed marriage and childbirth, higher educational attainment and increased labour force participation among women, wider access to family planning services, rapid urbanisation, and changing societal attitudes. As a consequence, the annual number of births in Asia has fallen significantly. From a peak exceeding 80 million per year in the late 1980s, annual births dropped to around 65 million in the early 2020s. Projections suggest a further decline to approximately 42 million births per year by the end of the century, about half the peak level (UN DESA, 2024). Table 1.3 provides forecasted TFRs for SEACEN member economies.

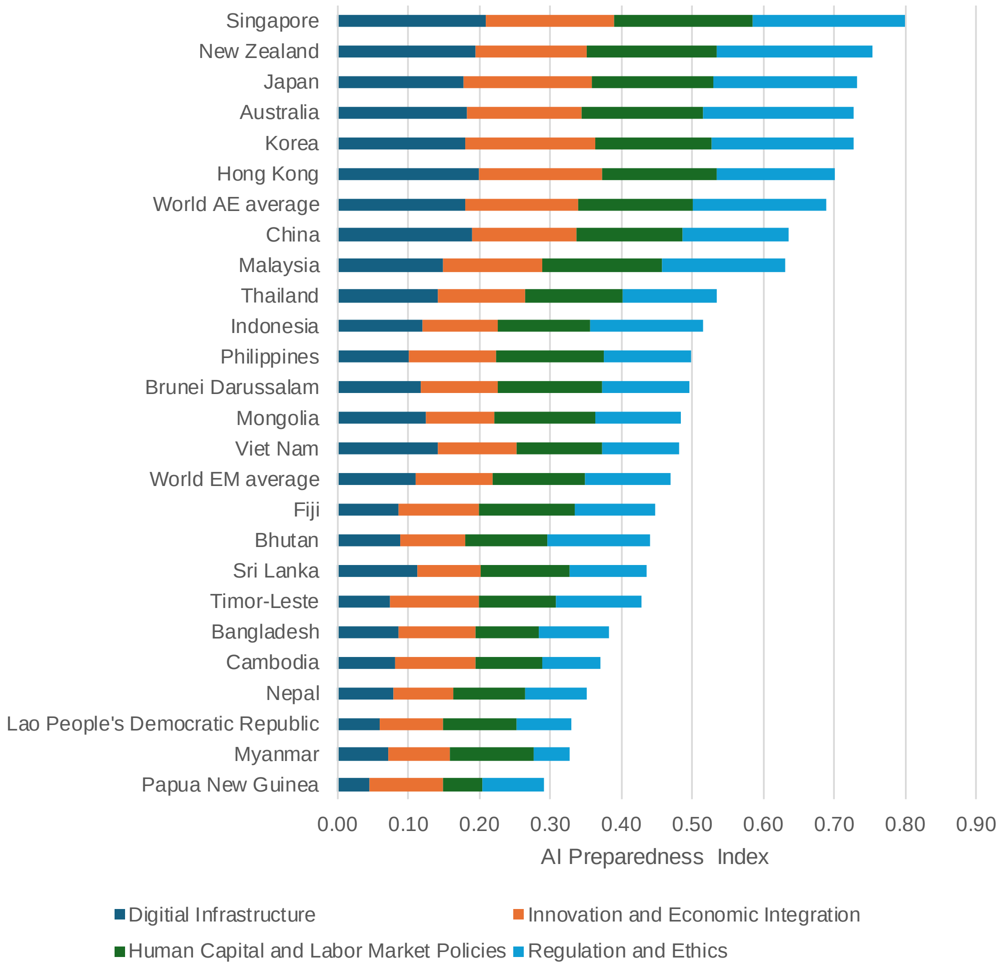
1.4 AI Adoption and Preparedness in Asia

Along with population aging, the emergence of AI is another fundamental structural change confronting Asia. AI adoption in Asia is advancing rapidly, but remains highly uneven across countries. Advanced Asian economies such as Singapore, Korea, and Japan, along with large emerging markets like China, are at the forefront of AI development and adoption. In contrast, many emerging and low-income economies in the region face more limited exposure, both because their occupational structures are concentrated in less AI-intensive sectors and because their digital infrastructure remains underdeveloped. This divergence implies that while some countries are well-positioned to harness significant productivity and innovation gains, others risk falling further behind.

Asian economies can harness AI by strengthening exposure, preparedness, and access. Three factors largely shape how effectively Asian economies can harness AI: exposure, preparedness, and access (Cerutti et al., 2025). Exposure captures the share of jobs and industries where AI can replace or complement human tasks. The related concept of complementarity highlights whether AI enhances or substitutes work in an occupation (Cazzaniga et al., 2024). In advanced Asian economies, a significant share of employment lies in “high-exposure, high-complementarity” jobs such as managers, ICT professionals, and teachers, where AI is more likely to augment productivity than displace workers. In contrast, clerical staff, telemarketers, and some sales and service workers fall into “high-exposure, low-complementarity” roles that face higher risks of replacement. Meanwhile, agricultural labourers, construction workers, and cleaners remain largely in low-exposure occupations.

Preparedness determines whether exposure translates into gains. The IMF's AI Preparedness Index (AIPI) evaluates countries on four dimensions—digital infrastructure, innovation and integration, human capital and labour policies, and regulation and ethics (Cazzaniga et al., 2024). Asia's advanced economies score highly, with Singapore ranking first globally (Figure 1.1). Singapore's score of 0.80 exceeds the 0.77 recorded for the United States and the Netherlands. Large emerging markets such as China, India, and Indonesia perform above the emerging-economy average, reflecting stronger infrastructure and human capital. By contrast, many low-income Asian economies remain far behind, with persistent gaps in broadband access, digital skills, and governance.

Figure 1.1: AI Preparedness Across Asia-Pacific Economies



Source: International Monetary Fund's AI-Preparedness Index – April, 2024.

Access—to advanced technologies, data, infrastructure, and partnerships—can also deepen divides. Japan and Singapore enjoy easier access to state-of-the-art AI hardware and cloud systems, while many emerging and low-income economies face cost barriers, weaker ecosystems, and geopolitical restrictions on technology sharing. To close these gaps, governments are rolling out national strategies. Singapore has launched successive AI roadmaps with strong governance frameworks; Korea has created a National AI Committee to expand R&D; India's AI Mission invests in computing infrastructure, skills, and research hubs; and China continues to prioritise AI in its industrial strategy, advancing generative AI models and large-scale data ecosystems despite export controls.

2. Macroeconomic and Financial Consequences of Population Ageing

This section explores theoretical and empirical literature concerning the macroeconomic and financial consequences of population ageing. It consists of four sub-sections: 1) effects on economic growth and productivity, 2) prices, wages and inflation, 3) saving, investment and current accounts, and 4) interest rates and financial markets.

2.1 Effects on Economic Growth and Productivity

Demographic changes have a multifaceted impact on an economy's growth potential. The standard growth model (Barro and Sala-i-Martin, 2004; Weil, 2014) indicates that population ageing and declining birth rate lead to a shrinking labour force, as older individuals tend not to participate in the labour market, thereby having a direct negative impact on production. Furthermore, given that individual productivity often follows a hump-shaped pattern over a lifetime, peaking in middle age, an increasing share of older workers can exert downward pressure on overall labour productivity.

Demographic change also influences physical capital accumulation and technological progress**.** A reduced labour force lowers the marginal productivity of physical capital, potentially leading to reduced investment and slower capital accumulation. Similarly, investment in technological innovation might decline if a shrinking population and market size reduce the expected profitability of technological innovations (Romer, 1990).

However, a declining labour force could also have positive effects on physical capital accumulation and technological development, and thereby output growth. In the neoclassical growth model, a lower labour growth rate leads to a higher physical capital-labour ratio, resulting in a positive impact on output growth per worker (Barro and Sala-i-Martin, 2004). In addition, as the labour force declines, firms may choose to increase their investment in physical capital and technological development to compensate for labour shortage (Acemoglu, 2002; Acemoglu and Restrepo, 2017).

As in theoretical literature, empirical evidence on the net effect of population change and ageing on overall productivity remains inconclusive. Some studies indicate a positive relationship between population growth and economic growth (Kremer, 1993; Bloom and Williamson). Conversely, others demonstrate the negative effect of population growth or fertility rate on economic growth (Mankiw, Romer and Weil, 1992; Barro and Lee, 2015). Most studies also show the negative effect of population ageing on economic growth (Liu and McKibbin, 2022; Park, Shin, and Kikkawa, 2022; Park and Shin, 2023). However, recent studies by Han and Lee (2020) and Lee and Song (2025) suggest that a shrinking working-age population, primarily driven by longer life expectancy and lower fertility rates, does not necessarily predetermine the growth prospects of Asia, especially if countries adapt through human capital development and technological adoption.

2.2 Prices, Wages and Inflation

The relationship between population aging and inflation is intricate, with multiple economic forces potentially pushing inflation in opposing directions. The overall impact depends on the interplay between various direct and indirect effects stemming from changes in the population's age structure.

Population aging generates both inflationary and disinflationary pressures. On the one hand, a contracting labour supply and lower saving rate among older cohorts, could drive up wages and prices. On the other hand, factors such as expectations of weaker future growth, reduced aggregate demand, and lower labour productivity and wage pressure could exert downward pressure on inflation over time.

Population ageing can exert upward pressure on inflation through reduced labour supply and altered consumption patterns. One of the primary channels through which population ageing can influence inflation is through its effect on the labour supply. A shrinking labour force, directly translated from a decrease in the proportion of the population in the working-age group relative to the number of retirees, exerts upward pressure on real wages. With fewer individuals available for employment, competition among firms to secure labour intensifies, possibly causing employers to offer more attractive compensation packages to attract and retain a smaller pool of potential workers. This rise in labour costs can potentially trigger a wage-price spiral. As wages increase, businesses face higher production expenses. To maintain profitability, these increased costs may be passed on to consumers in the form of higher prices for goods and services. This increase in the general price level can then lead to further demands for higher wages by workers seeking to maintain their real purchasing power, thus creating a self-reinforcing cycle of wage and price inflation.

It is predicted that as population ageing accelerates worldwide, rising wages will eventually drive a shift towards higher global inflation (Goodhart and Erfurth, 2014; and Goodhart and Pradhan, 2017). As stated in Goodhart and Erfurth (2014) and Goodhart and Pradhan (2017), the global economy has experienced disinflation for the past three decades, due in part to abundant, low-cost labour from countries like China and the resulting drop in import prices. They highlight Japan as a case in point. Despite rapid ageing in recent decades, Japan has largely avoided higher inflation by relocating production to Asian countries with abundant labour, thereby containing domestic wage pressures. They further predict as this demographic shock is now reversing and as the world ages, inflation and wage growth will rise.

The consumption behaviour of an ageing population is another key factor influencing inflation through its effect on aggregate demand. According to the life-cycle hypothesis, older workers tend to save less and consume more, which could lift aggregate demand and potentially fuel inflationary pressures. Juselius and Takats (2015) conducted a panel analysis of 22 countries from 1955 to 2010 and found a correlation between rising old-age dependency ratios and increases in inflation, lending some empirical support to this view.

On the other hand, population ageing can dampen inflation. Older adults often tend to concentrate their spending on specific sectors such as healthcare, tourism and other services, which may not produce broad-based inflation across the entire economy. Furthermore, with increasing life expectancies, many older adults are remaining economically active in the labour market for longer periods, sustaining their income and potentially mitigating significant declines in their savings. This extended economic activity alters their consumption and saving patterns compared to earlier generations of retirees. Yoon, Kim, and Lee (2018) provide evidence from 30 OECD economies showing that shifts in consumption patterns associated with ageing can, in certain circumstances, dampen aggregate demand, leading to disinflationary effects. Similarly, Lee et al. (2024), using data from Japanese prefectures and the U.S. states, find that inflation falls with the speed of ageing—that is, the change in the old-age dependency ratio—while the association of inflation with the degree of ageing, measured by the level of the old age dependency ratio is statistically weak and non-robust.

Population ageing may also dampen inflation through the expectation channel and reduced productivity. Expectation can play a role, exerting disinflationary pressure. Once economic agents in the ageing societies anticipate slower economic growth prospects resulting from a reduced growth in the labour supply (a smaller workforce), they may curtail spending ahead of any actual labour supply constraints. This pre-emptive drop in aggregate demand outpaces the decline in aggregate supply, thereby exerting downward pressure on inflation. In addition, as older, skilled workers retire or transition into lower-wage, less productive roles, overall economic productivity can decline (Fujita and Fujiwara, 2023). This loss of human capital and reduced labour productivity can inhibit wage growth and, by extension, limit inflation.

Excess saving and weak demand can also push down the equilibrium interest rate. If monetary policy lags in adjusting to this change, a tight monetary stance will exert persistent downward pressure on inflation (Auclert et al., 2021; Koester et al., 2021). Meanwhile, the government may adopt fiscal policies to moderate price changes, particularly as demographic aging incentivises policymakers to favour the older generation. Deflation can serve as an effective way to support the elderly, who are the main holders of nominal assets. Katagiri et al. (2020) explain that the very low rate of inflation recently observed in Japan was driven by rising longevity.

2.3 Saving, Investment and Current Accounts

A widely used theoretical framework for understanding how population ageing affects household saving is the life-cycle hypothesis. According to this hypothesis, individuals seek smooth consumption over the course of their lives, borrowing during periods of low income and saving when their earnings are higher. In particular, people typically have relatively high incomes during their working years but lower incomes before entering the workforce (childhood) and after retiring (old age). While income levels fluctuate significantly depending on one's employment status across different age brackets, consumption tends to remain comparatively stable. Consequently, individuals maintain high saving rates during their working years to fund retirement consumption, and their saving rates decline once they leave the workforce. Therefore, the life-cycle hypothesis predicts that an increase in the share of the elderly population who are presumed to be dissaving relative to working-age individuals will decrease the aggregate savings.

Empirical findings report that the observed age profile of saving roughly confirms the life-cycle model, showing saving rates rising during an individual's working years and declining in retirement (Higgins and Williamson, 1997). This implies that population ageing often correlates with lower household savings. Further studies, such as Demery and Duck (2006) and Horioka (2010) also reported negative relationships between population ageing and saving rates.

On the other hand, however, various studies present contrasting results. Poterba (1994) analysed data from six countries and found that individuals aged 60 and above continued to record positive saving rates. In some cases, older adults had saving rates on par with—or even higher than—middle-aged cohorts. Deaton and Paxson (1997) provided evidence that although population ageing progresses, the decline in saving rates remains relatively small, and its correlation with saving rates is not significant.

Furthermore, several factors that modify the basic life-cycle hypothesis frameworks include longevity, precautionary saving, bequest motives and pension system design. From the literature review done by Bosworth et al. (2004), individuals in their retirement may not dissave as rapidly as the life-cycle hypothesis would suggest, often maintaining positive saving or only slowly drawing down assets (Bosworth et al. 2004). This could be attributed to the rising life expectancy, precautionary saving (i.e., a buffer against uncertainty, such as future health expenditures, long-term care needs and longevity risk) and bequest motives. Li et al. (2007) found that an increase in longevity has a positive effect on savings, whereas an increase in dependency rates reduces them. The impact of demographic changes on private saving decisions also depends on the design of government pensions and social safety nets, among other factors (IMF, 2019).

Although researchers have paid less attention to the effects of population ageing on investment than on saving, a shrinking labour force is expected to reduce the demand for domestic investment demand by lowering marginal productivity of capital. Empirical evidence suggests that declining labour force growth and rising labour costs are associated with weaker capital accumulation, discouraging firms from undertaking new investments in rapidly ageing societies. Cutler et al. (1990) highlight the importance of demographic influences on the optimal investment rate. In most theoretical models, which assumes a closed economy, ageing lowers both future rates of saving and investment that move in tandem. At the same time, evidence from countries such as Japan indicates that firms in rapidly ageing societies have increasingly redirected investment from domestic production toward overseas operations in more labour-abundant economies.

Globalisation has weakened the traditional link between domestic savings and investment. The opening of the capital market and the expansion of cross-border capital flows allow countries not only to rely on domestic savings, but also to raise funds from abroad or invest surplus savings overseas. A change in saving lead to a change in the current account. In general, the current account tends to be positively associated with the share of prime-age individuals and negatively associated with the share of the elderly. In addition, ageing population and weaker labour force growth reduces the demand for domestic investment, which can prompt capital outflows. Thus, the impact of population ageing on the current account balance is determined by the relative magnitudes of the changes in saving and investment.

Differences in the speed of aging across countries are an important driver of international capital flows (Attanasio et al. 2016; Liu and McKibbin, (2019, 2021). Countries experiencing rapid ageing may initially experience a smaller decrease in savings than in investment, enabling them to export surplus funds overseas and run current account surplus. This can help mitigate negative domestic economic shocks, as returns from overseas investments compensate for declining productivity at home. In contrast, studies show that the increase in the dependency rate significantly lowers saving rates more sharply than domestic investment, worsening current account balances and implying capital inflows (Kim and Lee, 2008). Such dynamics have implications for central banks, which often consider exchange rate movements and external balances in formulating monetary policy, particularly in light of trade-offs posed by the monetary policy trilemma. (Obstfeld et al. 2005).

2.4 Interest Rates and Financial Markets

A shrinking labour force exerts opposing pressures on real interest rates. On the one hand, lower population growth raises the capital to labour ratio, reducing the marginal productivity of capital and depressing real interest rates. If investment falls faster than savings, the resulting surplus of savings also lowers the equilibrium rate. On the other hand, because older individuals tend to save less and consume more, a higher dependency ratio can reduce aggregate savings, increase demand, thereby pushing up equilibrium real interest rates.

Longevity further complicates the picture. With a fixed retirement age, longer life expectancy extends retirement years and encourages workers to save more during their careers, exerting additional downward pressure on interest rates.

In a closed economy, changes in aggregate savings directly influence real interest rates: lower savings push them up, while higher savings push them down. In an open economy, however, interest rates are shaped by the degree of financial integration and both domestic and global demographic trends.

Previous studies on advanced economies such as the U.S. and Japan have highlighted that population ageing would have a negative impact on real interest rates. Carvalho et al. (2016), using a model based on the life-cycle hypothesis and calibrated with data from average OECD countries, demonstrated that increased life expectancy contributed to a 1.5 percentage point reduction in the real interest rate.

Further evidence comes from Fujita and Fujiwara (2023), whose work indicated that changes in the demographic structure trigger significant long-term movements in per capita consumption growth and the real interest rate. Their analysis suggests that the ageing of the labour force was responsible for 40% or more of the declines observed in the real interest rate in Japan between the 1980s and the 2000s.

In the U.S. context, Eggertsson and Mehrotra (2015) and Eggertsson et al. (2019) propose that a declining birth rate ultimately leads to an excess supply of saving and a reduction in aggregate demand, resulting in lower real interest rates. This is consistent with Gagnon et al. (2021), who used an overlapping generations model and concluded that demographic factors account for approximately a 1.25 percentage point decrease in the equilibrium interest rate in the U.S. since 1980.

Carvalho et al. (2025) show, using a multi-country general-equilibrium model with imperfect capital mobility, that low-frequency movements in a country's real interest rate reflect not only domestic demographics but also global ones. The more financially integrated a country is, the greater the weight of global demographic factors and the smaller the influence of its own.

The way demographic changes influence private saving decisions is strongly mediated by the design of government pensions and broader social safety nets (IMF, 2019). Population ageing exerts significant financial pressure on pension systems, particularly Pay-As-You-Go (PAYG) schemes. The sustainability of these systems is strained by the rising ratio of beneficiaries (retirees) to contributors (workers), often reflected in increasing old-age dependency ratios. This challenge can be exacerbated in regions where the working-age population is projected to shrink.

Furthermore, increasing life expectancy extends the period over which pensions must be paid, adding to the fiscal burden. This demographic imbalance means that maintaining existing benefit levels typically requires difficult choices: imposing higher contribution rates on a relatively smaller workforce, reducing retiree benefits, or increasing government transfers funded through general taxation or borrowing.

Population ageing is likely to exert a significant influence on financial markets, beyond its adverse effects on government fiscal balances. Demographic shifts, particularly the transition of the Baby Boom cohort into high-saving and then dissaving years, have been linked to notable asset market movements. Some scholars argue that the surge in U.S. stock prices during the 1990s was partly fuelled by Baby Boomers' peak saving behaviour. Schieber and Shoven (1997) further contend that defined benefit pension funds, which once benefited from strong net inflows, will increasingly face net outflows as the population ages. This transition could alter both the pattern of asset returns and the composition of household financial product demand, with a shift toward safer, income-generating assets.

As more individuals retire, large cohorts may liquidate financial assets to support consumption, exerting downward pressure on asset prices. Poterba (2008) finds that a larger share of the population in prime working years is positively correlated with higher stock market valuations, as measured by the price-dividend ratio. These results suggest that ageing could influence asset prices through both supply and demand channels, although the magnitude and direction of the effects are likely to vary across countries and market structures.

Beyond asset markets, ageing poses broader risks to financial stability. The increasing fiscal burden of pensions, healthcare, and social security can lead to rising public debt and deficits, which may, in turn, strain sovereign bond markets. In addition, defined-benefit pension plans face the risk of underfunding if investment returns fall below expectations in a low-growth, ageing economy. Financial systems will need to adapt not only to changes in asset demand but also to heightened risks associated with fiscal pressures and shifting investment patterns. The interaction between demographic changes and financial market dynamics underlines the need for proactive policy responses to safeguard economic and financial stability in ageing societies.

3. The Role of Human Capital and AI-driven Technological Innovation in Mitigating the Negative Economic Impact of Ageing

This section discusses how human capital and AI-driven technological innovation can play a role in counteracting the challenges arising from a rapidly ageing population. It provides both theoretical and empirical evidence on how human capital development and technological progress can boost productivity growth and mitigate the adverse effects of a shrinking labour force.

3.1 Human Capital Development in Asia and Role of Human Capital

Human capital plays a critical role in economic growth. Human capital, encompassing an individual's skills, knowledge and intelligence, is central to improving labour quality. According to Becker (1964), human capital refers to an "individual's abilities, skills, and knowledge acquired through education, training, and work experience". Health is also considered a component of broader human capital. Given its multifaceted and complex nature, measuring human capital precisely at the individual level can be challenging. In practice, educational attainment often serves as a proxy for human capital stock acquired via formal schooling (Barro and Lee, 1993, 2015).

Human capital is a critical factor for economic growth, as demonstrated by the growth models. Mankiw, Romer and Weil (1992) emphasise that high human capital investment increases per-worker-output in the long-run. Lucas (1998) argues that an economy with a higher proportion of skilled workers can lead to stronger knowledge spillovers, enhancing returns on human capital investment. Romer (1990) emphasises that an educated labour force is instrumental in bolstering research and development (R&D) capabilities and accelerating innovation at both the firm and industry levels. In addition, Nelson and Phelps (1966), as well as Borensztein, De Gregorio, and Lee (1998), highlight the importance of human capital in assimilating foreign technology, which can be crucial for emerging Asian economies seeking to catch up with more advanced nations.

Human capital achievement is diverse in Asia. Many Asian countries have invested heavily in schooling, which has expanded access and helped achieve near-universal primary education. However, progress remains uneven, and significant gaps persist—especially at the upper-secondary and tertiary levels.

As shown in Table 3.1, the region encompasses a wide spectrum of educational outcomes. Advanced economies such as Japan, Korea, Singapore, and Australia have achieved exceptionally high human capital indicators. Their average years of schooling exceed 12 years, and their upper secondary enrolment rates are close to or above 95%.

In contrast, several developing Asian economies still face challenges in expanding access beyond the basic level. Cambodia, Lao PDR, Myanmar, and Papua New Guinea have much lower indicators. For example, only 40.7% of Lao PDR's youth and 49.6% of those in Cambodia are enrolled at the upper-secondary level, while tertiary participation remains minimal (below 15%). These figures illustrate structural barriers—such as poverty, limited school infrastructure, and geographic inequality—that constrain educational progression.

Beyond access, the quality of education and skill development is equally critical. Learning outcomes are often poor, with many students leaving school without the cognitive skills needed to be productive. As economies undergo structural transformation, workers must adapt to evolving skill demands. A well-trained, flexible workforce is, therefore, essential for sustaining growth. Greater public and private investment in education and training is needed to improve quality and reduce disparities across Asia.

As Asia's population ages at an unprecedented pace, more older workers are expected to enter the workforce, potentially negatively impacting economic growth. An increase in older workers may hinder economic growth if the older workers are less productive than the younger workers. This is because the human capital of an individual declines with age, owing to the deterioration of physical and cognitive abilities (Truxillo, Cadiz, and Hammer, 2015). A humped-shaped age profile of wages shows that the productivity of the workers peaks in mid-career and gradually declines as they enter older age brackets (Heckman, Lochner, and Todd, 2003).

Table 3.1: Human Capital Measures in Asia

Country	Average Years of Schooling (2015)	Enrolment rates (%, 2023)			
		Primary (net)	Lower Secondary (net)	Upper Secondary (net)	Tertiary (gross)
Australia	12.4	99.8	98.2	93.7	106.2
Brunei Darussalam	9.1	99.4	99.5	74.2	33.5
Cambodia	4.9	92.2	85.6	49.6	15.0
China	8.7				72.0
Fiji	10.2	97.4	97.2	78.2	68.4
India	7.4	99.3	94.9	75.7	32.7
Indonesia	8.6	99.5	85.6	57.5	42.6
Japan	12.8	99.9	100.0	98.1	64.6
Lao PDR	6.7	90.5	64.6	40.7	13.7
Malaysia	11.4	90.9	82.7	64.7	40.3
Mongolia	9.9	92.3	93.6	95.4	64.3
Myanmar	5.4	100.0	89.4	63.9	-
Nepal	5.4	98.0	96.2	81.0	14.0
Papua New Guinea	4.6	96.0	68.7	38.1	-
Philippines	9.0	89.5	89.1	79.7	39.6
Republic of Korea	12.8	100.0	98.2	94.5	103.3
Singapore	12.8	99.8	99.6	99.4	98.0
Sri Lanka	11.1	90.9	93.5	78.5	23.0
Thailand	8.8	98.4	99.9	81.4	44.0
USA	13.3	96.0	99.2	94.9	79.4
Vietnam	7.8	98.3	97.0	67.3	42.2

Source: Data on years of schooling are sourced from Barro and Lee Educational Attainment Database, and data on the net enrolment rates on primary, lower secondary and upper secondary education are sourced from UNESCO. Data on the gross enrolment rates on tertiary education are sourced from World Bank's World Development Indicator. Net enrolment rate measures the share of school-age children enrolled in school, while gross enrolment rate includes students of all ages enrolled relative to the school-age population. The data on Myanmar are from 2018, on the USA from 2022, and on primary education in Papua New Guinea from 2021.

In addition, older workers often find it challenging to adapt to rapidly evolving technologies. The knowledge and skills acquired by older workers during their formal education are often outdated, and older workers tend to have lower adoption rates of new technologies than younger workers (Meyer, 2011). In some cases, new technologies leave older workers behind. It is believed that older people tend to be less innovative than younger people. As a result, maintaining older workers' productivity in fast-changing work environments can pose significant challenges without targeted upskilling and support.

However, there are other studies suggesting that ageing does not necessarily lead to lower productivity, particularly when older workers continue to develop their human capital. Evidence indicates that if older workers are more educated and continuously develop their human capital after formal education by adapting to new technologies, having longer work experience, engaging in on-the-job training, and equipping themselves with proper skills, their productivity might not necessarily be lower than that of younger workers. With a longer lifespan, workers have a greater willingness to work longer, thus having a higher motivation to invest in their health and education (Prettner et al., 2013; Börsch-Supan and Weiss, 2016; Lee et al., 2022).

Firm-level studies across the countries suggest that the productivity peak tends to be around the ages 30–45, but the range varies across countries and industries, as summarised in Chomik and Piggott (2019). The Asian Development Bank (2018) reports that there are some sectors where workers may show greater productivity, even at the later stages of their careers. Burtless (2013) further argues that there is little evidence for the negative link between aging and productivity in the U.S.

Hanushek et al. (2025) provide new empirical evidence using German data that, after separating age and cohort effects, an individual can increase their literacy skills up to age 45 and numeracy skills up to 40. This contradicts the cross-sectional age skill profiles, suggesting that cognitive skills start to decline by age 30 if not earlier. Interestingly, white-collar and higher-educated workers with above-average skill usage show increasing skills even beyond their forties. This implies that older workers can be productive when they are better educated.

Asia must leverage older workers' human capital to address the shrinking workforce. The current generation of older workers can be better educated and have higher cognitive skills compared to the past due to the expanded access to formal education. As demonstrated in Han and Lee (2020), there is an upward shift of the age-productivity profiles over the period from 1986 to 2016 in Korea, as the completion of higher-level education among adults and old-aged people has risen over time. This implies that the average wage of old-aged workers declines gradually, reflecting that older workers in recent decades are more productive than in the past.

Continuous human capital development and technology adoption enable older workers to remain productive. Lee, Kwak, and Song (2022) underscore the importance of on-the-job learning and ICT-related training in mitigating the challenges amid rapidly changing technological environments in making the older workers more productive in the labour market. By updating their digital competencies and engaging in continuous learning, older workers can maintain their productivity well beyond traditional peak ages.

Asia must invest in the untapped potential of older workers by prioritising human capital development throughout their entire life course. Policies promoting lifelong learning—from formal education in youth through continuous skilling in later years—are vital for keeping pace with rapidly evolving job markets. Equipping older individuals with up-to-date technical and cognitive skills can lessen the impact of a shrinking workforce and maintain economic resilience. By fostering a culture of ongoing education and training, Asia can transform its demographic challenges into opportunities for sustained growth.

Asia must foster human capital development across all age groups and promote technological innovation to sustain its economic dynamism. Strong human talents with innovative capacity are essential to support technological advancement. Preparing workers with adequate skills to adapt to changing technologies requires investment in high-quality education early in life and continuous life-long learning. Encouraging older workers to extend their careers is critical for tapping into an underutilised resource and driving regional growth. Governments should focus on cultivating a more productive ageing workforce, equipping them with skills to engage with new technologies such as robotics and AI. By aligning human capital development with technological innovation, Asia can better adapt to demographic change and harness the potential of its silver demographic dividend.

3.2 The Role of Technological Innovation in an Ageing Economy

The advent of new technologies, particularly artificial intelligence (AI), offers a potential counterbalance to the economic challenges posed by population ageing. As ageing societies confront shrinking workforces and rising dependency ratios, technological innovations, such as digitalisation, automation, and information and communications technologies (ICT) and AI, can enhance productivity, reduce labour costs, and generate disinflationary pressures. These developments are crucial for supporting long-term growth and fiscal sustainability in advanced and rapidly ageing economies across Asia.

AI expands the traditional concept of automation by performing complex cognitive tasks, offering broad implications for the economy. Automation traditionally referred to machines performing manual or repetitive tasks previously done by humans. AI, however, goes further by enabling systems to replicate human cognitive functions, such as reasoning, prediction, and decision-making. While automation has historically replaced routine manual labour, AI has begun to venture into areas once regarded as exclusively human, including analytical and creative tasks. This represents a fundamental shift in the technological landscape and expands the potential for automation across all sectors.

AI is both a long-standing academic field and a rapidly evolving technology. The term “artificial intelligence” was first coined by John McCarthy in 1956 at Dartmouth College, where he envisioned machines capable of using language, forming abstractions, solving problems, and learning independently. More recently, the OECD (2023) defines AI systems as “machine-based systems that, for explicit or implicit objectives, infer how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.” This reflects a modern understanding of AI as a system capable of autonomous functioning and learning, tailored to a range of applications from virtual assistants to industrial robots.

AI functions as a transformative General-Purpose Technology (GPT). Like electricity, steam power, and the internet before it, AI qualifies as a GPT due to its broad applicability and potential to drive innovation across sectors. However, it differs from previous GPTs in its deep integration with cognition-based tasks. AI not only automates physical or routine processes but also enhances creativity, optimisation, and strategic decision-making. With high autonomy and the ability to self-improve, AI systems are reshaping production, service delivery, and research. The rapid pace of advancement is illustrated by the 55-million-fold increase in computing power used for training machine learning systems between 2010 and 2022 (Economist, 2024).

AI introduces both risks and opportunities in the labour market. Technological disruption from AI raises legitimate concerns about job displacement, especially in occupations dominated by routine tasks. Task-based studies emphasise both the risks of displacement and the potential for productivity gains. Acemoglu and Restrepo (2019) show that automation reduces wages and employment in affected roles, though it can also create new jobs through task reassignment and industry spillovers. At the same time, AI complements non-routine work, particularly in roles involving creativity, problem-solving, or human interaction. It also supports workers in highly exposed occupations, creating new opportunities for them (Pizzinelli et al., 2023). Additionally, AI drives demand and facilitates the emergence of entirely new occupational categories.

AI also boosts worker productivity. Recent studies highlight AI’s ability to significantly enhance performance across a variety of jobs. Generative AI and large language models (LLMs) help workers complete tasks more efficiently and accurately, with measurable productivity gains (Filippucci et al., 2024; Brynjolfsson et al., 2025). For example, generative AI tools have been shown to increase customer support productivity, reduce writing time for professionals while improving quality, and enhance coding output for software developers. Importantly, these improvements are not limited to highly skilled professionals. AI tools can assist less-skilled workers by reducing task complexity, improving learning, and enabling upskilling on the job.

Older adults face barriers to adopting AI technologies. Despite its potential, older populations tend to adopt AI technologies at lower rates due to digital literacy gaps and limited access. In the United States, workplace usage of generative AI tools drops from

34% for workers under 40 to 17% for those aged 50 and over (Bick et al., 2024). These gaps may hinder older adults from benefiting fully from the AI-driven economy, underscoring the need for targeted digital inclusion policies.

AI can enhance the productivity and employability of older workers. AI offers tools that can mitigate the limitations associated with ageing (Brynjolfsson et al., 2025). It supports older employees in cognitive tasks, facilitates decision-making, and automates routine processes, thereby extending their working lives. Flexible AI-enabled work arrangements and user-friendly interfaces can help older workers adapt and remain economically active (Bick et al., 2024). For instance, new technologies allow for innovative ways of team-working by changing the nature of how teams collaborate and operate. Flexible, AI-powered work arrangements and user-friendly interfaces can help older workers remain active (Bick et al., 2024). Emerging technologies are reshaping team collaboration by providing greater flexibility and enabling age-inclusive incentives and performance assessments, thereby contributing to effective teamwork and business success (OECD, 2020). Retraining and lifelong learning will be essential to ensure older workers are equipped to use these technologies effectively (Lee et al., 2022).

AI can improve health outcomes and caregiving for ageing populations. AI technologies hold promises for enhancing health and well-being in ageing societies. Wearable sensors and diagnostic tools allow for early disease detection and more efficient chronic care management. Robots and AI-enabled assistants reduce the burden on caregivers and compensate for labour shortages in health and social care sectors. These innovations can promote independent living, reduce healthcare costs, and improve quality of life for older individuals (ADB, 2024).

AI has the potential to raise long-term productivity and growth, though its diffusion remains uneven. By automating repetitive tasks and redirecting human effort toward creative and high-value work, AI is already transforming sectors such as pharmaceuticals, transportation, and finance, while accelerating scientific breakthroughs through enhanced R&D processes (Filippucci et al., 2024). By improving the efficiency of research, managerial, and other innovation-intensive tasks, AI also fosters new knowledge creation that feeds back into higher long-term productivity growth (Brynjolfsson et al., 2018; Baily et al., 2023). Yet, the broader economic impact may take time to materialise, as implementation remains costly and complex, and early productivity gains are concentrated in a limited set of firms and sectors (Brynjolfsson et al., 2019, 2021).

The long-term macroeconomic implications of these productivity gains remain uncertain, and evidence is still emerging. Acemoglu (2024) estimates that AI could raise the U.S. growth rate by 0.1 percentage points annually, while Goldman Sachs (2023) projects global GDP to increase by 7% and productivity growth by 1.5 percentage points over the next decade. Baily et al. (2023) similarly estimate that AI will accelerate technological progress and raise U.S. productivity growth by around one percentage point per year. However, the global impacts of AI adoption are uneven. Studies show that

AI exposure differs widely across occupations and countries, with advanced economies generally better positioned to benefit than emerging or developing economies (OECD, 2023; Pizzinelli et al., 2023; Cazzaniga et al., 2024; Cerutti et al., 2025).

Asia must harness AI and emerging technologies to adapt to demographic change. To mitigate the economic challenges of ageing, Asian economies must harness the opportunities presented by AI and other emerging technologies. This involves fostering innovation ecosystems, investing in digital infrastructure, and ensuring inclusive access to education and upskilling. Governments should prioritise attracting global talent and securing strategic technologies to remain competitive in the AI-driven global economy. In parallel, policies must support equitable AI adoption to prevent widening disparities between generations and regions. Studies underline the need for preparedness, social safety nets, and targeted fiscal interventions to ensure inclusivity in the adoption of generative AI (ADB, 2024, Brollo et al., 2024).

3.3 Synergies between Human Capital and AI in Ageing Economies

The preceding sections have examined human capital development and AI-driven technological innovation as distinct drivers of productivity growth in ageing economies. Yet their full potential lies not in isolation but in combination. How effectively human capital policies and AI adoption are integrated will largely determine whether Asian economies can sustain growth amid rapid demographic change.

Human capital policies therefore need to be designed with AI complementarity in mind. The objective is not to substitute humans wherever possible, but to raise the productivity of workers through effective collaboration between human capital and AI. While AI has clear advantages in computation, data processing, and pattern recognition, humans retain comparative strengths in judgment, contextual understanding, creativity, and responsibility. The most productive model is thus one of human–AI collaboration, combining the strengths of human intelligence with those of artificial intelligence. In ageing economies, where labour supply is shrinking, this complementarity becomes particularly important. By automating routine cognitive and physical tasks, AI can enable experienced workers—including older workers—to remain productive for longer by focusing on tasks where accumulated knowledge and experience are most valuable.

Such complementarities are especially relevant for addressing the economic challenges of population ageing. AI can help increase the labour force participation of older workers by reducing the physical and cognitive burdens associated with many occupations and by facilitating more flexible forms of work. For example, AI-assisted tools, digital platforms, and remote work technologies can allow older individuals to remain economically active even as traditional workplace demands become more difficult to meet. In this way, AI can help offset part of the negative impact of population ageing on the size of the labour force while preserving valuable human capital embodied in experienced workers.

Realising these synergies requires human capital policy to focus not only on accumulation, but also on utilisation and continuous upgrading throughout the life cycle. Lifelong learning systems therefore become increasingly important. In an AI-driven economy, skills may become obsolete more rapidly, and workers need access to mid-career retraining and flexible learning opportunities throughout their working lives. For older workers in particular, policies should support the development of digital and AI-related competencies, promote healthy and productive ageing through supportive healthcare systems, and remove institutional barriers that limit job mobility or task transitions later in life.

At the same time, policymakers must recognise that older workers often have weaker digital skills than younger cohorts. Without targeted policy intervention, the rapid diffusion of AI may therefore exacerbate the age dimension of the digital divide. Bridging this gap requires expanding access to digital training programs tailored to older workers, promoting user-friendly technologies, and encouraging firms to invest in age-inclusive workplace practices. Strengthening the digital capabilities of older workers should thus become a key priority for governments seeking to harness AI as a tool for inclusive growth in ageing societies.

Education systems must also prepare workers not to compete with AI, but to work effectively alongside it. This implies stronger digital literacy across all age groups, alongside continued emphasis on critical thinking, creativity, communication, and collaboration—competencies that complement AI rather than compete with it. Policies that gradually raise the statutory retirement age and provide incentives for continued labour force participation after retirement can further expand the pool of workers able to benefit from human–AI complementarity. When human capital investment and AI adoption are pursued in tandem, with policies explicitly designed to strengthen their interaction, the demographic challenge of population ageing and the technological opportunities presented by AI can become mutually reinforcing rather than competing forces in Asia’s long-term growth strategy.

4. Policy Challenges Related to Population Ageing and AI

Human capital and AI can mitigate the negative economic impact of population ageing, as we discussed in the previous section. At the same time, population ageing throws up policy challenges for monetary policy and financial stability while AI also poses some policy challenges of its own. This section examines the policy challenges arising from population ageing, with a focus on monetary policy, pension system sustainability, and financial stability. Population ageing can adversely affect key macroeconomic variables, potentially limiting the effectiveness of monetary and financial policies. The section explores how these policies can be adapted to mitigate the economic and financial impacts of ageing, while also addressing emerging challenges associated with the rise of AI.

4.1 Challenges to Monetary Policy

Population ageing adversely affects potential growth and the natural rate of interest (NRI), which is considered critical for the central bank. NRI is central to monetary policy. If the central bank can adjust its policy rate so that the real interest rate aligns with the NRI and there are no cost-push shocks, output remains at potential and inflation stays on target. However, since the NRI is unobservable and estimated with a lag, a declining trend in the NRI can lead central banks to overestimate it. This delay in adjustment may result in an overly tight policy stance (Koester et al., 2021; Bielecki et al., 2023).

In addition, a lower natural rate of interest significantly reduces the space available for central banks to cut interest rates during economic downturns, thereby increasing the likelihood of encountering the zero lower bound (ZLB) or the effective lower bound (Bielecki et al., 2023). To be more specific, with average nominal interest rates already depressed by a lower natural rate of interest and persistent low inflation, the ability of central banks to stimulate the economy with conventional instruments can be limited.

Central banks must assess how demographic changes—especially population ageing—affect inflation, taking into account each country's production and consumption structures. While ageing is often associated with deflation, it can also drive inflation through a shrinking labour force, rising wages, increased public spending, and fiscal deficits that may prompt monetisation. Delayed policy responses risk leaving central banks behind the curve—not only on deflation, but also on emerging inflation. A forward-looking approach that incorporates demographic trends into inflation forecasts is essential to avoid underestimating inflation and to maintain an appropriately accommodative stance.

Furthermore, population ageing can alter the transmission mechanism through which monetary policy affects the broader economy. Demographic shifts can alter the interest rate sensitivity of both households and firms. For instance, population ageing may weaken monetary policy transmission through structural changes to financial asset holdings and credit demand, thereby affecting the wealth and credit channels (Bodnár and Nerlich, 2022)

In addition, given the different consumption behaviours/patterns across age groups, consumption responses to interest rate changes vary across age groups. Studies such as those by Yoshino and Miyamoto (2019) suggest that the effectiveness of monetary policy diminishes as population ageing progresses, as older individuals are less responsive to changes in interest rates than younger cohorts. Wong (2018) further highlights that younger individuals, particularly homeowners refinancing or taking new loans, are more sensitive to monetary policy shocks. In contrast, Berg, et al. (2021) argue that older households, with higher net wealth and more interest-rate-sensitive assets like home equity and bonds, are more responsive to interest rate changes. Leahy and Tapar (2019) find that the response of private employment and personal income to an increase in interest rates is stronger in the U.S. states with the largest share between 40 and 65 years of age.

4.2 Challenges to Financial Stability

Because of a lower share of the contributors to the system and longer periods of benefit receipt associated with the increased longevity, population ageing poses a threat to the sustainability of the pension system. In addition, the growing proportion of retirees increases government spending on pensions, healthcare, and social security, potentially leading to higher fiscal deficits. If investment returns decline, defined-benefit pension systems may lead to a shortfall in funds needed to pay out pensions to retirees. In addition, as stated in Bloom et al. (2015), the difficulties in securing the fiscal integrity of the pension systems in the times of population ageing, are more pronounced in developing countries when they have not yet secured comprehensive social security coverage and/or resources to support large cohorts of retirees.

The interaction between demographic change and financial market dynamics underscores the need for central banks and financial authorities to adopt proactive and integrated policy approaches. Population ageing affects not only pensions and fiscal balances but also financial market behaviour, with profound implications for asset prices, investment patterns, and overall financial stability. As ageing cohorts transition from saving to dissaving phases, demand for safe, income-generating assets is likely to rise, while large-scale asset liquidations may exert downward pressure on asset prices. To mitigate these risks, central banks and financial regulators should incorporate demographic trends into macroprudential surveillance, stress testing, and financial market forecasting. Policymakers may also coordinate with fiscal authorities to ensure long-term sustainability and support the development of financial products aligned with the needs of ageing populations.

4.3 AI and Monetary Policy

AI is expected to impact monetary policy through both direct and indirect channels (Hartmann et al., 2025). Direct impacts concern potential changes to the monetary policy transmission itself – that is how changes in monetary policies are transmitted to the financial system and the wider economy (i.e., inflation, employment and growth). Indirect impacts relate to how AI might reshape macroeconomic variables, thereby changing the landscape in which monetary policy operates.

AI has the potential to reshape key channels of monetary policy transmission, particularly through its impact on price-setting and labour market dynamics. Businesses using AI-driven algorithmic pricing may adjust prices more frequently, increasing price flexibility and potentially steepening the Phillips curve, thereby strengthening the impact of monetary policy on inflation. At the same time, AI-enabled price discrimination based on individual customer data and risks of algorithmic collusion could blur the link between policy changes and consumer prices. Moreover, automation may reduce workers' bargaining power, flattening the Phillips curve and dampening wage responsiveness to policy. The rise of the AI-driven gig economy may further disrupt traditional transmission mechanisms, making consumption and employment responses more volatile and harder to predict.

The financial sector is another critical pathway through which AI can directly affect monetary transmission. Banks incorporating AI could enhance their operational efficiency, improve risk assessment, and expand digital offerings, potentially accelerating and strengthening the bank lending and interest rate channels. Conversely, AI might diminish the relevance of the bank capital channel, possibly softening lending adjustments by less capitalised banks, especially during periods of monetary tightening. Furthermore, AI could spur greater bank disintermediation, with FinTech and BigTech firms playing an enlarged role in credit provision. Transmission through these non-bank channels might also accelerate and strengthen interest rate pass-through and lending responses to policy changes, potentially boosting the impact of policies targeting longer-term rates if AI enhances the role of intermediaries, such as investment funds.

AI's potential influence on productivity, and, aggregate supply and demand carries implications for monetary policy. One significant indirect channel is AI's potential influence on productivity and, consequently, the natural rate of interest. There appears to be broad agreement that widespread AI adoption will likely lead to productivity gains over time, although estimates of the magnitude vary considerably. Higher productivity growth, by increasing the marginal productivity of capital, tends to exert upward pressure on the natural interest rate, suggesting that higher policy rates might be needed to maintain price stability. This could help counteract downward pressure on the natural rate from factors like population ageing. However, this effect isn't guaranteed. If AI displaces existing jobs faster than it creates new ones, or if the necessary sector and labour reallocations induce greater inequality, this could reduce the upward pressure from productivity gains on the natural rate.

AI's impact on aggregate supply and demand has important implications for inflation. On the supply side, AI-driven productivity gains could ease labour shortages and lower production costs. However, these benefits may be offset by rising aggregate demand, particularly through increased investment. The effect on consumption is uncertain, depending on how AI reshapes employment, worker bargaining power, and wage growth. As a result, it remains unclear whether AI will ultimately lead to inflationary or disinflationary pressures.

Monetary policy responses will vary depending on the net effect. If AI leads to a positive output gap and inflationary pressures, an increase in the policy rate is expected. In contrast, if disinflationary pressures prevail, a policy rate cut would be more likely. AI can influence inflation through both disinflationary and inflationary channels. By significantly boosting productivity, it reduces unit production costs and enables greater output at lower prices. AI also lowers operational expenses by optimising supply chains and automating tasks. These efficiency gains expand aggregate supply, ease price pressures, and contribute to disinflation.

At the same time, AI adoption can generate inflationary pressures. Large-scale investments in data centres, infrastructure, and related technologies increase aggregate demand before productivity benefits fully materialise, pushing prices upward. Rising incomes from productivity improvements can further stimulate consumption, while AI-driven global growth may place additional upward pressure on commodity prices, particularly energy, minerals, and metals.

The net impact depends on both timing and expectations. In the short-run, demand-side effects may dominate, resulting in higher inflation. Over the longer term, however, productivity-driven supply gains are likely to prevail, making AI a stronger disinflationary force. Expectations also play a critical role: if households and firms do not anticipate higher future productivity, AI adoption is initially disinflationary, whereas if significant productivity gains are expected, inflationary pressures may emerge immediately (Aldasoro

5. Key Findings from the Country Case Studies and Policy Recommendations

This integrative chapter provides the background and objectives of the study, discusses the major issues related to the effects of ageing and AI-driven technological innovation on the economy, and assesses the challenges posed by population ageing and AI to monetary and financial policy. Chapters 2 to 8 are devoted to case studies of individual SEACEN member economies, focusing on these related issues.

Chapter 2, “Implications of Demographic Change and Artificial Intelligence Development for Monetary Policy: The Case of Korea,” presents the macroeconomic implications of AI diffusion amid rapid population aging, focusing on Korea as a small open economy experiencing the fastest demographic transitions in the world. By developing a two-country overlapping generations model with incomplete international capital mobility, the study examines how the diffusion of AI – through the channels of TFP growth, changes in factor income shares between labour and capital and heterogenous age-specific labour productivity – reshapes Korea’s trajectories of economic growth, the real interact rate, fiscal stability and external balance over the next 50 years.

The study’s key findings highlight the asymmetric impacts of AI on the Korean economy. U.S productivity gains induce capital outflows from Korea, leading to slower growth and faster debt accumulation, while higher foreign returns improve the net foreign asset (NFA) position. Conversely, domestic productivity gains in Korea yield higher growth and stronger fiscal revenues but weaken the NFA position as capital inflows increase. Both TFP scenarios exert upward pressures on Korea’s equilibrium real interest rate. Moreover, an AI-induced rise in the capital income share in Korea boosts the real interest rates and temporary growth, yet undermines fiscal sustainability and external balance. Finally, an AI-induced shift in age–productivity profile toward a later peak in Korea expands effective labour, and pushes up the real interest rate. These key findings highlight the complex trade-off that AI introduces among growth, fiscal stability and external resilience. This calls for the monetary authorities to refine the real interest rate estimates and integrate fiscal, labour and structural policies to ensure that AI-driven growth is both sustainable and inclusive.

In Chapter 3, “Impact of the Adoption of Artificial Intelligence on Monetary Policy: Evidence from Sri Lanka on the Labour Productivity Channel,” the potential implications of Artificial Intelligence (AI) adoption on monetary policy transmission in Sri Lanka are examined using a Dynamic Stochastic General Equilibrium (DSGE) framework. While AI technologies such as machine learning, natural language processing, and computer vision are widely recognised for their productivity-enhancing effects, their interaction with monetary policy remains underexplored in the Sri Lankan context. To address this gap, the study employs a DSGE model with sticky prices, incorporating both total factor productivity and labour-augmented productivity, the latter assumed to result from greater AI adoption.

The study’s results show that while both AI and total factor productivity shocks lower inflation and ease monetary policy conditions, TFP shocks have stronger effects on output and investment, while AI shocks, transmitted mainly through labour productivity, generate more moderate responses that require relatively milder policy adjustments. Furthermore, when considering different elasticities of substitution between capital and labour, the AI labour-augmented productivity shock is found to yield a more amplified response when factor inputs are substitutes rather than complements.

Chapter 4, “The Silver Shift Meets Digital Surge: Demographic Change and AI in Malaysia’s Economic Landscape,” investigates how population ageing and artificial intelligence (AI) adoption shape Malaysia’s macroeconomic outlook using the G-Cubed model of McKibbin and Wilcoxen (2013) - a multi-country, multi-sector general equilibrium model. Ageing alone initially pushes prices upward due to labour shortages and higher fiscal spending, but over time, declining productivity lowers potential growth, produces disinflation, and reduces the natural real interest rate (r*). When ageing coincides with broad-based AI adoption, productivity and labour efficiency improve. Although AI generates short-term disinflation, stronger investment and consumption eventually raise potential output and r*, offsetting demographic headwinds.

The analysis also considers two stress scenarios. Under ageing with greater-than-expected fiscal pressure, rising healthcare costs increase risk premia, triggering capital outflows, currency depreciation, and temporarily higher inflation, even as real activity weakens. In the scenario where Malaysia lags global peers in AI adoption, competitiveness deteriorates and output contracts initially, but the effect is temporary: structural shifts toward non-tradable and domestic-oriented sectors support a gradual recovery in growth.

In Chapter 5, "Demographic Composition and India's Natural Interest Rate," the authors examine how demographic composition relates to India's natural interest rate, r*. A GDP-weighted global neutral-rate benchmark is included to net out common global trends, sharpening identification of domestic demographic effects. Using quarterly data for 2000–2024, the study combines total age dependency and its composition (youth and old-age dependency) with macro-financial covariates. Estimation relies on complementary designs: levels regressions with HAC inference, ARDL models reporting long-run multipliers and adjustment speeds, and a state-space model with time-varying slopes.

The study provides three main results. First, composition matters: youth and total dependency are positively associated with r*, whereas old-age dependency is negatively associated with a larger absolute magnitude. Second, these relations survive the global control and remain economically meaningful after conditioning on saving, debt, and potential growth, consistent with multiple transmission channels. Third, time-varying estimates show stable signs with modest drift, indicating a persistent demographic imprint on r*. The evidence implies that composition-aware demographic paths contain information about India's equilibrium real rate beyond global trends, providing a transparent baseline for integrating demography into neutral-rate assessments and medium-term policy calibration.

Chapter 6, "Monetary Policy Effectiveness in the Era of Demographic Ageing and AI Adoption: Evidence from Vietnam," examines whether two major structural forces—population aging and the rapid diffusion of artificial intelligence (AI)—shape the effectiveness of monetary policy in Vietnam. Motivated by evidence that older households respond less to interest rate changes and that AI adoption can alter firms' pricing behaviour and productivity, the study asks whether these developments modify the response of output and inflation to monetary tightening. Vietnam provides a relevant context, as the share of its population aged 65 and above increased from about 6% to over 9% between 2013 and 2024, while AI-related activity expanded rapidly following global advances in generative AI. Using monthly data from 2013–2024, the paper identifies monetary policy shocks from residual movements in the overnight interbank rate and estimates their effects with Jordà's (2005) local projections, augmented with interaction terms capturing aging and AI diffusion.

The empirical findings show that Vietnam's short-run monetary transmission is weak. Monetary tightening produces only small and statistically uncertain effects on both industrial output and inflation, indicating limited responsiveness to interest-rate changes. Incorporating aging and AI yields only mild directional variation: policy tightening becomes slightly less contractionary in older or more technologically advanced periods, but these differences are economically negligible and statistically insignificant. Overall, the results suggest no immediate need to adjust Vietnam's monetary policy framework, though continued monitoring of demographic and technological developments remains important as these structural forces evolve.

Chapter 7, "Simulating the Impact of Fertility and Life Expectancy Shocks on the Philippine Economy using the G-Cubed Model ," analyses how demographic changes shape macroeconomic outcomes in the Philippines. Using the multi-country, multi-sector G-Cubed model, the study simulates the effects of falling fertility and rising life expectancy on key economic variables. The results show that declining fertility slows income and output growth, reduces savings and investment, and widens both fiscal and trade deficits. It also lowers real interest rates and leads to currency appreciation. In contrast, higher life expectancy expands the labour force, raises output, savings, and investment, increases real interest rates, and depreciates the exchange rate, while narrowing fiscal and trade deficits.

The chapter underscores the importance of proactive policy measures to manage demographic transition. Supporting fertility, extending labour force participation among older workers, and improving productivity across all age groups will be essential for sustaining growth and maintaining macroeconomic stability in the decades ahead.

Asia as a whole is ageing rapidly, while AI is emerging as a transformative technology that will shape the region's economic future. However, demographic structures and AI readiness vary widely across economies, implying that there is no single policy pathway for leveraging human capital and AI to address the economic challenges of population ageing. Policymakers therefore need to tailor their strategies to national circumstances while recognising that demographic change and AI technological transformation will increasingly interact to shape macroeconomic outcomes across the region. The papers in this volume demonstrate the complexity of the impacts of population ageing and AI on economies. Combining both ageing and AI adds a further level of complexity, which requires a modelling framework to disentangle the core issues and better understand the quantitative magnitudes of the different implications.

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CHAPTER 2

IMPLICATIONS OF DEMOGRAPHIC CHANGE AND ARTIFICIAL INTELLIGENCE DEVELOPMENT FOR MONETARY POLICY: THE CASE OF KOREA

Jae Won Lee[1], **Woong Yong Park**[2], **Seolwoong Hwang**[3] and **Seung Jun Jung**[4]
Bank of Korea

1. Introduction

The rapid advancement of artificial intelligence (AI) in recent years has attracted considerable attention in both academic and policy circles. A growing body of evidence from randomised controlled trials and large-scale natural experiments shows that the adoption of generative AI significantly improves productivity and work quality across a wide range of occupations, including customer support, writing, and software development (Brynjolfsson, Li, and Raymond, 2025). These findings suggest that AI is no longer a latent technology but has already begun to transform production processes as a general-purpose technology.

From a macroeconomic perspective, AI functions as a technology shock that raises total factor productivity (TFP), alters the marginal productivity and accumulation path of capital, and reshapes task allocation and organisational structures (OECD, 2024; IMF, 2024). Specifically, AI may (i) increase TFP directly, (ii) enhance capital productivity and accelerate capital deepening, (iii) improve labour productivity through automation and task augmentation, and (iv) exert heterogeneous effects across different age groups. Recent empirical studies indicate that less-experienced and older workers tend to benefit disproportionately from AI assistance, thereby narrowing skill gaps (Brynjolfsson, Li, and Raymond, 2025). At the same time, technological progress tends to reduce the relative price of capital, reinforcing the long-run decline in the labour share of income (Karabarbounis and Neiman, 2014). Such distributional shifts may, in turn, affect aggregate demand, saving, and investment behaviour, with important implications for monetary policy transmission.

1. Bank of Korea and Seoul National University. Email: Jwlee7@bok.or.kr, jwlee7@snu.ac.kr

2. Seoul National University. Email: woongyong.park@snu.ac.kr,

3. Bank of Korea, Economic Research Institute Email: hsw@bok.or.kr

4. Bank of Korea, Information Technology Department, Email: seungjun@bok.or.kr

The significance of these forces is particularly pronounced in Korea, where the dual structural transitions of rapid population ageing and accelerating AI diffusion coincide. Although the current rate of AI adoption among Korean firms remains below the OECD average, surveys suggest that investment and interest are expanding quickly, with particularly rapid uptake in finance, semiconductors, and manufacturing (OECD, 2024). Meanwhile, Korea is experiencing one of the fastest demographic transitions in the world. According to Statistics Korea, the share of the elderly population (65+) surpassed 20% in 2024, marking the country's entry into a "super-aged society," and is projected to exceed 37% by 2045, the highest among OECD members. The working-age population (15–64) peaked in 2017 and is projected to fall below half of the total population by the 2070s (Statistics Korea, 2024). These demographic dynamics exert downward pressure on potential growth and the real interest rate, thereby influencing the neutral rate of interest (r*). In New Keynesian (NK) models, the natural rate of interest denotes the real interest rate consistent with potential output and stable inflation, while in empirical and policy discussions, the neutral rate typically refers to the medium-term equilibrium real rate that neither stimulates nor restrains economic activity. Hence, even though the framework in this study is a real (non-monetary) model and cannot directly capture nominal dynamics or monetary policy responses, its analysis of real-rate determinants provides valuable implications for the long-run evolution of the neutral rate.

Taken together, these structural forces suggest several channels of interaction between AI and demographics. First, higher TFP raises potential growth and the equilibrium real interest rate. Second, changes in capital deepening and factor shares can alter the saving–investment balance, with ambiguous effects on growth and interest rates. Third, the heterogeneous productivity distribution across age groups interacts with the rising share of elderly workers, reshaping aggregate productivity, wage structures, and monetary policy transmission through wages, prices, expectations, and asset prices.

This paper seeks to quantify these dynamics by developing a two-country overlapping generations (OLG) model with incomplete international capital mobility and borrowing constraints. We focus on the Korean case, given its uniquely rapid demographic transition. In the model, AI shocks are introduced through TFP growth, heterogeneous age-specific labour efficiency distribution, and shifts in factor income shares. We then evaluate how these shocks affect long-run growth, the real interest rate, and macro-financial stability under alternative scenarios. By doing so, the paper identifies the conditions under which the structural headwinds of population ageing may be offset—or amplified—by the technological tailwinds of AI, and draws implications for the medium- to long-term design of Korea's monetary policy framework.

2. Model Specification and Data[5]

2.1 Model

This study develops a two-country open-economy (OLG) model to analyse the effects of advances in AI. The model is calibrated to the Korean case, ensuring that the dynamics of interest rates, growth, and other key variables realistically reflect the ongoing demographic transition. The foreign block, representing the rest of the world, is calibrated using data from the United States, which is assumed to represent the global economy. The main assumptions of the model are as follows.

Households enter the labour market at age 25, retire at 60, and face age-specific survival risk up to a maximum age of 99. Young households face borrowing constraints that limit debt relative to expected lifetime income, reflecting observed credit frictions. The time frequency is a year. Aside from mortality risk, agents perfectly foresee paths for demographics and productivity.

Korea's external openness is built-in via a two-country structure (Korea and a foreign block) with trade and cross-border asset holdings. The government (in Korea) levies income taxes, purchases goods and services, issues bonds, and manages foreign-exchange reserves, which are modeled as a time-varying share of GDP to match institutional practice.

A central feature is imperfect international financial integration along the transition path. To capture persistent rate differentials observed between Korea and abroad, we introduce two frictions grounded in the data and literature. First, Korean households' foreign saving is governed by a simple portfolio rule (a fixed fraction of net assets), ensuring outward investment despite higher domestic real rates. Second, foreign households face investment costs that rise with the scale of capital outflows to Korea; in reduced form, this behaves like a risk premium and closes arbitrage only gradually as integration deepens. In the long-run integrated steady state, these frictions vanish and real rates converge.

Market clearing is standard. In Korea, the next period's capital and government bonds must equal the saving supplied by Korean households plus foreign residents' claims on Korea; abroad, the capital stock is financed by foreign households' saving, Koreans' foreign assets, and the foreign reserve position of Korea. Net foreign assets and the current account are defined in the usual way, which we track alongside private saving, investment, and government spending.

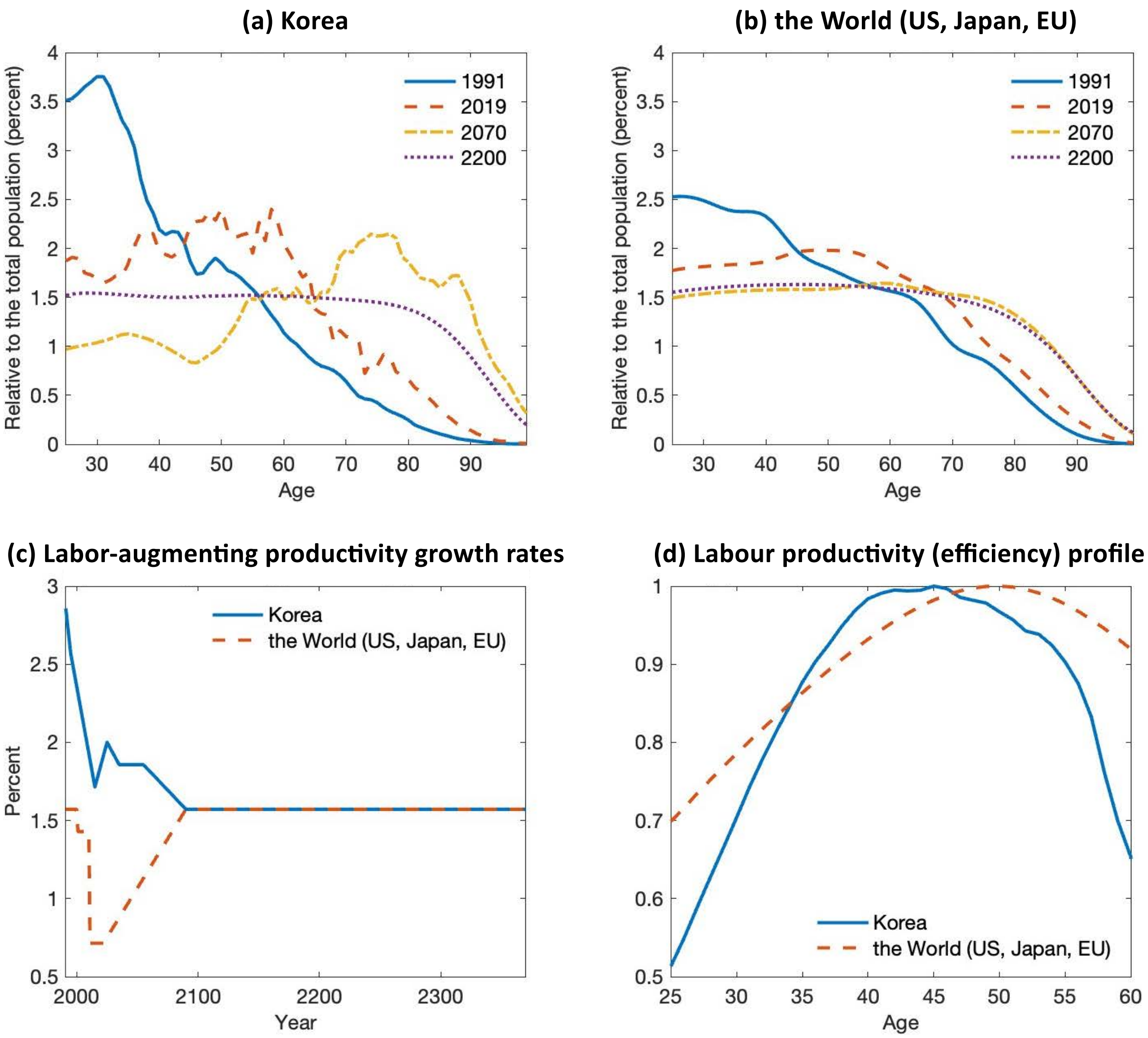
On the production side, firms operate in competitive markets using Cobb–Douglas technology; aggregate effective labour productivity embeds an age-efficiency profile and trend productivity. Capital is accumulated in the standard way and depreciates over time.

5. The model employed in this study is described in detail in BOK Working Paper No. 2025-12, "Demographic shifts and the real interest rate in an open economy: The case of Korea" (Lee, Park, and Hwang, 2025).

2.2 Data

Figure 1 illustrates the exogenous demographic and productivity trends assumed in the model. For Korea, age-specific population and conditional survival rates are derived from Statistics Korea's medium-variant population projections, while data for the foreign block are based on the UN *World Population Prospects* (2019). Population structures are projected up to 2070 using these sources, after which birth and death rates are assumed to remain constant at their 2066–2070 averages, leading both Korea and the foreign block to converge to a stable zero-growth population structure (Figure 1-(a), (b)).

Figure 1: Major Exogenous Variables



Source: UN World Population Prospects (2019), Han and Kim (2016), Eggertsson, Mehrotra, and Robbins (2019), Kwon (2015), Fernald (2014).

Age-specific labour productivity for Korea follows Han and Kim (2016), who estimate productivity by employment type, while foreign productivity profiles are based on Eggertsson, Mehrotra, and Robbins (2019). Korea's labour-augmenting productivity growth rate is interpolated annually from Kwon (2015) total factor productivity (TFP) estimates, and for the foreign block, the U.S. TFP growth rates from Fernald (2014) are used to represent global technological trends. In both cases, TFP growth rates are converted into labour-augmenting productivity growth using the production function (Figure -(c), (d)).

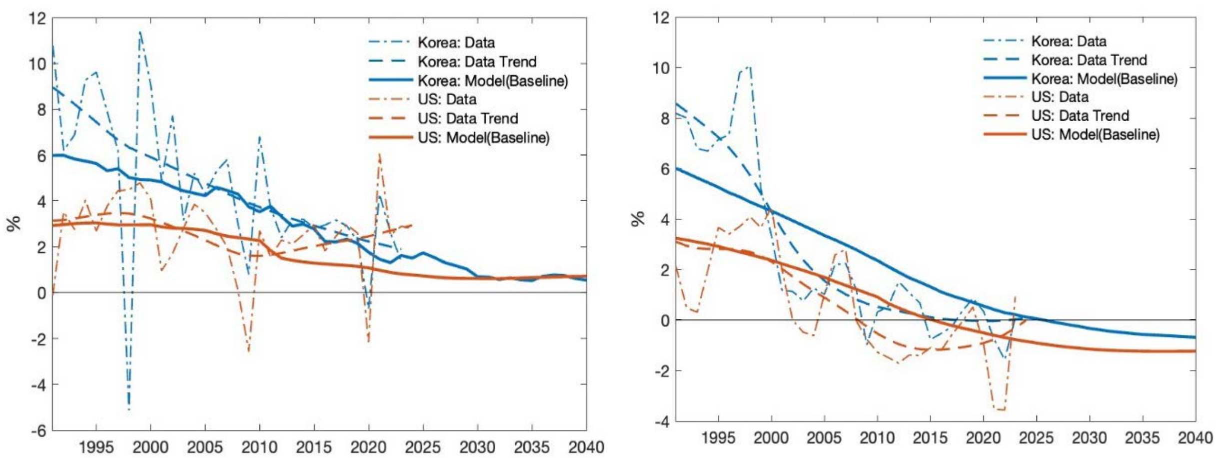
We calibrate the model to match conditions around the early 2000s (including the level of Korea's real interest rate), then feed in observed demographic structure (fertility, survival) and total factor productivity through 2000–2024. Fiscal ratios (tax and government-consumption shares) and reserve-to-GDP ratios are allowed to vary over time to mirror institutional trends. Parameter values for preferences and life cycle (e.g., an intertemporal elasticity of substitution around 0.4 and a discount factor just under 0.95) are set to deliver realistic consumption–saving behaviour over the working and retirement phases.

3. Growth and Real Interest Rate Projections under Baseline Scenario

Before we investigate the impact of the advancement of AI technology, we first present how well our model matches the long-term trend of output growth and the real interest rate. The quantitative analysis is based on the following baseline assumptions. The demographic structure and TFP of Korea and the rest of the world follow official projections (e.g., population forecasts), while all other variables are assumed to remain at their recent levels.

Figure 2: Baseline Model Projections

(a) Real GDP growth Rate | **(b) Real interest rate**



Note: Trend estimates of the policy interest rate—Korea's call rate and the U.S. federal funds rate—are derived by subtracting the past one-year inflation rate and removing cyclical components using an HP filter.

Source: Authors' simulation results.

3.1 Growth

Under the baseline assumptions, the model's projections of growth (Figure 2-(a)) track the observed trends in the data reasonably well. In this framework, the primary drivers of growth dynamics are total factor productivity (TFP) and demographic change, and these two forces alone explain a substantial portion of the downward trend in growth. For Korea, the model closely matches the decline since 2000, while for the United States it captures the trajectory from the 1990s through 2010. However, beginning in the 2010s, the U.S. trend diverges upward from the model's estimates, suggesting the influence of temporary shocks or additional structural factors not captured by the framework.

Setting aside the recent U.S. deviation, the model reproduces the past three decades of trends for both economies, indicating that demographic ageing and productivity decline operate as structural headwinds to growth. In the model, ageing slows labour-force growth through a shrinking inflow of younger cohorts, while an increasing share of older workers—who have relatively lower labour productivity—reduces overall labour productivity. Together, these effects structurally dampen long-run economic growth.

Consistent with this view, studies that integrate demographics into broader structural analyses project Korea's potential growth to slow to about 0.5%–1.2% by the 2040s.[6] Our life-cycle framework is intentionally conservative: it isolates only two forces—demographic ageing and trend productivity—rather than producing a full macroeconomic forecast that incorporates policy shifts or cyclical fluctuations. Even through this narrow lens, the model indicates that, in isolation, these factors could lower Korea's growth rate to below 1% by the 2040s (see Figure 2-(a)).[7] This should be interpreted as the structural trajectory implied by the age profile of the population and trend TFP, assuming that other policies and institutions remain near their recent norms. In other words, absent countervailing measures—such as sustained labour-supply expansions (higher participation, delayed retirement, targeted immigration) and productivity-enhancing reforms—the baseline forces of ageing and slowing TFP growth will continue to weigh on Korea's medium- to long-run growth potential.

6. According to prior studies, Korea's potential growth rate is projected to decline to the following levels: 0.5% on average for 2036–2040 (Cho, 2023), 0.8% for 2031–2040 (Hwang et al., 2023), 0.7% for 2040–2044 (Lee et al., 2024), 0.7% for 2031–2040 (Kim et al., 2025), and 1.2% in 2040 (NABO, 2025).

7. If Korea's demographic conditions (birth rate and life expectancy) and total factor productivity (TFP) were to remain at their 1991 levels, the economic growth rate in 2040 would be 1.3 percentage points and 0.7 percentage points higher than the baseline, respectively.

3.2 Real Interest Rate

The model also successfully tracks the downward trajectory of real interest rates. In the data, Korea's real rate fell by about 4.2%p from 2000 to 2024 (from roughly 4.3% to near zero), while the foreign block declined by about 2.3%p. The model's equilibrium rates show similar declines (≈–4.2pp for Korea and ≈–3.2pp for the foreign economy), indicating that the baseline captures most of the observed trend (Figure 2-(b)). The mechanisms are intuitive. Rising life expectancy boosts retirement saving and expands the supply of loanable funds, exerting downward pressure on real rates. Persistently low fertility reduces labour-force growth, raises the capital–labour ratio, and lowers the marginal product of capital—another factor pushing real rates down. Because international financial integration is incomplete, part of Korea's additional saving is invested abroad, which dampens—but does not eliminate—the domestic impact on rates and allows a wedge with foreign rates to persist for some time.

Between 1991 and 2024, Korea's real rate consistently exceeded the foreign rate, but both displayed a pronounced downward drift that the baseline model captures well. The wedge reflects incomplete international financial integration during the transition: Korea and the foreign economy (U.S.) gradually opened to complete integration, allowing domestic and foreign rates to diverge for extended periods even as capital flows adjusted. This treatment is consistent with evidence that Korea maintained current-account surpluses, built up net foreign assets, and actively managed foreign-exchange reserves—features that shaped how domestic saving was allocated between home and abroad, and thus the path of the domestic real rate.

Within this framework, demographic ageing reduces real rates through two main channels highlighted by the model: (i) longer life expectancy increases retirement saving and the supply of loanable funds, and (ii) persistently low fertility slows labour-force growth, raises the capital–labour ratio, and lowers the marginal product of capital. The result is a structural decline in the equilibrium real rate, even as Korea's rate remains above the foreign rate during the transition due to frictions.

Extending the horizon, the baseline projection shows Korea's real rate drifting below zero in the 2020s, falling into the –1% range by the 2050s, and then gradually rising toward a fully integrated steady state of about 0.03% as demographic and financial-integration dynamics stabilise. These should be understood as structural trajectories, not short-term forecasts; they trace the path implied by demographics and trend productivity under the baseline scenario.

Next, based on this framework, we examine the impact of AI technological advances on growth and real interest rates.

4. AI and Total Factor Productivity (TFP)

4.1 Literature Review

Research on the impact of artificial intelligence (AI) on total factor productivity (TFP) has grown rapidly in recent years. At the micro level, experimental studies provide robust evidence that AI can significantly raise productivity in specific tasks and occupations. Brynjolfsson, Li, and Raymond (2025), using a randomised controlled trial (RCT) involving 5,172 customer support agents, report that the use of generative AI tools increased the number of resolved cases by an average of 15%, with particularly strong effects among less-experienced workers. This finding suggests that AI does more than enhance the efficiency of skilled employees: it can also narrow skill gaps through knowledge sharing and learning. Similarly, Noy and Zhang (2023) show that in a writing experiment, AI use shortened task completion time by about 40% while also improving output quality. Together, these results provide empirical confirmation that AI contributes not only to higher labour productivity but also to greater organisational efficiency.

At the macroeconomic level, projections on the consequence of the AI adoption are more heterogeneous. Aghion and Bunel (2024) argue that if AI not only improves existing processes but also accelerates the production of new knowledge and ideas, it could raise global TFP growth by 0.8 to 1.3%p annually over the next decade. This supports the view of AI as a general-purpose technology (GPT) that can boost the overall pace of innovation. In contrast, Acemoglu and Restrepo (2019) provide a more cautious assessment. They highlight that while AI may automate certain tasks and simultaneously create new ones, the aggregate productivity impact could be limited—less than 0.1%p per year—if complementary investments and institutional foundations (e.g., education, regulation, competition policy) are insufficient.

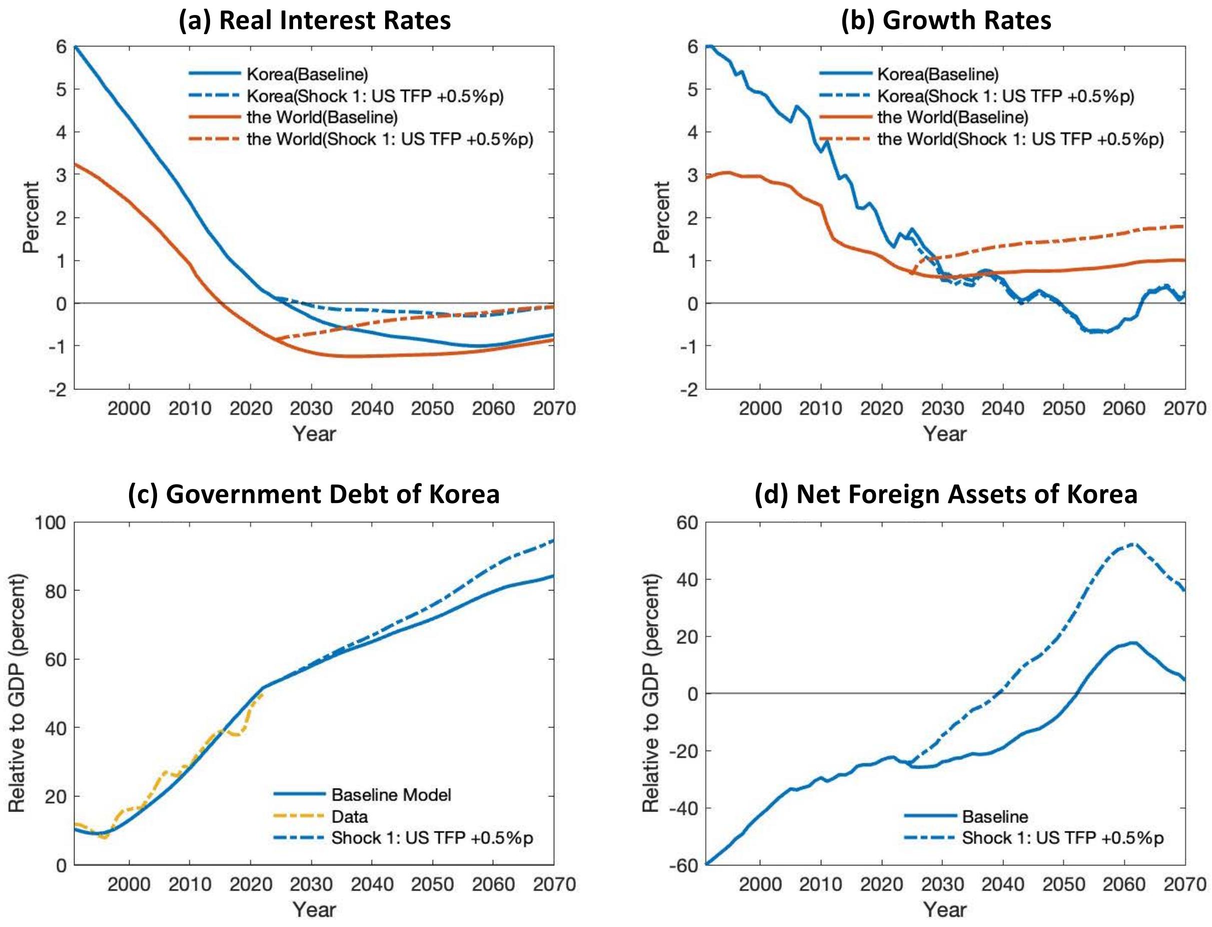
International organisations have also released assessments. The OECD (2024) notes that while AI has significant potential to alleviate productivity stagnation, uneven adoption across firms and industries could widen productivity gaps across countries and sectors. The IMF (2024) stresses that the macroeconomic benefits of AI are highly contingent on policy in areas such as education, fiscal support, and technological infrastructure. Without complementary policies, the gains from AI may remain concentrated in large firms or specific industries, limiting broader spillovers to the economy.

In summary, the literature consistently shows that AI generates immediate, substantial productivity gains at the firm and task levels, while the medium- to long-term macro effects vary widely—from less than 0.1%p to more than 1%p per year—depending critically on the surrounding institutional and policy environment. We take an approximate median of the expectations on the boost in TFP by the AI adoption made in the literature and investigate how it affects the economic growth and the evolution of the real interest rate in Korea.

4.2 Scenario 1: Higher TFP Growth in U.S.

Once we assume that U.S. TFP growth rises by 0.5%p from 2025 onward, the model generates several noteworthy dynamics for Korea and the global economy. First, higher U.S. productivity directly raises the marginal product of capital, which in turn elevates U.S. real interest rates. This makes investing in U.S. assets more attractive, inducing capital to flow from Korea to the U.S. and simultaneously reducing U.S. capital outflows. As a result, the U.S. economy experiences stronger investment and higher long-run growth, while Korea faces a mild downward adjustment in its growth trajectory due to slower domestic capital accumulation (Figure 3-(a), (b)).

Figure 3: Scenario 1- U.S. TFP +0.5%p



Note: Assumes that U.S. TFP growth increases by an additional 0.5%p per year over the period 2025–2075.
Source: Authors' simulation results.

Second, the decline in Korea's growth relative to the baseline has fiscal implications. With weaker output growth, tax revenues expand at a slower pace, leading to a somewhat faster accumulation of government debt as a share of GDP. This suggests that even when external technological progress generates favourable conditions abroad, Korea's fiscal challenges linked to population ageing remain largely unmitigated (Figure 3-(c)).

Third, Korea's net foreign asset (NFA) position improves more rapidly under this scenario.[8] As Korean investors reallocate capital toward higher-yielding U.S. assets, their external asset holdings expand, while higher foreign returns raise net investment income from abroad. This accelerates the transition of Korea into a net creditor position, highlighting the external balance sheet effects of asymmetric TFP shocks (Figure 3-(d)).

Overall, the scenario illustrates the asymmetric transmission of global AI-driven productivity gains: while the U.S. enjoys higher growth and stronger capital inflows, Korea experiences slower growth and rising fiscal pressures, albeit with a faster improvement in its net foreign asset position. These results underscore the importance of considering both domestic and external dimensions of AI-driven productivity shocks when evaluating Korea's long-run growth and monetary policy environment.

4.3 Scenario 2: Higher TFP Growth in Korea

In this scenario, we assume that advances in AI raise Korea's TFP growth rate by an additional 0.5%p annually for a period of 50 years starting in 2025. With higher total factor productivity, the marginal product of capital in Korea rises, which pushes up the equilibrium real interest rate. As a result, the interest rate differential between Korea and the rest of the world widens (Figure 4-(a)).

The increase in Korea's capital returns induces capital inflows from abroad. This inflow supports stronger domestic investment and leads to a noticeable improvement in Korea's growth performance relative to the baseline. However, given Korea's relatively small size in the global economy, these changes have virtually no impact on the world real interest rate (Figure 4-(b)).

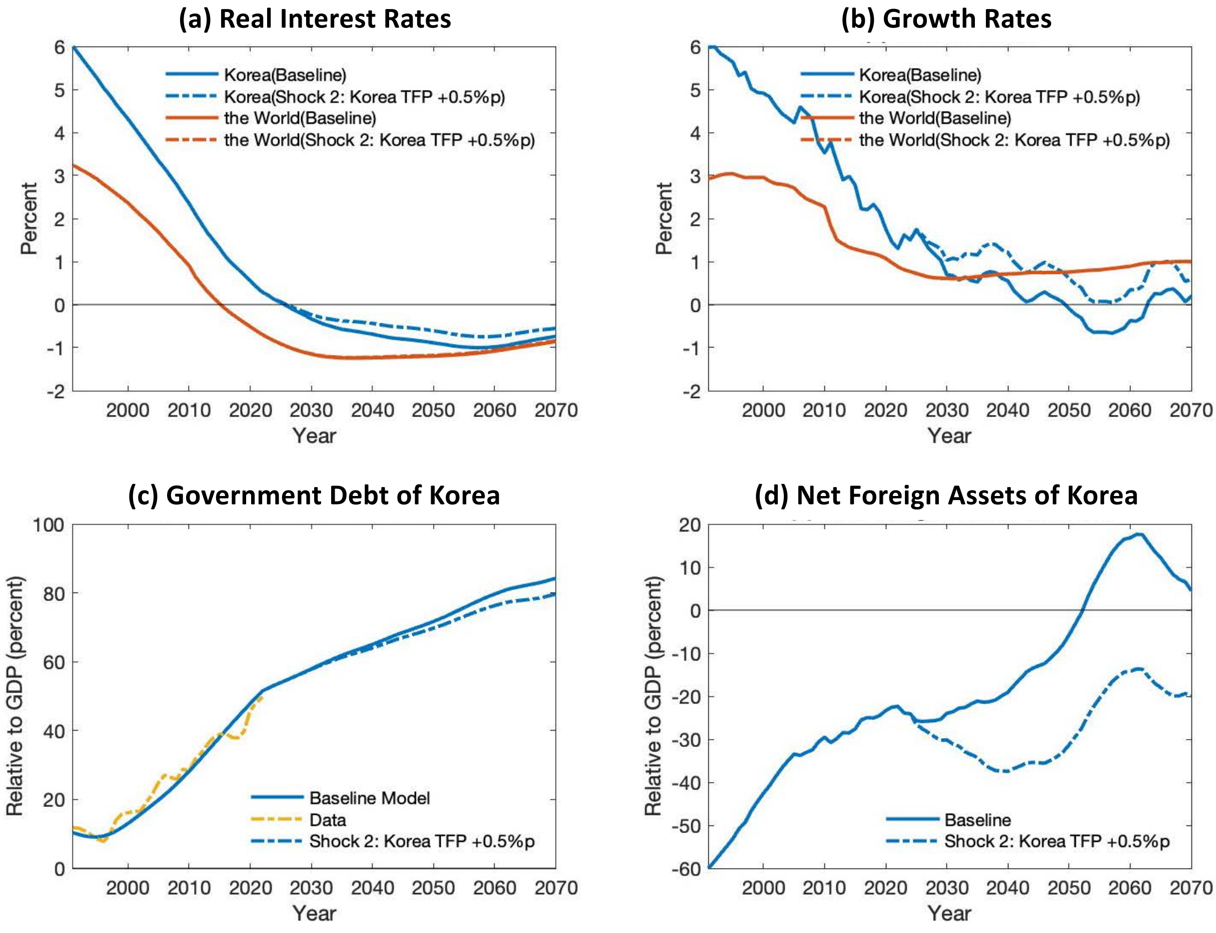
Higher growth in Korea also has fiscal consequences. Stronger output expansion boosts tax revenues, which in turn, slows the pace of government debt accumulation compared with the baseline path. This suggests that productivity-driven growth improvements could help mitigate some of the fiscal pressures associated with population ageing (Figure 4-(c)).

On the external side, however, the improved attractiveness of domestic investment reduces the demand for foreign assets. Consequently, Korea's net foreign asset (NFA) position shifts from a gradual improvement under the baseline to a decline under this scenario. The stock of NFAs shrinks as capital inflows substitute for outward investment, reflecting a reallocation of savings toward domestic rather than foreign assets (Figure 4-(d)).

8. Korea became a net external creditor (including reserve assets) in 2014. However, this transition is not explicitly captured in the model. The simulation results are nevertheless used to analyse changes in Korea's net external asset position under each scenario.

Overall, the results indicate that an AI-driven productivity boost in Korea would lift domestic growth and equilibrium real interest rates, ease fiscal pressures by moderating debt accumulation, but at the cost of a weaker external balance sheet as the net foreign asset position deteriorates.

Figure 4: Scenario 2-Korea TFP +0.5%p



Note: Assumes that Korea TFP growth increases by an additional 0.5%p per year over the period 2025–2075.
Source: Authors' simulation results.

4.4 Policy Implications

The simulation exercises highlight the asymmetric effects of AI-driven productivity shocks depending on whether they originate abroad or domestically. Taken together, these findings yield several important insights for Korea's long-run growth dynamics, fiscal sustainability, external balance, and the conduct of monetary policy.

4.4.1 Global versus Domestic Productivity Gains

When AI-induced productivity gains occur in the United States (Scenario 1), Korea experiences capital outflows, slower growth, and faster debt accumulation, despite a more favourable net foreign asset trajectory. Conversely, when productivity gains are concentrated in Korea (Scenario 2), the economy benefits from higher growth, stronger tax revenues, and slower debt accumulation, but this comes at the expense of a deterioration in the external balance sheet. These results mirror established open-economy models in which asymmetric productivity shocks drive international capital flows (Obstfeld and Rogoff, 1996; Gourinchas and Rey, 2014).

The contrast underscores a key vulnerability for small open economies: foreign-led AI innovations can generate spillovers that are uneven or even adverse, while domestic productivity gains yield more direct benefits but also carry external adjustment costs. This duality suggests that Korea's economic trajectory will depend not only on its own AI adoption capacity but also on how global AI diffusion unfolds.

4.4.2 Implications for the Equilibrium Real Interest Rate

Both scenarios suggest upward pressure on Korea's equilibrium real interest rate (r*), albeit through different channels. In Scenario 1, U.S. TFP growth raises global returns and pulls up Korea's rates through financial integration. In Scenario 2, Korea's own productivity gains directly lift domestic capital returns and widen the rate differential with the rest of the world. This is consistent with the broader literature emphasising that productivity is a key determinant of r* (Rachel and Summers, 2019; Holston, Laubach, and Williams, 2017). For Korea, two implications follow.

First, U.S.-led AI innovations could raise global rates and push monetary policy in Korea to the restrictive region, even if domestic growth remains subdued.

Second, Korea-led AI innovations would lift domestic r*, thereby expanding policy space. However, if central bank fails to adequately incorporate these structural shifts into its neutral rate assessment, policy rates could remain below the new equilibrium r*. In such a case, monetary policy would operate in an excessively accommodative stance, increasing the risks of overheating, asset price pressures, and financial instability. Policymakers must therefore refine their estimation of r* to fully account for AI-driven structural changes and adjust policy rates accordingly.

4.4.3 Growth, Fiscal Sustainability, and External Balance Trade-offs

From a fiscal perspective, the results reinforce a familiar message: growth is the most effective form of debt stabilisation. In Scenario 2, higher productivity growth alleviates fiscal pressures by expanding output and boosting revenues, even without explicit fiscal consolidation. This echoes findings in the secular stagnation literature that link weak productivity to debt accumulation and reduced fiscal space (Eggertsson, Lancastre, and Summers, 2019).

However, the simulations also show that domestic productivity gains worsen Korea's net foreign asset position, reflecting a shift in savings allocation from foreign to domestic investment. This trade-off implies that growth-friendly policies could paradoxically weaken external buffers, an issue also highlighted in recent IMF external sector assessments of advanced economies (IMF, 2023).[9] For policymakers, this raises the question of optimal sequencing between growth, fiscal sustainability, and external resilience. Strengthening fiscal institutions (e.g., medium-term expenditure frameworks) and building foreign exchange reserves may be necessary to balance these competing objectives.

5. Capital-augmenting Technology and Rising Capital Income

5.1 Literature Review

Over the past few decades, a broad body of research has documented the decline in the labour income share and the corresponding rise in the capital income share across many advanced and emerging economies. The causes have been attributed to capital-biased technological progress, automation, globalisation, and the growing dominance of "superstar" firms. Within this context, artificial intelligence (AI) has emerged as a transformative force with potentially profound effects on the distribution of income between labour and capital.

Karabarbounis and Neiman (2014) argue that the long-run decline in the relative price of investment goods, combined with an elasticity of substitution between capital and labour greater than one, has induced firms to substitute capital for labour, thereby reducing the labour share. Given its characteristics as a scalable technology with low marginal costs once the fixed costs of training and computing are sunk, AI can be understood as reinforcing this mechanism of capital-biased technical change.

Acemoglu and Restrepo (2019), using a task-based framework, emphasise that AI and automation simultaneously displace routine tasks while generating new ones. Whether the net effect favours labour or capital depends crucially on the scale of complementary investments in education, organisational restructuring, and data infrastructure. Without such complementary policies, the substitution effect dominates, leading to a decline in the labour share.

Another strand of the literature highlights the role of market concentration. Autor et al. (2020) show that the rise of highly productive, large "superstar firms," which typically employ a lower share of labour relative to sales, has contributed to aggregate declines in the labour share. AI adoption, by amplifying economies of scale and data-driven network effects, may accelerate this trend by increasing industrial concentration and market power.

9. See Lane and Milesi-Ferretti (2007), who emphasise that weaker net foreign asset positions reduce external buffers and heighten vulnerability to external shocks.

Barkai (2020) presents evidence from the United States that both labour and capital shares have declined, while the profit share has increased significantly. This suggests that AI adoption could also contribute to rising markups and economic rents, leading not only to a redistribution from labour to capital but also to a shift toward profits more broadly.

International organisations have underscored the same risks. The IMF (2017) concluded that technological progress, particularly automation, has been one of the primary drivers of the global decline in labour's share of income. The OECD (2024) emphasised that AI has the potential to alleviate productivity stagnation, but the distributional impact will depend heavily on how adoption diffuses across sectors and firms. Similarly, IMF (2024) highlighted that without adequate fiscal, educational, and infrastructure policies, the gains from AI adoption are likely to remain concentrated among large firms and specific industries, limiting its aggregate benefits.

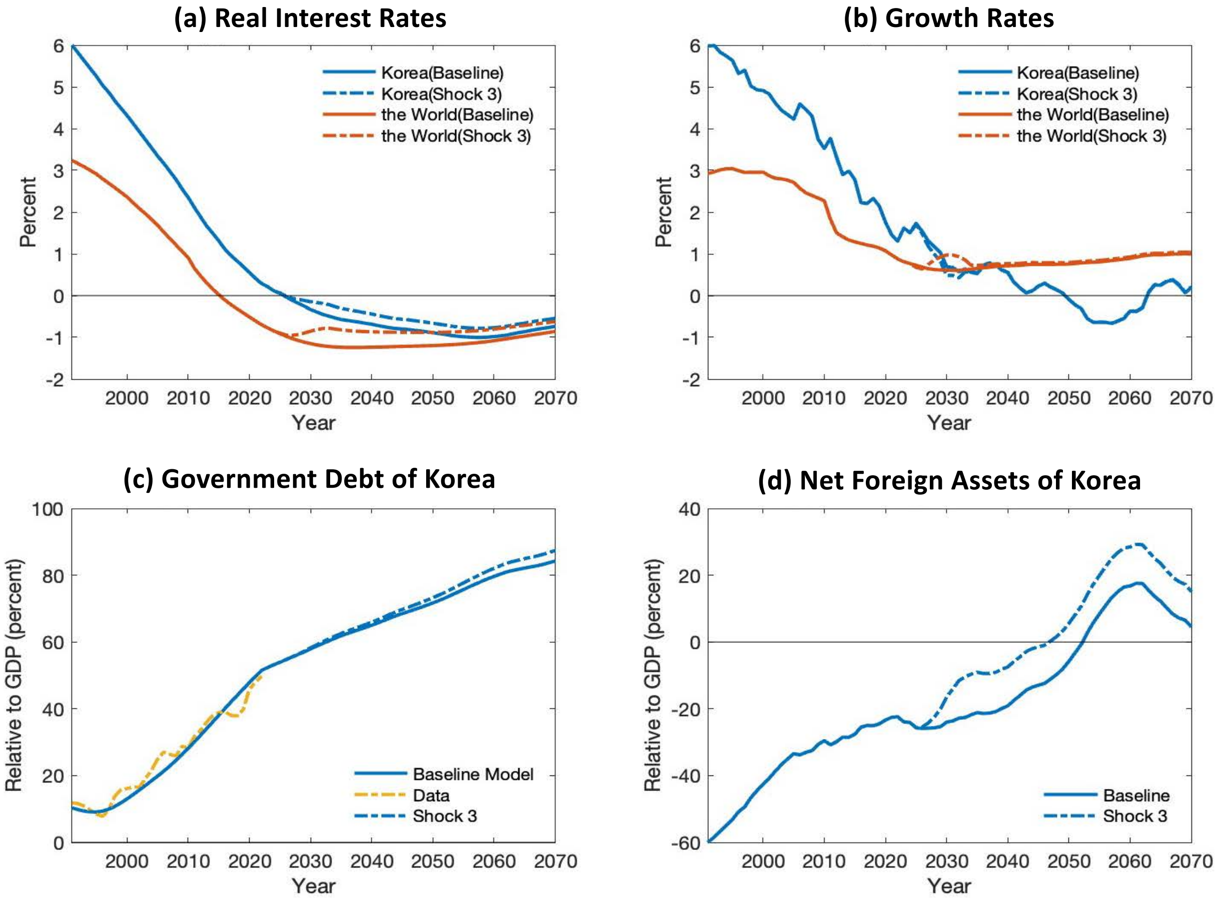
Taken together, the literature suggests that AI is likely to place downward pressure on the labour income share by raising the marginal product of capital, accelerating task automation, and contributing to market concentration. At the same time, the extent of these effects is conditional on institutional and policy factors, such as labour market flexibility, education and training systems, competition policy, and redistributive taxation. In short, AI is not only a technological shock but also a distributional one, with implications that extend well beyond productivity and growth.

5.2 Scenario 3: Higher Capital Income Share in U.S.

In this section, we conduct a simulation under the assumption that advances in AI lead to more capital-intensive technological progress, thereby raising the U.S. capital income share from its baseline level of 30% by an additional 1%p. Specifically, we assume that the capital share rises gradually over a period of 10 years, remains elevated for 40 years, and then returns to its original level over the following decade.

Because the production technology in this model follows a Cobb–Douglas specification, an exogenous increase in the capital income share mechanically raises the marginal product of capital (MPK), consistent with a capital-biased technological improvement that shifts income toward capital. As a result, the simulation shows that during the initial 10 years of adjustment, the higher MPK leads to an increase in U.S. real interest rates (Figure 5-(a)). This, in turn, triggers capital outflows from Korea and toward the United States, causing foreign real interest rates to move upward in tandem.

Figure 5: Scenario 3-U.S. Capital Income Share +1%p



Note: Assumes that U.S. capital income share rises gradually over a period of 10 years by 1%p, remains elevated for 40 years and then returns to its original level over the following decade.
Source: Authors' simulation results.

The growth effects, however, are asymmetric. In the U.S., stronger capital accumulation and productivity improvements temporarily raise the growth rate (Figure 5-(b)). In contrast, Korea experiences lower growth due to capital outflows. Once the adjustment in income shares stabilises, capital flows gradually cease. At this stage, the temporary growth effects dissipate, but the upward pressure on interest rates persists because of the permanently higher capital returns in the U.S.

From an external balance perspective, the concentration of capital in the U.S. leads to greater foreign investment by Korea, resulting in a sharp improvement in Korea's net foreign asset (NFA) position (Figure 5-(d)). On the fiscal side, however, weaker domestic growth reduces tax revenues, which slightly accelerates the pace of government debt accumulation compared with the baseline (Figure 5-(c)).

In summary, a rise in the U.S. capital income share driven by AI-induced technological change reshapes global capital allocation and exerts mixed effects on Korea. While Korea benefits from an improved external asset position, it faces lower growth and a deterioration in fiscal balances, underscoring the multifaceted nature of such distributional shocks.

5.3 Scenario 4: Higher Capital Income Share in Korea

In this scenario, we assume that AI-driven technological change raises Korea's capital income share by 1%p. The adjustment path mirrors the U.S. case: the capital share rises gradually over 10 years, remains elevated for 40 years, and then returns to its baseline over the next decade.

The simulation shows that Korea's higher capital income share increases the marginal product of capital, leading to a rise in the domestic real interest rate (Figure 6-(a)). This attracts capital inflows from abroad, boosting capital accumulation and domestic growth. During the initial 10-year adjustment period, Korea's growth rate rises by an average of about 0.3%p relative to the baseline (Figure 6-(b)).

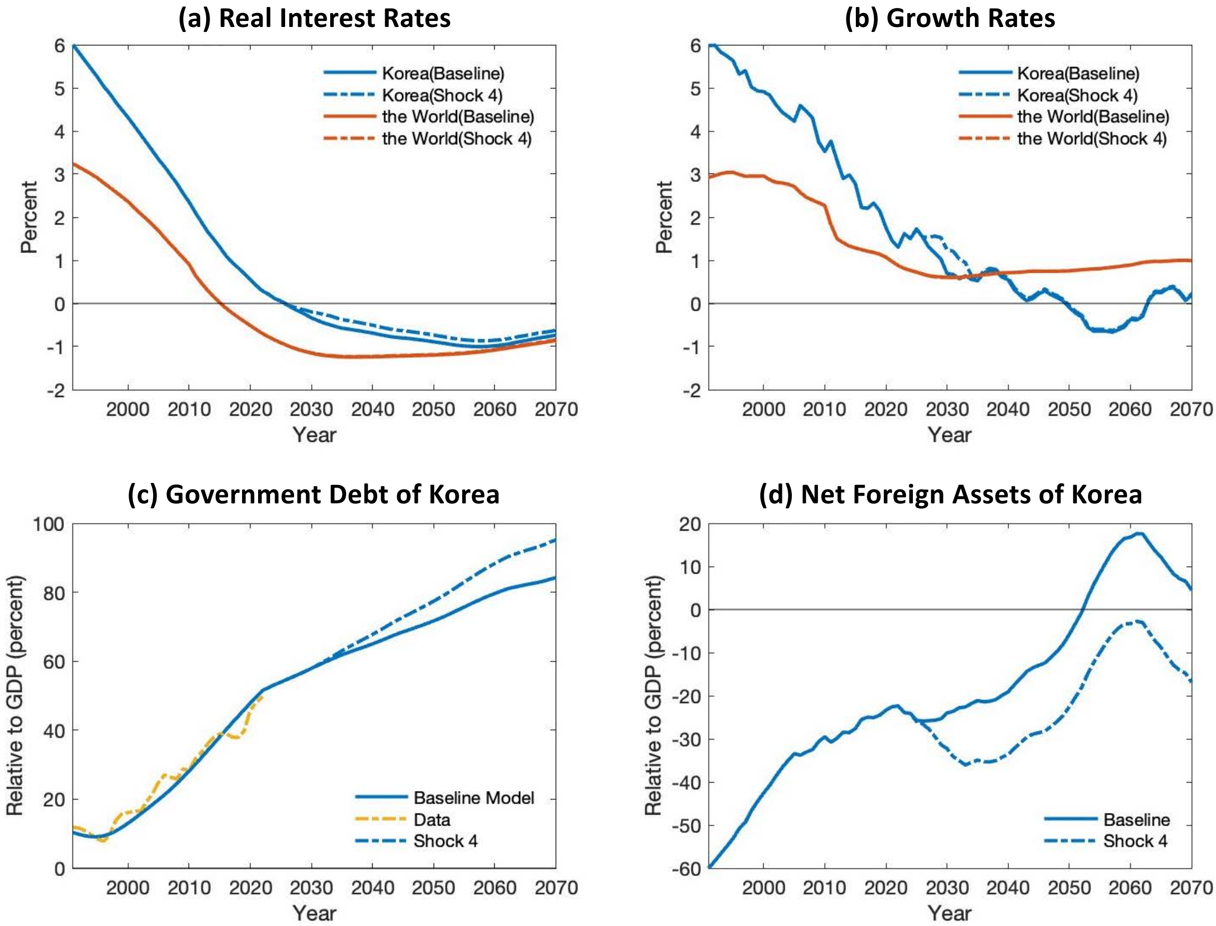
Because Korea is a small open economy, the global real interest rate is barely affected. The growth benefits are therefore concentrated domestically, while the world interest rate remains essentially unchanged.

From an external perspective, the attractiveness of Korean investment increases foreign holdings of domestic assets, which worsens Korea's NFA position (Figure 6-(d)). In other words, stronger growth comes at the cost of rising external liabilities, as foreign investors receive a larger share of capital income from Korea.

On the fiscal side, the results are also notable. Although higher growth could expand the tax base, the model assumes that government revenues are primarily financed through labour income. Thus, the decline in the labour income share reduces overall tax revenues, leading to a faster accumulation of government debt compared with the baseline (Figure 6-(c)).

Taken together, the results suggest that a higher capital income share in Korea generates short-term growth gains but also undermines external balance and fiscal sustainability. The combination of stronger output and weaker debt dynamics underscores the complex trade-offs inherent in distributional shifts driven by AI.

Figure 6: Scenario 4-Korea Capital Income Share +1%p



Note: Assumes that Korea capital income share rises gradually over a period of 10 years by 1%p, remains elevated for 40 years and then returns to its original level over the following decade.

Source: Authors' simulation results.

5.4 Policy Implications

5.4.1 Monetary Policy Transmission

The rise in the capital income share—whether driven by U.S. or Korean AI adoption—reshapes monetary policy transmission channels. As Karabarbounis and Neiman (2014) highlight, capital-biased technological change lowers labour's share, weakening the wage–price pass-through while amplifying the role of asset prices and investment. For Korea, this means that central bank must recalibrate its neutral rate estimates and inflation models to account for a growing capital share. Otherwise, monetary policy may systematically misjudge underlying conditions, either remaining too accommodative or too tight.

5.4.2 Fiscal Sustainability

The fiscal consequences are asymmetric across scenarios. In Scenario 3 (U.S. capital share rising), Korea's weaker growth reduces tax revenues, worsening debt dynamics despite stronger NFA positions. In Scenario 4 (Korean capital share rising), short-term growth gains temporarily expand the tax base; however, since the model assumes that fiscal revenues are primarily derived from labour income, the decline in the labour income share reduces overall tax receipts, leading to faster debt accumulation. As noted by Armenter (2015), a persistent decline in the labour share can erode the labour-based tax base and shift the burden of taxation toward capital income, thereby heightening long-term fiscal pressures. In this context, the introduction or strengthening of capital income taxation could be considered as a complementary policy instrument to maintain fiscal sustainability (Piketty and Saez, 2013; IMF, 2017).

5.4.3 External Balance and Resilience

The deterioration of Korea's NFA position in Scenario 4 highlights external vulnerabilities. As Lane and Milesi-Ferretti (2007) argue, weaker external balance sheets reduce the economy's resilience to shocks, exposing it to sudden stops or reversals in capital flows. Thus, while higher domestic capital returns can boost growth, they simultaneously weaken external buffers. Policymakers should offset these risks by building reserves, deepening local capital markets, and diversifying external asset portfolios.

5.4.4 Distributional and Structural Policies

Finally, AI-induced shifts in factor shares are inherently distributional. Acemoglu and Restrepo (2019) stress that without complementary policies in education, organisational change, and data infrastructure, substitution dominates, leading to labour share declines. For Korea, this implies that fiscal and labour-market policies must complement innovation strategies. Vocational training, targeted upskilling, and inclusive technology diffusion are essential to ensure that AI-driven productivity gains are broadly shared, preventing widening inequality.

6. Age-specific Labour Productivity and the Impact of AI Diffusion

6.1 Literature Review

Recent empirical and experimental studies consistently show that AI, particularly generative AI, generates heterogeneous effects on productivity depending on age, skill level, and work experience.

First, evidence is strong for greater productivity gains among less-experienced and lower-skilled groups, which often correspond to younger cohorts. Brynjolfsson, Li, and Raymond (2025), in a randomised controlled trial (RCT) of customer-support workers, report that the use of generative AI increased average task throughput by 15%, with effects especially pronounced among less-experienced employees. This suggests that AI not only enhances the efficiency of skilled workers but also accelerates knowledge diffusion and provides a "learning acceleration effect" that effectively shifts forward the career productivity curve. Similarly, Noy and Zhang (2023) show that in an experimental writing task, AI usage reduced completion time by about 40% while improving output quality by 18%, with the largest quality improvements observed among lower-ability workers.

Second, a growing body of evidence suggests that the relative disadvantage of older workers may be mitigated by technological assistance. Acemoglu and Restrepo (2019) argue that automation displaces labour in some tasks while creating new ones, and that without complementary institutional support, older workers in particular risk falling behind. At the same time, however, demographic ageing tends to accelerate corporate adoption of automation and robotics as substitutes for shrinking labour supply. These technologies can reduce the physical burden on older workers and standardise task difficulty, thereby narrowing productivity gaps. Park, Shin, and Kikkawa (2022), in a cross-country panel analysis, show that as indicators of technological progress such as life expectancy, labour productivity, robot density, and total factor productivity (TFP) increase, the contribution of older cohorts (aged 50–60+) to growth improves, while higher robot density reduces productivity gaps between peak-age workers and older groups.

Third, the possibility of a "shift in the age–efficiency profile peak" has been raised. Biomedical and labour economics research traditionally identified productivity peaks around workers' mid-40s[10]. However, cumulative improvements in health, education, and digital tools suggest that these peaks may move to later ages and become flatter over time. AI contributes to this dynamic by providing knowledge access, memory support, documentation, and coding assistance, thereby extending the marginal returns to experience. Park, Shin, and Kikkawa (2022) find that "as life expectancy and labour productivity rise, the range of age cohorts with positive contributions to growth expands toward older workers; moreover, increases in robot density reduce the negative contribution of older workers." This offers empirical support for mechanisms in which productivity peaks shift to older ages and age–efficiency profiles become flatter.

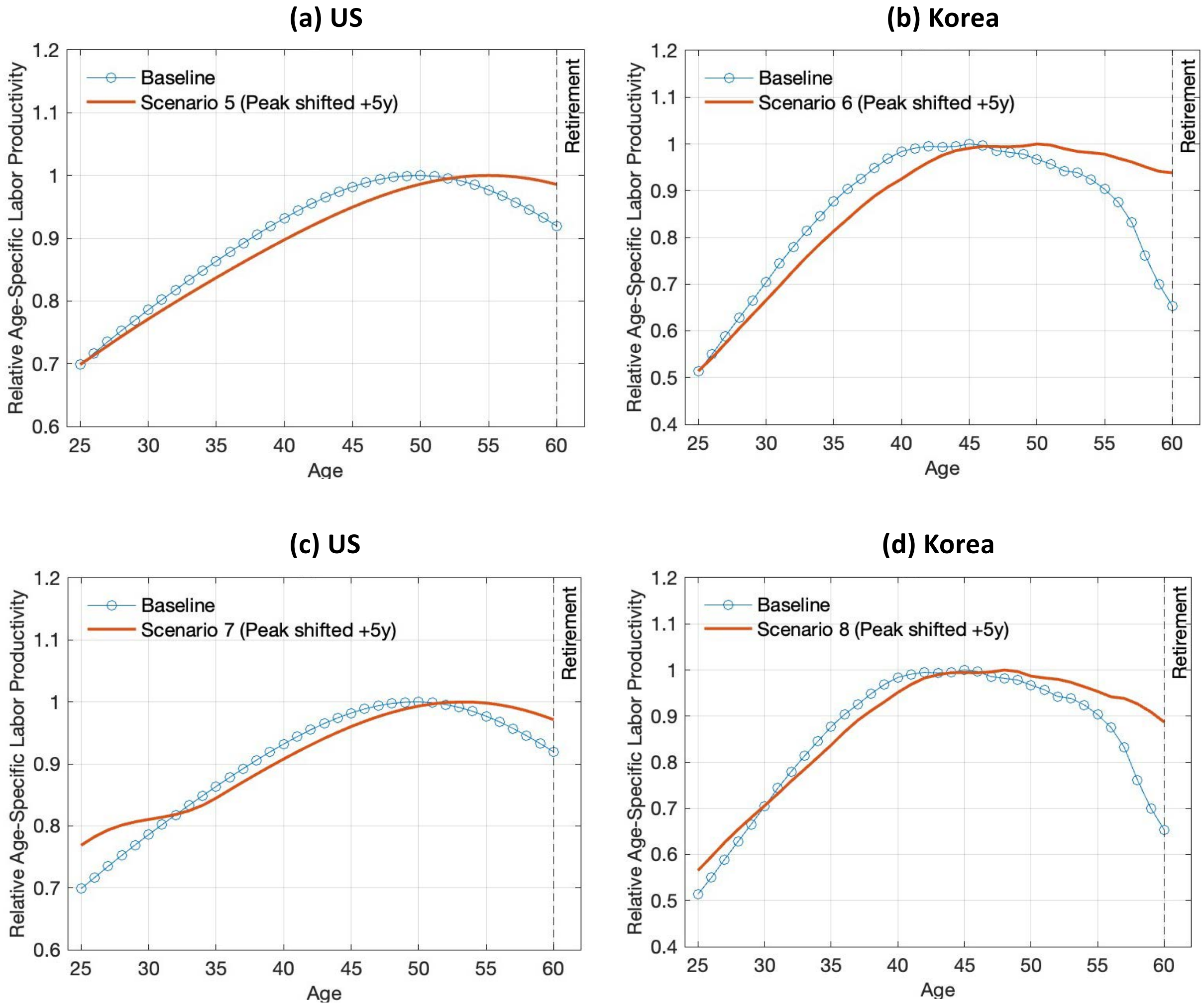
In summary, (i) AI accelerates learning curves and raises productivity for younger, less-experienced cohorts; (ii) automation and digital tools mitigate productivity declines among older workers; (iii): (i) and (ii) combined with rising life expectancy shift productivity peaks to later ages and flatten age–efficiency profiles; and (iv) the magnitude and distribution of these effects depend heavily on institutional and policy environments, without which AI could amplify rather than reduce generational disparities.

10. Skirbekk (2004, Population and Development Review).

6.2 Scenario 5 & 7: Changes in the U.S. Age-specific Productivity

In Scenario 5, we assume that the diffusion of AI, combined with cumulative advances in health, education, and digital technologies, shifts the age–productivity profile in the United States. Specifically, the peak of labour productivity, which has traditionally occurred around age 50, is delayed to age 55—a shift of about five years (Figure 7-(a)). This change raises the relative contribution of middle-aged and older cohorts within the age–efficiency profile, while reshaping the weighting of effective labour in the overall demographic structure. Given that the U.S. demographic distribution in 2025 is relatively tilted toward younger cohorts, the rightward shift in the productivity peak induced by AI shocks leads to a decline in the aggregate supply of effective labour (Figure 8-(a)).

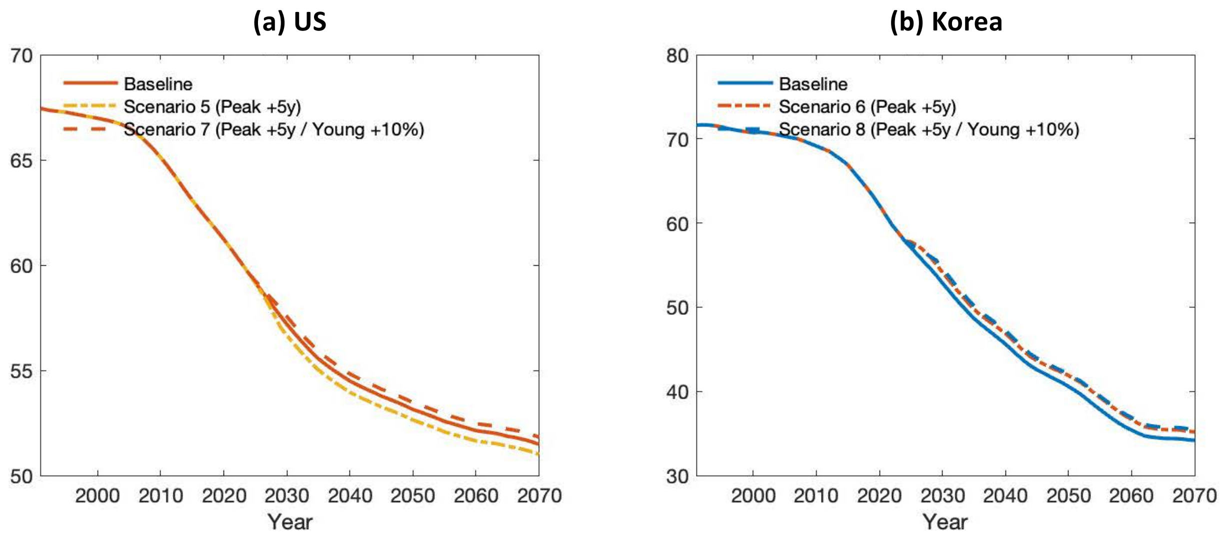
Figure 7: Labour Productivity Profile



Source: Han and Kim (2016), Eggertsson, Mehrotra, and Robbins (2019).

This reduction in effective labour lowers the marginal product of capital, which in turn, exerts downward pressure on the equilibrium real interest rate. As Figure (9-(a)) illustrates, U.S. real rates fall modestly below the baseline, and capital flows into Korea cause Korean real rates to decline in tandem.

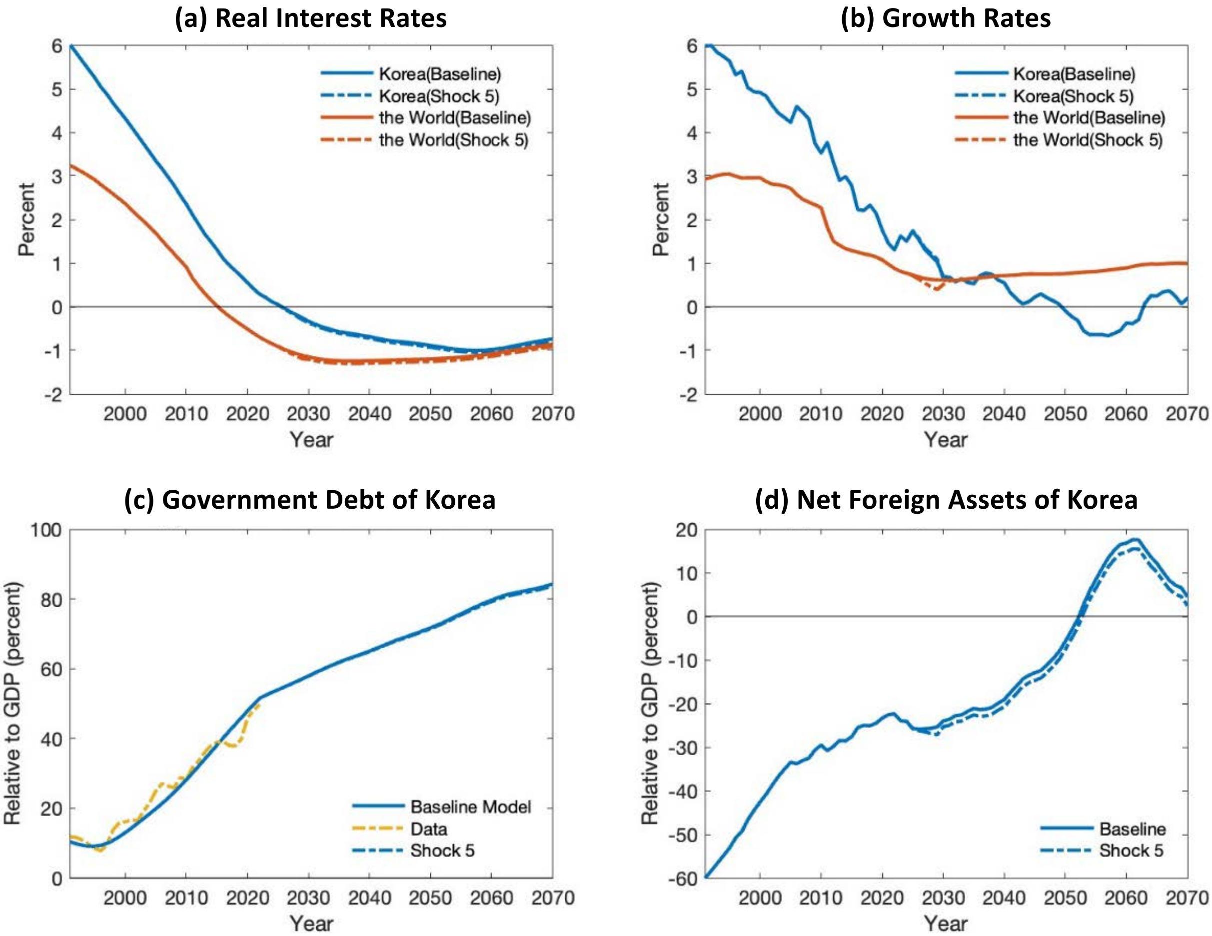
Figure 8: Effective Labour



Source: Authors' simulation results.

Furthermore, the slowdown in U.S. productivity directly translates into weaker growth. As shown in Figure (9-(b)), U.S. growth rates decline relative to the baseline. Coupled with lower capital returns in the U.S., foreign investors expand their demand for relatively higher-yielding Korean assets (Figure 9-(d)). This results in a short-run increase in capital inflows to Korea, providing limited upward pressure on Korea's growth rate, though the overall effect remains modest.

Figure 9: Scenario 5-U.S. Labour Productivity Peak Shift in 5 Years

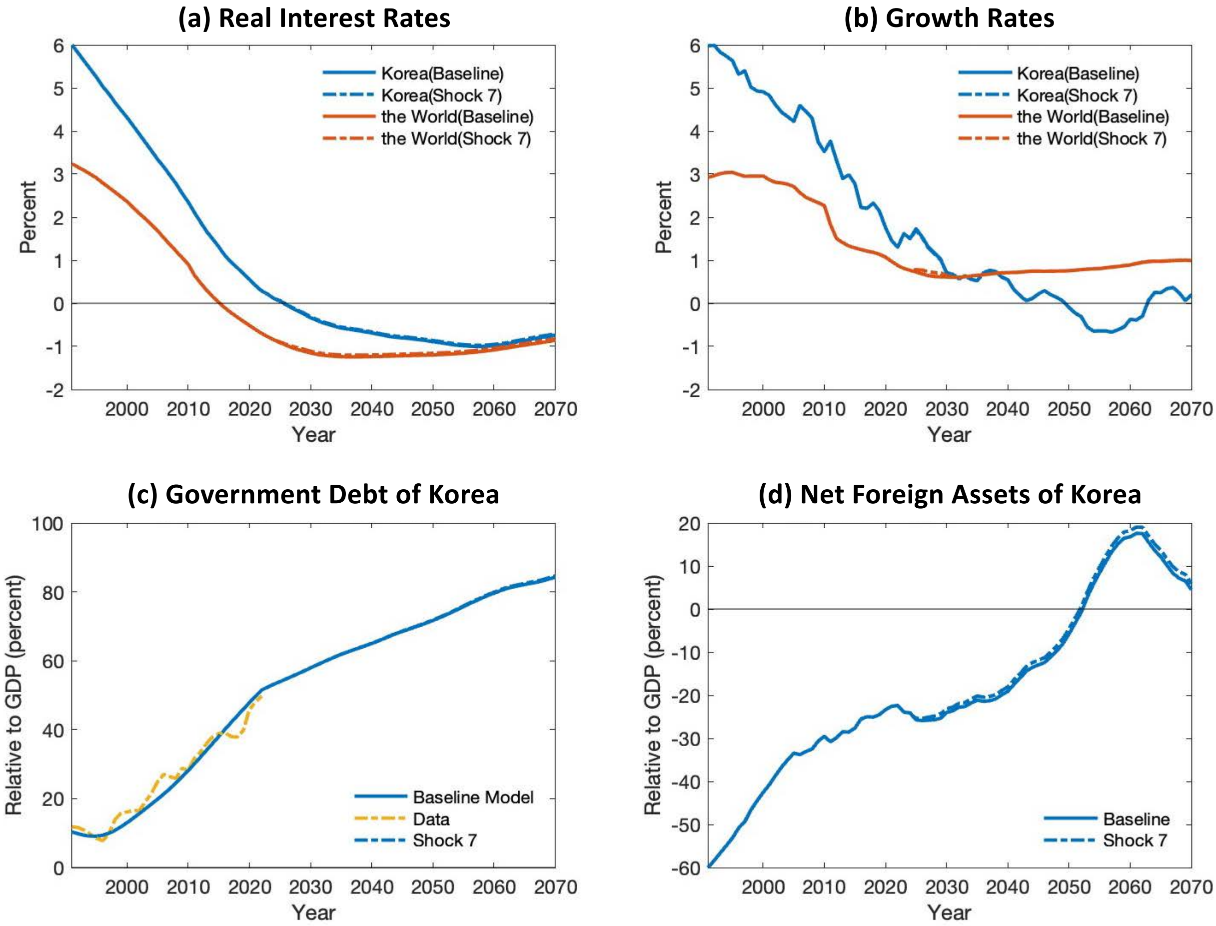


Note: Assumes that the U.S. labor productivity peak shifts from age 50 to 55 over five years.
Source: Authors' simulation results.

Given existing research showing that less-experienced and lower-skilled groups (which often correspond to younger cohorts) tend to experience greater productivity gains from AI usage, in Scenario 7, we assume that in the U.S., in addition to the productivity-peak shift, AI shocks also boost productivity for younger and lower-skilled age cohorts. Accordingly, we assume that labour productivity at age 25 increases by roughly 10%, with the effect gradually tapering off (see Figure 7-(c)). Because the share of younger age cohorts in the U.S. is relatively high, the productivity rise among that group leads to an overall increase in effective labour—unlike in Scenario 5 where the shift in the peak alone reduced effective labour (see Figure 8-(a)).

This productivity improvement among lower-skilled workers triggers effects different from Scenario 5. First, the increase in U.S. effective labour supply raises the marginal product of capital (MPK), which pushes up the real interest rate; concurrently, capital flows outward to Korea, generating upward pressure on Korean real interest rates. Moreover, the rise in U.S. effective labour boosts growth, and as Korean investors hold more foreign assets, Korea's net foreign asset (NFA) position improves. Since interest rates rise modestly, government debt increases slightly in step with those higher rates (see Figure 9).

Figure 10: Scenario 7-U.S. Age-Specific Labour Productivity Changes



Note: Assumes that, in addition to the five-year shift in the productivity peak, the productivity of younger and lower-skilled workers in the U.S. rises by about 10%

Source: Authors' simulation results.

6.3 Scenario 6 & 8: Changes in the Korea Age-specific Productivity

The Scenario 6 assumes that advances in AI, combined with improvements in education, health, and digital technologies, shift Korea's age–productivity profile so that the peak of labour productivity moves from age 45 to 50 (Figure 7-(b)). Such a shift increases the relative contribution of middle-aged cohorts and leads to an expansion of effective labour in the overall demographic structure. Unlike the U.S. case (Figure 8-(a)), where the later productivity peak reduces effective labour, Korea experiences an increase (Figure 8-(b)), as its more advanced ageing means a larger share of the population benefits from the rightward shift in the productivity peak.

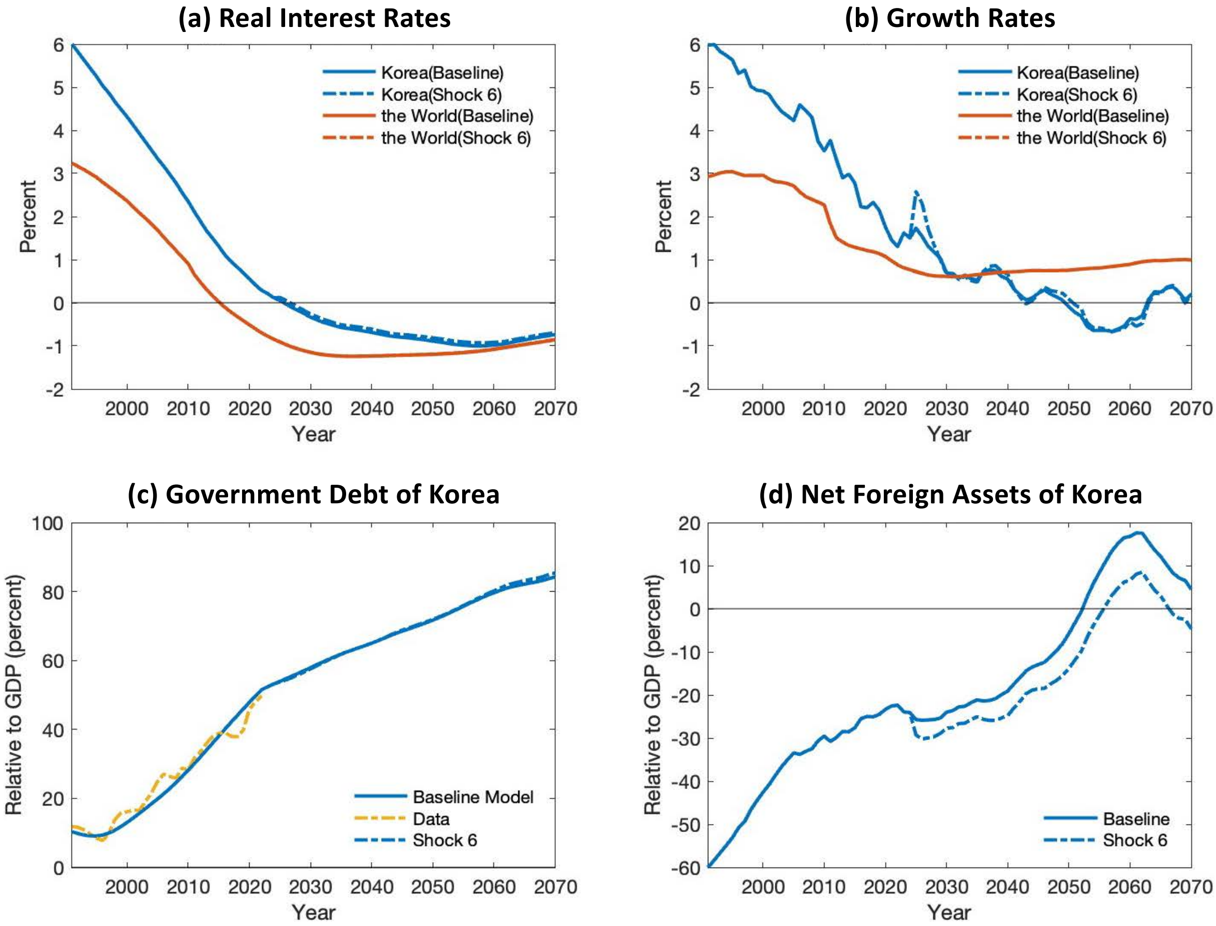
Scenario 8 extends Scenario 6 by assuming that, in addition to the rightward shift in the productivity peak, the labour productivity of younger workers rises by 10% (Figure 7-(d)). However, since Korea's population ageing is already well advanced, the additional contribution of higher youth productivity to total effective labour is limited (Figure 8-(b)). Consequently, the overall impact of Scenario 8 on effective labour, interest rates, growth, debt, and net foreign assets is broadly similar to that observed in Scenario 6 and is, therefore, not presented separately.

The Scenario 6 simulation results indicate that the increase in effective labour raises the marginal product of capital and causes Korea's real interest rate to rise slightly above the baseline (Figure 11-(a)). Higher real rates attract foreign capital inflows, which in turn, lift Korea's growth rate above the baseline during the adjustment period (Figure 11-(b)). Unlike the U.S. case discussed in Section 6.2, where a later peak reduced growth, in Korea the shift in the productivity peak serves as a growth-enhancing factor.

However, the stronger attractiveness of Korean assets reduces the incentive for outward investment, which results in a deterioration of Korea's net foreign asset (NFA) position (Figure 11-(d)). On the fiscal side, stronger growth temporarily improves tax revenues and slightly moderates the pace of government debt accumulation (Figure 11-(c)). Yet, the decline in NFA implies that future income balance payments abroad could weigh on long-run fiscal sustainability.

In summary, a later productivity peak in Korea produces three key outcomes: (i) higher effective labour, (ii) an increase in real interest rates and growth, and (iii) a decline in NFA despite stronger short-run performance. This highlights that demographic structures crucially shape how AI-driven productivity shifts translate into macroeconomic outcomes.

Figure 11: Scenario 6-Korea Labour Productivity Peak Shift in 5 Years



Note: Assumes that Korea's labor productivity peak shifts from age 45 to 50 over five years.
Source: Authors' simulation results.

6.4 Policy Implications

6.4.1 Real Interest Rate Estimation and Monetary Policy

The simulations show that AI-induced changes in age–productivity profiles can exert structural effects on the equilibrium real interest rate (r*). In the U.S. case (Scenario 5), a later productivity peak reduces effective labour and lowers r*, whereas in Korea (Scenario 6), effective labour expands and pushes r* upward. These asymmetric results suggest that policymakers need to redesign neutral rate estimation frameworks. It is not sufficient to rely only on demographic size or TFP trends; the movement and reshaping of age-specific productivity curves must also be incorporated. Otherwise, there is a risk of maintaining an overly accommodative stance when r* is structurally higher (as in Korea) or an overly tight stance when r* is lower (as in the U.S.).

6.4.2 Growth and Structural Context

As discussed earlier, productivity shocks often involve trade-offs between growth and external balance. What is distinctive in the present simulations, however, is that the decline in effective labour in the U.S. case reflects purely a compositional effect of relative age-specific productivity weights. In a more realistic setting where the shift in the productivity peak is accompanied by a rise in TFP, such as in Scenarios 1 and 2, the adverse effect of declining effective labour can be dominated. This highlights the importance of jointly modeling both age-specific productivity profiles and aggregate TFP shocks when assessing the macroeconomic consequences of AI. Relying solely on demographic compositional effects risks underestimating the true impact of technological change.

6.4.3 Labour Market, Education, and Intergenerational Policies

AI diffusion accelerates learning curves for younger and less-experienced workers while mitigating productivity declines for older cohorts. However, these potential gains will only materialise under adequate institutional and policy support. Without such measures, AI could deepen generational disparities rather than reduce them, raising broader concerns over distributional and intergenerational equity (Acemoglu and Restrepo, 2019; IMF, 2024).

Moreover, as AI adoption reshapes firm-level production processes, there are growing concerns that automation and task substitution may reduce employment opportunities—particularly for younger cohorts entering the labour market. To prevent rising youth unemployment and ensure a smoother transition, targeted policies are needed to strengthen education systems oriented toward AI-related industries, expand retraining and reemployment programmes for those on the verge of entering the workforce, and enhance lifelong learning systems that promote adaptability across all age groups.

For ageing economies such as Korea, ensuring that the productivity benefits of AI are broadly shared across generations is essential not only for macroeconomic sustainability but also for maintaining social cohesion and trust in the face of rapid technological transformation.

7. Concluding Remarks

This paper has examined the macroeconomic implications of artificial intelligence (AI) diffusion under the dual structural forces of rapid population ageing and shifting productivity dynamics, with a particular focus on Korea as a small open economy. Using a two-country overlapping generations (OLG) model with imperfect capital mobility and borrowing constraints, we analysed how AI-induced shocks—captured through total factor productivity (TFP) growth, changes in capital and labour income shares, and shifts in age–efficiency profiles—affect growth, real interest rates, fiscal balances, and external positions.

Several key insights emerge. First, AI-driven improvements in TFP exert powerful effects on long-run growth and the real interest rate (r*). When productivity gains are concentrated abroad, as in the U.S., Korea faces capital outflows, slower growth, and accelerated debt accumulation, despite a more favourable external balance. Conversely, when domestic productivity rises, Korea enjoys higher growth and stronger fiscal revenues but at the cost of a weaker net foreign asset (NFA) position. These results highlight the asymmetric nature of global versus domestic AI innovations and the trade-offs they pose for small open economies.

Second, changes in the distribution of income between labour and capital carry complex consequences. A higher capital income share raises real interest rates and temporarily boosts growth but also reshapes capital flows in ways that undermine external and fiscal sustainability. This underscores the distributive dimension of AI shocks: they are not only technological in nature but also structural shifts that alter policy trade-offs across monetary, fiscal, and external domains.

Third, shifts in age-specific productivity profiles induced by AI, health, and education advances illustrate how demographic structures shape the macroeconomic impact of technology. A later productivity peak in the U.S. reduces effective labour and depresses r*, while in Korea it raises effective labour and supports growth. These asymmetric results show that compositional effects alone may misrepresent the broader impact of AI; when coupled with aggregate TFP gains, effective labour may rise rather than fall. This points to the importance of modeling demographic and technological drivers jointly when evaluating long-run macroeconomic dynamics.

Finally, across all scenarios, the simulations underscore that AI diffusion magnifies existing policy challenges in ageing societies. Monetary authorities must refine neutral rate estimates to incorporate both demographic and technological factors. Fiscal authorities must prepare for the possibility that growth-enhancing policies may weaken external buffers and complicate debt stabilisation. Labour market and education policies must ensure that AI's productivity benefits extend across age and skill groups, thereby safeguarding intergenerational equity.

In conclusion, AI represents not only a technological revolution but also a structural transformation with far-reaching macroeconomic consequences. For Korea, where rapid ageing coincides with accelerating AI diffusion, the challenge is to harness AI's productivity gains while mitigating associated risks to fiscal sustainability, external resilience, and social cohesion. Achieving this balance will require an integrated policy framework that combines monetary, fiscal, labour, and structural policies to ensure that AI-driven growth is both sustainable and inclusive.

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CHAPTER 3

IMPACT OF THE ADOPTION OF ARTIFICIAL INTELLIGENCE ON MONETARY POLICY: EVIDENCE FROM SRI LANKA ON THE LABOUR PRODUCTIVITY CHANNEL

Janaka D Maheepala[1*] and **Kasun D Pathirage**[2*]

1. Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technological advancements of the 21st century, reshaping production processes, services, and economic decision-making across the globe. Its applications span a wide spectrum of functions such as automation in manufacturing and agriculture, predictive analytics in financial markets, machine learning in healthcare, and algorithmic support for policymaking and governance. As with any general-purpose technology, AI carries both opportunities and challenges for economies worldwide. For instance, McAfee and Brynjolfsson (2017) argue that AI can significantly enhance productivity and create new industries, while Acemoglu and Restrepo (2020) highlight concerns about job displacement and inequality. These contributions highlight that although it has the potential to enhance productivity, reduce costs, and create new industries, its adoption could likely raise concerns, such as increased job displacement, pressure on wages, widening inequality, and new forms of economic vulnerability.

The ability to enhance labour productivity is one of the key channels through which AI adoption can affect the economy. For example, Hatzius et al. (2023) find that AI adoption is driving a significant boost to US labour productivity gains, with the largest improvements seen in knowledge-intensive sectors, highlighting its impact on the broader economy. However, Hornstein (2024) highlights that the magnitude of the impact can vary substantially, ranging from virtually non-existent to substantially large, even surpassing the impact of the information technology sector boom during the 1990s. The fact that there are very wide-ranging impacts and that they are yet to be fully understood due to the evolving nature of the technology further complicates

1. Deputy Director, Statistics Department, Central Bank of Sri Lanka (maheepja@cbsl.lk)

2. Deputy Director, Economic Research Department, Central Bank of Sri Lanka (kasun.pathirage@cbsl.lk)

* The views and opinions expressed in this paper are those of the authors, and they do not necessarily represent the views of the Central Bank of Sri Lanka. Any errors, omissions and mistakes are of the authors alone.

the assessment of its possible economic impact. As far as developing countries such as Sri Lanka are concerned, it is essential to understand these dual aspects, given that their economic structures and labour markets may be more sensitive to disruptive technologies due to the limited availability of buffers.

The interaction between AI and the economy can be two-fold: while AI technologies influence key macroeconomic variables such as output, employment, and inflation, the trajectory of AI adoption itself is shaped by the broader economic environment, including aggregate demand conditions, wage dynamics, and structural rigidities. This interdependence makes it critical for policymakers to carefully assess both the direct and indirect channels through which AI affects the economy. Central banks, in particular, are tasked with navigating these dynamics, as they are far-sighted institutions that design and implement monetary policy with the objective of safeguarding price stability and supporting sustainable growth. Their decisions rely heavily on the assessment of future surges in inflation, output, and other macroeconomic indicators. For instance, when the aggregate demand increases, surpassing productive capacity, inflationary pressures intensify. Similarly, when wage pressures mount, they feed into cost-push inflation. In such contexts, the integration of AI-related impacts on the analytical frameworks of central banks becomes vital for timely and effective policy measures.

In Sri Lanka, the Government has recently launched the National AI Strategy (2024–2028), demonstrating a strong determination to promote the responsible use of artificial intelligence for national development. The strategy, supported by budgetary allocations and the establishment of a National AI Centre, aims to enhance digital infrastructure, capability, and governance to support the National Digital Strategy 2030 (Committee on Formulating a Strategy for Artificial Intelligence (CFSAI), 2024b, 2024a; Ministry of Digital Economy, 2024). This strategy provides a long-term plan to transform Sri Lanka into a digitally empowered and innovative economy that includes everyone. It is guided by six main principles that focus on being inclusive, innovative, sustainable, global, human-centred, and fair. The strategy focuses on key areas such as improving digital infrastructure and connectivity, developing digital skills and literacy, promoting digital government services, strengthening cybersecurity and privacy, expanding digital financial services, and supporting digitalisation in different sectors, including small and medium businesses. It also highlights the importance of a strong legal and regulatory framework, digital identity systems, good governance, effective data management, stakeholder engagement, and private sector investment. The plan aims to improve broadband access, support entrepreneurship, and build partnerships between the public and private sectors to increase productivity, competitiveness, and job opportunities in the digital economy.

These initiatives show Sri Lanka's strong commitment to using artificial intelligence and digital technology to drive inclusive and sustainable development. The Information and Communication Technology Agency (ICTA) is spearheading major initiatives such as introducing a Unique Digital ID by 2026, expanding GovPay digital payment services, adopting a cloud-first policy for government institutions, and implementing the Digital Revenue Economy Programme. Together, these efforts highlight the Government's goal of using new technologies to support national progress while managing potential risks responsibly. Meanwhile, on the monetary policy front, the Central Bank of Sri Lanka conducts its monetary policy under a Flexible Inflation Targeting (FIT) framework to keep inflation at the targeted 5% level (Central Bank of Sri Lanka, n.d.). Monetary policy decisions are guided by a data-driven, forward-looking process supported by the Forecasting and Policy Analysis System (FPAS), of which the Quarterly Projection Model (QPM), a semi-structural macro model, remains the core modelling framework.[3] The QPM analyses the medium-term dynamics of key macroeconomic variables, including inflation, output, the exchange rate, and the short-term policy interest rate, allowing policymakers to simulate different scenarios and assess their implications. The growing use of AI across both government and private sectors, encouraged under the new national digitalisation strategy that promotes technology-driven transformation and responsible innovation, has made the Central Bank's role more challenging and increasingly important. At the same time, the emergence of AI has opened new avenues to strengthen the conduct of monetary policy. For example, AI-based forecasting techniques such as machine learning driven nowcasting models and neural network-supported growth projections have the potential to enhance the accuracy and timeliness of near-term inflation and growth forecasts. The use of big data sources, including Google Trends, PortWatch trade analytics, and nighttime lights data, may further improve the capacity to assess economic activity. Moreover, natural language processing methods such as text mining and sentiment analysis are increasingly applied to central bank communications, news articles, and social media to capture inflation expectations and policy-related sentiments.

The economic impact of AI can occur through various channels, including, among others, its impact on labour, as well as overall productivity, demand-side pressures, changes to policy transmission via new financial products and improved analyses, and changes to supply channels. These possibilities highlight how the link between AI and monetary policy transmission can become more complex, along with further evolution of AI and increased adoption. The Central Bank, through its forward-looking analyses framework, can evaluate the possible path of inflation relative to its target and determine the monetary policy stance required to maintain inflation at the targeted level and support sustainable growth. Although the QPM has been effective in guiding policy decisions, some limitations exist in capturing the supply-side dimensions of the economy and wage dynamics, both of which are critical in understanding the implications of AI adoption. For example, the QPM does not explicitly identify labour market frictions or the productivity shocks that AI-driven technologies might generate. Instead, such impacts are only indirectly captured through the output gap, which limits the model's ability to isolate and analyse the channels through which AI influences inflation and growth. Nevertheless, if such impacts can be assessed and quantified with reasonable

3. See Amarasekara et al. (2018) for a baseline illustration of the QPM for Sri Lanka.

accuracy, the existing framework is flexible enough to internalise them in arriving at projections. Furthermore, Sri Lanka currently lacks a comprehensive measure of private sector wage movements, relying mainly on the minimum wage rate index, which does not adequately capture actual wage trends or labour market dynamics. To address this gap during monetary policy analyses, the Central Bank is also evaluating alternative wage rate indices based on international best practices and the currently available sources.

These characteristics of the existing framework highlight the need for complementary modelling approaches to capture the economic effects of AI more comprehensively. Dynamic Stochastic General Equilibrium (DSGE) models, for example, provide a richer framework by incorporating micro-foundations that allow the analysis of wage formation, labour supply, and productivity shocks, factors that are highly relevant in the evaluation of AI impact. By adopting such models alongside the QPM, policymakers can assess how AI-driven changes in the supply aspects of the economy and wage dynamics might affect inflationary pressures and broader macroeconomic outlook. Furthermore, the insights derived from these models can be integrated back into the QPM framework, thereby improving its usefulness in monetary policy decisions.

Despite the growing application of AI in various industries and sectors in Sri Lanka, research carried out on its aggregate economic impact is limited. To date, much of the focus has been on AI as a tool for efficiency and innovation rather than as a macroeconomic drive with potential implications for inflation, wages, and monetary policy. In this context, the current study makes an important contribution by assessing one of the key channels through which AI could affect the economy, namely the impact of changes to labour-augmented productivity. In this effort, the analyses also contribute to the improvement of the analytical foundations of monetary policy in Sri Lanka. Specifically, we consider a small open economy DSGE framework, calibrated to the Sri Lankan economy, to evaluate how the transmission of a traditional total factor productivity (TFP) shock differs from a labour augmented productivity shock, which we assume occurs due to increased adoption of AI (we refer to this shock as an 'AI labour productivity shock'). In this study, our focus is not on estimating the impact of AI-related shocks but rather on highlighting the differences and similarities in the transmission of these two shocks. When considering shocks of similar strengths, we find that the responses are broadly similar in their directions. However, in terms of the magnitude, the TFP shock results in a much more pronounced and often more persistent response in most variables. This behaviour is explained by the fact that TFP shocks augment the productivity of both capital and labour, whereas the AI labour productivity shock affects only labour. It is important to note that this represents a simplifying assumption adopted for analytical clarity. In practice, AI adoption can also affect capital utilisation, organisational efficiency, and broader technological progress, thereby contributing to overall total factor productivity. Accordingly, the model abstracts from these wider technological effects and focuses solely on the labour-augmented channel, which should be recognised as a limitation of the present analysis. We extend the analyses by considering the sensitivity of responses to the elasticity of substitution between capital and labour. This analysis reveals that there can be qualitative differences across the two shocks. We find that higher substitutability between capital and labour results in an amplified response in output and inflation during an AI labour productivity shock, compared to a scenario where factor inputs are complements. In contrast, during a TFP shock, higher substitutability results in a relatively attenuated response in both output and inflation. These observations highlight the potential for heterogeneous effects among different types of firms, as well as the importance of accurate calibrations and disaggregated modelling for policy purposes. We complement these analyses by evaluating optimal monetary policy rules during the two shocks under the assumption that optimality refers to minimising the combined volatility of inflation, output gap, exchange rate depreciation and policy rate changes. This analysis reveals that during an AI labour productivity shock, a higher importance can be placed on stabilising the exchange rate, given that some policy space is created due to its relatively muted response on domestic inflation, when compared against a TFP shock. Overall, our comparative assessment shows that it is important for policymakers to correctly disentangle the two types of shocks, since the required policy response is different in the two instances. Nevertheless, in the case of Sri Lanka, we conclude that the possibility of policy mistakes at an aggregate level is minimal, as under FIT, inflation and its projections remain the key guides for policy decisions, and since the responses of inflation broadly capture the differences between the two shocks. Still, it needs stressing that our attempts in this paper focus only on one of many channels through which AI can have a considerable macroeconomic impact, and there is the need to study the effects of other channels as well.

The rest of the paper is structured as follows. After the introduction in Section 1, Section 2 provides an outline of the model framework used and its calibration. Section 3 presents key results and discussions, while Section 4 provides some concluding remarks.

2. The Model

In order to study the effects of a productivity improvement of the labour supply, possible via the increased adoption of AI, we consider an extension of the seminal work of Galí and Monacelli (2005) (which we will refer to as GM). Our focus is to study the monetary policy-relevant impact of AI adoption in an emerging market economy such as Sri Lanka. Given that monetary policy is broadly focused on medium-term economic activity, we employ a DSGE model for this purpose, since they are widely used to evaluate macroeconomic effects at business cycle frequencies. Accordingly, we consider a small open economy framework rather than a closed economy setup. GM provides a simple, yet powerful, open economy New Keynesian framework. In this model, the production sector is assumed to be based only on labour. Given our focus on studying productivity improvements in the labour supply, which in the current context is deemed to occur due to enhanced adoption of AI, it is important to consider the substitution and/or complementarity of labour and capital as factors of production. Accordingly, instead of the simple setup in GM, and in many New Keynesian models focused on monetary policy, we consider that production is carried out by utilising both capital and labour. In particular, we assume that intermediate goods producing firms combine capital and labour to produce intermediate goods using a constant elasticity of substitution (CES) aggregation technology, given by:

$$Y_t(j) = A_t \left[\omega\left(K_t(j)\right)^{\frac{\sigma-1}{\sigma}} + (1-\omega)\left(\chi_t N_t(j)\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \quad \textbf{\textit{(Eq. 1)}}$$

where, $\omega \in (0,1)$ is the relative importance of capital, and $\sigma > 0$ is the elasticity of substitution. $Y_t(j)$ is the output produced by the intermediate goods firm j using the demanded quantities of capital, $K_t(j)$, and labour, $N_t(j)$. A_t represents a total factor productivity shock that would affect the productivity of both capital and labour, whereas χ_t is a labour augmented productivity improvement, which we assume happens due to the adoption of AI. This technology specification is the single most important augmentation in our model compared to that of GM. As a result, several new equations are added (e.g. optimal capital-labour ratio, Euler equations in the households due to the presence of capital, etc.), and amendments are required to key equations such as the marginal cost.

In addition to the above, several other modifications are made so that the model can appropriately represent an emerging economy like Sri Lanka. In summary, these modifications include partial indexation of imported inflation to domestic prices,[4] partial mean reversion of the terms of trade,[5] assuming limited efficiency in converting investment into capital (investment adjustment costs) and wage rigidity,[6] and a hybrid uncovered interest rate parity condition.[7] These assumptions are based on previous studies using structural macro models for Sri Lanka, as well as specific experiences with the Sri Lankan economy. Regarding the monetary policy rule, we consider a Taylor-type rule, similar to many other DSGE models in the literature, where the short-term interest rate is assumed to respond slowly to deviations of expected inflation from its

4. Motivated by the fact that, in addition to global prices and exchange rate movements, prices of imported consumer goods could also be affected by domestic price movements due to factors like distribution and retail costs, presence of imported intermediate goods, and any taxes, fees and administrated components.

5. To account for the practical implication that changes in terms of trade are not instantaneous, but can occur gradually, due to factors such as, among others, pre-agreed export contracts and administered prices. In effect, this assumption partially relaxes the theoretical no arbitrage competitive advantage assumption in GM, during the short term.

6. These are common assumptions in many empirical DSGE models.

7. To account for the presence of a mix of agents with rational and adaptive expectations.

steady state and the output gap. Given that inflation in a small open economy, such as Sri Lanka, is heavily dependent on exchange rate developments, central banks in such economies often take measures to reduce the volatility of the exchange rate as well. Therefore, monetary policy is assumed to respond slightly to the expected exchange rate depreciation as well. Accordingly, the monetary policy rule is given by:

$$\hat{\imath}_t = \rho^i \hat{\imath}_{t-1} + \left(1-\rho^i\right)\left(\phi^\pi \mathbb{E}_t\{\hat{\pi}^c_{t+1}\} + \phi^y(\hat{y}_t - \hat{y}^n_t) + \phi^e(\mathbb{E}_t\{\hat{e}_{t+1} - \hat{e}_t\})\right) + \varepsilon^i_t \quad \textbf{\textit{(Eq. 2)}}$$

where, i_t is the nominal policy interest rate, π^c_t is the consumer price index based inflation, y_t is output, y^n_t is the flexible price output, representing the potential of the economy, e_t is the nominal exchange rate, and ε_t is a monetary policy shock. The parameters ρ^i, ϕ^π, ϕ^y, and ϕ^e represent monetary policy smoothing, and responsiveness of monetary policy on expected inflation deviations, output gap and expected exchange rate depreciation, respectively. The list of equations summarising the model is provided in Appendix A.

2.1 Model Calibration

The model is calibrated by considering past studies undertaken on the Sri Lankan economy, and with reference to long-term averages of key macro variables. These values, along with brief descriptions on how they are calibrated, are provided in Table 1.

Table 1: Calibrated Parameters

Parameter	Calibrated Value	Notes
Discount Factor (β)	0.985	Based on the calibration in Ehelepola (2014) (Consistent with a relatively higher interest rate for Sri Lanka than the traditional values used in DSGE models calibrated for advanced economies)
Risk Aversion Coefficient (γ)	1.32	Based on the estimates in Karunaratne and Pathberiya (2014)
Frisch Elasticity of Labour Supply (φ)	1.06	Based on the estimates in Karunaratne and Pathberiya (2014)
Elasticity of Substitution between Capital and Labour (σ)	0.7	By considering that in countries such as Sri Lanka, labour and capital cannot be easily substituted for one another, and based on the overall ranges of values discussed by Duffy and Papageorgiou (2000)
Labour Share of Income (s^L)	0.39	Based on the estimates (average between 2003 and 2019) in Feenstra, Inklaar and Timmer (2015)

Parameter	Calibrated Value	Notes
Deprecation Rate (δ)	0.0375	Based on the calibration in Ehelepola (2014)
Investment Adjustment Cost Parameter (ψ_I)	2.4	Based on the estimates in Jegajeevan (2016)[8]
Share of Imports in the Consumer Basket (α)	0.27	Based on estimated expenditure shares in the Colombo Consumer Price Index (CCPI)
Elasticity of Substitution Among Labour Varieties (ϵ_w)	6	Based on the calibrations in Jegajeevan (2016)
Calvo Parameter – Prices (θ_p)	0.75	Based on the calibration in Ehelepola (2014) and the assumptions related to the prior distribution in Jegajeevan (2016)[8]
Calvo Parameter – Wages (θ_w)	0.75	Based on the assumptions related to the prior distribution in Jegajeevan (2016)[8]
Persistence of Imported Inflation (ρ^{π^M})	0.6	Based on an AR(1) regression of the CCPI-based imported inflation
Domestic Indexing of Imported Goods (λ^{π^M})	0.25	Based on a regression of imported inflation, exchange rate depreciation, foreign inflation and domestic inflation
Mean Reversion of Terms of Trade (ψ_s)	0.17	Based on a regression of imported inflation, exchange rate depreciation, foreign inflation and domestic inflation
Weight on Expected Depreciation in Hybrid UIP (λ^{UIP})	0.49	Assuming approximately 50:50 shares, while ensuring model stability
Interest Rate Smoothing (ρ^i)	0.6	Authors' baseline calibration
Monetary Policy Response to Expected Inflation (ϕ^π)	1.5	Authors' baseline calibration

8. The model used by Jegajeevan (2016) comprises several more price dynamics such as separate rigidities in export prices, etc. Accordingly, we consider their prior distribution assumption for calibration purposes, when the assumption in this paper differs from the said paper. However, when assumptions broadly align, say, for example, related to investment dynamics, we consider their estimated value for our calibration.

Parameter	Calibrated Value	Notes
Monetary Policy Response to Output Gap (ϕ^{y})	0.1	Authors' baseline calibration
Monetary Policy Response to Expected Exchange Rate Depreciation (ϕ^{e})	0.05	Authors' baseline calibration
GDP Share of Consumption $\left(\frac{C}{Y}\right)$	0.724	Average shares based on the Sri Lankan data (Only the most recent vintage of National Accounts considered to preserve consistency)
GDP Share of Investment $\left(\frac{I}{Y}\right)$	0.139	Average shares based on the Sri Lankan data (Only the most recent vintage of National Accounts considered to preserve consistency)
GDP Share of Government Spending $\left(\frac{G}{Y}\right)$	0.192	Average shares based on the Sri Lankan data (Only the most recent vintage of National Accounts considered to preserve consistency)
GDP Share of Net Exports $\left(\frac{NX}{Y}\right)$	-0.055	Average shares based on the Sri Lankan data (Only the most recent vintage of National Accounts considered to preserve consistency)

Source: Compiled by Authors.

3. Results and Discussion

In order to evaluate the impact of an improvement to labour productivity due to the adoption of AI, we consider a labour-augmented productivity shock, represented by the variable χ_t. When utilising DSGE models for policy purposes, it is not easy to distinguish between a total factor productivity shock and a labour augmented productivity shock. Thus, it would be interesting to evaluate how responses differ across these two key channels of productivity. Figure 1 summarises a comparison of the impulse responses of the calibrated model to these two structural shocks, a total factor productivity (TFP) shock, and a labour-augmented productivity (AI) shock. Shocks with similar strengths (same standard deviation) of one per cent are used to generate these responses, enabling comparison.[9] From a macroeconomic perspective, both these shocks represent augmentations to the overall productivity of the economy. Accordingly, one could consider the effects of both these shocks to be similar to one another. In fact, we can observe that the impulse responses are broadly similar, differing mainly in the magnitude of the effects. However, structurally, there are some differences in how these shocks propagate to the broader economy. Accordingly, we can observe some differences in

9. We assume a persistence of 0.7, in each case.

the magnitude of effects due to the structural positioning of the shock, as well as to some extent, due to differences in their transmission channels. From a monetary policy perspective, these differences underscore the importance of a careful examination of such phenomena, allowing policy responses to be calibrated accordingly.

When we consider how the two shocks affect production, the impact of TFP is larger than that of the AI shock, since the impact of the AI shock is only through labour, which constitutes only a part of the productive inputs. As a result, we see the impact of TFP to be larger in most activity-related variables, such as GDP, consumption, and investment. This is simply the impact of productivity improvements experienced in both capital and labour compared to those experienced only in labour. In other words, when two shocks are similar in strength, the responses of macro variables have different magnitudes by construction.[10] In both cases, the increase in consumption leads to a fall in labour supply as households prefer more leisure amidst higher consumption, which is analogous to an increase in wealth. In turn, this leads to a fall in the wage rate, as the decline in labour hours outweighs the upward pressure on wages due to the decline in the marginal utility of consumption amid the increased level of consumption. In this situation, the behaviour of the labour supply can be interpreted as the income effect being the dominant force, i.e., as workers enjoy higher consumption, their perceived wealth is increased, motivating them to prefer more leisure. However, given Sri Lanka's limited AI adoption and the relatively small share of an AI-ready workforce in both formal and informal sectors, there is a risk that rapid technological diffusion could initially result in job losses, reduced household consumption, and rising inequality and poverty, before longer-term productivity benefits are fully realised.

Apart from the impact on production, the other direct impact of the increase in productivity, in either channel, is the reduction in the marginal cost of firms. As a result, we see a corresponding fall in domestic inflation. This drives overall consumer price inflation also down, which results in a monetary policy loosening as reflected by the fall in the policy rate. However, the drop in interest rate is less strong than the fall in inflation, resulting in a relatively higher ex-ante real interest rate. This attracts foreign capital, which can explain the observed appreciation in the nominal exchange rate. This appreciation leads to a relative reduction in imported inflation; however, its magnitude is less than that of domestic inflation, which moves as a result of productivity improvements lowering marginal cost. Following Galí and Monacelli (2005), we define terms of trade

10. At the time of writing this manuscript, there is a scarcity of estimates of DSGE-related AI-induced shocks. Most DSGE models are based on quarterly data. Given that it has not been more than 8-10 quarters since the noticeable pickup in AI, identifying AI-induced shocks could still be challenging, and the existing literature also seems to be inconclusive regarding any quantifications. For example, Acemoglu (2024) claims the productivity improvements via AI in the US could be modest, at around 0.53% over 10 years. Going by this estimate, the quarterly magnitude can be derived to be around 0.013%, which is comparatively much less than a TFP shock for the US, as estimated in Adolfson et al. (2007) of about 0.4%. On the other hand, by incorporating different assumptions, particularly on sectoral movements, Guerrón-Quintana et al. (2025) find a relatively larger macro impact due to AI.

as the price of foreign goods in terms of domestic goods. Accordingly, the above relative behaviour of imported and domestic inflation leads to an increase in terms of trade, although it gets corrected over time. This means exports become more competitive in the world market.[11] The behaviour of terms of trade is also more pronounced with the TFP shock due to its higher impact on domestic inflation. With regard to the flexible price economy, in the absence of nominal rigidities, the response in output is stronger, and as a result, we see the output gap turning negative with a larger magnitude for the TFP shock. At the same time, the trajectory of flexible consumption, which suggests a gradual fall towards the steady state from the initial increase, means that households would borrow against future and consume today, i.e., the real neutral rate is found to be negative.[12] Importantly, when the ex-ante real policy rate is considered, its drop is found to be slower than that of the real neutral rate, leading to a tighter monetary policy stance.[13] This, in turn, is consistent with the negative output gap we observe in the impulse responses.

When comparing the two shocks and their impact on monetary policy, a key consideration is the magnitude of their effect. Since TFP shock affects production technology directly, i.e., as it affects the productivity of both factor inputs, its impact is larger. In contrast, the AI shock affects only via labour input. Further, during AI shocks, the reaction of the real neutral rate is also smaller than that during the TFP shock.[14] As a result, the level of policy reaction during TFP needs to be considerably larger than during the AI shock. Accordingly, we see that the monetary policy stance is also less tight in the case of an AI shock. Interestingly, this leads to a faster recovery of the output gap in the case of a TFP shock. Moreover, depending on the parametrisation, the magnitude of the overshooting of the output gap could also be different.

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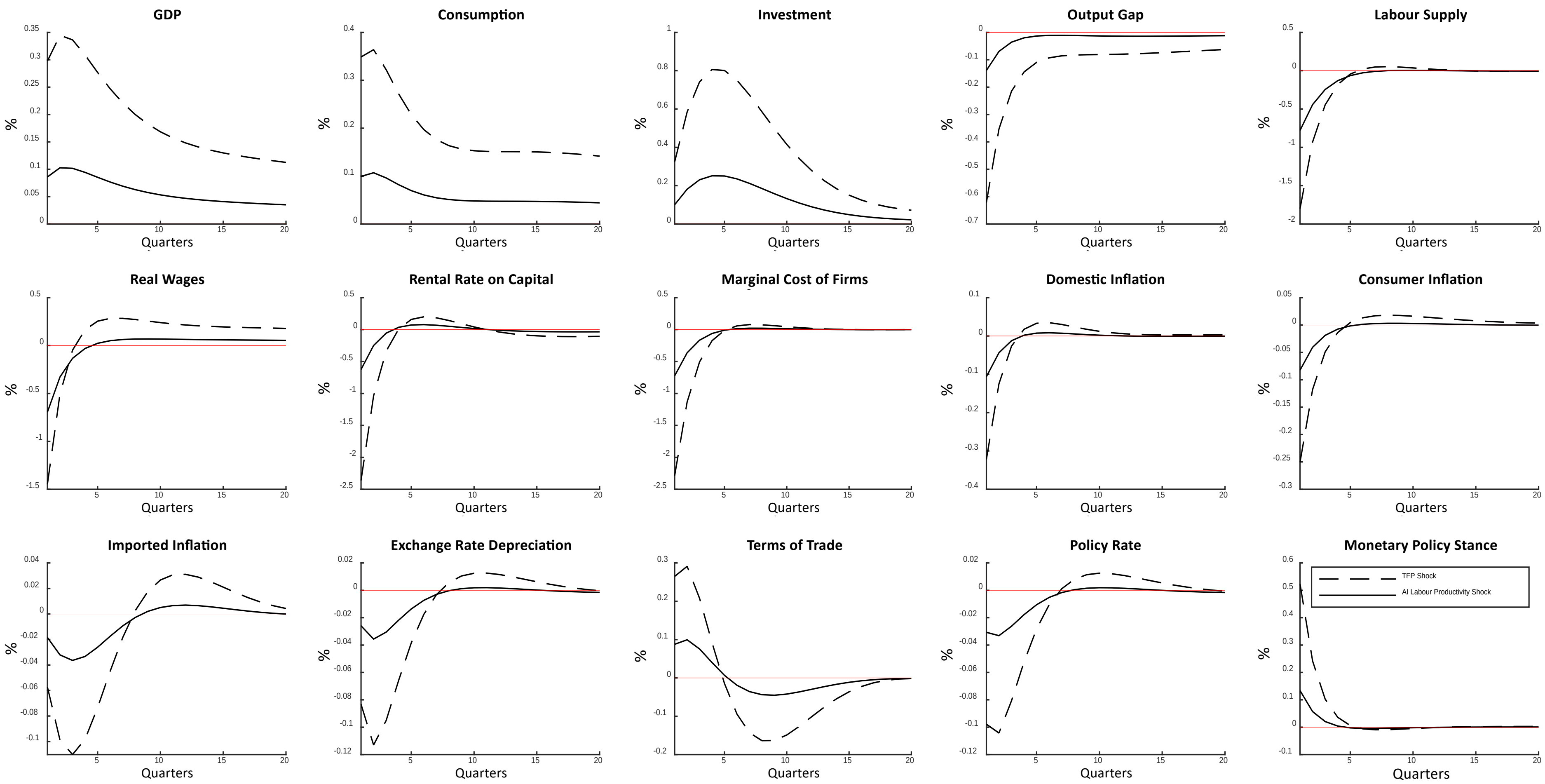
11. It needs to be highlighted that the way terms of trade is defined in Galí and Monacelli (2005), and also in many DSGE models, can be thought of as the inverse of the way terms of trade is defined when it comes national account statistics. In national accounts terms of trade is defined usually as the division of export price by import price. It captures how much imports can be bought from a unit export, and severs as an indicator of the living conditions of the domestic economy.
12. We extend the model with a flexible price block in order to derive the flexible price output, which we use to define the output gap. The real neutral interest rate is the resulting interest rate in this flexible price block, which is mainly a function of how flexible price consumption is smoothed dynamically.
13. We have considered the difference between the ex-ante real policy rate and the real neutral rate $(\hat{\imath}_t - \mathbb{E}_t\{\hat{\pi}^c_{t+1}\} - r^n_t)$ as the monetary policy stance.
14. Note that the behaviour of the real neutral rate is governed mainly by the behaviour of flexible price consumption. With a TFP shock, flexible price output increases more than during an AI shock, and also, the relative pace of normalisation is faster with a TFP shock. As a result, we see the trajectory of the real neutral rate to be a more pronounced reduction with a TFP shock (a larger drop in real neutral rate explains the larger increase in consumption, and the faster normalisation of the real neutral rate explains the faster correction in flexible price consumption).

Figure 1: Impulse Responses to TFP and AI Shocks



Source: Compiled by Authors.

The primary source of divergence in the macroeconomic responses to the two shocks considered here lies in the relative factor input shares. Therefore, accurate estimates of related structural parameters, such as the labour share of income and elasticity of substitution between capital and labour, become very important. Given that the latter is usually difficult to estimate from directly observable quantities, it is interesting to consider the sensitivity of the model responses to this parameter. Figure 2 illustrates how the responses differ when we consider different levels of substitution between capital and labour. We consider two possibilities of substitution at $\sigma = 0.4$, where capital and labour are complements, and $\sigma = 1.5$, where capital and labour are substitutes.[15] In the latter, firms can substitute capital for labour and vice versa more freely than in the former scenario. In the baseline calibration, we have considered a case where $\sigma = 0.7 (< 1)$, implying that capital and labour are complements rather than substitutes, reflective of the fact that switching between capital and labour could be rather difficult for most Sri Lankan firms, given constraints such as shallow capital markets, weak financial literacy, particularly among small and medium-sized firms, etc. Panel (a) of Figure 2 illustrates the case of a TFP shock, while panel (b) illustrates an AI labour productivity shock. During a TFP shock, the economy with factor substitutability $(\sigma = 1.5)$ leads to a more pronounced increase in the capital to labour ratio, since the fall in labour hours in this economy is larger. Note that since the stock of capital is predetermined, its changes take place slowly relative to labour hours. Furthermore, when productivity improves, firms can employ fewer amounts of factor inputs due to higher productivity. However, as capital changes slowly, firms utilise less labour, i.e., labour demand falls. In an economy with factor substitutability, the substitution is easier, and therefore, labour falls more in such an economy than in a factor-complementing economy. However, the lower labour hours lead to a lower output when σ is larger, and so does consumption. Moreover, when substitution is easier, the larger drop in labour means that capital becomes more valuable, particularly as capital changes slowly. Therefore, when σ is larger we see a relatively muted drop in rental on capital, which in turn drives the drop in marginal cost also to be smaller, pushing the drop in inflation also to be smaller.

When we consider an AI labour productivity shock, we see a contrasting behaviour across the two economies. Note that in this instance, productivity improvement happens only for labour. As a result, the marginal product of labour is higher; thus, firms would want to shift to more labour. This is easier in the case of higher σ, and as a result, we see a lower drop in labour hours, and also in the capital to labour ratio. Furthermore, the lower drop in labour leads to a higher output in the economy due to factor substitutability and a relatively higher wage rate. Note that in this instance, the productivity of capital does not change directly. However, the overall improvement in output also leads to a lower marginal product of capital, but the drop is larger when

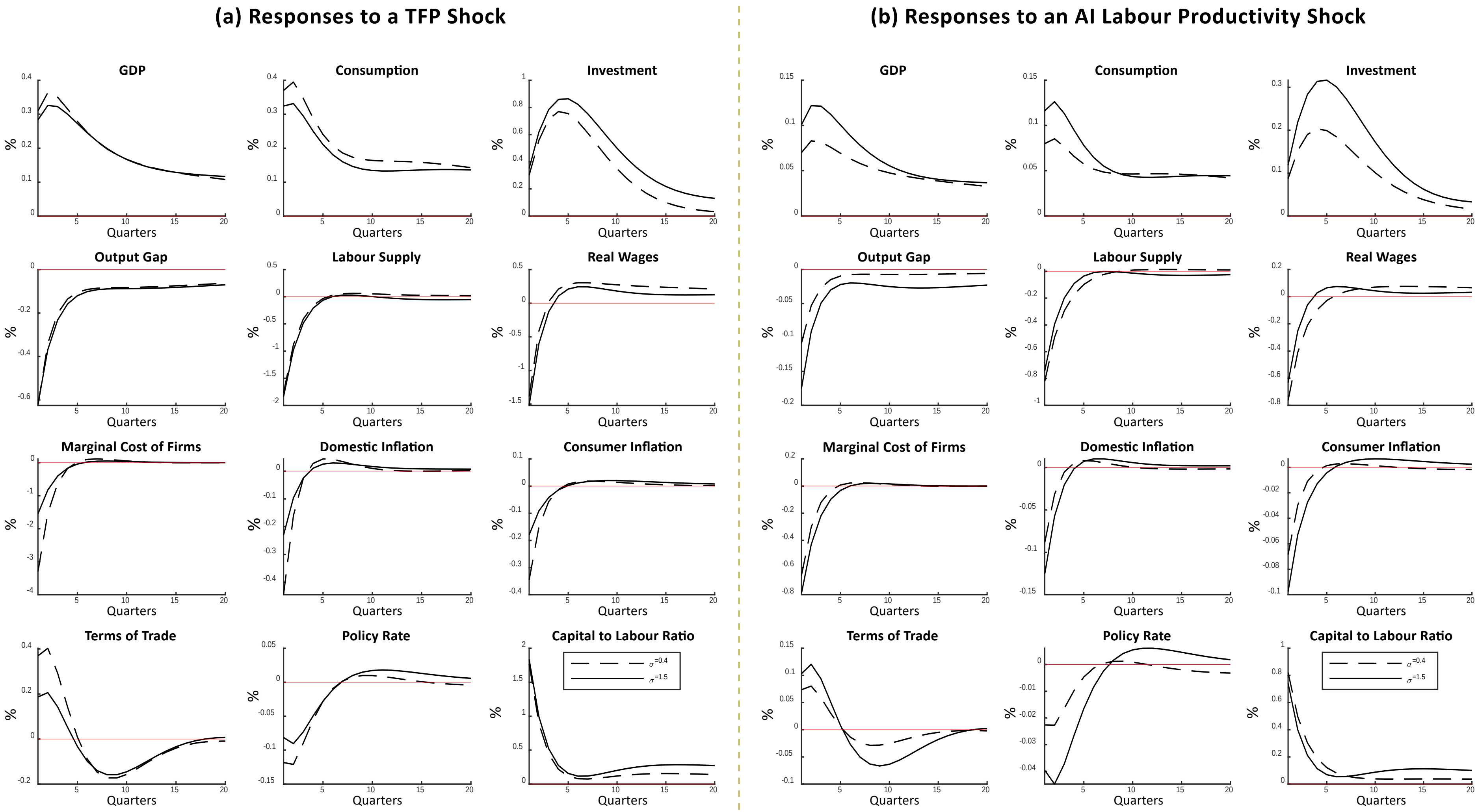
15. We consider two possibilities for the elasticity of substation between capital and labour that are different from the baseline calibration, which forms a relatively broad range of values, simply to better illustrate the differences.

capital and labour are substitutes, as demand for capital is lower. As such, we see a sharper drop in rental on capital with higher σ, which in turn translates into lower marginal cost and inflation. Overall, we can observe contrasting behaviours across the two shocks when comparing two economies with complementary and substitutable factor inputs. This highlights the importance of accurately identifying the elasticity of substitution when using similar models for policy purposes. Moreover, this observation highlights an important implication for micro analyses. Given that different industries inherently have varying degrees of elasticities of substitution, they could face different effects during TFP and AI productivity shocks. Firms with high substitutability of factor inputs would find that an AI labour productivity shock would result in a higher output and lower costs than a firm with less substitutability. One could also interpret this observation as highlighting the importance of labour mobility and higher adaptability during key technological shifts.

These observations highlight the importance of recognising the origin of technology shocks. They do seem to have similar responses in most macro variables. However, their transmission channels differ, and therefore, their impacts can be distinct. In the case of the AI shock considered here, transmission occurs through the relative prices of factor costs, whereas TFP affects both factor inputs in a similar manner. As a result, the required policy response is also found to be sharper during TFP shocks. This is an important distinction between the responses to the two shocks that is relevant for monetary policy. From a policy practitioner's perspective, this implication underscores the importance of accurately identifying the origin of shocks. This is particularly important in the case of Sri Lanka, given that statistics on the labour market are relatively less extensive. As labour market statistics are a key piece of information that helps identify the origin of these shocks, their limitations can become a constraint for policy analyses.

Nevertheless, given that the response of inflation is also muted during the AI shock, the operational implication of this difference may not be substantial for Sri Lanka. Under the Flexible Inflation Targeting (FIT) framework, inflation, specifically its medium-term projections, plays a major role in monetary policy deliberations in Sri Lanka. Our results from these analyses suggest that any divergence in the macroeconomic responses between the TFP and AI type shocks is mainly driven by the differences in the responses to inflation. Given this background, the chances of policy mistakes due to misidentification of TFP and labour-augmented AI productivity shocks remain minimal in the context of Sri Lanka. However, the divergence of macroeconomic responses highlights the importance of further research into other channels of the macroeconomic effects of AI.

Figure 2: Sensitivity to Elasticity of Substitution



Source: Compiled by Authors.

3.1 Optimal Policy

To evaluate how policy should respond to these two key shocks, we consider simple loss function-based optimal policy combinations. We calculate optimal monetary policy rules as a policy that minimises the variability of inflation, output gap, exchange rate depreciation, and the change in the policy rate. I.e., we aim to minimise,

$$\mathcal{L} = \lambda^{\pi} var(\hat{\pi}_t^c) + \lambda^y var(\hat{y}_t - \hat{y}_t^n) + \lambda^e var(\hat{e}_t - \hat{e}_{t-1}) + \lambda^i var(\hat{\imath}_t - \hat{\imath}_{t-1}) \qquad \textbf{(Eq. 3)}$$

by searching over a relatively large array of values of the policy rule parameters.[16] Our objective in this analysis is not to provide policy recommendations, but rather, we are interested in the direction of welfare-optimal policy in the face of the two shocks: TFP and AI. For the definition of the loss function, we consider the weights $\lambda^{\pi} = \frac{\theta_p}{\kappa_p}$, $\lambda^y = 1 + \varphi$, $\lambda^e = 1$ and $\lambda^i = 0.25$. The resulting optimal policy parameters are illustrated in Table 2. As per this exercise, a substantial level of policy smoothing is suggested as optimal in the model. With a TFP shock, a substantially large response on inflation is suggested, highlighting an important role in stabilising overall inflation. Regarding the stabilisation of the exchange rate, a larger weight seems optimal during the AI shock than during the TFP shock. Given that the same objective function is used to derive these optimal parameters, this exercise suggests that during an AI shock, focusing more on stabilising the exchange rate is optimal in terms of minimising the volatility of the considered target variables.

Table 2. Optimal Monetary Policy Parameters

Parameter	TFP Shock	AI Shock
ρ^i	0.949	0.988
ϕ^{π}	63.999	46.414
ϕ^y	2.290	18.453
ϕ^e	0.000	7.025

Source: Compiled by Authors

The intuition for this optimal policy path can be derived based on the impulse responses. We can observe that the response of consumer price inflation is more pronounced during a TFP shock, and the behaviour of domestic inflation largely drives

16. We consider values in the ranges of, $\rho^i \in (0,0.99)$, $\phi^{\pi} \in (1.01,200)$, $\phi^y \in (0,200)$ and $\phi^e \in (0,200)$.

this. However, during an AI labour productivity shock, domestic inflation is relatively muted, increasing the relative importance of imported inflation. Accordingly, when an AI labour productivity shock perturbs the economy, a relatively higher weight on stabilising the exchange rate is found to be welfare-optimal.

4. Concluding Remarks

In this paper, we examine the macroeconomic impact of AI via the possibility of AI improving labour productivity on an aggregate level. Our main focus is on how this channel can affect monetary policy in Sri Lanka. Accordingly, we employ a relatively standard small open economy DSGE model, broadly along the lines of Galí and Monacelli (2005), calibrated to the Sri Lankan economy. Contrary to many New Keynesian models used for monetary policy analyses, where production is traditionally captured via a Cobb-Douglas production function or assumed to be carried out only with labour, we consider a CES-type production function with capital and labour representing production activity at an aggregate level. This enables us to look into any impact due to changes in the elasticity of substitution between labour and capital.

We focus on studying the effects of a TFP and an AI-labour productivity shock. In a broad sense, the responses to both shocks are found to be qualitatively similar, as they both involve improving the productivity of the economy. However, the responses during a TFP shock are found to be relatively larger, since it affects the productivity of both capital and labour, whereas the AI labour productivity shock impacts the productivity of labour alone. We also note that the difference in policy responses during the two shocks broadly follows the overall differences in key macro variables like output and inflation. As a result, we can conclude that as long as monetary policy is broadly anchored on these aggregate variables, like in a FIT framework employed in Sri Lanka, the possibilities of policy mistakes due to incorrect disentangling of the two shocks remain minimal.

We also evaluate the differences in responses for two different elasticities of substitution, one representing an economy where capital and labour are substitutes, and the other where they are complements. During a TFP shock, the economy where capital and labour are substitutes is found to record an attenuated response in output and inflation, compared against the case where the factor inputs are complements. When there is a TFP shock, the productivity of both capital and labour increases. However, as capital is predetermined, its changes are sluggish, and therefore, firms end up utilising a lesser amount of labour. When substitutability is larger, the fall in labour is also larger, resulting in a lower output. Further, since the drop in hours is large, capital becomes relatively more valuable, so we see a relatively muted drop in rental rate of capital, resulting in a muted response of marginal cost, and in turn inflation. On the other hand, when there is a labour-augmented AI shock, labour becomes more valuable, and it can change freely. So, labour drops less when factors are substitutable, and leads to results that are opposite to those during the TFP shock. These observations suggest that there could be heterogeneous impacts on different firms that face different levels of substitutability of capital and labour.

We complement the analyses by evaluating optimal policies to minimise the volatility of inflation, output gap, exchange rate depreciation and policy rate changes. We find that, compared to a TFP shock, where a larger response to inflation is justified due to higher economic impact, in the presence of an AI labour productivity shock, a relatively larger sensitivity to the exchange rate is found to be optimal. This could be justified by the key observation that during AI labour productivity shocks, the response to inflation is relatively muted, releasing more policy space to stabilise the exchange rate.

The analyses undertaken in this paper provide an attempt at studying the macroeconomic impacts of AI adoption. Although only one possible transmission channel is studied in this model, there are many more channels through which macroeconomic impact can be created. Going forward, it is important to promote research related to these areas within the Central Bank.

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Appendix A

Dynamic Equations

$$\widehat{y}_t = s^L\,(\widehat{n}_t + \widehat{\chi}_t) + \widehat{a}_t + s^K\,\widehat{k}_{t-1}$$

$$\widehat{k}_{t-1} - \widehat{n}_t - \widehat{\chi}_t = \sigma\left(\widehat{w}^H_t - \widehat{\chi}_t - \widehat{R}^{k^H}_t\right)$$

$$\widehat{mc}_t = s^K\,\widehat{R}^{k^H}_t + s^L\left(\widehat{w}^H_t - \widehat{\chi}_t\right) - \widehat{a}_t$$

$$\widehat{w}^C_t = \gamma\,\widehat{c}_t + \widehat{n}_t\,\varphi$$

$$\widehat{\pi}^W_t = \beta\,\widehat{\pi}^W_{t+1} + \kappa_w\left(\gamma\,\widehat{c}_t + \widehat{n}_t\,\varphi + \alpha\,\widehat{s}_t - \widehat{w}^H_t\right)$$

$$\widehat{w}^H_t = \widehat{\pi}^W_t + \widehat{w}^H_{t-1} - \widehat{\pi}^H_t$$

$$\widehat{R/W}_t = \widehat{R}^{k^H}_t - \widehat{w}^H_t$$

$$\widehat{K/N}_t = \widehat{k}_{t-1} - \widehat{n}_t$$

$$\widehat{c}_t = \widehat{c}_{t+1} - \frac{1}{\gamma}\left(\widehat{i}_t - \widehat{\pi}^C_{t+1}\right)$$

$$\widehat{r}_t = \widehat{i}_t - \widehat{\pi}^C_{t+1}$$

$$\widehat{MPS}_t = \widehat{r}_t - \widehat{r}^n_t$$

$$\widehat{\pi}^H_t = \beta\,\widehat{\pi}^H_{t+1} + \widehat{mc}_t\,\kappa_p$$

$$\widehat{\pi}^C_t = \widehat{\pi}^H_t\,(1-\alpha) + \alpha\,\widehat{\pi}^M_t$$

$$\widehat{\pi}^M_t = \rho^{\pi^M}\,\widehat{\pi}^M_{t-1} + \left(1-\rho^{\pi^M}\right)\left(\left(1-\lambda^{\pi^M}\right)\left(\widehat{\Delta e}_t + \widehat{\pi}^*_t\right) + \widehat{\pi}^H_t\,\lambda^{\pi^M} - \psi_s\,\widehat{s}_{t-1}\right) + \varepsilon^{\pi^M}_t$$

$$\widehat{s}_t = \widehat{\pi}^M_t + \widehat{s}_{t-1} - \widehat{\pi}^H_t$$

$$\widehat{q}_t = \beta\left(\frac{1}{\beta} - (1-\delta)\right)\widehat{R}^{k^C}_{t+1} + \beta\,(1-\delta)\,\widehat{q}_{t+1} - \left(\widehat{i}_t - \widehat{\pi}^C_{t+1}\right)$$

$$\widehat{R}^{k^H}_t = \alpha\,\widehat{s}_t + \widehat{R}^{k^C}_t$$

$$\widehat{q}_t = \psi\left(\widehat{I}_t - \widehat{I}_{t-1}\right) - \beta\,\psi\left(\widehat{I}_{t+1} - \widehat{I}_t\right)$$

$$\widehat{k}_t = \delta\,\widehat{I}_t + (1-\delta)\,\widehat{k}_{t-1}$$

$$\widehat{y}_t = \widehat{c}_t\,\frac{C}{Y} + \widehat{I}_t\,\frac{I}{Y} + \frac{G}{Y}\,\widehat{g}_t + \frac{NX}{Y}\,\widehat{nx}_t$$

$$\widehat{i}_t = \widehat{i}^*_t + \lambda^{UIP}\,\widehat{\Delta e}_{t+1} + \widehat{\Delta e}_t\left(1-\lambda^{UIP}\right) + \widehat{\zeta}_t + \varepsilon^{UIP}_t$$

$$\widehat{\Delta e}_t = \widehat{e}_t - \widehat{e}_{t-1}$$

$$\widehat{i}_t = \rho^i\,\widehat{i}_{t-1} + (1-\rho^i)\left(\widehat{\pi}^C_{t+1}\,\phi^\pi + \phi^y\,\widehat{x}_t + \widehat{\Delta e}_{t+1}\,\phi^e\right) + \varepsilon^i_t$$

$$\widehat{\Delta i}_t = \widehat{i}_t - \widehat{i}_{t-1}$$

$$\widehat{a}_t = \rho^a\,\widehat{a}_{t-1} + \varepsilon^a_t$$

$$\widehat{\chi}_t = \rho^\chi\,\widehat{\chi}_{t-1} + \varepsilon^\chi_t$$

$$\widehat{g}_t = \rho^g\,\widehat{g}_{t-1} + \varepsilon^g_t$$

$$\widehat{i}^*_t = \rho^{i*}\,\widehat{i}^*_{t-1} + \varepsilon^{i*}_t$$

$$\widehat{\pi}^*_t = \rho^{\pi*}\,\widehat{\pi}^*_{t-1} + \varepsilon^{\pi*}_t$$

$$\widehat{nx}_t = \rho^{nx}\,\widehat{nx}_{t-1} + \varepsilon_t^{NX}$$

$$0 = s^K\,\widehat{R}_t^{k^n} + s^L\,(\widehat{w}_t^n - \widehat{\chi}_t) - \widehat{a}_t$$

$$\widehat{y}_t^n = s^L\,\left(\widehat{\chi}_t + \widehat{l}_t^n\right) + \widehat{a}_t + s^K\,k\_n_{t-1}$$

$$k\_n_{t-1} - \widehat{l}_t^n - \widehat{\chi}_t = \sigma\,\left(\widehat{w}_t^n - \widehat{R}_t^{k^n}\right)$$

$$\widehat{w}_t^n = \gamma\,\widehat{c}_t^n + \varphi\,\widehat{l}_t^n + \alpha\,\widehat{s}_t^n$$

$$\widehat{s}_t^n = \widehat{s}_{t-1}^n + piM\_n_t$$

$$piM\_n_t = {\varepsilon^{\pi^M}}_t + \rho^{\pi^M}\,piM\_n_{t-1} + \left(1 - \rho^{\pi^M}\right)\,\left(\left(1 - \lambda^{\pi^M}\right)\,(\widehat{\pi}_t^* + de\_n_t) - \psi_s\,\widehat{s}_{t-1}^n\right)$$

$$\widehat{r}_t^n = \gamma\,(\widehat{c}_{t+1}^n - \widehat{c}_t^n)$$

$$\widehat{x}_t = \widehat{y}_t - \widehat{y}_t^n$$

$$\widehat{y}_t^n = \frac{NX}{Y}\,\widehat{nx}_t + \frac{G}{Y}\,\widehat{g}_t + \frac{C}{Y}\,\widehat{c}_t^n + \frac{I}{Y}\,inv\_n_t$$

$$k\_n_t = \delta\,inv\_n_t + (1 - \delta)\,k\_n_{t-1}$$

$$\widehat{r}_t^n = {\varepsilon^{UIP}}_t + \widehat{\zeta}_t + \widehat{i}_t^* + \lambda^{UIP}\,de\_n_{t+1} + \left(1 - \lambda^{UIP}\right)\,de\_n_t$$

$$q\_n_t = \beta\,\left(\frac{1}{\beta} - (1 - \delta)\right)\,rC\_n_{t+1} + \beta\,(1 - \delta)\,q\_n_{t+1} - \widehat{r}_t^n$$

$$q\_n_t = \psi\,(inv\_n_t - inv\_n_{t-1}) - \beta\,\psi\,(inv\_n_{t+1} - inv\_n_t)$$

$$\widehat{R}_t^{k^n} = \alpha\,\widehat{s}_t^n + rC\_n_t$$

$$\widehat{\zeta}_t = \rho^{\zeta}\,\widehat{\zeta}_{t-1} + {\varepsilon^{\zeta}}_t$$

$$\widehat{\mathcal{E}\Delta e}_t = \widehat{\Delta e}_{t+1}$$

Endogenous Variables

Variable	Description
$\widehat{c}$	Consumption
$\widehat{y}$	GDP
$\widehat{k}$	Capital
$\widehat{n}$	Labour Hours
$\widehat{I}$	Investment
$\widehat{w}^H$	Real Wages Deflated by Domestic Price Level
$\widehat{R}^{k^H}$	Rental on Capital Deflated by Domestic Price Level
$\widehat{mc}$	Real Marginal Cost
$\widehat{\pi}^H$	Domestic Inflation
$\widehat{\pi}^C$	Consumer Inflation
$\widehat{\pi}^W$	Wage Inflation
$\widehat{R}^{k^C}$	Rental on Capital Deflated by Consumer Price Level
$\widehat{w}^C$	Real Wages Deflated by Consumer Price Level
$\widehat{s}$	Terms of Trade
$\widehat{\Delta e}$	Exchange Rate Depreciation
$\widehat{i}$	Policy Rate
$\widehat{nx}$	Net Exports
$\widehat{a}$	Total Factor Productivity
$\widehat{\chi}$	Labour Augmented AI Productivity
$\widehat{g}$	Government Expenditure
$\widehat{i}^*$	World Interest Rate
$\widehat{\pi}^*$	World Inflation
$\widehat{c}^n$	Consumption in the Flexible Price Economy
$\widehat{y}^n$	GDP in the Flexible Price Economy
$\widehat{l}^n$	Labour Hours in the Flexible Price Economy
$\widehat{w}^n$	Real Wages in the Flexible Price Economy
$\widehat{R}^{k^n}$	Rent on Capital in the Flexible Price Economy
$\widehat{s}^n$	Terms of Trade in the Flexible Price Economy
$\widehat{r}^n$	Real Neutral Rate
$\widehat{x}$	Output Gap
$\widehat{\pi}^M$	Imported Inflation
$\widehat{\zeta}$	Risk Premium
$\widehat{q}$	Tobin's Q
$\widehat{e}$	Exchange Rate
$\widehat{\Delta i}$	Change in Policy Rate
$\widehat{R/W}$	Rent to Wage Ratio
$\widehat{K/N}$	Capital to Labour Ratio
$\widehat{\mathcal{E}\Delta e}$	Expected Exchange Rate Depreciation
$\widehat{r}$	Ex-Ante Real Policy Rate
$\widehat{MPS}$	Monetary Policy Stance
k_n	Natural Level of Capital
inv_n	Natural Level of Investment
de_n	Natural Level of Exchange Rate Deprecation
q_n	Natural Level of Tobin's Q
piM_n	Natural Level of Imported Inflation
rC_n	Natural Level of Rental on Capital

Exogenous Variables

Variable	Description
ε^{a}	TFP Shock
ε^{X}	AI Shock
ε^{g}	Government Expenditure Shock
ε^{i*}	World Interest Rate Shock
$\varepsilon^{\pi*}$	World Inflation Shock
ε^{UIP}	UIP Shock
ε^{i}	Monetary Policy Shock
ε^{NX}	Net Exports Shock
$\varepsilon^{\pi^{M}}$	Imported Inflation Shock
ε^{ζ}	Risk Premium Shock

CHAPTER 4

THE SILVER SHIFT MEETS DIGITAL SURGE: DEMOGRAPHIC CHANGE AND AI IN MALAYSIA'S ECONOMIC LANDSCAPE[1]

Mikael Azwa, Akmal Zulkarnain, Christopher Ho Chun Wai, Zul-Fadzli Abu Bakar and **Helmi Ramlee**

1. Introduction

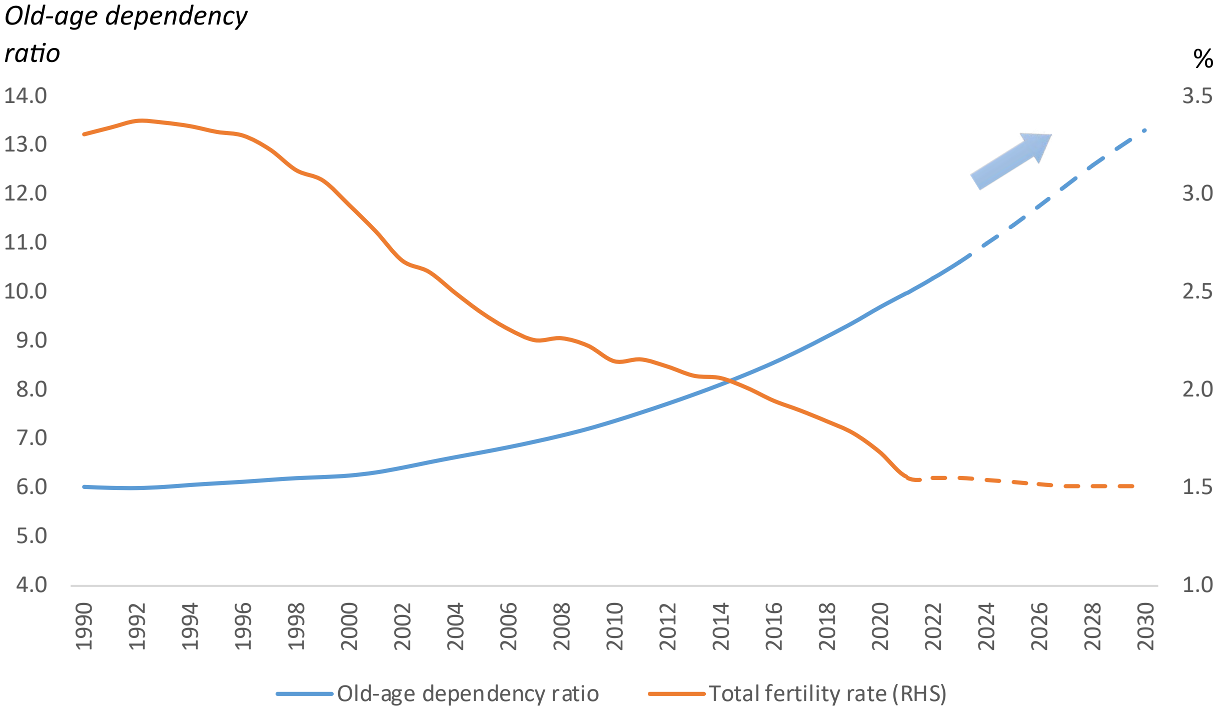
Malaysia, like many other upper-middle-income economies, is entering a critical phase of demographic transition. The country is experiencing population ageing at an increasing pace, marked by a rising old-age dependency ratio and a shrinking share of working-age population projected over the coming decades. Malaysia's old-age dependency ratio is expected to more than double by 2050 (World Bank, 2020), while fertility rates have fallen below replacement levels (Figure 1). This demographic shift occurs relatively rapidly as Malaysia is set to transition from an ageing to an aged society in 24 years (2020–2044), a pace comparable to that of Japan (23 years) and South Korea (17 years), and significantly faster than several other economies such as France (115 years) and the United States (69 years).

At the same time, rapid progress in artificial intelligence (AI) adoption is reshaping the global economic landscape. AI offers transformative potential for productivity gains, although it presents its own set of challenges. In Malaysia, several estimates suggest that generative AI has the potential to unlock up to USD113.4 billion in productive capacity, equivalent to nearly a quarter of the country's Gross Domestic Product (GDP) (Ng et al., 2023).[2] However, digital readiness remains uneven, with only 19% of Malaysians feeling adequately equipped with digital skills (PwC, 2021), leaving older workers particularly vulnerable to technological displacement. Ernst et al. (2019) highlighted that AI could disproportionately affect low-skilled workers, exacerbating inequalities in the process and necessitating substantial policy intervention.

1. The views expressed in this chapter represent those of the authors and do not represent the official views of Bank Negara Malaysia. We thank Raja Syamsul Anwar, Nooraihan Mohd Radzuan and Muhammad Iqbal Heru Wirasto for useful feedback and assistance. Corresponding author is Mikael Azwa (mikael.amir@bnm.gov.my).

2. This represents the value of gross output potentially produced by the resources freed up due to the productivity gains enabled from implementing generative AI. This estimate is based on ADB data on the economic structure of the Malaysian economy as of 2018. Source: MyDIGITAL & Microsoft (2023)

Figure 1: Malaysia's Actual and Projected Old-age Dependency Ratio vs Fertility Rate, Percentage



Note: Old-age dependency ratio is expressed as the number of dependents per 100 working age population.
Source: United Nations' World Population Prospects 2024 database.

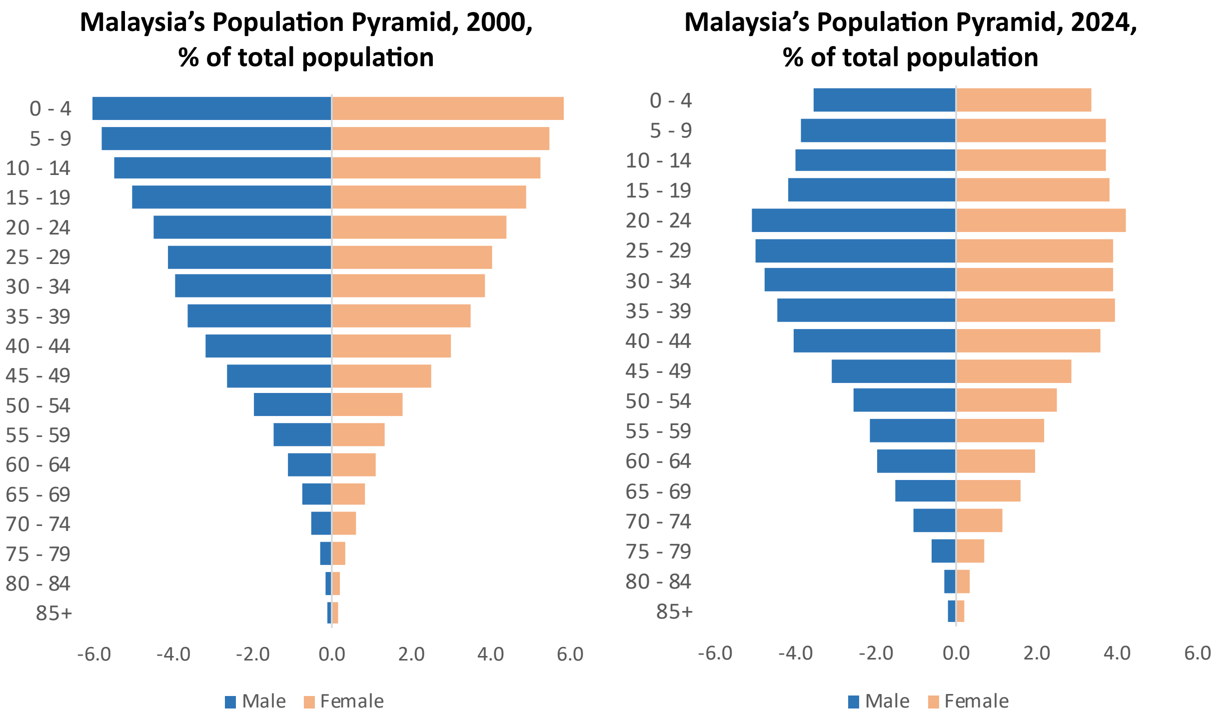
The confluence of demographic ageing and AI adoption presents two profound structural forces that could fundamentally reshape Malaysia's macroeconomic dynamics. While ageing is expected to reduce labour supply and weigh on potential output, successful AI adoption could counterbalance these effects (Acemoglu and Restrepo, 2017). Ascertaining the net impact on the economy is less straightforward, as it depends on the pace of technological adoption and the adaptability of the labour force.

For Malaysia, these insights are particularly relevant. The share of elderly population is projected to increase from 8.0% in 2025 to 14.5% by 2040 (DOSM, 2016 DOSM, 2025). Concurrently, Malaysia is advancing its digital transformation and automation agenda, raising questions about how these structural shifts will interact with demographic ageing to shape future growth trajectories. Ageing also poses fiscal sustainability challenges due to the lower coverage of the social protection system and the defined-benefit pension arrangements for civil servants.[3] While the Employees Provident Fund (EPF), a defined-contribution scheme, serves as the de-facto retirement savings mechanism for private-sector employees, coverage for employees in the informal sector remains

3. This assumes adequate and well-targeted coverage. Inadequate coverage today may underestimate future fiscal costs, as the government may be compelled to reactively expand support to address social vulnerability. This delayed expansion could lead to higher long-term fiscal costs. Evidence from low- and middle-income countries shows that countries with stronger pre-existing social protection systems were better able to respond to crises (World Bank, 2025).

relatively low, raising the risks of old-age poverty among informal sector employees. This in turn could result in higher fiscal liability for the government, which may need to extend social financial support to elderly individuals lacking sufficient retirement savings. The pressures on medium- to long-term fiscal sustainability are compounded by the government's need to address broader economic challenges of ageing, such as upskilling the workforce, redesigning lifelong learning systems, and enhancing healthcare infrastructure to meet the needs of an older population.

Figure 2: Population Pyramid of Malaysia in 2000 vs 2024, % of Total Population



Source: Department of Statistics, Malaysia (DOSM).

Against this backdrop, this paper examines the macroeconomic implications of population ageing and AI adoption in Malaysia using a multi-country, multi-sector dynamic general equilibrium setup (McKibbin and Wilcoxen, 1999), from the same family of models that has previously been used to simulate other structural shifts such as the economic implications of COVID-19 (McKibbin and Fernando, 2021), the reciprocal tariff scenarios (McKibbin et al., 2025) and climate change (Fernando et al., 2021). This paper makes four key contributions to the understanding of how demographic ageing and AI adoption jointly influence Malaysia's macroeconomic landscape:

1. **First, it develops a set of quantitative scenarios tailored to Malaysia**, simulating the macroeconomic implications of ageing, AI adoption, and their interactions.
2. **Second, it extends the analysis to fiscal sustainability** by incorporating age-related expenditure pressures and a sovereign risk premium shock, highlighting potential fiscal stress under demographic transition.

3. **Third, it investigates asymmetric global AI diffusion** through a "laggard adoption" scenario, wherein Malaysia's major trading partners experience AI-driven total factor productivity (TFP) gains while Malaysia does not – capturing relative competitiveness losses.
4. **Fourth, it translates the simulated outcomes into long-term monetary-policy implications**, focusing on the evolution of the natural rate of interest (r*) and the complementarity between monetary, structural, and fiscal policy responses.

The remainder of the paper is organised as follows: **Section 2** reviews the existing literature on the economic impact of demographic change and technological advancement, with a focus on their effects on productivity, labour markets, and monetary policy. **Section 3** outlines the modelling framework. **Section 4** presents the simulation results, **Section 5** discusses on policy implications, and **Section 6** concludes.

2. Literature Review

The negative impact of population ageing on output growth is well-documented. Lee and Shin (2019) and Park, Shin, and Kikkawa (2020) undertook a panel analysis, including Malaysia, and confirmed significant long-term negative implications on economic growth. However, the channels through which this negative impact occurs are less clearly established. In the United States, Maestas et al. (2023) found that the key drag arises primarily due to the decline in labour supply, with a secondary contribution from slower productivity growth. Aksoy et al. (2019), focusing on Organisation for Economic Co-operation and Development (OECD) countries, identified reduced investment and capital accumulation as key dampening contributors to long-term growth. The negative impact of ageing also materialised on the fiscal front, as the upward pressure on pension and healthcare expenditures constrains the space for productive public spending (Bodnar and Nerlich, 2022). Collectively, these studies highlight ageing as a structural headwind, operating through multiple, interrelated channels.

Another strand of research seeks to more critically assess the implications of ageing in the presence of behavioural responses. These studies challenge the assumption that ageing occurs without some form of adaptation from the population. Without accounting for these adaptations, the estimated impact of ageing would, in effect, undermine society's resilience and capacity to evolve. For example, Kotschy and Bloom (2023) and Bloom et al. (2013) emphasised that ageing typically spurs efforts towards greater female and elderly labour force participation, alongside policy reforms.

One such major adaptation is technological advancement and automation. For example, Acemoglu and Restrepo (2017) found that some countries exhibit a positive relationship between ageing and economic growth, which can be explained by their response to accelerate technological adoption in the face of an ageing population. Park, Shin, and Kikkawa (2020) found that higher life expectancy, when combined with a technology shock, allows the older workforce to contribute more positively to growth and prolongs their productive years well into their 50s and 60s.

Of importance to monetary policy is the interaction between ageing, AI and monetary policy through the natural rate of interest (r*). Bielecki et al. (2020) demonstrated that population ageing is a key factor behind the recent decline in the Euro Area's r*, primarily through the interplay between slowdown in productivity growth and shifts in savings and investment preferences. Given a fixed retirement age, persistently low birth rate leads to a shrinking population and labour force, which in turn dampens productivity growth. Sluggish productivity growth means that households expect a slower increase in their labour income, weakening their incentive to borrow for lifetime consumption smoothing and encouraging higher savings instead. At the same time, lower mortality rate extends the expected retirement period without labour income, prompting workers to save more during their working years.

These demographic shifts result in higher overall savings and put downwards pressures on the r*, which in turn raises the likelihood and duration of zero lower bound (ZLB) episodes, thereby reducing the effectiveness of monetary policy. Delayed incorporation of demographic effects into monetary policy decisions also contributes to a deflationary bias (Bielecki et al., 2020). The paper extends earlier insights by Eggertsson et al. (2019) and Gagnon et al. (2016), who associated demographic trends with the secular stagnation hypothesis[4], and by Kara and von Thadden (2016), who explored how population ageing may reduce the efficacy of standard monetary policy instruments.[5]

Lastly, direct studies of AI-monetary policy interaction are still limited, although some implications can be inferred from the broader macroeconomic consequences. Cerutti et al. (2025) projected that AI would spur inflationary pressures in the short term, as initial AI-related productivity gains raise aggregate demand through higher investment as well as stronger current and expected income growth, prompting modest monetary tightening. Over time, sustained TFP growth and capital accumulation expand supply capacity, exerting downward pressure on inflation that more than offset the earlier demand-driven inflationary pressures, leading to lower interest rates in the long-run. In contrast, Aldasoro et al. (2024b) found AI to be disinflationary in the shorter term and inflationary in the longer term, as the effects from stronger consumption and investment dominate over the longer horizon. This result captures the scenario where AI-related productivity shocks are not fully anticipated, due to uncertainties around its adoption,

4. Popularised by Summers (2014), the secular stagnation hypothesis posits that structural factors such as ageing population, weak productivity growth and high savings result in a lowered r*, making it more challenging for monetary policy to stimulate demand and for central banks to avoid prolonged periods near or at the zero lower bound (ZLB).

5. Additional work has emphasised how monetary transmission channels could weaken in ageing societies. For instance, Wong (2016) found that older households are less responsive to interest rate changes, diminishing the potency of the intertemporal substitution channel. Imam (2015), using dynamic panel estimation, asserted that the overall effectiveness of monetary policy declines with population ageing, except for the expectation and wealth channels, which remain operative. These findings imply that monetary policy may need to adapt to a structurally changing macroeconomic environment as population ageing becomes more entrenched.

practicality, and future trajectory. In the near term, this unanticipated productivity gains due to AI boost supply and lower costs, putting downward pressure on inflation. Over time, as the rise in income and demand overtake these gains, prices and wages increase. These disparities partly reflect the differences in behavioural responses to AI, such as whether the workforce can seamlessly adapt to rapid technological progress and whether economic agents fully anticipate future productivity gains.

3. Modelling Framework

This study employs the G-Cubed economic model to simulate various scenarios associated with demographic change and AI-adoption. The G-Cubed model, originally developed by McKibbin and Wilcoxen (1999, 2013), integrates features from both dynamic stochastic general equilibrium (DSGE) models and computable general equilibrium (CGE) models, offering a tool for analysing long-term macroeconomic dynamics. Further technical details may be found in McKibbin and Wilcoxen (1999, 2013), with partial explanations of some key features of the model relevant to our simulations included in **Annex A**.

For this study, we utilise the 6W version of the G-Cubed model, which encompasses 21 regions – covering most Southeast Asian economies – and six distinct sectors: energy, mining, agriculture, durable goods manufacturing, non-durable goods manufacturing, and services.[6] Each country features a dual household structure: one group comprises forward-looking agents who optimise consumption over time, while the other consists of liquidity-constrained, non-optimising households that base consumption decision on current income. Firms operate across sectors using a combination of primary inputs, namely, capital (*K*) and labour (*L*), alongside intermediate inputs such as energy (*E*) and materials (*M*). These inputs are sourced both domestically and internationally, creating interlinkages across economies and sectors.

The 6W model is first used to establish a baseline projection for Malaysia and global economies over the next decade, assuming no impact from demographic shocks or AI adoption. Subsequent simulations assess the impact of the two megatrends and their implications on Malaysia's nominal r* (proxied using simulated nominal policy rate), with results presented as deviations from the baseline scenario.

6. Malaysia, United States, Japan, Western Europe, Australia, South Korea, China, India, Indonesia, the Philippines, Vietnam, Thailand, Pakistan, Bangladesh, Sri Lanka, Other Asian Economies bloc, Latin America bloc, Rest of Africa bloc, Middle East and North Africa bloc, Other Advanced Economies bloc, and Rest of World bloc.

3.1 Modelling Scenarios

3.1.1 Modelling Population Ageing, AI-Adoption, and its Intersection

This study first investigates three core scenarios: (1) population ageing at a steady rate; (2) broad-based AI adoption, and (3) a combined scenario involving both ageing and AI adoption. The first scenario provides a reference projection of how an ageing population affects key macroeconomic variables. The second scenario assesses the effects of AI adoption, while the third explores the interaction between the two forces. This approach provides a lens through which to assess how these structural shifts may shape Malaysia's future economic trajectory and the implications for the conduct of monetary policy.

Table 1 presents the shock specifications. In the reference ageing scenario (Scenario 1), labour supply as a percentage of GDP is assumed to decline gradually starting in 2026, reaching a 3.0 percentage points deviation from the baseline by 2035. This reflects the slow and steady demographic trend of a shrinking working-age population.[7] A broad-based, gradual decline in labour efficiency across all sectors is also modelled, reaching a 0.5 percentage points deviation from the baseline in 2035. Concurrently, government transfers are assumed to rise gradually at a similar pace, reaching a 0.5 percentage points positive deviation from the baseline over the same period, capturing the anticipated expansion in social protection spending, for example, in the form of cash handouts. Overall public spending is assumed to increase immediately by 0.5 percentage points starting in 2026 to support funding developmental expenditures on public healthcare.[8] These include investments in health infrastructure – such as new hospitals and clinics – as well as digital health systems, in response to the growing elderly population and the corresponding increase in demand for public healthcare services. In addition to increased development expenditure, operating expenditure on healthcare is also expected to rise. While development spending may be financed through increased public debt issuance, particularly via Malaysian Government Securities (MGS), operating expenditure will need to be supported by higher revenue collections. To account for this, we model a gradual increase in government tax collection from 2026 onwards, to reach a 0.5 percentage points deviation from baseline in 2035.

7. Within the 6W G-Cubed modelling framework, this shock is transmitted to the entire system through multiple channels, including the wage equation. A decline in labour supply affects wage-setting dynamics, and changes income and consumption patterns. This in turn affects sectoral and household demand for labour, investment, wealth accumulation, and price dynamics – ultimately influencing real output and inflation dynamics.

8. These assumptions reflect the fiscal pressures typically associated with ageing societies and their implications for aggregate demand, public debt dynamics, revenue collection and taxes, and long-term fiscal sustainability.

The AI adoption (Scenario 2) introduces productivity shock through a gradual rise in TFP starting in 2026, resulting in a 2.0 percentage points positive deviation from the baseline in the services sector and a 1.5 percentage points deviation in the manufacturing sector by 2035. This asymmetric shock is based on the sectoral taxonomy of AI intensity (Calvino et al., 2024), which suggests that the services sector is more prone to early AI adoption.[9] Furthermore, labour efficiency in both manufacturing and services sectors is assumed to gradually improve by 0.5 percentage points over the same period, capturing AI's potential to augment worker productivity. To reflect the government's stance on digital transformation, particularly under the New Industrial Master Plan (NIMP) 2030, the model incorporates a 10 percentage points temporary increase in investment tax credits from 2026 to 2028.[10] Additionally, equity premium in the services sector is reduced permanently by 0.5 percentage points from 2026 onwards, representing improved investor confidence and reduced risk perception due to enhanced digital infrastructure and regulatory clarity.

The third scenario combines the shocks from the ageing and AI adoption scenarios to assess the net macroeconomic impact. The resulting effects on inflation, GDP growth, the natural rate of interest, and other macroeconomic indicators are analysed and discussed in Section 4.

Table 1: Reference Population Ageing and AI-adoption Scenarios

Scenario 1: Reference Population Ageing Scenario		
Shock	**Sector**	**Magnitude and pace**
Decline in labour supply	Broad-based (Across all six sectors)	Gradual decline to reach 3 percentage points *negative* deviation from baseline by 2035
Decline in "effective labour" (*labour-efficiency loss*)	Broad-based (Across all six sectors)	Gradual decline to reach 0.5 percentage points *negative* deviation from baseline by 2035

9. Services sector, especially knowledge-intensive areas such as finance, healthcare and IT, is more prone to early AI adoption due to abundant digital data, fewer physical infrastructure constraints, and easier integration with existing digital workflows. In contrast, manufacturing sector faces slower diffusion due to legacy systems and supply chain complexity.

10. The Malaysian government has introduced several digital transformation initiatives under the NIMP, including the rollout of high-speed broadband and full 4G coverage, alongside the staged expansion of 5G, through the National Digital Network (JENDELA). It has also provided financial support for SME digitalisation, such as grants and tax incentives under programmes like the "Industry4WRD Intervention Fund" to help firms adopt new digital technologies.

Increase in government transfers	N/A	Gradual increase to reach 0.5 percentage points *positive* deviation from baseline by 2035
Increase in overall government spending	N/A	Immediate increase to reach 0.5 percentage points *positive* deviation from baseline
Increase in government tax		Gradual increase to reach 0.5 percentage points *positive* deviation from baseline by 2035
Scenario 2: Reference AI-adoption Scenario		
Shock	**Sector**	**Magnitude and pace**
Increase in TFP (*capital- and labour-augmenting technological shock*)	Services	Gradual increase to reach 2.0 percentage points *positive* deviation from baseline by 2035
	Durable and non-durable manufacturing	Gradual increase to reach 1.5 percentage points *positive* deviation from baseline by 2035
Increase in "effective labour" (*labour-efficiency gain*)	Services	Gradual increase to reach 0.5 percentage points *positive* deviation from baseline by 2035
	Durable and non-durable manufacturing	Gradual increase to reach 0.5 percentage points *positive* deviation from baseline by 2035
Lower equity premium (*improved sentiments and outlook*)	Services	Immediate decline to reach 0.5 percentage points *negative* deviation from baseline
Increase in investment tax credits (*government incentive for AI-adoption investments*)	Durable and non-durable manufacturing, services	Temporary increase by 10 percentage points from 2026 to 2028
Scenario 3: Intersection Between Demographic Change and AI		
A combination of shocks from Scenarios 1 and 2		

Our chosen magnitude and pace of shocks across the scenarios draw on insights from previous studies that simulate productivity and demographic shocks and their impacts on the economy, such as Liu and McKibbin (2025) and McKibbin et al. (2011). We also leverage on broader observed trends in population ageing and the associated decline in labour force participation documented in the literature. The magnitude and pace of these shocks are then calibrated to reflect Malaysia's data, context, and policy environment.

3.1.2 Modelling Population Ageing and Its Impact on Fiscal Stress

To enrich the insights from the three core scenarios, this study introduces a fourth scenario that examines the macroeconomic implications of population ageing under conditions of fiscal stress. This scenario is motivated by the recognition that population ageing may place greater-than-expected pressure on public finances. In 2022, approximately 1.7 million individuals – roughly 10% of the national labour force – were employed in the public sector (DOSM, 2025; ILO, 2025). Under this stress scenario, the Malaysian government faces rising obligations under its defined-benefit pension scheme for civil servants, administered by the public pension fund, *Kumpulan Wang Persaraan* (*Diperbadankan*) (KWAP).[11] However, while the fund has grown to RM185.6 billion (~USD41.5 billion) by end-2024 (KWAP, 2025), the government's obligations for annual pension and gratuity payments have continued to rise steadily, placing increasing strain on the federal operating budget. Combined with rising public healthcare expenditures, these fiscal pressures are assumed to materialise in the absence of structural reforms or revenue-enhancing measures.

Building on the assumptions of Scenario 1, the fiscal stress scenario introduces several key departures (Table 2). First, government transfers are still assumed to be gradually increasing, similar to Scenario 1, but at a higher quantum – reaching a 3 percentage points deviation from baseline by 2035 – to reflect a more pronounced rise in age-related spending. Second, overall government expenditure is also projected to rise more sharply, reaching a 3 percentage points deviation from baseline over the same period, capturing broader fiscal commitments such as healthcare infrastructure, elderly care services, and administrative costs. Third, a surprise temporary premium shock of 1.5 percentage points is introduced from 2030 to 2035. This shock captures the possibility of a sudden, unanticipated increase in the risk premium, reflecting heightened concerns over fiscal sustainability.[12]

11. Established in 2007 with a seed fund of RM41.9 billion (USD12.7 billion), KWAP's mandate is to support the federal government in financing pension liabilities for public sector retirees.

12. This fourth scenario allows for a more comprehensive view of how fiscal vulnerabilities may amplify the economic consequences of ageing, and how these dynamics interact with monetary policy constraints in Malaysia.

Table 2: Population Ageing and Fiscal Stress Scenario

Scenario 4: Population Ageing and Fiscal Stress		
Shock	**Sector**	**Magnitude and pace**
Decline in labour supply	Broad-based (*across all sectors*)	Gradual decline to reach 3 percentage points *negative* deviation from baseline by 2035
Increase in government transfers	N/A	Gradual increase to reach 3 percentage points *positive* deviation from baseline by 2035
Increase in general public spending (*capturing higher development expenditure on public health*)	N/A	Immediate increase to reach 3 percentage points *positive* deviation from baseline by 2035
Increase in government tax collection	N/A	Gradual increase to reach 3 percentage points *positive* deviation from baseline by 2035
Surprise risk premium shock	N/A	Temporary shock by 1.5 percentage points from 2030 to 2035

3.1.3 Modelling Laggard AI-adoption effects to Malaysia

To complement the domestic-focused scenarios, this study introduces a fifth scenario that explores the implications of Malaysia lagging its key trading partners in adopting AI technologies. This multi-country scenario is particularly valuable in highlighting the importance of national readiness for AI adoption.[13] In this scenario, we examine the macroeconomic consequences of a global AI boom – led by major economies and Malaysia's key trading partners (United States, China, and the European Union) – while Malaysia remains a passive participant in this technological wave.

This scenario is modelled by introducing an increase in TFP across the United States, China, and the European Union to reach a 1.5 percentage points deviation in the manufacturing sector and a 2.0 percentage points deviation in the services sector by 2035, reflecting accelerated AI-driven productivity gains in these economies. In contrast, Malaysia's TFP remains unchanged over the same period. Given Malaysia's passive participation, there will be no public spending or tax incentives aimed at AI adoption. Additionally, the scenario incorporates a shift in import preferences in the US, China, and EU, where demand for electronics in these countries becomes increasingly

13. G-Cubed model has a built-in specification to simulate multi-country dynamics, allowing for the analysis of asymmetric technological shocks across economies.

domestically sourced or diverted to more productive exporting countries. Specifically, the import preference for electronics in these economies is adjusted to divert away from Malaysia's export market by 5% annually from 2026 to 2035, using the non-durable manufacturing sector as a proxy.[14] This scenario captures the possibility that countries adapt to a shifting trade and geopolitical landscape, where advanced economies are increasingly favouring domestic and technologically competitive suppliers over traditional low-cost production hubs.[15] While Malaysia has increasingly attracted foreign investments in Electrical & Electronics (E&E) and AI-related segments, our simulation captures the scenario where these investments are not sufficient to offset the competitive advantage of economies with faster AI adoption.[16] As a key assembly and packaging hub, Malaysia's E&E exports currently constitute a significant share of its net exports. A shift in global sourcing patterns away from Malaysian producers could have substantial implications for trade balances, industrial output, and employment in export-oriented sectors.

This scenario enables an assessment of the risks associated with limited domestic productivity gains and the erosion of external competitiveness.

Table 3: Lagged AI-adoption Scenario

Scenario 5: Lagged AI-adoption in Malaysia		
Shock	**Sector**	**Magnitude and pace**
Permanent TFP increases in the US, China, and EU	Services and manufacturing	Gradual increase to reach 3 percentage points *positive* deviation from baseline by 2035
Malaysia's TFP remains unchanged	N/A	N/A
Negative shock in import preferences for non-durables manufacturing exports from the US, China, and EU towards Malaysia	Non-durable manufacturing	Gradual decline to reach 3 percentage points *negative* deviation from baseline by 2035

14. This configuration is particularly relevant for Malaysia, given its deep integration into the global E&E value chain.

15. Recently, through ambitious initiatives like Made in China 2025, the Chinese Government aims to significantly expand domestic capabilities, particularly in sectors such as semiconductors, electric vehicles, and renewable energy. These policies actively encourage local sourcing, with the aim to reduce dependence on foreign suppliers (BCG, 2025).

16. In 2024, Malaysia attracted around RM170.4 billion (USD40.7 billion) strategic foreign investments, especially from the United States, Germany and China, into digital transformation and technology sub-sectors (MIDA, 2025).

4. Results

4.1 Scenario 1 – Population Ageing

Figures 3 and 4, respectively, present the key macroeconomic outcomes under the first two main simulations: (1) population ageing and (2) AI adoption, each considered independently.[17] A comprehensive set of results is available in Annex B. All figures illustrate deviations from baseline projections by the G-Cubed model. Figure 3 is organised into four panels, each corresponding to these indicators: CPI inflation and policy rate (proxy for nominal r*), real GDP (levels and growth), fiscal deficit, and the trade balance.[18] The panel configurations are as follows:

- The top-left panel captures the percentage point difference in CPI inflation compared to the baseline;
- The top-right panel displays the deviation in real GDP and GDP growth relative to the baseline;
- The bottom-left panel shows the percent change in the fiscal deficit, expressed as a share of baseline GDP; and
- The bottom-right panel illustrates the change in the trade balance – including both goods and services – as a percentage of baseline GDP.

Under scenario 1, the short-term impact of ageing is an increase in the labour premium. Firms compete for a smaller pool of labour, which drives upward pressure on wages. In the model, this wage pressure increases labour costs, contributing to higher CPI inflation in the near term. The rise in government spending exerts additional inflationary pressure, particularly in the first two years of the forecast horizon. Together, these forces result in a deviation of CPI inflation from the baseline by approximately 0.4 percentage points in the second year. The consideration of higher inflation outweighs the small negative output, as the central bank seeks to anchor inflation expectations, and consequently, the policy rate is adjusted upward during the period.

17. The two reference scenarios – with a third scenario that combines the impact from the first two – and two extensions outlined in Section 4 are derived after adjusting our model setup to reflect a range of plausible outcomes for Malaysia, given its current trajectory of population ageing and pace of AI adoption. A key point to note is that this paper represents one of the earliest attempts to explore the intersection of demographic ageing, AI adoption and monetary policy in the Malaysian context. As such, the results may diverge, at times quite significantly, from those produced by partial analyses conducted in previous studies.

18. The inclusion of trade balance dynamics underscores the importance of external linkages for a small open economy like Malaysia and highlights the implications of demographic shifts on the resilience of its external sector.

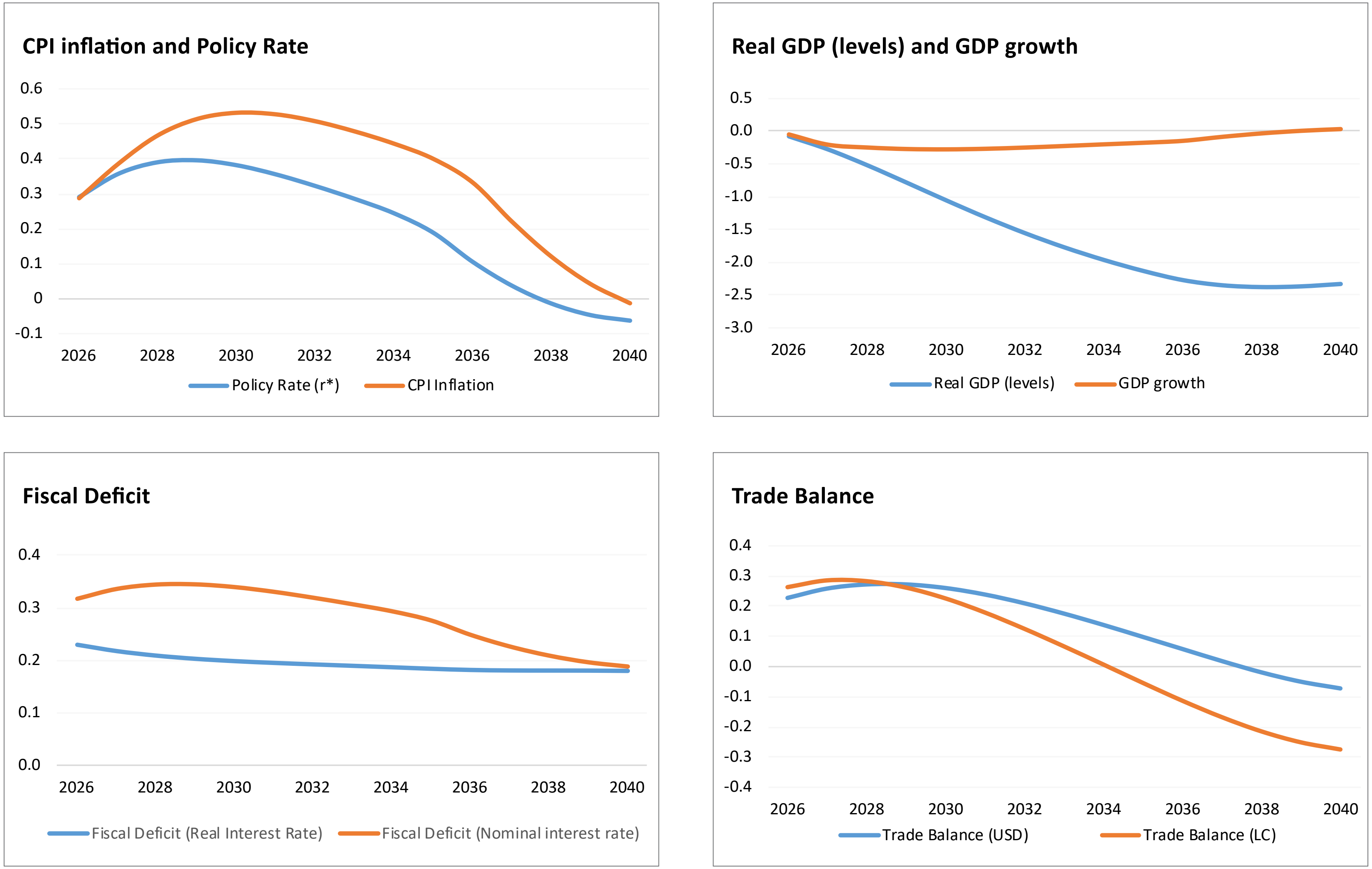
From year three onward, the sustained decline in labour supply begins to exert a more pronounced drag on overall productivity, which in turn weighs on real GDP. Real GDP gradually declines, reaching a trough of 2.8 percentage points below the baseline by 2038. This slowdown in output generates deflationary pressures, as reflected in the downward trend in CPI inflation during the same period. Disinflationary forces dominate over the medium to long term.

As disinflationary pressures intensify and real output continues to weaken, the policy rate is subsequently lowered, before reaching permanently negative deviations from baseline around the year 2038. Similar to findings documented in Papapetrou and Tsalaporta (2020), Bodnár and Nerlich (2022) and Eggertsson et al. (2019), population ageing tends to reduce long-term potential output, exert disinflationary pressures on the economy, and lower r*. Our model offers additional insight on the temporal dynamics of population ageing: in the short- term, ageing is inflationary; over the medium- to long-term, however, the depressing effects of declining productivity begin to dominate, leading to lower real output and sustained disinflationary pressures, which in turn drive down the policy rate and r*.

Another consequence of ageing is the permanently higher fiscal deficit, as illustrated in the bottom left-hand panel of our simulation results in Figure 3. The increased government spending on healthcare and pensions is projected to raise the fiscal deficit by approximately 0.3 percentage points of GDP relative to the baseline. Given the Federal Government's commitment to the deficit limits set by the Public Finance and Fiscal Responsibility Act of -3% of GDP, this projected increase in spending could be relatively manageable under a moderate pace of ageing. Nonetheless, under a more accelerated scenario, especially with no corresponding adjustment in the tax base, this could be a point of concern in the context of long-term fiscal sustainability, a case which will be covered in Scenario 3.

The trade balance initially improves, before deteriorating over the longer term. Initially, the slowdown in economic activity dampens import demand while export continues to be sustained. During this period, investment also declines more than national savings, leading to capital outflows and exchange rate depreciation, which improves trade balance in the near term. Over time, the effects from a smaller share of working-age population translate into reduced export productive capacity, leading to lower exports. Our simulation projects the trade balance to turn negative from 2030 onwards. Detailed charts on import and export dynamics are provided in Annex B.

Figure 3: Results for Malaysia under the Scenario 1: Population Ageing (deviation from baseline for each year)



Source: Authors' simulation results.

4.2 Scenario 2 – AI-adoption in Malaysia

In the short-term, the positive supply-side shocks due to the technological innovation lead to a reduction in production costs and an expansion in output. Producers benefit from higher productivity and lower marginal costs, which exert downward pressure on inflation. Inflation falls below baseline in the first two years of the forecast horizon, reaching a trough of approximately 1.1 percentage points below baseline by year four (Figure 4, top left panel).

Concurrently, the economy experiences a surge in output (Figure 4, top right panel), but inflationary pressures remain subdued due to the expansion in supply. Real GDP peaks around 2031 at 2.3 percentage points above baseline. Temporary government investment tax credits (2026-2028) and lower equity premiums further stimulate private sector investment, reinforcing supply expansion. This is broadly aligned with the more optimistic strand of the literature on AI and productivity, including Aghion and Bunel (2024). However, other contributions, such as Acemoglu (2024), offer a more cautious perspective, suggesting that macroeconomic gains from AI may be modest and unevenly distributed.

However, inflation begins to steadily normalise around baseline levels over the longer term. This reversal back to baseline is primarily due to the catch-up in aggregate demand. In response to higher incomes, improved investment and the stronger consumption, demand-driven effects gradually dominate in the longer term. This observation aligns with findings from Aldasoro et al. (2024a) and Aldasoro et al (2024b), especially if households and firms do not fully anticipate the economic gains from AI ahead of time, due to uncertainties around its adoption, practicality, and future trajectory. To a lesser extent, inflationary pressures also stem from the strength of imports that cause exchange rate depreciation pressures and in turn increases imported inflation, although this factor would later dissipate given recovery in trade balance.[19]

19. BNM's (2022) Economic and Monetary Review, where a 5% appreciation in the USD/MYR exchange rate is associated with a 0.2 percentage points reduction in core CPI inflation over a one-year horizon. The full evolution of NEER may be found in Annex B. While BNM's (2022) analysis is limited to the bilateral USD/MYR exchange rate, the same conclusion can be reasonably extended *in qualitative terms* to the Nominal Effective Exchange Rate (NEER). This is because the USD/MYR pair tends to move in close alignment with Malaysia's NEER over the medium term, given the significant weight of the USD in Malaysia's trade and financial transactions.

The trade balance initially deteriorates as a surge in investment drives a sharp increase in imports, while higher returns on capital attract foreign inflows that appreciate the currency, further weighing on the trade balance (Figure 4, bottom left-hand panel). As consumers of capital goods, Malaysian industry players are reliant on imports of machinery and equipment to realise their investments.[20] For example, in recent years, investments surged due to multinational technology firms[21] establishing large-scale data centre facilities in Malaysia as part of global AI adoption, with Malaysia being a key regional hub.[22] As predicted by the model, there has been a sharp increase in capital goods imports during this period, particularly machinery and equipment (M&E), with import levels being the highest in recent years (DOSM, 2025). The simulation nonetheless indicates that over the longer horizon, the increase in productive capacity and improved price competitiveness eventually lead to exports outpacing imports, thereby improving the trade balance.[23]

The policy rate responds accordingly, reverting to baseline after the initial decline, in tandem with rising inflation to maintain price stability. Over the long-term, r* trends back to baseline forecasted levels. Despite the reversion in policy rate, real GDP remains above baseline throughout the simulation horizon.

4.3 Scenario 3 – Intersection between Demographic Shifts and AI

A combined simulation of the D2 and D3 scenarios is conducted to examine the interaction between demographic headwinds and technological advancement in Malaysia. Figure 5 outlines selected results from this simulation, focusing on CPI inflation (top left-hand panel), real GDP (top right-hand panel), and the policy rate (proxy for nominal r*) (bottom panel).

Consistent with the findings of Acemoglu and Restrepo (2017), our results suggest that AI adoption can partially offset the medium- to long-term disinflationary effects associated with population ageing. In the top left-hand panel, the inflation trend stabilises higher relative to the ageing-only scenario. Moreover, AI adoption cushions the medium- to long-term drag on growth caused by a shrinking labour supply and declining productivity. This also echoes the findings of Park, Shin, and Kikkawa (2020), who argue that productivity gains from technological shocks can sustain output growth even as the contribution of labour diminishes near statutory retirement ages.

20. Particularly from the United States and the European Union.

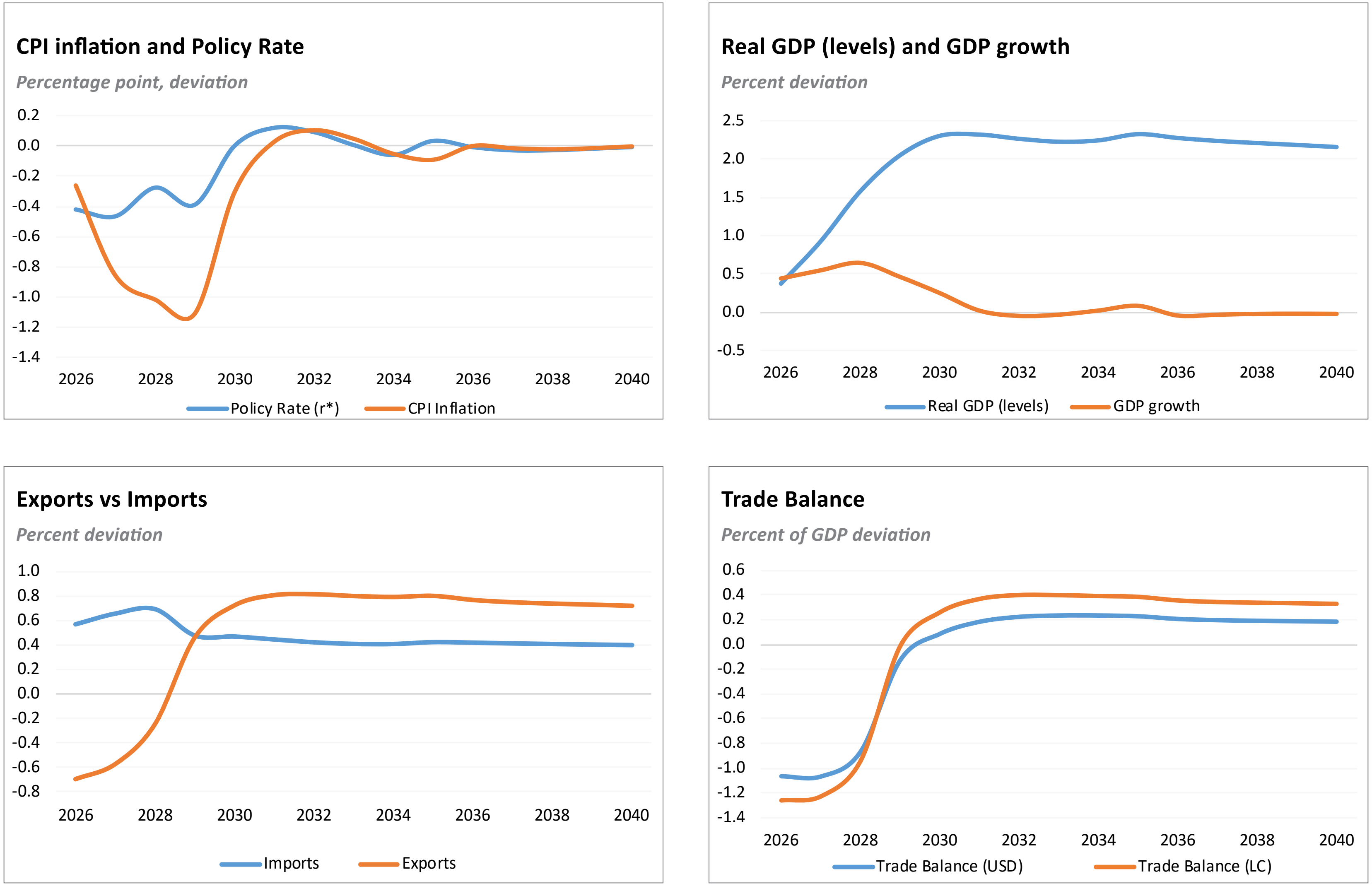
21. Including NVIDIA, ByteDance, Amazon, Microsoft, and others.

22. Notably, Amazon Web Services has committed approximately USD6.2 billion (≈ RM29 billion) to develop its Asia Pacific (Malaysia) Region by 2038, while Google has announced a USD2 billion (≈ RM9.4 billion) investment to establish its first data centre and cloud region in Greater Kuala Lumpur.

23. This is consistent with Jakubik et al. (2025), who found a significant positive correlation between AI adoption and trade performance. For a small, open economy like Malaysia, which is deeply integrated into global trade networks, this trend could bode well for long-term external sector resilience.

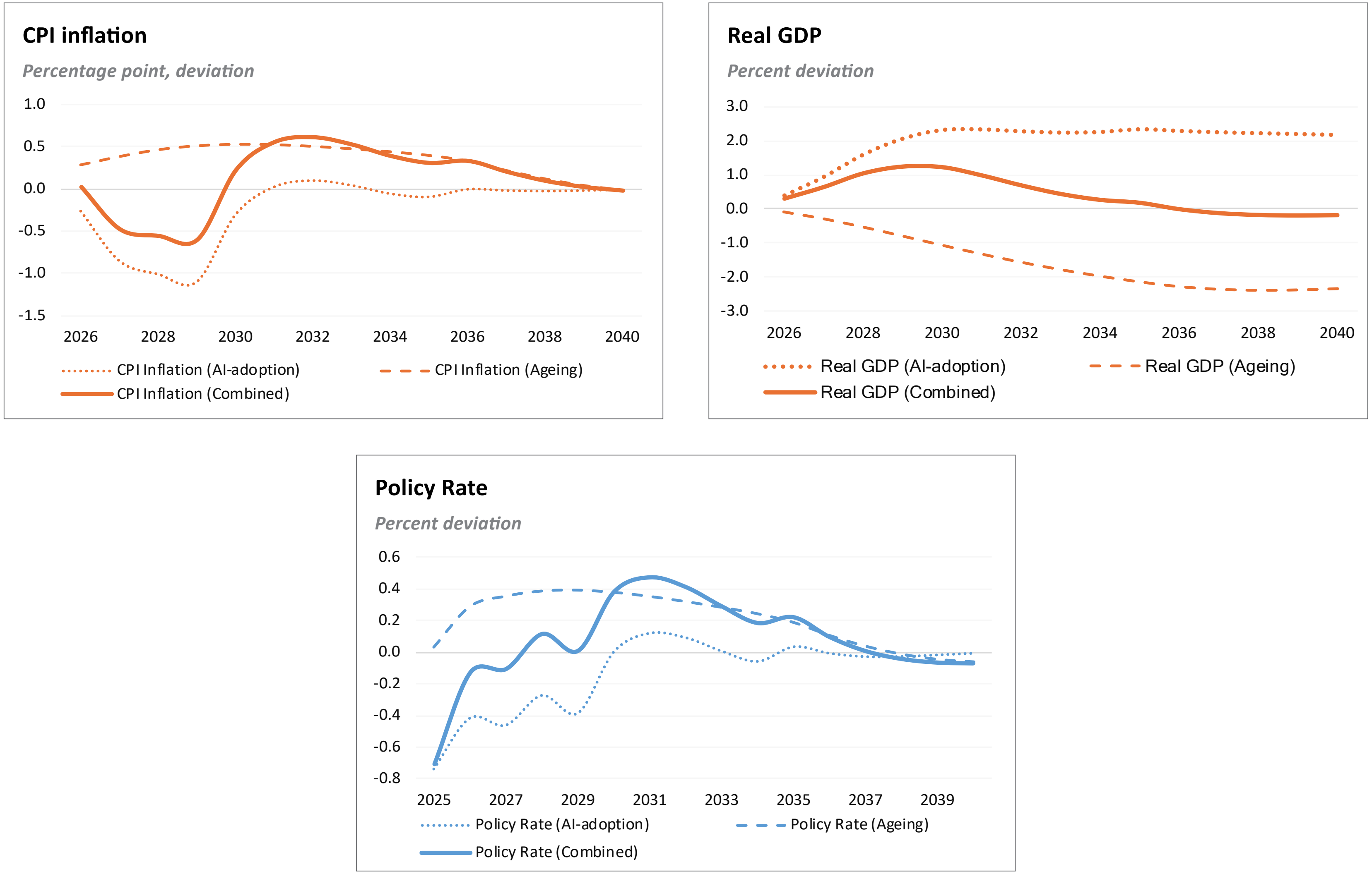
In our simulation setup, the productivity gains from AI adoption eventually more than offset the losses from ageing, which leads r^* to trend higher than baseline in the medium-term. In part, this is due to our assumptions of policy support to accelerate AI adoption through tax credit incentives. More generally, Cerutti et al. (2025), Kearney and EDBI (2020) and the McKinsey Global Institute (2018) emphasise that the mitigating impact of AI on demographic challenges crucially depends on the successful implementation of policies that promote broad technological diffusion. It is worthwhile to note that in Malaysia's case, AI readiness is improving but uneven. While large-scale AI investments have been announced, firm-level adoption and talent constraints remain significant barriers (Cisco, 2024; Oxford Insights, 2024).

Figure 4: Results for Malaysia under Scenario 2: AI-adoption (deviation from baseline for each year)



Source: Authors' simulation results.

Figure 5: Results for Malaysia under the Three Scenarios
(deviation from baseline for each year)



Source: Authors' simulation results.

4.4 Extension: Scenario 4 – Demographic Shifts with Additional Fiscal Stress

As an extension of Scenario 1, we introduce a new simulation in which Malaysia experiences population ageing under conditions of fiscal stress. Similar to the earlier scenario, ageing population leads to a contraction in labour supply. However, this new scenario adds two critical elements: (1) a significant increase in government health spending given greater-than-expected outlays and the absence of tax adjustment to cover the increased spending; and (2) the emergence of a surprise country risk premium relative to the US.

The higher health spending reflects a policy decision by the Malaysian government to accommodate old-age care, including generous cash transfers and a substantially expanded healthcare budget. Meanwhile, the country risk premium arises later in the simulation as a surprise shock, capturing a sudden shift in investor sentiment as investors begin to perceive heightened solvency risks. These concerns stem from the growing public debt and widening fiscal deficit, both direct consequences of the government's expanded fiscal commitments.

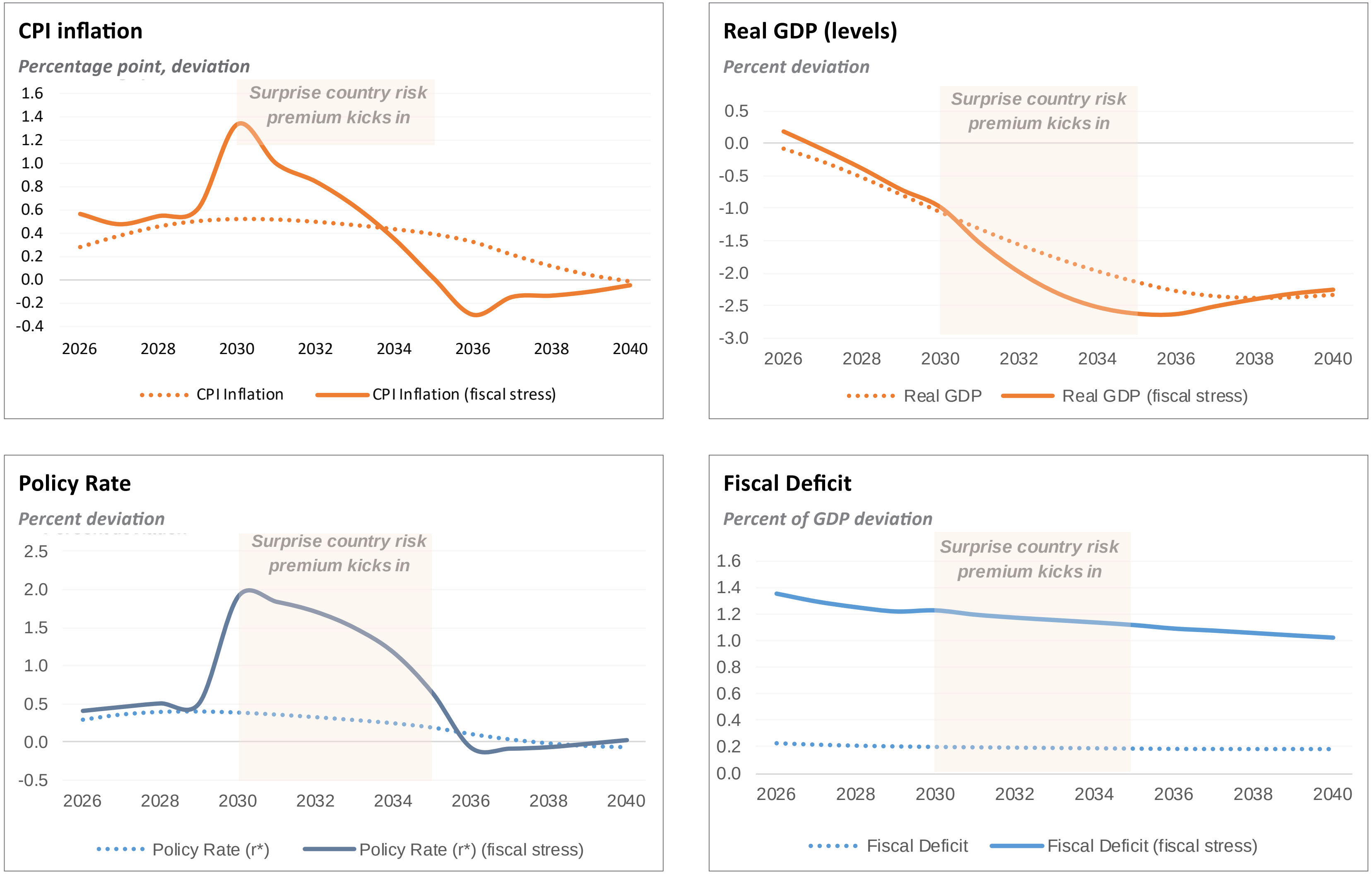
Figure 6 presents the outcomes of the fiscal stress scenario. For comparison, solid lines represent outcomes of Scenario 4 (with stress) and dashed lines depict Scenario 1 (without stress). In the initial period, the combination of ageing and fiscal expansion generates mixed macroeconomic outcomes. The contraction in labour supply reduces productive capacity, exerting upward pressure on inflation. At the same time, increased government spending on healthcare and old-age support temporarily supports aggregate demand. As a result, CPI inflation rises, peaking around 2026 (Figure 6, top-left panel), while real GDP increases transitorily before the effects of supply constraints begin to dominate and it enters a period of sustained decline (top-right panel). The central bank responds with a tightening of monetary policy, raising the policy rate more aggressively than in Scenario 1 (bottom-left panel), given the sharp increase in inflation and heightened concerns about inflation expectations, even as output begins to weaken.

Over the medium-term, the economic activity weakens further. The introduction of a surprise country risk premium in 2030, driven by persistent deficits and rising public debt, leads to higher borrowing costs and exchange rate depreciation. These exchange rate pressures temporarily amplify inflation beyond its already elevated level, prompting another upward adjustment in the policy rate.

The inflationary pressure from the external stress, however, is short-lived. As the economy continues to contract, the structural drag from a shrinking labour force and broad weaknesses in the economy bring inflation lower, eventually turning disinflationary.

Of note, the fiscal deficit in Scenario 4 remains permanently higher than in Scenario 1 (Figure 6, bottom-right panel), reflecting sustained government spending and weaker revenue performance due to declining output. Meanwhile, nominal r* continues its declining trend before stabilising to baseline by the end of the simulation horizon.

Figure 6: Extension: Population Ageing under Conditions of Fiscal Stress (deviation from baseline for each year)



Source: Authors' simulation results.

4.5 Extension: Scenario 5 – Lagging Adoption of AI

In the final scenario, we investigate the implications of Malaysia being a passive participant in the global wave of technological adoption. Specifically, we simulate a case where China, the Euro area, and the United States reap the benefits of productivity growth stemming from AI adoption, while Malaysia does not. These countries, having enhanced their productive capacities, divert their supply of E&E away from Malaysia's export markets, either toward domestically sourced inputs in a re-shoring effort or toward other more productive exporting countries. While we could incorporate the impact of ageing, we exclude it here to better isolate the effects of loss of competitiveness.

In the immediate aftermath, inflation rises (Figure 7, top left panel), driven by a sharp depreciation in Malaysia's exchange rate (Figure 7, top right panel). As major trading partners reallocate supply chains and reduce imports from Malaysia, combined with higher returns on capital abroad and sustained capital outflows, the ringgit depreciates. The central bank responds by raising the policy rate to anchor inflation expectations, despite the concurrent slowdown in economic activity. Investment contracts by approximately 0.8 percentage points from baseline, reflecting lower expected returns due to both the productivity disadvantage and weakened external demand. Consumption declines by 0.4 percentage points, consistent with softening labour market conditions. This leads to a decline in real GDP, reaching a trough of -0.4 percentage points deviation from baseline in 2028 (Figure 7, bottom panel).

The trade balance temporarily improves, as the drop in imports outpaces the decline in exports (Figure 7, bottom left panel). This initial gain, however, masks deeper weaknesses in economic activity. Over the longer horizon, the trade balance deteriorates as the reduction in exports eventually overtakes the decline in imports. The trade balance remains lower from baseline at the end of simulation period, reflecting Malaysia's diminished role in global supply chains.[24]

Nonetheless, unlike the ageing scenario, where economic activity remains persistently subdued, domestic economic activity, particularly investment, begins to recover after around 2030. This turnaround reflects several intertemporal dynamics. First, there is reallocation towards non-tradable and internally driven sectors, partially offsetting these external shocks. Second, price and wage adjustments improve marginal costs and competitiveness over time. Third, capital adjustment mechanisms (e.g.,

24. Over the long-run and beyond the simulation period, spillovers from productivity gains from the rest of the world can eventually spill over into higher demand for Malaysian exports, given the combination of households' constant elasticity of substitution (CES) utility functions in all countries and Armington elasticities in trade.

Tobin's Q) gradually restore investment as the marginal value of capital stabilises.[25] As the economy recovers through price and wage adjustments and resource reallocation, Tobin's Q gradually recovers, prompting a rebound in investment.[26]

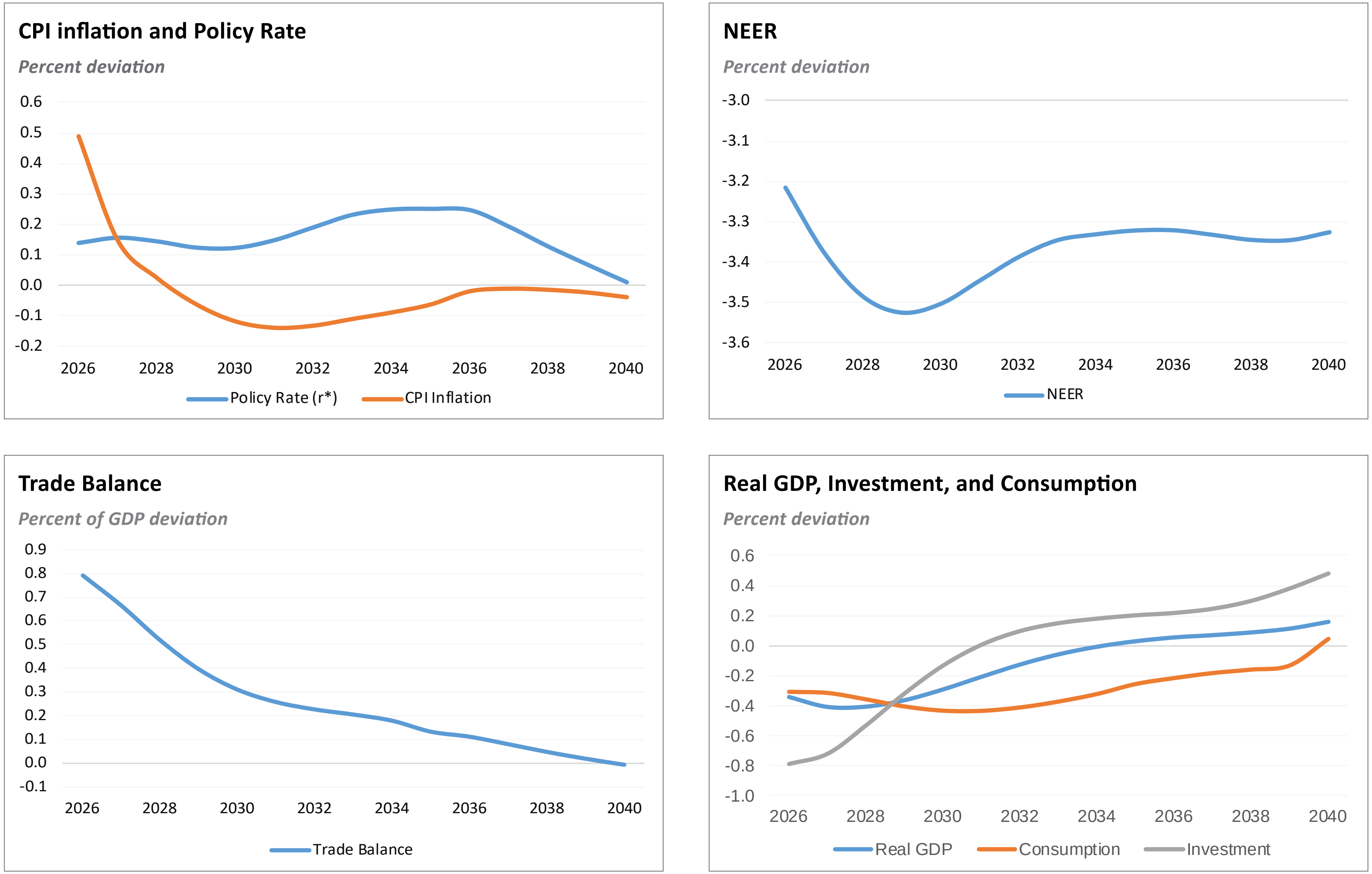
Thus, while Malaysia's initial lag in AI adoption results in short-run contractionary effects, the impact is, unlike that of ageing, less permanent. Structural rebalancing allows investment to eventually recover. Such rebalancing is less feasible under ageing due to constraints from domestic resources, unless policies are introduced to expand the labour supply (e.g., immigration policy). Importantly, underlying this economic recovery is the assumption that the economy is able to seamlessly reallocate resources into domestic sectors.

Inflationary pressures begin to subside after the initial increase, following the slowing of domestic demand which dampens aggregate price pressures. Over time, as economic activity gradually recovers towards baseline and inflation stabilises, policy rate converges closer to its pre-shock level. Notably, nominal r*, after the temporary disturbances, appears to be relatively unchanged.

25. One key mechanism is the capital adjustment process governed by Tobin's Q, which measures the ratio of the market value of capital to its replacement cost. When Tobin's Q is above unity, it signals that the return on new investment exceeds its cost, incentivising firms to invest. Initially, the lag in AI adoption depresses profitability, lowering Q and discouraging investment. However, as the economy adjusts, through price and wage flexibility, and reallocation of resources, Tobin's Q gradually recovers, prompting a rebound in investment.

26. As highlighted in footnote 24, beyond the simulation horizon, productivity spillovers from the rest of the world can also eventually support domestic economy recovery through greater demand for Malaysian exports.

Figure 7: Extension: Lagged AI-adoption for Malaysia (deviation from baseline for each year)



Source: Authors' simulation results.

5. Policy Implications

The results of this study highlight the need for a coordinated and forward-looking policy approach to address the structural challenges posed by demographic ageing and the opportunities presented by AI adoption. Rising healthcare and pension expenditures are expected to lead to sustained fiscal deficits. If left unaddressed, elevated sovereign risk due to concerns over fiscal sustainability is a plausible outcome that can exaggerate the macroeconomic risks from ageing. This underscores the urgency of structural reforms, some of which include the broadening of tax base, upsizing of age-related spending, and reforming public pension schemes to ensure long-term fiscal sustainability. The strengthening of automatic stabilisers could be a step towards improving fiscal discipline and responsiveness to demographic shifts.

From a monetary policy perspective, the decline in r* associated with ageing increases the risk of zero lower bound episodes and possibility of secular stagnation. This may warrant the incorporation of unconventional tools to preserve future monetary stability. Of importance is the role of AI as a remedy that can mitigate or even offset the dampening impact of ageing. Its benefits are contingent on inclusive diffusion. Malaysia's digital readiness remains uneven, particularly among older workers and small and medium enterprises. Prioritising investments in digital infrastructure, workforce reskilling, and targeted support could help facilitate a broad diffusion of AI-led productivity gains.

Malaysia's integration into global value chains exposes it to vulnerabilities stemming from shifts in global sourcing preferences. A delayed adoption of AI scenario underscores the risks of technological inertia, potentially leading to diminished export competitiveness and a worsening trade balance. To mitigate external shocks and sustain economic resilience, Malaysia should focus on promoting technology-driven exports and investing in high-value digital sectors. Enhancing innovation and productivity, particularly in export-oriented industries, will be key to maintaining competitiveness. Additionally, diversifying the trade base can reduce overreliance on specific markets or sectors, thereby strengthening the country's ability to navigate global disruptions.

Finally, the ability to reallocate resources across sectors can prepare the country to adapt to these impending structural shifts. Labour policies would ideally be geared towards promoting continuous learning among the workforce, and intersectoral labour mobility. Immigration policy may eventually assume a pivotal role in expanding labour supply and alleviating demographic constraints. In this regard, developing a well-calibrated immigration framework, such as one oriented towards skills-based selection and the streamlining of foreign worker integration processes may become increasingly necessary.

6. Conclusion

This paper examines the macroeconomic implications of demographic ageing and AI adoption in Malaysia using a multi-country, multi-sector dynamic general equilibrium framework. The findings reveal that demographic ageing, in isolation, exerts short-term inflationary pressures due to wage competition and fiscal expansion, but leads to long-term disinflation and output decline. These dynamics lower the natural rate of interest and increase the risk of zero lower bound episodes, posing challenges for conventional monetary policy.

In contrast, AI adoption generates short-term disinflation through productivity gains and long-term growth via stronger investment and consumption. This raises the natural rate of interest. When considered jointly, AI adoption can partially offset the adverse effects of ageing, but the net impact depends on the pace of technological diffusion, the adaptability of the labour market, and the presence of supportive policy measures.

The fiscal stress scenario demonstrates that ageing-related expenditures, if not accompanied by revenue-enhancing reforms, can amplify macroeconomic vulnerabilities. Higher sovereign risk premia, imported inflation, and capital outflows compound the challenges, underscoring the importance of prudent fiscal management. Meanwhile, the laggard AI adoption scenario shows that technological passivity results in temporary contraction due to competitiveness losses. However, structural rebalancing enables eventual recovery, albeit less robust than in proactive adoption scenarios.

Overall, the twin transitions of demographic ageing and AI adoption are not merely additive shocks but interact in complex ways that reshape Malaysia's macroeconomic landscape. Addressing these structural shifts requires an integrated approach that combines monetary, fiscal, and structural strategies to harness the benefits of AI while mitigating the risks of demographic ageing. The success of this transition will depend on Malaysia's ability to adapt its institutions, upgrade its workforce, and sustain inclusive growth in an era of profound structural change.

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Annex A: G-Cubed 6W Model[27]

The G-Cubed model is a multi-country, multi-sector, intertemporal general equilibrium model that integrates features of econometric general equilibrium modelling, international trade theory, and modern macroeconomics. It is designed to capture both short-run macroeconomic dynamics and long-run structural adjustments in response to policy changes and external shocks. This family of models has been used extensively to estimate the impact of various environmental and economic shocks and policies (see McKibbin and Wilcoxen, 2023; McKibbin et al., 2021; and McKibbin et al., 2018).

This study employs the 6W version of the G-Cubed model, which includes 21 regions and six sectors:

- **Sectors:** Energy, mining, agriculture, durable goods manufacturing, non-durable goods manufacturing, and services.
- **Regions:** Malaysia, United States, Japan, Western Europe, Australia, South Korea, China, India, Indonesia, the Philippines, Vietnam, Thailand, Pakistan, Bangladesh, Sri Lanka, Other Asian Economies bloc, Latin America bloc, Rest of Africa bloc, Middle East and North Africa bloc, Other Advanced Economies bloc, and Rest of World bloc.

A.1 Model Structure

Drawing on the general equilibrium literature, each of the 21 regions in the 6W G-Cubed is modelled as its own 6-sector econometric general equilibrium model.
Each region in the model includes:

- Two types of households:
  - Forward-looking households that maximise intertemporal utility subject to a lifetime budget constraint.
  - Liquidity-constrained households that consume their current after-tax income in each period.
- Firms that operate in six different sectors and choose inputs to minimise costs subject to a nested CES production function.
  - Inputs include capital (K), labour (L), energy (E), and materials (M), with intermediate goods sourced both domestically and internationally.
  - Trade is modelled using the Armington assumption, where goods are differentiated by country of origin.

27. This section is largely reproduced from McKibbin, W. J., and Wilcoxen, P. J. (2013). A global approach to energy and the environment: The G-cubed model. in Handbook of Computable General Equilibrium Modelling (Vol. 1, pp. 995-1068). For more details on the documentation of the G-Cubed family of models, please refer to G-Cubed models | G-Cubed

- Stocks and flows of both physical and financial assets are tracked both within and cross-countries. For instance, budget deficits in the model setup accumulate into government debt, while current account deficits build up as external liabilities or foreign debt.

- Government and monetary authorities, which follow fiscal and monetary rules.
    - Governments in each region collect tax revenues and undertake expenditures. The difference between these flows results in either a fiscal surplus or deficit, which in turn accumulates into the region's stock of government debt.
    - Monetary policy follows a Henderson-McKibbin Taylor rule, where the nominal interest rate can be modelled to respond to not only deviations of inflation and output from target levels, but also other policy deviations.

The share of forward-looking versus liquidity-constrained households is calibrated based on empirical estimates. Capital accumulation is determined endogenously while labour supply is influenced by demographic trends. The elasticity of substitution between inputs varies by sector and is drawn from empirical literature and previous G-Cubed calibrations. Meanwhile, nominal rigidities are introduced through adjustment costs in wages and prices, which slow the response of the economy to shocks.

A.2 Monetary Policy Rule

Monetary policy in the model follows a forward-looking Taylor rule (the *Henderson-McKibbin Taylor Rule*) of the form:

$$i_t = \beta_1 i_{t-1} + \beta_2(ER_t^e - ER_{t-1}^e - ER_t^*) + \beta_3(\pi_t - \pi_t^*) + \beta_4(w_t - w_t^*) + \beta_5(y_t - y_t^*)$$

where ER_t is the exchange rate as USD per unit of local currency, π_t is the CPI inflation rate, w_t is the aggregate wage rate, and y_t is the aggregate output. Asterisks (*) represents the policy target set by the central bank, while the β_i parameters govern the responsiveness of monetary policy to inflation, output gaps, and exchange rate deviations respectively. This rule allows the model to generate an endogenous path for the nominal policy rate, which is used in this study as a proxy for Malaysia's natural rate of interest (r*).

A.3 Demographic and Technological Shocks

In this study, demographic changes are introduced through adjustments to the effective labour supply growth rate and the growth in labour productivity. G-Cubed uses a catch-up framework to generate labour productivity growth rates, assuming that the US is the world frontier in productivity across most sectors.[28] For all other economies in the model, sectoral productivity projections gradually converge towards the worldwide productivity frontier, closing the productivity gap by 2% per year[29] (Bertram et al., 2022). Deviations from these baseline settings are then used to simulate demographic shocks.

AI adoption is modelled as a sector-specific TFP shock, primarily affecting the services and manufacturing sectors. The magnitude and timing of the shock are calibrated based on external estimates of AI diffusion and productivity impacts.

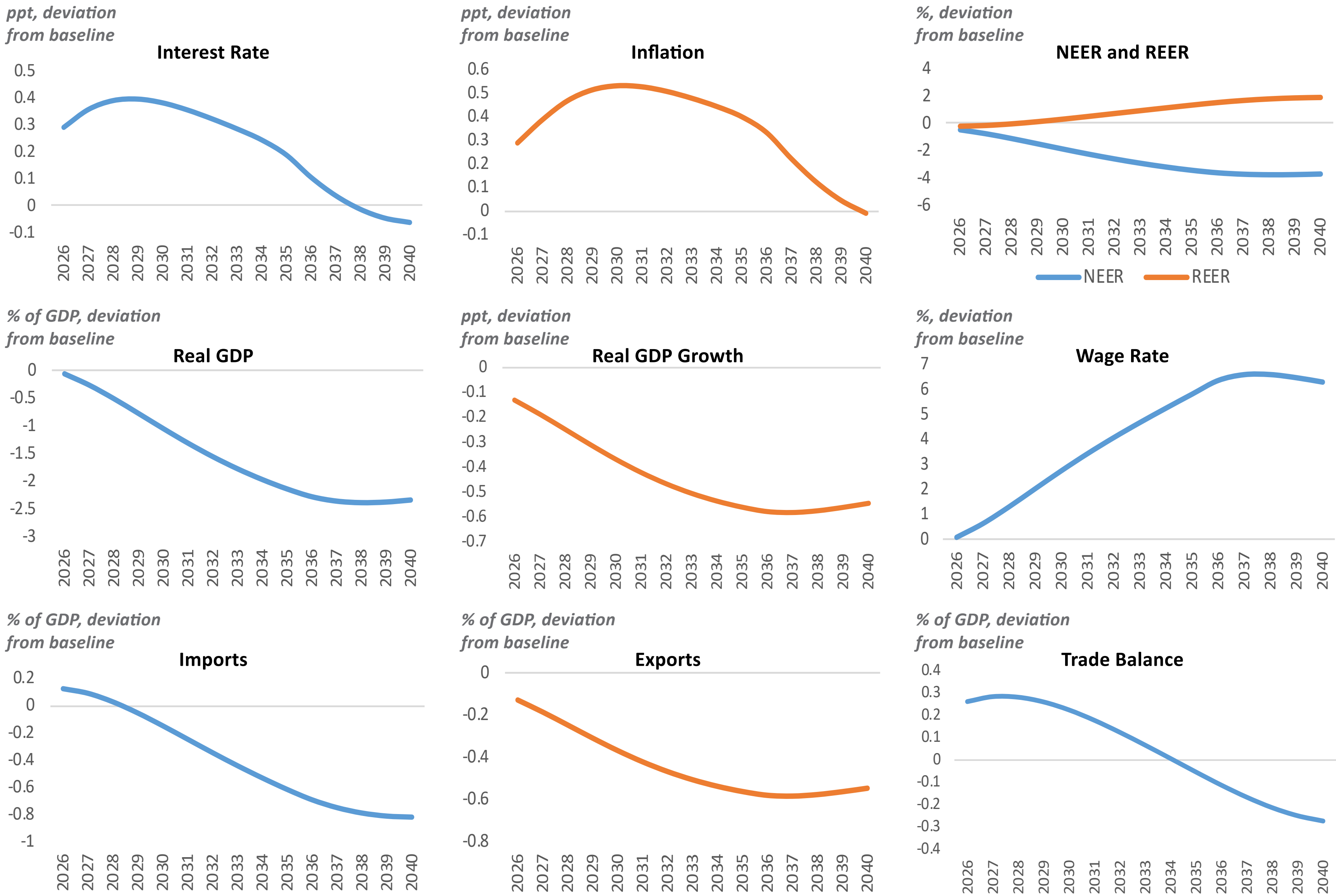
The model is calibrated using national accounts data, input-output tables, and international trade data. Behavioural parameters are drawn from the literature and previous G-Cubed applications. The model is solved using a recursive algorithm that iterates on expectations until a stable manifold is achieved.

28. There is an exception is for the renewable sectors, which are assumed to grow more quickly relative to others. See Bertram et al. (2022)

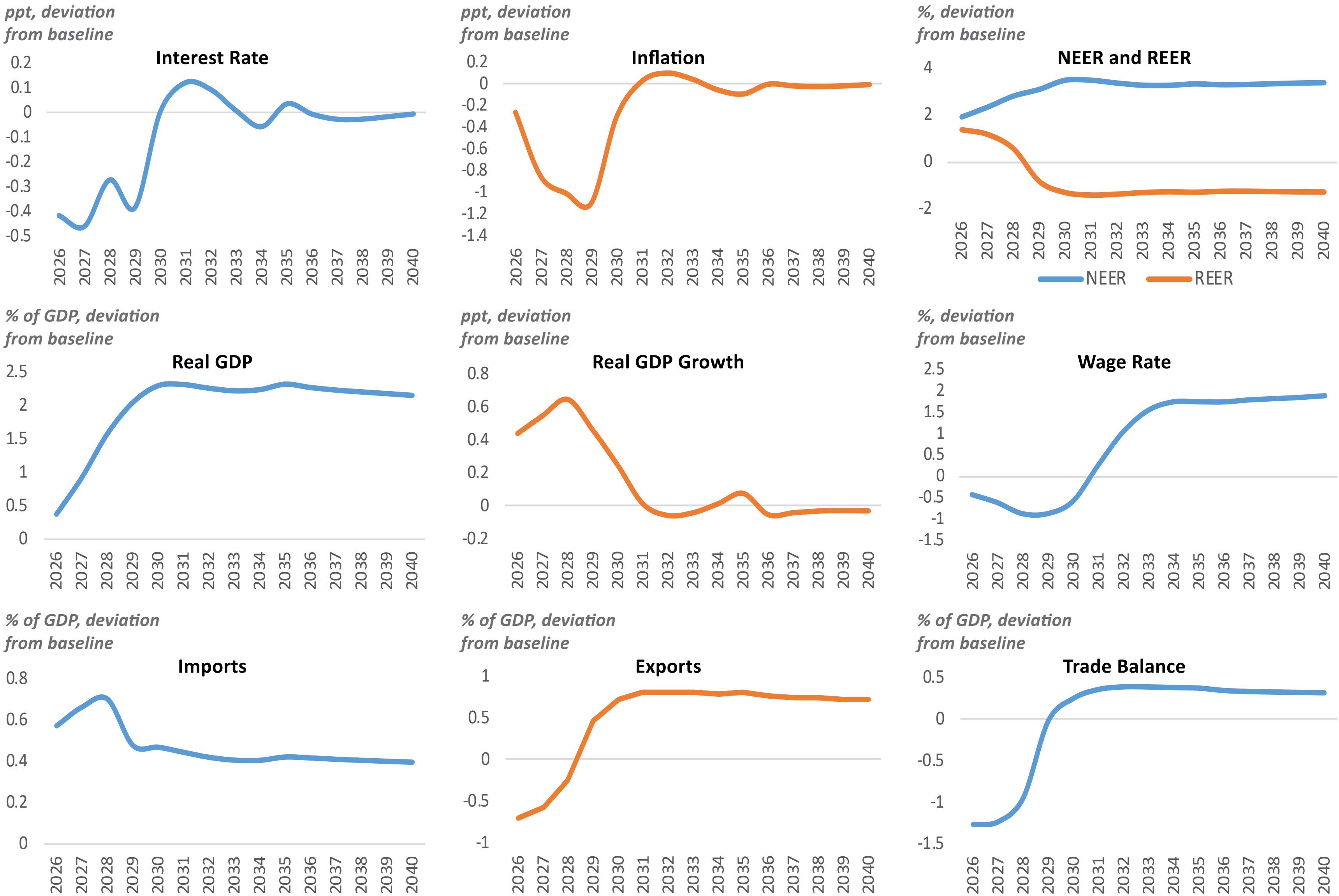
29. Some of these regions in G-Cubed are expected to catch up more quickly due to economic reforms (or more slowly to the frontier due to institutional rigidities), but the calibration of the catch-up rate attempts to replicate recent growth experiences of each country and region in the model.

Annex B: Full Results

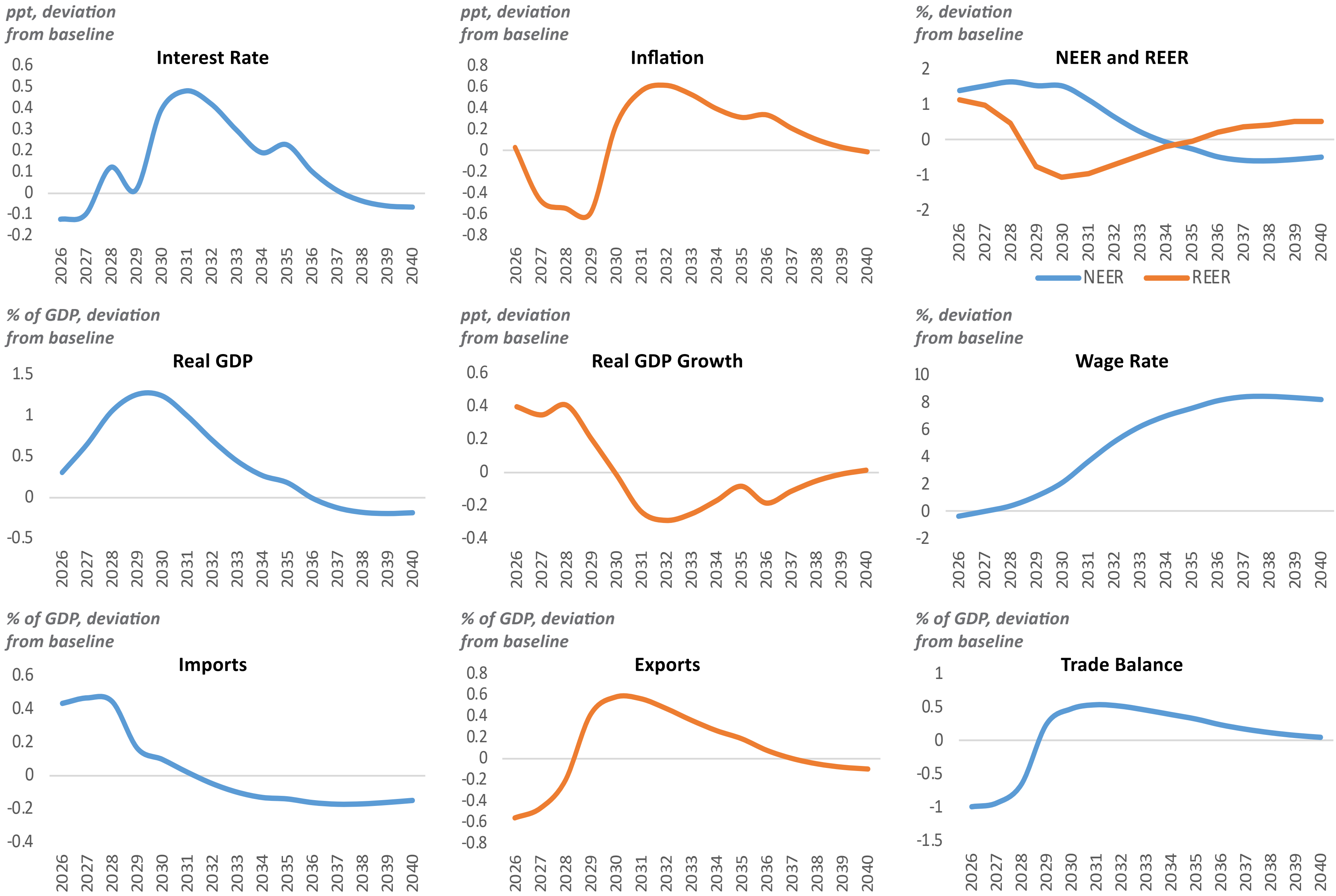
Scenario 1 (Reference Population Ageing Scenario):



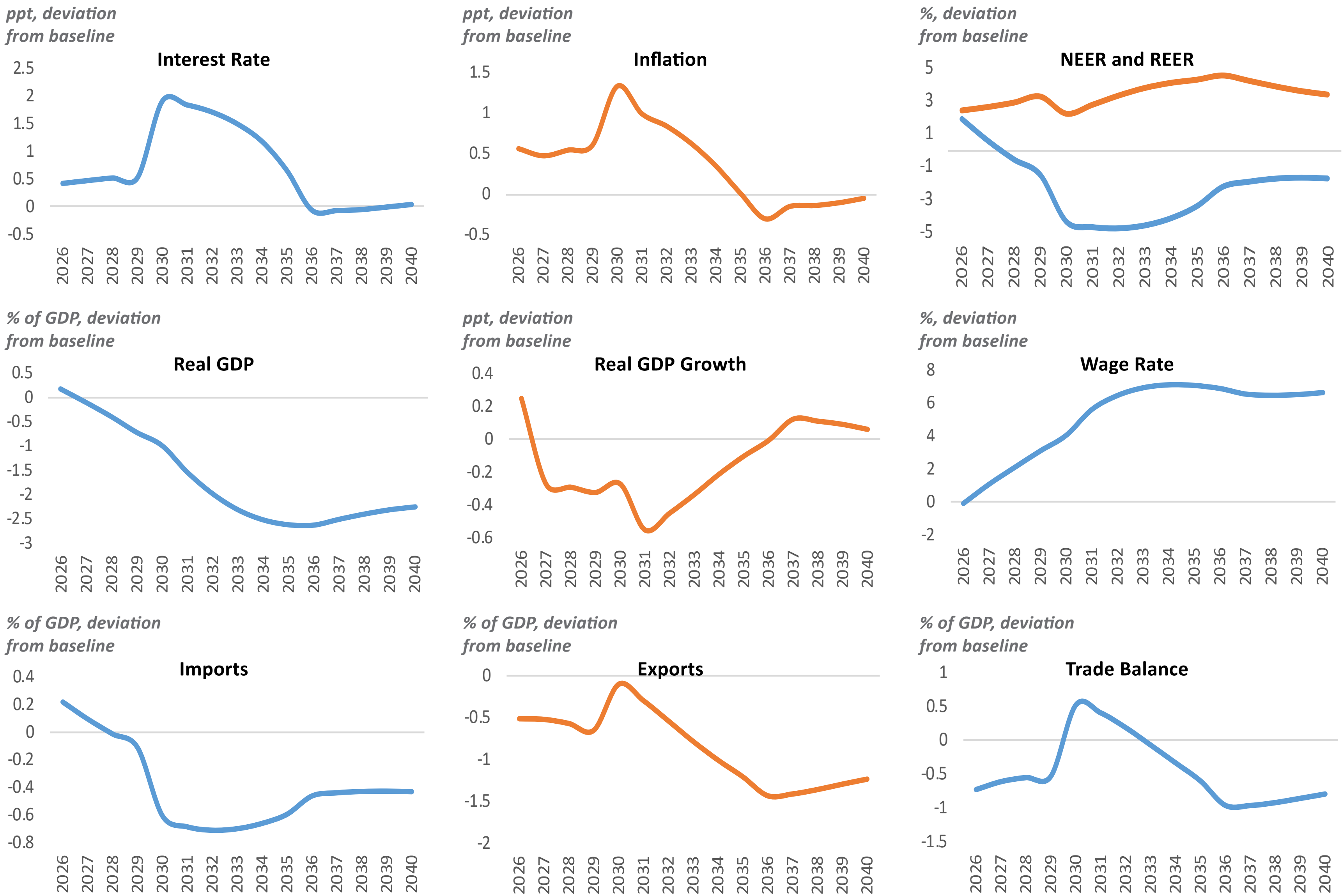
Scenario 2 (Reference AI-Adoption Scenario):



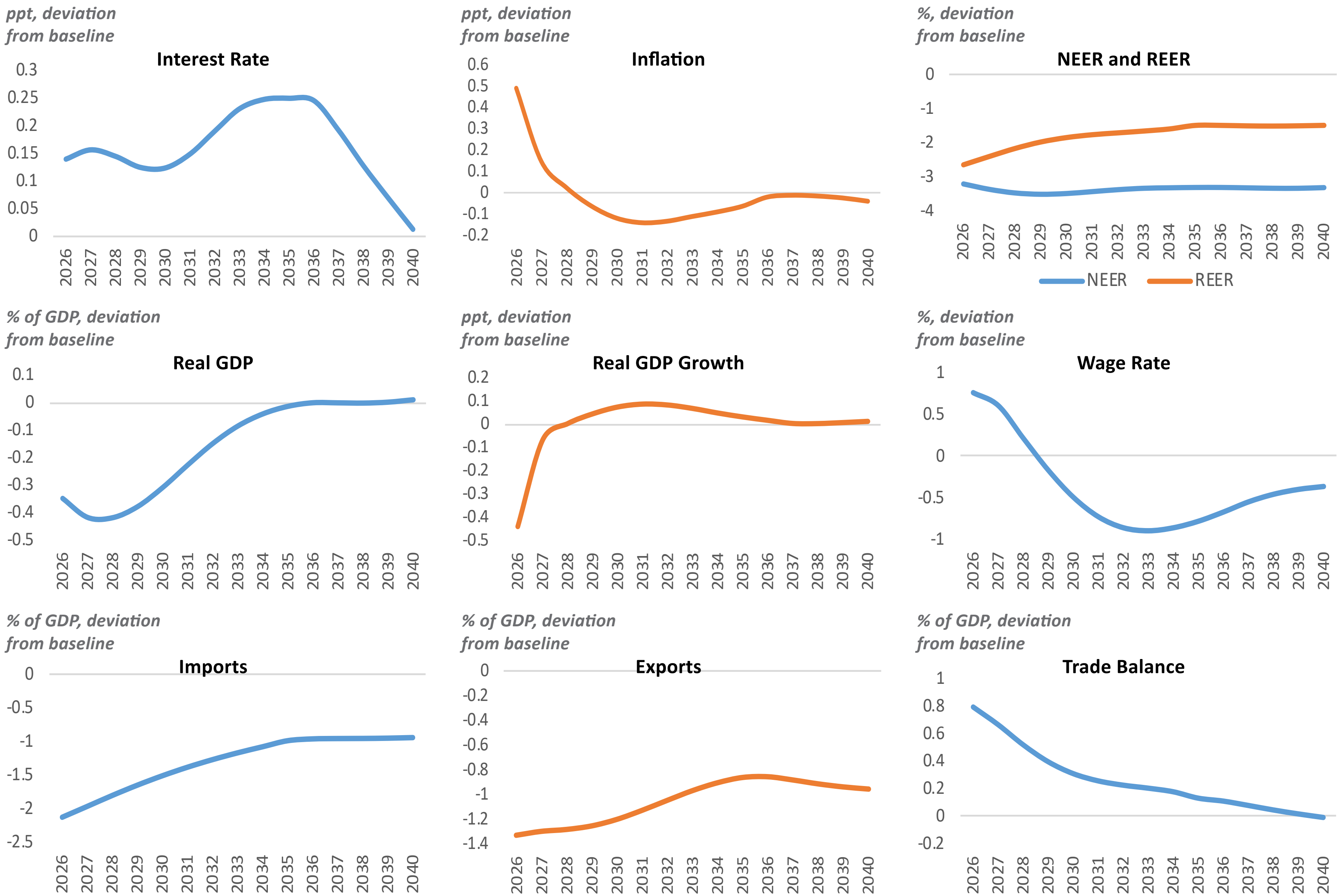
Scenario 3 (Intersection between demographic shifts and AI):



Scenario 4 (Population Ageing and Fiscal Stress):



Scenario 5 (Lagged AI-Adoption in Malaysia):



CHAPTER 5

DEMOGRAPHIC COMPOSITION AND INDIA'S NATURAL INTEREST RATE

Soumya Bhadury[1] and **Harendra Behera**[2]

1. Introduction

Natural (neutral) real interest rates, r^*, underpin the formulation of the monetary policy framework and the assessment of its stance, while also shaping the fiscal cost of debt and the valuation of long-duration assets[3]. Over the past few decades, many economies have experienced a decline in r^*, suggesting a tighter policy space and a greater role for structural forces. Within this broad pattern, the composition of the population—youth, working-age, and old-age cohorts—has moved markedly, raising the question of whether changing cohort shares help explain the evolution of r^* in emerging economies.

India's elderly population has increased from 24.7 million in 1961 (5.6% of the total) to 104 million in 2011 (8.6%), growing at roughly three times the pace of the overall population (Giridhar et al., 2014). Consistent with this, the old-age dependency ratio (OADR)—the ratio of the elderly to the working-age population—rose from about 5% in 1960 to 9% in 2018 and is projected to approach 19% over the next three decades. In standard life-cycle frameworks, a higher old-age dependency ratio, implying a smaller working-age share, tends to weigh on aggregate saving as retirees draw down, rather than build, wealth. India's evolving demographic profile is therefore poised to influence the neutral rate by altering saving and investment behaviour and long-term demands related to education, housing, marriage, and retirement (Behera, 2024).

We focus on whether total dependency and its components (youth and old age) have distinct linkages with the neutral rate after accounting for global co-movement in real rates. Youth dependency is declining as large cohorts enter prime working ages, while old-age dependency is rising with longevity; these shifts can pull in different directions through saving behaviour, labour supply, and innovation intensity. The policy question is whether, and by how much, cohort composition correlates with r^* in ways

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1. Corresponding author. Reserve Bank of India. Email: *soumyasbhadury@rbi.org.in*.

2. Reserve Bank of India

The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Reserve Bank of India.

3. Natural rate and neutral rate are used synonymously in the chapter.

that matter for medium-term policy calibration. Against this background, we examine whether alternative measures of demographic structure—the total dependency ratio (TDR), youth dependency ratio (YDR), and old-age dependency ratio (OADR)—are differentially associated with India's natural (neutral) real interest rate, r^*, after controlling for a common global component, and we offer three main contributions. First, we separate total dependency, youth and old-age dependencies and assess their association with r^*. This cohort split allows us to test whether the effects of ageing differ in level and persistence from those of a shrinking youth share. Second, to isolate domestic demographic signals from common global forces, we condition on an external global neutral-rate control. Third, we estimate both long-run relationships and adjustment dynamics, and we allow the demographic slopes to vary over time.

Our empirical approach combines complementary designs. We begin with static regressions using heteroskedasticity- and autocorrelation-robust inference. We then estimate an error-correction model (ARDL) to recover long-run multipliers and speeds of adjustment. Finally, we use a state-space model that permits gradual time variation in the demographic coefficients. Quarterly data span 2000Q1–2024Q4. India's r^* series is taken from an external semi-structural estimate that reports uncertainty bands (Behera, 2024). We regress India's r^* on the total, youth, and old-age dependency ratios, controlling for the national saving rate, general-government debt-to-GDP, a proxy for potential output, and a GDP-weighted global r^* benchmark that absorbs common, slow-moving forces.

We preview three findings. First, youth and total dependency are positively associated with India's r^*, while old-age dependency is negatively associated. Second, these associations persist—albeit with attenuated magnitudes—after adding the global control and macro covariates. Third, demographic slopes evolve gradually over time, indicating that the strength of the r^*–demography link is time varying in nature. The analysis has two implications. For measurement, accounting for cohort composition helps organise medium-term movements in r^* and clarifies the role of common global forces. For policy, the demographic transition can interact with other structural drivers to influence the neutral rate over horizons relevant for monetary strategy and debt management.

The remainder of the paper proceeds as follows. Section 2 reviews related work. Section 3 describes data and measurement. Section 4 presents the empirical results and robustness. Section 5 discusses implications and concludes.

2. Related Literature

Longer-horizon analyses for advanced economies document a secular decline in r^* and strong low-frequency co-movement (Armelius et al., 2024; Zhu, 2016a; Ademmer and Rush, 2024). Within this broad view, demographics provide a coherent explanation for persistent movements in r^*. Aksoy et al. (2019) show for OECD economies that population age structure has economically and statistically significant effects on macroeconomic outcomes, including real interest rates, in a pattern consistent with life-cycle behaviour. Higher dependency-age shares are associated with lower output, investment, and real interest rates, whereas higher working-age shares are associated with higher values of these outcomes.

Three mechanisms organise these findings and are directly relevant for the evolution of r^* (Aksoy et al., 2019). First, fertility and the resource envelope of workers determine investment in human capital, so shifts in fertility and worker resources change education/skill accumulation and, in turn, macro-outcomes. Second, age composition shapes saving behaviour and portfolio choice, altering the supply of loanable funds over the life cycle as cohort shares move. Third, the share of young workers influences innovation, so demographic profiles that reduce the young-worker share are associated with lower innovation intensity. Together, these channels produce life-cycle patterns in macro variables—including real returns—that align with the estimated demographic effects.

Cross-country evidence supports both the demographic channel and a common global component in r^*, such as trend productivity, safe-asset scarcity, and risk/term premia, as distinct from country-specific drivers. Armelius et al. (2024) estimate r^* for Denmark, Norway, and Sweden over 1990Q1–2022Q4 using an extended Laubach–Williams model with a dynamic-factor component and Bayesian filtering, and find a secular decline in r^*. Using frequency-domain methods for Asia–Pacific, Zhu (2016) links the low-frequency component of real rates to demographic trends and financial-sector development, with weaker links to asset-price cycles, credit-to-GDP and investment. Taking a longer horizon across advanced economies, Ademmer and Rush (2024) attribute about half of the post-1970s decline in the natural real rate to slower trend growth and demographics, with a further contribution from global spillovers. Complementing this evidence, Holston, Laubach and Williams (2017) document sharp declines in equilibrium real rates for the United States, Canada, the Euro area and the United Kingdom, while broader narratives emphasise secular-stagnation and global-savings-glut (Summers, 2014; Bernanke, 2005, 2017). A related study by the Bank of England suggests demographic ageing can account for a large share—on the order of three-quarters—of the multi-decade decline in natural rates since 1980 (Bank of England, 2017). Together, these results indicate a prominent global component in r^* and support cohort-specific analyses of demographic structure.

A second line of work quantifies the role of cohort composition. In an overlapping-generations model calibrated to the euro area, Papetti (2019) estimates that—based on demographic projections—demographics alone could lower r^* by about 0.4–1.7 percentage points between 1990 and 2030, mainly through reduced effective labour input and higher longevity-driven saving. The magnitudes depend on substitution elasticities and policy settings that influence older-cohort productivity, participation and retirement. Lisack, Sajedi and Thwaites (2017) report related global results: falling birth and death rates can account for a large share of the decline in world real rates since the 1980s, and the rising share of the population in the high-wealth 50+ age bracket boosts safe-asset demand and compresses term premia. These cohort-specific mechanisms imply that the effects of old-age and youth dependency on r^* need not be equal.

Country evidence aligns with these patterns and clarifies mechanisms. For Japan, Han (2019) shows in a semi-structural model that ageing lowers r^* primarily via reduced trend potential growth, with the effect strengthening as demographic pressures build. Ho (2020) documents sensitivity of estimated demographic elasticities to Bayesian priors and to the omission of capital intensity and life-cycle consumption; posterior estimates can shift materially under alternative priors. This sensitivity underscores the value of incorporating information on capital intensity and life-cycle consumption, and of testing robustness to prior choices and alternative specifications.

Finally, there are policy implications of a lower r^* that relate to transmission and financial intermediation. Evidence suggests that a secular decline in r^* can weaken short-run monetary transmission and tighten the long-run supply of bank credit (e.g., Wang, 2020). FRB/US-based simulations suggest that when the nominal neutral rate is low (around 2–3%), QE and forward guidance can only partially substitute for conventional rate cuts—delivering less 'equivalent' easing than would be available when r is higher—so policy space remains materially compressed at the effective lower bound (Bernanke, 2017). Against this background, studies on India offers two complementary facts. At the state level, rising working-age shares are associated with faster growth—consistent with a demographic-dividend channel (Aiyar and Mody, 2011). At the national level, estimates of India's r^* declined after the global financial crisis and have edged up post-pandemic, with wide uncertainty bands (Behera, 2024). Taken together, these patterns motivate our inquiry into whether demographic composition helps explain India's r^*, but they do not by themselves establish a causal link.

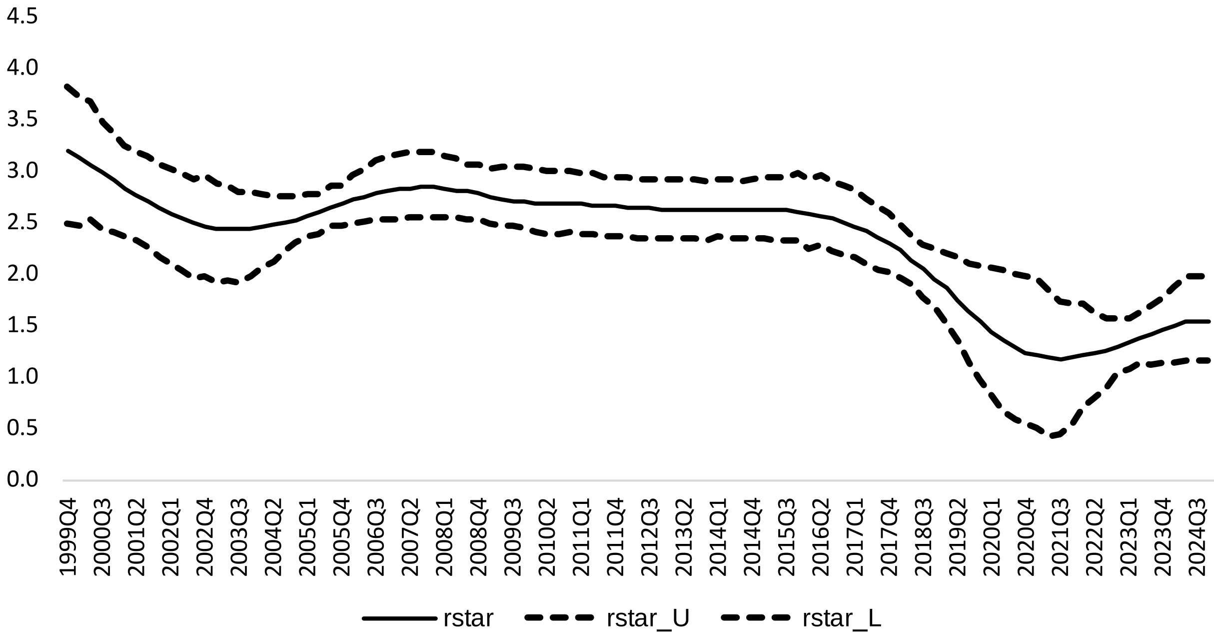
3. Data and Measurement

This section records sources, construction, and alignment of the variables used in the empirical analysis.

3.1 Outcome: India's r^*

The outcome variable is the quarterly point estimate of India's r^* from Behera (2024), who implements a Laubach–Williams-style semi-structural state-space framework and reports uncertainty bands. We take r^* as external estimate rather than estimating it within our system. For descriptive context, Figure 1 plots Behera's point estimate and reported confidence band.[4]

Figure 1: India's Natural Rate of Interest (in % with 90% CI)



Note: The solid line presents the posterior mean estimates of r^*; dashed lines show the 90% credible intervals. Estimates are produced over the indicated sample and are subject to revision as new data become available and as filtering endpoints move.

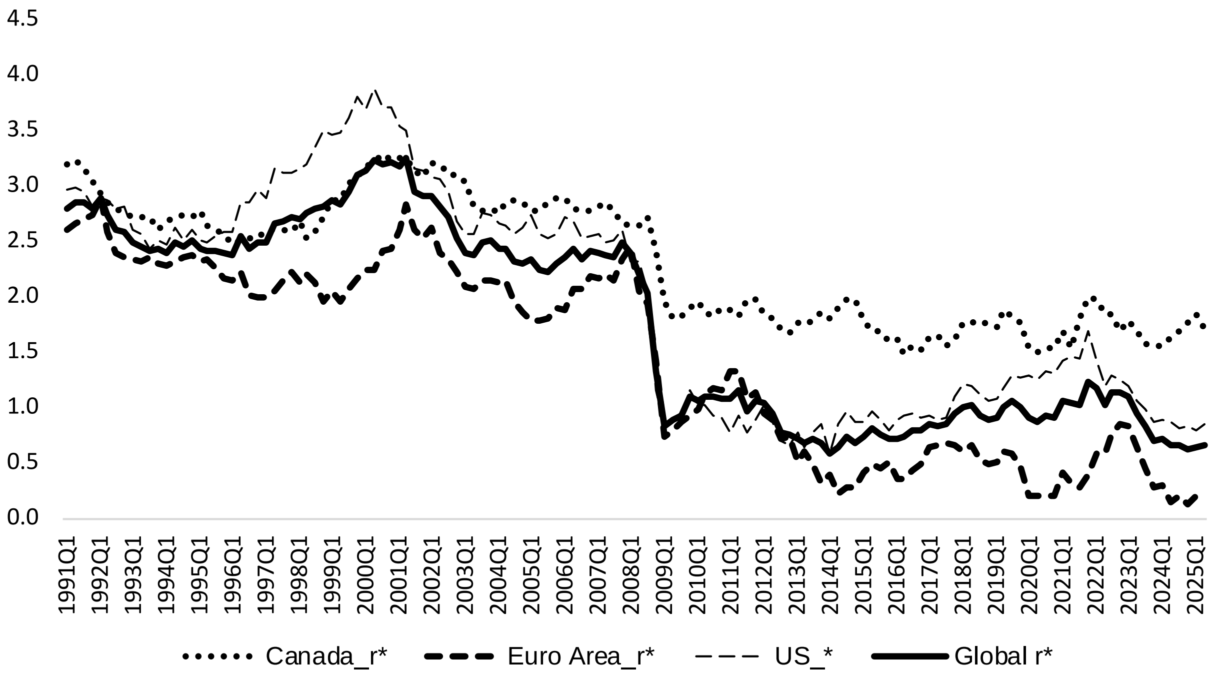
Source: Behera (2024)

4. Our regressions treat the Behera (2024) series as observed; we do not propagate its filtering uncertainty into the slope estimates, which is standard.

3.2 Global Natural Rate, $r^{*,G}$

We construct a quarterly global neutral rate $r^{*,G}$ as a GDP-weighted average of Holston–Laubach–Williams r^{*} estimates for the United States, the Euro area, and Canada, with current-price GDP (USD) weights from the IMF World Economic Outlook (April 2025).[5]

Figure 2: Global Natural Rate of Interest (in %)



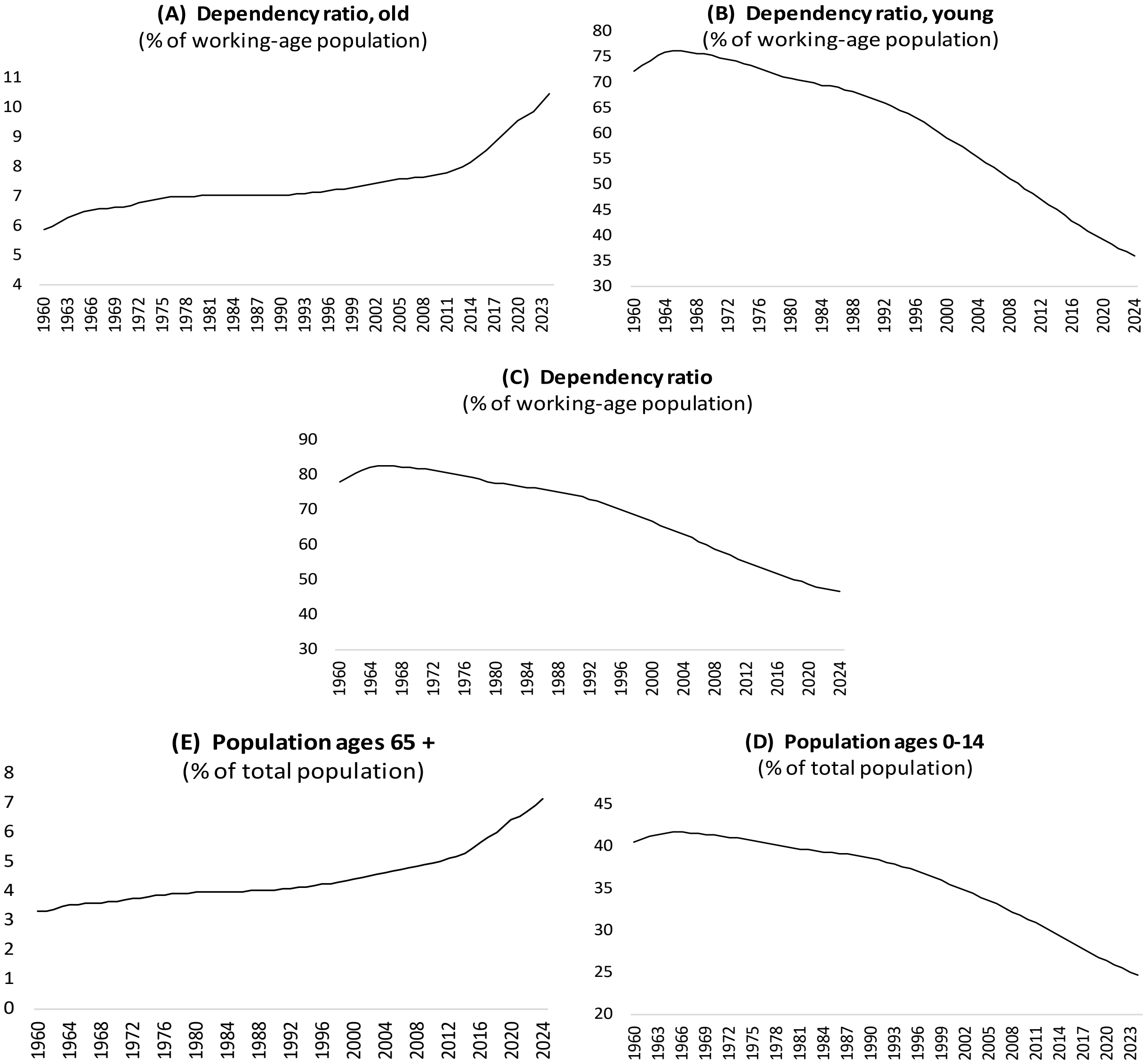
Note: Quarterly GDP-weighted composite of HLW r^{*} for the United States, Euro area, and Canada. Weights are based on current-price USD GDP from IMF WEO (April 2025), updated annually.

3.3 Demographic Regressors

Annual World Development Indicators (WDI) series are converted to quarterly frequency by using step (carry-forward) interpolation, which holds the annual value constant across the four quarters. Because demographic stocks evolve slowly, this conversion has negligible effect on quarterly variation or inference. The baseline regressors are the total, young, and old-age dependency ratios. For descriptive analysis and robustness, we also use two age-share series—population aged 0–14 and 65+—from the same source. Figure 3A–3E plot these series and report variable definitions.

5. Results are similar when the United Kingdom is added to the HLW composite.

Figure 3: Demographic Ratios



Note: Population ages 65+ (% of total) — Share of the population aged 65 and above. Population follows the de facto concept (all residents regardless of legal status or citizenship). Population ages 0–14 (% of total) — Share of the population aged 0–14. Population follows the de facto concept. Age dependency ratio (% of working-age population) — Dependents (ages <15 or ≥65) per 100 working-age persons (ages 15–64). Age dependency ratio, young (% of working-age population) — Younger dependents (ages <15) per 100 working-age persons (ages 15–64). Age dependency ratio, old (% of working-age population) — Older dependents (ages ≥65) per 100 working-age persons (pages 15–64).

3.4 Role of Global Natural Rate ($r^{*,G}$)

We quantify the link between India’s neutral real rate r^* and a GDP-weighted global neutral rate $r^{*,G}$ using 1999Q4 – 2024Q4 data. Contemporaneously, the two series are moderately correlated (r = 0.46). The co-movement is stronger during the post-GFC decline in neutral rates (2008Q4–2016Q4: r = 0.66) and weaker— negative— under the inflation-targeting period (2017Q1–2024Q4: r = -0.27). Bivariate Granger causality indicates unidirectional predictability with causality from $r^{*,G}$ to India’s r^* at 3- and 4-quarter lags (p = 0.01 and p = 0.02; F = 3.74 and 3.02). At 2 and 5 quarters the null is not rejected (p = 0.10 and 0.07) at 5%. The reverse causality—India’s r^* to $r^{*,G}$ — is not statistically significant at any lag from 2 to 5 quarters. These results document moderate overall co-movement, stronger alignment during 2008Q4–2016Q4, weaker association thereafter, and unidirectional causality from the global to the Indian neutral rate at 3–4 quarters.

Table 1: Granger Causality between Global $r^{*,G}$ and India’s r^*

Direction \ Lag	2-quarter	3-quarter	4-quarter	5-quarter
Global $r^{*,G}$ → India r^*	0.097* (2.39)	0.0138** (3.74)	0.0220** (3.02)	0.0725* (2.11)
India r^* → Global $r^{*,G}$	0.960 (0.04)	0.989 (0.04)	0.959 (0.16)	0.279 (1.28)

*Note: Bivariate causality tests indicate unidirectional predictability with causality from the GDP-weighted global $r^{*,G}$ to India’s r^* concentrated at medium horizons (3–4 quarters), with no evidence of reverse predictability with causality at any horizon considered (2–5 quarters). Table reports p-values with F-statistics in parentheses; Significance: * 10%, ** 5%, *** 1%***.*

3.5 Channels and Additional Controls

We augment the regressions with standard macro controls drawn from consistent sources. Saving/GDP is measured as gross domestic savings (% of GDP) from the World Development Indicators, defined as GDP minus total final consumption. Trend (potential) growth is the HP-filtered trend of real output (λ = 1,600) constructed from national accounts. Debt/GDP corresponds to general government gross debt (% of GDP) from the IMF’s World Economic Outlook. Unless scale dictates a log ratio, controls enter in levels. Data vintages and release calendars are aligned to preclude look-ahead bias and mechanical timing advantages.[6]

6. Annual saving and debt ratios are mapped to quarterly frequency using step interpolation (the annual value is held constant across the four quarters of each year).

4. Methodology and Results

We present results in four steps: (i) levels estimates with HAC inference; (ii) ARDL (1,0) long-run multipliers and adjustment speeds; (iii) “channels” specifications conditioning on Saving/GDP, Debt/GDP, and Potential Growth; and (iv) time-varying-parameter (TVP) estimates of the demographic slope. The dependent variable is India’s neutral real rate r^* taken from Behera (2024). All regression include a global neutral-rate, $r^{*,G}$ as control. Coefficients are reported as basis points (bps) of r^* per one-percentage-point (pp) change in the demographic regressor.[7]

4.1 Baseline Levels Estimate (HAC)

The static specification is

$$r_t^* = \alpha + \beta D_t + \gamma r_t^{*,G} + \delta' X_t + \varepsilon_t \quad (1)$$

where D_t is one demographic regressor at a time (DEPTOT, YDR, OADR), $r^{*,G}$ is the global neutral rate, and X_t contains channels when invoked (saving/GDP, debt/GDP, potential growth). HAC (Newey-West) corrected standard errors are reported for the estimated coefficients. For interpretation in bps per pp, $\beta_{bps/pp} = 100 \cdot \beta$.

Results and interpretation. Table 2 shows a consistent composition pattern in levels: DEPTOT and YDR are positively associated with r^* (6.70 and 6.14 bps/pp), whereas OADR is negatively associated with a larger absolute magnitude (−56.90 bps/pp). Adding the global neutral-rate control attenuates magnitudes to 5.46 (DEPTOT), 5.09 (YDR), and −51.31 (OADR) bps/pp while improving fit (Adj.R2 rises from 0.58→0.67 for DEPTOT; 0.62→0.70 for YDR; 0.85→0.87 for OADR). The attenuation is consistent with international co-movement in neutral rates; preservation of signs and precision indicates a distinct domestic demographic signal.

7. Sample spans are those implied by data availability; the exact number of observations (N) is reported in each table.

Table 2: Levels Estimates (HAC) - Baseline and + Global Neutral Control

Regressor (D_t)	Specification	β (bps)	SE (bps)	t-stat	Adj. R^2	N
DEPTOT	Baseline (demography only)	6.71	1.24	5.39	0.58	100
DEPTOT	+ Global r^* control	5.46	1.18	4.64	0.67	100
YDR	Baseline (demography only)	6.14	1.05	5.88	0.62	100
YDR	+ Global r^* control	5.09	0.99	5.14	0.71	100
OADR	Baseline (demography only)	-56.9	5.95	-9.57	0.85	100
OADR	+ Global r^* control	-51.31	5.31	-9.66	0.87	100

Note: Dependent variable: India r^*. Coefficients in basis points (bps) for 1-percentage points (pp) change in Dt.[8]

4.2 ARDL (1,0): Long-run Multipliers and Speeds

We estimate

$$r_t^* = \varphi r_{t-1}^* + \theta D_t + \gamma r_t^{*,G} + \delta' X_t + u_t, \quad (2)$$

with long-run multiplier $LRM = \dfrac{\theta}{1-\varphi}$ and half-life $HL = \ln(0.5)/\ln(\varphi)$. Empirically, the LRMs are close to the HAC slopes (DEPTOT ≈ +6.18 bps; YDR ≈ +5.66 bps; OADR ≈ −53.58 bps), and persistence φ is near unity for youth/total (long half-lives), somewhat lower for old-age. The ECM form,

$$\Delta r_t^* = \kappa\left(r_{t-1}^* - \lambda_0 - \lambda_1 D_{t-1} - \lambda_2 r_{t-1}^{*,G} - \lambda_3' X_{t-1}\right) + \theta \Delta D_t + \gamma \Delta r_t^{*,G} + \delta' \Delta X_t + e_t \quad (3)$$

links $\kappa = -(1-\varphi)$ and $(\lambda_1, \lambda_2, \lambda_3) = (\theta, \gamma, \delta)/(1-\varphi)$.

8. Global neutral-rate control $r^{*,G}$. GDP-weighted average of Holston–Laubach–Williams r^* for the United States, Euro area, and Canada; weights use current-price GDP (USD) from IMF WEO (April 2025), held piecewise-constant within year and aligned to quarterly frequency (Section 3.2).

Results. LRMs in Table 3 close to level slopes—6.18 (DEPTOT), 5.66 (YDR) and −53.58 (OADR) —indicating that the static estimates are not driven by transitory dynamics. Persistence is very high for DEPTOT and YDR (phi-use symbol=0.99; half-lives of 75.84 and 69.41 quarters, respectively) and somewhat lower for OADR (phi-use symbol=0.98; half-life of 32.97 quarters). As is typical with persistent series in finite sample, the LRM confidence intervals are wide and include zero, so the LRMs are not always statistically different from zero at conventional levels. We therefore treat them as indicative of long-run magnitudes that are broadly consistent with the HAC level estimates, while placing greater weight on the stability of coefficient signs across specifications.[9]

Table 3: ARDL (1,0) Long-Run Multipliers, Persistence, and Half-lives

Regressor (D_t)	ϕ (persistence)	Half-life (quarters)	Short-run effect (bps/pp)	Long-run multiplier (bps/pp)	LRM 95% CI [low, high] (bps)
DEPTOT	0.99	75.84	0.06	6.18	[-27.6, 39.9]
YDR	0.99	69.41	0.06	5.66	[-21.7, 33.1]
OADR	0.98	32.97	-1.12	-53.58	[-157.5, 50.3]

Note: φ is AR(1) persistence in r^*. Half-life = ln(0.5)/ln(φ), 0<φ<1. Long-run multipliers (LRM) and 95% CIs from model outputs; short-run is the contemporaneous θ.

4.3 Conditioning on Channels: Saving, Debt, and Potential Growth

Controls are introduced sequentially—$r^{*,G}$, then saving rate, debt-to-GDP, and potential growth.

Results and Interpretation*.* Table 4 yields three findings. First, magnitudes remain economically large in the fully conditioned model (E): DEPTOT 6.41 bps/pp, YDR 5.61 bps/pp, OADR −42.55 bps/pp. Second, precision improves markedly along the sequence (SEs fall, t-statistics rise) and fit improves sharply (Adj.R^2 ≈ 0.97 in model E for DEPTOT/YDR and 0.97 for OADR; AIC/BIC fall monotonically). This pattern is consistent with saving, debt, and trend growth capturing (or proxying for) part of the low-frequency variation through which demographics may operate, rather than reversing the sign of the demographic association. Third, the absolute magnitude on OADR exceeds that on YDR in every column, underscoring composition: population aging lowers the neutral rate more forcefully, while youth and total dependency push in the opposite direction.

9. Given ϕ≈0.98–0.99, persistence is high and LRMs are imprecisely estimated—hence we emphasise sign stability and cross-design consistency rather than precise point magnitudes.

Table 4: Channels Progression (A–E)

Regressor (D_t)	Model	β (bps/pp)	SE (bps)	t-stat	Adj. R²	AIC	BIC	N
DEPTOT	A: Demography	6.71	1.24	5.39	0.58	84.93	92.74	100
DEPTOT	B: Global r^*	5.46	1.18	4.64	0.67	60.48	70.9	100
DEPTOT	C: Saving/GDP	7.0	0.86	8.1	0.76	30.66	41.04	99
DEPTOT	D: Debt/GDP	7.46	0.49	15.37	0.92	-84.26	-73.88	99
DEPTOT	E: Potential Growth	6.41	0.38	16.73	0.97	-161.71	-146.14	99
YDR	A: Demography	6.14	1.05	5.88	0.62	73.98	81.8	100
YDR	B: Global r^*	5.09	0.99	5.14	0.7	51.05	61.47	100
YDR	C: Saving/GDP	6.28	0.72	8.73	0.78	21.45	31.83	99
YDR	D: Debt/GDP	6.58	0.41	16.07	0.93	-91.26	-80.88	99
YDR	E: Potential Growth	5.61	0.31	17.8	0.97	-169.43	-153.86	99
OADR	A: Demography	-56.9	5.95	-9.57	0.85	-16.2	-8.39	100
OADR	B: Global r^*	-51.31	5.31	-9.66	0.87	-31.35	-20.93	100
OADR	C: Saving/GDP	-54.27	5.18	-10.48	0.88	-36.59	-26.21	99
OADR	D: Debt/GDP	-52.8	4.41	-11.96	0.93	-89.33	-78.95	99
OADR	E: Potential Growth	-42.55	2.87	-14.81	0.97	-175.63	-160.06	99

Note: Models add sequentially: A Demography; B + Global r^*; C + Saving/GDP; D + Debt/GDP; E + Potential growth (g_t). β in basis points per 1-pp change in D_t . Adj. R², AIC, BIC, and N as reported.[10]

4.4 Composition versus Level

Youth and total dependency are positively associated with r^*, whereas old-age dependency is negatively associated with larger absolute magnitude. The pattern holds in HAC and ARDL specifications and is robust to the channel's progression.

10. Channels. Saving/GDP, Debt/GDP, and Potential Growth are introduced sequentially; variable definitions, sources, and vintages are in section 3 and Table 1. Specifications C–E report N = 99, starting in C, channel variables (saving/GDP, debt/GDP, potential growth) are entered at t−1. These controls are expected to affect r^* with a delay and are lagged to reflect this economic timing.

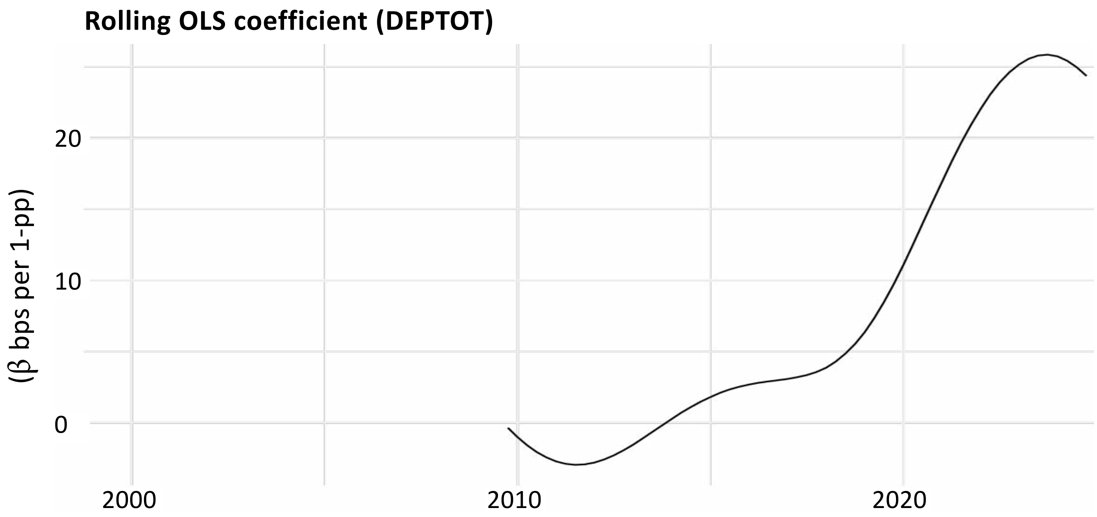
4.5 Time-varying Slopes (TVP)

We estimate a state-space model with measurement and state equations. Before providing TVP estimates, parameters are estimated by using rolling regression.

$$r_t^* = \alpha + \beta_t D_t + \gamma r_t^{*,G} + \delta^{'} X_t + \varepsilon_t,\ \beta_t = \beta_{t-1} + \eta_t,\ (4)$$

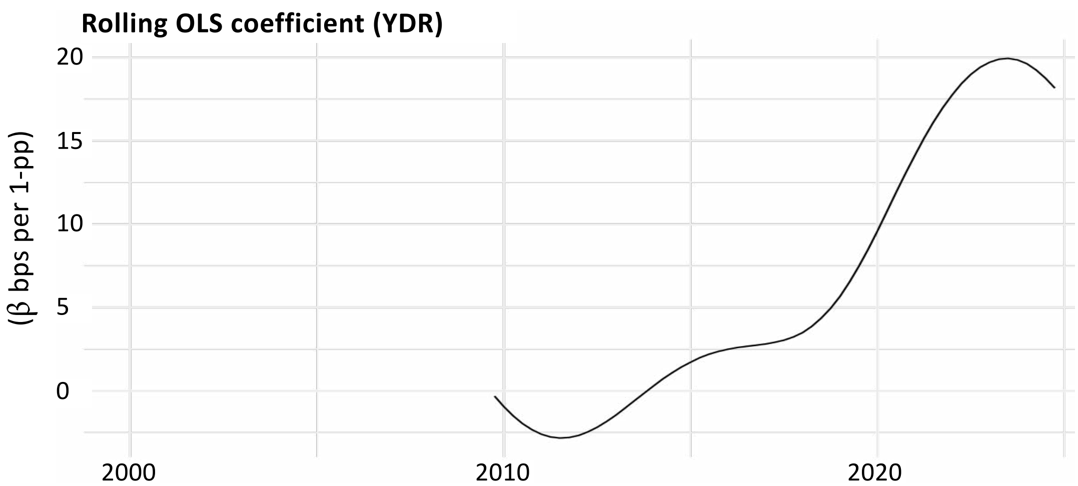
with $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ and $\eta_t \sim N(0, \sigma_\eta^2)$. Median paths with 68/95% intervals show the DEPTOT slope drifting up (≈6.8→8.4 bps), the YDR slope drifting up (≈6.1→7.5 bps), and the OADR slope remaining negative but attenuating in magnitude (≈−65→−58 bps) by 2024Q4. Figure 4A–4C about here plot rolling-window coefficients.

Figure 4A: Rolling-window Coefficient-DEPTOT



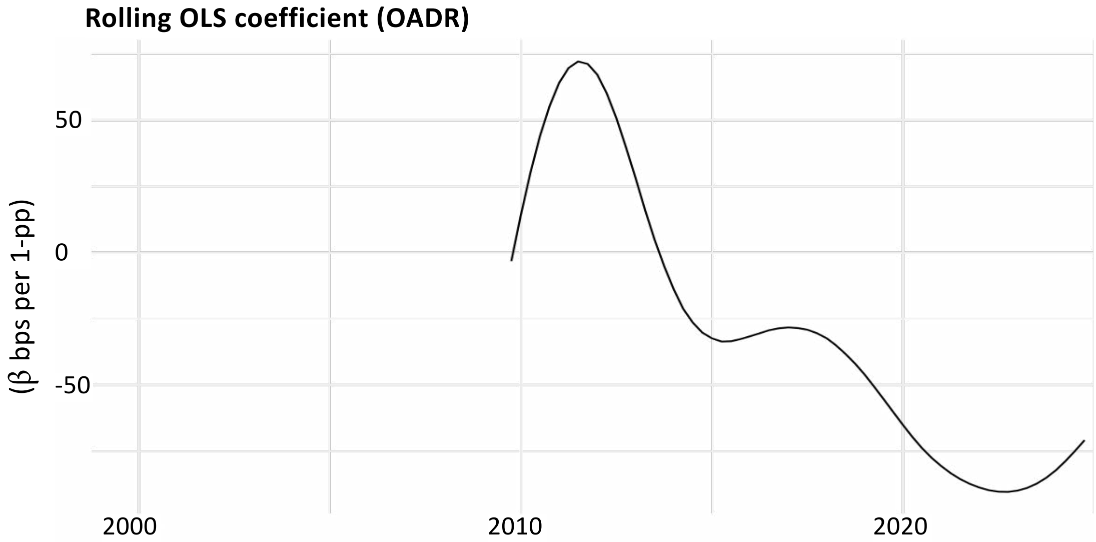
Note: Rolling-window plots display point estimates only; interval information is provided by TVP figures.

Figure 4B: Rolling-window Coefficient-YDR



Note: Rolling-window plots display point estimates only; interval information is provided by TVP figures

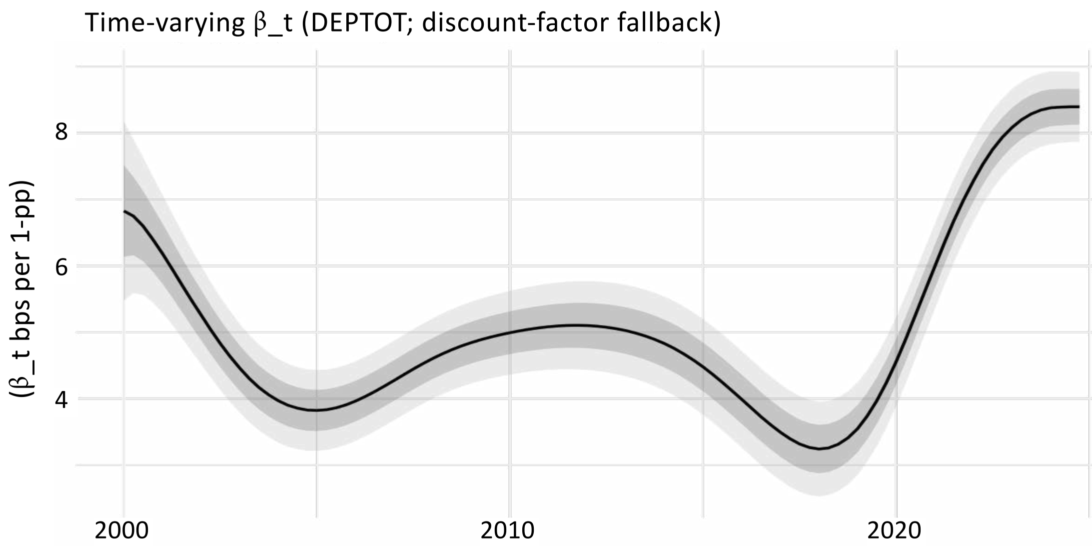
Figure 4C: Rolling-window Coefficient-OADR



Note: Rolling-window plots display point estimates only; interval information is provided by TVP figures.

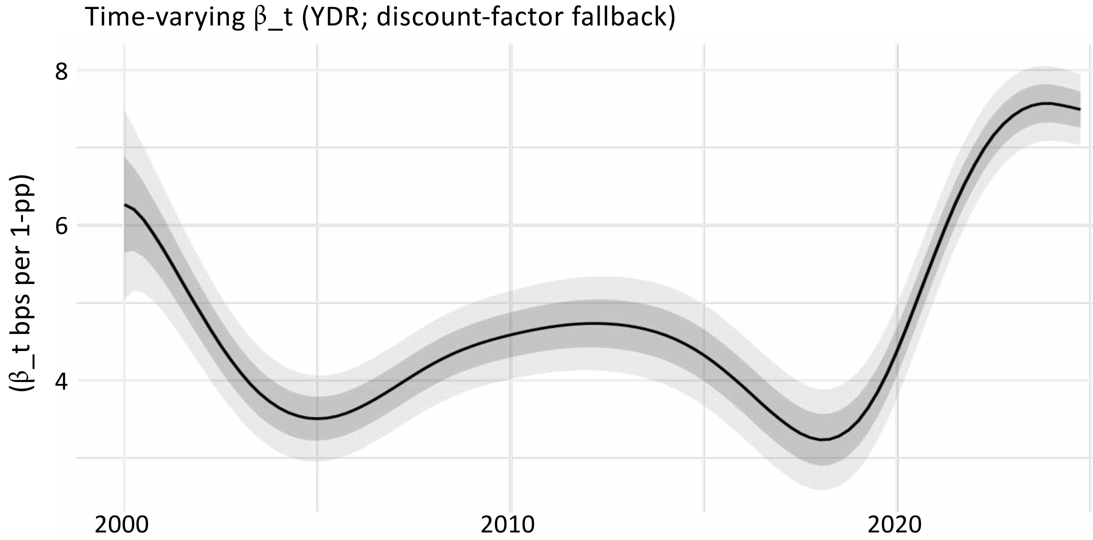
Figures 4D–4F show TVP medians along with interval estimates.

Figure 4D: TVP Slope-DEPTOT (median, 68/95%)



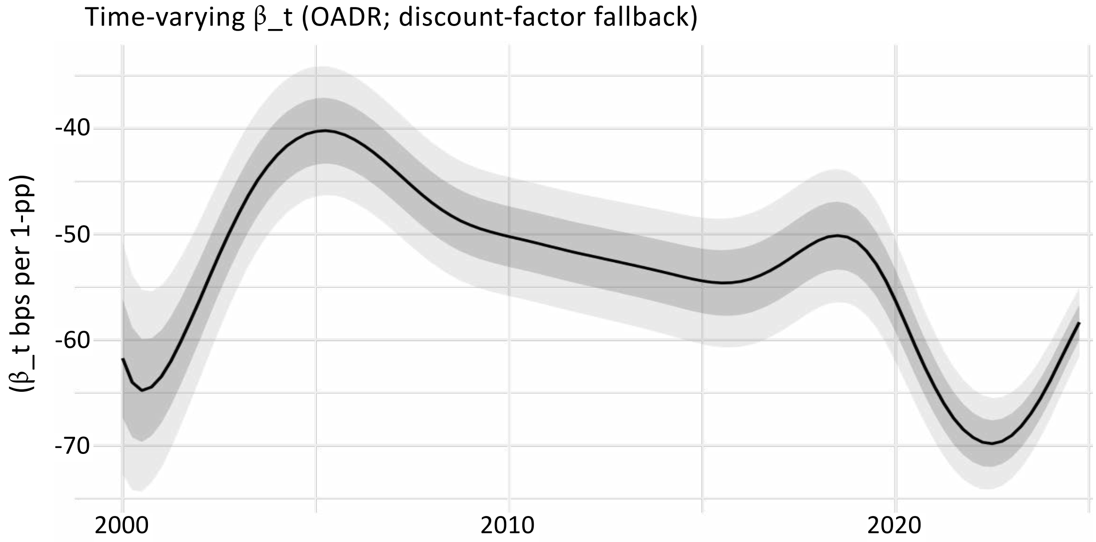
Note: Medians estimates (thick line) are presented with 68% and 95% confidence intervals (presented in darker and lighter shaded areas, respectively). See section 4.5 for the specification.

Figure 4E: TVP Slope-YDR (median, 68/95%)



Note: *Medians estimates (thick line) are presented with 68% and 95% confidence intervals (presented in darker and lighter shaded areas, respectively). See section 4.5 for the specification.*

Figure 4F: TVP Slope-OADR (median, 68/95%)



Note: *Medians estimates (thick line) are presented with 68% and 95% confidence intervals (presented in darker and lighter shaded areas, respectively). See section 4.5 for the specification.*

4.6 Comparisons with Other Studies

Prior work finds sizable demographic effects on equilibrium/real rates: Carvalho, Ferrero, and Nechio (2016) attribute at least ~1½ percentage points of the 1990–2014 decline in advanced-economy real rates to demographics, while Aksoy et al. (2019) show—using panel-VAR impulse responses for 21 OECD economies—that higher youth and old-age dependency reduce long-run real rates. Because our coefficients are estimated for the natural real rate, r^*, whereas some of these studies report effects on observed real rates, any cross-study comparison should be read as suggestive rather than one-for-one. In our fully conditioned model (E), the elasticities are DEPTOT = 6.41 bps per percentage point (pp), YDR = 5.61 bps/pp, and OADR = −42.55 bps/pp. Scaling by India's demographic shifts since 2000 (youth: a decline of 20–23 pp; old-age: an increase of ~3 pp) implies order-of-magnitude effects on r^* of around 1.1–1.3 percentage points via youth and around −1.3 percentage points via ageing over two decades.[11]

4.7 Discussion and Interpretation

The estimated gradients are economically large. Using the fully conditioned slopes and the observed shifts in India's age structure since 2000 (WDI), the change in youth dependency maps into an r^* effect of roughly 1.1–1.3 percentage points; the rise in old-age dependency implies a reduction of about 1.3 percentage points; and scaling by total dependency yields a comparable ~1.3 percentage point change. These calculations are illustrative and non-additive because each coefficient comes from a specification with a single demographic regressor. Adding the global neutral-rate control absorbs common low-frequency movements while leaving the demographic coefficients qualitatively intact, indicating that domestic composition carries information for India's r^* beyond global forces. The modest attenuation of coefficients as saving, debt, and trend growth are included is consistent with life-cycle mechanisms and suggests multiple transmission paths rather than a single confound. Composition matters: youth and total dependency are positively associated with r^*, whereas old-age dependency is negatively associated with a larger absolute magnitude. Time-varying estimates show stable signs with modest drift—end-sample slopes are around 8–8½ bps (total), 7–7½ bps (youth), and −58 to −60 bps (old-age)—with confidence bands that generally do not cross zero, widening around global stress episodes, reinforcing that demography's imprint on r^* is persistent rather than sample-specific.[12]

To relate coefficients to observed demographic changes, we map the fully conditioned slopes from Table 4 (Model E) into implied changes in r^* over 2000–2024 for each regressor separately. Over this period, total dependency declined by 20 pp, youth dependency declined by 23.13 pp, and old-age dependency rose by 3.13 pp (WDI, as in

11. These relationships are associational, conditional on controls, not causal.

12. Time-varying estimates preserve signs with modest drift; end-sample medians are close to, but not identical with, the Model-E slopes (see Figures 4D–4F).

section 3). Multiplying these changes by the corresponding Model-E coefficients yields illustrative, single-regressor effects of −128.26 bps (DEPTOT: 6.41×−20.01), −129.76 bps (YDR: 5.61×−23.13), and −133.18 bps (OADR: −42.55×3.13). These magnitudes are not additive across regressors and simply show the order of impact when each demographic dimension is considered on its own, using the same series employed in estimation.

5. Policy Implications

The results imply a clear ordering of demographic influences on India’s neutral real rate. Youth and total dependency are positively associated with r^*, whereas old-age dependency is negatively associated, and these signs are stable across level, ARDL, and time-varying specifications even after conditioning on a global neutral-rate control. Because India’s demographic transition features a declining youth share alongside a gradual rise in old-age dependency, the balance of forces points to persistent downward pressure on the neutral rate over the medium-term. This reading is not driven by global co-movements: once a GDP-weighted global r^* is included, the domestic demographic gradients remain economically and statistically meaningful. Policy baselines should therefore incorporate domestic composition—not just aggregate dependency—and treat the global control as a cross-check rather than a substitute.

For monetary strategy, the distinction between the ex-ante real policy rate and the neutral benchmark matters. The stance indicator should be evaluated against a demography-conditioned path that reflects projected youth and old-age shares (mapped to quarterly frequency as in section 3). This approach reduces the likelihood of mis-calibration when transitory shocks move observed real rates while the equilibrium benchmark evolves more slowly.

The evidence on transmission channels—attenuation of demographic coefficients when saving, debt, and trend growth are included—suggest that these variables act as transmission paths. Monitoring broad saving behaviour and debt conditions helps separate structural, demography-linked changes in r^* from cyclical fluctuations. Potential-growth assessments should be made jointly with the neutral-rate baseline: ageing that lowers trend growth also contributes to lower equilibrium real rates, and the two should be adjusted coherently rather than in parallel. This coordination is especially relevant for medium-term projections used in forecasting and risk-management exercises.

Term-structure and debt-management frameworks should likewise reflect a lower neutral anchor consistent with population ageing. If the old-age share continues to rise, portfolio preferences are likely to tilt toward safer assets, putting downward pressure on equilibrium real yields. Issuance strategies that implicitly assume a stable real term premium warrant stress tests under lower neutral-rate baselines and under scenarios where increased domestic saving compresses real yields further.

Finally, the results suggest that neutral-rate estimates are subject to considerable measurement uncertainty and are best treated as ranges and scenarios, with policy calibrated around a slowly moving benchmark rather than a precise point. Because our analysis relies on an externally estimated r^* for India, ranges and scenario analysis are the appropriate tools; the objective is not point-targeting, but risk-aware calibration of policy around a slowly moving benchmark.

6. Conclusion

India's demographic transition leaves a persistent and measurable imprint on its neutral real rate. Using an externally estimated equilibrium rate and a GDP-weighted global neutral control, the analysis isolates a domestic demographic signal that is economically large and statistically robust. Youth and total dependency are positively associated with r^*, while old-age dependency is negatively associated with a larger absolute magnitude. These associations remain intact even after adding savings, debt, and potential growth, and the estimated slopes evolve only gradually, consistent with slow-moving fundamentals.

The evidence indicates that neutrality assessments benefit from incorporating demographic composition alongside standard macro-financial indicators. Conditioning the neutral benchmark on projected cohort shares helps disentangle domestic structure from global co-movements and reduces scope for misinterpretation when observed real rates are affected by short-run shocks. Joint monitoring of saving behaviour, debt conditions, and potential growth alongside composition-aware baselines provides a coherent framework for interpreting medium-term movements in r^*.

Two qualifications merit emphasis. First, the estimates are reduced form and rely on an external measure of r^* with acknowledged uncertainty; we do not propagate that measurement uncertainty through the full set of coefficients. Second, while the channels attenuate coefficients in economically plausible ways, the empirical design does not by itself identify causal mechanisms.

Several extensions are natural. A structural multi-cohort framework (e.g., overlapping-generations with portfolio choice) estimated on Indian data could map policy-relevant shocks into r^* while disciplining identification with micro evidence on household saving and asset allocation. A multivariate state-space model that jointly estimates r^* and demographic slopes for a panel of economies—allowing for common global trends and idiosyncratic components—would place India's experience in comparative perspective. On measurement, alternative neutral-rate estimates from macro-finance term-structure models and Bayesian semi-structural variants could be incorporated and combined through model averaging, with full uncertainty propagation to elasticities. Finally, exploiting quasi-experimental variation—such as changes in retirement rules, pension design, or state-level demographic shocks—could strengthen causal interpretation, while real-time forecast evaluation would assess whether composition-aware baselines improve neutral-rate tracking and risk assessment.

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CHAPTER 6

MONETARY POLICY EFFECTIVENESS IN THE ERA OF DEMOGRAPHIC AGEING AND AI ADOPTION: EVIDENCE FROM VIETNAM

Nguyen Trung Anh* and **Do Thi Thu****

1. Introduction

Technological advances and demographic shifts are two transformative forces reshaping the economic landscape. In particular, the rapid diffusion of artificial intelligence (AI) and the steady ageing of populations have far-reaching implications for productivity, inflation, and how monetary policy transmits to the economy. Central banks, as stewards of price and financial stability, need to understand these structural changes. Recent analysis by the Bank for International Settlements (BIS, 2024) highlighted that the adoption of AI is occurring at a breathtaking pace, outstripping previous technological waves. At the same time, many countries, including emerging markets such as Vietnam, are experiencing rising old-age dependency ratios as fertility declines and life expectancy increases. These trends could alter aggregate demand and supply dynamics, influencing both inflationary pressures and the potency of monetary policy.

The theoretical channels are well established. According to life-cycle consumption theory, older households, who are typically net savers, are less responsive to borrowing costs, which weakens the effect of interest rate changes on consumption and investment. Evidence from advanced economies supports this view - Imam (2014) shows that a one percentage point increase in the elderly share reduces the effect of monetary policy on inflation by 0.1 percentage points. On the other hand, AI and digitalisation could alter firms' pricing behaviour and productivity, affecting how quickly monetary shocks pass through to the real economy. Studies suggest that AI-driven efficiencies may be disinflationary in the short-run if supply capacity expands faster than demand (Aldasoro et al., 2024). Conversely, if AI enables firms to adjust prices more flexibly, monetary policy could transmit to inflation more rapidly (Goldfarb and Tucker, 2019; Anghel et al., 2024; Adams et al., 2025).

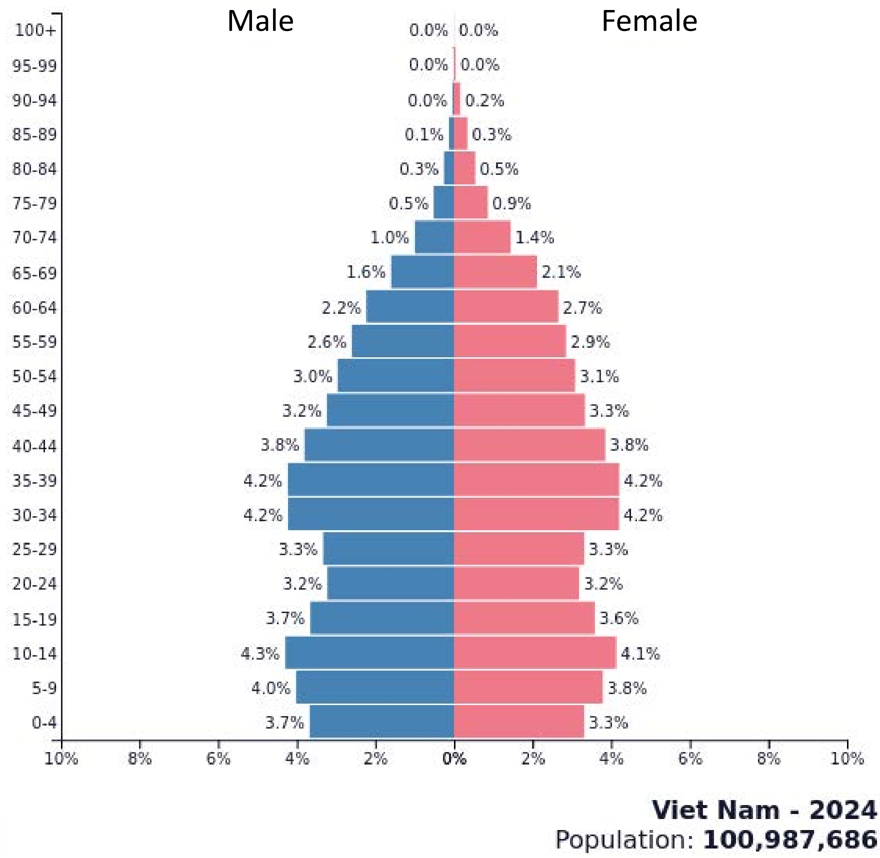
This paper examines how population ageing and AI adoption are shaping the effectiveness of monetary policy in Vietnam. Specifically, we investigate whether the impact of a monetary tightening shock on output and inflation depends on the share of

* Deputy Head of Division, State Bank of Vietnam.

** Lecturer, Banking Academy of Vietnam.

the elderly in the population and on the extent of AI diffusion. Vietnam is a particularly relevant case: it is a fast-growing emerging market that has begun to age demographically while simultaneously experiencing rapid digital adoption. Between 2013 and 2024, the share of the population aged 65 and above increased from about 6% to over 9%, while interest in AI-related technologies surged, especially after the global diffusion of generative AI tools such as ChatGPT in late 2022.

Figure 1: Population Pyramid



Note: *Vietnam's 2024 population pyramid shows a still-young but ageing structure, with the largest cohorts in the 25–39 age range and about 8% aged 65 or above. The narrowing base and widening upper tiers reflect falling fertility and rising longevity, signaling Vietnam's early transition toward an ageing society with implications for savings, labour supply and monetary policy transmission.*

Source: *populationpyramid.net*

Methodologically, we identify monetary policy shocks as residuals from a regression of the overnight interbank rate on a wide set of domestic and global controls. We then trace their effects using Jordà's (2005) local projection framework, which allows us to estimate impulse responses at different horizons without imposing strong structural assumptions. To capture structural transformations, we extend the local projections with interaction terms shock × Age65 and shock × AI index, constructed from Google Trends data via principal component analysis. We focus on short-run horizons of one, three, and six months, which are most relevant for assessing immediate monetary transmission in Vietnam.

The paper proceeds as follows. Section 2 reviews the related literature on demographics, AI, and monetary policy transmission. Section 3 describes the data sources, variable construction and empirical methodology. Section 4 presents the results on how monetary tightening shocks affect industrial output and inflation and how these effects depend on demographics and AI adoption. Section 5 discusses policy implications and places our findings in the broader context of Vietnam's evolving economy. Section 6 concludes.

2. Literature Review

Demographic change has been identified as an important structural factor influencing macroeconomic trends and policy effectiveness. A number of studies have found that population ageing leads to lower equilibrium interest rates and inflation pressure, a phenomenon sometimes referred to as the "demographic deflation" hypothesis. As the share of retirees rises relative to the working-age population, aggregate demand tends to soften because older individuals consume less and have fixed incomes, potentially reducing inflation ceteris paribus (Juselius and Takáts, 2018).

In terms of monetary transmission, ageing may reduce the sensitivity of the economy to interest rate changes. Imam (2014) found that in advanced economies, an increase in the elderly population diminishes the impact of monetary policy on both inflation and unemployment. The intuition is that younger populations have more debt and housing purchases, so they respond more vigorously to rate changes, whereas older populations are less credit-constrained and more reliant on savings, making them less reactive to borrowing cost fluctuations. In short, an ageing society could experience a weaker monetary policy multiplier, especially through the credit and interest rate channels (Imam, 2014; Juselius and Takáts, 2018). On the other hand, some channels like the wealth effect could offset this, since older households hold more interest-sensitive assets, and rate cuts could boost their income (interest earnings), possibly increasing the potency of policy in high-age societies through that channel. The overall net effect, therefore, remains an empirical question - one that is particularly relevant for economies like Vietnam where the elderly share of the population is rising steadily.

The rise of artificial intelligence and digitalisation is another development with ambiguous implications for macroeconomic outcomes. Many scholars posit that AI has the potential to boost productivity growth significantly (Brynjolfsson et al., 2023; Acemoglu and Restrepo, 2018). At a micro level, case studies have found that AI tools can dramatically raise worker efficiency. For instance, certain generative AI applications doubled the speed of coders or improved call-centre performance by 30% in experiments (Hornstein, 2024). If such improvements scale up, AI could act as a positive aggregate supply shock, increasing potential output. A macro model by Aldasoro et al. (2024), calibrated on industry-level AI exposure, concluded that AI adoption raises output, consumption, and investment in both the short-run and the long-run. However, the results on inflation are nuanced: if the productivity gains from AI are unanticipated by firms and households, AI tends to be disinflationary initially, as higher supply is not immediately matched by demand. Over time, stronger demand (due to higher incomes) can put some upward pressure on prices, moderating the disinflation. In contrast, if economic agents anticipate the productivity boost, demand rises in advance, which can lead to a short-run increase in inflation despite higher potential output.

For monetary policymakers, AI could influence both the Phillips curve and the broader transmission mechanism. One hypothesis is that widespread AI and digitalisation make prices more flexible and markets more competitive (the so-called "Amazon effect"), flattening the Phillips curve and reducing inflation sensitivity to domestic slack. Indeed, the BIS (2024) notes that firms adopting AI might adjust prices faster in response to shocks, which could alter inflation dynamics. Another perspective is that higher productivity from AI could allow economies to sustain higher growth for a given level of inflation, potentially prompting central banks to adjust their policy frameworks (Hornstein, 2024). With respect to monetary transmission, the evidence is still limited due to the novelty of AI diffusion. Conceptually, if AI-driven firms and industries respond more quickly to interest rate changes (either through faster scaling of production or quicker financial adjustments) then the short-run impact of monetary policy on output might strengthen. Conversely, if AI adoption raises efficiency and profit margins, firms may be able to absorb higher financing costs more easily, dampening the effect of interest rate hikes on prices and activity.

Overall, the literature points to ageing as likely dampening monetary policy effectiveness, while the effect of AI adoption is more uncertain, with plausible arguments on both sides. This paper contributes to this literature by providing empirical evidence from Vietnam, an emerging economy context, on how these structural factors condition the transmission of monetary shocks. We construct a composite proxy for AI adoption that integrates digital attention (Google Trends), research output (AI publications), and financial commitment (AI investment). While prior studies have considered individual indicators of AI diffusion, the combined approach applied to Vietnam's monetary transmission context represents a novel contribution.

3. Data and Methodology

3.1 Data Sources and Key Variables

We assemble a monthly dataset for Vietnam spanning January 2013 to December 2024. The period is constrained by data availability for all variables and covers roughly 12 years (144 months). The primary macroeconomic indicators come from official sources (State Bank of Vietnam (SBV), General Statistics Office) aggregated by Vietstock Finance's database of macro data. When available, we use official index levels (IIP index, CPI index). If only rates are published, we reconstruct a level index as follows: from month-on-month (m/m) rates by chaining monthly growth; from year-over-year (y/y) rates by solving a minimum-variance monthly growth decomposition that matches each 12-month cumulative growth constraint. We then work in log levels throughout and define the local-projection left-hand side as the cumulative log change between t and $t+h$, i.e., $\log Y_{t+h} - \log Y_t$, which has the usual interpretation as a cumulative percentage response. The variables used in the analysis include:

Table 1. : List of Variables and Data Sources

Variable	Definition & Source	Transformation/ Notes	Period & Key Features
Industrial Production Index (IIP_yoy_pct)	Year-on-year % change in industrial production (GSO, via Vietstock Finance)	Monthly, % change	2013–2024, Volatile; sharp dip in 2020 (COVID-19), recovery thereafter
Consumer Price Index (CPI_yoy_pct)	Year-on-year % change in CPI (GSO, via Vietstock Finance)	Monthly, % change, Used as main inflation proxy instead of GDP deflator	2013–2024, Reflects consumer price inflation, subject to administered pricing
Monetary Policy Shock (mp_shock)	Residual from regression of SBV overnight interbank rate (avg_ VNIBOR_ON) on domestic & global controls	Measured in percentage points; mean zero; positive = contractionary	Captures unexpected policy innovations (e.g., +0.5 = surprise tightening)
Credit Growth (Credit_yoy_pct)	Year-on-year growth in domestic credit (SBV, via Vietstock Finance)	% change, monthly	Control variable for financial cycle conditions
Population Ageing (Age65)	Share of population ≥65 years (GSO, WB). Annual data, interpolated to monthly.	Mean-centered in regressions	Slow upward trend: 6.2% (2013) → 9.0% (2024)
AI Adoption (AI_index)	Composite index constructed from (i) Google Trends (16 AI/ ML-related keywords), (ii) number of AI publications (OECD), (iii) AI investment in million USD (OECD)	Each component log-transformed or standardized; first principal component (PCA) extracted to form monthly index	Flat through 2016; rising steadily since 2018; sharp surge in 2022–2023 with ChatGPT and global AI breakthroughs

Ageing and AI variables: The ageing indicator (share of population aged 65+) is available annually, so we interpolate it to monthly frequency using a cubic spline. For AI-related indicators, we first construct a composite AI index via PCA combining monthly Google Trends and annual AI publications/investment (monthly-aligned). To reduce high-frequency noise in monthly signals, we use a 3-month centred moving average of the PCA composite in the interaction regressions, while reporting robustness to the unsmoothed index in the appendix.

Monetary policy shocks: To identify unexpected monetary policy innovations in Vietnam, we construct shocks as the residuals from a regression of the overnight interbank rate (the SBV's main operational target) on a broad set of domestic and global conditioning variables. This ensures that shocks reflect unexpected changes in the policy rate, rather than endogenous responses to inflation, output, exchange-rate pressures, or global financial conditions.

Formally, the regression is specified as:

$$i_t = \alpha + \beta' X_t + u_t,$$

where i_t is the average overnight interbank rate (VNIBOR ON) in month t, is a vector of conditioning variables capturing macro-financial and global conditions, and u_t is the residual, interpreted as the monetary policy shock (mp_shock_t).

The vector of controls X_t includes:

- Domestic variables: Industrial production ($\log IIP_t$), inflation ($\log CPI_t$), credit growth (log change of credit), exchange rates (bilateral VND/USD, NEER, REER), and government bond yield (10-year, $VN10Y_t$).

- Global variables: Fed Funds rate ($FEDFUNDS_t$), U.S. 10-year Treasury yield ($US10Y_t$), shadow policy rate ($WuXia_t$, pre-2022), global risk sentiment (VIX_t), U.S. Dollar Index (DXY_t), and commodity prices (Brent oil price, FAO global food price index).

Thus, the monetary policy shock series is defined as:

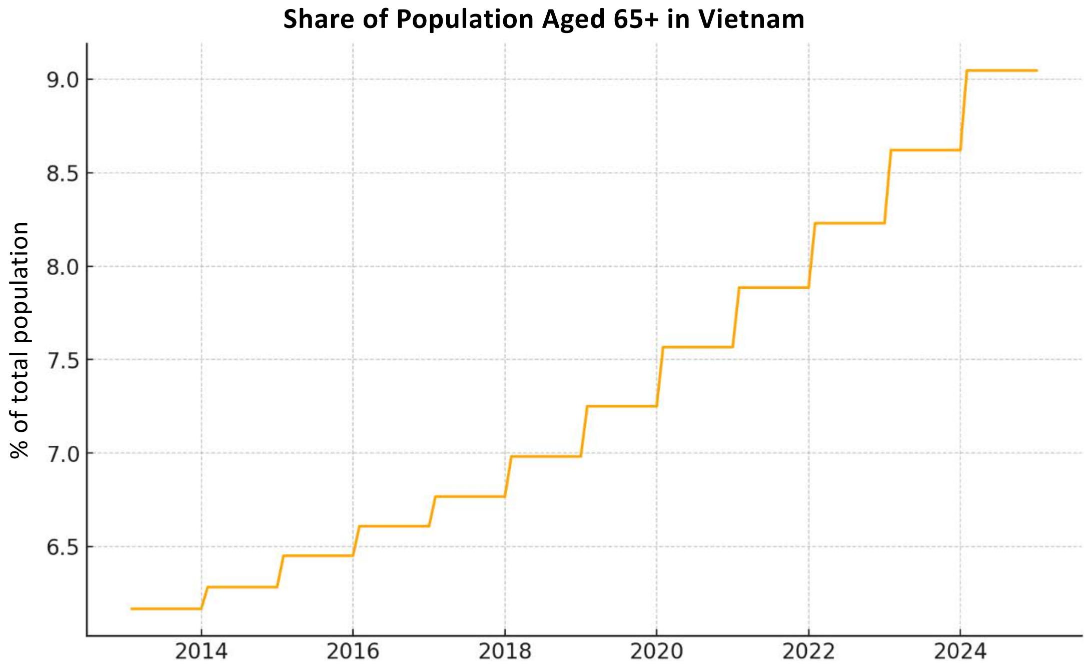
$$mp\_shock_t = u_t = i_t - \hat{i}_t, where\hat{i}_t = \alpha + \beta' X_t.$$

By construction, the shock series has mean zero and is measured in percentage points, with a positive value corresponding to a contractionary innovation (for example, +0.5 denotes a surprise 50-basis-point tightening).

In subsequent local-projection estimations, the dependent variables are expressed in log levels (i.e., $\log IIP$ and $\log CPI$), so that estimated impulse responses measure the cumulative percentage change in output or prices following a one-unit (percentage-point) monetary policy shock. This log specification ensures consistent interpretation between the level of the policy rate and the proportional responses of macroeconomic outcomes.

This approach improves on simple Taylor-rule residuals by incorporating both domestic and global drivers of interest rates, thereby reducing omitted-variable bias. Unlike VAR or sign-restriction methods (which are difficult to implement in short samples), the regression-residual approach is feasible with limited monthly data and directly interpretable. Nevertheless, we note that Vietnam's monetary policy also relies on credit quotas, foreign-exchange interventions, and administrative tools that may not be fully captured. We, therefore, interpret the shocks as conditional innovations consistent with a tightening narrative, rather than strictly exogenous causal instruments.

Figure 2: Share of Population Aged 65 and Above in Vietnam (2013–2024)**



*Note: **The share of elderly (≥65 years) rose from just over 6% in 2013 to about 9% in 2024, reflecting Vietnam's ongoing demographic ageing.*

Source: General Statistics Office of Vietnam.

Figure 2 illustrates the trajectory of Vietnam's demographic shift. The share of the population aged 65 and above has risen steadily from approximately 6.2% in 2013 to over 9.0% in 2024. This upward trend reflects the combined effects of declining fertility rates and increasing life expectancy. Because demographic data are officially released on an annual basis, we interpolate the series to a monthly frequency using a cubic spline method to match the frequency of our macroeconomic variables. This allows us to capture the smooth, continuous nature of demographic change in our monthly regression analysis.

Figure 3 shows the composite AI index (PCA) for Vietnam over 2013–2024. The series is relatively flat until 2016, rises gradually thereafter, and accelerates from 2019, with a sharp surge in late 2022–2023 following the release of ChatGPT and the global wave of interest in generative AI. The index integrates three components: (i) Google Trends search intensity for 16 AI-related keywords, (ii) the number of AI-related publications (OECD), and (iii) AI investment in Vietnam (million USD, OECD). Each component is standardised, and the first principal component (PCA) is extracted to form a single monthly indicator. The PCA captures the common dynamics across digital attention, research output, and financial commitment, offering a broader proxy of AI adoption than Google Trends alone.

Figure 3: Composite AI Adoption Index for Vietnam (2013–2024)

Note: *Higher values indicate greater adoption and diffusion of AI. The series is the first principal component (PCA) of standardizsed indicators, capturing common dynamics across digital attention, research output, and financial commitment. The red line marks the release of ChatGPT in late 2022, which coincided with a sharp acceleration in Vietnam's AI adoption index.*

Source: *Google Trends (16 AI-related keywords), OECD (AI publications and AI investment); authors' calculations.*

This index highlights that Vietnam's AI adoption trajectory has been driven by both rising public interest and tangible increases in research and investment activity. The sharp uptick in 2022–2023 suggests that global breakthroughs in generative AI coincided with a strong domestic acceleration in AI-related activities.

It is important to note the limitations of this measure. While combining Google Trends, publications, and investment reduces reliance on search intensity alone, the composite index should still be interpreted as a proxy for broad diffusion and adoption pressures rather than a direct measure of firm-level deployment. Search data may capture curiosity, while publication and investment data reflect inputs into the innovation process rather than realised productivity. Nevertheless, the composite PCA approach provides a richer and more robust measure than any single indicator, and helps capture the structural role of AI diffusion in conditioning monetary transmission in Vietnam. Ultimately, for this index to fully reflect AI adoption in Vietnam, it would need to be complemented by survey evidence or large-scale assessments of corporate adoption of AI technologies, which lies outside the scope and capacity of this research.

Finally, all variables are aligned to monthly frequency. The monetary policy shock and AI index are mean-centred when used in interaction regressions, so that the main shock coefficient can be interpreted at average levels of AI adoption and demographics.

3.2 Identification of Monetary Policy Shocks in Vietnam's Hybrid Framework

Vietnam's monetary policy operates under a hybrid framework in which the SBV simultaneously manages interest rates, credit growth, and exchange rate stability. The IMF's *Quarterly Projection Model for Vietnam* (2022) characterises this regime as a blend of price-based and quantity-based instruments, combining the policy rate and liquidity operations with indicative credit ceilings and a managed-flexible exchange-rate objective. This institutional arrangement implies that monetary conditions cannot be captured by the policy rate alone.

The monetary policy shocks used in this study - constructed in section 3.1 as residuals from a regression of the overnight interbank rate on a wide set of domestic and global variables - are interpreted as unexpected policy innovations. By design, these residuals captures short-term liquidity adjustments that are not explained by macroeconomic fundamentals, providing a measure of high-frequency monetary surprises consistent with short-run policy tightening or easing. A positive value corresponds to a contractionary innovation (for example, a surprise tightening of liquidity conditions). In the subsequent local-projection analysis, outcome variables are expressed in log levels (log IIP and log CPI), so that impulse responses measure cumulative percentage changes in output or prices following a one-percentage-point monetary shock.

To complement this rate-based measure, we construct a *Monetary Conditions Index (MCI)* that integrates movements in the policy rate, domestic credit growth, and the real effective exchange rate (REER) into a single indicator of overall monetary stance. Each component is standardised (in z-scores) and combined to reflect the joint influence of the price-based, credit, and exchange-rate channels that define the SBV's hybrid framework. A higher MCI value indicates tighter monetary conditions, either through higher interest rates, slower credit expansion, or an appreciation of the REER, while a lower value represents looser financial conditions. The MCI is defined as:

$$\mathrm{MCI}_t = 0.5\, z(r_t) + 0.3\, z(\mathrm{Credit}_t) + 0.2\, z(\mathrm{REER}_t),$$

where $z(x_t)$ denotes standardised deviations from sample means. The positive sign on REER reflects that an appreciation (higher REER) implies tighter monetary conditions, ensuring that larger MCI values correspond to an overall tightening stance.[1] The weights (0.5 for the policy rate, 0.3 for credit, 0.2 for REER) follow stylised conventions used in Trinh and Kim (2014) and IMF (2022) for Vietnam's hybrid regime. They reflect expert judgment about the relative importance of the three channels rather than econometric estimation, consistent with standard practice in IMF and central-bank analyses.

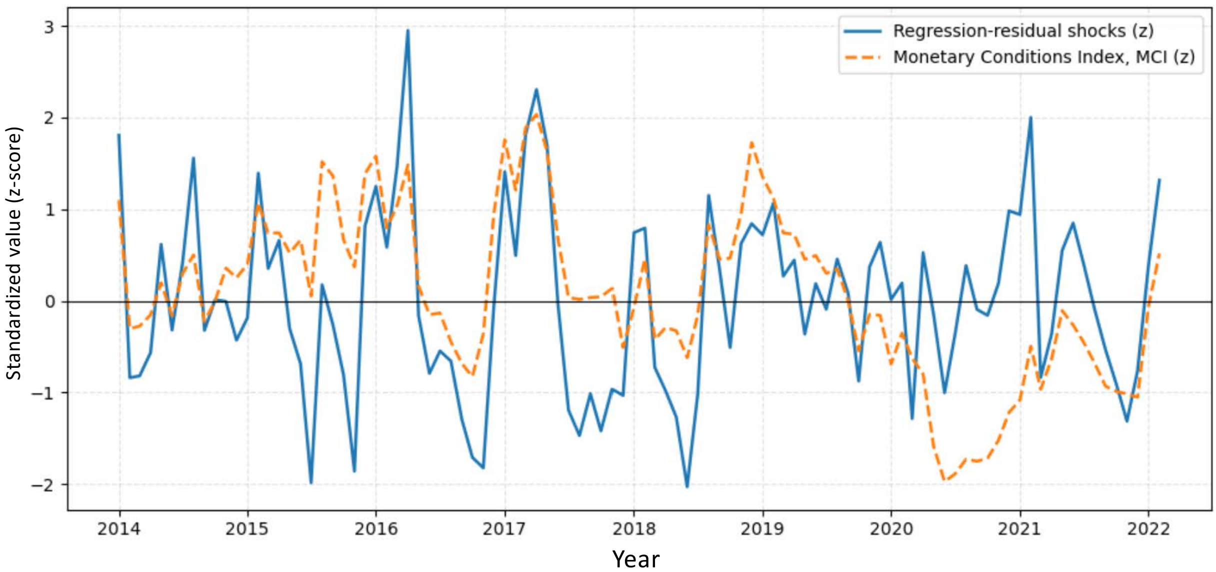
1. We employ standardised deviations (z-scores) to normalise the different units of measurement (percentages for interest rates, index levels for REER and percentage growth for credit) into a comparable scale. While other approaches exist, such as using deviations from trend (output gap logic), the z-score approach is transparent and avoids the endpoint bias associated with filtering techniques in short samples

Empirically, both the regression-based shocks and the MCI co-move closely with the SBV's known tightening and easing phases, tightening during 2015–2016 and 2022, and easing during 2020–2021. Their positive correlation of approximately 0.50 (Figure 4) indicates that the two indicators move broadly together, capturing similar directional shifts in monetary stance. Both series rise during periods of policy tightening and decline during liquidity easing, confirming that they reflect consistent changes in Vietnam's monetary conditions.

While the MCI tracks medium-term policy settings shaped by movements in interest rates, credit, and the REER, the regression-residual shocks represent high-frequency monetary surprises, capturing month-to-month adjustments in liquidity conditions that are not predictable from fundamentals. Their co-movement supports the interpretation of these residuals as credible high-frequency monetary shocks within the SBV's hybrid framework.

Given these complementarities, this study employs the regression-residual shocks as the baseline measure of unexpected monetary innovations and the MCI as a robustness indicator that reflects the broader multi-instrument nature of Vietnam's monetary framework. This dual-indicator approach aligns with the hybrid-policy interpretation advanced by IMF (2022) and Anwar and Nguyen (2018), providing a comprehensive basis for assessing the transmission of monetary policy in Vietnam.

Figure 4: Comparison of Standardized Regression-residual Shocks and the Monetary Conditions Index (MCI)



Note: Both indicators are standardised (z-scores). The correlation between the two series is 0.50, and their movements align with the SBV's known tightening (2015–2016, 2022) and easing (2020–2021) episodes.

3.3 Empirical Methodology: Local Projections

To study the dynamic effects of monetary policy shocks, we apply the local projections (LP) method introduced by Jordà (2005). Unlike VAR models, which impose a full system of equations, LPs estimate horizon-specific regressions directly. This provides flexibility, reduces the risk of misspecification in small samples, and allows us to trace impulse responses without strong structural assumptions.

For each forecast horizon h, the baseline specification is:

$$\log(y_{t+h}) - \log(y_t) = \alpha_h + \beta_h \, \text{mp\_shock}_t + \phi_h \log(y_{t-1}) + \theta_h \, \text{Credit}_t + \varepsilon_{t+h},$$

where:

- y_t is the level of the variable of interest (industrial production index – IIP or consumer price index – CPI), expressed in logs;
- $\log(y_{t+h}) - \log(y_t)$ represents the cumulative percentage change between t and $t + h$, which is standard in LPs using log-level data;
- mp_{shock_t} is the monetary policy shock, defined as the residual from the regression of the SBV overnight interbank rate on a broad set of domestic and global variables (see section 3.1); a positive value corresponds to a contractionary innovation;
- $Credit_t$ is credit growth (preferably monthly or log-change), included to capture financial-cycle conditions;
- α_h is a constant and ε_{t+h} the error term.

The parameter of interest, β_h, measures the average effect of an unexpected contractionary monetary policy shock on output or inflation at horizon h. We focus on horizons of 1, 3, 6 months, reflecting short- and medium-term dynamics. Longer horizons are avoided given the limited sample size and the fragility of LP estimates in emerging-market settings.

3.3.1 Heterogeneity Through Interactions

To examine how structural factors shape transmission, we extend the regressions with interaction terms:

$$\begin{aligned}\log(y_{t+h}) - \log(y_t) &= \alpha_h + \beta_h mp\_shock_t + \gamma_h(mp\_shock_t \times Age65_t) + \delta_h(mp\_shock_t \times AI_t) \\ &\quad + \phi_h \log(y_{t-1}) + \theta_h Credit_t + \varepsilon_{t+h}.\end{aligned}$$

where:

- $Age65_t$ is the share of the elderly population (standardised). γ_h captures how ageing conditions the impact of monetary shocks; a positive γ_h indicates that ageing dampens the contractionary effect.

- AI_t is the composite AI-adoption index (PCA), built from Google Trends, AI publications, and AI investment (see section 3.1). δ_h measures how AI adoption conditions transmission; a negative δ_h indicates that greater AI adoption amplifies the contractionary effect.
- Controls include one lag of the dependent variable and contemporaneous credit growth.

Interpretation is straightforward: β_h represents the baseline response at average levels of ageing and AI adoption, γ_h show how the response changes with demographic ageing, and δ_h shows how it changes with AI diffusion. We estimated the regressions for horizons *h = 1, 3, 6 months* and compute Newey–West (HAC) standard errors to correct for serial correlation in overlapping horizons.

3.3.2 Identification

The key identification assumption is that mp_shock_t reflects an exogenoous monetary policy innovation. By construction, the shock is the component of ON-rate changes unexplained by fundamentals such as output, inflation, credit, exchange rates, bond yields, or global conditions. This reduces endogeneity bias compared with Taylor-rule residuals. Including lagged outcomes and credit growth further mitigates omitted-variable concerns.

That said, monetary policy in Vietnam also involves credit quotas, FX interventions, and administrative measures that are not fully captured by ON-rate shocks. Thus, we interprete the shocks as conditional innovations consistent with a tightening narrative, rather than strictly exogenous causal instruments. Future work could complement this approach with high-frequency identification around SBV announcements or narrative-based strategies.

3.3.3 AI Measure

The AI index is constructed as the first principal component (PCA) of three standardised indicators:

1. Google Trends intensity for 16 AI/ML-related keywords,
2. Number of AI-related publications (OECD),
3. AI investment in Vietnam (million USD, OECD).

This PCA captures the common variation across digital attention, research, and financial commitment, providing a broader proxy for AI adoption. While the index is an indirect measure, robustness checks show that results are not sensitive to the specific weighting scheme. To fully measure adoption, future research would ideally complement this index with firm-level surveys or corporate adoption assessments, which are outside the scope of this study.

3.4 Estimation and Inference

All regressions are estimated using ordinary least squares (OLS). To address potential autocorrelation in the error terms arising from overlapping horizons in local projections, we compute HAC robust standard errors.

Impulse responses are reported as the estimated coefficients β_h (baseline effect of monetary shocks), and in the extended cases γ_h (interaction with ageing) and δ_h (interaction with AI adoption), plotted with 95% confidence intervals. The baseline IRFs captured the average short-run response of industrial output and CPI inflation to monetary policy shocks, while the extended regressions highlight how the transmission varies with demographic ageing and AI diffusion.

We focus on horizons of 1, 3 and 6 months, reflecting the short- and medium-run effects that can be estimated with reasonable precision in Vietnam's limited monthly sample.

This design allows us to examine three dimensions of monetary transmission in Vietnam:

1. the average short-run effect of policy shocks,
2. the demographic interaction through population ageing, and
3. the technological interaction through AI adoption.

In the next section, we present the estimated impulse responses and discuss their implications.

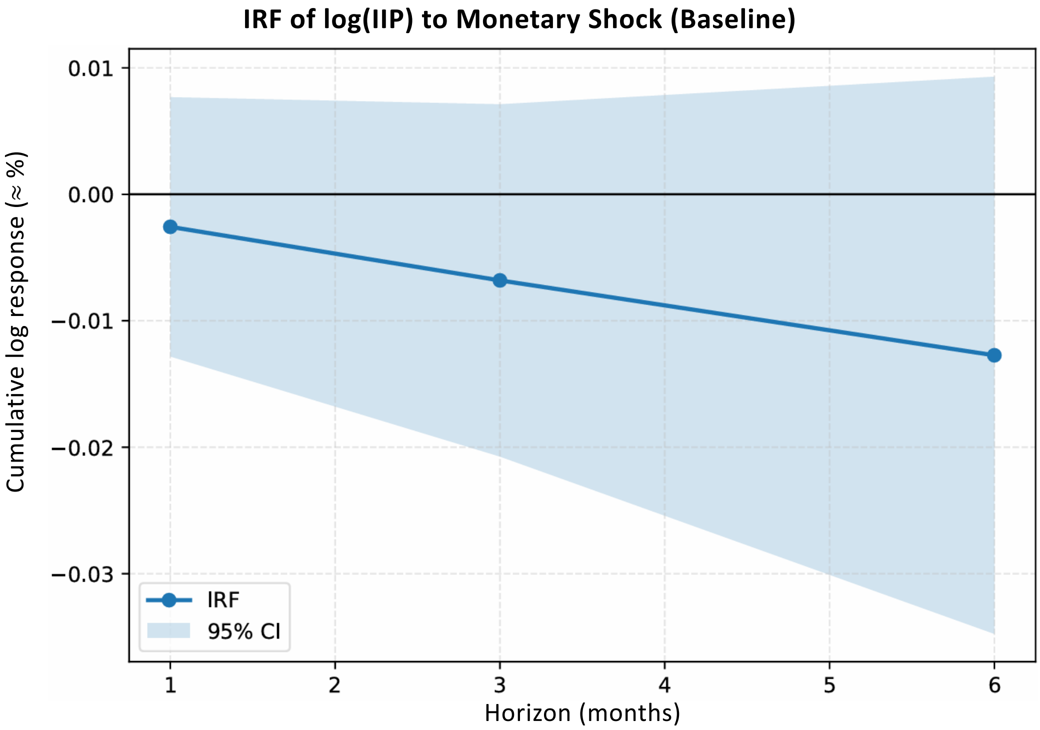
4. Results

4.1 Baseline Impulse Responses

This section presents the empirical results for the baseline specification, which estimates the average dynamic effects of a one-percentage-point monetary policy tightening shock on industrial output and consumer prices. The regressions are estimated in log levels with Newey–West (HAC) standard errors and include credit growth and other domestic and global controls to capture Vietnam's hybrid monetary framework.

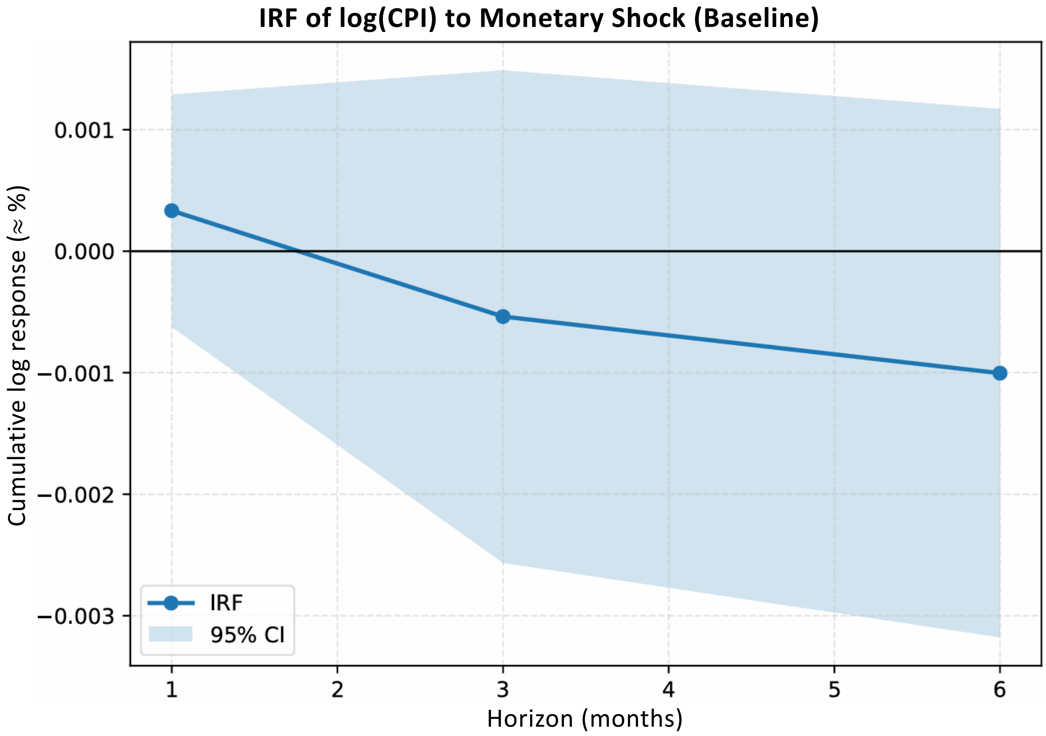
The impulse response of industrial output (Figure 5) reveals a small and short-lived decline in activity following the policy shock. The cumulative log response is about −0.005% after one month, −0.010% at three months, and −0.012% by month six. Although the direction of the effect accords with conventional theory (monetary tightening dampens output) the magnitude is extremely small; and the 95% confidence band remains wide and encompasses zero at all horizons. These results indicate that, once credit conditions and external variables are accounted for, the short-term impact of unexpected monetary tightening on real activity is negligible and statistically insignificant.

Figure 5: Impulse Response of Industrial Output (IIP) to a Monetary Policy Shock.



The response of consumer prices (Figure 6) is similarly muted. CPI shows a mild and transitory decrease, reaching roughly −0.001% at three months before stabilising. The estimated 95% confidence interval is again wide and includes zero throughout, implying no statistically significant inflation response. This finding is consistent with the structure of Vietnam's monetary system, where administered prices, exchange-rate smoothing, and quantity-based measures dilute the short-run effect of interest-rate shocks on consumer prices.

Figure 6: Impulse Response of CPI to a Monetary Policy Shock.



To further explore potential state dependencies in the transmission of monetary policy, we extend the analysis by interacting the identified shocks with structural variables capturing demographic ageing and AI adoption. While the local projection models are estimated for horizons h = 1,3,6 months, the visualisation of marginal effects focuses on h=3 months - which is the horizon at which output responses typically peak and statistical precision is highest. This approach allows us to illustrate how the effectiveness of monetary policy varies across different levels of ageing and AI.

4.2 Demographic Ageing as a Conditioning Factor

This section examines whether Vietnam's demographic structure, captured by the share of the population aged 65 years and above, conditions the transmission of monetary policy. The aim is to test whether ageing economies respond differently to policy tightening. The impulse responses for the interaction terms are shown in Figures 7 and 8, while the corresponding marginal-effect plots appear in Figures 9 and 10.

The results for industrial output (Figure 7) suggest that demographic ageing may slightly alter how monetary shocks propagate through the real economy. The estimated interaction term between the monetary policy shock and the elderly share is positive and rising across horizons, reaching about +0.2% after six months. Although the effect grows in magnitude, the 95% confidence band remains wide and includes zero at all horizons, indicating that the relationship is not statistically significant. Nonetheless, the direction of the estimate implies that economies with a higher share of older adults may experience a weaker contraction, or even a modest expansion, in output following a tightening shock.

Figure 7: Impulse Response of Industrial Output (Log IIP) to a Monetary Policy Shock Interacted with Age65.

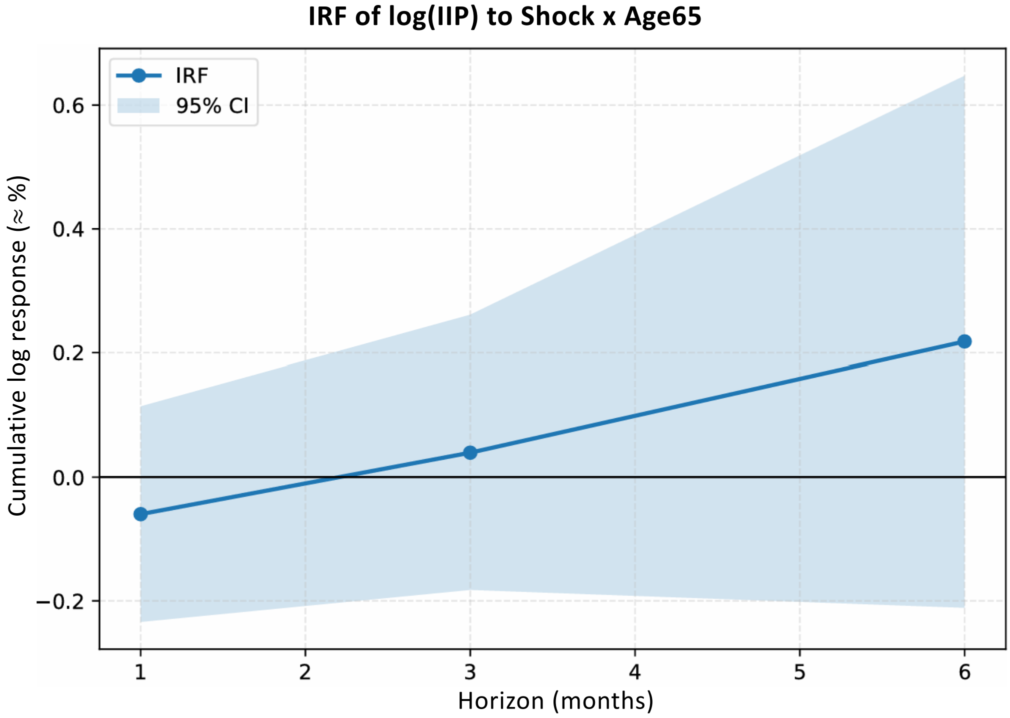
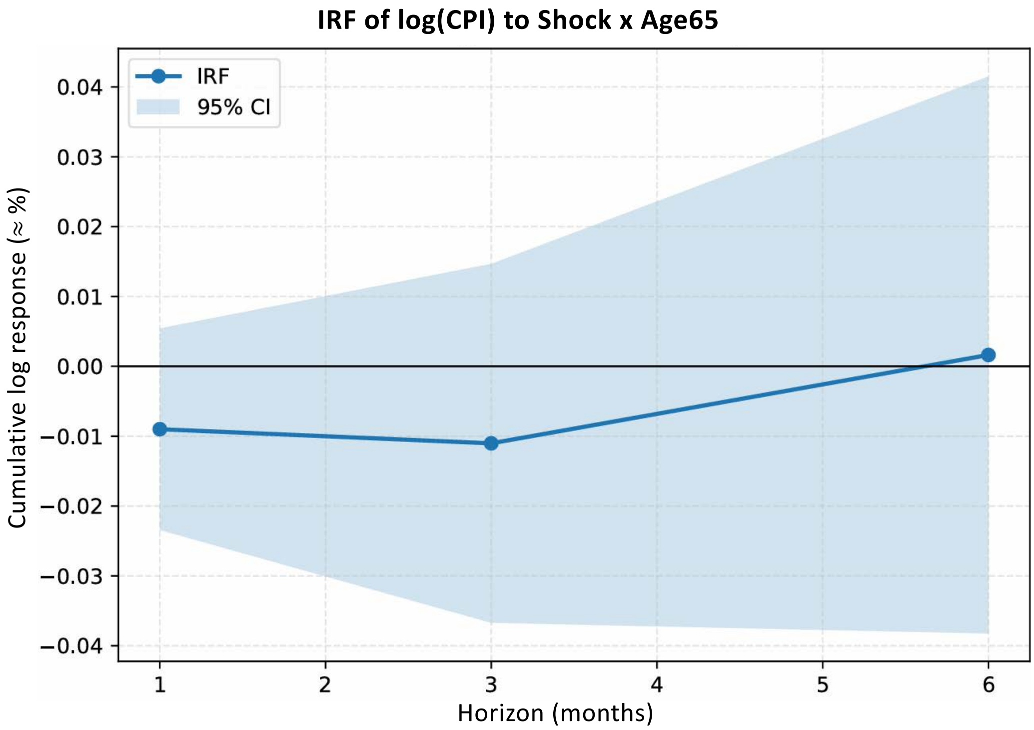


Figure 8: Impulse Response of Consumer Prices (Log CPI) to a Monetary Policy Shock Interacted with Age65



The inflation response in Figure 8 shows a broadly similar but smaller pattern in reverse sign. For younger demographic structures, monetary tightening is modestly disinflationary (around −0.01% at one to three months), while for older populations, the estimated effect becomes near zero or slightly positive by month six. Again, the confidence intervals are wide, and the results should be viewed as exploratory rather than conclusive.

The marginal-effect plots in Figures 9 and 10 clarify these patterns. For industrial output, the conditional effect of a tightening shock becomes slightly more negative as the elderly share increases, shifting from roughly −0.005% at 6.5% Age65 to about −0.02% at 9% Age65. For CPI, the marginal effect moves in the opposite direction, from slightly negative toward zero or slightly positive as the population ages. Both trends are extremely small in magnitude and fall well within the statistical confidence bands, but they are directionally consistent with the hypothesis that older economies exhibit muted sensitivity to monetary shocks because of lower credit demand and higher interest-income channels among retirees.

Figure 9: Marginal Effect of Monetary Policy Shocks on Industrial Output Across Ageing Levels (H = 3)

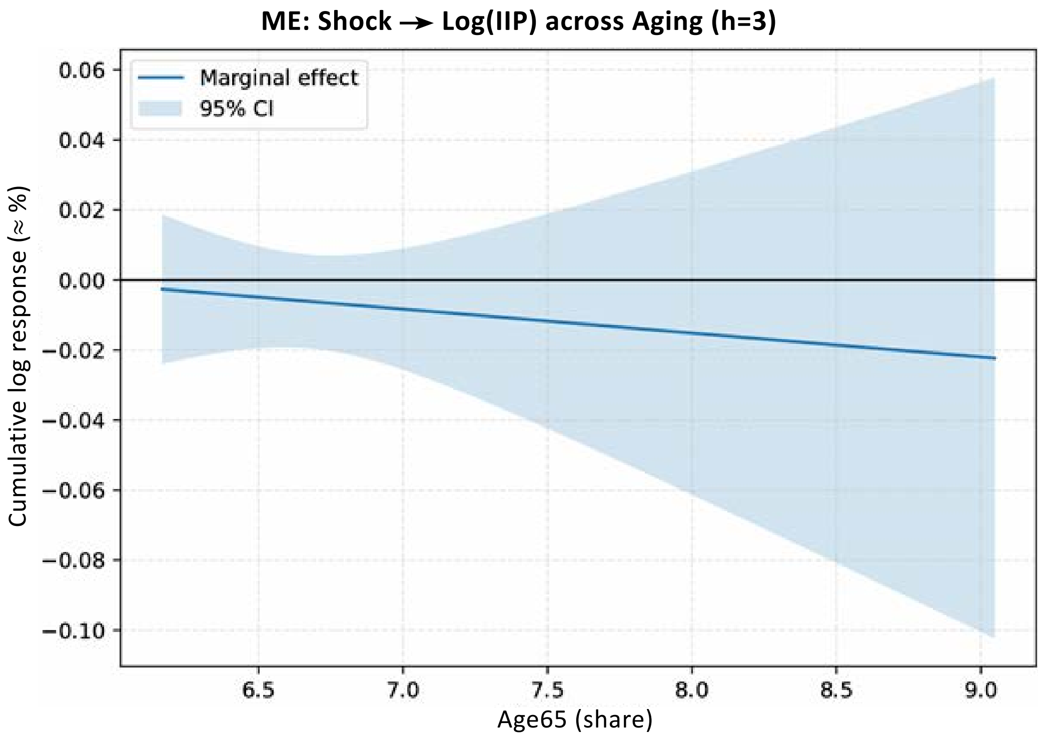
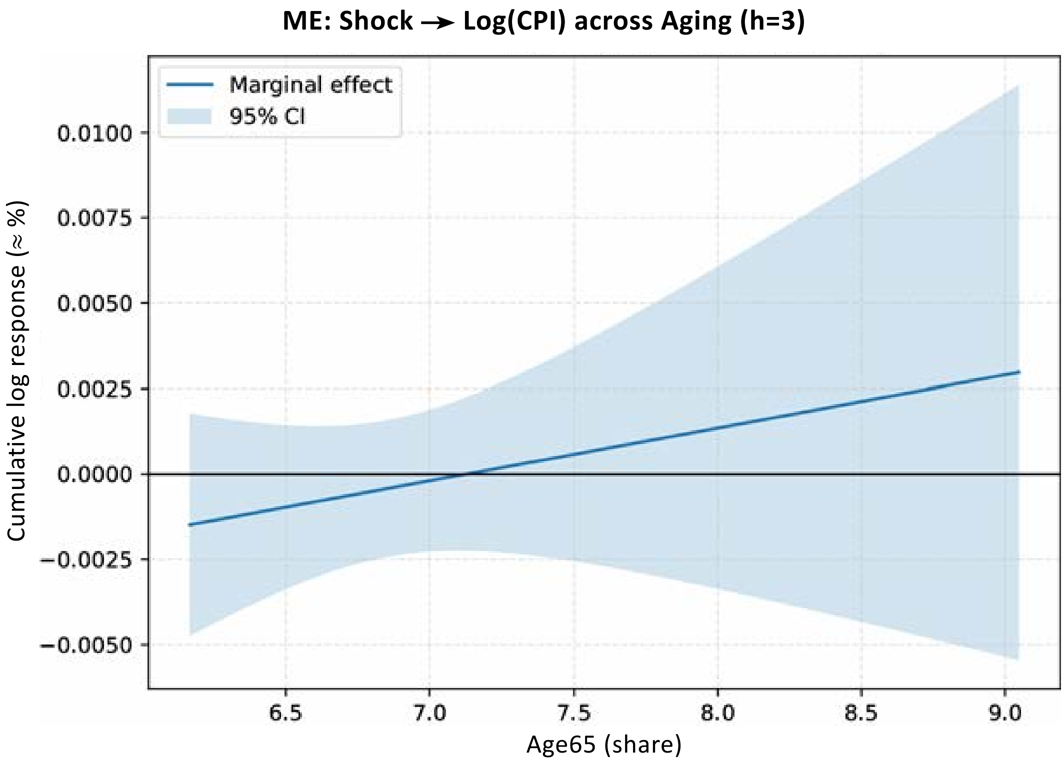


Figure 10: Marginal Effect of Monetary Policy Shocks on Inflation Across Ageing Levels (H = 3)



4.3 AI Adoption as a Conditioning Factor

This section explores whether the transmission of monetary policy depends on the level of AI adoption in the economy. The composite AI index (three-month moving-average PCA) serves as a proxy for the diffusion of digital and AI technologies across Vietnam's productive and financial sectors. The underlying hypothesis is that economies with greater technological integration might display altered sensitivities to monetary shocks because AI can influence productivity dynamics, price flexibility, and investment behaviour. The results are summarised in Figures 11 to 14.

The interaction impulse responses in Figures 11 and 12 show that the conditioning effect of AI adoption on monetary transmission is very small and statistically insignificant. For industrial output, the estimated response (Figure 11) is close to zero at the one-month horizon and turns slightly negative (about −0.015%) by month six, with wide confidence bands overlapping zero throughout. For consumer prices (Figure 12), the response follows a similar pattern: a negligible initial uptick followed by a mild decline of roughly −0.001% by month six. These results indicate that, within the sample period, higher AI adoption does not materially amplify or dampen the direct effect of monetary tightening on either output or inflation.

Figure 11: The Conditioning Effect of the AI Adoption Index (AI_Index_PCA) on the Response of IIP to a Monetary Policy Shock

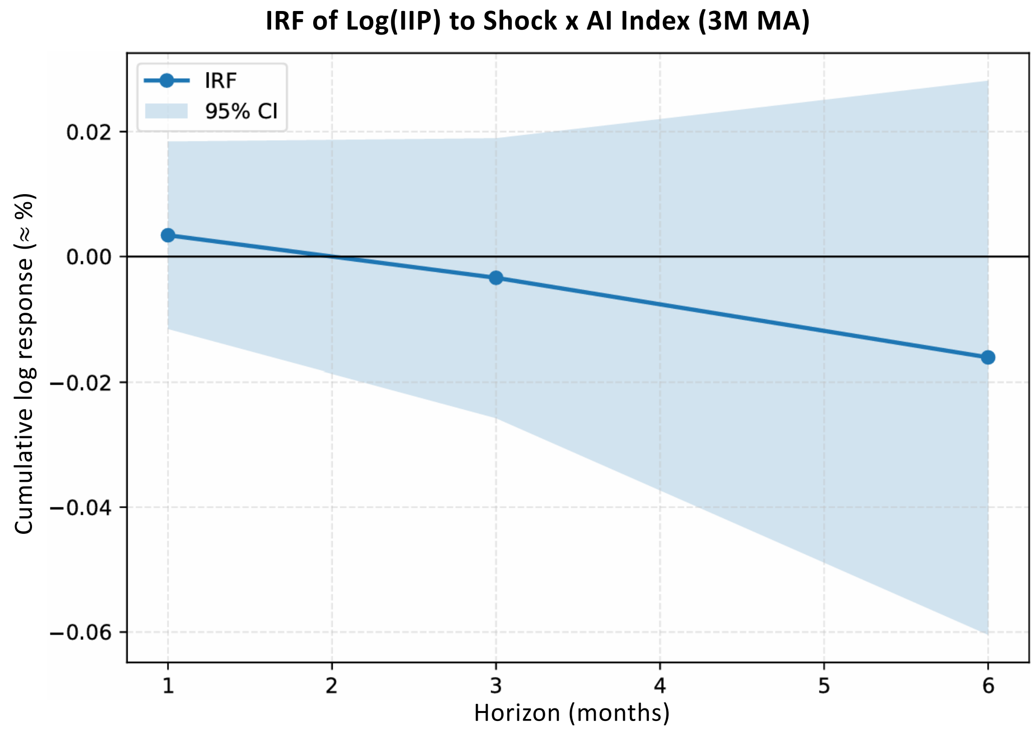
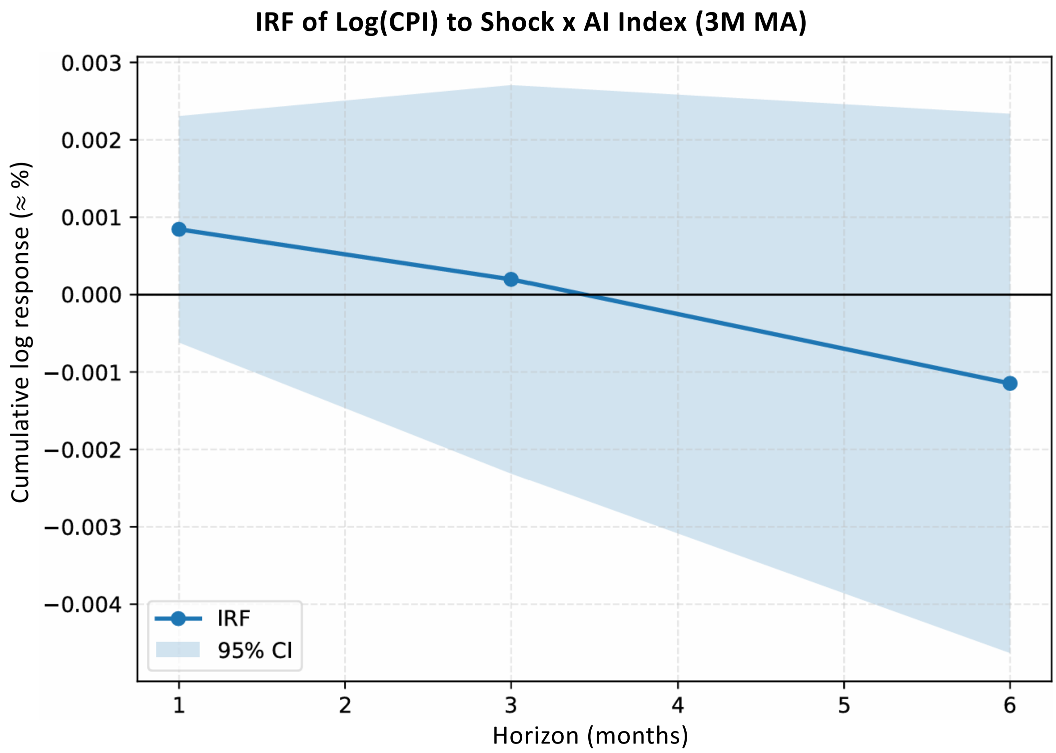


Figure 12: The Conditioning Effect of the AI Adoption Index (AI_Index_PCA) on the Response of CPI to a Monetary Policy Shock



The marginal-effect plots in Figures 13 and 14 provide further insight. At the three-month horizon, the conditional response of industrial output (Figure 13) becomes *slightly less negative* as AI adoption increases, from around −0.02% in low-AI environments (AI_index ≈ −2) to about zero in high-AI settings (AI_index ≈ +2). For CPI (Figure 14), the marginal effect also trends upward but remains close to zero across all values of the AI index. While these slopes suggest that greater digital integration may modestly cushion the contractionary effects of monetary policy (possibly by improving productivity or cost efficiency), the confidence intervals are wide and the results lack statistical precision.

Figure 13: Marginal Effect of Monetary Policy Shock on Industrial Output Across AI Adoption Levels (H = 3)

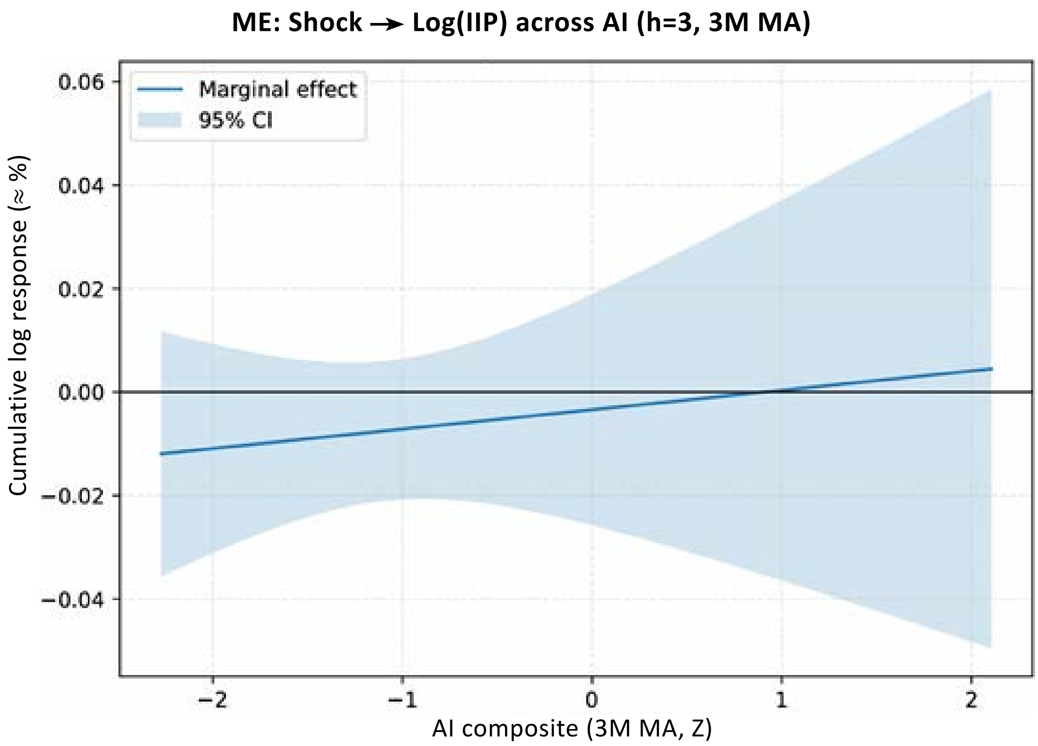
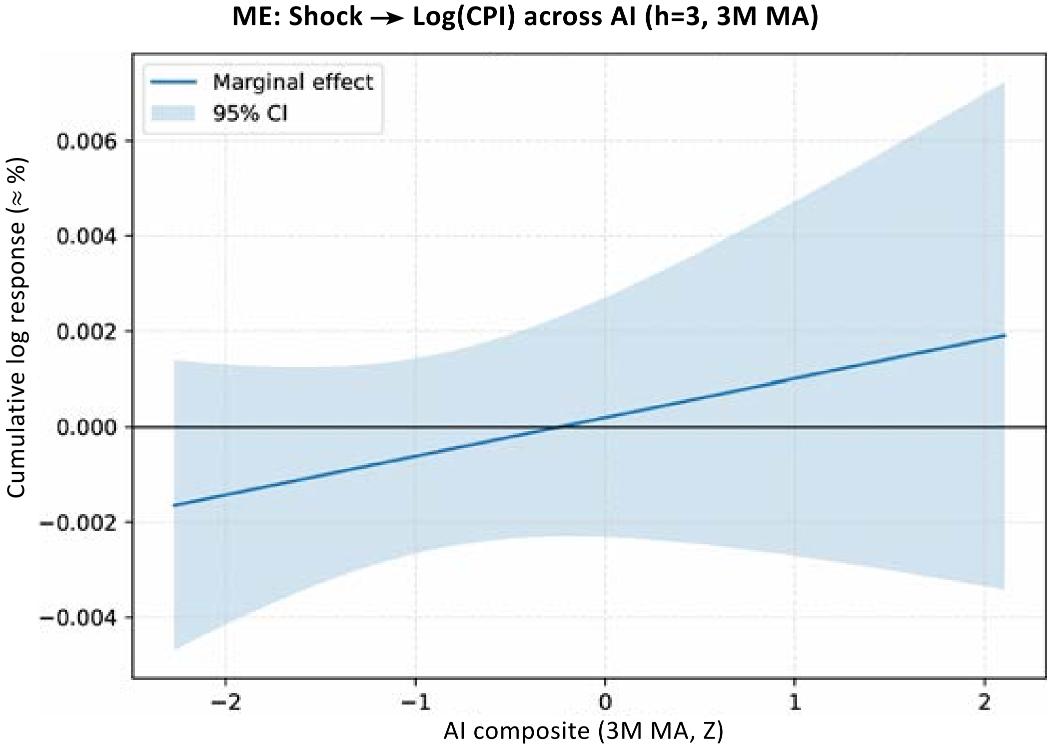


Figure 14: Marginal Effect of Monetary Policy Shock on Inflation Across AI Adoption Levels (H = 3)



4.4 Robustness Checks: The Monetary Conditions Index (MCI)

To assess the sensitivity of our results to the identification strategy, we re-estimated the local projections using the MCI as the measure of the policy stance instead of the regression-residual shocks. As discussed in section 3.2, the MCI captures a broader set of policy instruments, including exchange rate movements and credit conditions, which are integral to the SBV's hybrid framework.

Figures 15 and 16 present the impulse responses of industrial output and consumer prices, respectively, to a shock in the MCI. The results are qualitatively similar to the baseline findings. Specifically, the response of industrial output (Figure 15) shows a gradual decline that remains small in magnitude and statistically insignificant, mirroring the baseline output response. Similarly, the inflation response (Figure 16) continues to show a muted sensitivity to monetary tightening, with confidence intervals encompassing zero. These robustness checks confirm that the limited short-run transmission identified in the baseline specification is not driven solely by the construction of the monetary shock variable but reflects a genuine characteristic of the Vietnamese economy during the sample period.

Figure 15: Robustness Check - Impulse Response of Log IIP to a Shock in the MCI

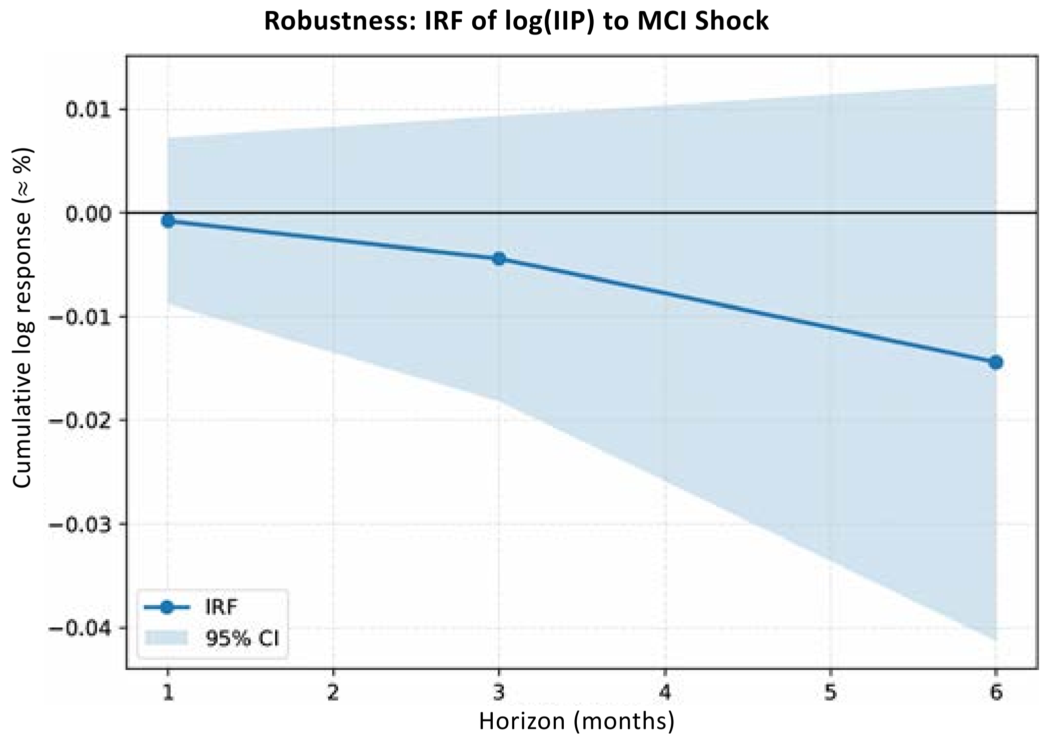
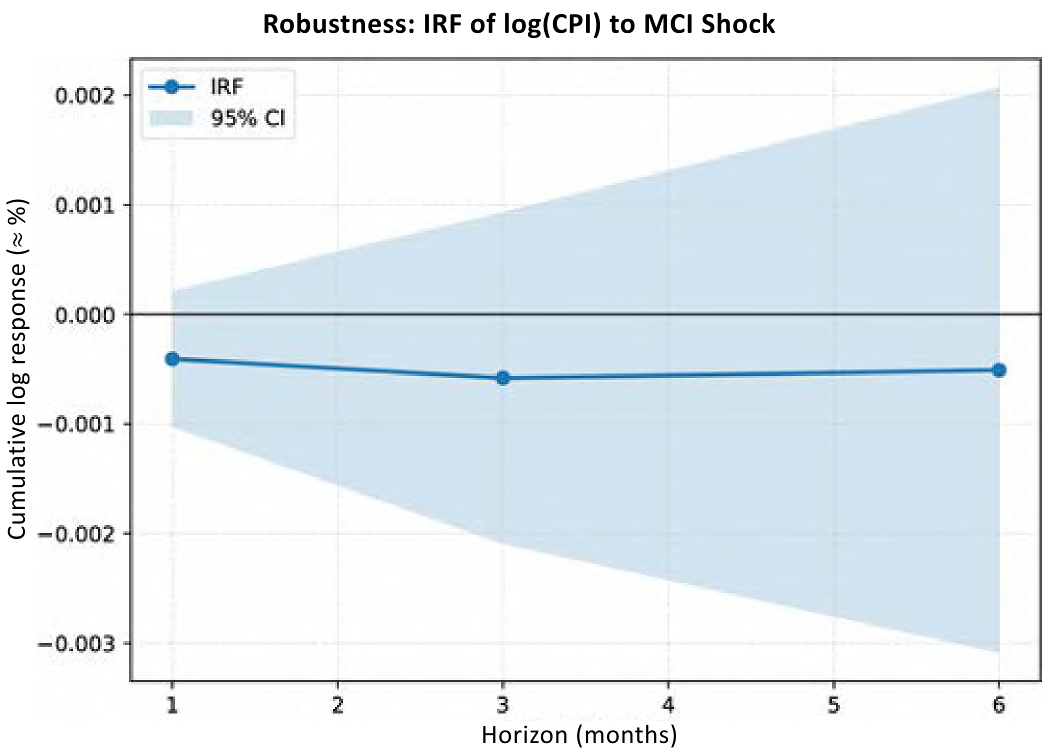


Figure 16: Robustness Check: Impulse Response of Log CPI to a Shock in the MCI



4.5 Summary of Findings

Overall, our empirical analysis yields four broad observations about the transmission of monetary policy in Vietnam, while acknowledging substantial statistical uncertainty.

Firstly, the baseline specification (estimated in log levels with credit controls) shows no statistically significant or economically meaningful response of either industrial output or inflation to monetary policy shocks. Point estimates are close to zero across all horizons, reinforcing the view that the short-run potency of monetary policy is limited.

Secondly, demographic ageing appears to influence transmission only marginally. The interaction terms are imprecise but marginal-effect estimates suggest that economies with a higher elderly share experiences slightly weaker or even neutral output and price responses to policy tightening.

Thirdly, AI adoption shows a similar pattern. While direct interactions are statistically insignificant, the slope of the marginal-effect curves hints that greater AI diffusion is associated with a modest attenuation of the contractionary impact of monetary policy.

Fourthly, these results hold up to robustness checks using the MCI. As detailed in the previous section, replacing the regression-residual shocks with the MCI (which accounts for exchange rates and credit growth) produces qualitatively similar impulse responses. This confirms that the weak transmission identified in our baseline is not an artifact of the identification strategy but rather a structural feature of the Vietnamese economy during this period.

Taken together, the findings point to a consistently weak short-run transmission mechanism, with tentative evidence of state-dependence along demographic and technological dimensions. These results underscore the importance of monitoring structural change even if current effects remain small.

5. Discussion and Policy Implications

While our empirical results are marked by statistical uncertainty, they offer some insights into the evolving nature of monetary policy transmission in Vietnam. The absence of statistically significant average effects does not imply irrelevance of monetary policy but instead reflects structural complexity and the early-stage nature of key megatrends like demographic ageing and AI adoption.

5.1 Interpreting the Muted Transmission of Monetary Policy

The very small and statistically insignificant baseline responses confirm that monetary policy shocks (identified through the interbank rate residual) have limited short-run traction on real activity and prices. This outcome is consistent with Vietnam's hybrid monetary framework, in which the SBV relies on multiple levers beyond the policy rate, including credit ceilings and exchange-rate operations. The addition of credit controls to the empirical model further indicates that much of the variation in output previously attributed to policy shocks actually reflects endogenous credit dynamics. Institutional features such as administered pricing, the role of state-owned enterprises, and partial dollarisation continue to dilute the interest-rate channel.

5.2 Mechanisms of Transmission: The Credit and Exchange Rate Channels

While our baseline results point to a weak interest-rate channel, it is crucial to unpack how demographic ageing and AI adoption might specifically interact with the credit and exchange rate channels, which are historically more potent in Vietnam.

The credit channel and life-cycle borrowing of Vietnam's monetary policy relies heavily on the credit channel, primarily managed through annual credit growth quotas assigned to commercial banks. The effectiveness of this quantitative tool depends on the private sector's demand for credit. Demographic ageing poses a structural challenge to this mechanism. According to the life-cycle hypothesis, credit demand peaks during working age (for housing and business formation) and declines in retirement. As Vietnam's population pyramid shifts (evident in the rise of the 65+ cohort from 6% to 9%), the natural demand for credit may soften. In an ageing Vietnam, the SBV could find that relaxing credit quotas (an expansionary policy) becomes less effective if there are fewer young households seeking mortgages or business loans. Our finding that the marginal effect of monetary shocks on output becomes less negative (i.e., less potent) as the population ages is consistent with this "credit demand saturation" hypothesis. If older households are less responsive to credit supply shocks, the SBV's primary lever (credit growth) may lose traction, forcing a greater reliance on price-based instruments which, as our baseline shows, are currently weak.

The exchange rate channel is arguably the strongest transmission mechanism in Vietnam due to the economy's high trade openness. Monetary tightening typically leads to currency appreciation, which curbs net exports. However, widespread AI adoption could alter this pass-through elasticity. If Vietnamese firms utilise AI to move up the value chain (transitioning from low-cost assembly to high-tech manufacturing and services), their pricing power may increase. Specialised, high-value exports are generally less sensitive to exchange rate fluctuations than commoditised goods. Consequently, as the AI index rises, the "expenditure-switching" effect of monetary-induced exchange rate changes may diminish. This aligns with our marginal effect results for inflation, where higher AI adoption appears to slightly mute the price response. If AI allows firms to absorb exchange rate shocks through productivity gains rather than price adjustments, the exchange rate channel of monetary policy may also face structural attenuation in the medium term.

5.3 Why Are the Effects of Demographics and AI Not More Prominent?

Although the interaction coefficients remain statistically weak, the marginal-effect plots show systematic, albeit small, directional patterns. Several factors explain this modest scale. Firstly, Vietnam's demographic and technological transitions are still in their early stages; the elderly share has only recently approached 9% and widespread AI difusion accelerated significantly only after late 2022. As these trends mature, their impact on transmission may become more pronounced.

Secondly, high-frequency cyclical shocks likely dominate short-term macroeconomic variability. In a small open economy like Vietnam, trade fluctuations, capital inflows and global supply chain disruptions can overwhelm the subtle conditioning effects of slow-moving structural variables. Finally, data limitations play a role. Our monthly panel covers roughly one decade, which may be insufficient to detect structural heterogeneity with high statistical confidence. Future research utilising longer time series or micro-level datasets will be essential to identify these channels more precisely.

5.4 Policy Implications

Our findings suggest several implications for policymakers. Firstly, regarding the policy framework, the current evidence suggests that immediate recalibration is not necessary. The structural shifts driven by ageing and AI are not yet strong enough to fundamentally alter the transmission mechanism, though continuous monitoring of these megatrends remains essential.

Secondly, the findings reinforce the value of maintaining a multi-instrument toolkit. The weak traction of the interest rate channel confirms that the SBV is correct to rely on complementary tools (such as credit growth guidance, exchange-rate management and macroprudential policies) to achieve its stability objectives.

Thirdly, there is a pressing need to invest in data infrastructure. To better understand the evolving transmission channels, policymakers require richer micro-level data, particularly concerning household life-cycle consumption patterns and firm-level AI adoption and price-setting behaviour.

5.5 Future Outlook: Managing the Transition to an Aged, Digital Economy (2025–2035)

While the empirical evidence from the 2013–2024 sample suggests that structural factors are currently secondary to cyclical shocks, this period represents only the nascent phase of Vietnam's *"twin transition"*. Looking ahead to the 2025–2035 horizon, the interaction between ageing and AI is likely to intensify, presenting new challenges for the SBV.

5.5.1 From "Ageing" to "Aged" Society

Vietnam is among the fastest-ageing nations in Asia. The World Bank projects that Vietnam will transition from an "ageing" society (7% of population over 65) to an "aged" society (14% over 65) by approximately 2035 - a transition that took France 115 years and the US 69 years. As the share of the elderly doubles from the current 9% level, the muted transmission effects identified in our impulse response functions could become statistically significant structural drags. The "demographic deflation" pressures identified in advanced economies may become a binding constraint, potentially pushing the natural rate of interest (r*) lower and reducing the policy space for conventional interest rate cuts during downturns.

5.5.2 AI as the Countervailing Force

If ageing threatens to dampen aggregate demand and monetary potency, AI adoption serves as a critical supply-side counterweight. The surge in AI interest following the release of generative AI tools in 2022 suggests Vietnam is positioned to adopt these technologies rapidly. If AI adoption transitions from *"digital attention"* (as measured by Google Trends) to broad-based *"industrial application"*, it could sustain productivity growth despite a shrinking labour force. For monetary policy, this creates a race between two forces: the demand-dampening effect of ageing and the supply-expanding effect of AI. If AI-driven productivity gains outpace demographic headwinds, the disinflationary pressure may be benign (good deflation), allowing the SBV to maintain accommodative settings without overheating the economy. However, if AI adoption lags while the population ages rapidly, the economy risks "stagflationary" supply constraints where the workforce shrinks without a compensatory rise in efficiency. Therefore, the "insignificant" results of the past decade should be viewed as a baseline. As Vietnam moves deeper into this demographic-technological transition, the heterogeneity of monetary transmission will likely widen, requiring the SBV to develop more granular models (potentially integrating the AI and ageing proxies developed in this paper) to calibrate the timing and magnitude of interventions.

6. Conclusion

This study examines how two structural forces (demographic ageing and AI diffusion) affect the effectiveness of monetary policies in Vietnam using monthly data from 2013–2024 and a local-projection framework. Across all specifications, including robustness checks utilising a broad MCI, monetary policy shocks exhibit muted and statistically uncertain effects on both output and inflation.

When conditioning on ageing and AI, the results reveal subtle directional heterogeneity: monetary tightening appears marginally less contractionary in older or more technologically advanced contexts. However, these effects remain economically small and statistically indistinguishable from zero within the current sample period.

The key takeaway is that Vietnam's short-run monetary transmission through the interest-rate channel is weak but potentially evolving. There is no current basis for recalibrating the policy framework, yet structural monitoring is warranted as the transition toward an "aged" society accelerates and AI adoption matures. Future work should extend the sample, incorporate firm- and household-level data, and explore model-based simulations (e.g., DSGE with heterogeneous agents) to clarify how the race between ageing and AI might reshape policy transmission in the coming decade.

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CHAPTER 7

SIMULATING THE IMPACT OF FERTILITY AND LIFE EXPECTANCY SHOCKS ON THE PHILIPPINE ECONOMY USING THE G-CUBED MODEL[1,2]

Reynalyn Punzalan-Wong, Karen Annette Lazaro Enriquez, Clarisa Joy Flaminiano, and **Dennis Bautista**

1. Introduction

Demographic shifts are reshaping the macroeconomic landscape globally and in the Philippines, with substantial implications for labour supply, capital markets, and output growth. In recent decades, the country has benefited from a rising working-age population and improvements in health and education outcomes (Asian Development Bank [ADB], 2020). The Philippines is currently halfway through its demographic dividend era and will transition in the next two decades into a declining working-age population with low fertility rate. In addition, the United Nations (UN) predicts that life expectancy rates worldwide will increase due to progress in medical science. Understanding the channels through which demographic shifts will alter the country's labour market conditions and production capacity can aid policymakers in designing early policy interventions to mitigate the potential adverse impact of demographic transitions on the economy.

The macroeconomic implications of demographic structure have been extensively examined in the literature. Persistently low fertility rate causes slower economic growth and fiscal challenges (Kearney and Levine, 2022). Using a static framework, Lutz et al. (2019) attribute the economic effect of fertility primarily to shrinking labour force. Cavallo et al. (2018) find that declining fertility and lower dependency ratios significantly increase saving rates, particularly in Asia. However, the effect diminishes as ageing intensifies, leading to saving deceleration and downward pressure on interest

1. The authors are Reynalyn Punzalan-Wong, Karen Annette Lazaro Enriquez, Clarisa Joy Flaminiano, and Dennis Bautista of the Department of Economic Research of the Bangko Sentral ng Pilipinas. The authors are grateful to Dr. Warwick J. McKibbin and Dr. Jong-Wha Lee, for their valuable insights and comments on the analysis. We also thank Geoffrey Shuetrim for his technical support with the G-Cubed model. The opinions and views expressed in this paper are solely those of the authors and do not necessarily represent the views of the Bangko Sentral ng Pilipinas (BSP).
2. We use GenAI on the Perplexity platform to enhance the conciseness and readability of this paper.

rates. Amaral (2023) also found that demographic transition alters asset supply and equilibrium interest rates in advanced economies. Using a global modeling exercise, McKibbin and Vines (2023) showed that demographic transitions, including fertility decline, interact with structural factors to shape long-term saving-investment balance and global capital flows.

Longer life expectancy also influences macroeconomic variables. Pascual-Saez et al. (2020) show that demographic shifts—such as rising share of retirees—reduce aggregate saving. Carvalho et al. (2016) explain the channels through which these effects are transmitted. First, slower population growth leads to higher old-age dependency – that is having more retirees who dissave relative to workers who save. This results in lower aggregate saving, putting upward pressure on real interest rates. Second, increased longevity raises precautionary saving during working years in anticipation of longer retirements, exerting downward pressure on interest rates.

Our study integrates demographic shocks into a structural global model to analyse Philippine macroeconomic dynamics. Previous studies on demographic channels focus on consumption–saving behaviour (Fujiwara, 2023), inflation dynamics (Gagnon et al, 2021; Juselius and Takats, 2015 and 2021), capital flows, and exchange rate movements (Lai, 2025). Meanwhile, existing G-Cubed applications cover multi-country or regional analyses (Armas, 2021; McKibbin, 1996). To the best of our knowledge, this study is the first to implement a country-level framework for the Philippines that incorporates fertility and life expectancy shocks within a general-equilibrium model. We embed selected demographic shocks into the G-Cubed model and trace their transmission through household consumption, saving, inflation, interest rates, current account, exchange rate, and monetary policy. This approach links sectoral and econometric insights to a coherent analysis of the Philippine economy. Ultimately, the G-Cubed model enables dynamic evaluation of demographic changes in the Philippines while accounting for international trade and global demographic trends.

The demographic shocks in our model are aligned with observed fertility and life expectancy trends and policies. The declining fertility in the Philippines is supported by reproductive health and broader social policies that continue to reinforce this downward trend. Moreover, the UN projects that the Philippine fertility rate will remain below replacement level for decades based on historical demographic patterns and global experience. Several health and wellness interventions are also in place to lengthen life expectancy in the country.

The remainder of the paper is organised as follows. Section 2 provides an overview of Philippine demographics. Section 3 reviews the related literature. Section 4 introduces the key features of the G-Cubed model and simulation process. Section 5 discusses the results, while Section 6 concludes and presents policy implications.

2. Overview of the Philippine Demographics and the Economy

2.1 Demographic Dynamics: The Coming Reversal

The Philippine population growth rate has declined by an average of 1.5 percentage points from 2000 to 2025 (Figure 1). Nevertheless, the working-age population continues to expand and is expected to peak at about 93 million individuals by 2050. This growth in the labour force has sustained the Philippine economic performance for the past decades. However, this trend is expected to reverse within two decades, as labour force growth slows and eventually contracts by 2050.

Life expectancy in the Philippines has risen steadily since the 1970s and is projected to reach about 73 years by 2050. At the same time, the fertility rate has declined sharply to 1.9 children per woman in 2022—already below the replacement level of 2.1 children per woman. Prolonged periods of below-replacement fertility combined with rising life expectancy can lead to population ageing and a contraction of the labour force (UN, 2022).

With the projected rise in life expectancy and with fertility rate remaining below replacement level (Figure 2), the Philippine labour force is seen to peak by 2050 (Figure 1). At the same time, the old-age dependency ratio (OADR)—defined as the proportion of retirees relative to workers—is projected to increase steadily (Figure 2). By 2050, the Philippine OADR is expected to reach 16%, marking the end of the demographic dividend and the onset of structural population ageing.

Figure 1: Philippines: Population and Working-age Growth

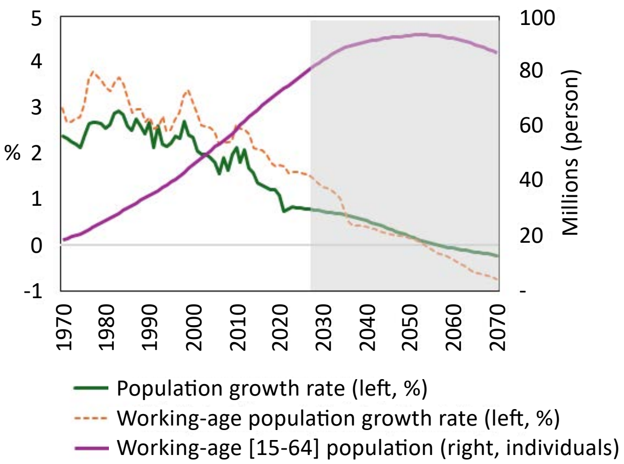
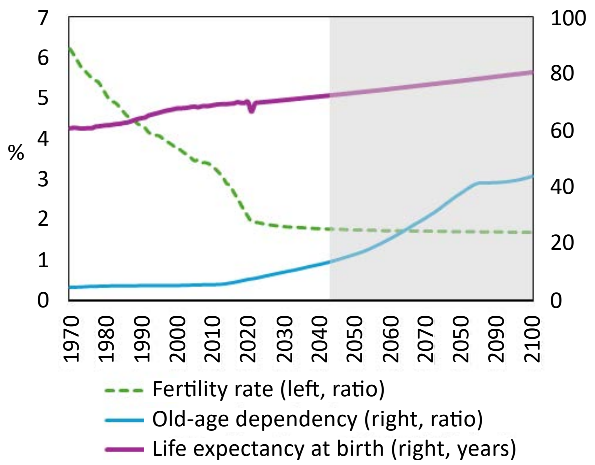


Figure 2: Philippines: Life Expectancy, Old-age Dependency and Fertility

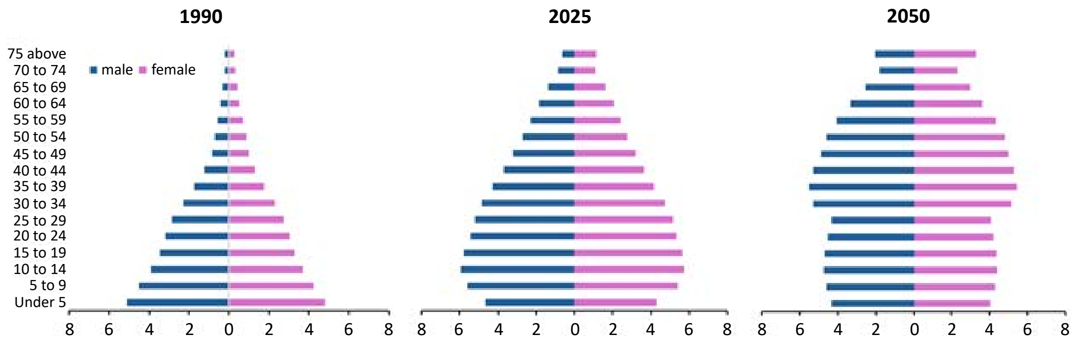


Note: *Working-age population refers to individuals aged 15 to 64. Life expectancy is life expectancy at birth. Old-age dependency ratio is computed as the number of people aged 65 or over for every 100 people aged 15 to 64. Fertility rate pertains to the number of children per woman. Population projections are under the medium fertility variant.*

Source: *Authors' illustration using data from UN Department of Economic and Social Affairs, Population Division (2024). World Population Prospects 2024, Online Edition.*

Figure 3 presents the age structure pyramid of the Philippines at different critical periods: 1990, 2025, and 2050. It illustrates the shift from a broad-based, youth-dominated age structure during the 1990s toward an increasingly rectangular and eventually top-heavy pyramid by 2050. The narrowing base (children and youth) and the expanding top (older adults) visually capture both the declining entry of new cohorts into the labour force and the rapid growth of the elderly population.

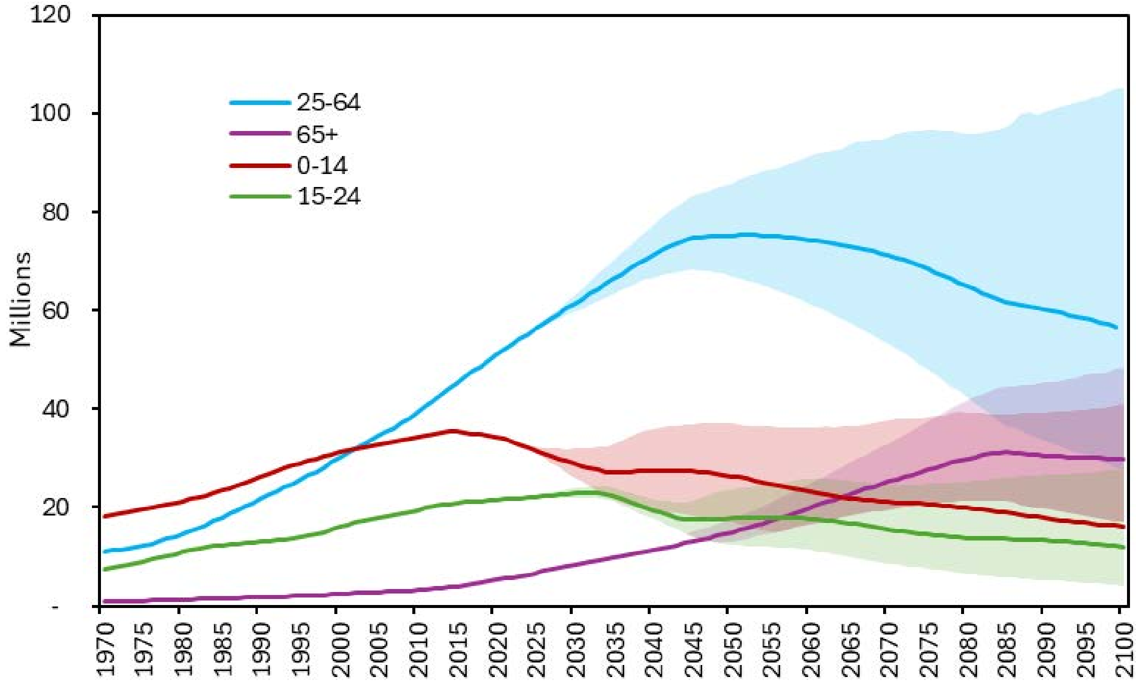
Figure 3: Philippines-Age Structure Pyramid (% of total population)



Source: Authors' illustration using data from UN Department of Economic and Social Affairs, Population Division (2024), World Population Prospects 2024, Online Edition.

These aggregate trends highlight two pivotal milestones: the peak of the working-age population around 2050 and the simultaneous transition to an ageing society (Figures 1 to 3). These evolving demographic compositions will reshape patterns of saving, labour market participation, and economic growth. For instance, Japan's population ageing has reduced potential output and influenced macroeconomic policies through shrinking labour force and rising dependency ratio (Han, 2024).

Figure 4: Philippines: Population by Broad Age Groups

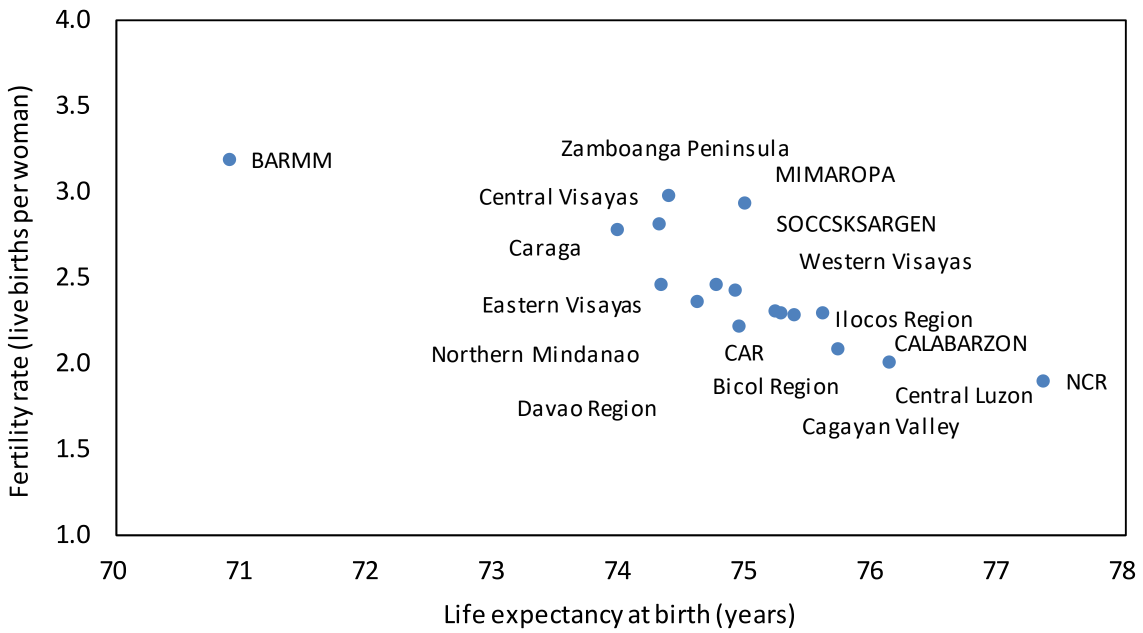


Note: Shaded areas represent 95% prediction interval.
Source: Authors' illustration using data from UN Department of Economic and Social Affairs, Population Division (2024), World Population Prospects 2024, Online Edition.

Figure 4 presents the total population disaggregated by broad age groups. The most notable feature is the pronounced expansion and subsequent plateau of the working-age group (age 25–64) around 2050. Meanwhile, the youth population (age 0–14 and age 15–24) is gradually shrinking, signaling a decline in future entrants to the labour force. By contrast, the elderly population (age 65+) begins to rise sharply by mid-century, underscoring the transition toward an ageing society.

Regional analysis further highlights the stark spatial disparities in Philippine demographic indicators (Figure 5). On the one hand, the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) is characterised by persistently high fertility rates and comparatively low life expectancy. This is an outlier given its distinct socioeconomic condition as a predominantly rural and poverty-affected area facing significant developmental constraints. On the other hand, the National Capital Region (NCR), Central Luzon, and other highly urbanised regions exhibit lower fertility rates

Figure 5: Fertility and Life Expectancy in Philippine Regions, 2025-2030



Source: Authors' illustration using data from Philippine Statistics Authority (PSA), 2010 Census-Based National, Regional, and Provincial Population Projections.

The Philippine demographic trends—marked by declining population growth, peaking working-age cohort, and rising old-age dependency ratio—are fundamentally reshaping the country's prospects for labour supply, saving, investment, and output growth. The effects are also expected to spill over into capital markets as asset prices adjust to maintain global balance.

2.2 Why Fertility Will Stay Depressed

The Philippine fertility rate fell from 2.7 in 2017 to 1.9 in 2022—below the 2.1 replacement level (PSA and ICF, 2023). The UN World Population Prospects projects that the Philippine fertility rate will remain below replacement level through 2100 and will decline to around 1.6–1.7 children per woman.[3] The low fertility is expected to persist as global evidence indicates that once fertility falls below replacement ratio, this trend will likely persist indefinitely (Bart, et al., 2024; Aitken, 2024).

The Philippines' current reproductive policies are intended to reduce unintended pregnancies and promote family planning (Department of Health [DOH], 2023; Likhaan Center, 2022). These include the Responsible Parenthood and Reproductive Health (RH) Law of 2012 and Executive Order No. 12 of 2017, which expand access to contraceptives

3. The 2020 Census-Based National Population Projections of the PSA show three scenarios: Scenario 1 assumes that the total fertility rate (TFR) will rebound from 1.9 children in 2021 to 2.1 children in 2025, which will be sustained until 2055; Scenario 2 assumes that the TFR remains at 1.9 until 2055; Scenario 3 assumes a continuous decline to 1.7 by 2055.

and mandate age-appropriate sexuality education in schools. The National Family Planning Program of the DOH and the United Nations Population Fund (UNFPA) likewise strengthen the community-based distribution of contraceptives and adolescent-friendly health services (UNFPA Philippines, 2023). In addition, the Universal Health Care Act (Republic Act No. 11223) improves access to maternal and reproductive health services nationwide (WHO and DOH, 2023). These reproductive policies have significantly reduced fertility among young adults (DOH, 2023; Likhaan Center, 2022).

Other government policies likewise contribute to the decline in birth rates. These include the expanded education opportunities, e.g., free tertiary education and comprehensive sexuality education in the K12 curriculum, which empower women to delay marriage and prioritise careers. Several studies have correlated smaller family size with better education (Philippine Institute for Development Studies [PIDS], 2023; International Center for Research on Women [ICRW], 2022). Moreover, PIDS (2023) finds that the fertility decline was driven mainly by improved material well-being, followed by shifts in marriage patterns and better family planning. Additionally, government population and development plans, such as the Philippine Population and Development Plan of Action (PPD-POA) 2023–2028, favor smaller families and reinforce social preferences for fewer children.

2.3 Healthcare Gains and Rising Longevity

Government policies that support longer life expectancy include expanded healthcare access, effective disease prevention, and improved nutrition. For instance, the Universal Health Care Act (Republic Act No. 11223) mandates that all Filipinos be enrolled in the national health insurance program. This law aims to reduce financial barriers to health care and expand access to preventive and curative services. Further, the DOH and other foreign organisations have several health programmes that contribute to the early detection and management of contagious and noncommunicable diseases (NCDs). These efforts, combined with expanded immunisation campaigns and integrated NCD screening, have reduced premature mortality and improved the overall health outcomes (DOH, 2023; WHO, 2023).

Moreover, the nutrition-focused policies of the government, such as the Philippine Plan of Action for Nutrition (PPAN 2023–2028) and child health programmes, are intended to address stunting and micronutrient deficiencies. These have increased the survival rates and long-term health of children.

Meanwhile, the ageing-related policies, such as the Expanded Senior Citizens Act and mandatory PhilHealth coverage for older adults, provide free medicines, vaccinations, and integrated care. These government programmes have enhanced the quality and length of life of older generations. In addition, government’s lifestyle interventions to curb smoking, improve diets, and promote physical activity further contribute to reducing chronic disease risks.

Altogether, these policies are intended to lengthen one's life expectancy beyond the current average age of 70 years toward 73 years by 2050 (National Nutrition Council, 2023; ERIA, 2024; WHO, 2023). However, rising life expectancy exerts financial pressure on fiscal budgets.

3. Review of Related Literature

The impacts of demographic changes on key macroeconomic variables have been extensively studied in the literature. Some of these research on demographic effects and studies that employ G-Cubed are discussed below.

3.1 The G-Cubed Model and Demographics

Bryant and McKibbin (2004) illustrate that population ageing in industrialised countries tends to lower aggregate growth over time, while expanding working-age populations bolster growth in developing countries. They also demonstrate how differences in the timing and intensity of demographic transitions across countries can generate significant effects on exchange rates, international trade, and capital flows. Liu and McKibbin (2020) further find that ageing and developed economies face declining productivity, investment, and wages, while emerging regions (such as Asia and Africa) experience demographic dividends and rapid growth. They show that global capital flows can cushion consumption declines in ageing economies but may increase financial risks in developing countries.

At the country level, McKibbin (2005) analyses the effects of both domestic and global demographic shifts on Japan's economy. He finds that Japan's ageing population substantially increases its current account surplus, pushes down real interest rates and investment, and causes long-term currency appreciation. He also analyses the spillover effects of foreign demographic shifts, showing that global ageing can reinforce or offset impacts on Japanese growth, trade, asset prices, and monetary variables. Further extending the G-Cubed model, Liu and McKibbin (2020) evaluate the aggregate and sectoral impacts of global and domestic demographic change on the Australian economy. Mining, energy, and durable manufacturing in Australia are most sensitive to external demographic shocks, especially those originating in Asia (China, Japan, Korea). Further, they point out that global demographic changes also affect real interest rates and trade balances. These sectoral and trade impacts are driven by Australia's trade dependencies.

3.2 Demographics and Real Interest Rates

Carvalho et al. (2025) propose a general equilibrium model showing that demographic trends—especially increasing life expectancy and slowing population growth—are major drivers of the decades-long decline in global real interest rates. Their empirical analysis across advanced countries confirms a strong and persistent association between ageing demographics and declining interest rates, particularly in economies with high financial openness. Countries that are more financially integrated globally have real interest rates that are more responsive to foreign rather than domestic demographic changes.

Braun et al. (2006) utilise a dynamic overlapping generations (OLG) model to demonstrate that Japan's dramatic declines in saving and interest rates since the 1990s are due to demographic changes (i.e., ageing and lower fertility) and slower productivity growth. Fujita and Fujiwara (2023), using a search and matching model, likewise find that Japan's ageing labour force—especially the result of fewer young workers entering after the 1970s—significantly contributes to declining consumption growth and real interest rates.

3.3 Demographics and Macroeconomic Imbalances

Using a neoclassical growth model for 18 OECD countries, Domeij and Flodén (2006) show that population ageing drives international capital flows by altering countries' saving rates and current account balances. Ferrero (2010) demonstrates that demographic differences between the US and its trading partners contribute a significant and nearly permanent component to the US trade deficits. He attributes this finding to an ageing population and changes in labour force participation.

Sposi (2021) uses a dynamic, multi-country general equilibrium model to show that differences in working-age population growth rates explain the direction and magnitude of international trade imbalances. Emerging economies have generally experience rapid increases in their working-age share, which boost national saving and lead to higher net exports (surpluses). Advanced economies, in contrast, see slower growth or declines in the working-age share, lowering saving and raising trade deficits.

3.4 Demographics and Capital Flows

Borsch-Supan et al. (2014) utilise a multi-country OLG model to show that as industrial economies age rapidly, substantial capital outflows are allocated toward younger, faster-growing regions. These capital flow dynamics alter global interest rates. In particular, the declining interest rates in ageing economies are partially offset by rising interest rates in younger economies that are able to use international capital inflows for productive investment. Higgins (1998) and Kim and Lee (2008) likewise confirm these dynamics. They find that rising dependency ratios significantly lower saving rates and worsen current account balances in both developed and developing economies. Carvalho et al. (2025) link the observed decline in real interest rates of advanced economies partly to demographic shifts.

3.5 Demographics and Exchange Rates

Lai (2025) suggests that longer life expectancy and population ageing can appreciate the real exchange rate and alter the trade balance, primarily through increased saving and changes in consumption patterns. This effect is compounded by macroeconomic policies focused on pension and healthcare systems in advanced economies, which further influence capital flows and currency valuations.

3.6 Demographics and Inflation

Juselius and Takats (2015) find a stable and significant correlation between demographics and low-frequency inflation across 22 countries from 1955 to 2010. They find that dependents (young and old) have an inflationary effect, while the working-age population has deflationary effect. Further, Juselius and Takats (2021) show that demographic trends have associated price dynamics. As such, they suggest adding demographic variables to the dynamic Phillips curve to explain some of the persistence in inflation. They further argue that, by ignoring the demographic component of inflation, central banks may fail to properly account for structural shifts that could affect price stability. Yoon, Kim, and Lee (2014) argue that demographic trends affect both real interest rates and potential output; thus, ignoring these impacts may result in misspecified policy and non-anchoring of inflation to its target. In addition, Mangiante (2022) points out that the magnitude of response to monetary shocks increases with old-age dependency ratio, as older households consume more services that have more rigid prices.

3.7 Demographics and Natural Rate of Interest

Demographics are increasingly recognised as critical factors in analysing the natural rate of interest (NRR), as population ageing and shifts in age structure influence long-term equilibrium rates and inflation dynamics. Laubach and Williams (2003) demonstrate that the neutral real interest rate is closely linked to trend output growth—a relationship shaped in part by demographic dynamics that influence long-run equilibrium rates. Juselius and Takáts (2018) show that demographic shifts, especially changes in age composition, exert a persistent and substantial impact on inflation trends, reinforcing the connection between demographics and the natural rate of interest in long-term monetary policy analysis. Finally, Ademmer and Rush (2024) find that demographic factors, particularly age structure, combined with slower economic growth, significantly contribute to the decline in the natural rate of interest in the United States.

4. Methodology

4.1 Key Features of the G-Cubed Model

We employ the G-Cubed 6W model to assess the macroeconomic impacts of demographic shifts on the Philippine economy.[4,5] The model incorporates 21 countries and regions linked via trade and financial assets. Each region comprises six production sectors: energy, mining, agriculture, durable manufacturing, non-durable manufacturing, and services. Each region features a representative firm, household, government, financial market, and central bank. Households supply labour, save, and consume goods and services. There are two types of individuals: a liquidity-constrained individual who consumes a fixed proportion of income, and an unconstrained individual who consumes a constant proportion of overall wealth. Firms are price takers that optimise inputs and investment to maximise after-tax profits. Sectoral outputs are generated through a CES production function. Governments raise revenue through taxes and bond issuance, subject to an intertemporal budget constraint. Financial assets are mobile across countries, and their flows determine each country's net trade position and current account balance.

The key features of the G-Cubed model are the incorporation of real-world economic frictions. First, there are nominal wage rigidities. Nominal wages are sticky and are set based on expectations of inflation and employment, resulting in slow labour cost adjustments. Second, there is a rising cost to capital installation. Investment in physical capital involves adjustment costs that slow down changes in the capital stock. In contrast, financial capital is perfectly mobile among countries. Third, there is limited labour mobility. Labour is perfectly mobile across sectors within a country but immobile between countries. Fourth, some households and firms have limited foresight and form their expectations based on available information. These rule-of-thumb consumers cause inertia in consumption, investment, and price-setting behaviours. And fifth, there are policy rule rigidities. The government adjusts taxes, spending, and debt incrementally and does not immediately correct fiscal imbalances. Meanwhile, the central bank (CB) uses Henderson-McKibbin-Taylor rule that responds gradually to inflation, output gap, and exchange rate movements, which can be adjusted to reflect its monetary objective.[6] These frictions cause macroeconomic shocks to propagate realistically and gradually through the global economy. Further details on the G-Cubed model are provided by McKibbin and Wilcoxen (1995, 2013).

4. The full documentation for the G-Cubed model can be accessed at: *https://documentation.gcubed.com/gcubed/*

5. The equations for the G-Cubed model_6W are provided in the link: *https://documentation.gcubed.com/gcubed/version/6W/model_6W_191.html#36*

6. The Henderson-McKibbin-Taylor–type policy rule includes inflation, output, exchange rate, income, and money supply. In our simulation, we set to zero the parameters for exchange rate, income, and money supply.

In this paper and for simulation purposes, we modify the specification of the Philippines' Taylor rule to include the inflation gap, the output gap, and the lagged policy rate, consistent with the BSP's inflation targeting framework; and retain the G-Cubed's parameter estimates.

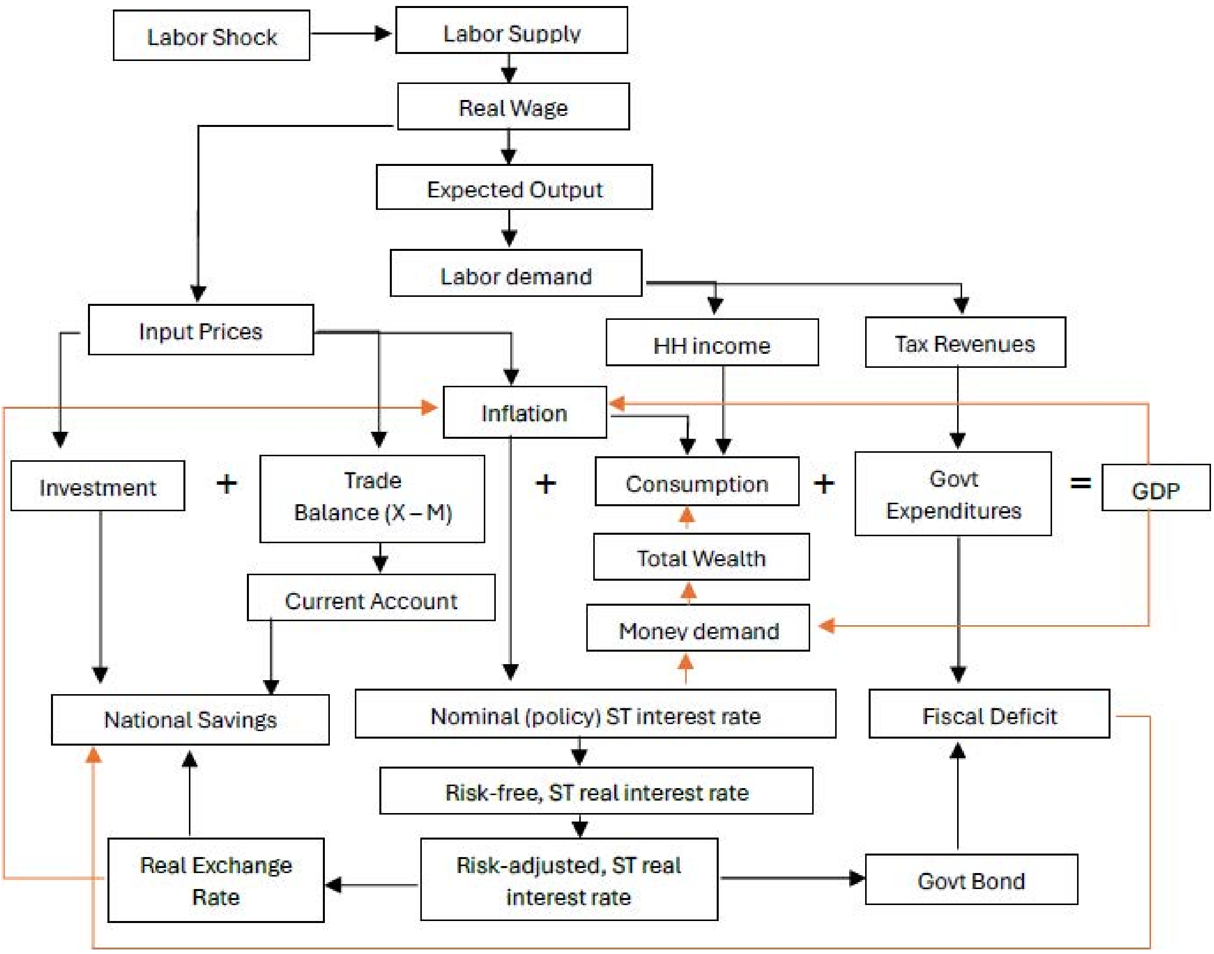
4.2 Demographic Shocks in the G-Cubed Model

Population shocks arising from demographic shifts (i.e., fertility and life expectancy rates) are introduced as shocks to the exogenous labour supply within a region or sector in the G-Cubed model (Figure 6).[7] These shocks alter real wages, the marginal product of labour, and the desired capital stock. First, a labour shock shifts labour supply. Firms demand labour up to the point where the real wage equals the marginal product of labour. However, as nominal wages are sticky, the difference is reflected in unemployment and inflation. Second, given that some firms are forward-looking and capital is costly to adjust, some firms anticipate that the change in labour supply will affect potential output and profitability. As such, these firms alter their desired capital stock, investment path, and aggregate demand for labour.

Higher longevity enters the G-Cubed model as a positive labour shock, while a lower fertility rate is treated as a negative labour shock. We exclude the first few years of simulation from our analysis. Frictions in the G-Cubed model and the lagged realisation of demographic changes suggest that any immediate adjustments in economic variables after the introduction of shocks are not attributable to the demographic shifts themselves. McKibbin (2005) suggests that the immediate response to shocks is due to revisions in expectations or asset price movements rather than demographic factors.

7. The region's labour shock in the G-Cubed model is represented by the SHL variable.

Figure 6: Transmission of Demographic Shocks in the G-Cubed Model Through the Labour Market

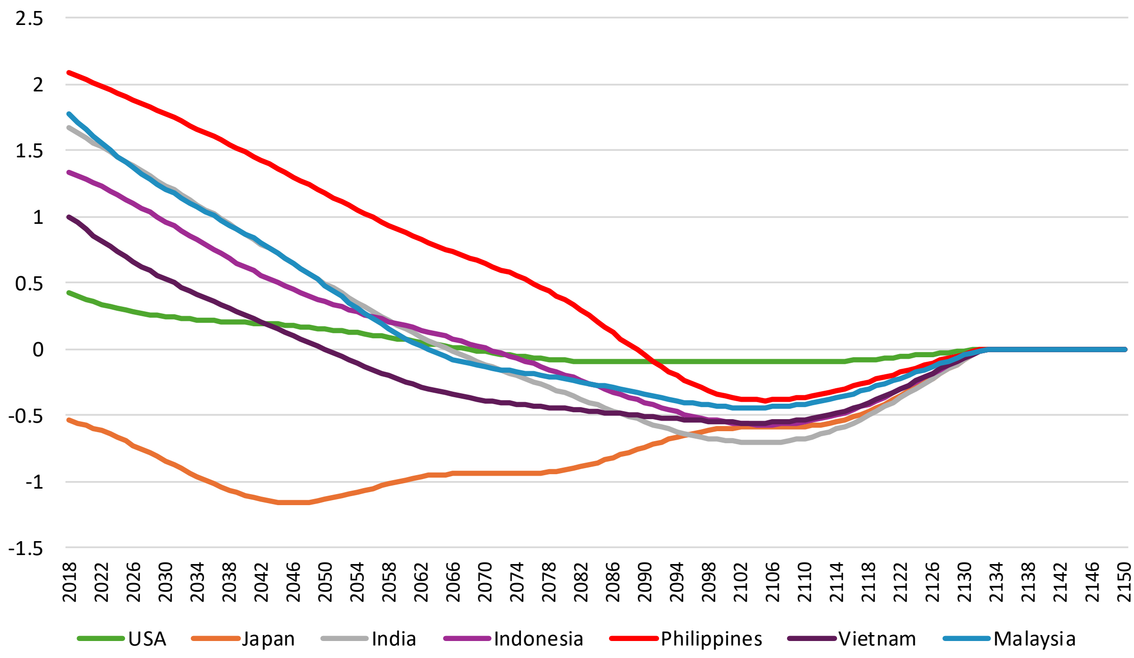


Source: Authors' illustration based on the G-Cubed 6W model documentation.

4.3 Baseline Projections

We maintain the labour force growth rates for all countries, including the Philippines, in the G-Cubed model (Figure 7). These are based on the UN population midpoint projections. We revise only the midpoint of the Philippine inflation target from 2.5% to the BSP's 2025 inflation target of 3.0%. We retain the rest of the values and assumptions from the original 6W version of the G-Cubed model, including 2018 as our base year. Although our initial conditions do not reflect the latest macroeconomic conditions, the results can still be used to illustrate the impacts of longer life expectancy and lower fertility rates on key economic variables. After running several simulations using different magnitudes of demographic shocks, the directional impacts on economic variables are the same, since the G-Cubed model's steady-state equations are log-linearised. Thus, we focus more on interpreting the direction of deviations than on the magnitude of the impact on key variables.

Figure 7: Labour Force Growth Rates (%) Assumptions in the G-Cubed Model



Source: Authors' illustration using data from the G-Cubed 6W model.

The baseline scenarios contain assumptions on labour force growth for 21 countries, including the Philippines, in the G-Cubed model. This allows the baseline scenario to capture demographic shifts that are happening simultaneously in other parts of the world. Some of the labour force assumptions based on the UN's population medium fertility projections are shown in Figure 7.

We use a simple autoregressive process, AR(1), to generate life expectancy and fertility shocks. The fertility and life expectancy shocks are estimated using actual and projected rates from 1980 to 2100. The estimated standard deviations of 0.06 for fertility and 0.4 for longevity are then fed into the G-Cubed model as permanent labour supply shocks arising from demographic transition. Although we do not establish the equivalence or conversion ratio from fertility to labour force, the simulation results still hold, as the G-Cubed model gives the same direction of shocks regardless of their magnitude.

5. Simulation Results

The effects of lower fertility and higher life expectancy rates on key macroeconomic variables are illustrated in Figures 8 and 9, respectively. The results are summarised in Table 1. Decreasing fertility rates are likely to slow economic growth, while higher life expectancy is likely to enhance production. The net impact of demographic transition depends on the age structure of the Philippine population during the transition years, the degree of openness, and size of the economy (Liu and McKibbin, 2020).

Table 1: Short-run Impact of Demographic Shocks

Variables	Lower Fertility (-0.06)	Higher Life Expectancy (+0.40)
Consumption	↓	↑
Saving	↓	↑
Investment	↓	↑
Fiscal Deficit	↓	↑
Trade Deficit	↑	↓
Current Account Deficit	↑	↓
Gross Output	↓	↑
Real Interest Rate	↓	↑
Exchange Rate (↓ appreciatione; ↑ depreciatione)	↓	↑
Monetary Policy Response (Nominal Interest Rate)	↓	↑

Source: Based on the authors' simulation results.

5.1 Effects of Lower Fertility Rate

Figure 8 depicts the impact of declining fertility rates on the Philippine economy. A negative fertility shock directly decreases labour supply. The rise in marginal product of labour causes higher real wage. Firms respond by hiring fewer workers, resulting in unemployment in the short run. This higher wage temporarily boosts household income. However, household income eventually declines due to lower employment and reduced output.

Following the decrease in income, consumption declines and remains permanently below the baseline. Similarly, lower income forces households to draw down their saving. The anticipated slowdown in future economic growth discourages firms from investing in new capital, thereby lowering investment. McKibbin et al. (2020) provide evidence that saving and investment are affected by the relative size of age-based cohorts with different saving rates and labour productivity.

The nominal policy rate initially increases in response to upward wage pressure. As production and consumption weaken, the policy rate eventually falls below the baseline. Consequently, real interest rates decline, reflecting lower saving and investment. With interest rate parity in place, the falling real interest rate results in peso appreciation. This simulation is consistent with Japan's experience, where population ageing explains a significant portion of Japan's persistently low interest rates (Fujita and Fujiwara, 2023), as well as long-term currency appreciation (McKibbin, 2005).

The G-Cubed model does not explicitly identify the natural rate of interest (NRR). Nevertheless, we still use the risk-adjusted short-run real interest rate to infer the future path of the natural rate. Holston, Laubach, and Williams (2017) show that the direction of short-term market rates is anchored on the direction of the NRR. A declining fertility rate is expected to lower the NRR, consistent with the literature (Eggertsson, Mehrotra, and Robbins, 2019; Gagnon, Johannsen, and López-Salido, 2021; and Ho, 2024).

The government continues to operate with a fiscal deficit, with reduced tax revenues partly offset by lower interest payments. The trade deficit widens due to lower productivity and currency appreciation. The current account deficit further deteriorates as saving drops and the trade balance worsens. Overall, aggregate output permanently declines below the baseline.

5.2 Effects of Higher Life Expectancy Rate

Figure 9 illustrates the effects of longer life expectancy on the Philippine economy. Higher life expectancy acts as a positive labour shock that increases labour supply. The marginal product of labour falls and results in a lower real wage. With lower labour costs, firms hire more workers. Firms also increase their demand for capital to support the expectation of higher production. As employment rises, household income eventually exceeds the baseline.

With higher income, consumption increases above the pre-shock level. Households increase precautionary saving to finance longer life expectancy. De Nardi et al. (2009) provide evidence that saving increases with higher life expectancy. Firms increase their investment as the marginal product of capital rises. The fiscal deficit worsens with higher social service expenditures, though increased tax revenues from higher income partly offset this.

The nominal policy rate initially decreases in response to lower wages but eventually increases due to currency depreciation, rising import prices, and higher inflation. The real interest rate rises with peso depreciation according to the interest rate parity condition but eventually declines before returning to its long-run equilibrium. Similarly, the NRR initially increases as more elderly people remain in the labour force, but the NRR eventually declines as the real interest rate falls.

The trade deficit initially widens due to higher consumption, but as the domestic currency depreciates and productivity improves, the country eventually operates a trade surplus. With initially higher real interest rates, capital flows into the country and the current account deficit widens. However, as the trade balance improves and the interest rate declines, capital flows out of the country and current account balance improves over time. Overall, output growth rises in the initial decades, then weakens subsequently as the population declines.

6. Conclusion and Policy Implications

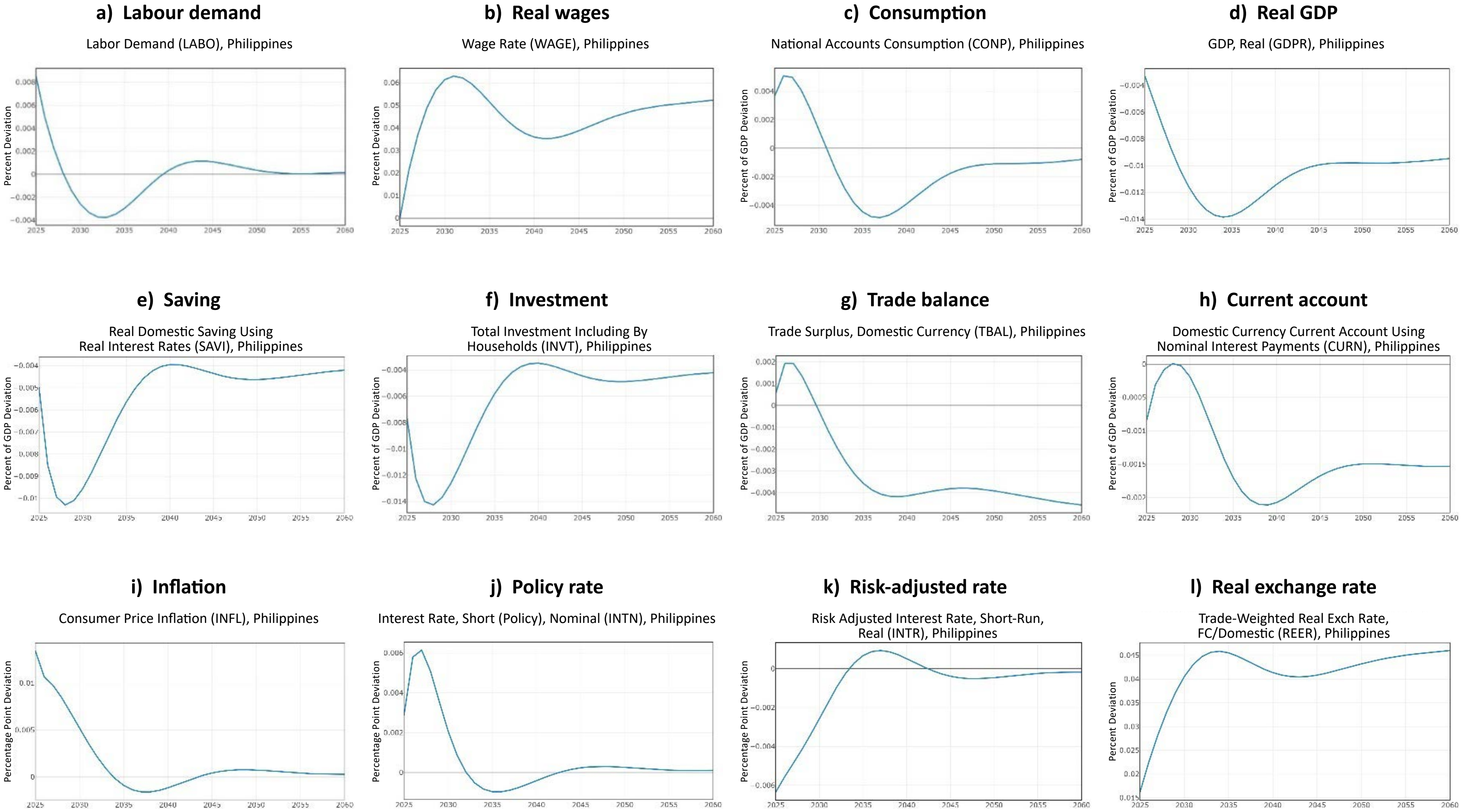
The Philippines is currently halfway through its demographic dividend era. In the coming decades, the Philippine working-age cohorts will reach their peak, while the fertility rate continues to decline. Persistently low fertility contracts the working-age population, leading to lower growth, consumption, saving, and investment. It also contributes to wider current account and trade deficits, as well as lower real interest rates and currency appreciation. Meanwhile, higher life expectancy offers opportunities for a larger labour force, higher output, increased consumption, saving, and investment. It tends to raise real interest rates, depreciate the exchange rate, and narrow current account and trade deficits.

The declining fertility and rising life expectancy gradually reshape the country's demographic profile, creating both challenges and opportunities for sustainable growth. While a smaller labour force may modestly reduce the tax base and increase fiscal pressures over time, longer lifespans can strengthen the workforce and ease pension costs if proactive policies—such as raising the retirement age and implementing adaptive labour market reforms—are adopted. Balanced measures, including fertility incentives and investment in health, education, and reskilling, can enhance human capital, extend working years, and support economic resilience (Myrskylä et al., 2025). By fostering longevity and productivity, these strategies can sustain labour force growth and efficiency, and help prolong the demographic dividend, thereby supporting long-term fiscal and economic stability.

These demographic trends also carry important considerations for monetary policy. Over the next two decades, an ageing population and slower labour force growth will gradually influence economic conditions, offering opportunities for more stable and predictable growth rather than immediate challenges. Evolving consumption patterns—such as greater demand for healthcare and services—alongside slower workforce expansion may encourage investment in productivity-enhancing technologies. For a central bank operating under an inflation targeting framework, this underscores the importance of forward-looking strategies. Considering the effects of demographic factors on the natural rate of interest can better inform the monetary policy stance as conditions evolve, while clear communication can reinforce confidence in policy continuity. Conventional tools will remain effective in the near term, but preparing for a lower-rate environment and exploring complementary measures can enhance resilience. In essence, demographic ageing is a gradual trend that provides an opportunity for proactive, well-calibrated policy adjustments rather than a source of immediate concern.

This research can be further enhanced by updating the Input-Output Table for the Philippines and using 2024 as the base year for simulations. Beyond fertility rates and life expectancy, considering migration, urbanisation, and age-structure dynamics as drivers of demographic change will enrich the analysis. To capture demographic shocks, other models that can better capture unexpected policy or behavioural shifts may be considered aside from an AR(1) process. Accounting for technological factors, notably the potential impact of AI and robotics on productivity and labour markets, could significantly alter outcomes. Further, international migration by overseas Filipinos can also be analysed since they contribute significantly to the Philippine economy. Finally, productivity changes were modeled as permanent shocks driven by demographics, without accounting for dynamic responses to technology or policy interventions. These areas present opportunities for future extensions of the study.

Figure 8: Impacts of Declining Fertility Rate on the Philippine Economy

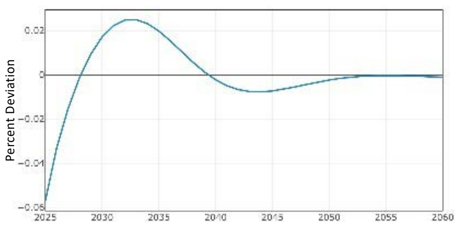


Source: Authors' simulation results.

Figure 9: Impacts of Rising Life Expectancy on the Philippine Economy

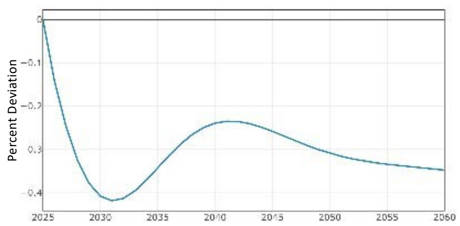
a) Labour demand

Labor Demand (LABO), Philippines



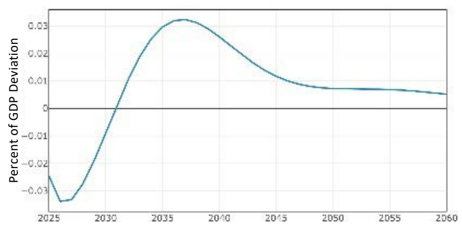
b) Real wages

Wage Rate (WAGE), Philippines



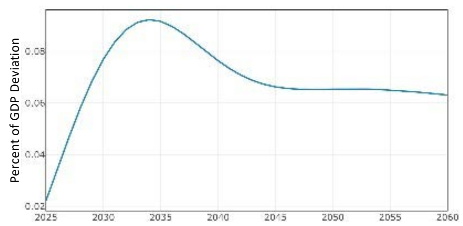
c) Consumption

National Accounts Consumption (CONP), Philippines



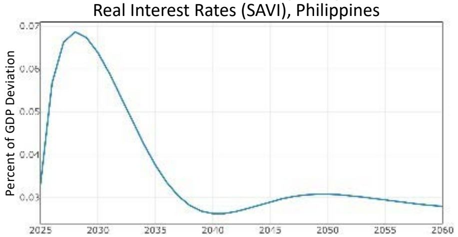
d) Real GDP

GDP, Real (GDPR), Philippines



e) Saving

Real Domestic Saving Using
Real Interest Rates (SAVI), Philippines

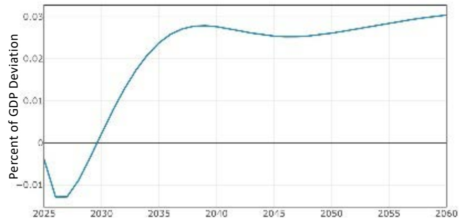


f) Investment

Total Investment Including By
Households (INVT), Philippines

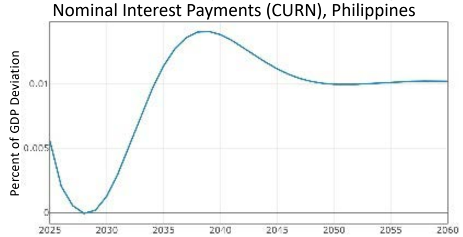
g) Trade balance

Trade Surplus, Domestic Currency (TBAL), Philippines



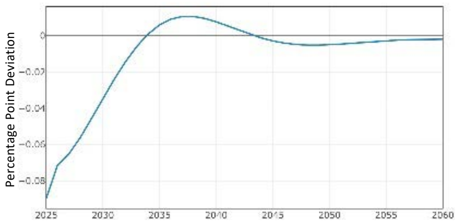
h) Current account

Domestic Currency Current Account Using
Nominal Interest Payments (CURN), Philippines



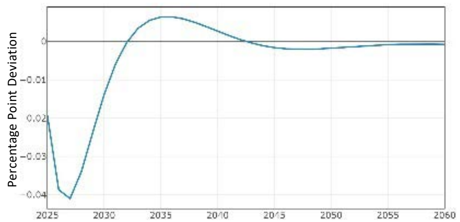
i) Inflation

Consumer Price Inflation (INFL), Philippines



j) Policy rate

Interest Rate, Short (Policy), Nominal (INTN), Philippines



k) Risk-adjusted rate

Risk Adjusted Interest Rate, Short-Run,
Real (INTR), Philippines

l) Real exchange rate

Trade-Weighted Real Exch Rate,
FC/Domestic (REER), Philippines

Source: Authors' simulation results

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Harnessing the Synergy of Artificial Intelligence (AI) and Human Capital Restructuring in Ageing Economies

This collaborative research study focuses on the macroeconomic and financial consequences of population ageing in Asia and explores how synergies between AI-driven technological innovation and human capital development can help mitigate its adverse effects. Drawing on theoretical insights, empirical evidence, and country case studies from SEACEN member economies, the analysis highlights how ageing affects growth, inflation, saving and investment behaviour, interest rates, and the transmission of monetary policy. The findings stress that ageing is not mechanically deflationary or growth-reducing, its net effects depend critically on institutional settings, labour market adaptability, and the pace of technological adoption.

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