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The Implications of Demographic Structural Changes for Technological Advancements in the Post-Demographic Transition China: Dual Indirect Channels Through Saving and Human Capital

(ポスト人口転換期の中国における人口構造変化が技術進歩へ及ぼす影響 ―貯蓄と人的資本を介した二つの間接的経路―)

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ABRSTRACT

In recent decades, countries worldwide have experienced two major challenges: demographic structural changes and rapid technological advancements. These concurrent changes have significant implications across various societal aspects. China, in particular, has witnessed remarkable economic growth and healthcare improvements, leading to increased life expectancy and declining fertility rates since the 1990s. These demographic transitions in China's population have resulted in a shrinking working-age population and a growing elderly population. Notably, China has recently entered a phase of negative population growth in 2023, presenting future challenges related to continuous aging and persistently low fertility rates. At the same time, technological advancements associated with the Fourth Industrial Revolution are rapidly transforming the world, with China playing a significant role in this progress. The widespread adoption of disruptive technologies is expected to have profound effects on society and the economy. Therefore, comprehending the interaction between demographic changes and technological advancements is crucial for addressing the challenges posed by demographic structural changes while harnessing the potential of technological advancements to drive productivity and economic growth.

The relationship between technological advancements and demographic structural changes is complex and lacks comprehensive research, leading to inconclusive findings. Previous studies have primarily focused on analysing overall demographic trends, without considering age-specific dynamics by separating declining fertility rates and population aging, and their compound effects. The causal mechanisms underlying the relationship and the intricate interaction between technological advancements, workforce dynamics, and demography remain unclear. Additionally, the role of human capital and skill levels in shaping the outcomes of technological advancements has often been overlooked. Moreover, the economic implications of automation vary across different regions, further contributing to the complexity of the issue. Therefore, there is a need for a comprehensive understanding of the interplay between technological advancements and demographic changes, taking various contextual factors into consideration.

Furthermore, the impact of demographic changes on development is a complex issue that presents theoretical and practical challenges. These changes can directly affect economic growth by altering the size of the labour force, but they can also have indirect effects by influencing other factors, particularly saving and human capital, as emphasized by the demographic dividends theory (DDT). In light of these considerations, this study adopts the theoretical framework of the DDT and addresses the following research questions to provide a comprehensive understanding of the linkages: (1) What are the implications of demographic structural changes driven by different age-specific dynamics on global technological advancements? (2) What are the implications of demographic structural changes driven by different age-specific dynamics on technological advancements in China? Each research question is further divided into three sub-questions, aiming to explore the magnitude, mechanisms, and contextual heterogeneities of the implications in a nuanced and detailed manner.

The primary objective of this study is to provide a comprehensive and nuanced understanding of the relationship between demographic structural changes and technological advancements, specifically the implications for China. To address limitations in the existing literature, the study examines both the overall implications of demographic changes and the specific dynamics related to the declining child dependency ratio and increasing old-age support ratio. Furthermore, the study aims to uncover the mechanisms through which demographic changes influence technological advancements, building on the demographic dividend theory (DDT) with supporting empirical evidence. Additionally, the study explores variations across countries at different economic development levels, as well as differences between regions and sectors within China, by taking the heterogeneity of the phenomenon into account.

This study makes several contributions to the existing literature. Firstly, it addresses a research gap by examining the specific implications of demographic structural changes on global technological advancements, particularly in the context of automation progress. Secondly, it goes beyond examining the magnitude of these implications and delves into the causal mechanisms underlying the interactions between demographics and technological advancements, which has been lacking in previous studies. Thirdly, the study

overcomes data limitations and enhances robustness by employing multiple proxies and methodologies to measure technological advancements, especially in developing country contexts like China. This not only provides valuable insights for China's long-term sustainable development but also offers important lessons for other developing countries experiencing similar demographic transitions.

In line with objectives, this study firstly delves into the implications of demographic structural changes on technological advancements in the global context, where the technological advancement is proxied by the adoption of automation robots. The second part of the paper investigates the implications of demographic structural changes on technological advancements in the context of China, where technological advancements are proxied by several indicators, including the estimated TFP using Data Envelopment Analysis (DEA) Malmquist, Stochastic Frontier Analysis (SFA), and Ordinary Least Squares (OLS) methods, the number of patent applications per thousand employees, and the number of R&D expenditures per thousand employees due to the constraint of data availability. The study employs mediation analysis, specifically a causal stepwise approach, to examine the hypothesized dual indirect mechanisms of saving and human capital. Interaction models are also used to supplement the analysis. Extensive robustness analyses have been conducted to ensure the validity and consistency of the results.

The first part of the analysis confirms that demographic structural changes, such as reduced child dependency and a shrinking working-age population, have diverse effects on technological advancements. However, the impact of a higher old-age support burden on technological progress is not significant. Saving plays a positive role in promoting the adoption of robots, while human capital development serves as an additional indirect channel, albeit with varying effects across different demographic dynamics. Moreover, findings highlight significant differences between China and other high-income countries, with China's technological advancements surpassing the global average. Factors contributing to China's unique trajectory include rapid demographic transitions, substantial economic growth, technological advancements, and the development of human capital.

Findings from the second part reinforce indirect mechanisms of saving and human capital in the context of China while highlighting diverse impacts driven by age-specific

dynamics. The decline in the child dependency ratio promotes progress through increased saving and education, while the impact of the old-age support ratio is mixed, affecting health conditions and changing saving patterns. Significant regional disparities are observed, as technological impacts are influenced by demographic structural changes and various factors such as savings, human capital levels, economic conditions, and urbanization. Internal migration may play a prominent role in explaining these disparities. Moreover, the study reveals that demographic changes in the workforce composition also have significant but varying effects on technological advancements across sectors. Sectors with younger workers, higher education levels, and lower child dependency burdens experience faster progress, while the effects of an aging population are less clear. Over time, the correlation between demographic changes, human capital, and technological advancements strengthens.

In summary, this study emphasizes the significant impact of demographic structural changes on technological advancements in China's post-demographic transition phase. The decline in the child dependency ratio positively influences technological advancements through increased savings and human capital accumulation. However, the effects of the rising old-age support ratio on technological advancements are multifaceted and vary in direction. The study underscores the complexity of the relationship between demographics and technological advancements, with variations observed across countries, regions, and sectors. To address these challenges and maximize benefits, recommended policy actions include pension system reform, investment in human capital and early childhood development, and hukou system reform are provided. These measures will mitigate the negative impacts of the demographic transition while leverage technological advancements for long-term and sustainable development in China.

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Congratulations, You Made It! This heartfelt expression signifies the culmination of my Ph.D. journey and the impending farewell to the life I have built in Kobe, Japan. However, I see it not just as the conclusion of an academic pursuit, but as a profound achievement that has shaped my life in countless ways. As I reflect upon this transformative experience, I am overwhelmed with gratitude for the unwavering support and assistance I have received along the way, without which I would not have reached this momentous milestone.

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LIST OF ACRONYMS

AI: Artificial Intelligence

AYS: Average years of schooling

BEA: U.S. Bureau of Economic Analysis

DDT: Demographic Dividends Theory

DE: Direct Effects

DEA: Data Envelopment Analysis

DMU: Decision-Making Unit

DTM: Demographic Transition Model

DTT: Demographic Transition Theory

EYS: Expected Years of Schooling

FDI: Foreign Direct Investment

FE: Fixed Effects

GDP: Gross domestic product

GFCF: Gross Fixed Capital Formation

GII: Global Innovation Index

GMM: Generalized Method of Moments

HCI: Human Capital Index

HIC: High-Income Countries

IFR: International Federation of Robotics

IMF: International Monetary Fund

IoT: Internet of Things

LIC: Low-Income Countries

LMIC: Lower-Middle-Income Countries

MLE: Maximum Likelihood Estimation

MOE: Ministry of Education

MOHRSS: Ministry of Human Resources and Social Security of China

NBS: National Bureau of Statistics of China

OECD: Organization for Economic Co-operation and Development

OLS: Ordinary Least Squares

PAYG: Pay-As-You-Go

PPP: Purchasing power parity

PRC: People's Republic of China

PWT: Penn World Tables

R&D: Research and Development

RE: Random Effects

SDT: Second Demographic Transition

SFA: Stochastic Frontier Analysis

TDR: Total Dependency Ratio

TE: Total Effects

TFP: Total Factor Productivity

TFR: Total Fertility Rate

TVET: Technical and Vocational Education and Training

UMIC: Upper-Middle-Income Countries

UN: United Nations

WDI: World Development Indicators, World Bank

WIPO: World Intellectual Property Organization

WPP: World Population Prospects

TERMINOLOGY

Child-Dependency Ratio (CDR): The number of children (0-14 years old) to the working-age population (15-64 years old) (UN).

Human Capital Index: It is an international metric that measures the human capital that children born today can expect to attain by their 18th birthdays (World Bank Human Capital Project).

Life Expectancy at Birth: The average number of years that a newborn could expect to live, if he or she were subject to the age-specific mortality rates of a given period (UN).

Old-Age Support Ratio (OADR): The number of old-age dependents (persons aged 65 years or over) to the working-age population (15-64 years old) (UN).

Replacement-Level Fertility: Total fertility levels of about 2.1 children per woman. This value represents the average number of children a woman would need to have to reproduce herself by bearing a daughter who survives to childbearing age. If replacement level fertility is sustained over a sufficiently long period, each generation will exactly replace itself in the absence of migration (UN World Population Prospects).

Robot: An industrial robot is defined to be an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications, according to the definitions contained in the international standard ISO (IFR).

Total Dependency Ratio: The dependency ratio relates the number of children (0-14 years old) and older persons (65 years or over) to the working-age population (15-64 years old) (UN World Population Prospects).

Total Factor Productivity: In economics, it is the portion of output not explained by the number of inputs used in production, reflects output per unit of some combined set of inputs (Durlauf & Blume, 2008).

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CHAPTER 1: INTRODUCTION

The demographic structure of a country plays a crucial role in shaping its socioeconomic development (Bloom, Canning & Fink, 2010). During the process of demographic transition, characterized by declining fertility rates and increasing life expectancy, significant changes occur in the size and age composition of the population, known as demographic structural changes. These changes have far-reaching implications for various aspects of the economy and society (Lee & Mason, 2014), including technological advancements, which is widely recognized as a key driver of economic growth. Despite previous studies examining the impact of demographic structural changes on economic growth, there is limited research specifically focusing on their implications for technological advancements. This knowledge gap calls for a comprehensive and systematic theoretical foundation, as well as in-depth analysis, to better understand the relationship between demographic structural changes and technological progress. Such understanding is essential for policymakers and researchers to mitigate the challenges driven by demographic transition and navigate the opportunities for a long-term development.

1.1. BACKGROUND OF THE STUDY

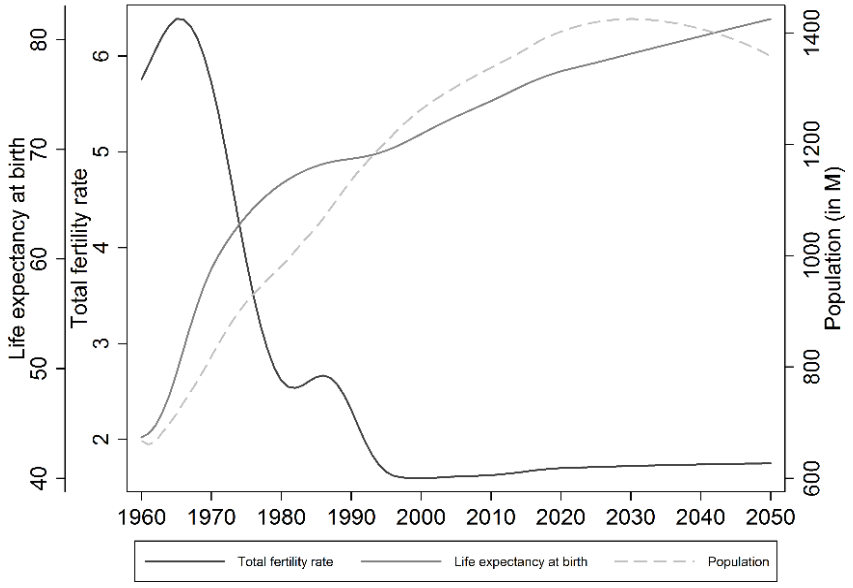
In recent decades, many countries have faced two significant challenges that have shaped their economic and social landscapes: substantial demographic structural changes and prominent technological advancements. These simultaneous changes have raised important concerns among economists regarding the future of work, production, economic dynamics, and reshaped social norms.

On one hand, demographic structural changes resulting from declining fertility rates and increasing life expectancy will lead to shifts in the dependency ratio, with a decreasing proportion of child dependents and an increasing proportion of elderly, implying significant impacts for various aspects of society, including labor markets, social security systems, healthcare, and overall economic productivity.

In the case of China, during the 1978–2019 period, China's economy proliferated, leaping to the world's second-largest economy, with a growth rate of 14.6 percent at current

prices, a 270-fold increase in the GDP, and a 184-fold increase in per-capita GDP. Alongside this economic success, improvements in healthcare have had a significant impact on the population. Life expectancy at birth in China has steadily risen from 44 years in the early 1960s to the current level of 77 years (Figure 1.1A). However, during this time, China also faced changes in its fertility rates. The total fertility rate (TFR) reached its peak in the mid-1960s at 6.4 births per woman but experienced a significant decline thereafter. The introduction of the one-child policy in the 1980s led to a continuous decrease in the TFR, dropping below the replacement level of 2.1 in the early 1990s and continuing to decline over the past three decades.

Figure 1.1A: Fertility, Life Expectancy, and Population Size



Source: World Development Indicators (2021)

The changes in fertility and life expectancy at birth have significantly influenced the age structure of the Chinese population. The working-age population (aged 15-64) has experienced significant growth, increasing from 370 million in the early 1960s to a peak of 996 million in 2015. However, it has since started to decline and is currently at a level of 875.6 million in 2022, with further decline expected in the future. In contrast, the population aged 65 and older has seen a steady increase, rising from 24.5 million in the early 1960s to the current level of 209.8 million. The population aged 0-14 has shown

marginal growth, increasing by 23 percent from 205 million in the early 1960s to 253 million, significantly lower compared to the overall population growth rate of 204 percent.

These demographic changes have led to shifts in dependency ratios. The old age dependency ratio, which measures the ratio of the population aged 65 and older to the working-age population, has exhibited a steady upward trend. It increased from 6.5 percent in the early 1960s to 12.9 percent in 2015 when the working-age population size reached its peak. As the share of working-age population has declined and the elderly population continues to grow, the old age dependency ratio has sharply increased to the current level of 19.6 percent. On the other hand, the child dependency ratio, which measures the ratio of the population aged 0-14 to the working-age population, has steadily decreased from 76.5 percent in the mid-1960s to the current level of 28.4 percent.

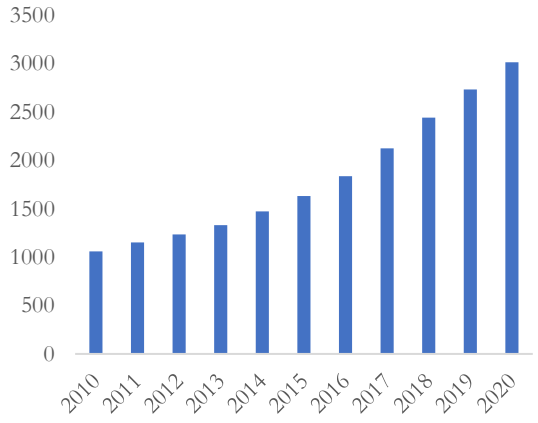
Notably, China has officially entered a phase of "negative population growth" in 2022- the first population decline since 1961, and the dramatic change in its demographic structure is expected to continue for longer, presenting two main challenges. The first challenge is the rapid aging of its population. With a current elderly population of over 209.8 million, accounting for more than 14.9 percent of the total population, China is home to the largest elderly population in the world. The transition to an "aged society" has been swift, and according to UN projections, China is expected to become a "super-aged society" within the next 12 years. This demographic trend poses challenges for a developing country like China, as it may face the issue of "getting old before getting rich" (Wu, 1980; 1986). The second challenge is the persistently low fertility rate. China's total fertility rate (TFR) reached a historic low of 1.08 in 2023, with only 9.56 million new births recorded, marking a significant drop by over 60 percent from 24 million in 1990. Despite the implementation of policies such as the "comprehensive two-child" policy in 2016 and the new "three-child policy" in 2021, the effectiveness of these measures in reversing the declining fertility trend is yet to be fully realized.

On the other hand, technological advancements are also evolving at an extraordinary rate in the context of demographic transition, leading to a profound transformation across all aspects of society. The global society is amid the Fourth Industrial Revolution, a period marked by the transition from traditional mechanical systems to

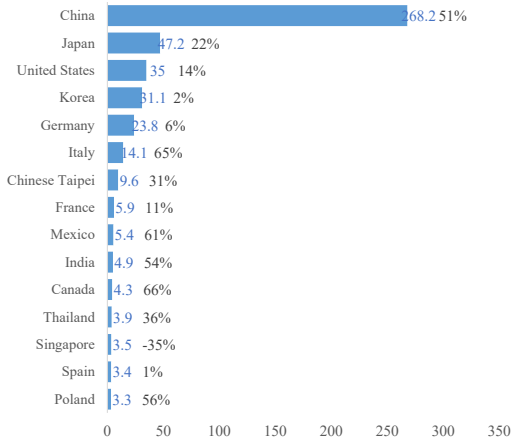
disruptive technologies. The advent of robotics, artificial intelligence (AI), Big Data, and many other groundbreaking innovations are prevailing worldwide, revolutionizing industries, shifting in business landscapes, reshaping the labor market, and altering the skills required of the human workers. A prime example of this transformative trend is the widespread adoption of automation robotics. According to the International Federation of Robotics (IFR), the number of industrial robots operating worldwide reached a remarkable milestone of 3 million in 2020, nearly tripling the count from a decade ago (Figure 1.1B Panel A). This surge in robotics has been further accelerated by the global COVID-19 pandemic, as robots have proven to be resilient and unaffected by the health risks that humans face (IMF, 2021). Looking forward, the IFR projects that the global installation of robots will continue to experience robust growth, with an anticipated annual increase of over 690,000 units by 2025. Notably, China has emerged as a dominant player in this technological revolution, standing as the largest market for robotics worldwide (Figure 1.1B Panel B). In 2021, China achieved a remarkable record with an annual installation of 268,200 units, representing a staggering 51 percent rise compared to the previous year, surpassing the rest of the world combined (IFR, 2022).

Figure 1.1B: Operational stock of industrial robots-World (in 1,000 units)

Panel A: Operational stock of industrial robots-World (in 1,000 units)



Panel B: Annual Installations of industrial robots 15 largest markets in 2021 (in 1,000 units; annual growth rate)



Source: World Robotics (2021)

The convergence of demographic structural changes and technological advancements has brought about more complexities and new questions for the labor market and the overall economic outlook. The rapid progress in technological advancements has the potential to not only replace human labor but also automate cognitive tasks traditionally performed by humans. While negative population growth may lead to a decline in the labor force supply, there is an expectation that technological advancements will help compensate for this decrease by boosting productivity and contributing to overall economic growth. Brynjolfsson and McAfee (2012; 2014) highlighted the potential of technology, such as automation and AI, to drive productivity growth and reshape the labor market in the context of demographic changes.

Against this backdrop, understanding the interplay between these two parallel changes is crucial for formulating effective policies and strategies to navigate the challenges and seize the opportunities they present.

1.2. PROBLEM STATEMENT

Are technological advancements intrinsic responses to the dramatic demographic structural changes? This is a topic that lacks comprehensive research and has produced inconclusive findings. While some studies have explored the implications of demographic factors on automation, such as the slowdown in population growth and aging (e.g., Abelianisky and Prettner, 2017 & 2021; Acemoglu and Restrepo, 2017 & 2021), their studies have notable limitations. The existing studies have predominantly focused on univariate analysis of demographic trends, specifically population growth and aging, without considering the compound effects and differences arising from age-specific demographic dynamics such as low fertility and population aging. Moreover, although these studies examine whether certain demographic factors promote automation, they neglect the important research question concerning the underlying causal mechanism.

The impact of demographic changes and the interaction between technological advancements and the workforce or demography is a multifaceted topic that has yet to reach definitive conclusions. Existing studies have put forth several competing

hypothetical mechanisms to explain how these factors interact and shape each other's outcomes, but none of them fully elucidate the issue.

One perspective suggests that automation can replace human labour by decreasing labour demand, leading to "substitutional effects" (e.g., Prettner et al., 2017; 2019; 2020). However, others argue that a decline in the working-age population can result in higher labour costs, increased competition with autonomous robots, and higher unemployment rates, causing income inequality and reduced employability for certain groups ("crowd-out effects") (e.g., Acemoglu, 2018; Chen and Xu, 2018). On the contrary, historical evidence suggests that the development and maintenance of machines require additional human workers, leading to positive employment outcomes ("complementary effects") (e.g., Graetz, 2018; Dauth et al., 2018).

Furthermore, empirical studies have shown that the employment consequences of automation vary across regions. For example, Graetz and Michaels (2018) found that robots contribute to a decline in the proportion of low-skilled workers without reducing overall employment in 17 countries. However, Carbonero et al. (2020) observed the opposite that robot adoption increased the global employment, particularly in developing economies. Similarly, Cho and Kim (2018) identified a complementary relationship between robotization and employment but a substitutional relationship with working hours in South Korea. There are many studies (e.g., Acemoglu and Restrepo, 2021; Dottori, 2020) employed the "shift-share approach" to examine the effects of robot exposure on regional employment in various countries, while these results across the United States, EU countries, Germany, and Italy, are mixed.

The complex relationship between the them are supported by Jimeno (2019), who conducted a comprehensive survey in reviewing the macroeconomic implications of demographics and technological changes, but with a focus on several theoretical frameworks, including task-based framework (Acemoglu and Restrepo 2018), DSGE framework (Lin and Weise, 2018), growth models (Benzell et al., 2015), state-of-the-art models (i.e., Carvalho et al. 2016; Basso and Rachedi, 2017), and others. The paper highlighted three main sources of uncertainty regarding the relationship between technological change and macroeconomic outcomes. Firstly, the extent to which new

machines and human labour will complement or substitute each other in the production of existing tasks is uncertain. Secondly, the speed at which tasks performed by human labour can be automated is a key factor. Lastly, the rate at which new tasks are created adds to the complexity of the analysis.

Another important uncertainty that has been neglected is the crucial interrelated factor of human capital - the skills level of workers may lead to different results. Different levels of skills can lead to varying levels of technology adoption, productivity gains, and economic growth, while neglecting the variations in skills levels among workers can limit the understanding of how technological advancements and demographic changes interact. For instance, Sachs & Kotlikoff (2012) found that machines substitute directly for young unskilled labour but complement older skilled labour. Acemoglu and Restrepo (2021) also found an increasing demand of automation driven by the aging workforce, which is supported by Blanas et al. (2019), Basso and Jimeno (2021), and Rutledge et al. (2020) that technological advancements in industries has led to a decrease in the demand for low and medium-skill workers, the young, and women, particularly in manufacturing sectors, but there has been an increase in the demand for high-skill workers, older workers, and men, particularly in service industries. These suggest that considering the role of skills and human capital in the context of technological advancements and demographic changes is essential for obtaining a more accurate and comprehensive understanding of their interactions.

The impact of technological advancements is multifaceted and subject to ongoing debate. On one hand, technology is seen as a driver of economic growth (e.g., Romer, 1990; Mankiw, Romer, and Weil, 1992; Acemoglu and Restrepo, 2018), with studies showing that automation, such as “Robotic Process Automation,” can reduce costs and improve productivity in various industries (e.g., Ansari et al., 2019; Lin et al., 2021; Goudzwaard et al., 2019; Jang et al., 2020). However, concerns exist regarding the potential negative consequences. Scholars argued that technological changes can exacerbate inequality, favoring certain skills (e.g., Acemoglu, 2002; Prettner and Bloom, 2020; Piketty, 2014). There are fears that automation may lead to job displacement, with studies predicting a significant risk to American jobs (e.g., Frey and Osborne, 2013; Manyika, 2017).

Although the mentioned studies provide valuable theoretical insights and empirical evidence into the significance of technological advancements, they have overlooked the crucial context of demographic transition. By neglecting these demographic dynamics, the studies may not capture the full complexity of the relationship between technological advancements and demographic dynamics.

In summary, while existing studies have made valuable contributions to understanding different aspects of technological advancements, there are clear limitations need to be addressed for a sound understanding. These limitations include the need to explore the specific relationships between technological advancements' outcomes and demographic structural changes driven by age-specific dynamics, both collectively and separately. Additionally, it is important to examine the mechanisms involved in this relationship, taking the role of human capital into account. Notably, the heterogeneity should be also incorporated.

1.3. RESEARCH QUESTIONS

The effect of demographic changes on economic growth is a highly complex issue that encounters theoretical challenges and practical difficulties. Demographic changes can directly impact economic growth through alterations in the size of the labor force. However, they can also have indirect effects by influencing other factors and depending on other covariates. To determine the overall effect, it is necessary to conduct a decomposition analysis at granular levels. Therefore, this study proposes the following research questions, aiming to provide a comprehensive understanding of their linkages.

RQ 1. What are the implications of demographic structural changes driven by different age-specific dynamics on technological advancements (proxied by automation technologies) globally?

1.1 To what extent does saving facilitate technological advancements for lower child-dependency ratio and higher old-age support ratio respectively?

1.2 To what extent does human capital facilitate technological advancements for lower child-dependency ratio and higher old-age support ratio respectively?

1.3 To what extent do technological implications with respect to China differ from other countries?

RQ 2. What are the implications of demographic structural changes driven by different age-specific dynamics on technological advancements (proxied by various other indicators) in China?

2.1 To what extend do these mechanisms facilitate technological advancements in China for lower child-dependency ratio and higher old-age support ratio respectively?

2.2 To what extend do the implications of demographic structural change on technological advancements differ across regions?

2.3 To what extend do the implications of demographic structural change on technological advancements across sectors?

1.4. OBJECTIVES OF THE STUDY

In this study, the primary focus is on exploring implications of demographic structural changes on technological advancements for China. The research aims to address the existing limitations of the existing studies in understanding this complex relationship.

Firstly, the study aims to achieve a comprehensive understanding by considering both the integrated implications of demographic structural changes and the specific dynamics related to different age groups. This involves examining various demographic factors such as the child-dependency ratio, which reflects low fertility, and the old-age support ratio, which indicates population aging. Additionally, the study also takes the overall population growth rate and other relevant socio-economic factors into account.

Secondly, the research aims to delve into the mechanisms through which demographic structural changes influence technological advancements. It extends the existing theoretical framework by proposing and analysing hypothesized dual indirect mechanisms. These mechanisms include the role of savings, as well as the impact of human capital development. The study also seeks to extensively provide empirical evidence to support these hypotheses and deepen the understanding of the underlying mechanisms.

Thirdly, the study acknowledges the complexities and challenges of data availability and potential heterogeneity. To overcome these limitations, the research employs various proxies for technological advancement, such as robots, total factor productivity (TFP), research and development (R&D) expenditure, and patent applications. This multi-dimensional analysis allows for a more comprehensive assessment of the relationship between demographic structural changes and technological advancements.

Moreover, the research takes into account different levels of analysis, including the global stage, the country-specific context of China, and regional and sectoral variations within China. By considering these different perspectives, the study aims to capture the nuances and variations in the relationship between demographic structural changes and technological advancements across different contexts.

Overall, the study aims to provide a more comprehensive and nuanced understanding of the relationship between demographic structural changes and technological advancements for the implications on China. By addressing the research objectives outlined above, the study seeks to contribute valuable insights and knowledge to the existing literature in this field, with implications for policymaking and future research.

1.5. SIGNIFICANCE OF THE STUDY

Knowledge Generation. Although the existing literature extensively explores the role of demographic structural changes as endogenous factors in economic growth and macroeconomic implications, limited attention has been given to the technological outcomes. Previous studies have consistently demonstrated a strong and positive association between the proportion of working-age population and economic growth as well as productivity (e.g., Eastwood and Lipton, 2011; Kelley and Schmidt, 2005, 2007). This relationship has been particularly emphasized in the context of successful growth in Asian countries (e.g., Bloom et al., 2000; Song, 2013; Hu et al., 2021). These findings highlighted the significance of demographic factors in shaping growth dynamics and underscored the pivotal role played by an expanding working-age population in driving economic development.

However, it is important to note that economic growth and productivity is not necessarily equivalent to technological advancements. Chomik and Piggott (2021) identified three key factors for productivity growth: the quality of the labor input, including human capital factors like health, education, training, and experience; the presence of complementary inputs such as infrastructure capital and production capital; and technological advancements, which involve methodological improvements in combining labor and capital. It is widely recognized that the technological change offers a more sustainable approach to driving growth compared to simply increasing inputs.

Additionally, while there exists literature on technological advancements, little attention has been paid to the specific contexts of developing countries, if any. Mondolo (2022) presented a comprehensive picture of the implications stemming from a complex and multifaceted of technological change, such as automation, AI, ICT, and other digital technologies, but previous studies have primarily focused on developed economies within the OECD countries, the United States, or European regions due to richer data availability and public attention (i.e., Abeliansky and Prettner, 2021; Behaghel and Brynjolfsson, 2019; Lin, Wu, Chen et al., 2021). Considering the significant regional diversities that has been widely discussed (i.e., Graetz and Michaels, 2018; Cho and Kim. 2018; Chiacchio et al., 2018; Dauth et al., 2017; Dottori, 2020), this highlights a research gap in exploring the implications of technological changes within the context of developing countries.

To address these knowledge gaps and contribute to the existing literature, this study places significant emphasis on understanding the interplay between demographic structural changes and technological advancements, particularly within the context of China. Firstly, this study not only focuses on technological advancements as a key variable of interest, drawing on various measurements as outlined in previous literature (Oberdabernig, 2015), but also provides unique insights into automation progress on a global scale. By exploring the cutting-edge advancements in automation, this research contributes to a comprehensive understanding of technological trends worldwide. Moreover, China serves as a crucial case study in this research due to its significant population size and status as a global development centre in the past decades. Findings from this study have the potential to offer valuable insights and lessons for other developing countries that are currently experiencing

similar challenges and undergoing significant demographic transitions and technological advancements. Through an examination of China's unique features and replicable experiences, this study not only provides insights into future institutional reforms within China but also offers guidance for policymakers and researchers in other developing countries facing similar circumstances.

Mechanisms Exploration. Despite the valuable contribution of the previous research on the macroeconomic implications of demographic factors, such as population aging and technological advancements, there is a need for further investigation into the causal mechanisms underlying their interactions (e.g., Abelianisky and Prettner, 2017 & 2021; Acemoglu and Restrepo, 2017 & 2021). Existing studies proposed task-based frameworks to examine the relationship between automation and a univariate demographic dynamic, but there was a lack of comprehensive understanding of the underlying mechanisms and neglection on the multifaced natures of demographic changes. As Jimeno (2019) highlighted, it is crucial to develop a fully-fledged general equilibrium model that considers the complex relationship between technological advancements and simultaneous demographic structural changes, including the endogenously determined conditions of capital and human capital to reveal the comprehensive transmission mechanisms.

To overcome these limitations, this study extends and builds upon a general equilibrium model and theoretically extends it using an accounting identity approach (Abelianisky and Prettner, 2017; 2021). The theory extension unravels the causality between automation outcomes and multifaceted demographic structural changes, with a specific emphasis on the endogenous saving mechanism. Furthermore, this study highlights the significance of the human capital factor in shaping contingent changes in the context of the post-demographic transition, aligning with the theory of demographic dividends. In addition to theoretical explorations, this paper empirically examines the hypothesized mechanisms using rigorous econometric techniques such as mediation analysis and interaction approaches to explicit the varying effects and mechanisms driven by age-specific demographic dynamics.

Comprehensive Data Mobilization: Although previous research has extensively examined from a broad perspective of technological progress and technological diffusions,

it is worth noting that these empirical studies have encountered challenges due to limitations in available data. For example, Oberdabernig (2015) conducted a survey to explore the implications of technological upgrading and identified multiple channels for technology diffusion, including education and training (i.e., Nelson and Phelps, 1966; Findlay, 1978; Wang and Blomstrom, 1992; Seck, 2012), infrastructure and institutions (i.e., Findlay, 1978; Seck, 2012), investment to adapt foreign technologies (i.e., Zeira, 2007), and trade (i.e., Bustos, 2011).

However, these studies faced significant data limitations. They often relied on a few proxies to measure technological diffusion, such as R&D expenditure, patents, labor or total factor productivity (TFP), high-technology exports, and imports of computers and machinery. Unfortunately, data availability for these indicators could be limited, especially in developing countries, where data on technology proxies are scarce or unavailable for certain periods or countries. This lack of comprehensive and consistent data across countries and time periods would introduce estimation bias and limit the accuracy of empirical findings. It is crucial to acknowledge these data constraints and carefully consider the implications when interpreting the results of previous studies.

In order to bridge the data gap and provide a more comprehensive understanding of technological advancements, this study adopts various methodologies and utilizes multiple proxies. Firstly, a long and internationally comparable dataset on automation innovations spanning the period from 1993 to 2019 is employed, allowing for a deeper analysis of cutting-edge technological advancements on a global scale. Furthermore, to gain insights into the specific context of China, this study utilizes a range of proxies to capture different dimensions of technological advancements. These proxies include estimations of total factor productivity (TFP) based on data envelopment analysis (DEA), stochastic frontier analysis (SFA), and ordinary least squares (OLS) methods. Additionally, patent application density and research and development (R&D) expenditure density data from 1990 to 2020 are also incorporated.

By incorporating a variety of methodologies and drawing upon diverse and reliable data sources, this study goes beyond the limitations of prior research. It aims to provide a more nuanced and precise analysis of technological advancements, enabling a

comprehensive understanding of its progress across different contexts. Through these comprehensive approaches, this study ensures a thorough exploration of the implications of technological progress, offering valuable insights into its multifaceted impact.

1.6. STRUCTURE OF THE DISSERTATION

The dissertation comprises six Chapters organized as follows.

Chapter 2 provides a comprehensive review of demographic and societal factors in China, including demographic structural changes, technological advancements, and human capital development. This chapter establishes a solid foundation for research questions and discussions surrounded at the megatrends of variables of interest in China.

Chapter 3 reviews previous studies on both theoretical frameworks and empirical evidences on the implications of demographic dynamics and technological outcomes, and a broader concept of technological advancements, namely productivity, respectively, in the context of world and China.

Chapter 4 introduces an extended general equilibrium framework that establishes connections between demographic structural changes and technological advancements in theory. It outlines the methodologies and econometric models, including mediation analysis and the interaction analysis, to test the theoretical assumptions. Additionally, this Chapter presents six hypotheses corresponding to the sub-research questions and provides details on the empirical models, data, and descriptive statistics.

Chapter 5 shifts the focus to the empirical examination of the overall and separated effects of demographic dynamics on technological advancements. It extensively investigates the hypothesized indirect mechanisms of saving and human capital development using various proxies for technological advancements across different contexts. This Chapter concludes with detailed explanations of the results corresponding to each research question respectively.

Chapter 6 summarizes and discusses the main findings and limitations of the empirical study. It is followed by the conclusions and policy implications drawn from the

research. The Appendix includes additional empirical results presented at the end of the dissertation.

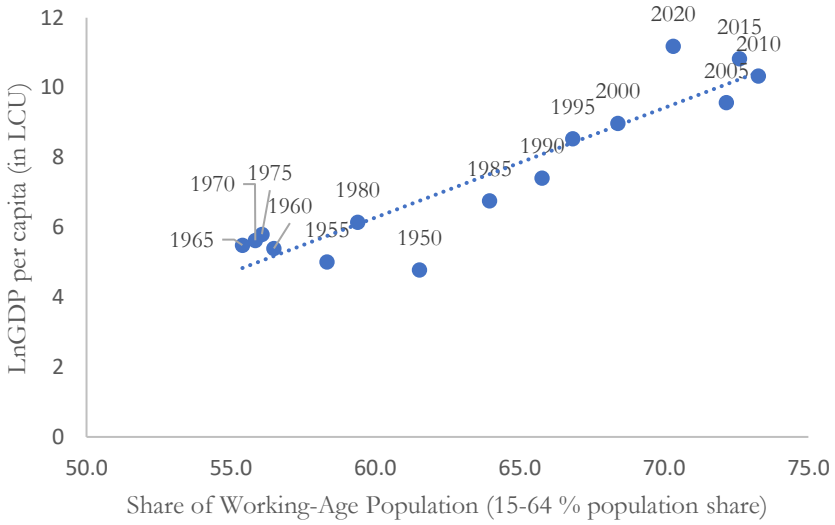
CHAPTER 2: OVERVIEW OF DEMOGRAPHIC AND SOCIETAL CHANGES IN CHINA

Demographic structural changes play a crucial role in shaping the economic and social landscape of a nation (Bloom, Canning, and Sevilla, 2003). As a country undergoes a demographic transition, marked by shifts in birth rates, death rates, natural population growth rates, and the population age structure, it experiences profound implications for the society. In addition, demographic changes are intricately intertwined with societal changes, reflecting reallocation of various types of production factors. Understanding the demographic trends and their interactions with other factors is vital for comprehending the complex dynamics of economic development. Therefore, overview of the paralleled societal implications along with these demographic changes, including human capital development and technological advancements help to shape a comprehensive understanding of the multifaceted impacts of demographic structural changes.

China, as one of the world's most populous country, provides a fascinating case study in demographic structural changes with far-reaching implications not only domestically but also globally. This Chapter delves into an in-depth overview of China's demographic changes and societal changes during the post-demographic transition period, and provides a holistic view of the dynamics that have shaped the country's development. As clearly depicted in Figure 2.1, demographic structural changes have played long-lasting role in keeping the economic growth momentum of the country in the past decades (Feng, Cai, and Gu, 2013). Therefore, by comprehensively reviewing the interplay between demographics and societal changes, this Chapter lays the foundation for the subsequent analysis on the implications of these changes for technological advancements in China.

Specifically, this Chapter provides detailed discussions of the demographic structural changes in China, including its historical background, current trends, projections, and comparisons with a few other countries. Alongside these examinations, this Chapter also explores societal changes that have unfolded in China over the same period. They include the rapid human capital development with respects to both education and health indicators, and expediated technological advancements.

Figure 2.1: Demographic Structure is Positively Associated with China's Economic Development



Source: World Development Indicators and National Bureau of Statistics of China (2022)

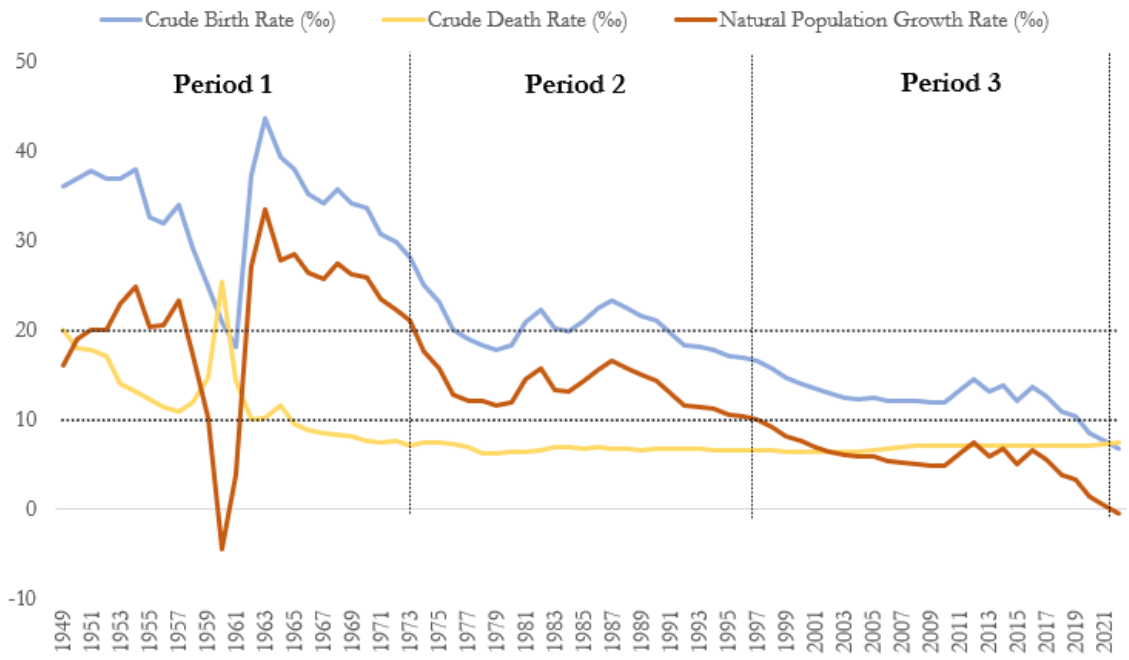
2.1. HISTORY OF DEMOGRAPHIC CHANGES IN CHINA

This section provides a tentative overview of the development trajectory of China's demographic changes since the year of 1949- the creation of the People's Republic of China (PRC), by exploring key shifts in demographic factors including birth rates, mortality rates, population age structure, and others during the process of demographic transition.

2.1.1 Birth Rate, Death Rate, and Natural Population Growth Rate

There are three major featured stages in China's demographic transition history since 1949 (Figure 2.1.1), including (1) the period of 1949-1973, where a natural growth rate consistently above 20‰; (2) the period of 1974-1997, where a natural growth rate fell in between 10‰ to 20‰; and (3) the post-1998 period, where a natural growth rate fell sharply below 10‰.

Figure 2.1.1: Three Featured Stages of the trajectory of China's Demographic Changes from 1949 to 2022



Source: China's Statistics Yearbook (1990-2023)

1) Period 1: 1949-1973

From 1949 to 1973, China experienced high birth rates, with a natural growth rate consistently above 20‰, except for a few years affected by three-year natural disaster period (1959-1961). During this period, birth rate started at 36‰, fluctuated, and peaked at 43.6‰ in 1963, before gradually declining to 28.07‰ in 1973. While during the same period, the death rate had a significant decline, except for a notable increase during the three-year natural disaster period in the early 1960s. This period of high birth rates contributed to the rise of the "60s generation" as the dominant age group in China.

Specifically, after the establishment of New China in 1949, the improved social stability, economic development, and healthcare conditions led to a significant decline in the death rate and a high birth rate. In 1949, the national birth rate was 36‰, the death rate was 20‰, and the natural growth rate was 16‰, with a total population of 542 million by the end of the year. From 1950 to 1957, the death rate dropped from 18‰ to 10.80‰ due to successful control of infectious diseases, whereas it surged to its highest point of 25.43‰

in 1960 due to the natural disaster shocks, resulting in a negative natural growth rate of -4.57‰, which is the only time since the establishment of the PRC in 1949. By 1957, the death rate had dropped to 10.8‰, and the natural growth rate rose to 23.2‰, reaching a total population of 647 million. The population increased by 105 million during the 8 years from 1949 to 1957, marking the "first peak of population growth" after the establishment of the country.

Between 1959 and 1961, the occurrence of natural disasters and economic disruptions had a significant impact on the Chinese people. This led to a notable rise in the death rate and a considerable decline in the birth rate, where the death rate experienced a sharp increase, reaching 14.6‰ in 1959 and further escalating to 25.4‰ in 1960. Conversely, the birth rate plummeted to a mere 20.9‰. As a consequence, there was a substantial decrease in the natural growth rate, resulting in two consecutive years of negative population growth in 1960 and 1961.

Right after that, China entered another high population growth phase, when its economy gradually improved, and the abnormal population situation was reversed. During 1962 to 1970, the birth rate peaked at 43.6‰, and the average birth rate remained at 36.8‰. The death rate declined from 20‰ in 1949 to below 10‰ in 1965 and continued to decrease annually, reaching 7.6‰ in 1970. As a result, the increase in the birth rate and the decrease in the death rate led to an average annual natural growth rate of 27.5‰ and an average annual increase of 26.88 million births during this phase.

2) Period 2: 1974-1997

About more than 20 years after 1974, the birth rate was almost halved, except for two small peaks in 1982 and 1987. Compared to the Period 1, the overall natural growth rate of China's population declined and fell in the range of 10‰ to 20‰. The policy of family planning (one-child policy), implemented as a basic national policy since the 1980s, contributed to the decline in birth rate from 33.43‰ in 1970 to 17.82‰ in 1979. The birth rate fluctuated in the 1980s due to policy adjustments and changes in the age structure of women of childbearing age. Overall, the birth rate continued to decline since 1974. In the meantime, the death rate slightly decreased and fluctuated between 6.48‰ and 6.90‰ during this period. Overall, the death rate showed a slightly decreasing trend, declining

from 7.34‰ in 1974 to 6.21‰ in 1979 and then fluctuating with gradually decreasing amplitude.

In particular, the family planning measures in the late 1970s marked a fundamental shift in China's population development that the population transited from uncontrolled and spontaneous growth to a controlled growth phase. The population control policies, which was established and gradually improved, had effectively curbed the high birth rates and growth trends before 1980. During this period, the birth rate and natural growth rate rapidly declined from 24.95‰ and 17.57‰ in 1974 to 18.2‰ and 11.9‰ in 1980, respectively. In the 1980s, the Chinese government further elevated family planning and population control polices as a fundamental national policy, when the population control became more restricted. However, this policy seemed to work with significant delays as the birth rate started to rise again due to a few other reasons.[1] The birth rate increased from 18.2‰ in 1980 to a peak of 23.3‰ in 1987. The net increase during this period was 143 million, with an average annual population growth of 15.84 million.

3) Period 3: 1998-2022

With the continuous enhancement and refinement of family planning initiatives, effective measures were taken to control the high birth rate of the late 1980s, compounded by a decrease in the number of women of childbearing age and a shift in people's attitudes towards marriage and childbirth, such that a steady decline in the birth rate in 1990s. Starting from 19.7‰ in 1991, the birth rate continuously decreased to 15.6‰ in 1998, when the natural growth rate fell below 10‰ for the first time. It further went down to 12.1‰ by 2008, marking a significant decline of 3.5 per thousand population over a span of 10 years. Since then, the birth rate has remained stable at a low level around 10‰. In the meantime, the death rate has maintained a stable downward trend albeit slight rises in the later stage. After 1998, the death rate kept declining until 2003, but experienced fluctuations afterward. This slight rise can be attributed to the aging population, as China entered the stage of population aging in 2000.

[1] The population born during the second peak of population growth in the early 1960s reached reproductive age and due to amendments to the marriage law in the early 1980s, allowing individuals to marry and have children at a younger age, so that the birth rate did not raise immediately (NBS, 2009)

As a result, from 2000 onwards, the population growth rate eventually stabilized at a growth rate of around 5‰ until 2017, and the annual net population increase remained below 10 million, signifying China's transition into a phase of stable population growth. This period also marks a historic transition from high birth and death rates to low birth, low death, and low growth- a post-demographic transition period as defined in the last stage of the Demographic Transition Model (DTM).

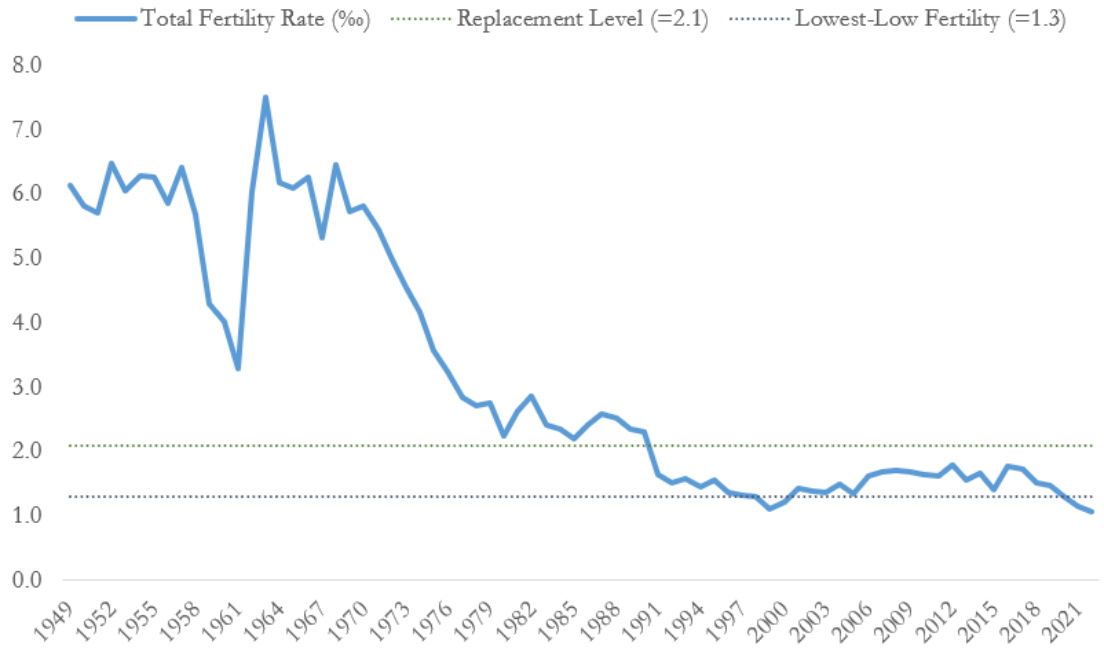
2.1.2 Total Fertility Rate

In addition to previously described demographic factors, the Total fertility rate (TFR), also known as the general fertility rate, is also broadly adopted as a measurement in understanding and assessing the demographics. TFR refers to the average number of children born to women of reproductive age in a country or region, and it is obtained by summing the single-year age-specific rates at a given time (Chen & Duan, 2019). Internationally, a TFR below 2.1 is considered a threshold for low fertility rates. At this level, in the absence of international migration, the rates of births and deaths gradually converge, leading to population stability. Furthermore, a TFR below 1.3 is often referred to as a "lowest-low fertility," indicating potential challenges for population replacement, reproduction, and future population development (Kohler et al., 2020).

Although the National Bureau of Statistics in China does not release the total fertility rate data series, many scholars have done various preliminary estimations based on official statistics of the number of births and the population of women of childbearing age that published in China's Population Statistics Yearbook (i.e., Chen & Duan, 2019; Ren & Liang, 2023). It is noteworthy that the estimation of the TFR based on different data has become a topic of much discussion in recent years (especially after 2015). For instance, there was an estimation of TFR of 1.047 in 2015 that derived from the 1 percent population sample survey by a few researchers (i.e., Zhai, 2016), whereas the officially published number of births by the National Bureau of Statistics for the same year was 16.55 million, corresponding to a total fertility rate of approximately 1.54. The discrepancy in TFR estimation is likely due to the limitations in survey data collection methods in China, and

government officials from National Bureau of Statistics has raised a few specific reasons for the potential estimation bias.[2]

Figure 2.1.2: The Trend of the Total Fertility Rate



Source: Stocktaking of estimations based on China's Population Yearbook (1990-2022)

By stocktaking these preliminary results (Figure 2.1.2), changes in TFR also revealed a dramatic demographic transition in China. Specifically, since the establishment of China in 1949, the TFR remained high throughout 1970, with averages of 5.44 in the 1940s, 5.87 in the 1950s, and 5.68 in the 1960s, which was significantly above the replacement level of 2.1. This led to rapid population growth in this period. Since the entrance to the 1970s, the TFR started decreasing significantly, from 5.4 in 1971 to 2.3 in 1990, but remained higher than the replacement level of 2.1. China's population increased from 852 million to 1.14 billion during the same period, with an average annual growth rate of 1.7 percent.

[2] Firstly, accurate reporting in household surveys is challenging, with potential underreporting of births and the 0-year-old age group due to recall bias or intentional concealment. Secondly, China's significant population mobility adds further obstacles to collecting accurate data, particularly for the 0-year-old age group. Additionally, underreporting of births outside the family planning policy, driven by fear of penalties, can also contribute to inaccurate estimations of the total fertility rate (TFR) (NBS, 2020).

However, since 1991, the TFR fell below replacement level with a consistent downward trend, and during 1998 to 2018, China's TFR remained around 1.3 to 1.6 with a slight fluctuation, driven by ongoing socioeconomic development, continuous adjustments and improvements in the fertility policy, and the influence of population inertia. For instance, the TFR of Beijing Olympic Games in 2008, the Year of the Dragon in 2012, and adjustments in the fertility policy in 2016-2017[3] have all contributed to TFR surpassing 1.7 in those specific years. In contrast, the TFR dropped to a low point of 1.41 in 2015 (Year of the Sheep), stepped into a further downward trend since 2019, and reached the lowest point of 1.1 in 2022. The main reasons for the recent decline in TFR are a decrease in the population of women of childbearing age and a decline in the desire to have children.

2.1.3 Population Pyramids: A Visual Representation of China's Demographic Structural Changes

The population pyramid is another vital tool for demographic analysis as it visually represents the distribution of ages across and sex structure of a population, providing valuable insights into population dynamics (Foot & Venne, 1990). By investigating past population pyramids, it is useful to obtain insights into the current composition and other factors influencing the present population. This historical perspective also forms the foundation for predicting and planning future population changes, enabling the development of effective population policies and strategies.

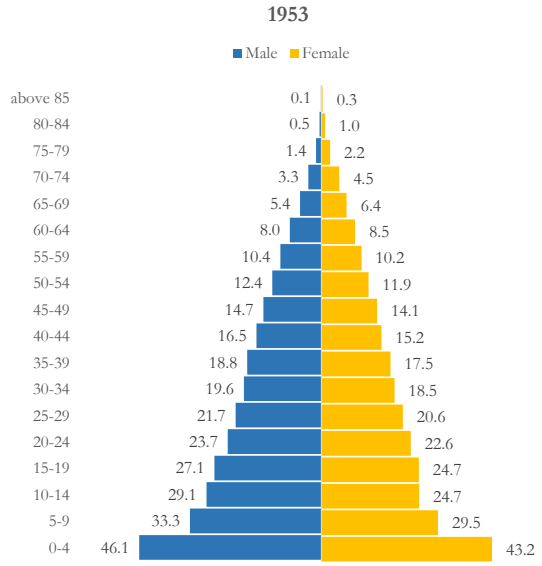
Historically, China has conducted seven population censuses over the past 74 years, with each coincided with crucial milestones in population dynamics. The population pyramids based on each census results (Figure 2.1.3) revealed not only the population structural changes overtime, but population planning policies progressed gradually.

The first census was conducted in 1953, shortly after the establishment of the PRC in 1949. This period witnessed a series of conflicts, including the World War II and the Chinese Civil War, leading to significant casualties, particularly among the working-age population. Upon the first census, China's total population had reached 602 million,

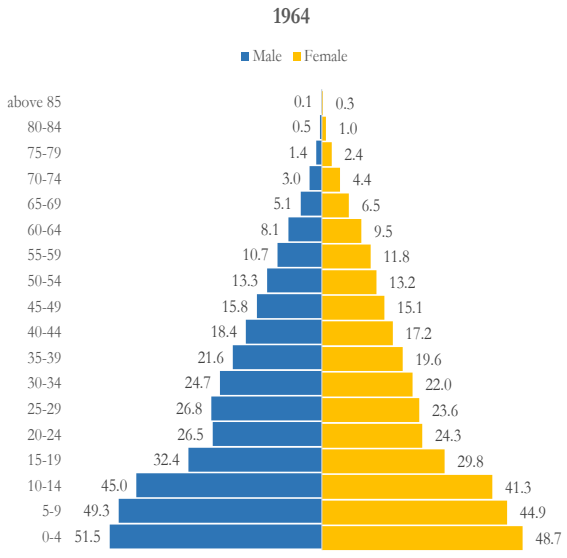
[3] The implementation of the universal two-child policy.

reflecting a remarkable increase of 127 million from 1949, with an average annual growth rate of 6 percent. With a total population of 602 million, the census recorded a remarkable increase of 127 million since 1949, reflecting an average annual growth rate of 6 percent. The population exhibited a pyramid-like structure with a substantial proportion of young children and adult workers, indicating a phase of vigorous growth. Additionally, the gender distribution was relatively balanced, with males accounting for 51 percent and females comprising the remaining 49 percent.

Figure 2.1.3: Changes of China's Population Pyramid (unit: million)



Source: China 1st Census Data from National Bureau of Statistics (1953)



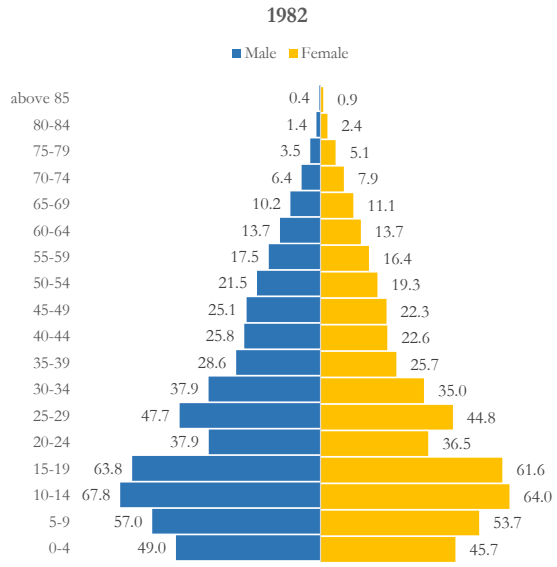
Source: China 2nd Census Data from National Bureau of Statistics (1964)

Due to limitations in transportation and communication infrastructure, the release of the second population census data from 1962 was delayed until 1964. The census revealed a national population of 723 million, indicating an increase of 121 million individuals compared to the previous census, and a growth rate of 20.1 percent. The population structure in 1960 showed a continued rise in the number of newborns. The proportion of the working-age population slightly declined from 56.4 percent to 53.2 percent, while the proportion of young-age children (0-14 years) increased from 36.2 percent to 40.7 percent.

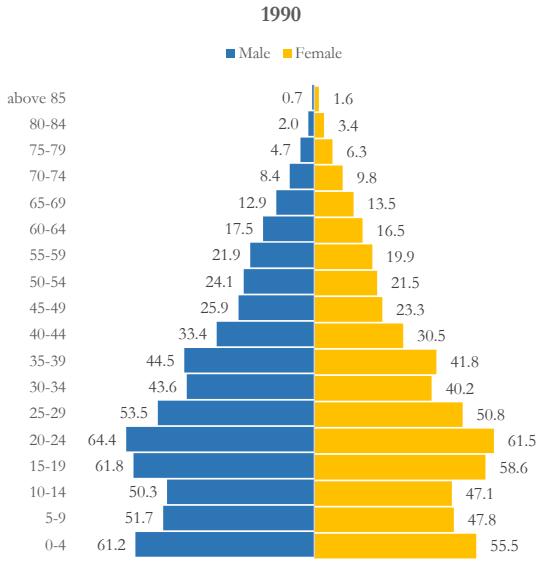
By the third population census in 1982, China's population had reached 1.03 billion, with a 20-year interval since the previous census and an average compound growth rate of 19.5 percent per decade. The population composition in 1982 began to display the characteristics of an emerging "olive-shaped" pattern. Compared to previous censuses, there were prominent working-age adults in 1982, marked by an increase of more than 223 million over two decades and accounting above 58.8 percent of the total population. On the other hand, both the absolute number of new births and the proportion of young-age children (about 33.6 percent) started to show a declining tendency, indicating that during the initial period of intensified family planning, especially after 1970, the birth rate in China exhibited a noticeable decline.

The fourth population census conducted in 1990 revealed a total population of 1.16 billion in China, indicating a significant decline in the growth rate of 12.42 percent compared to the previous rate of around 20 percent. The population structure exhibited a distinctive "three-tiered pyramid" pattern, with a notable increase observed in the age groups ranging from 0 to 4 years between 1982 and 1990. In particular, the expansion of the working-age population was significant, reaching 721 million individuals and accounting for 63.7 percent of the total population. Especially, more than 246 million young age people at 15-24 ages in 1990, who belonged to new birth cohorts during the population growth boom period in early 1960s-1970s, had officially entered the labor market, accounting for 34 percent of the labors. However, it is important to note that a slight gender imbalance emerged among newborns. Specifically, the proportion of female newborns (0-4 years) declined to 47.5 percent of the same age cohort population, compared to 48.5 percent of the entire population. This long-standing phenomenon of a preference for boys over girls in China, along with the shortage of young females, posed challenges to fertility in the years to come (Banister, 2004; Ebenstein, 2010).

Figure 2.1.3: Changes of China's Population Pyramid (unit: million) (cont'd)



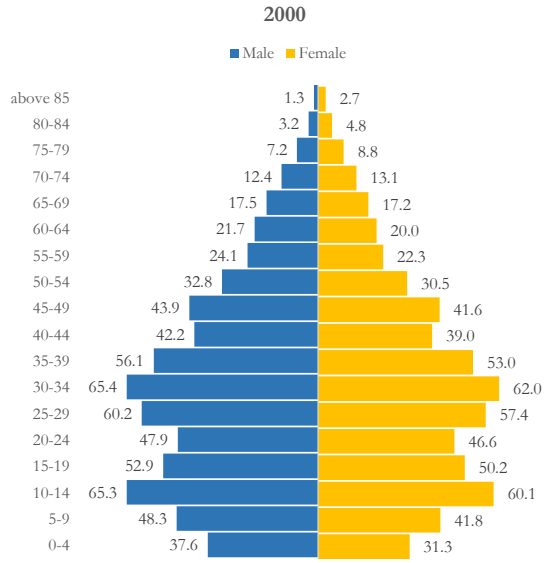
Source: China 3rd Census Data from National Bureau of Statistics (1982)



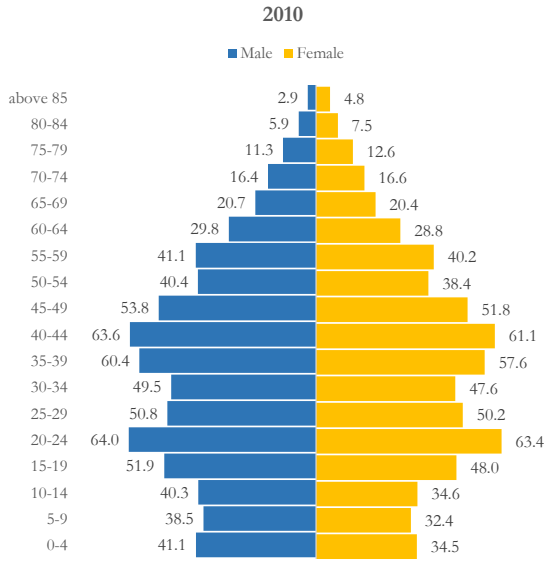
Source: China 4th Census Data from National Bureau of Statistics (1990)

Subsequent to that, the fifth and sixth population censuses revealed a population of 1.24 billion and 1.33 billion respectively, representing growth rates of 7.12 percent and 7.25 percent. These figures below also signified a transition to a phase of stable and slow population growth in China, where new birth cohorts shrink remarkably. In 2000, the proportion of younger cohort population (0-14 years) had declined from 28 percent in 1990 to 23 percent, and even deteriorated along the transition process to 17 percent in 2010. In contrast, the proportion of aged cohort population started expanding rapidly. For instance, the group of aged 65 and above in 1990 represented merely 5.6 percent to the entire population, but it kept increasing to 7.1 percent in 2000, and frog leaped to 8.9 percent by the end of 2010. These figures indicated that the accelerated process of population aging had led to a shift towards an elderly age structure. In addition, the proportion of female newborns (0-4 years) continued dropping to 45.6 percent of the same age cohort population, compared to 48.8 percent of the entire population. The phenomenon of "preferred boys to girls" had persisted, leading to imbalanced gender ratios and posing challenges for fertility patterns.

Figure 2.1.3: Changes of China's Population Pyramid (unit: million) (cont'd)



Source: China 5th Census Data from National Bureau of Statistics (2000)



Source: China 6th Census Data from National Bureau of Statistics (2010)

In sum, the transition of China's population structure can be observed from the "pyramid" shape in 1950, to the "flat-bottomed pyramid" in 1960, and further to the "olive-shaped" structure in 1980, before eventually evolving into the "double-tiered pyramid" in 1990. Despite the continuous population growth, the structural changes in the population have indicated a shift from the high growth "pyramid" shape since around 1960, with a noticeable slowdown in the growth rate due to the implementation of the family planning policy in the 1970s. It also led to a decrease in the proportion of children and an increase in the proportion of elderly individuals, which accelerated the transformation of the age structure. By the third population census in 1982, the age structure had already shifted towards an adult type by the fourth population census in 1990. Subsequently, the population age structure continued ageing, particularly after the 1990s, and the process of population aging accelerated led to a shift towards an elderly age structure in 2000 and 2010.

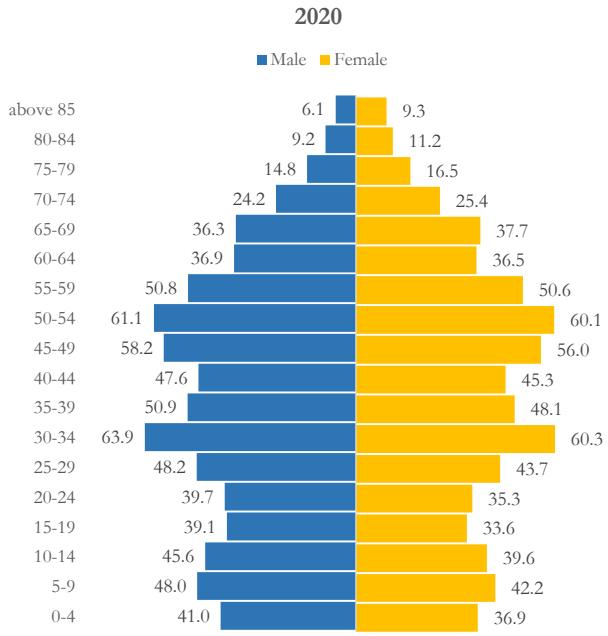
2.2. POST-DEMOGRAPHIC TRANSITION CHINA: FACTS AND PROJECTIONS

Earlier discussions on China's demographic transition in a long-term past have presented dramatic changes of its demographic structure, including birth rate, death rate, natural growth rate, TFR, and population age structure. China has undergone significant demographic changes since the 1990s, impacting its population structure. Over the past three decades, fertility rates have consistently remained below replacement levels, indicating a decline in the average number of children born to each woman. Simultaneously, there has been a remarkable decrease in mortality rates, particularly infant mortality, which has decreased from 2 percent in the 1960s to 0.66 percent in the 1990s, comparable to rates observed in developed countries. Furthermore, the average life expectancy has increased to 76 years, approaching the levels found in developed nations and surpassing those seen in less developed countries. These demographic transformations in China reflect changes in reproductive patterns as well as advancements in healthcare and living conditions, contributing to improved population dynamics (Wang and Mason, 2008). In particular, the latest census data shows that China's population fell 850,000 to 1.41 billion in 2022 – the first decline in 60 years (NBS, 2023). All these changes imply that China is undergoing a transition to the post-transitional society.[4]

Therefore, this section focuses on the post-transition era in China since 1990s and delves into the significant shifts and developments in China's population dynamics in this specific period. This section also provides discussions on its population projections with respect to different scenarios, as calibrated by the World Population Prospects (UN, 2022). By examining the current demographic structure and offering insights into future projections, this section aims to deepen the understanding of China's population dynamics and its implications for various aspects of society and recent development.

[4] Post-transitional societies are characterized by low birth and low death rates. Population growth is negligible, or even enters a decline (Notestein, 1945).

Figure 2.2: Current Population Pyramid in China (unit: million)



Source: China 7th Census Data of National Bureau of Statistics (2020)

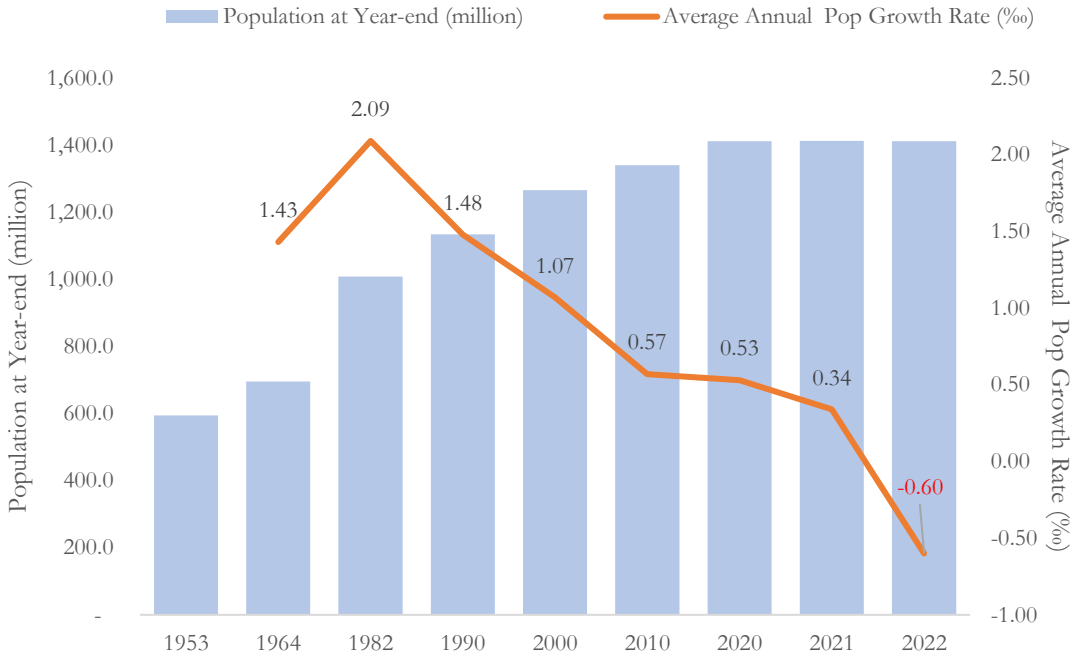
On May 11, 2021, the NBS released the seventh population census results and provides the latest update of China's demographics. It points to a total population of 1,411.78 million persons, up by 72.06 million since the 2010 census. The age composition was as follows: 0-14 years accounting for 17.95 percent; 15-59 years accounting for 63.35 percent, and those aged 60 and over comprising 18.7 percent (with those aged 65 accounting for 13.5 percent. In terms of the population share aged 60 and over, this represents an increase by 5.44 percent compared with the 2010 census (NBS, 2021). The population pyramid (Figure 2.2) visually represents the characteristics of the current population in 2020. Compared to previous census results, it can be clearly seen that the population growth rate (new birth) has noticeably slowed down, aging has accelerated, there is a shortage of young labor force, and there is also an increasing gender imbalance between male and female populations, among other issues. These facts serve as the initial points for the following in-depth discussions and projections.

2.2.1 Accelerated Slowdown (to Negative) in Population Growth

China has a population of about 1.41 billion, and is currently experiencing a period of slow growth, with clear indications that it has entered a phase of negative growth (NBS, 2023). Census results (Figure 2.2.1A) show that in 2020, China's total population was recorded as 1,411.78 million, reflecting a decade of sluggish growth at the average annual growth rate of 0.53 percent, exhibiting a decline of 0.04 percentage points from the rate of 0.57 percent observed during the period of 2000-2010. By 2021, the total population reached 1,412.60 million, with a net increase of only 480,000, representing a new record low in recent data. More prominently, the total population decreased to 1,411.75 million in 2022, a reduction of 850,000 compared to 2021. This decline- the first time since 1949, signifies a turning point and the onset of a period of negative population growth.

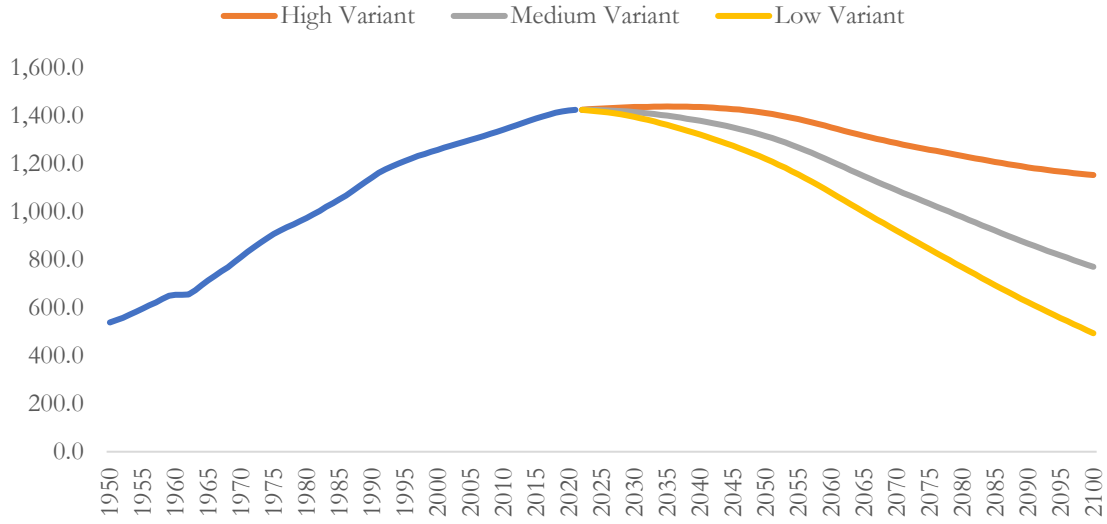
The latest UN medium variant estimates foresee China's share of population aged 65 and over rising steadily from 12.7 percent in 2020 to reach 33.4 percent by 2100 (Figure 2.2.1B). In both low and medium scenarios, the working-age population share and share of children both steadily decline, and the total population have peaked in 2022 and 2023 respectively. High variant probabilistic forecasts see China's population will peak at 1.44 billion in 2037. Notably, a persistently low total fertility rate would lead to sustained negative population growth. After reaching its peak in 2022 in the medium scenario, the total population in China will experience a gradual decline at an average growth rate of -0.27 percent until 2050, followed by an accelerated decline at an average growth rate of -0.82 percent until 2100.

Figure 2.2.1A: China's Total Population and Population Growth Rate



Source: China Census Data and NBS (1953-2022)

Figure 2.2.1B: China's Total Population and Projections (in million)

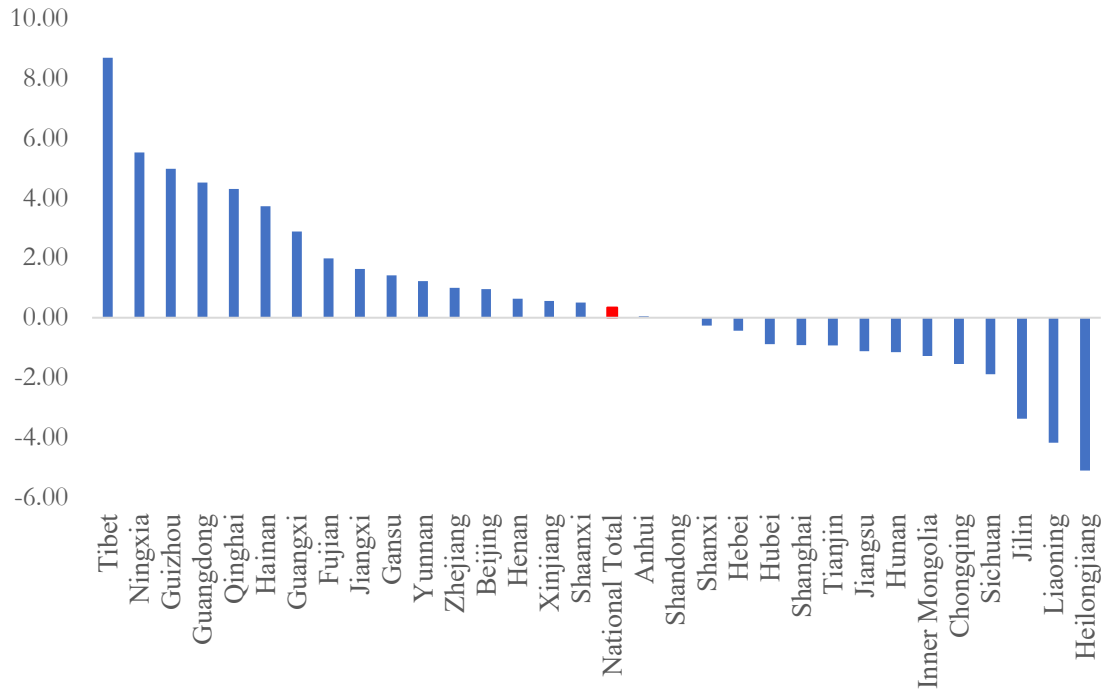


Source: UN World Population Prospects (2022)

The population growth also varies across regions. According to recent release of NBS data, in 2021, Guangdong province stands out as having the highest number of births with 1.18 million, while populous provinces like Henan, Shandong were the top provinces

in terms of births at 0.793 million and 0.75 million births respectively. However, Guangdong alone accounted for over 26 percent of the national total births while Henan, Shandong, and Hebei have seen a decline in the number of births by over 40 percent in the past five years (NBS, 2021). In relative terms of natural population growth rate (Figure 2.2.1C), the divergence is evident across provinces. In 2021, there are 13 provinces experience negative population growth rate, with Heilongjiang, Jilin, and Liaoning clustered in the north-eastern region witnessed -3.4 per thousand, -4.2 per thousand, and -5.1 per thousand respectively. On the other hand, only three provinces — Ningxia, Guizhou, and Tibet — recorded a natural population growth rate of higher than 5 percent. The released data for 2022 at -0.6 per thousand indicates a further decline in the growth rate compared to 2021 from 0.34 per thousand, and the trend reflects the overall phenomenon of a declining population growth rate across all places.

Figure 2.2.1C: China's Population Growth Rate Across Regions (per thousand)



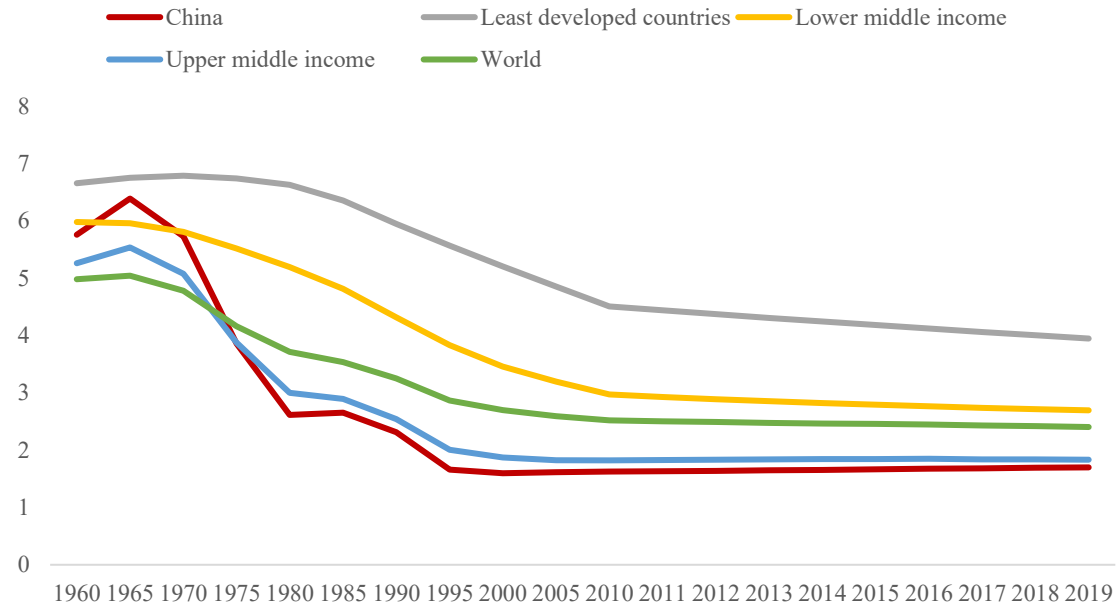
Source: China Statistics Yearbook (2021)

2.2.2 Prominently Low Fertility and Low Mortality

China's TFR, as described earlier, has been also on a downward trajectory for half a century and become below replacement level (2.1) since the early 1990s (Feng, 2011).[5] In 2016, the "National Population Development Plan (2016-2030)" estimated China's population to reach 1.42 billion by 2020 and a peak population of around 1.45 billion around 2030, by assuming a TFR between 1.5 and 1.6 in 2015 and predicted rates of 1.8 for 2020 and 2030.

However, the actual TFR maintained its declining momentum since 2016. Based on existing estimations (Ren, Liang et. al., 2023), China's total fertility rate was about 1.15 in 2021, and further dropped below 1.1 in 2022, which is only half of the replacement level (2.1) and ranks among the lowest globally. The average TFR through 2016-2022 is only 1.4, indicating a significant low level. It also suggests that the impact of the "comprehensive two-child policy" on fertility is overestimated.

Figure 2.2.2A: China's International Comparison of TFR (births per woman)



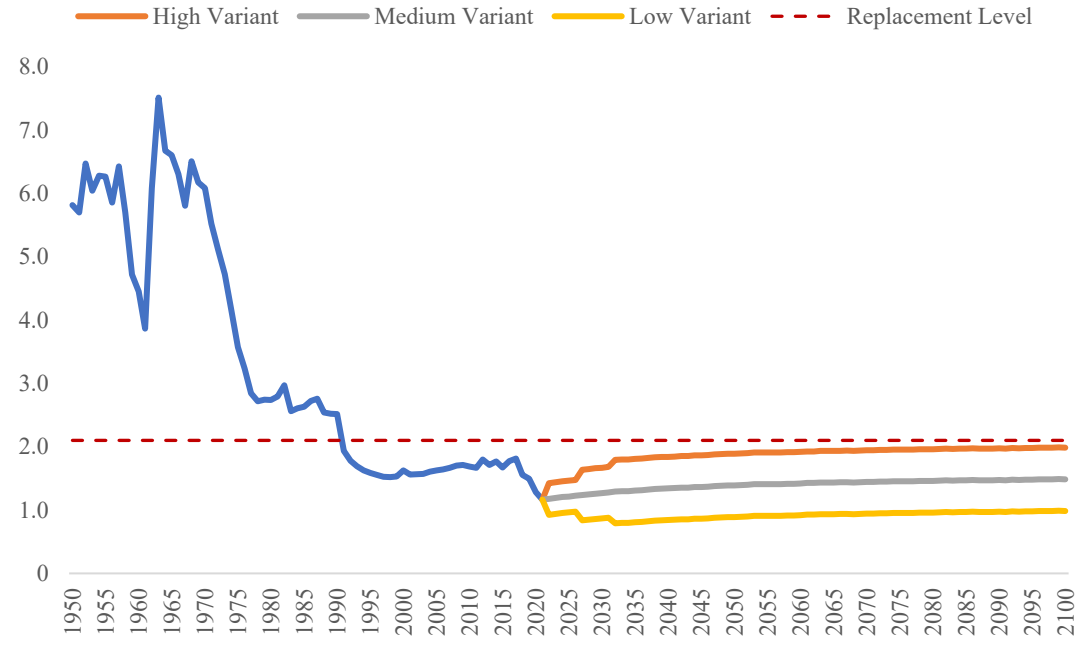
Source: World Development Indicators (2023)

[5] Coal and Freeman (1993) find this pattern to be consistent with the demographic transition of China's North-East Asian neighbourhood, except that in China's case it happened at lower per capita incomes. This is, however, a pattern that is not uncommon in countries undergoing a demographic later in the 20th century, in the case of transition economies especially (see Johnston, Liu, Yang and Zhang, 2016; Johnston, 2018).

Internationally, according to the World Population Prospects 2022, France, the United States, Brazil, the United Kingdom, Germany, and Japan had total fertility rates of 1.79, 1.66, 1.64, 1.56, 1.53, and 1.3, respectively (UN, 2022). Furthermore, a comparison between China and the world, and other country groups at similar level of development reveals that China's TFR at 1.69 in 2019 has been even lower than many global peers: the average TFR of all upper middle-income countries, lower middle-income countries, least developed countries, and the world are about 1.83, 2.69, 3.94, and 2.40, respectively. It highlights China's bottom position at the global stage.

The United Nations' projection for China's total fertility rate (TFR) is also pessimistic. According to the latest "World Population Prospects 2022," parameters will maintain a sluggish momentum in a long-term span in all projection scenarios, despite a slight increase in TFR from 2023 onwards. Under the medium scenario, the fertility rate is expected to rise to 1.27 by 2030, 1.34 by 2040, and 1.39 by 2050, reaching approximately 1.48 by 2100 (Figure 2.2.2B). As the effects of fertility accumulation wane, the TFR is projected to maintain below the replacement level (2.1), reemphasizing a sustained negative population growth outlook due to a persistent low total fertility rate.

Figure 2.2.2B: Projections of China's TFR (births per woman)



Source: UN World Population Prospects (2022)

2.2.3 Expediated Steps into "Super-Aged" Societies

In addition to low fertility, China's rapid entry into an "aged" society has exceeded expectations, with the proportion of the population aged 65 and above reaching 14.2 percent in 2021, marking the entrance to the "aged society" at an accelerated pace (Figure 2.2.3A).[6] According to the UN forecast, the share of aged 65 and over population will continue increasing onward and peak at 32.3 percent around 2083. Under the medium scenario, the proportion will increase at a much faster pace and peaks at 42.2 percent around early 2080s. Yet in the low variant scenario, the turn-point of ageing in China will not come until 2090s, suggesting the ageing and super-aging issues in China has just started and will become a very long-term challenge to the society.

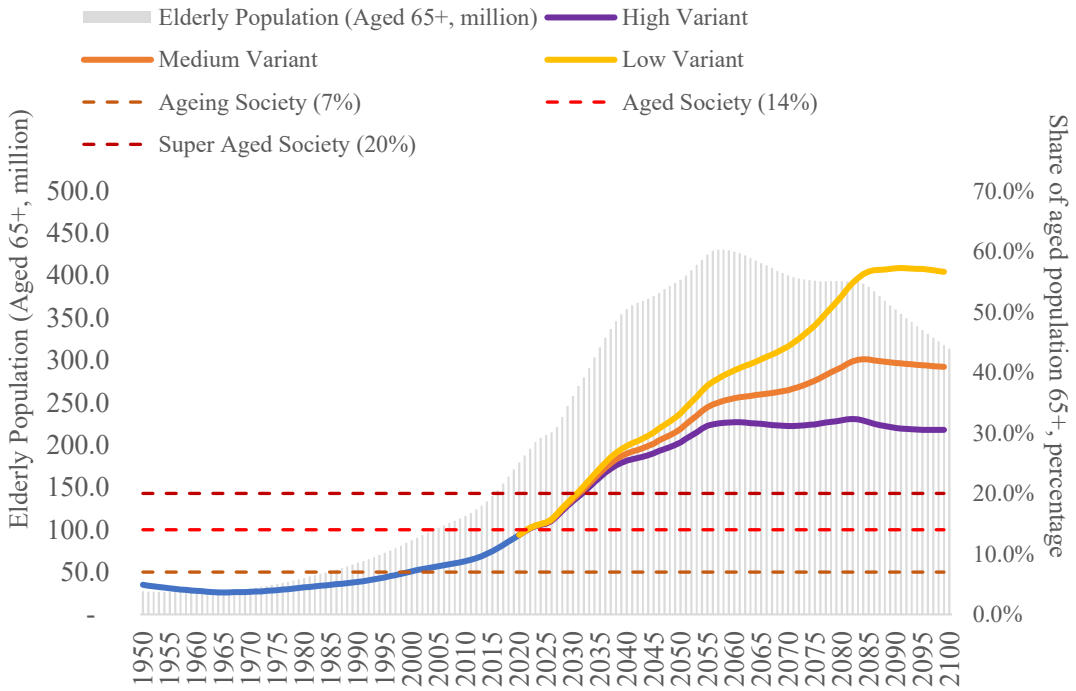
In China, this transition from an "aging society" in 2000 to an "aged society" only took 21 years. In contrast, it took 115 years for France to go through this transition, 45 years for the United Kingdom, and 69 years for the United States (Glinskaya, 2018). By 2022, it rose to 14.9 percent, and it is projected to surpass 20 percent around 2032, entering a "super-aged society." The proportion is expected to continue rapidly increasing to approximately 35.5 percent in 2060 with a short period of stabilization afterwards, and then peak to around 42.1 percent after 2084. On average, the rate of population aging has annually increased by 0.2 percentage points from 2001 to 2010, and then leaped to 0.5 percentage points from 2011 to 2022. Besides, the issue of "the oldest old" is also prominent. In 2020, the population aged 80 and above in China has exceeded 35.8 million, accounting for 2.5 percent. It is projected that by 2030, 2050, 2073, and 2100, the proportions will reach 3.8 percent, 10.3 percent, 17.1 percent, and 20.8 percent, respectively.

There are also significant regional disparities in aging, with pronounced aging in the northeast and Sichuan-Chongqing region. According to the China's seventh census data, 13 provinces are undergoing above-national average ageing challenges, whereas the rest 18 are moderately less. In 2021, only Tibet among all provinces had a proportion of the

[6] According to UN, the World Health Organization (WHO) and the United Nations define an "aging society" as one in which more than 7% of the population is 65 years or older, an "aged society" as a society in which more than 14% of the population is 65 years or older, and a "super-aged society" as a society in which more than 21% of the population is 65 years or older (UN, 1956).

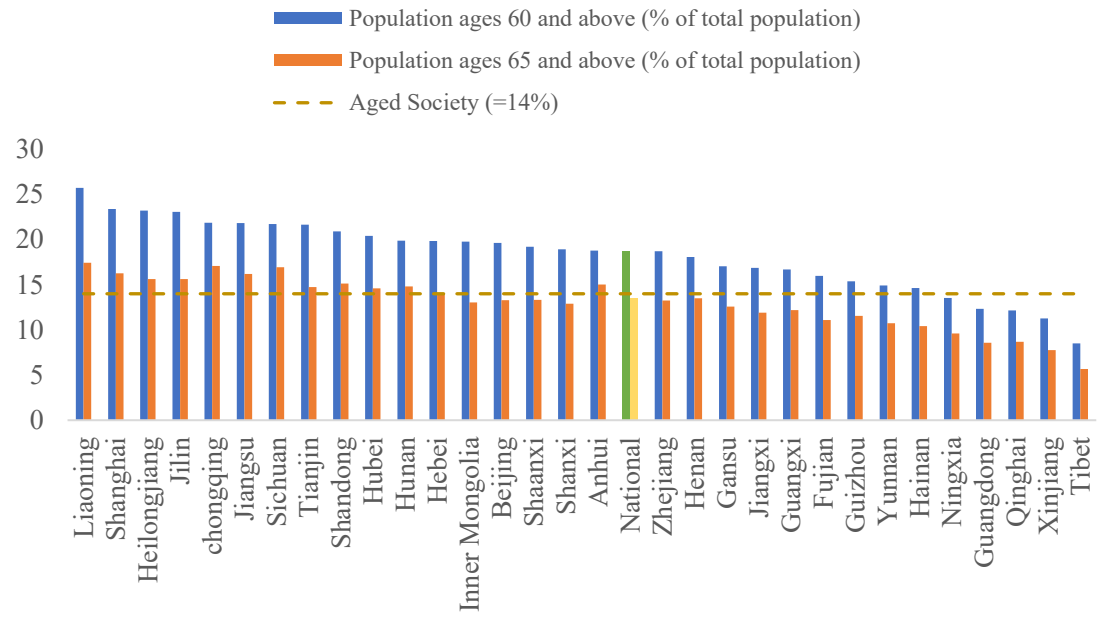
population aged 65 and above below 7 percent, indicating it had not yet entered the aging phase. Another nineteen provinces including Xinjiang, Guangdong, Qinghai, and Ningxia had the elderly proportions ranging from 7 percent to 14 percent, indicating a swift transition to the preliminary stage of aging. Twelve provinces, including Hubei, Tianjin, Hunan, Shandong, and Shanghai, had proportions higher than 14 percent, implying aged societies. Among them, Liaoning, Chongqing, Sichuan, Shanghai, Jiangsu, Heilongjiang, and Jilin had proportions as high as 17.4 percent, 17.1 percent, 16.9percent, 16.3 percent, 16.2 percent, 15.6 percent and 15.6 percent respectively in the seventh census results. NBS's estimation shows that their proportion have increased further in the next two years (NBS, 2023).

Figure 2.2.3A: Projections of China's Elderly Population (aged 65 and above)



Source: UN World Population Prospects (2022)

Figure 2.2.3B: Regional Disparities Among Places

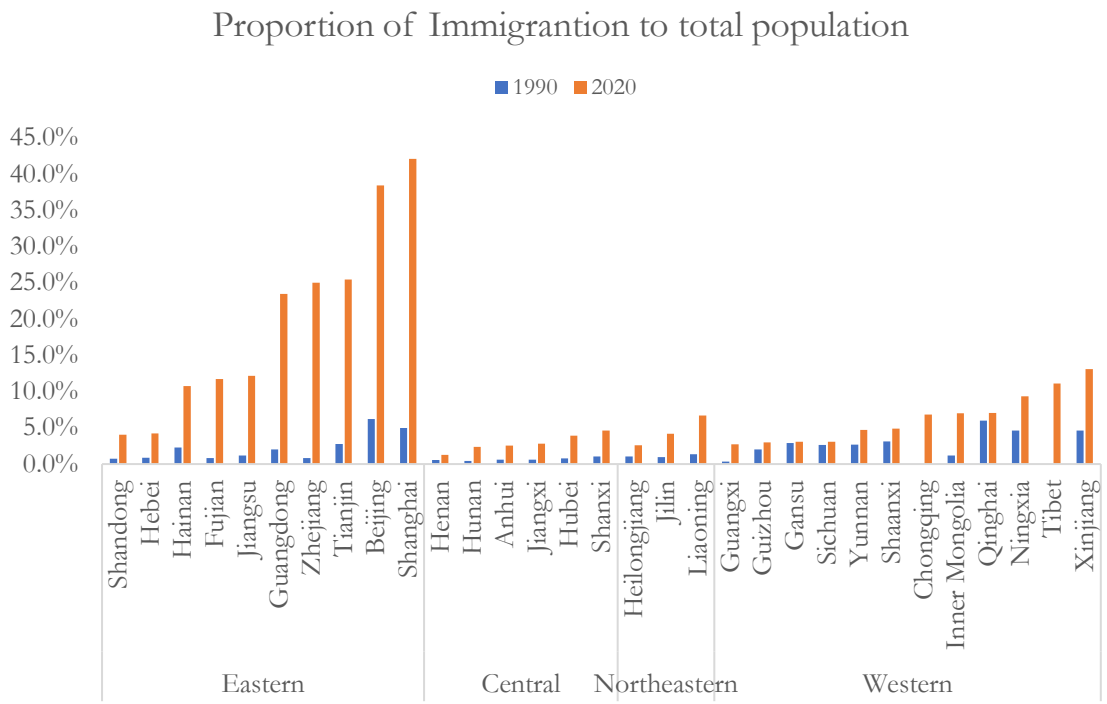


Source: China's 7th Census Data (2021)

The phenomenon of regional disparity is also supported by a few previous studies. For instance, Liu et al. (2014) found that the degree of population ageing is the highest in the East and lowest in the Western region based on provincial panel data for the period 1989–2011 (Liu et al., 2014). Autonomous regions, including Tibet, Xinjiang and Qinghai are absolutely China's "youngest" regions, with Tibet not having so far reached the 7 percent population share of residents aged 65 and over (Johnston, 2018). On the other hand, richer regions such as Guangdong and Fujian, are also marked by younger population.

Notably, one potential explanation to the regional disparities is the migration patterns, which has shaped significantly both demographic structure and economic dynamics of the country (e.g., Liu et al. 2014). The following Figure 2.2.3C presents the distribution and a comparison of immigration population across regions from 1990 to 2020.

Figure 2.2.3C: Comparison of Immigration Population Among Regions



Source: China's 5th and 7th Census Data (2021)

The eastern region of China, which includes highly developed areas such as Beijing, Shanghai, and Guangdong, has traditionally been a destination for internal migration. These regions have experienced a large influx of migrants from other parts of the country seeking better economic opportunities. These migrant workers have contributed to the region's demographic structure and labor market dynamics, with a relatively higher proportion of working-age population and a more diverse workforce.

In contrast, the western regions of China, which include less developed areas such as Tibet and Xinjiang, have witnessed a different migration pattern. These regions have experienced a net outflow of population, particularly among the younger and more educated individuals, who often migrate to the more prosperous eastern regions to seek for better employment opportunities and monetary returns. This outmigration has reshaped the demographic structure with a higher proportion of elderly and a lower labor force participation rate in the western regions.

The central and north-eastern regions of China exhibit a mix of migration patterns. Some areas within these regions have experienced net outmigration, like the western regions, while others have attracted internal migrants from rural areas seeking employment opportunities in urban areas. The complex migration patterns in these regions also have implications for the demographic structure, labor market dynamics, and the potential interaction between demographic factors and technological advancements.

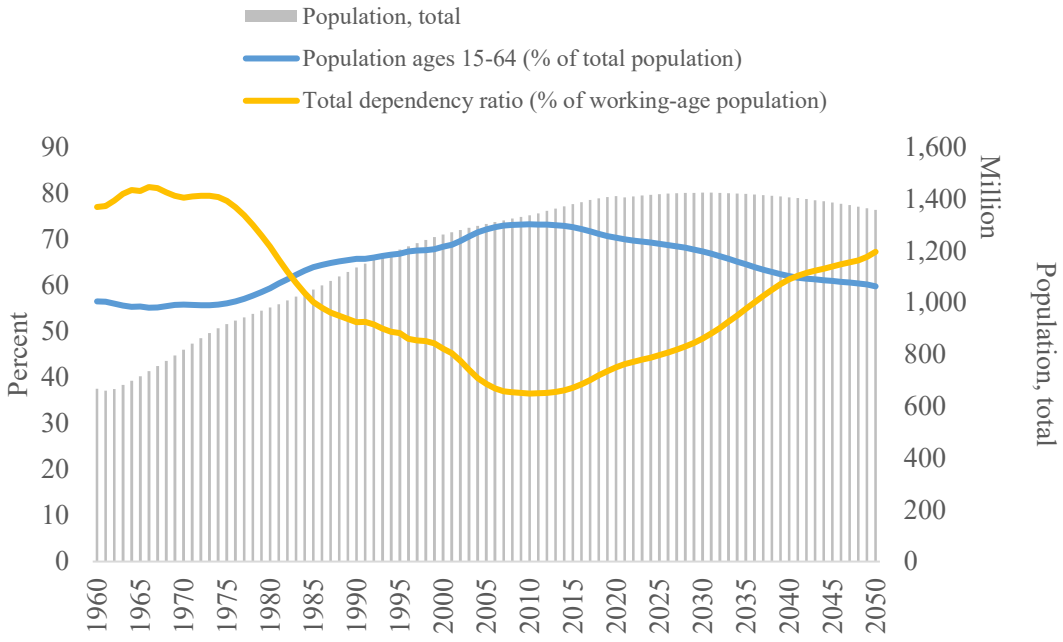
Migration patterns in China have important implications for the demographic structure and labor markets in different regions. These migration flows can shape the interaction between demographic factors, such as the old-age support ratio and the child dependency ratio. Therefore, the regional disparities phenomenon inspires this study to investigate more granularly at the province level in addition to the overall examination of the country.

2.2.4 Shrinking Working-Age Labor Force

China has witnessed negative population growth and a rapid aging population, resulting in a shrinking working-age population. Census data reveals that between 2010 and 2020, the population aged 15-64 decreased from 933 million to 892 million, with the proportion declining from 70 percent to 63.3 percent. Projections indicate a continued decline, with the working-age population's proportion expected to reach 59.7 percent by 2050 (Figure 2.2.4). Notably, the peak of both the proportion and size of the working-age population occurred in 2010 and 2013, respectively, followed by a significant decline.

Considering the large population in China, the decline in the labor force suggests an increasing number of dependents in the nation. According to UN data, the total dependency ratio (TDR) in China reached its lowest point in 2010 at 0.36, indicating that, on average, each dependent (children or the elderly) was supported by 2.7 adult workers. However, the TDR has been steadily increasing and reached 0.42 in just 10 years. It is projected to continue growing to 0.48 by 2030 and 0.67 by 2050. By then, on average, each dependent (children or the elderly) will need to be supported by 2 and 1.5 adult workers, respectively, suggesting high population burden for the country's development.

Figure 2.2.4: Working-age population and Dependency Ratio, China



Source: UN World Population Prospects (2022)

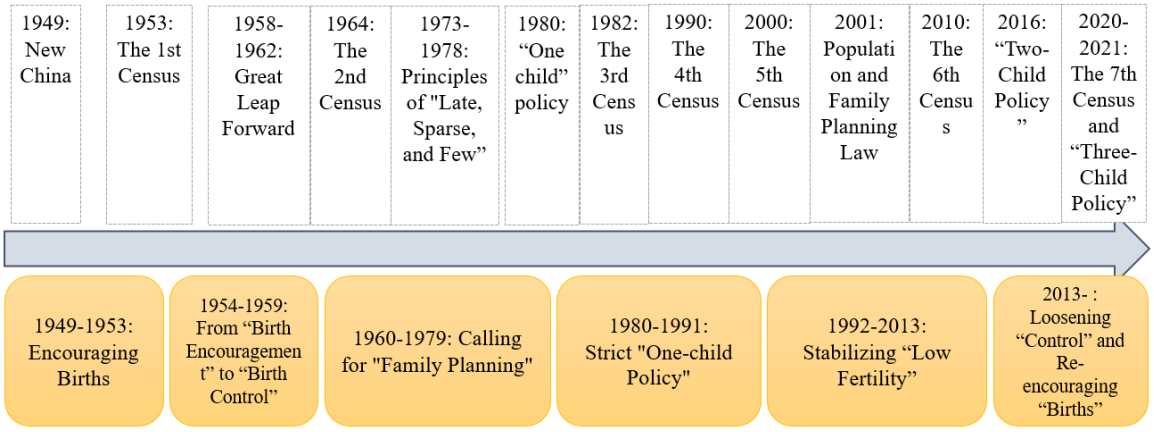
The shrinking working age population suggests the disappearance of the direct demographic dividend along with a significant rise in labor costs (Cai, 2018). Yet, China's transition from a population dividend period to a population burden period is under the situation of "getting old before getting rich." China remains a developing country and is against the backdrop of low fertility and super-ageing in the long term. Its proportion and size of the working-age population in China peaked in 2010 and 2013, while Japan, the United States, and the United Kingdom reached their peaks in 1991, 2009, and 2013, respectively, with much higher per capita income levels than China (UN, 2021).

2.3. EVOLUTION OF POPULATION POLICIES IN CHINA: A HISTORICAL PERSPECTIVE

By observing the demographic structural changes above, it becomes evident that there were distinct peaks in the birth rates around 1950, 1960, and 1980, representing three waves of "baby booms" in China. These also closely coincided with important periods of changes in population policies, highlighting the policy influences on China's fertility in the past.

Therefore, this section aims to explicit the evolution of China's population policies and complement the policy context for the demographic interpretation.

Figure 2.3: Timeline of China's Key Population Policies and 6 Main Stages



Source: Created by author based on literature

i. Encouraging Births (1949-1953)

During the early years of New China's establishment, the government implemented policies aimed at promoting population growth by imposing restrictions on contraception and abortion. On April 20, 1950, the Ministry of Health and the Health Department of the Military Commission jointly issued an official letter for female cadres in organizational troops, which aimed to prevent illegal abortions and ensure the well-being of mothers and future generations.[7] Building upon these regulations, the Ministry of Health formulated the new policy in 1952, by extending the guidelines to female cadres nationwide.[8] In 1953, the Ministry of Health further reinforced these efforts by prohibiting the import of contraceptives and related drugs through customs, citing a misalignment with national policies. These policies were instrumental in fostering a societal mindset and practice that encouraged larger family sizes.

ii. From "Birth Encouragement" to "Birth Control" (1954-1959)

[7] Original title of the document in Chinese is《机关部队妇女干部打胎限制的办法》
[8] Original title of the document in Chinese is《限制节育及人工流产暂行办法》

After the first census in 1953, which witnessed a rapid population increase, concerns about overpopulation emerged prominently. This prompted both the central government and the academic communities to reconsider birth control policies, leading to a shift to the policy of birth control. In March 1955, the central government addressed the issue of birth control in a report from the Ministry of Health, acknowledging its significance as a policy matter impacting people's lives. In early 1956, the central government issued the "National Agricultural Development Outline (1956-1967)", which explicitly called for the promotion of birth control and the advocacy of planned childbirth in densely populated areas, excluding ethnic minority regions. [9] In 1957, the "New Population Theory" was published, which advocated for population control. This paper emphasized that as a planned economy, socialism required the inclusion and control of population within its planning framework (Ma, 1959).

iii. Calling for "Family Planning" (1960-1979)

After reflecting on the "Great Leap Forward" and the end of the "Three Difficult Years," the pressure of actual population growth revived the ideas of population control and birth control. In 1962, Premier Zhou Enlai stressed the importance of "birth control," and the State Council also officially elevated "family planning" to a policy level.[10] These measures resulted in a subsequent slowdown in population growth. In that year, the State Council established the Family Planning Committee, and provincial and prefecture-level authorities began establishing family planning institutions. In July 1971, the State Council explicitly called for the diligent implementation of family planning, making "planned population growth" the official population policy. In 1973, at the first national conference on family planning work, the "late, sparse, and few" policy principle was formally proposed and promoted nationwide. In 1978, the State Council approved the report on the National Health Conference, which further clarified the concept of "late, sparse, and few," and introduced a new requirement for couples to have a maximum of one or preferably two children. [11]

[9] Original title of the document in Chinese is《1956 -1967 年全国农业发展纲要》
[10] Original title of the document in Chinese is《关于认真提倡计划生育的指示》
[11] Original title of the document in Chinese is《国务院批转卫生部关于全国卫生工作会议的报告》

iv. Strict "One-child Policy" (1980-1991)

From 1980 to 1984, there was a stricter enforcement of the "one-child policy" to promote the birth control measures. In September 1980, the central leadership team issued an open letter emphasizing the need to control the total population within 1.2 billion by the end of the 20th century, and it urged the idea of "one couple, one child."[12] This marked the official introduction of the "one-child policy," although the language at the time was still phrased as a "call" rather than a mandatory measure. Following the third population census in 1982, the Chinese government acknowledged the pressing challenges posed by China's population. In 1984, the population policy was explicitly defined, replacing previous approaches with clear conditions of prohibition and approval for rural areas. The new policy stipulated that a second child could be allowed in rural areas with approval, but unauthorized second births or multiple births exceeding the plan were strictly prohibited. The government also cracked down on corruption and malpractice in the implementation of the family planning policy (State Council, 1984). As a result of the strict implementation of the family planning policy, the rapid population growth was effectively controlled. By the 1990s, the transition of the population had reached a preliminary stage, with the total fertility rate dropping below the replacement level of 2.1. In 1991, the central leadership team and the State Council issued the decision to strengthen family planning work and strictly control population growth based on the actual capacity for birth control and the gap between policies, with the aim of keeping the total population below 1.3 billion and the natural population growth rate below 12. 50‰ by the end of 2000.[13]

v. Stabilizing "Low Fertility" (1992-2013)

The strict "One-child Policy" in China had successfully helped China achieve its population control targets of the total population (12.6 billion) and natural population growth rate (annual average at 10.3‰) by 2000, marking the entrance to a new stage of population policy, in stabilizing the low fertility level. In March 2000, the central leadership team and the State Council issued a decision to stabilize the low fertility rate

[12] Original title of the document in Chinese is《关于控制我国人口增长问题致全体共产党员、共青团员的公开信》

[13] Original title of the document in Chinese is《关于加强计划生育工作严格控制人口增长的决定》

and improve population and family planning work.[14] The decision focused on comprehensive population and development planning, maintaining the existing birth control policy, implementing integrated population management, combining state guidance with voluntary participation, promoting overall progress while providing targeted guidance, and prioritizing comprehensive human development. On December 29, 2001, China enacted the Population and Family Planning Law, which legalized the existing policy provisions, stating that "*the state would stabilize the current birth control policy, encourage delayed marriage and childbirth, and promote couples having only one child. However, if conditions specified by laws and regulations were met, couples could request to have a second child, subject to approval by the provincial, autonomous regional, or municipal people's congress or their standing committee*."[15] In December 2006, the central government issued a decision to comprehensively strengthen population and family planning work and address population issues. It emphasized the need to insist on China's approach to solving population issues, maintaining a stable and low fertility rate, and improving population quality.[16]

vi. Loosening "Control" and Re-encouraging "Births" (2013-Present)

Since the "12th Five-Year Plan" period (2010-2015), significant changes have occurred in China's population development. For instance, the birth rate of China had declined to 12.1‰, the death rate was 7.15‰, the natural growth rate was 4.95‰, and the total fertility rate was around 1.6, classifying China as a country with low fertility rates worldwide by 2012. Therefore, issues such as population aging, declining proportion of the working-age population and childbearing women, and imbalanced sex ratios at birth became more prominent. Family sizes have become smaller, leading to weakening functions in elderly care and child rearing of the society, such that there was an increasing demand to adjust and improve the population policy at that time.

[14] Original title of the document in Chinese is《中共中央国务院关于加强人口与计划生育工作稳定低生育水平的决定》

[15] Original title of the document in Chinese is《中华人民共和国计划生育法》

[16] Original title of the document in Chinese is《中共中央国务院关于全面加强人口和计划生育工作统筹解决人口问题的决定》

Against this backdrop, in December 2013, the central leadership team and the State Council issued opinions on adjusting and improving the birth control policy. The opinions emphasized that family planning being as a fundamental national policy and initiating the implementation of the population policy allowing couples who are both single children to have two children.[17] From January 1, 2016, the "Comprehensive Two-Child Policy" was officially implemented national wide, marking a loosening of the comprehensive family planning policy that had been in place for over 40 years, and the beginning of the gradual adjustment and improvement of the new fertility policy. As a result, the number of births in that year reached a peak of 17.86 million in 2016, the highest since 2000.

The further adjustment of the "Three-Child Policy" came shortly after the announcement of the results of China's 7th national population census. On May 31, 2021, the Communist Party of China conducted a meeting to hear a report on major policy measures to actively address population aging during the 14th Five-Year Plan period (2020-2025). [18] During the meeting, it was proposed to further optimize the fertility policy and implement a policy allowing couples to have three children, along with supportive measures levels. Governments at all levels are required to strengthen overall planning, policy coordination, and implementation.

In addition, supportive measures were also introduced at various governmental levels. For instance, the National Health Commission and 17 other ministries issued a policy Guidance in 2022, which systematically proposed 20 specific measures.[19] After that, various departments introduced concrete policies, such as exploring the inclusion of flexible employees in the coverage of maternity insurance, allowing unmarried women who have given birth to receive birth subsidies without a marriage certificate, and including assisted reproductive technology projects in the scope of medical insurance fund payment according to procedures. In different regions, measures related to housing, taxation, finance, and other aspects have been introduced to encourage and support eligible couples to actively have children.

[17] Original title of the document in Chinese is《中共中央关于全面深化改革若干重大问题的决定》
[18] Original title of the document in Chinese is《关于优化生育政策促进人口长期均衡发展的决定》
[19] Original title of the document in Chinese is《关于进一步完善和落实积极生育支持措施的指导意见》

In addition, the gradual delayed retirement policy has also been piloted in a few provinces to alleviate the pressure of shortage of labor in the society. In 2021, the Ministry of Human Resources and Social Security (MOHRSS) of China has officially issued the "14th Five-Year Plan for the Development of Human Resources and Social Security," by explicitly proposing the gradual implementation of the delayed statutory retirement age and the gradual increase of the minimum years of contributions required to receive basic pension, following principles such as small adjustments, flexible implementation, classified advancement, and overall consideration. In 2022, the State Council issued the government work report for "the Development of the National Aging Industry and the Elderly Care Service System," and it outlines the to adjust the retirement age gradually. Specifically, the delayed retirement policy may cover the following adjustment measures, where (1) female workers under the age of 50 (women born in 1972 and later); (2) female cadres and male workers under the age of 55, mainly those engaged in manual labour (people born in 1967 and later); (3) male cadres under the age of 60 (men born in 1962 and later) are primarily affected. Therefore, in January 2023, the Jiangsu Government issued an official notice[20] and mentioned that enterprise employees are allowed to delay their retirement for the delay no less than one year. Meantime, the Human Resources and Social Security Department of Shandong Province issued the notice on the delayed retirement policy for technical occupations with an extension for a period of 1 to 3 years, but not exceeding the age of 65.[21] These pilots highlight China's commitment in leveraging various policy tools to face the demographic challenges.

2.4. CHINA'S DEMOGRAPHIC TRENDS IN A GLOBAL CONTEXT

Demographic structural changes are not unique in China. Many developed economies underwent significant transitions much earlier, while several developing countries, including Vietnam, Indonesia, and Malaysia, have already been experiencing notable demographic changes characterized by population ageing, low fertility rates, and

[20] Original title of the document in Chinese is 江苏人力资源和社会保障厅印发《企业职工基本养老保险实施办法的通知》

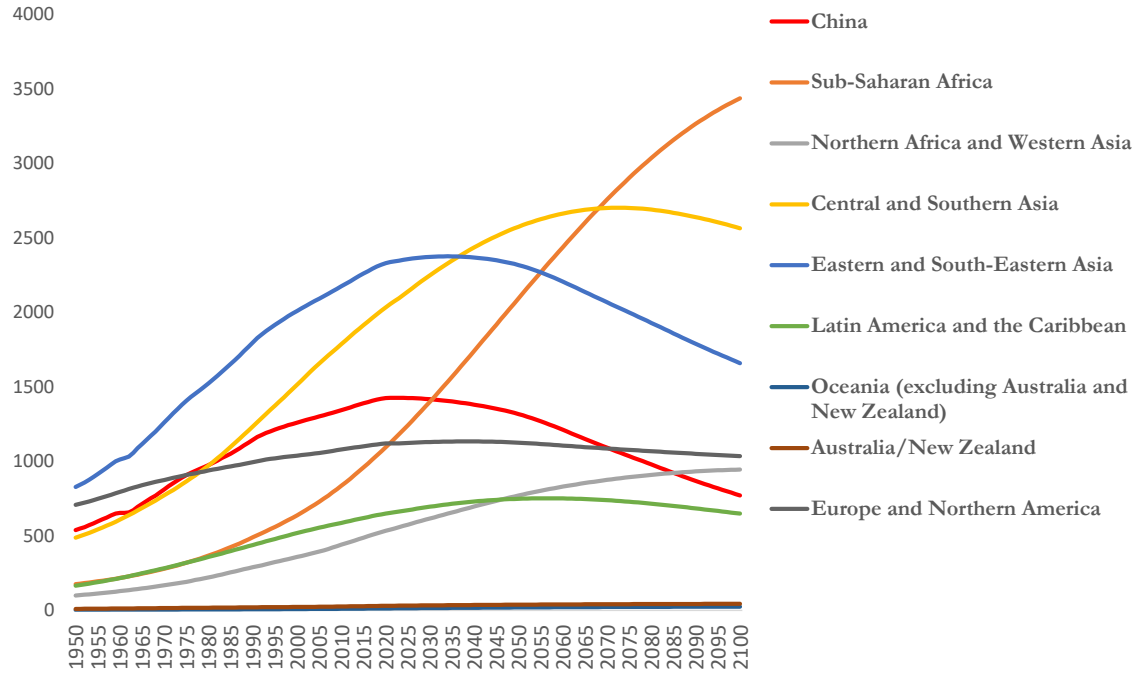
[21] Original title of the document in Chinese is 山东省人力资源和社会保障厅发布《进一步规范企事业单位高级专家延长退休年龄有关问题的通知》

increasing life expectancy at earlier stages of development compared to their developed counterparts. However, countries at different economic levels, with diverse cultural and societal contexts and institutional arrangements, will encounter distinct challenges and opportunities. The shift towards an older population in these countries also has implications for labor markets, social welfare systems, and the overall societal structure. This section aims to navigate the complexities of the evolving global demographic landscape and place China's demographic changes within a global context. The insights gained will be invaluable for policymakers as they formulate strategies to address these challenges.

2.4.1 Population Decline: China's Rapid Descent

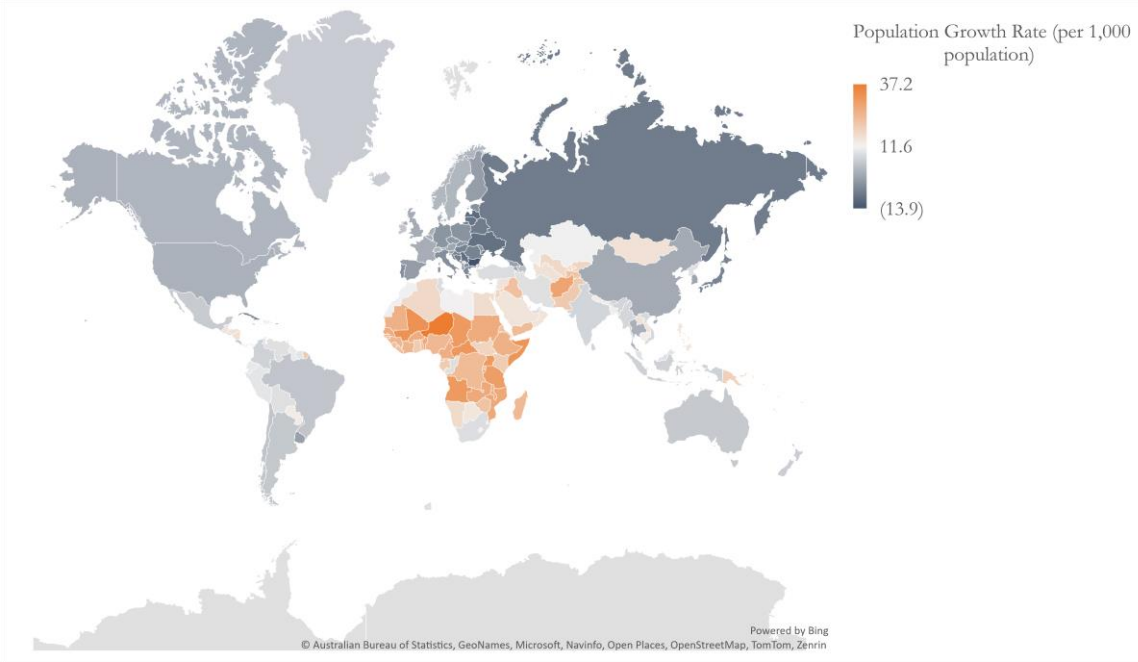
From the global perspective, with the exception of the Sub-Saharan Africa region, the populations in the remaining global regions are projected to gradually reach their peak and decline throughout the century (Figure 2.4.1A). The majority of global population growth is expected to be contributed by the Sub-Saharan Africa region, which is predicted to become the most populous region among the eight geographical regions by 2060. On the other hand, populations in the remaining regions will sequentially reach their peak and then decline. Around 2034, the populations of East Asia and Southeast Asia are estimated to reach their maximum at approximately 2.4 billion, where it is mainly attributed to the declining of China's population. Central Asia and South Asia are projected to reach a peak of around 2.7 billion by approximately 2072. Europe and North America are forecasted to maintain relative stability, with a peak population of approximately 1.13 billion expected around 2038. The population of Latin America and the Caribbean region is anticipated to reach its peak of 752 million around 2056.

Figure 2.4.1A: Population by Regions (in million)



Source: UN World Population Prospects (2022)

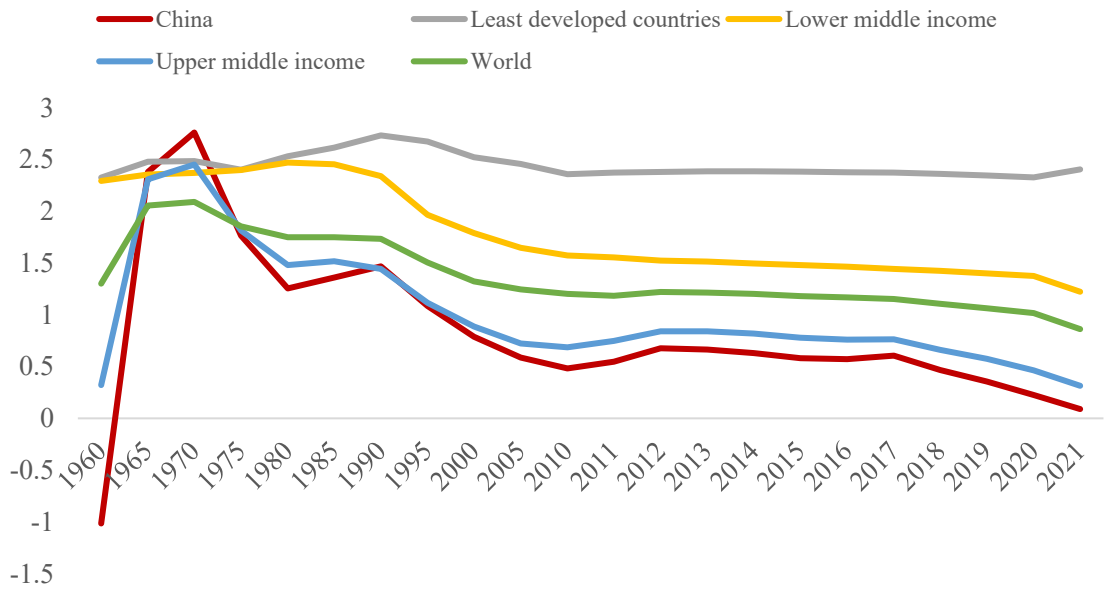
Figure 2.4.1B: Population Growth Rate by Countries (per thousand population)



Source: UN World Population Prospects (2022)

In 2022, notably 41 countries and regions experienced a decline in population growth according to the UN's estimation (Figure 2.4.1B). Countries with declining populations was primarily observed in Eastern Europe and East Asia, where China, Japan, and South Korea contributed the most. Ukraine, Bulgaria, and Monaco are examples of countries with natural population growth rates below -0.10 per thousand, while Serbia, Lithuania, Russia, Romania, Japan, and Hungary maintained their rates ranging from -0.05 to -0.10 per thousand. Italy, Germany, and Portugal had natural population growth rates around -0.03 per thousand.

Figure 2.4.1C: Population Growth Rate by Regions (%)



Source: UN World Population Prospects (2022)

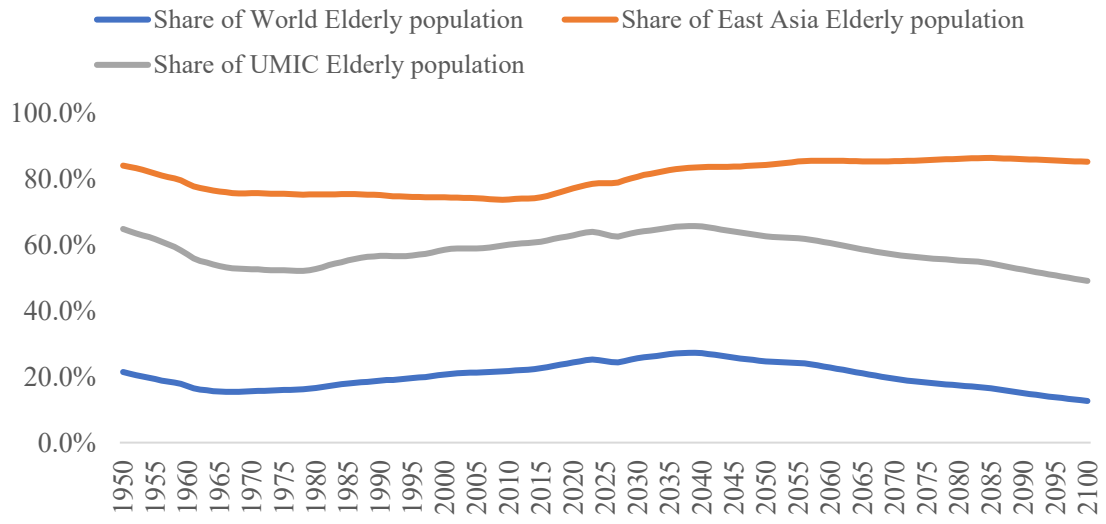
In addition, China is also a fast runner when compared to countries with similar level of national income. UN data shows that high-income and upper-middle-income countries were the frontrunners in negative population growth, with projections from UN indicating that high-income countries (HIC) may experience such declines by 2038, followed by upper-middle-income countries (UMIC) in 2044. In contrast, lower-middle-income countries (LMIC) are anticipated to face negative population growth until 2090, while low-income countries (LIC) are not expected to encounter this phenomenon before 2100. However, in 2021, China has experienced a lower population growth rate at 0.09 percent than not only global average (0.86 percent), but even the average level of UMICs

at 0.31 percent (Figure 2.4.1C). The global population forecast reveals a more deteriorating situation of China and calls for prompt action from policymakers. It also serves as a significant motivation for this study.

2.4.2 Global Ageing and Challenges in East Asia

Aging is a megatrend globally, and nowhere is this trend more pronounced than in East Asia. Therefore, the large population in China implies significant impact to the region and the world in a long term. According to the UN estimation (Figure 2.4.2A), China's elderly population aged 65 and above is more than 200 million in 2023, and it will reach 315 million and 395 million, respectively by 2035 and 2050. To date, the large elderly population in China accounts for more than 78.5 percent of the total elderly population in the East Asia region, and more than 60 percent of the total elderly population in all upper-middle income countries. The impact will maintain especially significant in the East Asia Region, where the proportion is projected to increase to over 80 percent for a sustained period until 2100. The global ageing issue will be also more pronounced as China's elderly population is projected to contribute to the global base by 27 percent by 2040- on average one fourth of individuals aged 65 or above will be Chinese.

Figure 2.4.2A: China and Global Elderly Population (%)

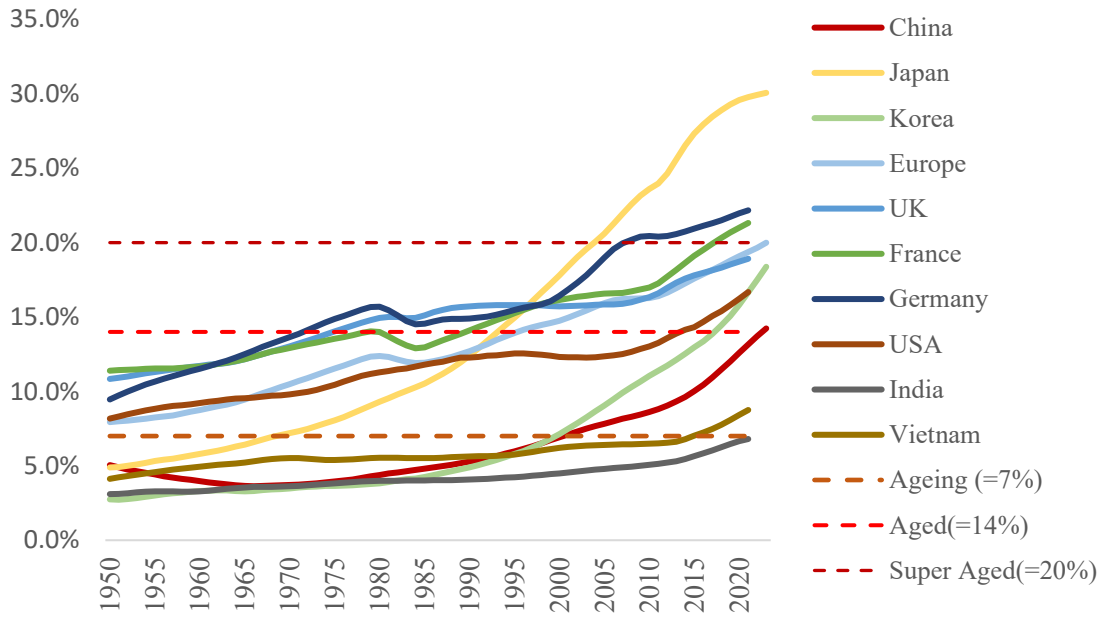


Source: UN World Population Prospects (2022)

It is evident that different nations are experiencing distinct patterns of aging. Currently, 21 countries including Japan and Italy have entered the stage of super-aged societies, whereas 36 countries, such as Korea and Spain, have reached the stage of aged society. These countries predominantly belong to the developed regions of Western Europe. It is worth noting that countries in East Asia, in particular Japan and South Korea, face more severe aging issues compared to other regions including Europe (Figure 2.4.2B).

Among these countries, Japan stands out with the highest proportion of elderly individuals, accounting for a remarkable 30 percent of its total population. 21 other countries, including Italy, Portugal, and Finland, have an elderly population exceeding 20 percent representing a state of "super aged" society. While 36 countries, like Spain, Belgium, and Switzerland, have an elderly population ranging from 14 percent to 20 percent, representing a state of "aged society."

Figure 2.4.2B: The Ageing Issues in China, Korea, Japan, and Selected European Countries



Source: UN World Population Prospects (2022)

In addition, Japan is one of the most rapidly aging countries in the world, and its transition from an aged society to a super-aged society took 13 years from 1993 to 2005. Korea is also an aged society with population aged 65 and above being more than 18.4

percent by 2023 and is projected to enter super-aged society in an accelerated pace in 2025, where it takes Korea only 9 years to transition from an aged society to a super-aged society (UN, 2022). In addition, Korea's latest total fertility rate has declined to 0.8 by the year of 2022- the lowest country in the world.[22] In contrast, although Europe region maintains its proportion of elderly population above 14 percent since 1995, the speed of incremental increase is at only 0.016 percentage points per year on average, and it has just reached the "super-aged societies" definition after 29 years in 2023.

2.4.3 Shrinking Working Age Population and Growing Dependency Burden

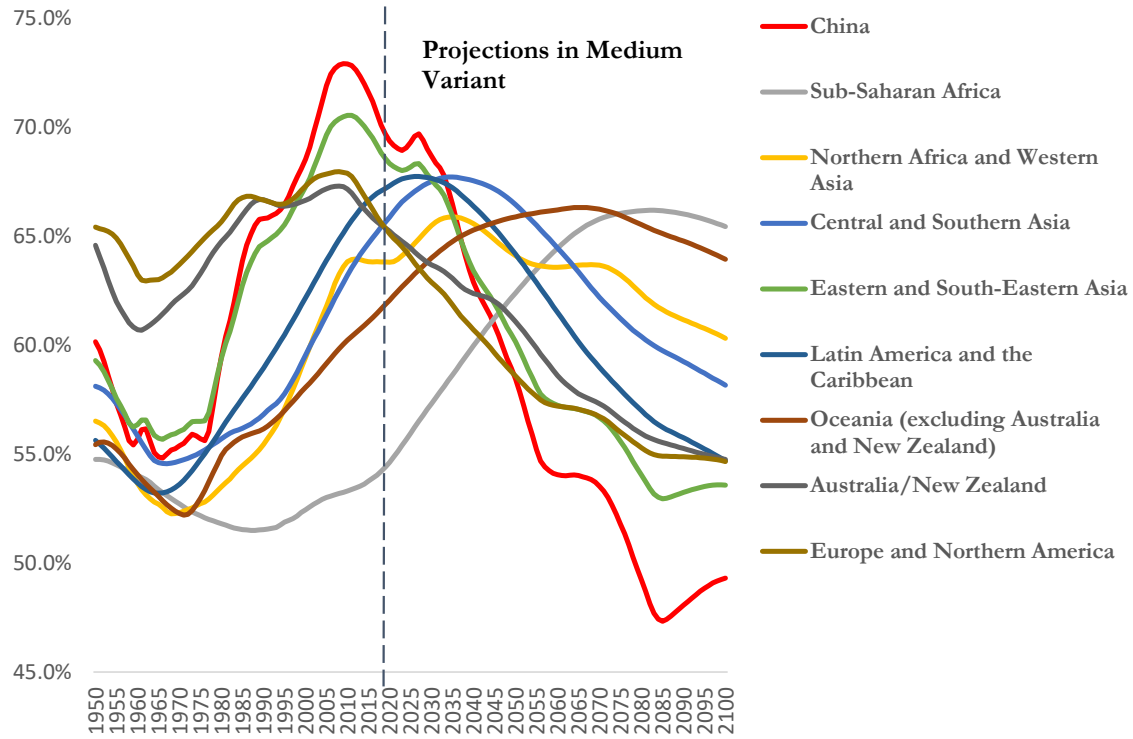
The examination of the working-age population reveals a more challenging scenario for China's demographic dividend compared to many other countries worldwide (Figure 2.3.3A). As previously discussed, China reached its peak working-age population proportion of 70 percent in 2010, followed by a downward trend. According to UN's projections, the lowest point of the working-age population will occur around 2085, at approximately 47.3 percent. It is worth noting that the East and Southeast Asia regions, where China's population is concentrated, exhibit a similar pattern of peaking in 2010 but experiencing a more gradual decline thereafter. The bottom of the decline slope is projected to be around 53 percent by 2085, approximately 6 percentage points higher than China's estimate. While Europe and Northern America had already experienced their peak working-age population at an earlier stage, their transition period is significantly longer, with the lowest point projected to be reached by the end of the century, at around 55 percent. In contrast, regions other than Sub-Saharan Africa will also face a decline in their working-age momentum, albeit at a more moderate level.

Distinct patterns also emerge between developed and developing countries. Developed nations, including Germany, France, Italy, Japan, the United Kingdom, the United States, and South Korea, witnessed their working-age populations peak in the years 1986, 1988, 1991, 1992, 2007, 2009, and 2013, respectively. In contrast, China and Brazil reached their peak in 2010 and 2018, respectively. By examining the total dependency ratio (Figure 2.2.3B), it can be observed that in 2020, countries like Brazil and China as

[22] The UN World Population Prospects estimates (in medium variant scenario) that the TFR of Korea is 0.88 in 2023, second lowest in the world to China Hong Kong SAR region at 0.77 in the same year.

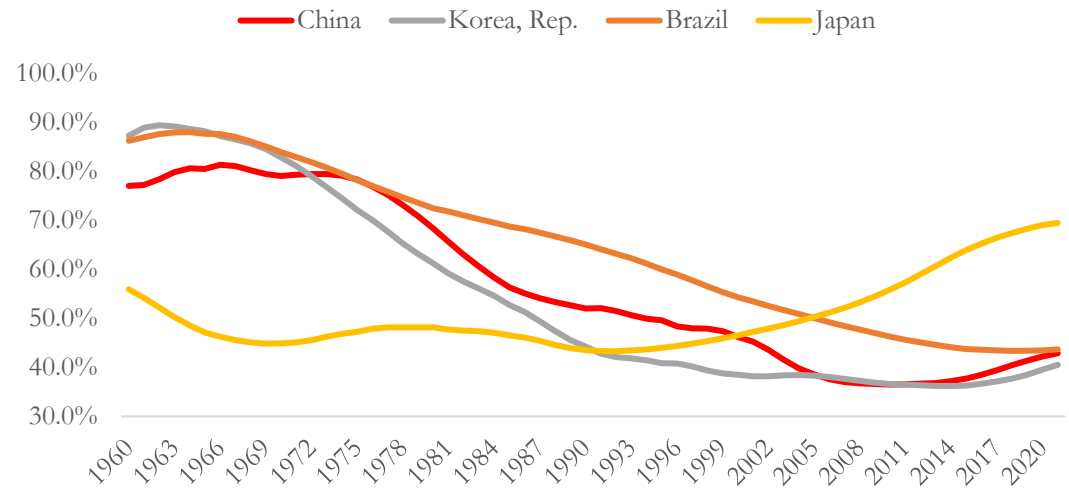
developing countries, along with the HIC of South Korea, had the TDR of 43.5 percent, 42.2 percent, and 39.5 percent respectively.

Figure 2.4.3A: The Collapses of Working-age Population in China and the World



Source: UN World Population Prospects (2022)

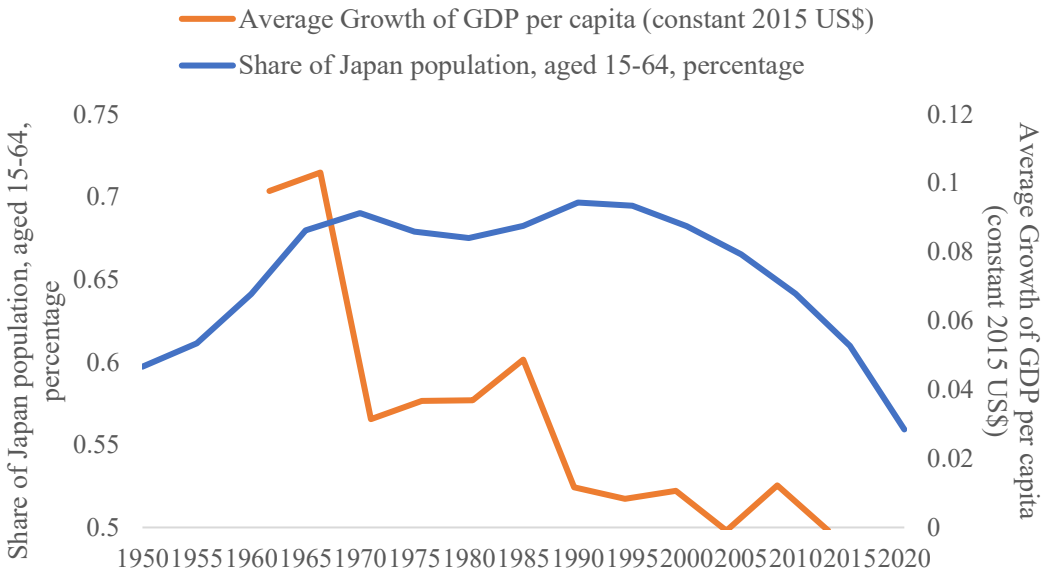
Figure 2.4.3B: The Increasing TDR in China, Korea, and Brazil



Source: UN World Population Prospects (2022)

It is noteworthy that Japan, where a decline in the working-age population and the increasing dependent burden since early 1990s implies its dissipation of the demographic dividend, leading to a period known as the "lost three decades" in its economy (Figure 2.3.3C). The demographic transition trajectory of South Korea currently mirrors the path previously taken by Japan, suggesting that South Korea may face similar challenges in the near future.

Figure 2.4.3C: Economic Growth Rate and Working-age Population Share in Japan



Source: World Development Indicators (2022)

The working-age population serves as the foundation for economic development, and international experience suggests a certain level of positive correlation between the growth rate of the working-age population and GDP growth. As the trends of aging and declining birth rates intensify, societies will inevitably encounter limitations on their production capabilities and an exacerbation of social burdens, leading to a deceleration in potential economic development. Previous international comparison also indicate that China is in a much more challenging situation than many other countries. It thus urged for China to look into the demographic structural challenges and take immediate reactions to embark on a new path of innovation-driven development instead of traditional labor-intensive development in China.

2.5. HUMAN CAPITAL DEVELOPMENT IN CHINA

In the classical Solow-Growth model (Cobb–Douglas function), it is widely accepted that in addition to labor input, both capital input and total factor productivity are all also crucial factors to a country's economic development. [23] Later on, Mankiw, Romer, and Weil (1992) have augmented the Solow-Swan exogenous growth model to illustrate that the case of output determined by an aggregate production function dependent on labor input, capital input, labor-augmenting technology, and human capital:

$$Y_t = K_t^{\alpha} H_t^{\beta} (A_t L_t)^{1-\alpha-\beta}$$

where K_t is fixed capital input, H_t is human capital input, $A_t L_t$ is effective labor input in which A_t is labor-augmenting technology, and L_t is labor.

In this context, the impact of demographic structural changes on a country's development level is influenced by fluctuations in labor supply. However, it also depends on changes in technology level and the level of human capital within the population. It is essential to consider the interactions between demographic structural changes and the other two key drivers of innovation, namely technology and human capital, when assessing their effects. With the adoption of higher levels of technology and a better-educated workforce leveraging their enhanced human capital, it becomes possible to compensate for, or even enhance the production efficiency.

In this section, the objective is to review the development of human capital through both education and health perspectives over the past few decades in China, following by an assessment on the country's technological progress in the subsequent section. By carefully considering these factors, it will help gain insight into the implications of demographic structural changes in China during the post-demographic transition period.

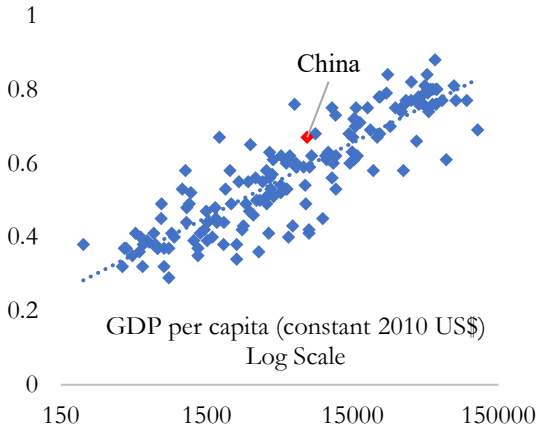
2.5.1 Enhancing Human Capital

Human capital refers to the knowledge, skills, and health that people accumulate throughout their lives, enabling them to realize their potential as productive members of

[23] $Y = TFP * K^{a} * L^{1-a}$

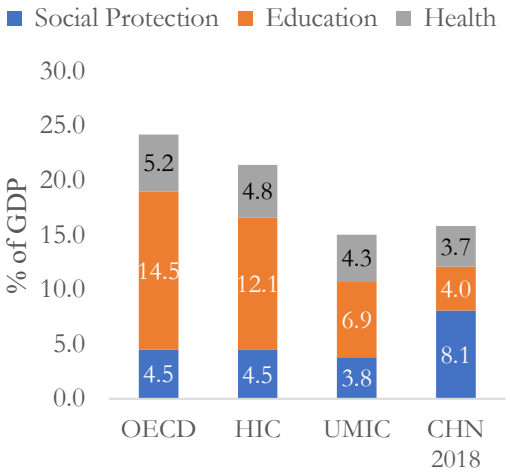
society (World Bank, 2019). Overall, China has achieved remarkable progresses in its human capital development. For instance, According to Bank Human Capital Index[24], China currently has ranked 47 in the world, higher than most upper middle-income countries but below most OECD countries (Figure 2.5.1A). In addition, China's social spending[25] on human development has amounted above the average level of upper-middle income countries, although a gap remains when compared to OECD and other higher income countries. During the period of 2010-2015, China steadily increased the public spending on health, education, and social protection, and peaked at 15.8 percent of GDP[26] as opposed to an average of 14.6 percent of GDP in upper middle-income countries excluding China. It is also at a similar level of welfare states in such as Korea and Mexico, which accounts for around 15 percent of GDP (Figure 2.5.1B).

Figure 2.5.1A: Human Capital Index vs Per Capita GDP



Source: World Development Indicators (2022)

Figure 2.5.1B: Global Comparison of Social Spending on Human Capital (% of GDP)



Source: Authors' estimation based on data from World Development Indicators, WHO, ILO, UNESCO, and line ministries of China (2021)

[24] It is an international metric, which provides combined results of both health and education outcomes is also widely adopted as a broader conception. World Bank Human Capital Project: https://www.worldbank.org/en/publication/human-capital

[25] To be consistent with OECD's definition, public social spending refers to financial flows controlled by general Government (different levels of government and social security funds. The public social spending in human development includes investment in education, health, and social protection. This analysis combines the global datasets from the Bank, IMF, ILO, WHO, UNESCO, and OECD, and adjusts the estimations by statistically compromising the components to ensure the results are consistent and comparable.

[26] The latest globally comparable data is available in 2018. More recent data of 2019 and 2020 are estimated by using domestic government fiscal spending data, but they cannot serve for international comparison purposes.

2.5.2 Promoting Higher Educational Attainment

According to the Seventh Population Census report, China has made significant improvement in educational attainment. Firstly, there has been a consistent growth in the size of the educated population, with numbers increasing from 1.19 billion in 2010 to 1.27 billion in 2020. Secondly, there has been a continuous rise in the proportion of individuals with a completed higher education, which has grown from 8.93 percent in 2010 to 15.47 percent in 2020. Thirdly, the illiteracy rate among individuals aged 15 and above has also shown a steady decline, dropping from 4.08 percent in 2010 to 2.67 percent in 2020. Fourthly, the average number of years of education for individuals aged 15 and above has consistently increased from 9.08 years in 2010 to 9.91 years in 2020 (NBS, 2021).

In particular, the younger population has played a significant role in driving the continuous improvement in educational attainment in China. Among individuals aged 16 to 59, the average years of education have risen from 9.67 years in 2010 to 10.75 years in 2020. The population with a high school education or above has reached 385 million, accounting for 43.8 percent of the total population, marking a 12.8 percentage points increase compared to 2010. Furthermore, the proportion of individuals with a higher education or above has reached 23.6 percent, reflecting an 11.3 percentage points increase since 2010 (NBS, 2021).

In an international context, China's human capital development[27] has shown significant improvement over the past 30 years, although it still lags behind other developed economies, particularly OECD countries (Figure 2.5.2A). For instance, in 1990, China's expected years of schooling (EYS) stood at 8.8 years, which was approximately 69 percent of the average level of OECD countries, at 12.8 years in the same year. However, by 2019, China's EYS had increased to 14 years, representing around 83 percent of the average level in OECD countries in 2019. This increase in EYS has been at an average rate of 2 percent per annum. In comparison, OECD countries such as Australia, France, and Germany have experienced marginal increases of 0.88 percent, 0.33 percent, and 0.60 percent, respectively. Even developing countries such as Chile and Colombia have also

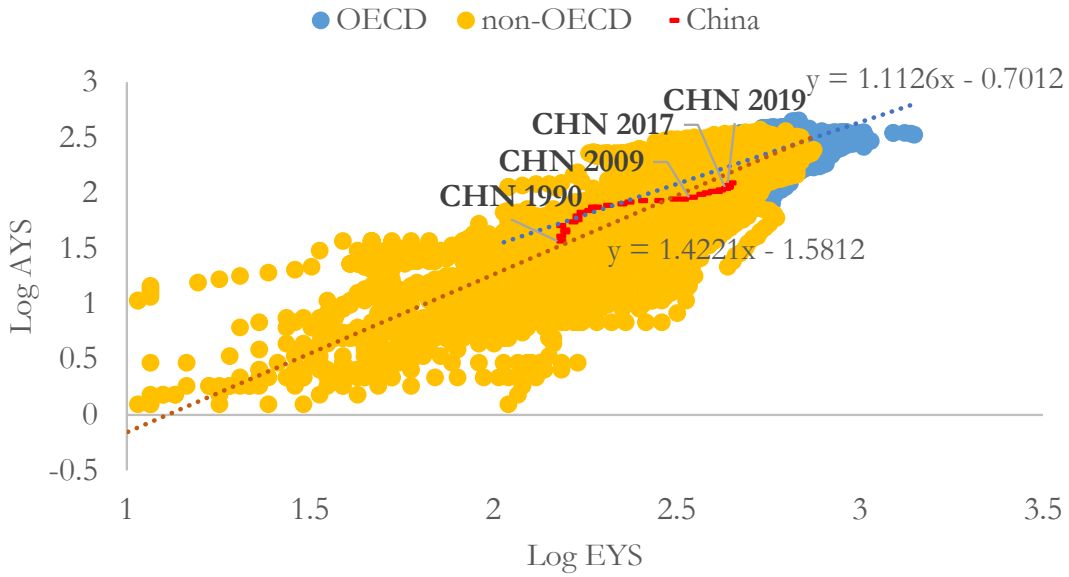
[27] Educational attainment is widely proxied by expected years of schooling and average years of schooling in empirical studies (WB, 2021).

witnessed a less rapid increase in EYS, with growth rates of 0.9 percent and 1.9 percent, respectively.

Average years of schooling (AYS) is another indicator that widely used to assess educational attainment on a global scale (Barro & Lee, 2013; Hanushek, 2000; World Bank, 2019). In 1990, China's AYS stood at 4.8 years, which was even 1 year below the global average. However, there has been a consistent increase afterwards, reaching 8.1 years in 2019 - only 0.4 years less than the global average level. In comparison, the most developed countries, including OECD countries, had an average AYS of 8.56 years in 1990, which increased to 11.75 years by 2019.

The enhancement of human capital through education has a profound impact on both individual labor market outcomes and broader economic development. Whalley and Zhao (2010) conducted an estimation and found that the contribution of human capital to China's economic growth is more significant than previously indicated in existing literature. Their study reveals that human capital accounted for 38.1 percent of economic growth during the period of 1978-2008, and its contribution became even more substantial in subsequent stages of development.

Figure 2.5.2A: Average Year Schooling and Expected Years Schooling



Source: World Development Indicators (2021)

One of the main drivers to the education improvement, especially higher education to train young skilled workers in China, is the rapid expansion of higher education system in China. Since the start of the 21st century, China has implemented policies to expand higher education, resulting in a continuous increase in the proportion of the population with higher education or above. This has led to significant improvements in the educational structure of the population. In 1999, China experienced a rapid expansion in university enrollment, with the college enrollment rate increasing by over 43 percent in a single year. Over the past 20 years, China has made consistent progress in significantly expanding its higher education system.

According to the Ministry of Education (Figure 2.5.2B), the proportion of individuals with a higher education has increased from 1.4 percent to 15.5 percent. In 2000, the number of college graduates was 1 million, which accounted for approximately 0.5 percent of the total youth population. However, the total number of students obtaining a higher education has since increased by more than 10 times, indicating that over 50 percent of the birth cohort population will be competing in the labor market after graduation.

In recent years, there has been a significant expansion in Technical and Vocational Education and Training (TVET) schools, with an incremental admission of 1.16 million, 2 million, and 2 million students each year from 2019 to 2021. Similar expansions have also been observed in general colleges and postgraduate schools. Additionally, in 2020, the overall admission rate for the college entrance exam (*gaokao*) exceeded 90 percent for the first time.

It is noteworthy that the lower death rate and longevity in the post-demographic transition China will also intensify the labor market competition, especially considering that youth population (15-24) is projected to increase by about 1.7 million per year on average from 2023 to 2032 based on UN data. Considering various demographic factors, including the projected increase in the youth population, it is estimated that the number of college graduates will continue experiencing significant growth. Specifically, it is anticipated that the number of college graduates will increase by over 0.36 million per year on average over the next 10 years. This trend indicates a continuous improvement in the human capital of the economy (Figure 2.5.2C).

These developments signify the substantial growth and accessibility of higher education in China, as well as the increasing human capital of labors in the labor market.

Figure 2.5.2B: Rapid expansion of higher education system in China

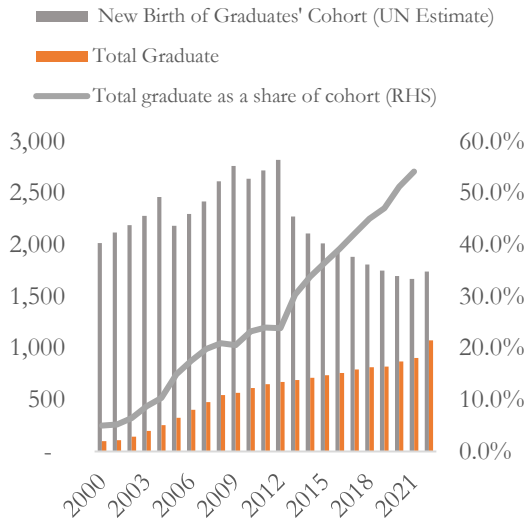
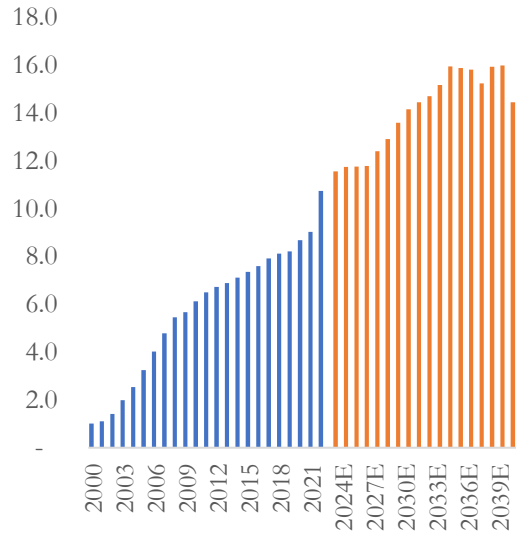


Figure 2.5.2C: College graduates are projected to continue increasing in next few decades



Source: Authors' creation based on National Bureau of Statistics and UN data (2022)

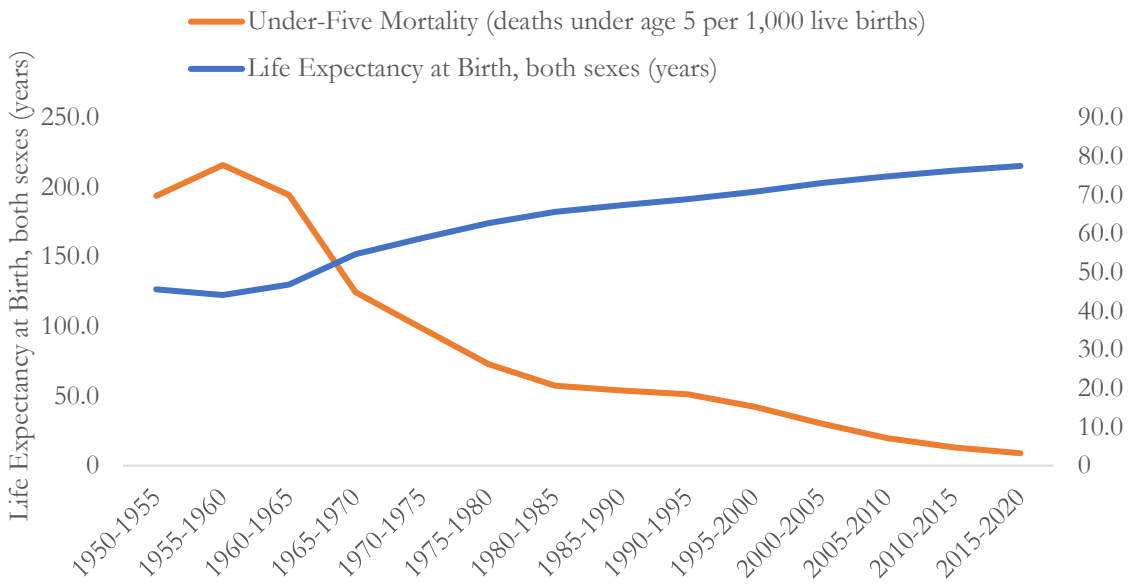
2.5.3 Improving Health Conditions: Declining Mortality and Increased Lifespan

Health is considered as another crucial aspect of human capital because it directly influences an individual's well-being, productivity, and overall potential, as reflected in the Human Capital Index (World Bank, 2022). The declining mortality rate and longer life expectancy in China are two indicators of the nation's commitment to improving the health and well-being of its population, resulting in a higher quality of life and greater longevity for its citizens.

Specifically, China has witnessed a remarkable decline in (under-five child) mortality rate since 1950, reflecting significant improvements in child healthcare and well-being (Figure 2.5.2A). Since 1950, when 20.8 percent of children died before the age of 5, rapid mid-century mortality gains were driven primarily by a policy of "simple preventative measures and widespread access to primary care" (Bannister, 1987; Lee and

Wang, 1999).[28] The Cooperative Medical Scheme covered most of the rural sector by the 1970s and benefited from effective targeting that was the result of devolved village (brigade)-level financing (Gu and Tang 1995).[29] Therefore, the child mortality share fell to 10.0 percent by 1970, and further dropped to 7 per thousand of children in 2021. In the meantime, life expectancy at birth in China has also experienced a remarkable increase from 43.7 years in 1950 to 78.2 years in 2021, implying seven decades over which roughly half year was added to life expectancy per calendar year (Figure 2.5.3A).[30] This substantial improvement can be attributed to advancements in healthcare, better living conditions, and improved public health initiatives.

Figure 2.5.3A: Life Expectancy and Under-Five Mortality, China



Source: UN World Population Prospects 2022

[28] The number of "barefoot doctors" increased from some 100,000 in 1957 to 1.5 million by 1965 (Parish 1985: 6).
[29] Decentralisation enabled better targeting and hence a process that had started in Beijing, Tianjin and other port cities (Benedict, 1996; Campbell, 1997, Feng 2011) ultimately reached rural villages too.
[30] Owing to an interruption in the transition begun in 1950 around sporadic food crises in the years up to and including 1961, it is also proposed that the China's demographic transition started in 1962 when the crude death rate began to steadily and consistently decline (Liang, Tu and Chen, 1986: 1355).

2.6. TECHNOLOGICAL ADVANCEMENTS IN CHINA

Technological progress is widely regarded as a pivotal driver of economic progress (Solow, 1956; Rosenberg, 1974; Hausmann, 2020), and there are various indicators commonly being employed to assess the extent of technological advancements. For instance, Total Factor Productivity (TFP) is a measure of overall efficiency and technological progress in an economy, capturing the contribution of factors such as technology, innovation, and managerial skills to economic growth (i.e., Solow, 1957; Comin & Mestieri, 2018). The number of patent applications filed reflects the ability to protect intellectual property for innovation (i.e., Hall & Trajtenberg, 2005; Sampat & Ziedonis, 2005). Research and development (R&D) spending is another measure of investment technological development, by reflecting the commitment to advancing knowledge and technological capabilities (i.e., Hall & Lerner, 2010). Recently, the adoption and deployment of advanced technologies such as robotics and automation are also used to proxy the level of technological sophistication and innovation in an economy (i.e., Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018).

Studies (i.e., Huang & Sharif, 2015) demonstrates that China is progressively assuming a leadership position in global technological advancements across various metrics. The country has exhibited remarkable growth and influence in terms of R&D intensity, R&D personnel, number of scientific publications, and number of patent applications etc. Therefore, using some representative indicators, this section aims to provide an overview of China's technological advancements over the past decades.

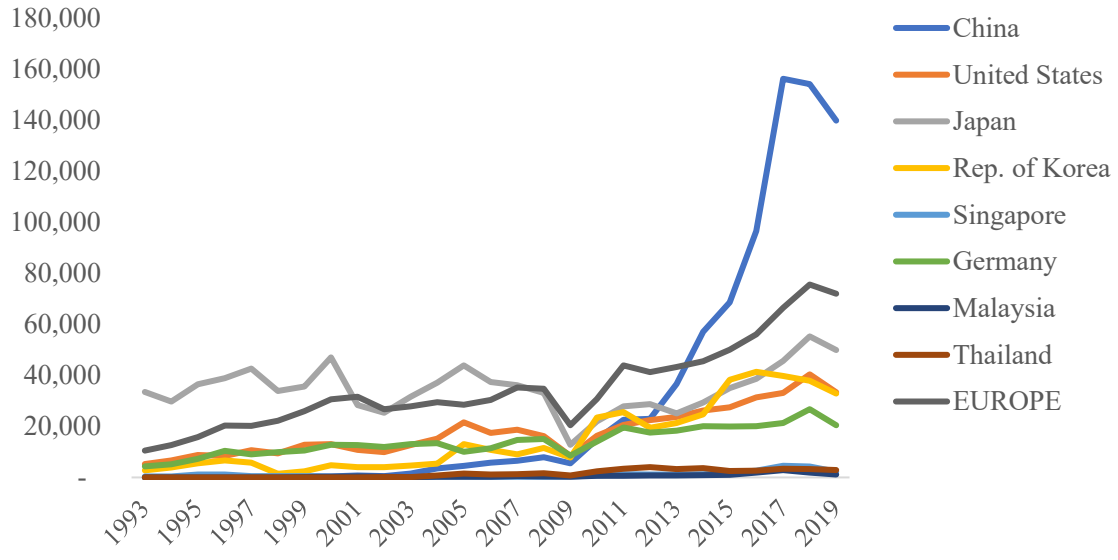
2.6.1 Robotics and Automation

Automation, or the process by which work performed by humans is replaced by machines, is centered at the technological progress in recent decades (i.e., Barley, 2020). Automation, interchangeably with industrial robot in many contexts, is characterized as an autonomously managed, reconfigurable, versatile manipulator, capable of programming in three or more dimensions, and can be stationary or portable for application in industrial automation contexts, as per the definition outlined in the international standard ISO (IFR, 2022).

According to data from the International Federation of Robotics (IFR), China's industrial robotics market has experienced remarkable growth. In 2019, China set a new record with 140,000 robot installations, which is 253 times higher than the level in 1999- the first year that data is available for the country. It accounted for 36.7 percent of the total global installations, surpassing Europe by about two times and the United States by four times in the same year. China has consistently maintained its position as the world leader in annual robot installations since 2013, even during the challenging period of the COVID-19 pandemic. It is reported that China in 2021 installed 268,000 industrial robots, more than the rest of the world taken together (IFR, 2022).

In addition to the strong growth in robot installations, China also demonstrates its leadership in utilizing advanced technologies through the number of operational industrial robots (Figure 2.6.1B). The operational stock of industrial robots in China has reached an impressive 782,725 units in 2019, showing a remarkable growth of 1423 times since 1999. China now accounts for more than 30 percent of the total operational robots worldwide, surpassing both the whole Europe and the United States by 1.3 times and 2.6 times, respectively, in 2019. These figures highlight China's prominent position in harnessing advanced technologies and significant progress in technological advancements (IFR, 2022).

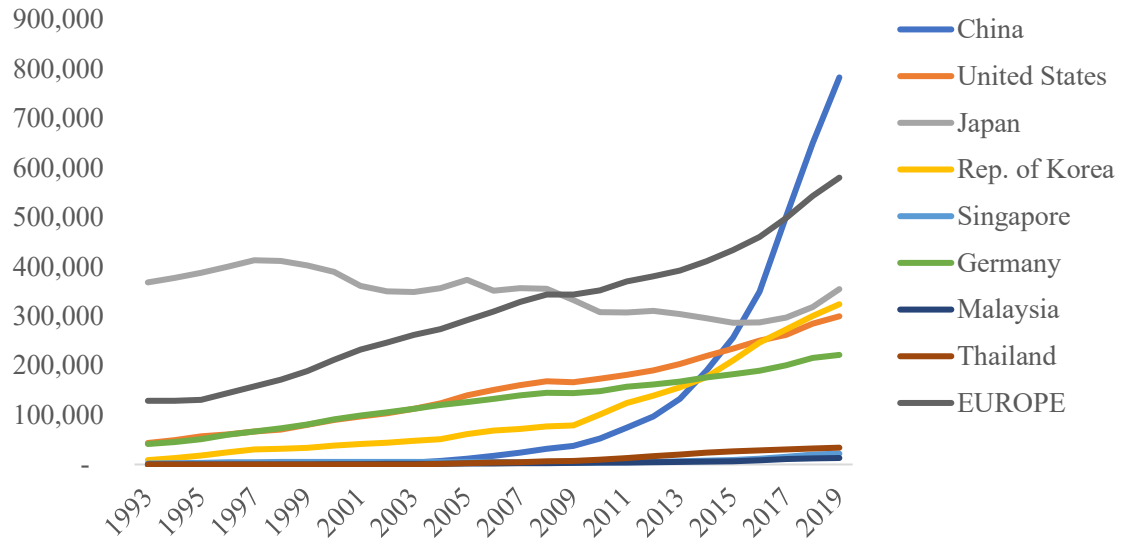
Figure 2.6.1A: Annual Installations of Industrial Robots in Selected Economies



Source: International Federation of Robotics (2020)

Robot density, which measures the number of operational industrial robots per worker, serves as a significant gauge for automation adoption in the manufacturing sector worldwide (IFR, 2022; Acemoglu and Restrepo, 2021). In China, the robot density has witnessed a remarkable surge, reaching 322 units per 10,000 employees in the manufacturing industry in 2021. This surpasses the United States and secures China's position as the fifth-highest robot density in the world. By comparison, the global average robots' density in the manufacturing industry stands at 141 robots per 10,000 employees. The global top 5 most automated countries in terms of robot density in the manufacturing sector include South Korea, Singapore, Japan, Germany, and China.

Figure 2.6.1B: Operational Stock of Industrial Robots in Selected Economies



Source: International Federation of Robotics (2020)

China's remarkable progress in automation is a testament to the success of its technology-driven development strategies. Recognizing the significant trend of population aging and shortage of labour, the Chinese government has announced plans to further promote the robotization of industries. The Ministry of Industry and Information Technology (MIIT) recently released 14th Five-Year Plan for the robotics industry in 2021,

by emphasizing the importance of innovation and aiming to establish China as a global leader in robotic technology and industrial advancement.[31]

2.6.2 Total Factor Productivity (TFP)

In economics, total-factor productivity (TFP) is usually measured as the ratio of aggregate output (e.g., GDP) to aggregate inputs, and is widely adopted as a measure of technological change despite various caveats (i.e., Lipsey & Carlaw, 2004). Although there is no universal consensus on the actual estimation of TFP,[32] Penn World Table by Groningen Growth and Development Centre[33] has provided two estimations in tracking the changes of TFP at the global level: TFP Level at Current PPPs (US=1) and TFP at Constant National Prices (2017=1). Specifically, TFP at Constant National Prices (2017=1) reflects total factor productivity (TFP) levels at constant prices against the reference year in 2017, whereas TFP Level at Current PPPs (US=1) tracks total factor productivity (TFP) levels at constant purchasing power parity (PPP) rates for a country relative to the US in terms of the prices in that period (i.e., current prices). [34]

In other word, these two parameters serve as indicators to assess technological advancements from two different angles: TFP at Constant National Prices (2017=1) reflect the TFP progressiveness that examines the change in productivity levels within China over time compared to the reference level set in 2017, shedding light on the country's own technological progress and efficiency improvements. On the other hand, the TFP Level at Current PPPs (US=1) measures the TFP gap between China and the technological frontier represented by the United States, providing insights into China's relative position in the global context.

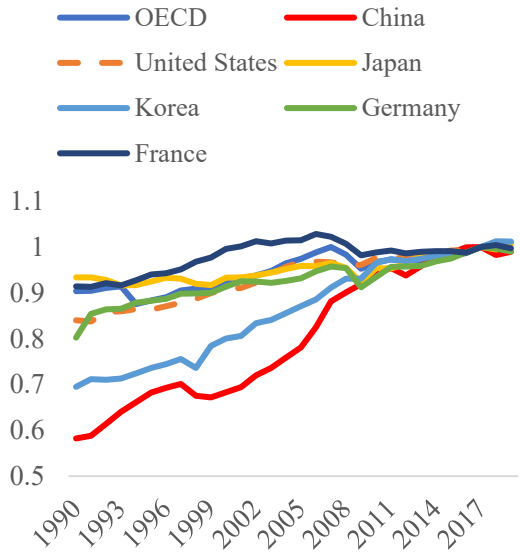
[31] The Ministry of Industry and Information Technology, the National Development and Reform Commission, the Ministry of Education, and other eight departments jointly released the "14th Five-Year Plan for the Development of Intelligent Manufacturing." Link: https://www.gov.cn/xinwen/2021-12/28/5664873/files/1760823a103e4d75ac681564fe481af4.pdf

[32] Existing studies have various approaches to estimate TFP, i.e., parameter estimation including OLS (i.e., Solow,1957) and Stochastic Frontier Approach (SFA) (i.e., Lovell and Schmidt, 2008), and non-parameter methods such as Data Network Analysis method (DEA) (i.e., Farrell, 1957), and they show significantly different features. More discussions are provided in Chapter IV.

[33] Official website: https://www.rug.nl/ggdc/productivity/pwt/?lang=en

[34] See explanation notes in https://data-planet.libguides.com/PennWorldTables

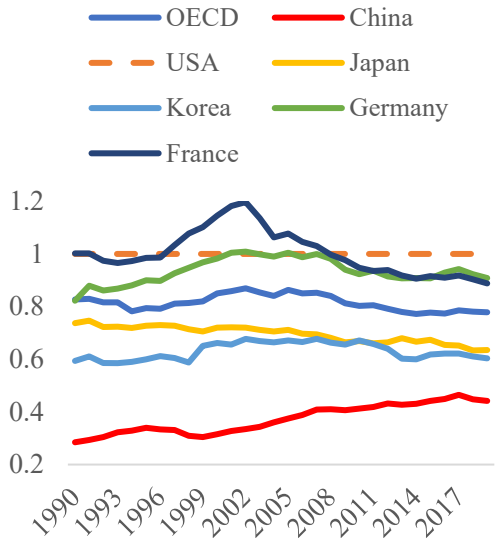
Figure 2.6.2A: Trajectory of China's Total Factor Productivity (TFP) Growth against Global Innovation Leaders



Source: Penn World Table 10.0

Note: TFP at constant national prices (2017=1)

Figure 2.6.2B: Benchmarking China's Total Factor Productivity (TFP) against Global Innovation Leaders



Source: Penn World Table 10.0

Note: TFP level at current PPPs (USA=1)

The results indicate a significant improvement in total factor productivity (TFP) in China. Over the past few decades, China has experienced a remarkable progress in TFP, with an increase of 171 percent. In comparison, the average TFP level in OECD countries and the United States increased by 110 and 119 percent respectively during the same period (Figure 2.6.2A). In addition, the gap between China and the United States in terms of TFP has been narrowing. In 1990, China's TFP level was approximately 28 percent of the level in the United States. But by 2019, it had climbed to 44 percent (Figure 2.6.2B). This suggests that China has made substantial progress in catching up to the United States in terms of productivity and technological level, and increasing global competitiveness.

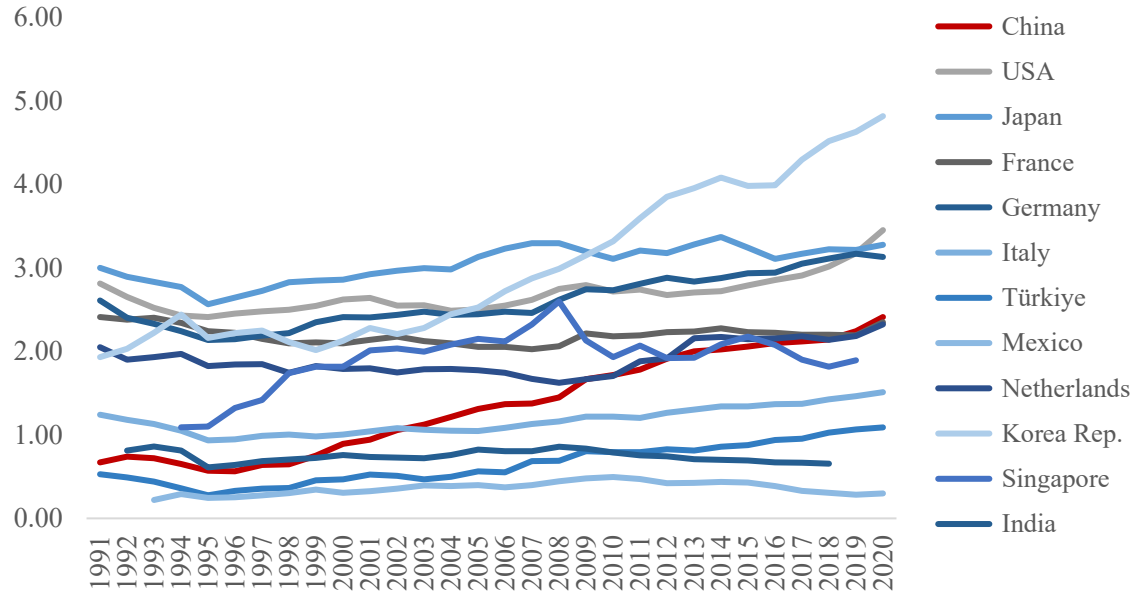
2.6.3 Research and Development (R&D) Expenditure

In recent years, China has demonstrated its commitment to research and development (R&D) activities by allocating a significant portion of its Gross Domestic Product (GDP) towards this sector. In 2021, China's total expenditure on research and experimental

development (R&D) in the entire society amounted to 2,786.4 billion RMB, representing a growth of 14.2 percent compared to the previous year. The ratio of R&D expenditure to the Gross Domestic Product (GDP) has reached 2.44 percent, showing an increase of 0.03 percentage points from the previous year. In contrast, the ratio in 1991 was only 0.67 percent, indicating an average 8.7 percent annual increase. From an international perspective, China ranks high among major countries, surpassing innovation-driven nations like France (2.35 percent) and the Netherlands (2.32 percent), and being closed to the average level of OECD countries (2.67 percent) (Figure 2.6.3A).

To date, China has already become the world's second-largest conductor of R&D and become the world's second largest R&D performer. Notably, China's R&D spending in 2020 reached 582 million USD, accounting for an impressive 80 percent of the expenditure of the United States in the same year. It means an annual growth rate at 10.8 percent from 2019. In comparison, innovation-led countries like Japan, Germany, Korea, and France had spent about 172, 146, 102 and 72 million respectively in 2019. These figures underscores China's rapid growth and increasing influence in the field of technological innovation (Figure 2.6.3A).

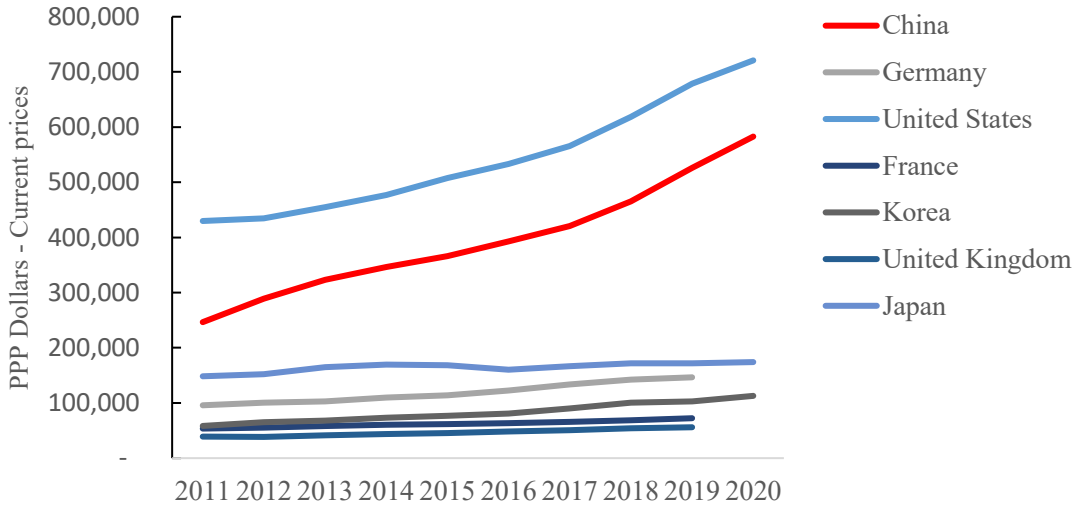
Figure 2.6.3A: Global Comparing of R&D Expenditure (% of GDP)



Source: China Statistical Yearbook on Science and Technology (2022)

In addition, according to the Global Innovation Index (GII) published by the World Intellectual Property Organization in 2022, China's performance in science and technology innovation stands at 11th place out of 132 economies, marking a one-position improvement from the previous year. China's rank has steadily climbed since 2013, maintaining a consistent upward trajectory for ten consecutive years (WIPO, 2022).

Figure 2.6.3B: China's R&D Expenditure is Catching Up Rapidly (in million)



Source: OECD (2022)

This Chapter provides a comprehensive overview of China's demographic transition, including its historical context, current demographic structural features, the evolution of population policies, and China's position in the international context. It also highlights China's recent advancements in human capital development and technological progress over the past decades. While the post-demographic transition period in China presents challenges such as labor shortages and many other social issues, it needs to be cautious to draw pessimistic conclusions because the rapid growth in human capital and technology may have the potential to mitigate some of the negative impacts. Therefore, it is needed to conduct deeper investigation into the intricate interplay between demographic structure, human capital, and technological advancements to gain a more comprehensive understanding of the situation.

CHAPTER 3: LITERATURE REVIEW

To lay a solid foundation to understand the dynamic interplay between demographic structural changes and technology advancements, this Chapter provides an introduction to the existing literature, focusing on theoretical frameworks and empirical evidences. The first section of this Chapter explores the theoretical frameworks that have been developed to analyze the interplay between demographics and technologies. These frameworks provide a conceptual basis for understanding how demographic factors, such as population size, growth rate, and fertilities interact with technological progresses and economic growth. The second section reviews empirical evidences on the impact of demographic factors on technology advancements, and a broader concept of technological advancements, namely productivity, respectively. These theoretical and empirical knowledge are crucial for understanding the macroeconomic implications of the demographic-technology relationship and its relevance for the overall economic performance.

3.1. EVOLUTION OF THEORETICAL FRAMEWORKS

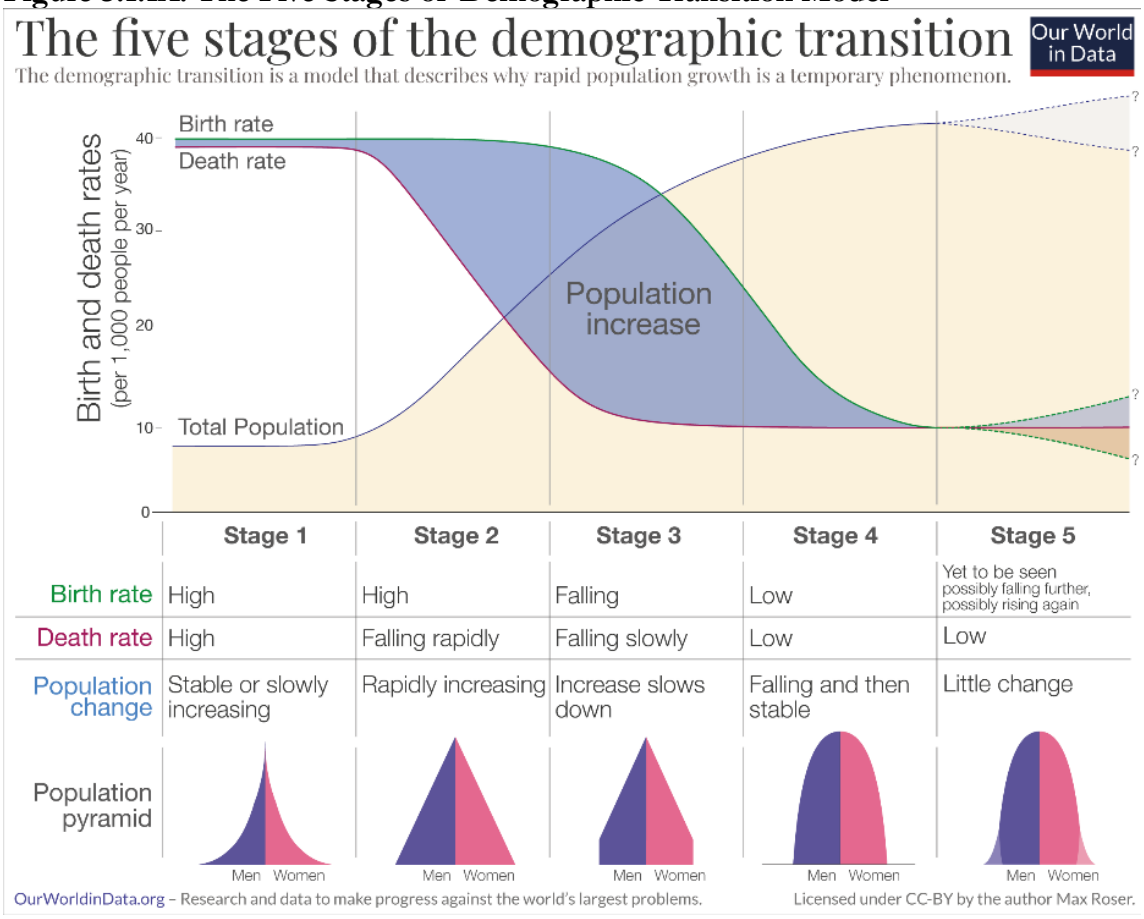
This section delves into the evolution of theoretical frameworks that explore the intricate relationship between demographics and technologies in economics. This study carefully synthesizes prominent frameworks that have significantly contributed to the understanding of their dynamic interactions.

3.1.1 Demographic Transition Theory (DDT)

The predictable patterns of population growth have long been recognized by researchers. Szreter (1993) first proposed the demographic transition, which was later revised by Mason (2001) and Lesthaeghe and Vanderhoeft (2001). Caldwell (2006) further summarized the demographic transition in a conceptual model known as the Demographic Transition Theory (DTT) or Demographic Transition Model (DTM) (Figure 3.1.1A). It is a sociological and demographic framework that seeks to explain the changes in population dynamics and structure observed in different societies over time. It provides a conceptual model to understand the patterns of population growth, fertility, mortality, and migration.

The Demographic Transition Theory (DTT) posits that as countries undergo economic and social development, they follow a pattern of distinct phases that lead to changes in population characteristics. This transition involves a shift from a high incidence of death and fertility, accompanied by high birth rates and low life expectancy, to a stage of low mortality and fertility, characterized by low birth rates and high life expectancy. Moreover, the process of economic development in a country is closely intertwined with this demographic transition (Szreter, 1993).

Figure 3.1.1A: The Five Stages of Demographic Transition Model



Source: Roser (2013) based on Caldwell (2006)[35]

While there are variations in the specific stages and duration across different regions and countries, the general framework includes the following phases:

[35] See link: https://ourworldindata.org/world-population-growth

- Stage 1 (pre-transition): In this stage, both birth rates and death rates are high, resulting in a slow population growth. Traditional agrarian societies (like the United States during the 1800s) typically exhibit these characteristics. It is widely believed that populations maintained a delicate equilibrium between fertility and mortality until the late 18th century and it was ended in Western Europe. During this stage, population growth is typically sluggish due to constraints imposed by the available food supply, such that any fluctuations in birth rates are quickly balanced out by corresponding changes in death rates (Galor, 2012).
- Stage 2 (early transition): As countries experience economic development and improvements in healthcare and living conditions, mortality rates decline significantly while birth rates remain high, leading to a rapid increase in population size. Caldwell (2006) provided examples of countries in Stage 2, including Yemen, Afghanistan, Iraq, and many countries in Sub-Saharan Africa.
- Stage 3 (mid-transition): In Stage 3 of the demographic transition, societies undergo significant social and economic changes that lead to a decline in birth rates, while death rates remain low. This stage represents a period of population stability, as factors like urbanization, increased access to education, and shifting societal norms contribute to the reduction in fertility rates. It is during this phase that the concept of demographic dividend emerges (to be discussed more in detail), highlighting the potential for economic growth by increasing the ratio of the working-age population to the dependent population. Notably, several countries have entered this stage, including Colombia, India, Mexico, the UAE, and various countries in Sub-Saharan Africa, such as South Africa, Zimbabwe, Gabon, and Ghana. These countries have witnessed a significant decline in fertility rates as they transition to Stage 3, signifying the beginning of this transformative phase.
- Stage 4 (late transition): Birth rates and death rates stabilize at a relatively low level, resulting in a slow population growth rate or even population decline. This stage is characterized by low birth rates, low death rates, and an aging population. As of 2023, some countries that are considered Stage 4 include Argentina, Canada, Australia, Bangladesh, Brazil, Singapore, El Salvador, India, Indonesia, Malaysia, Maldives, Mexico, Myanmar, Nepal, the United States, and most countries within

Europe, where the TFR is between 2.0 and 2.5 (World Bank, 2022). These countries exhibit relatively low birth rates, reflecting a declining population growth trend and a shift towards a more developed demographic pattern.

- Stage 5 (post transition): Notably, some scholars (i.e., Chesnais, 1990; Waugh, 2000; Blue & Espenshade, 2011) delineated a fifth stage in the Demographic Transition Theory, while Stage 5 is a contested period that may predict higher or lower fertility levels. It is characterized by low mortality rates, below-replacement fertility levels but uncertainties in fertility. On the one hand, notably, some countries, such as Eastern European countries including Germany, Italy, Sweden, Japan, Korea, including current China, have experienced birth rates falling well below the replacement level, leading to a declining population. As the large cohort born during the early transition periods, it places significant economic burden and social implications on the shrinking working-age population. On the other hand, some demographers such as Myrskylä, Kohler, and Billari (2009) have empirically argued that at very high levels of development, although not as high as the pre-transitional period, fertility will raise again (Myrskylä, Kohler, and Billari, 2009).

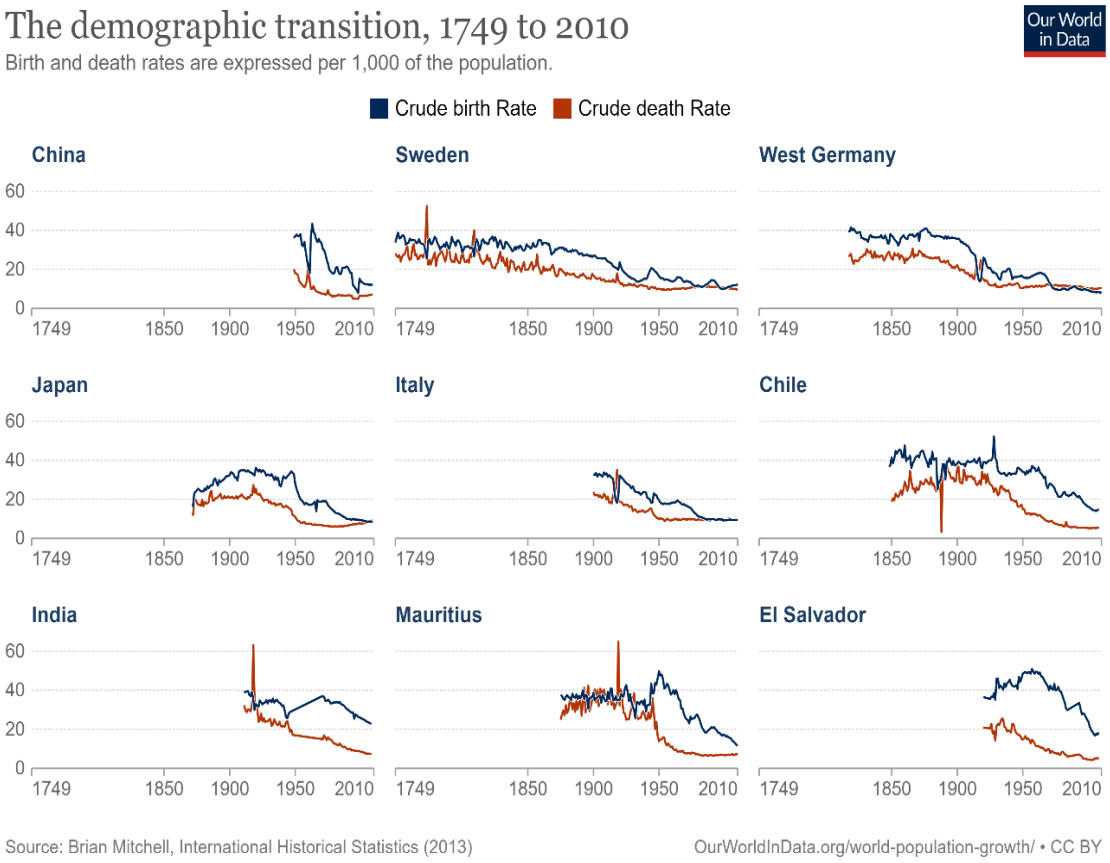
The Stage 5 has also been referred to the "second demographic transition (SDT)" (van de Kaa 1987; Lesthaeghe, 2010), that focuses on shifts in family structures, reproductive behavior, and gender roles. The SDT builds upon the original DTT by emphasizing the societal changes that occur once low fertility and mortality levels have been achieved. Specifically, Van de Kaa (1987) argued that as societies become more affluent and advanced, people's motivations and values regarding family and reproduction change. Traditional norms and expectations regarding marriage and childbearing give way to individual choices and preferences such as personal autonomy, career aspirations, and the pursuit of personal happiness and fulfillment. A shift towards individualism, greater gender equality, increased emphasis on self-expression, and the rise of non-traditional family forms and reproductive behaviors can also be observed. The SDT is characterized by delayed marriage, rising cohabitation rates, higher levels of non-marital childbearing, increased divorce rates, and the postponement of childbearing to later ages (i.e., Cliquet, 1991; Lesthaeghe and Neels, 2002; Zaidi & Morgan, 2017).

Although the theoretical basis for the second demographic transition is still debated with different interpretations and variations proposed over the years, it has been influential in understanding and explaining the social and demographic changes observed in many developed countries. It helps to shed light on the complex interplay between social, economic, and cultural factors that shape fertility patterns. In addition, it is also evident that that most countries that reached Stage 4 of the demographic transition, characterized by low fertility and mortality, will experience sub-replacement fertility.

The SDT theory has also been adapted and modified to explain demographic trends in specific contexts. In China, for instance, Feng (2011) explored the long-term implications of China's demographic transition, examined the challenges that China faces with its aging population and declining birth rates, and highlighted the social implications of the second demographic transition. This study also discussed the role of the Chinese state in birth control China's one causing an abnormal sex ratio at birth and explored different policy options and their potential impact on population size and future trends (Feng, 2011).

Overall, DTT provides not only a theoretical framework for understanding the complex interplay between social, economic, and demographic factors in shaping population dynamics over time, but also reflects the empirical evidence for the demographic transition over a long-term history (Figure 3.1.1B). The figure below presents the historical process of the demographic transition for nine very different countries in Europe (Sweden, Germany, Italy), Latin America (Chile and El Salvador), Africa (Mauritius), and Asia (China, Japan, and India). It is evident that although different countries started the demographic transition at different historical timepoint and are currently in different stages of the transition, common patterns can be observed from the transition process: in all countries, transition begins with a decline in mortality rates (implying population boom), and then a decline in fertility brings the population boom to an end.

Figure 3.1.1B: Historical Evidence of Demographic Transition Model in Selected Countries



Source: Our World In Data based on Mitchell (2013)

DTT is a relevant and valuable theoretical framework for studying population changes and their implications for societies, and it provides a theoretical foundation for this analysis focusing on China's post-demographic transition. Yet, it is noteworthy that because not all countries have completed a demographic transition, nor all countries have gone through a demographic transition at the same pace, such that some countries take a long time whereas others have passed through faster. Therefore, empirical studies on demographic transitions should acknowledge the limitations and complexities of population dynamics across different country contexts. It is important to consider the country variations and the specific characteristics of each country when using global data for empirical analyses.

3.1.2 Demographics, Technology, and Productivity Growth

It has become evident that the demographic transition is a lengthy process intertwined with economic development, in particular, the industrial and social structure changes of global society. As a result, economists have devoted significant attention to comprehending the role of demographics in economic development over a long period of history.

The role of population in economic growth has been a crucial topic discussed by classical economists. Malthus (1798) presented one of the most renowned explanations on the principle of population. According to the Malthusian theory, limited land in agricultural production combined with outpaced population growth driven by increased living standards leads to diminishing return. According to this theory, in the absence of technological advancements or changes in the availability of land supplies, population would reach a stable equilibrium, while even technological progress would only result in population expansion without improving per capita income, ultimately resulting in the "Malthusian trap" of stagnation or economic decline (Galor & Weil, 1999). The idea that "technology constrains population growth" had garnered significant attention and has been supported by numerous pieces of confirming evidence, particularly during the pre-industrial period in European countries such as Britain, Germany, Austria, and Japan (i.e., Kremer, 1993; Ashraf & Galor, 2011; Madsen et al., 2019; Gehrke, 2020; Kumon, 2019). In addition, due to the varying paces of the demographic transition across countries, studies were emerging in later-comer industrial contexts such as Bangladesh (i.e., Chowdhury and Hossain, 2018), Nigeria (i.e., Aiyar, Dalgaard & Moav, 2008; Michael & Odeyemi, 2017), and other developing countries in South Asia and Sub-Saharan Africa regions (i.e., Yaqoob et al., 2022; Osei-Appaw & Christian, 2022).

However, the Malthusian theory had faced significant criticism due to its excessively pessimistic outlook and failure to account for technological advancements. Boserup (1981), for example, contended that population growth compels people to seek ways to increase food production and resource efficiency, leading to the development of new technologies and more efficient production methods. The Boserupian theory, rooted in the works of Smith, Marx, and Durkheim, emphasized the role of population growth in driving changes in labor organization and expanding the productive capacity of resources

(Marquette, 1997). This perspective highlighted the crucial mechanism of "agricultural intensification" that had been overlooked by the Malthusian school of thought (Boserup, 1976; 1986; 2011). The history of many developing countries in particularly Sub-Saharan Africa has provided supportive evidence (e.g., Boserup, 1985; Marquette, 1997).

The positive side of population growth in technology and productivity has also been supported by other economic theorists. For instance, Adam Smith held an optimistic view on the relationship between population and economic growth, emphasizing the positive role of population growth in fostering economic development through market scale and division of labor. Youno (1928) introduced the concept of increasing returns, highlighting the influence of market size and industrial specialization. Harrod-Domar model of Keynesian growth theory also provided micro-economic foundations to demonstrate the existence of equilibrium, despite unstable, due to the exogenous treatment of population (Solow, 1956).

To address limitations of classical economic theories, neo-classical growth theory represented by Solow (1956) incorporated population (labor), capital, and technology as key drivers for economic growth. It argued that any changes in the Cobb–Douglas production function can be attributed to technological advancements, which may arise from changes in economic organization, and other factors. But in this model, technological advancements were considered as exogenous, and its emergence was characterized by randomness and unpredictability. Simon (1986) argued that a larger population can stimulate innovation and technological progress, leading to economic growth. Nonetheless, this idea contradicted the observation that scientific and technological progress had not occurred in countries with large populations like China and India. Endogenous growth theory (Jones, 1995) extended the new neoclassical growth theory by incorporating research and development (R&D) activities into growth models and emphasized the "scale effects" and positive externalities brought by the knowledge and human capital of a large population. But it should be noted that both neo-classical and endogenous growth theories treat the population growth exogenously, overlooking the intrinsic influence of demographic structure.

The fallibility of the Malthusian was also attributed to the rapid economic and technological development in the post-Industrial Revolution era, where many European economies had escaped from the "Malthusian trap" by entering a stage characterized by increase in per capita income but declines in birth rates and fertility rates (Becker et al., 1999). This phenomenon had sparked discussions among economists in making population endogenous to the growth model. Becker (1960) developed a microeconomic model that endogenizes fertility rate by considering the trade-off between costs and benefits of raising children. Becker and Lewis (1973) further incorporated the quality of population and proposed the Quantity- Quality tradeoff theory to explain the declining fertility rates with increasing income levels. It has served as one of the most influential theories in explaining the phenomenon of declining fertility in the modern society. Therefore, the theoretical framework of this study also adopts the notion from Quantity-Quality tradeoff theory, and Chapter 4 will present more discussions in detail.

After then, the Quantity-Quality tradeoff theory was further developed and augmented in Becker & Barro (1988) and Becker et al. (1990), by introducing fertility, human capital as an endogenous factor in the economic growth model. Their theory emphasized that the demographic transition to a low-fertility and economic development depends on the initial level of human capital: when the return on human capital is low, parents choose to have more children and lower human capital; conversely, parents prefer to have fewer children and higher human capital when the return on human capital surpasses a threshold. This provided a strong explanation on two distance states of the "Malthusian trap" and the modern society of developed countries, respectively. Based on the neo-classical model and human capital theory, Mankiw, Romer, and Weil (1992) endogenized the growth of technology based on the level of human capital. However, it is important to note that in addition to human capital, technological advancements might also be influenced by other factors such as endogenous capital allocation efficiency.

Later on, the Unified Growth Model, proposed by Galor and Weil (2000), introduced the constraint of subsistence consumption and integrated demographics and economic growth as endogenous factors. The model suggested that at low per capita income levels, parents prioritize meeting minimum survival needs before allocating

resources to child-rearing and human capital accumulation. As per capita income surpasses the subsistence constraint due to accumulating human capital and technological advancements, a transition to a modern society occurs. With higher returns to technology, shifts from quantity to quality of human capital happens, and the population size becomes less important, resulting in a decline in population growth rate.

The Unified Growth Model (Galor and Weil, 2000; 2011) offered an endogenous framework in exploring the interplay between the demographic transition and economic growth. It considered factors like population size, fertility rates, mortality rates, human capital accumulation, and life expectancy (Cervellati and Sunde, 2011; d'Albis et al., 2018). The model elucidated how technological progress boosts education returns, leading to a tradeoff between population quantity and quality, driving population transitions and economic growth. However, the model had limitations in explaining phenomena observed in developing countries where income per capita was lower than 19th-century Europe, yet the fertility rate was much higher (Galor and Weil, 2000).

By reviewing the evolvement of existing theories, it is evident on the existence of potential mechanism between demographics and technological advancements. However, although these theories had been able to explain some historical facts in certain countries, there were also drawbacks in explaining certain phenomenon in other specific context. Moreover, these models primarily considered the role of population growth or fertility, by overlooking the important dimension of demographic structure, which represented the multifaceted features related to both benefits and costs of different demographic dynamics that could bring to the society.

Therefore, this study, followed the demographic dividends theoretical framework proposed by Bloom, Canning and Sevilla (2003) and Lee and Mason (2006, 2016), argues that in addition to the changes in the size of labor population, both saving and human capital are duel indirect mechanisms through which “demographic dividends” are materialized to facilitate technological advancements. Chapter 4 will provide more detailed discussions on the demographic dividend’s theory.

3.2. EFFECTS OF DEMOGRAPHICS ON TECHNOLOGY

3.2.1 Effects of Demographics on Technology

This section focuses on empirical evidence that sheds light upon the influence of demographic factors on technological advancements in recent decades. Through rigorously soliciting and analyzing empirical studies, it aims to discern the extent to which demographic factors play a role in shaping technology adoption and innovation in different contexts and scenarios, to build sound understandings to Research Question 1.

Although discussions in this nexus only start to emerge, divergent results had been found. To start with, Jones (2010) represented an early effort to examine the impact of age on innovation, highlighting a shift in contemporary times where innovators achieved their peak insights at considerably older ages compared to a century ago. This change was not solely attributed to population aging but also to a significant decline in innovative output from younger individuals. The study estimated a significant 30 percent decrease in innovation potential throughout the 20th century, indicating that present societies, influenced by population aging, exhibited reduced levels of innovation. Additionally, the research emphasized the pivotal role of investing in training and human capital during early life-cycle stages to explain these dynamics. Bloom et al. (2020) supported this perspective, highlighting that despite escalating research demands, modern society's innovation capabilities had sharply declined across industries, products, and firms. Similarly, Scott (2021) argued that increased longevity, with a higher proportion of older workers, leads to decreased innovation.

Derrien, Kecskés, and Nguyen (2022) investigated the role of age structure of the workforce on innovation, arguing that younger people are primarily key player in innovation due to their creativity, risk tolerance, and interactivity, and the results indicated that a younger age structure leads to more innovation in the United States. A quantitative study by Engbom (2017) found that labor force aging over the last 30 years in the United States explains 40 to 50 percent of the decline in work activities including the innovation distribution. However, Azoulay et al., (2020) pointed the extremely opposite in the context of the United States, that prior experience of older workers leads to greater rates of

entrepreneurial success, and this phenomenon is prevailing across technology sectors where great innovation is required.

In the context of European countries, Aksoy et al. (2019) conducted a study using a sample of 19 OECD countries and found a strong correlation between a higher proportion of younger and middle-aged workers and a higher rate of innovation activities. This suggested that an aging demographic profile is likely to lead to a decline in innovation. Wasiluk (2014) supported this observation by using a quantitative dynamic model, which indicated that an aging workforce exhibits lower frequency and preference for adopting technology diffusion compared to a younger workforce in Germany, mainly due to the shorter work tenure expectations of older workers. Aiyar and Ebeke (2016) also found similar results, emphasizing that an aging workforce significantly reduced labor productivity but highlighted the importance of complementary skill sets between older and younger workers. These findings partly aligned with the study conducted by Lee and Song (2020) in the context of Japan and Korea, which highlighted the role of complementarity between technologies and older workers in driving productivity.

Some simultaneously emerging but independent studies with a specific focus on cutting-edge technological advancements, such as automation and robotics, also provided mixed findings. For example, Acemoglu and Restrepo (2017; 2021) focused on the influence of population aging and they showed positive incentives, as population ageing encourages the adoption of automation technologies and foster economic growth. Studies by the Asia Development Bank (Zhongming et al., 2018; Park, Shin & Kikkawa, 2020) also suggested positive associations between population aging and technological advances. All these results emphasized the crucial role of technology in navigating demographic challenges. However, Basso and Jimeno (2019) presented mixed results regarding the relationship between automation and demographic structure. They argued that while population aging stimulates innovation, the effects on per capita income growth may be limited because automation can only partially offset the decline in productivity caused by an aging workforce's expectations.

In addition to the existing literature, although few, there is another relevant body of research exploring the relationship between low fertility and automation. Abelianisky and

Prettner (2017; 2021) investigated the impact of demographic shifts on technological progress and emphasized that the slowdown in population growth served as a motivation for automation advancements on a global scale. Jimeno (2019) examined the macroeconomic implications of declining fertility (or low population growth) through mechanisms including saving and natural interest rates, endogenous growth in innovation and automation, and the creation rate of new tasks. This analysis highlighted that although population aging created incentives for automation, per capita growth would decelerate during the demographic transition, and the decline in labor supply would lead to reduced innovation due to the labor supply effect on research and development (R&D). Consequently, fewer new tasks would be created and resulted in a decrease in automation.

In summary, the literature review highlighted the inconclusive discussions on the relationship between demographics and technological advancements, with limited focus on developing contexts. Therefore, further research is needed to gain a better understanding of how demographics impact technological progress in diverse environments.

3.2.2 Effects of Demographics on Productivity

This section extends its analysis to explore the relationship between demographic factors and productivity- a broader dimension of technological progress that has received significant attention in empirical studies for a long time. This part puts a focus on how demographic factors influence productivity particularly in China, aligning with Research Question 2.

The Asian Productivity Organization report by Phang (2011) provided an extensive analysis of the impact of population aging on labor productivity in Asian countries such as Japan, Korea, Singapore, and Taipei, China. Their findings underscored the cost burden imposed by population aging on overall productivity and the economy in these diverse contexts. Similarly, a report by the Asian Development Bank (Park & Shin, 2012) examined 12 developing Asian economies and projected a shift from “demographic dividends” to a “demographic tax” due to the demographic transition towards an aging population. This highlighted the negative consequence of demographic changes on productivity. Skirbekk (2008) introduced an industry-wide task demand model that

demonstrates an inverted "U-shaped" curve in age-specific productivity, with peak productivity occurring in middle age (35-44) while declining toward the end of one's career. These findings suggested that population aging would contribute to declining labor market productivity.

Contrasting results have been observed in the literature. Malmberg, Lindh, and Halvarsson (2008) conducted empirical estimations at both individual and plant levels and found a positive relationship between aging (increasing mean age of the workforce) and workers' productivity. Their findings suggested that higher shares of older adults in manufacturing plants are associated with higher productivity, indicating no significant negative impact of aging on productivity. These results are consistent with earlier micro-level evidence from Lindh and Malmberg (1999) for OECD countries, McMillan and Baesel (1990) for the United States, and Malmberg (1994) for Sweden. Gómez & Hernández de Cos (2003) also highlighted a positive, albeit diminishing, return to the increasing proportion of mature workers (35-54).

In the realm of productivity, there is a body of literature focusing on technological productivity, specifically Total Factor Productivity (TFP), which measures efficiency improvements. Feyrer (2007) examined cross-country data and found a positive impact of the age structure (40-49) of the workforce on TFP, with divergent patterns observed between the United States and Japan, suggesting country-specific differences. Kögel (2005) explored this issue through the lens of the life-cycle theory and highlighted that global variations in TFP were primarily driven by a country's age structure, particularly youth dependency. Similarly, Gordo and Skirbekk (2013) utilized a task-based framework using data from 1986 to 2006 in Germany. They discussed the relationship between age and technological changes, revealing that older workers demonstrate better adaptability to technology changes and engage more in cognitive-intensive tasks. This could be attributed to factors such as higher human capital among older individuals in developed countries, reduced physical limitations due to advanced technology, synergy between older and younger workers, and improved production technology and work environments that accommodate different age groups (Göbel & Zwick, 2013).

The implications of demographics on productivity have sparked extensive debates, as evident in studies by Bloom and Sousa-Poza (2013), Mahlberg et al. (2013), Lovász and Rigó (2013), Prettner (2013), and Imrohoroğlu and Kitao (2012). Chomik and Piggott (2021) provided a comprehensive summary of the effects of population aging on productivity, categorizing them into three components: human capital, physical capital, and endogenous technology. They highlighted that while some channels can have positive effects on productivity, others may have negative effects, resulting in uncertain net effects depending on the direction and magnitude of these factors. Inspired by this, this study also investigates the mechanisms of saving and human capital between the intricate interplay between demographic structural changes and productivity, and more discussions is illustrated in Chapter 4.

A naturally subsequent question is what are the implications in the context of China? In the domestic context, implications of the interplay between demographic factors and technological productivity have received relatively limited research compared to global evidence. Cai (2009) suggested that an aging demographic structure in China may not negatively impact total factor productivity (TFP), but rather promoted education expansion. Kang (2009) analyzed data from 28 provinces in China between 1983 and 2007 and found a significant positive effect of population age structure and human capital, such as education, on TFP, with a threshold effect observed. Huang et al. (2018) simulated the effects of the "comprehensive two-child policy" implemented in China after 2015 and indicated that short-term increases in birth rates and TFP promotion can be expected, while the impact gradually diminishes over time.

Heterogeneity is an important factor to consider in China. Zhang (2009) examined county-level data from Shandong province and identified significant differences between China (or at least parts of China) and international experiences, showing that younger workers aged 15 to 29 exhibit the highest productivity. Zhang (2013) demonstrated that the impact of an aging population on TFP growth differs across regions, with a positive effect in the eastern region but not in the west, and a potential negative impact in the central region. Heterogeneity is not only observed across regions but also among age-specific dynamics, resulting in diverse implications. Li and Zhao (2019) employed a unidirectional

causality approach to examine the impact of demographics on technological innovation in China. Their study revealed that the old-age support ratio has a sustained influence on technological innovation, while the child dependency ratio exhibits a significant unidirectional causal effect in the short term. These findings highlighted the importance of considering both spatial and age-related heterogeneity when examining the relationship between demographics and technological innovation.

In conclusion, the literature review reveals contrasting findings regarding the relationship between demographics and technological advancements. While some studies suggest positive effects, others indicate negative or mixed implications. Moreover, it is important to note that existing research predominantly focuses on developed countries, potentially leading to biased implications when applied to developing environments. Furthermore, limited number of studies conducted in the context of China, and the presence of heterogeneity across regions and age-specific dynamics further emphasize the importance of nuanced analysis. With significant demographic structural changes and ongoing technological advancements, a more detailed and context-specific examination is crucial to fully understand the interplay between demographics and technological innovation.

CHAPTER 4: METHODOLOGIES

As highlighted in the previous literature review, contrasting findings have emerged regarding the relationship between demographics and technological innovation. Additionally, the majority of existing studies have predominantly focused on developed country contexts, potentially yielding biased implications when applied to developing environments. Moreover, there is a noticeable lack of research conducted in the specific context of China, despite its significant demographic shifts and ongoing technological advancements.

Given the complexities and dynamics of demographic changes and technological advancements, and research in this area has been relatively nascent and lacks a cohesive theoretical framework or consensus, therefore, this study seeks to establish a framework and to adopt a nuanced approach to understanding their interactions. Specifically, this study examines age-specific dynamics of demographic structure changes in facilitating technological advancements through saving and human capital, followed by empirical investigation on their relationship.

4.1. THEORETICAL FRAMEWORK

This section introduces the framework of the Demographic Dividends Theory (DDT), originally formulated by Lee and Mason (2006). This framework serves as the basis for the theoretical framework proposed by Abelianisky and Prettner (2017 and 2021). By building upon these theoretical foundations, empirical analyses are conducted in the following section to further explore the topic.

To start with, Bloom, Canning, and Sevilla (2003) investigated the labor mechanism of demographic dividends by explaining that a decrease in the dependency ratio allows for a larger working-age population relative to the dependent population. This demographic shift can lead to increased labor supply, potentially resulting in higher productivity and economic growth. With a larger pool of workers, there is the potential for increased specialization, division of labor, and innovation, all of which can contribute to economic development. Indirectly, they argue that a decline in the dependency ratio allows

for a higher savings rate among the working-age population. As the number of dependents decreases relative to the working-age population, individuals and households have more resources available for saving and investment. Higher savings rates can fuel capital accumulation, leading to increased investment in infrastructure, technology, and other productive assets. This, in turn, can stimulate economic growth and development.

Lee and Mason (2006, 2016) have contributed to the understanding of the relationship between demographic transition and economic development by introducing the concept of demographic dividends. These dividends, classified as direct and indirect, are observed at different stages of the demographic transition model (DTM). The direct dividend occurs during the early stages of the transition when the labor force experiences a more rapid increase compared to the dependent population. This demographic shift allows for the allocation of resources towards economic development, as there is a larger working-age population available to contribute to the economy.

On the other hand, the indirect dividend is associated with the later stages of the DTM. As fertility rate declines and the growth rate of the labor force decreases, the improvement in old-age mortality becomes more significant. In this stage, countries with a growing aging population have a strong incentive to accumulate savings to meet the financial needs of retirees in the future. In addition, Lee and Mason also highlighted the importance of intergenerational transfers and the potential for knowledge spillovers through human capital investments in education and health during the demographic transition- another indirect mechanism. The intergenerational transfer of knowledge and skills from older to younger generations, combined with investments in education and training, can further boost human capital accumulation and lead to the increase of productivity and technological advancements.

4.1.1 The Indirect Mechanism Through Saving

The concept of the “demographic dividend” on saving aligns with the life-cycle hypothesis, which suggests that individuals tend to save more during their working years and consume

more during childhood and old age.[36] Consequently, the demographic dividend occurs when the proportion of dependents (children and elderly) to the working-age population is lower, leading to a higher saving rate. Empirical studies have provided support for this argument. Studies from Mason, for example, revealed a negative relationship between higher fertility rates and savings, while lower child dependency ratios were associated with higher saving rates (Mason, 1981; 1988). Other researchers, including Higgins and Williamson (1997) and Kinugasa and Mason (2007), have also confirmed a positive correlation between lower dependency ratios (both young and old) and higher saving rates. Furthermore, Loayza et al. (2000) observed a negative association between both young and old dependency ratios and the saving rate.

Based on this framework, the hypothesis is proposed that the adoption of automation technologies is influenced by demographic dynamics through the mediation of saving. To test this hypothesis and derive valuable insights into the relationship between demographic structural changes and automation, this study extends the model developed by Abelianisky and Prettner (2021).

In the analysis, a closed economy with three production factors is considered: human labor, traditional capital, and automated capital (e.g., robotics). Imperfect substitution is assumed between human labor and traditional capital, while perfect substitution is assumed between robotics and human labor. Population growth, traditional capital, and automated capital are subject to investment and depreciation over discrete time intervals (from *t* to *t+1*). Drawing on the classical Solow-Swan growth model, household savings s are represented as a fraction of total household income, which can be transferred to investment $s \in (0,1)$.

i. Agent of Household

The population size at time *t*, denoted as N_t, is assumed to grow at a rate of *n* over the period from *t* to *t+1*. The population in the next period *t+1* follows

$$N_{t+1} = (1+n)N_t \quad (4.1.1-1)$$

[36] The "life-cycle hypothesis" (LCH) is discussed in Ando & Modigliani (1963) and Jappelli & Modigliani (1998).

As mentioned previously, the population growth rate, denoted as n, decreases over time according to the Demographic Transition Model (DTM). In simplified frameworks, it is commonly assumed that the labor force, denoted as L_t is equivalent to the population size N_t, and it also declines in line with the decrease in population growth rate n. However, this assumption will be later in the later exercise.

Assuming that the national income at time t denoted as Y_t, and domestic saving in period $t+1$ is expressed as S_{t+1}, then

$$S_{t+1} = sY_t$$

where s represents the saving rate. The saving is allocated in two forms: traditional capital and robotics. Under the assumption of indifferent preference, the rate of return for both types of investment is assumed to be identical.

ii. *Agent of Firms*

In line with the approach proposed by Prettner (2019, 2020), this paper extends the Cobb-Douglas production function to incorporate automated capital as a perfect substitute for human workers. Thus, the aggregate output or national income is represented by

$$Y_t = AK_t^{\alpha} (L_t + P_t)^{1-\alpha} \quad (4.1.1-2)$$

K_t represents the level of traditional capital and P_t represents the level of automated capital. The elasticity of output with respect to traditional capital is given by α, where $\alpha \in (0, 1)$. The total function productivity (TFP) A is omitted for simplicity, while this does not alter the central idea of the theory. Thus, the marginal rates of return for human L, capital K, and robots P can be expressed as

$$w_t = (1-\alpha)\left(\frac{K_t}{L_t+P_t}\right)^{\alpha} \quad (4.1.1 - 3)$$

$$R_{t+1}^{autom} = (1-\alpha)\left(\frac{K_t}{L_t+P_t}\right)^{\alpha} \quad (4.1.1 - 4)$$

$$R_{t+1}^{trad} = (1-\alpha)\left(\frac{K_t}{L_t+P_t}\right)^{\alpha} \quad (4.1.1 - 5)$$

In a market-clearing equilibrium condition under perfect market competition, a equivalent constraint of the marginal wage rate of human w_t, the interest rate of robots R_{t+1}^{autom}, and the interest rate of capital R_{t+1}^{trad} is established, that is, so that $w_t = R_{t+1}^{autom} = R_{t+1}^{trad}$. As a result, P_t can be derived by solving the equation

$$Pt = \frac{1-\alpha}{\alpha} Kt \; - Lt \quad (4.1.1-6)$$

and

$$Kt = \frac{\alpha}{1-\alpha}(Pt \; + Lt) \quad (4.1.1-7)$$

These expressions can be used to rearrange the aggregate production function (4.1.1 - 2).

$$Y_{t=}\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}(Pt \; + Lt) \quad (4.1.1-8)$$

The significance of equations (4.1.2-8) is evident. In contrast to the Solow (1956), which assumes economic convergence to a steady state without technological progress *A*, the introduction of robotics *P* leads to sustained long-term growth as long as the accumulation of automation capital is positive and sustainable.

iii. <u>*Demographic Dynamics and Robotics*</u>

The investment in a closed economy at time *t*, denoted as I_t, is equal to the savings rate $s \in (0, 1)$ multiplied by the national income Y_t, expressed as $I_t = S_t = sY_t$. This investment will be allocated to the accumulation of two forms of capital in the next period $t+1$.

$$K_{t+1} \; + \; P_{t+1} \; = \; sY_t \quad (4.1.1-9)$$

By substituting equation (4.1.2-7) for K_{t+1} and equation (4.1.2-8) for Y_t, it can be derived that robot density per human worker/person p_{t+1} in the next period $t+1$, given $Lt \equiv Nt$:

$$p_{t+1} = s(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}\frac{1+p_t}{1+n} - \alpha \quad (4.1.1-10)$$

Assuming all else equal, the robot's density per person p_{t+1} is affected by parameters including the population growth rate *n* and the national saving rate *s*. Optimal behaviour of all agents will lead to the general equilibrium result, suggesting that a higher density of robots can be achieved by the decline in the population growth rate and raises in the saving rate.

iv. *Accounting Identity between Saving and Demographic Structure*

A decomposition of the saving rate *s*, which denotes the proportion of national income Y allocated to aggregate savings *S*, will lead to

$$s = \frac{S}{Y} = \frac{S}{Y} * \frac{WAP}{N} * \frac{N}{L} * \frac{L}{WAP} = \frac{\frac{S}{N}}{\frac{Y}{L}} * \frac{WAP}{N} * \frac{L}{WAP} = \frac{S}{N} * \frac{WAP}{N} * \frac{L}{WAP} \div \left(\frac{Y}{L}\right) \quad (4.1.1 - 11)$$

For simplicity, the average saving per capita $\frac{S}{N}$ is denoted as δ, the proportion of working age population in total population $\frac{WAP}{N}$ is denoted as θ, labor participation ratio $\frac{L}{WAP}$ is denoted as l, and the labor productivity $\frac{Y}{L}$ is denoted as y, respectively.

Given that the total population *N* is the sum of the working-age population (*WAP*) and the dependent population (*DEP*), where *DEP* comprises children (*CHLD*) and old-age dependents (*OLD*), it is apparent that *N* = *WAP* + *DEP* = *WAP* + *CHLD* + *OLD*. Therefore, θ is governed by

$$\theta = \frac{WAP}{N} = \frac{WAP}{WAP + DEP} = \frac{1}{1 + \frac{DEP}{WAP}} = (1 + \frac{DEP}{WAP})^{-1} \quad (4.1.1 - 12)$$

the logarithm transformation of (4.1.2 - 12) is equivalent to

$$ln(\theta) = -ln\left(1 + \frac{DEP}{WAP}\right) \quad (4.1.1 - 13)$$

In economics, equation (4.1.1-13) suggests that the growth rate of the proportion of working-age population θ is equivalent to the negative growth rate of (1+TDR), where TDR represents the total dependency ratio of a country.

By applying the logarithm transformation[37] to equation (4.1.1-13), the identity equation (4.1.1-11) of *s* can be expressed as follows:

$$ln(s) = ln(\delta) + ln(l) + \ln(\theta) - ln(y)$$
$$= ln(\delta) + ln(l) - ln(y) - ln(1 + OADR + CDR) \quad (4.1.1-14)$$

Where OADR represents the old-age support ratio, and CDR represents the child dependency ratio of a country, respectively. It is evident that a country's demographic structure, namely *OADR* and *CDR*, are endogenous in determining the saving ratio s. A higher TDR is associated with a lower saving ratio, *ceteris paribus.*

v. <u>*Saving Mechanism between Demographic Structural and Robots Density*</u>

By substituting equation (4.1.1 - 11) into equation (4.1.1 - 10):

$$p_{t+1} = \delta_t \theta_t \frac{l_t}{1+n}(1-\alpha) - \alpha \ (4.1.1-15)$$

Ceteris paribus, this equation (4.1.2-15) demonstrates that a higher robot's density in period *t+1* is influenced by multiple factors: a negative association with population growth rate *n*, a positive association with proportion of working-age population θ, a positive association with labour force participation ratio *l* (if $L_t \neq N_t$), and a positive association average saving per capita δ.

It suggests that demographic structural changes drive the growth in robot's density, depending on several covariates, including population growth rate *n*, average saving level of a country, and labour market performance. More importantly, demographic structural changes influence the growth in robot's density through the mechanism of saving. These theoretical insights can be summarized as follows.

[37] The application of logarithm transformation in economic analysis offers several advantages. Firstly, it facilitates the conversion of non-linear functions, such as equation (10), into linear forms, simplifying parameter estimation. Additionally, logarithmic transformations provide meaningful economic interpretations, such as elasticity, which measures the sensitivity of a dependent variable (Y) to a percentage change in an independent variable (X) (Wooldridge, 2015). Moreover, employing logarithms can help address heteroscedasticity in the data, enhancing the reliability of statistical analysis (Nau, 2019).

Proposition. *In a closed economy characterized by equation (4.1.2 - 8), under perfect market competition, investments derived from domestic savings are allocated equally between traditional capital K and automation capital (robotics) P.*

1. *Ceteris paribus, a lower population growth rate (n) at period t contributes to a faster growth in robot's density*
2. *Ceteris paribus, a higher working-age population share (θ) or a lower TDR at period t leads to a faster growth in robot's density*
3. *Ceteris paribus, the national saving rate (s) mediates the growth in robot's density, and a higher saving rate is associated with a faster increase in robot's density.*

Proof 1. By taking the derivative of equation (4.1.2-15) with respect to the population growth rate n

$$\frac{\partial_{P_{t+1}}}{\partial n} = -\frac{\delta_t \theta_t l_t}{(1+n)^2}(1-\alpha) < 0$$

It indicates that a higher population growth rate *n* is associated with a decrease in robot's density in *t+1*.

Proof 2. By taking the derivative of equation (4.1.2-15) with respect to the population growth rate θ

$$\frac{\partial_{P_{t+1}}}{\partial \theta} = \frac{\delta_t l_t}{(1+n)}(1-\alpha) > 0$$

It indicates that an increase in the proportion of working-age population θ is positively associated with the growth in robot's density in *t+1*, if $l \in (0,1), n > -1, and\ \delta > 0$. That is, a lower dependency ratio *TDR* negatively associated with the robot's density in *t+1* as shown in (4.1.2-13).

Proof 3. By taking the derivative of equation (4.1.2-15) with respect to the population growth rate P_{t+1}

$$\frac{\partial_{P_{t+1}}}{\partial P_t} = s(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}$$

It indicates that the growth in the robot's density from period t to $t+1$ is influenced by the saving rate s. Although there is no predetermined expectation on their correlation, it is generally expected to be positive, given that the national saving rate s in many countries is equal to or greater than 0.

4.1.2 The Indirect Mechanism Through Human Capital

The second demographic dividends mechanism through human capital proposed by Lee and Mason (2016) originates from the Quality-Quantity Theory. The theory suggests that as fertility decreases in the context of demographic transition, parents tend to invest more in the health and education of each child.

i. Quality-Quantity Theory

- Theoretical Foundations

Specifically, the theory was originally proposed by Becker (1960) and Becker and Lewis (1973). They argued that as the relative benefits of child quality increased, parents prioritized investing in the quality of their children over having a larger number of children. Moreover, Becker and Lewis posited that the income elasticity of child quality was sufficiently high, leading to a decrease in quantity but an increase in income levels. Barro and Becker (1989) expanded on this theory by considering the interplay between child quality and quantity when analyzing changes in fertility rates. Conditioning on two types of costs: child-rearing costs not involving human capital and expenditures that raises its human capital, they emphasized that due to a stronger sense of altruism between parents and children, a higher population growth rate will negatively impact the growth rate of income per capita. Research has provided further insights into the relationship between educational attainment and fertility choices, indicating that as the educational attainment of parents, especially women, increases, the opportunity cost of having children also rises. This in turn can incentivize parents to have fewer children or delay their decision to have children (Galor 1999; Galor and Weil 2000). Prettner et al. (2013) examined the interaction between quantity and quality of children in the family budget constraint. They find that as income increases, expenditures on child quality rise while the number of children decreases, suggesting the income effect on both the rise in quality and the decline in quantity. Lee and

Mason (2016) built upon the previous work of Becker (1991) but specifically distinguished between parental expenditures on health and education per child as human capital investment and the other types of spending on children, such as food and clothing consumption, predicting that increasing income effect would lead to lower fertility and higher quality of children. Empirical evidences support the notion that as incomes increase, families tend to opt for having fewer children but investing more in their education. This behavior implies that parents have a higher elasticity of demand for the quality of children, prioritizing their education, compared to the quantity of children (i.e., Wang & Zhang, 2018).

- Empirical Evidence

In addition to theoretical discussion, empirical evidence both at the macro and micro levels consistently demonstrate a strong link between women's education and lower fertility rates.

Examining trends at the societal (macro-) level, it has been found that higher education of women is associated with lower fertility rates. For instance, Becker, Cinnirella, and Woessmann (2013) controlled for various factors and utilized instrumental-variable techniques and suggested a causal relationship between education and fertility on historical data from Prussia in the 19th century (Becker, Cinnirella, and Woessmann, 2013). Another study from Fabrice Murtin empirically investigated main drivers for the reduction of the number of children per women for a few countries from 1870 to 2000, and it was found that improving education is the main socioeconomic determinant of the demographic transition (Murtin, 2013).

Micro studies, which focuses on individual-level data, provided further support to build the causal relationship between fertility and education, rather than a correlation. For instance, Duflo, Kremer, and Dupas (2015) employed a large RCT (Randomized Control Trial) evaluation in western Kenya, and their study found that subsidies to education had a significant impact on reducing the rate of pregnancies in adolescent girls (Duflo, Kremer, and Dupas, 2015). Another study in Kenya focusing on the primary education policy change by one-year extension from 1985 onwards found that the additional education provided to women resulted in a reduction in the number of children (Luke Chicoine, 2012) Other empirical studies in Indonesia (i.e., Brievora and Duflo, 2004) and Nigeria (i.e., Osili

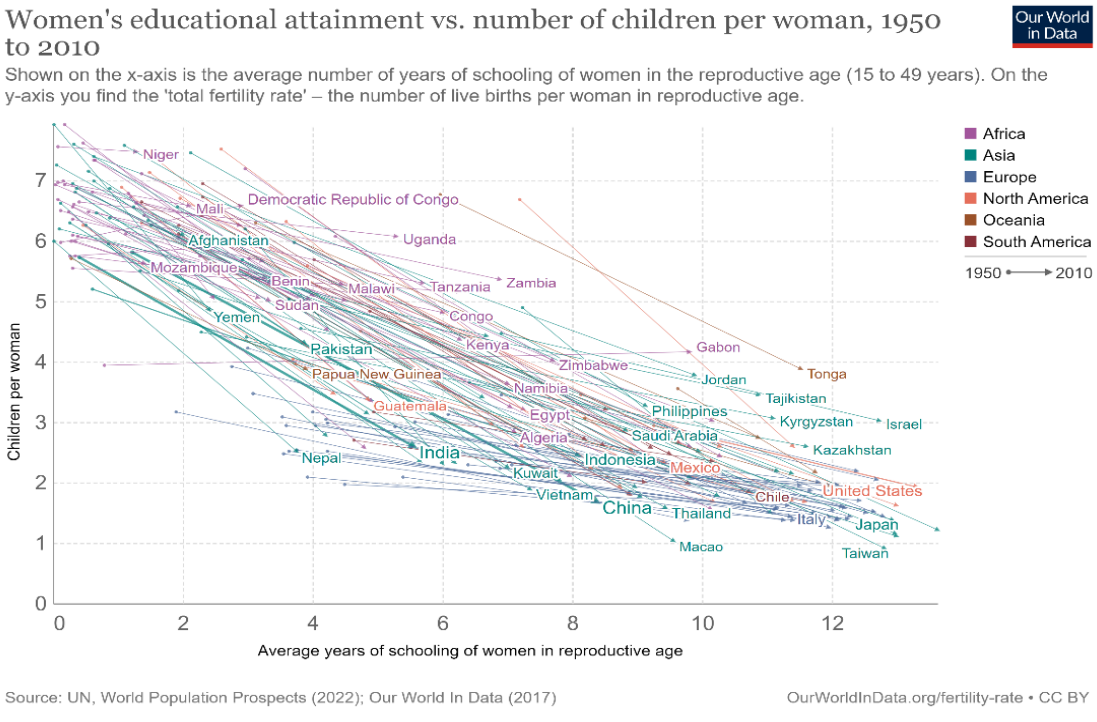
and Long, 2008) equally found that an increase of women's education reduces early fertility.

The evidence from both macro and micro studies is compelling and suggests that increasing education plays a crucial role in reducing fertility rates.

- Data Evidence

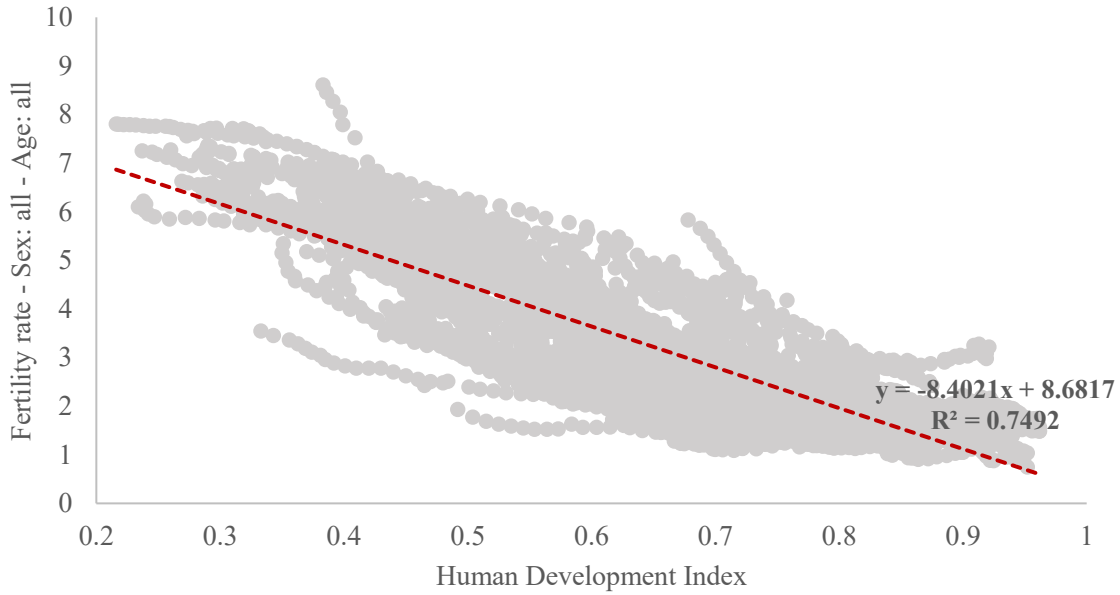
Data can also provide visual evidence of the negative association between increases in women's education and decreases in fertility rates across different countries and over time. By examining UN data spanning from 1950 to 2010, a clear negative relationship between women's education and fertility rates can be observed (Figure 4.1.2A). Back in the 1950s, when women had less than 2 years of education, the fertility rate was high, ranging between 5 and 8 children per woman. However, women's education had significantly improved after 60 years, with many countries having 8 or more years of education on average in 2010. Consistent to previous discussions, the upward changes in women's education level are associated with a downward change in the number of children per women.

Figure 4.1.2A: Increasing Female's Education Attainment and Falling Fertility



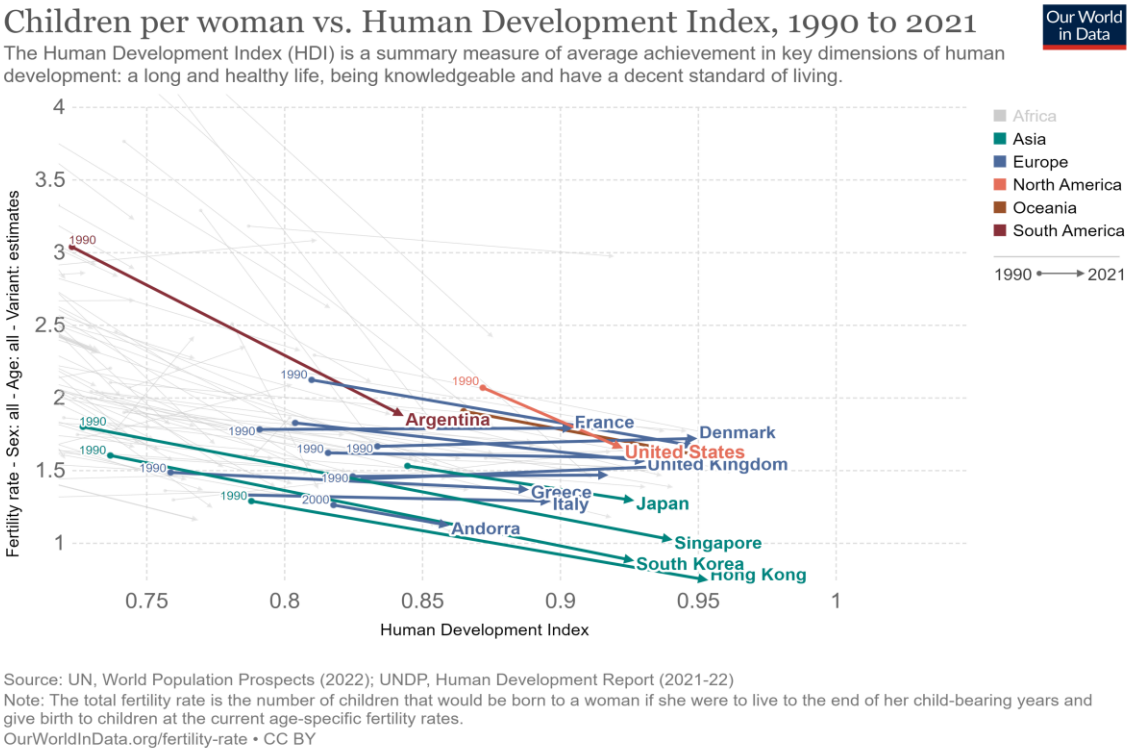
Source: Our World in Data based on UN World Population Prospects (2017)

Figure 4.1.2B: Negative Association between Fertility Rate and Human Capital Development (Pooled Countries Over 1990 to 2021)



Source: UN World Population Prospects 2022

Figure 4.1.2C: Changes in Fertility Rate in Selected High Human Developed Countries



Source: Our World in Data based on UN World Population Prospects 2022

Indeed, not only women's education but also the overall human capital level of a nation, as often measured by World Bank Human Capital Index (HCI), also reveals a similar negative relationship with fertility rates. Analysis of UN data from 1990 to 2021 demonstrates a clear and significant negative association between the HCI and fertility rates (Figure 4.1.2B). This cross-sectional analysis, encompassing all countries across different years, demonstrates that as human capital improves, there would be a corresponding decrease in fertility rates.

In addition, when focusing on countries that have achieved a very high level of human capital development, typically indicated by an HCI above 0.85, a consistent association between higher development and declining fertility rates can also be observed over time. Specifically, using the same dataset while limiting the analysis to countries that reached an HCI above 0.85 during the past few decades, it becomes apparent that improvements in human capital, starting from the initial year in 1990 and progressing until the end year in 2021, have predominantly led to a substantial decline in fertility rate (Figure 4.1.2C). This reinforces the existence of Quality-Quantity Theory.

These previous discussions have provided a comprehensive overview of the fundamental Quality-Quantity Trade-off theory for the second demographic dividend. Through discussions on its theoretical development, empirical evidence, and data interpretations, it can be consistently concluded that there exists a strong negative correlation between the improvement of human capital and the reduction of fertility. This finding reinforces the inspiration that in the context of low-fertility post-demographic transition dynamics, investments in human capital- such as enhancing the quality of the labour force through education and skill development, may play a crucial role in mitigating the shortage of labour quantity.

ii. Human Capital and Technological Advancements

Next, does human capital truly contribute to technological advancements? With previous theoretical foundations and empirical evidence in quantity-quality tradeoff, the following tends to delve in the interplay between human capital and technological advancements by following Nelson and Phelps (1966). According to their model, technological advancements are influenced by two factors. Firstly, the larger the technological gap

between a region and the global technological frontier, the faster the rate of technological progress (i.e., later-come advantage). Secondly, the level of human capital in a country affects its ability to learn, absorb, and assimilate cutting-edge technologies. Therefore, higher levels of human capital enable a country to better adopt and implement world-leading technologies, leading to faster technological progress.

The model assumes the existence of two technology levels for the frontier country and later-come country respectively. For the later-comer countries, the productivity level of leading countries is exogenously determined at $A_m(t)$, to distinguish it from another type of technology level that put in practice in later-comer countries $A(t)$, where $A_m(t) > A(t)$.

Firstly, it is assumed that the level of technology in frontier countries is denoted as $A_m(t)$, and it follows an exponential growth pattern with an exogenous growth rate of λ, where hypothetically λ>0. Therefore, it can be derived that:

$$A_m(t) = A_m(0)e^{\lambda t} \quad (4.1.2\text{-}15)$$

Assuming the technological level of the later-comer country is denoted as:

$$A(t) = A_m\big(t - \omega(H)\big) \qquad (4.1.2\text{-}16)$$

where $\omega(H)$ represents the time lag for the diffusion of world frontier technology from the technological frontier country to the later-comer country, and H represents the level of human capital in the later-comer country. When $\omega'(H) < 0$, meaning a higher level of human capital, the time lag for technology diffusion will be reduced. By substituting equation (4.1.2-16) into equation (4.1.2-15), it can be derived:

$$A(t) = A_m(0)e^{\lambda(t-\omega(H))} \qquad (4.1.2\text{-}17)$$

The derivative of equation (4.1.2-17) with respect to H yields

$$\frac{\partial A(t)}{\partial H} = -\lambda\omega'(H)A_m(0)e^{\lambda(t-\omega(H))} = -\lambda\omega'(H)A_m(t) \qquad (4.1.2\text{-}18)$$

Given $\omega'(H) < 0$, so that $\frac{\partial A(t)}{\partial H} > 0$. It suggests a positive relationship between human capital and the technology level of the catching-up country. In other words, a higher level of human capital leads to faster technological progress and technological advancements.

Subsequentially, it is assumed that the technology level of the later-comer country is determined by its human capital level *(H)* and the technology gap between the country and the world technological frontier in $A_m(t) / A_i(t)$.

Such that the growth rate of technology level in the later-comer country is determined by

$$\frac{\dot{A_i}(t)}{A_i(t)} = C(H_i)\left[\frac{A_m(t) - A_i(t)}{A_i(t)}\right] \qquad (4.1.2\text{-}19)$$

where $C(H_i)$ represents the technology catching rate of the technological later-comer country, and H_i represents the human capital stock level of country/region *i*, satisfying the condition that $C(0) = 0, and\ c'(H_i) > 0$.

By substituting equation (4.1.2-16) and (4.1.2-15) into equation (4.1.2-19), it can be derived:

$$\dot{A_i}(t) = C(H_i)\left[A_m(0)e^{\lambda t} - A_m(0)e^{\lambda(t-\omega(H))}\right] \qquad (4.1.2\text{-}20)$$

It becomes evident that, firstly, a higher level of human capital stock in a country leads to a faster speed of catching up to the world technology frontier, resulting in faster growth of technological advancements. Secondly, the growth rate of technological advancements in a country is positively related to the technology level gap between the later-comer country and the world technology frontier.

A larger technology gap provides the technology-catching countries with a wider range of options for learning and imitation, increasing the likelihood of leveraging its latecomer advantage to achieve greater technology imitation benefits. The concept of

"latecomer advantage" or "advantage of backwardness" has been extensively studied in the literature (Gerschenkron, 1962; Lin, 2003; Lin, 2018), suggesting that countries that start industrialization later can experience accelerated growth by rapidly adopting modern institutional arrangements, efficient capital allocation, technology transfer, and best practices from advanced economies. This phenomenon helps explain the occurrence of conditional convergence, where countries catch up with early industrialization leaders at a faster pace.

4.2. ANALYTICAL FRAMEWORK

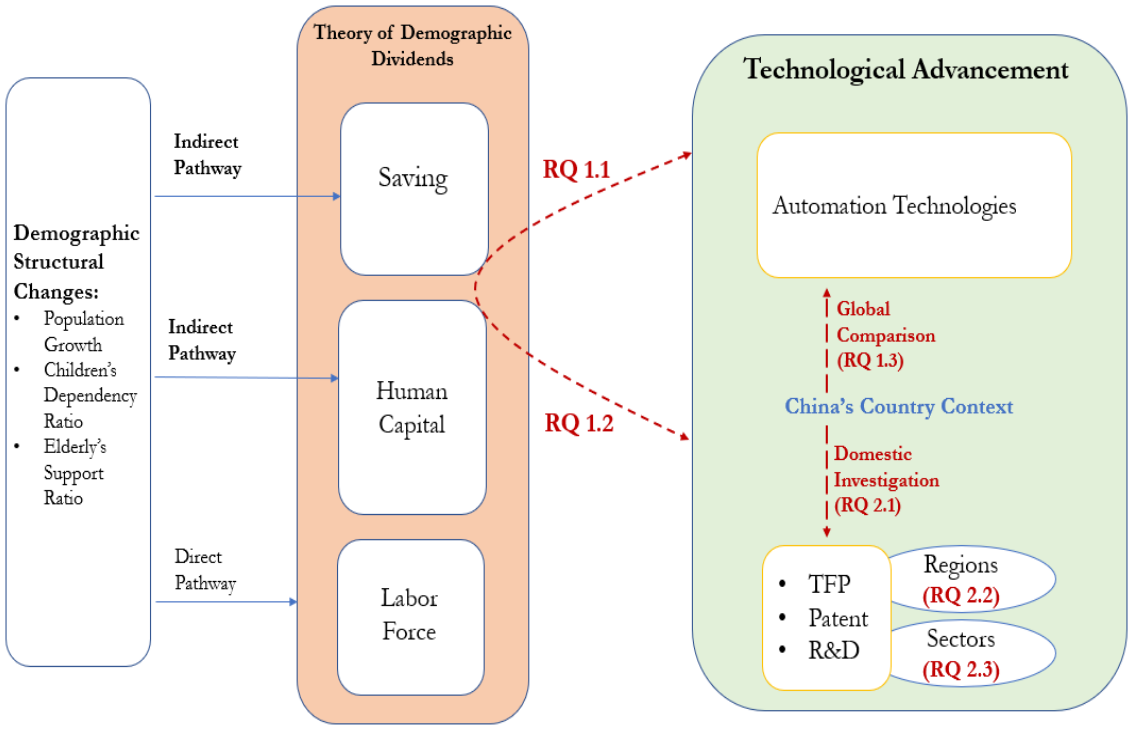
Previous research on the societal implications of demographic structural changes has primarily focused on labor inputs, capital inputs, and overall economic development using the classical Cobb-Douglas Production function (i.e., Solow, 1957; Mankiw, Romer, and Weil, 1992). However, as discussed earlier, demographic structural changes can also have implicit implications through the mechanism of the second demographic dividend, namely saving and human capital investment (Lee and Mason, 2016). Given that factors such as capital formation, R&D investment, education, human capital investment can impact technological development, this section aims to examine whether demographic structural changes can play a significant role in influencing technological development. Additionally, the section seeks to explore the pathways of the second demographic dividend and establish theoretical mechanisms to bridge demographic structural changes to technological development outcomes.

The analytical framework in Figure 4.2 below is built upon the previous discussions from literature review of the second demographic dividends theory, and efforts in the theoretical extension in its dual channels through saving and education.

First, demographic structural changes refer to shifts and transformations in the composition and characteristics of a population over time. These changes typically involve variations in the size, distribution, age, and gender structure of a population. It has a multifaceted nature, manifesting a joint effect of age-specific dynamics such as changes in child dependency ratio and old-age support ratio. In the post-demographic transition stage, it is characterized by raises in old-age support ratio (the proportion of elderly individuals

in the population is rising) and declines in child dependency ratio (the proportion of children in the population is falling) in parallel, that attributed to a set of societal and behavioral changes such as increased longer life expectancy and population ageing, decreased fertility rates and mortality rates, shifts in the geographic distribution of populations, improved access to contraception, changes in family size and composition, and increased women's participation in the labor force (Lesthaeghe, 2010). Demographic structural changes can have significant social, economic, and political implications, as they can impact labor force dynamics, public systems, family structures, behaviors, and overall societal well-being. Understanding these dynamics is crucial for policymakers and societies to anticipate and address the implications of demographic shifts. Therefore, this study focuses on the declines in the child-dependency ratio and raises in the old-age support ratio, while considering the deceleration of population growth rate, and analyze its impact on technological advancements.

Figure 4.2: An Illustration of the Analytical Framework



Source: Created by author based on Lee and Mason (2016), Mankiw, Romer and Weil (1992), and Égert et al, (2019)

Secondly, according to the demographic dividends theory (DDT), when fertility and mortality levels experience long-term changes, it leads to a transformation in the age distribution of the population, involving a shift from a more children and fewer elderly to less children and more elderly. Such changes in the age structure can contribute to a conducive environment for economic development through multiple mechanisms. The first pathway of the demographic dividend arises from the faster growth of the labor force compared to the dependent population during the initial stages of the demographic transition.

Meanwhile, there are indirect consequences happening in the later demographic transition stages as well, so-called the second dividend. There are two primary pathways, namely saving and human capital. Firstly, as the working-age population reaches maturity, the expectation of retirement becomes a significant incentive for individuals to save in preparation for their post-retirement financial needs. This increased savings can create a pool of funds that can be directed towards productive investments. Secondly, as fertility declines, the decrease in the youth dependency ratio allows for more resources allocated towards investment in human capital, such as education and skills training, which in turn boosts the productivity in a longer-term (Lee and Mason, 2006).

However, there are ongoing debate and uncertainties surrounding the extent to which the second demographic dividends can directly boost technological advancements. For instance, Bloom, Canning, and Sevilla (2003) found that improvements in health and education, which are key components of the second demographic dividend, leading to a positive impact on technological advancements and economic growth. However, the study also noted that the relationship between demographic transition and technological advancements is complex and influenced by various factors. Lee and Mason (2011) also acknowledged the need for supportive policies and institutions to fully realize these dividends. In addition, Bongaarts (2017) discussed the demographic transition in Africa and highlighted that while declining fertility rates in Africa can create a demographic dividends opportunity into economic benefits, including technological advancements, but it depends on a range of context-dependent factors such as investments in education, healthcare, and infrastructure. Therefore, these studies highlighted further research and

analysis are needed to understand the specific mechanisms and context-specific conditions to facilitate the translation of demographic dividends into technological advancements.

Against this backdrop, the study presents two sets of research questions. Research Questions 1.1 and 1.2 are designed to explore the broader connections between demographic structural changes and their effects on savings and human capital, respectively, within a global context. Research Question 1.3 directs attention towards assessing the implications of demographic structural changes by considering the diversity of country contexts, specifically comparing China with the rest of the world and other similar country groups. Moving forward, Research Questions 2 delves into the specific context of China and investigates two indirect mechanisms of the demographic dividends in 2.1, followed by examinations on regional and sectoral heterogeneities considering the diverse and abundant nature of China's population in 2.2 and 2.3 respectively.

4.3. HYPOTHESES

This section introduces hypotheses formulated in accordance with research questions outlined in Chapter 1 of the study. The hypotheses can be categorized into two main designs, each consisting of three sub-hypotheses. The first design, hypotheses 1.1 to 1.3, examines the implications of demographic structural changes on technological advancements at the global context, where technological advancement is proxied by the adoption of automation robots. The second design, hypotheses 2.1 to 2.3, investigates implications of demographic structural changes on technological advancements in the context of China, where technological advancements are proxied by various other indicators (i.e., the estimated TFP, number of patent applications, and R&D expenditures) due to the constrain of data availabilities. A comprehensive discussion of these hypotheses is provided below.

Hypothesis 1.1: Demographic structural changes driven by different age-specific dynamics have varying effects on the growth in robots' density while depending on the saving ratio.

Hypothesis 1.1 is created based on findings involving the relationship between child dependency ratio, old-age support ratio, saving, and technological progress. Numerous empirical studies have examined the relationship between demographic changes and economic outcomes including technological progresses, and they often find that demographic changes have significant positive implications (i.e., Bloom, Canning, & Fink, 2010; Galor, 2005; Acemoglu & Restrepo, 2017; Acemoglu & Restrepo, 2021).

However, studies also highlighted that the implications are complex and context contingent, being influencing by various factors (Bloom, Canning, and Sevilla, 2003; Lee and Mason, 2011; Bongaarts, 2017). One important factor that cannot be neglected is the age-specific dynamics, including two paralleled trends, namely decreases in the child-support ratio and increases in the old-age support ratio.

Earlier studies have widely agreed upon a negative relationship between child dependency ratio and saving through the life-cycle hypothesis theoretical framework (i.e., Mason, 1988; Modigliani & Cao, 2004). Empirically, Kelley and Schmidt (1996) found a positive relationship between low-child fertility rates and saving rates, and they also noted that the relationship is stronger in countries with high levels of dependency (i.e., a large proportion of the population that is not of working age). The results have been supported by other macroeconomic evidence (i.e., Fry and Mason 1982; Mason, 1988), microeconomic evidence found across countries (i.e., Loayza et al., 2000; Hyung, 2013; Gudmundsson & Zoega, 2014), and even in different individual countries such as China (Joe, Dash, and Agrawal, 2015), India (Jain & Goli, 2022), East Asia (Lee, Mason, and Miller, 1997), and the European countries (Tuğba & Yavuzaslan, 2019).

Nevertheless, existing studies and extensive empirical evidence hold different views on the relationship between old-age support ratio and saving. For instance, the IMF (2004) using a panel of 115 countries found a strong negative impact of the elderly dependency ratio on saving and the current account balance. Luhrmann (2003) and Helliwell (2004) also supported that the adult dependency ratio tended to worsen current accounts. This effect is also found in high-income countries like OECD (Xiong, Celebi, and Welfens, 2022). However, the significant effect was not found in Hyung (2013) using a 15 high-income countries' data from 1975 to 2010. Similarly, Ong (2022) could not find

profound negative effects of population aging on aggregate saving in ASEAN countries. In contrast, Lee and Mason (2011) in their study across 23 developed and developing countries found that population aging could lead to increased demand for financial assets, which can further support the saving rates.

In this context, the hypothesis is proposed based on the notion that the effects of different age groups on saving can vary, such that it leads to various technological development outcomes.

Hypothesis 1.2: Demographic structural changes driven by different age-specific dynamics have varying effects on the growth in robots' density while depending on the level of human capital.

Likewise, hypothesis 1.2 is created based on findings involving the relationship between child dependency ratio, old-age support ratio, and technological progress, but through the lens of human capital.

From the child dependency perspective that driven by the lower fertility rate, a substantial body of research supports a significantly negative association between fertility and human capital, both in theoretical and empirical contexts. The theoretical aspect is supported by classic studies such as Becker and Lewis (1973) and Lee and Mason (2011), arguing that parents with fewer children can invest more resources in each child, leading to higher levels of human capital. Empirical analysis using various indicators further confirms this relationship. Cigno and Rosati (2002) and Bloom and Canning (2003) provided empirical evidence of the positive relationship between low-child fertility rates and human capital in Egypt and Ireland respectively. There are many other studies that provide consistent directions but different dimensions such as education and training by Shiue (2017) and Murphy at al. (2008), health by Liu and Liu (2019), life expectancy at birth by Cervellati and Sunde (2015).

However, ongoing discussions have raised complicated pictures between old age and human capital. For instance, Bloom, Canning, and Fink (2010) argued that population aging can have both positive and negative effects on human capital. On the one hand, older

workers might have more experience and knowledge, which can contribute to higher levels of human capital. On the other hand, an aging population might lead to a decline in the size of the workforce, which can limit opportunities for human capital development. This argument is further supported by Lee & Mason (2014). Specifically, OECD (2018) highlighted the negative effect on human capital in Japan, noting that its aging population in Japan had led to limited opportunities for human capital development. A study in the United States noted that older workers may face age discrimination and have difficulty accessing training and education opportunities (OECD, 2019). In contrast, Day and Dowrick (2004) argued that the replacement of older less-educated workers by the younger and more educated workers leads to higher human capital level of the country. Fougère & Mérette (1999; 2009) and Han and Lee (2020) had identified the positive relationship between population ageing, human capital, and productivity in OECD, Canada, and Korea respectively.

On this basis, the hypothesis is formulated based on the understanding that the impact of different age groups on human capital can vary, which in turn influences technological development outcomes.

Hypothesis 1.3: Demographic structural changes have varying effects on the growth in robots' density, but the effects are more significant in China compared to the global average.

Hypothesis 1.3 stems from the understanding that demographic structural changes, particularly those related to child dependency ratio and old-age support ratio, can have varying effects on various factors and, consequently, technological advancements (Bloom, Canning, and Sevilla, 2003; Lee and Mason, 2011; Bongaarts, 2017).

As inspired by the theory outlined in *Proof 1-3,* many factors may play a role in the adoption of robotic technologies such as population growth rate, the saving rate, economic conditions etc. Not only demographic factors, but China also has its own individual country characteristics in many aspects when compared to other countries, including its the population size, economic growth rate, savings rate, and social and institutional

infrastructures for the development of technologies. Given the unique demographic dynamics and context in China, it is anticipated that these differences will manifest in the level and pace of technological advancements compared to other countries around the world. Confirmative findings can also be found in relevant studies. For instance, Huang & Khanna (2018) highlighted that there are significant differences between China and the world in terms of technological advancements.

Therefore, it is hypothesized that there will be significant differences in technological advancements between China and the rest of the world.

Hypothesis 2.1: Demographic structural changes driven by age-specific dynamics have varying effects on the growth in technological advancements while depending on the saving ratio and human capital.

Hypothesis 2.1 is built upon the hypotheses 1.1 and 1.2, in considering that child dependency ratio and old-age support ratio can have varying effects on both saving and human capital accumulation and, consequently, technological advancements.

In addition, this hypothesis is also derived from a number of earlier studies in the context of China. For instance, Chen & Feng (2019), Li & Zhang (2018), and Zhang & Wang (2019) found that demographic changes, such as an aging population and a decline in the working-age population, have a negative impact on TFP. On the other hand, Li and Zhao (2021) noted an inverted "U" shape between the birth rate on productivity: that is, too low or too high birth rates would reduce human capital. Li and Zhao (2019) found that population aging in China has a significant long-term impact on technological innovation but not in short-term, whereas there is a notable nonlinear causal effect between the child dependency ratio and technological innovation in the short term.

This hypothesis is then formulated based on the understanding that the impact of different age groups on saving and human capital can vary, resulting in diverse outcomes in technological development.

Hypothesis 2.2: Significant heterogeneities are found across provinces, and demographic implications on technological advancements are more significant in regions with higher capital and human capital endowments.

Aligned with hypothesis 1.3, hypothesis 2.2 is derived from understanding that demographic structural changes, specifically fluctuations in child dependency ratio and old-age support ratio, may generate diverse influences based on multiple factors, impacting technological advancements' outcome.

China's regional heterogeneity in demographic structure, saving, and human capital is characterized by distinct patterns across different provinces and regions. For example, coastal regions such as Guangdong and Shanghai generally have lower fertility rates, higher proportions of working-age population, and higher levels of economic development. In contrast, western and northeastern regions like Xinjiang and Liaoning face challenges of aging populations and lower levels of human capital investment. Moreover, there are regional disparities in saving rates, with affluent regions like Beijing and Zhejiang exhibiting higher saving rates compared to less developed regions. These variations in demographic structure, saving behavior, and human capital development contribute to regional disparities in economic growth, productivity, and overall development within China.

This hypothesis is also inspired by previous studies. For instance, Wei and Hao (2011) highlighted that the impact of human capital on TFP varies across regions in China, depending on the level of schooling. In the eastern region, secondary education has a significant effect on productivity growth. In the central region, primary and university education play a major role in promoting total factor productivity (TFP) growth. On the other hand, in the western region, primary education stands out as the most influential factor. These regional differences highlight the importance of considering the specific levels of schooling when assessing the impact of human capital on economic development across China. Additional studies that offer supportive opinions include the works of Qi (2015), Dai, Li, and Lu (2017), and Zhang, Wan, Luo, and Wang (2019).

Based on this evidence, it is hypothesized that there will be notable disparities in the impacts across regions in China.

Hypothesis 2.3: Significant heterogeneities are found across sectors, and demographic implications on technological advancements are more significant in sectors with higher human capital endowments.

Similar to hypothesis 2.2, hypothesis 2.3 delves into the relationship between workforce structure, human capital, and technological advancements in the context of different industries. The hypothesis suggests that the workforce structure, which is influenced by the population's demographic structure, plays a crucial role in shaping technological advancements' outcomes (i.e., Lindh and Malmberg, 1999; Bloom, Canning, and Fink, 2010; Acemoglu and Restrepo, 2017).

China's heterogeneity across industries is evident when considering not only different levels of human capital but also variations in the workforce structure. Industries in China employ workers with varying educational backgrounds, skills, and expertise. For instance, high-tech industries typically tend to have a more knowledge-intensive workforce, requiring specialized training and advanced degrees. On the other hand, labor-intensive sectors may rely more on manual labor and basic skills. This heterogeneity emphasizes the importance of considering industry-specific workforce structures and levels of human capital when examining technological advancements and its impact across different sectors in China.

Additionally, many studies support the argument that workforce structure and human capital have significant implications on TFP in China across industries. For instance, Chen & Feng (2019) found that demographic changes, such as changes in the workforce structure and a decline in the working-age population, have a negative impact on TFP. Yet, Li & Liu (2019) and Wang & Zhang (2019) argued that human capital has a positive impact on TFP across manufacturing sectors, potentially offsetting the negative impacts brought by the workforce aging. Li (2016) also revealed that the age of the labor force significantly impacted TFP growth, with the highest contribution coming from young and middle-aged workers (40-49 years old) compared to other age groups.

Based on this evidence, it is hypothesized that there will be significant variations in the sectoral implications in China.

4.4. ESTIMATION MODELS

This section introduces the econometric methods that will be used to test the relationship between demographic structural changes and technological advancements, with a special focus on the dual indirect mechanisms through which the impact is transmitted.

The primary method employed for this purpose is mediation analysis. Mediation analysis is a statistical method used to examine the mediating effect of intermediate variables in the relationship between an independent variable and a dependent variable. In this study, mediation analysis will be utilized to explore the linkage between demographic structural changes and technological advancements through the identified dual mechanisms: saving and human capital.

Secondly, due to limitations in data availability in using robots as proxies for technological advancements in China at a granular level across different places and sectors, an alternative indicator TFP, which measure of the overall efficiency with which inputs are converted into outputs, and a few other indicators will be used instead. For the estimation of TFP in China, the data envelopment analysis (DEA) method will be employed in this study. DEA is a nonparametric technique used to estimate the efficiency and productivity of decision-making units, such as regions and sectors, based on their input-output relationships.

Finally, this section outlines the specific models that will be employed for the empirical analysis, building upon the theoretical framework presented in Section 4.1. These models will incorporate the relevant variables related to demographic structural changes, technological advancements, and the mediating indirect mechanisms identified in the study. The econometrical examinations will help examine their relationships and quantify the implications of demographic changes on technological development in China.

4.4.1 The Mediation Estimation Method: A Review

1) Methodologies

The Mediation Estimation Analysis developed by Baron and Kenny (1986) is a valuable tool for understanding the underlying pathways through which variables influence one another, allowing researchers to gain insights into the indirect effects and pathways involved in a causal relationship (Baron and Kenny, 1986). It allows us to assess whether the relationship between the independent variable (X) and the dependent variable (Y) is mediated by one or more intermediate variables, known as mediators (M). Mediation analysis examines a hypothetical causal process in which a mediating variable (M) plays a role in the relationship between an independent variable (X) and a dependent variable (Y), and it can be represented as X → M → Y.

The theory behind mediation analysis is rooted in the concept of causal pathways. It proposes that the effect of an independent variable on a dependent variable can be decomposed into two components: the direct effect, which operates independently of any mediators, and the indirect effect, which operates through one or more mediators. This approach has been extensively employed in diverse fields such as psychology, social sciences, economics, and others.

The mediation analysis requires the following three steps:

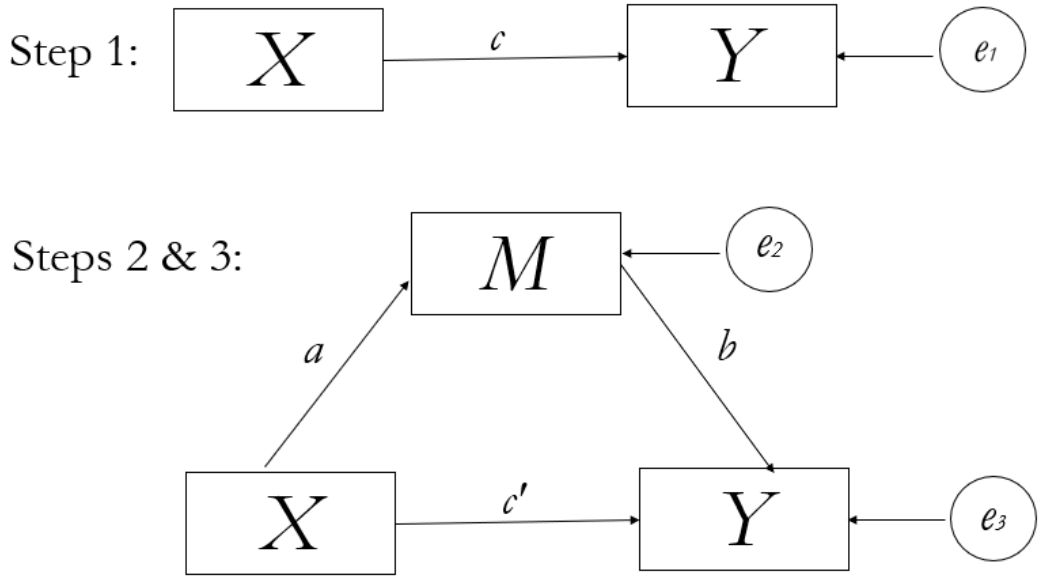
Step 1: Establish the relationship between the independent variable (X) and the dependent variable (Y). In this step, the direct relationship between X and Y is examined without considering any mediators. The association between X and Y, while controlling for any relevant covariates, can be estimated using regression analysis or other appropriate statistical techniques. The total effect of X on Y, including both the direct and indirect effects, is established through this step.

Step 2: Determine the effect of the independent variable on the mediator (M). In this step, the relationship between X and M is assessed, representing the direct effect of X on the M. The association between X and M, while controlling for covariates, can be estimated using regression analysis. Through this step, it is determined whether the mediator variable is significantly influenced by X.

Step 3: Assess the effect of the mediator on the dependent variable. This step control for the mediator variable (M) and assess the effect of X on Y. This step involves

estimating the direct effect (c') of X on Y while including M as a covariate in the analysis. Additionally, the effect of the mediator variable on the dependent variable (b) is also assessed. The combined effect of the mediator (*ab*) and the direct effect (c') represents the total effect of X on Y. All these parameters can be estimated using regression analysis or other appropriate methods. This step helps determine if the dependent variable is significantly affected by the mediator variable, after considering the influence of the independent variable.

Figure 4.4.1: Illustrative Diagram of The Mediation Estimation Analysis



Source: Created by author based on Baron and Kenny (1986)

The relationship between the variables X, M, and Y can be illustrated through the use of Figure 4.4.1, where the practical regression analysis is divided into two parts. In Step 1, the direct effect of the independent variable X on the dependent variable Y is demonstrated, with the path coefficient denoted as c. With no involvement of a third variable, the coefficient c represents the total effect of the independent variable on the dependent variable. In Steps 2 and 3, the relationship between the independent variable X and the dependent variable Y is examined, while controlling for the mediator variable V.

In this scenario, the mediator variable is affected by the independent variable (coefficient *a*) and in turn influences the dependent variable (coefficient *b*). Together, these

coefficients determine the indirect effect between the variables. The direct effect of the independent variable on the dependent variable, after accounting for the mediator, is represented by the coefficient c' The total effect in Step 2 & 3 is thus equal to the sum of the direct effect and the indirect effect, which can be expressed as *total effect* = $a*b + c'$. By comparing Step 1 with Step 2 and 3, the equation $a*b + c'$ is derived, where c is the total effect, c' is the direct effect, and $a*b$ is the indirect effect, also known as the mediating effect. Mediation analysis aims to examine the presence and magnitude of the $a*b$ effect and its proportion in the total effect, reflecting the significance of the mediating effect.

In summary, the stepwise approach for mediation analysis involves three steps as previously described to assess the mediating effect of a variable between an X and Y.

$$Y = cX + e_1 \cdots\cdots\cdots\cdots\cdots\cdots (1)$$

$$M = aX + e_2 \cdots\cdots\cdots\cdots\cdots\cdots (2)$$

$$Y = c'X + bM + e_3 \cdots\cdots\cdots (3)$$

If the coefficient c is significant in Step 1, the coefficient a is significant in Step 2, and the coefficient b in Step 3 is significant, then the mediating effect is considered significant. If, the above conditions are met that c in Step 1, a in Step 2, and b in Step 3 are significant, but the coefficient c' in Step 3 is not significant, it is referred to as complete mediation. Other interpretations of the results such as partial mediator and shadow mediator may also exist depending on the changes of the direction and magnitude the coefficients (i.e., Wen and Ye, 2014).

In addition to the stepwise regressions, there are also different other methods to assess mediation, including Sobel test, bootstrapping, and causal mediation analysis techniques.

- Sobel test: The Sobel test calculates a z-score to determine the significance of the indirect effect. It assumes that the product of the path coefficient between X and M and the path coefficient between M and Y follows a normal distribution. A significant z-score indicates evidence of mediation.

- Bootstrapping: Bootstrapping is a resampling technique that estimates the distribution of indirect effects by repeatedly sampling from the dataset. It generates a confidence interval around the indirect effect, allowing you to assess its significance. Bootstrapping is a more robust and flexible method compared to the Sobel test, especially when the assumptions of normality are violated.
- Causal mediation analysis: Causal mediation analysis extends traditional mediation analysis by incorporating causal assumptions and considering the presence of unmeasured confounders (i.e., Pearl, 2014). It utilizes structural equation modeling or other causal inference techniques to estimate direct and indirect effects under specified causal assumptions.

It is noteworthy that the mediation analysis is complex and Baron and Kenny's (1986) approach has limitations, and there are various considerations and potential challenges depending on the specific research context. Therefore, this study not only adopts the classical stepwise regression approach, but also Sobel test and interaction terms[38] to complement the investigations on the dual indirect mechanisms between demographic structural changes and technological advancements.

2) Results Interpretation

Mediation analysis is a statistical technique used to measure how the inclusion of a third variable alters the relationship between an independent variable and a dependent variable (MacKinnon, Krull, and Lockwood, 2000). There are mainly three types of results may be found in the tests, namely mediation, confounding, and suppression, which requires careful interpretation of the researcher. To help better understand, this section briefly illustrates their differences, and more detailed explanations can be found in MacKinnon et al. (2000).

- Mediation: Mediation refers to the process by which an independent variable affects a dependent variable through a mediator variable. It involves breaking down the relationship into a direct effect (independent variable to dependent variable) and an

[38] Conventional mediation analysis techniques are designed for scenarios involving a single independent variable X linked to a single mediator (Wen and Ye, 2014), making it difficult to ascertain the effect in a multi-covariate setting. To address this issue, introducing an interaction term between X and M allows for the exploration of a combined effect, wherein the association between the independent variable X and the outcome Y relies on the varying values of the mediation variable M.

indirect effect (independent variable to mediator variable to dependent variable). Mediation analysis helps researchers understand the causal mechanisms underlying the relationship between variables and identify the specific pathways through which the effects occur.

- Confounding: Confounding occurs when a third variable is related to both the independent and dependent variables, leading to a false distortion or accentuation of the relationship between them. Unlike mediation, confounding does not imply a causal relationship but rather suggests that the third variable explains the observed association. Researchers need to account for confounding variables to obtain accurate estimates of the independent variable's true effect on the dependent variable.
- Suppression: Suppression refers to a scenario where the addition of a third variable in the analysis amplifies the link between the independent and dependent variables. This phenomenon arises when the third variable functions as a suppressor, boosting the predictive accuracy of the relationship by unveiling a more robust association. Suppression effects can be identified when the addition of the third variable leads to a change in the magnitude or direction of the relationship between the independent and dependent variables.

4.4.2 DEA-Malmquist Estimation on Total Factor Productivity (TFP)

1) Methodologies

There is no universal consensus within academia regarding the precise definition of productivity and efficiency (i.e., Vincent 1968; Lovell, 1993; Cooper, Seiford, & Tone, 2006), and there is also ongoing debate and variation regarding the best practices and techniques for its estimation. Total Factor Productivity (TFP), which captures the overall productivity and efficiency of inputs and outputs, has been extensively discussed in terms of its estimation methods and approaches, while they raised different advantages and problems (i.e., Antle, & Capalbo, 1988; Van Beveren, 2012; Li, Huang, & Drakeford, 2019).

Among many, Data Envelopment Analysis (DEA) Malmquist method is currently widely used in various fields, including economics, finance, healthcare, and environmental

studies, to assess and compare the performance and productivity of different entities over time. It provides a comprehensive framework for evaluating and benchmarking productivity change, aiding decision-making and resource allocation processes over time.

The concept of Malmquist index was first introduced by Malmquist (1953) to construct the consumer quantity index, and further developed by Caves et al. (1982) for production analysis in 1982 with the creation of Malmquist productivity index- the output-based Malmquist productivity index as the ratio of two output distance functions (Malmquist 1953; Caves et al., 1982). It became particularly crucial in the analysis of production following the introduction of the distance function and technical efficiency in relation to the Data Envelopment Analysis (DEA) method by Charnes et al. (1978). Building upon the DEA method, Färe et al. (1990, 1994) translated the Malmquist productivity index from a theoretical concept into practical applications. Ray and Desli (1997) and Grifell and Lovell (1999) proposed additional modifications to the model, introducing the concept of the generalized Malmquist index (i.e., Charnes, Cooper, and Rhodes, 1978; Färe, Grosskopf, Lovell, and Yaisawarng, 1990, 1994).

Specifically, the non-parametric DEA-Malmquist method operates under the assumption that during a given time period $t = 1,2,\cdots T$ and decision-making unit (DMU) *i, N* types of inputs $x^{t}_{i,\,n\,(n=1,\,2..N)}$ are used to generate output $y^{t}_{i,\,n\,(n=1,\,2..N)}$. When there is a consistent adjustment for scale and the input element is robust and disposable, following Shephard (1970) or Färe (1988), the output distance function of the production activities in period *s* relative to the production possibility set in period *t* can be represented as:

$$D_0^t\left(x^s, y^s\right) = \inf\left\{\theta\left(\left|x^s, y^s / \theta\right.\right) \in S^t\right\} = \sup\left(\left\{z\left(\left|x^s, zy^s / \theta\right.\right) \in S^t\right\}\right)^{-1}$$

The production is technically efficient if $D_0^t(x^s, y^s) = 1$, only if when a production point $\left(x^s, y^s\right)$ lies on the production frontier, the production is considered technically efficient. In this case, production achieves output maximization under unchanged inputs. Otherwise, it is technically inefficient if $D_0^t(x^s, y^s) < 1$.

The Malmquist index assesses the changes in productivity of a specific DMU_0 between two distinct time periods *t* and *t+1*, such that four distance functions

$D_0^t(x^t, y^t)$, $D_0^t(x^{t+1}, y^{t+1})$, $D_0^{t+1}(x^t, y^t)$, $D_0^{t+1}(x^{t+1}, y^{t+1})$ can be estimated, where the distance function $D^t(x^t, y^t)$ is the reciprocal of the C^2R model's optimal value at the production point (x, y).[39]

$$\left(C^2R\right)=\begin{cases}\max z=\left(D_c^t\left(x^{k,s},y^{k,s}\right)\right)^{-1}\\ x_n^{k,t}\geq\sum_{k=1}^{k}\lambda^{k,t},x_n^{k,t},n=1,2,...,N\\ z_c y_m^{k,t}\geq\sum_{k=1}^{k}\lambda^{k,t},y_m^{k,t},m=1,2,...,M\\ \lambda^{k,t}\geq 0,k=1,2,...,K\end{cases}$$

The Malmquist TFP index for periods *t* and *t+1* is respectively

$$M_0^t(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}$$

$$M_0^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}$$

The geometric average of the two Malmquist indices above is the Malmquist TFP index

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = [\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} * \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}]^{1/2}$$

where M_0 measures the productivity change in DMU_0 between period *t* and *t + 1*. $M_0 > 1$ indicates the progress in the total factor productivity of the DMU_0 from period *t* and *t + 1*; $M_0 = 1$ represents the status quo, indicating no change in the total factor productivity; when $M_0 < 1$, it signifies a decay in the TFP of DMU_0 from period *t* and *t + 1*, respectively.

It is noteworthy that the estimated results from DEA method represent the relative TFP indexes' change from period *t-1* to *t,* i.e.,

[39] In addition to C^2R model, DEA model also includes Farrell model, BCC models, etc. The evaluation of distance function thus will also differ (i.e., Shi, 2016). This study mainly adopts the DEA C^2R model as the basic evaluation method.

$$TFPI_{it} = \frac{TFP_{it}}{TFP_{i,t-1}}$$

Such that the relevant TFP level can be derived by

$$TFP_{it} = TFP_{it} * TFP_{i,t-1} \quad (4.4.2\text{-}1)$$

Following Van (2007), Van (2012), and Yin (2015), the TFP growth rate from period *t-1* to *t* can be estimated by[40]

$$TFPG_{it} = \ln(TFP_{it}) - \ln(TFP_{i,t-1}) \quad (4.4.2\text{-}2)$$

Moreover, although the Malmquist index can be broken down into three components: technical efficiency change, technological progress change, and scale efficiency change (as described by Banker, 1984; Fare et al., 1997, 2011), this study will primarily examine the overall changes in TFP over time in China, leaving specific decompositions apart.

2) Parameter Calibration

Research Question 2 of this study is focused on China's country context across places and production sectors, such that the estimation of TFP is based on the decision-making units (DMU) at 31 provinces of mainland China, and 90 sectors in accordance with China's *Industrial Classification for National Economic Activities in 2011*[41], respectively.

Supposing that the aggregate production function follows Hicksian-neutral technological progress

$$Y = A(t) * f(K, L) \quad (4.4.2\text{-}3)$$

where Y represents total output, $A(t)$ represents the level of technological advancements (indicated by TFP), *K* represents capital input, *L* represents labor input in the period *t*.

[40] Tian, Lu, and Jin (2017) suggested to use (TFPI-1)*100% to derive the TFPG estimation, while the difference between two methods would be minor.

[41] Details for the GB/T4754 − 2011 can be found https://www.cas.cn/ggfw/tzgg_1/201201/P020120120521186361137.pdf

It becomes evident that the estimation of $A(t)$ requires the data inputs of output Y, capital input K, and labor input L, respectively.

i. *Output Data Y*

This study uses real GDP of provinces (and sectors) as the output value, and it is derived based on nominal GDP data following

$$Real\ GDP = \frac{Nominal\ GDP}{GDP\ Deflator} \qquad (4.4.2\text{-}4)$$

The nominal GDP data and the GDP deflator index are retrieved from *China Statistical Yearbook* to obtain real GDP at constant price in 1990.

ii. *Labor Input Data L*

There are two main approaches for measuring labor input in existing studies, including (1) the effective labor input, which is estimated based on the production of number of labor force and the average hours of work, and (2) the number of employed persons as an indicator of labor input. Considering the data availability on "average hours of work" is only available since 2017, this study employs the total number of employed persons at year-end to measure the labor input. The labor force data is retrieved from *China Statistical Yearbook.*

iii. *Capital Input Data K*

The measurement on the capital input data K is less straightforward because no such data existence, while the existing studies commonly utilizes the perpetual inventory method proposed by Goldsmith (1951) to estimate capital stock (i.e., Martin, 2002; Jun, Wu, & Zhang, 2007; Zhang, 2008; Kijek et al., 2023), that

$$K_{it} = K_{it-1}\left(1-\delta_{it}\right) + {I_{it}}/{P_t} \qquad (4.4.2\text{-}5)$$

where K stands for capital stock, δ stands for the depreciation rate, I stands for the total capital investment, and P stands for the price index to adjust for constant prices. The initial capital stock K_0 is also needed to construct the full time series of the capital input data.

Firstly, the existing research studies have identified three methods for the proximation of capital investment *I* in year *t*, including (1) capital investment based on productive accumulation, that only considers the increase in capital stock due to new investments (i.e., Zhang and Zhang 2003), (2) the total fixed asset investment (i.e., Wang, 2000; Huang et al., 2002), and (3) Gross Fixed Capital Formation (GFCF) that captures both investments in fixed assets and changes in inventories (i.e. Zhang, 2004; Shan 2008; Kijek et al., 2023). Considering the data availability and the potential overestimation on non-reproducible capital expenditure[42], this study adopts the GFCF value to estimate the capital investment in year *t*.

Secondly, this study follows Zhang (2004) to estimate the price adjustment parameter *P,* that using the GFCF index measured in constant prices provided in "China's Gross Domestic Product Accounts (1952-1995)" to estimate the fixed asset investment price index from 1990 to 1996 and using the fixed asset investment price index published in China Statistical Yearbook from 1996 onward. This approach relies on a relatively singular data source and allows for the estimation with higher consistency, to avoid potential issues arising from statistical discrepancies for different time periods. This study also follows previous literature and adopts different approaches to deal with the missing data for Tianjin and Guangdong respectively (i.e., Gong and Xie, 2004).

Thirdly, this paper adopts 1990 as the base year for the initial year of capital stock by following the method used by Hall & Jones (1999), by adding the geometric mean of investment growth and the depreciation rate. Specifically, the GFCF as of 1990 divided by 10 percent is used as the initial capital stock for the entire country, and the series is then converted to 2000 constant prices. The initial capital stock for each province is estimated by multiplying the proportion of the GDP of each province to the national GDP by the national capital stock.

Last but not least, the selection of the depreciation rate δ requires careful consideration. Existing studies based on historical statistical data show significant

[42] Qi (2015) argues that the total fixed asset investment approach will include both tangible and intangible assets directly involved in the production and provision of goods, services, and materials. However, the data also includes expenditures on non-reproducible capital such as land purchases, buildings, and old machinery. This inclusion of non-reproducible capital expenditure can indeed affect the accuracy of capital stock estimation (Qi, 2015).

variations in their findings. For instance, Wang et al. (2000) derived a rate of 5 percent, Gong et al. (2004) assumed it to be 10 percent, while Huang et al. (2002) considered the economic depreciation rate for buildings as 17 percent and the depreciation rate for equipment as 8 percent. Building upon the estimation by Huang et al. (2002), Zhang (2004) divided fixed assets into several categories and estimated their respective useful life. By taking the arithmetic weighted average of their proportions of value and depreciation rates, the final depreciation rate for fixed asset formation in China was determined as 9.6 percent. This estimation is also close to that of Schatzer et al. (2019). Therefore, this paper adopts the depreciation rate of 9.6 percent when calculating TFP.

2) Alternative Methods

As mentioned earlier, the estimation of TFP involves various methods, and this section will briefly outline two alternative approaches that have been adopted in this study to enhance the validity of the results.

i. Ordinary Least Squares (OLS) estimations

Recalling the Cobb-Douglas production function in (4.4.2-3), taking natural logs of (1) results in a linear production function provides

$$y_{i,t} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \varepsilon_{it} \quad (4.4.2\text{-}6)$$

Such that TFP estimation can be empirically derived from the following

$$\ln(A_{it}) = \beta_0 + \varepsilon_{it} = y_{i,t} - \beta_k k_{it} - \beta_l l_{it} \quad (4.4.2\text{-}7)$$

The productivity measure resulting from (4.4.2-7) requires the estimations of elasticity of capital-output and labour-output at the province level and sectoral level. Therefore, this study conducted preliminary regression using OLS estimators based on input data of K and L, and output data real GDP to derive the TFP as the residual of the function (4.4.2-7).

In addition to OLS, existing studies argue that OLS leads to estimation bias due to potential endogeneity issues of input data choices (i.e., Katayama et al., 2005; De Loecker, 2007), selection bias (i.e., Ackerberg et al., 2007), and omitted variable bias (i.e., Levinsohn and Melitz, 2002; Van Beveren, 2012). To address these issues, the TFP

estimation methods have been continuously evolving and developing. Methods such as dynamic GMM (DGMM) and system GMM (SGMM) are used to address the issue of endogeneity. More examples of the updated methods include fixed effects models (FE), random effects models (RE), where the random effects (RE) models can be further divided into stochastic frontier analysis (SFA) and the two-factor error component method.

ii. *Stochastic Frontier Analysis (SFA) method*

The Stochastic Frontier Analysis (SFA), initially proposed by Aigner et al. (1977) and Meeusen and Broeck (1977), has been widely applied in various fields such as economics and finance. Extensive discussions on SFA have been conducted in such as Fried et al. (2008), Greene (2008), and Kumbhakar and Tsionas (2011).

Specifically, SFA is a statistical method based on the idea that observed output can be decomposed into two components: the productive efficiency component, which represents the maximum attainable output (real GDP) given the inputs (such as labour and capital), with special consideration of the random noise component, which represents deviations from the maximum output due to factors beyond control. The model assumes that the productive efficiency follows a stochastic frontier, and the random noise component is assumed to follow a symmetric distribution (the half-normal or normal distribution) (Aigner et al., 1977).

The estimation for SFA model involves simultaneously estimating the parameters of the production function and the parameters of the stochastic frontier, based methods such as maximum likelihood estimation (MLE) and the generalized method of moments (GMM). The estimated parameters for the portion of output that cannot be attributed to the inputs is often interpreted as a measure of technological progress or efficiency- the TFP. Belotti et al. (2013) and Kumbhakar et al. (2015) have provided technical details in its application in Stata.

SFA offers advantages such as its feature in accounting for unobserved heterogeneity and random noise in production processes, and a framework to analyse inefficiency sources and identify factors contributing to productivity disparities across places or industries. On the other hand, SFA also has limitations because it relies on the

assumption of a specific functional form for the production function and stochastic frontier, by limiting the flexibility in capturing complex production relationships (i.e., Lian, 2018).

Extensive discussions on the features and limitations of various methods are ongoing, and comparisons between DEA method and SFA have also attracted great attentions. Sun et al., (2015) and Han and Liu (2019) argued that DEA method overlooks the influence of random errors so it may lead to biased results, while SFA offers such features. On the other hand, DEA also has advantages, as it does not require the specification of a functional form, such that potential structural biases caused by misspecification of production functions in traditional accounting methods and SFA can be avoided (i.e., Huang et al., 2020).

In summary, this section presents a comprehensive discussion on three methods for measuring TFP in China: Data Envelopment Analysis (DEA), Ordinary Least Squares (OLS), and Stochastic Frontier Analysis (SFA). Each method has its own distinct characteristics and advantages. Therefore, the study considers multiple approaches for cross-validation, to ensure the reliability and robustness of the estimation results.

4.4.3 Model Specification

The objective of this research is to examine the correlation between demographic structural changes and technological advancements, considering both the global and domestic contexts of China. Due to limitations in data availability at different levels, this study utilizes various indicators to measure technological advancements for two research questions respectively as previously discussed. At the global level (Research Question 1), the adoption of autonomous robots is employed as the indicator for technological advancements. At the domestic level (Research Question 2), the analysis incorporates the Total Factor Productivity (TFP) index, as well as measures such as patent applications and research and development (R&D) activities to assess technological advancements. In so doing, the study aims to provide a comprehensive understanding of the relationship between demographic changes and technological progress.

However, the estimation model used across all exercises, with the exception of Research Question 2.3 due to its different examination context[43], would remain consistent. This consistency in the estimation model ensures comparability and reliability of the results and allows for a comprehensive understanding and a coherent story of the relationship between demographic structural changes and technological advancements.

Firstly, the initial Model 0 is formulated using equation (4.1.2-10). This study examines the relationship between technological progress and the adoption of robots in Research Question 1, investigate a broader concept of technological advancements in Research Question 2. The relationship between robot's density and demographic structural changes are estimated by taking a logarithm transformation:

$$ln(p_{i,t}) = \boldsymbol{c} + \boldsymbol{\alpha}\, ln(n_{i,t-1}) + \boldsymbol{\beta}\, ln(s_{i,t-1}) + \boldsymbol{\gamma}\, ln(x_{i,t-1}) + \boldsymbol{d}_{t-1} + \boldsymbol{\varepsilon}_{i,t-1} \quad \textbf{(Model 0)}$$

The left-hand side of the equation is the dependent variable $p_{i,t}$, which indicates the number of robots per 1000 workers during time period *t.* It is replaced by other variables like TFP, patent application density, and research and development (R&D) staffing density in Research Question 2. The right-hand side of the equation encompasses population growth rate in the previous period $n_{i,t-1}$, the saving rate in period $s_{i,t-1}$, $x_{i,t-1}$denoting various covariates, and $d_{i,t-1}$, representing the country-year fixed effect.

This paper replaces the natural logarithm of the saving rate $ln(s_{i,t-1})$ by its endogenous components of the demographic structure as described in equation (4.1.2-14).

$$ln(p_{i,t}) = c + \alpha\, ln(n_{i,t-1}) + \beta[ln(l_{i,t-1}) - ln(y_{i,t-1}) - ln(1 + OADR + CDR)_{i,t-1}] + \gamma\, ln(x_{i,t-1}) + d_t + \varepsilon_{i,t}$$

Or when *(OADR+CDR)* is asymptotical to zero, the model can be approximated by[44]

[43] Research question 2.3 will take a deep dive across heterogenous sectors, which implies that the analytical unit will be at the worker-level (working-age and above). This will lead to the twist of model specification apart from the standard model setting. In so doing, this study follows Acemoglu & Restrepo (2018) with relevant adjustment based on China's context. Detailed discussion will be provided in Chapter 5.

[44] Following the L'Hôpital's rule, lim ln(1+x)=x when x→0.

$$ln(p_{i,t}) = c + \alpha\, ln(n_{i,t-1}) + \beta[ln(l_{i,t-1}) - ln(y_{i,t-1}) - (\mathrm{OADR} + \mathrm{CDR})_{i,t-1}] + \gamma\, ln(x_{i,t-1}) + d_t + \varepsilon_{i,t}$$

By relaxing constraints on parameters, Model 1 is derived:

$$ln(p_{i,t}) = \boldsymbol{c} + \boldsymbol{\alpha}\, ln(n_{i,t-1}) + \boldsymbol{\beta}\, ln(l_{i,t-1}) + \boldsymbol{\theta}\, ln(y_{i,t-1}) + \boldsymbol{\varphi}(OADR)_{i,t-1} + \boldsymbol{\sigma}(CDR)_{i,t-1} + \boldsymbol{\gamma}\, ln(x_{i,t-1}) + \boldsymbol{d}_{t-1} + \boldsymbol{\varepsilon}_{i,t-1} \quad \textbf{(Model 1)}$$

The right-hand side of the equation encompasses labor force participation ratio $l_{i,t-1}$, labor productivity $y_{i,t-1}$, $OADR$ and CDR representing the old-age support ratio and child dependency ratio in period *t-1* respectively, control variables $x_{i,t-1}$, and country-year fixed effect d_t

Furthermore, this study employs the *Mediation Analysis Method*, as described earlier to investigate the role of saving *s* as an intermediary mechanism between demographic structural changes and the robot's density,

Using a conventional model for mediation analysis, this study examines the mediating role of the variable saving *s* and the mediator human capital *h*, in sequential order, as formed in Research Question 1.1 and Research Question 1.2. The analysis follows a casual stepwise approach and presents the Sobel-Goodman test. The integrated effect can be estimated that

$$ln(p_{i,t}) = \boldsymbol{c} + \boldsymbol{\alpha}\, ln(n_{i,t-1}) + \boldsymbol{\beta}\, ln(l_{i,t-1}) + \boldsymbol{\theta}\, ln(y_{i,t-1}) + \boldsymbol{\varphi}(OADR)_{i,t-1} + \boldsymbol{\sigma}(CDR)_{i,t-1} + \boldsymbol{\tau} ln(s_{i,t-1}) + \boldsymbol{\gamma}\, ln(x_{i,t-1}) + \boldsymbol{d}_{t-1} + \boldsymbol{\varepsilon}_{i,t-1} \quad \textbf{(Model 2)}$$

It should be emphasized that the conventional method of mediation analysis is designed to handle only one independent variable X with a mediator that involves a single aspect, such that it is difficult to capture the combined impact of demographic changes, which encompass the composition of *OADR* and *CDR*.

Alternatively, Model 3 and Model 4 introduce the interaction terms between the independent variable X and the mediating variable V- *s* and *h* respectively. This interaction approach uncovers an integrated impact, where the association between the independent variable X and the outcome Y depends on the value of the mediating variable V. Furthermore, this framework facilitates a direct comparison of variables of interest, such as *TDR, OADR*, and *CDR*.

$$\ln(p_{i,t}) = \boldsymbol{c} + \boldsymbol{\alpha}\ln(n_{i,t-1}) + \boldsymbol{\beta}\, ln(l_{i,t-1}) + \boldsymbol{\theta}\, ln(y_{i,t-1}) + \boldsymbol{\varphi}(OADR)_{i,t-1} + \boldsymbol{\sigma}(CDR)_{i,t-1} + \boldsymbol{\tau} ln(s_{i,t-1}) + \boldsymbol{\mu}\, ln(s_{i,t-1}) * (TDR)_{i,t-1} + \boldsymbol{\gamma}\ln(x_{i,t-1}) + \boldsymbol{d}_{t-1} + \boldsymbol{\varepsilon}_{i,t-1} \quad \textbf{(Model 3)}$$

equivalently

$$\ln(p_{i,t}) = \boldsymbol{c} + \boldsymbol{\alpha}\ln(n_{i,t-1}) + \boldsymbol{\beta}\, ln(l_{i,t-1}) + \boldsymbol{\theta}\, ln(y_{i,t-1}) + \boldsymbol{\varphi}(OADR)_{i,t-1} + \boldsymbol{\sigma}(CDR)_{i,t-1} + \boldsymbol{\tau} ln(s_{i,t-1}) + \boldsymbol{\mu}\, ln(s_{i,t-1}) * (OADR)_{i,t-1} + \boldsymbol{\omega}\, ln(s_{i,t-1}) * (CDR)_{i,t-1} + \boldsymbol{\gamma}\ln(x_{i,t-1}) + \boldsymbol{d}_{t-1} + \boldsymbol{\varepsilon}_{i,t-1} \quad \textbf{(Model 4)}$$

4.4.4 Estimation and Validation Methods

To ensure robustness and validity, this study employs various methods to address potential issues with data processing. In Research Question 1, the baseline model utilizes three distinct global datasets with an interval of 3 years with different initial years spanning from 1993 to 2017, 1994 to 2018, and 1995 to 2019, respectively, allowing a comprehensive result comparison. Additionally, two alternative datasets with an interval of 5 years spanning from 1993 to 2018 and 1994 to 2019 are used for further validation. Similar practices are used in Research Question 2, employing separate datasets covering a 3-year interval (1990-2019) and a 5-year interval (1990-2019) respectively.

This study handles missing data differently from the existing literature[45]. Rather than imputing values, it does not make special treatments when data are unavailable for several reasons. Firstly, the dataset covers a longer time range compared with previous studies (e.g., Acemoglu and Restrepo, 2020; Abeliansky and Prettner, 2021), providing extensive data availability compared to previous studies. Secondly, the focus of the study

[45] For instance, Abeliansky and Prettner (2021) employ the zero-skewness transformation technique, Acemoglu and Restrepo (2020) employ regional averages, and Graetz and Michaels (2018) utilize a perpetual inventory method assuming certain conditions.

is the country-level comparison, whilst data manipulation may generate potential bias. The data cleaning process is limited to standard logarithm transformations as specified in the models, and missing data points are automatically excluded from the regression analysis. The data cleaning process involves applying standard logarithm transformations as specified in the models. Any missing data points are automatically excluded from the regression analysis.

Finally, this paper undertakes multiple estimation approaches to ensure the results are robust. They include pooled OLS (POLS), fixed-effect (FE) estimators, and random-effect (RE). To provide additional assessments, models in this paper include other controlled variables such as the proportion of trade of the economy and the proportion of services value added in GDP.

4.5. DATA

In the empirical analysis, there are many variables being extracted from official data sources, meanwhile some others are calculated such as demographic factors, TFP, human capital measures, and control variables. The following section introduces main estimation methods and data sources for the construction of key variables and presents a summary of statistics.

4.5.1 Variables Creation

i. Variables for Demographic Structural Change

The first key group of independent variables is the measurement of demographic structure. In line with Model 0 and 1, *old age-support ratio (OADR)*, *child-dependency ratio (CDR),* and *total dependency ratio (TDR)* are key figures being used in the analysis. In addition to the proportional changes of the demography, following Abeliansky and Prettner (2017 and 2021), changes in the quantity of total population as proxied by *the population growth rate* is also included in the model for Research Question 1. However, it is changed to the combination of changes in the *birth rate* and the *death rate* in a separate manner in the model setting for Research Question 2. It is because that the unique feature of mounted

population of internal migrant workers[46] in China and the special *household registration system (hukou),*[47] population growth rate captures not only the natural changes of population dynamics of each province over time but is also driven by the movement of migrant population in a certain period from place to place, which potentially lead to biased results. Variables have been taken logarithm transformation to approximate the growth rate as model specified.[48]

ii. Variables for Technological Advancements

Another primary concern of this paper is the measurement of technological advancements. As discussed in Chapter 2, extensive discussions on the selection of appropriate indicators are ongoing. Due to data availability at various levels, this paper utilizes a few widely adopted indicators to avoid potential data selection bias and build a comprehensive picture.

Specifically, this study draws upon multiple international data series to construct the dependent variable in Research Question 1. Data from the International Federation of Robotics (IFR) spanning 1993-2019 on the annual stock of industrial robots is used to estimate the automation progress in different countries. Furthermore, to measure the progress of *robot's density*, the study combines the stock of robots with working hour-adjusted employment data from Penn World Tables (PWT 10.0) and calculated the robot stock per thousand industrial workers.

This study considers several indicators for technological advancements in Research Question 2. The first group of dependent variables is the estimated values of TFP by following the DEA-Malmquist method as scratched in 4.4.3. The estimators based on OLS and SFA are also provided to ensure the robustness of the results. It is noteworthy that appropriate transformation from TFP Index to the relative TFP level is taken, and the

[46] According to NBS data, China's internal migrant workers is amounted at about 300 million as of 2023, representing more than 20 percent of the total population in China.
[47] The unique household registration system in China requires each person to register his/her household address, which is usually their birthplace, so that the estimation of population growth rate cannot distinguish the difference between registered population and current residents.
[48] Logarithm transformations are commonly employed in economic analysis due to their several advantages. Firstly, they enable the conversion of non-linear functions into linear functions, simplifying parameter estimation. Secondly, logarithmic transformations provide meaningful interpretations in terms of elasticities, which indicate the responsiveness of the dependent variable (Y) to a percentage change in the independent variable (X). Lastly, logarithm transformations can help address heteroscedasticity issues in the data, enhancing the reliability of the analysis (i.e., Wooldridge, 2015; Nau, 2019).

changes of the TFP is thus estimated based on their logarithm values. In addition, this paper also uses the *number of patent application* and the *R&D spending* data to not only provide different views from productivity, but also to complement the validity of the results. The paper also follows earlier studies and constructs the *number of patent application per employee* and the *value of R&D spending per employee* by dividing the latter two by the total number of employment (i.e., Zhao & Li, 2021; Wang et al., 2022). Variables have been taken logarithm transformation to approximate the growth rate as model specified.

iii. Variables for Mediators

This study aims to build the mediating relationship between demographic structural changes and technological advancements through two indirect channels: saving ratio *s* and human capital development *h.* To achieve robust results, several indicators are also employed to represent each of them respectively.

Saving ratio: The measurement of saving ratio at the global level is straightforward and the internationally comparable data can be retrieved from public sources. Therefore, this paper uses two sets of indicators: *saving ratio (%) as a percentage of GDP and GNI of a country* respectively obtained from World Development Indicator for Research Question 1. While in Research Question 2, the focus of this analysis is at the provincial level, such that the official estimation of the *investment rate (%)* from the Provincial National Accounts of China is adopted.

Human Capital: Human capital is a broad concept that includes not only education and training but also many other aspects such as the health outcomes (Flabbi, Gatti, 2018). In line with the aim of this research to provide a comprehensive understanding in this regard, the empirical analysis uses distinct variables for the multi-dimensional notion. Firstly, Research Question 1 relies on the *Human Capital Index (HCI)*, which is an overall index that combines both health and education dimensions to investigate the aggregated effect.[49] Additionally, this study complements the overall HCI with self-standing views from the lens of education, and health respectively. Explicitly, following existing studies, this paper also uses *the proportion of population with secondary education and above (%)*

[49] Detailed explanations in the methodology can be referred to (Kraay, 2018).

as the main indicator for education attainment (i.e., Barro and Lee, 2013; Heckman, Lochner & Todd, 2008; Psacharopoulos and Patrinos, 2004), and *the life expectancy at birth* as the main indicator for health (i.e., Cutler et al., 2019; Preston & Ho, 2010; Murphy & Topel, 2006). Additional analyses using *average years of secondary schooling* and *average years of secondary schooling of female* are also conducted.

Due to the shift of the research focus to regional distributions and the availability of feasible data in domestic context of China for Research Question 2, this analysis, in line with indicators selected in Research Question 1, constructs the *proportion of population with secondary education and above (%)* based on population census data to represent education attainment of each place. However, considering the lack of aggregated human capital for different places over time, as suggested by previous studies (i.e., Lundahl & Pozzoli, 2012; Li, 2020), this study uses *the ratio of fiscal spending to the regional GDP* as a proxy. The rational lie at social spending often encompasses investments in both education and healthcare systems, which measures governments' aim to enhance the knowledge, skills, and overall well-being of population through the allocation of resources to education and health services (i.e., Schultz, 1961; Becker, 2009).

Some studies (i.e., Li and Zhao, 2022; Li, 2020; Qi, 2015) use the average years of education of the employment to measure human capital in practice, which is calculated based on the weighted average of educational attainment of primary school, junior high school, high school, and college and above for the total labor force (or population). The estimation method is governed by multiplying values of 6 years, 9 years, 12 years, and 16 years, respectively to the proportions of the population with education at the levels of primary school, junior high school, high school, and college and above. That is, $H = 6L_1 + 9L_{2+}12L_3 + 16L_4$, where L_i *(i=1, 2, 3, 4)* indicates the proportion of educated people in the labor (or population) with complete education in each category. This study, however, does not employ this method because of two reasons. Firstly, the assigned values for each level of education are likely to be underestimated because the criteria are set as the floor of each category (i.e., 16 years also include graduate school and doctoral studies). Secondly, the education system in China has also remarkably changed over the past 30 years (i.e., the development of junior college and secondary technical school), such that the education

statistics in each category have also changed overtime in the official Statistics Yearbook. Therefore, this method requires dynamic adjustments over years and leads to pronounced inconsistency.

iv. *Covariates*

In addition to the key independent, dependent, and mediating variables, to reduce the bias and risks of omitted variables, this study also includes relevant socioeconomic factors as control variables in empirical models.

GDP Per Capita and Labor Force Participation Ratio: These two primary control variables are governed by (4.1.2-14) as parts of the accounting identity in explaining the saving ratio. Therefore, data on GDP per capita (2017 adjusted PPP) and labor force participation rate (ILO: percent of aged 15 and above of the total population) are retrieved from the *World Development Indicator* for Research Question 1. The underlying reasons for the inclusion of them lie at that, higher GDP per capita implies a stronger economic basis for both the employment and development of advanced technologies. In addition, labor force participation rate reflects the institutional governance and environment of the regional labor market, which is an essential competing force to the human-substitutional technologies (i.e., robots). Similar indicators are also generated and included in Research Question 2 relying on relevant information obtained from China's Statistics Yearbook.

Openness: Openness is also vital for technological advancements for several reasons. Firstly, it allows access to foreign capital, technology, and managerial knowledge, which can lead to the adoption of advanced production techniques and improved efficiency. Secondly, through international trade and engagement with global markets, firms are exposed to competition and market forces, which incentivize them to innovate and upgrade their technological capabilities. Thirdly, openness facilitates knowledge spill overs, as interactions with foreign firms and exposure to new ideas and practices can lead to the diffusion of technological knowledge through "learning by doing." Therefore, as in Abeliansky and Prettner (2021), *the total value of trade (exports and imports) over GDP* is used to capture the openness for Research Question 1. T*he ratio of total Foreign Direct*

Investment to regional GDP is used to measure the level of openness in each province for Research Question 2 as suggested by Wang et al., (2022).

Industrial Structure: Economic development is a process of gradual transformation from manufacturing-led to services-led structure (i.e., Nayyar, Cruz, & Zhu, 2021). The industrial transformation brings about the reallocation of production factors, division of labor, promotion of technology obsolescence and upgrades, scale effect of industrial agglomeration, and the divergence in productivity. Drucker (2007) found that there are significant differences in labor productivity across different industries, and these differences are attributed to the industrial structure. To reflect the magnitude of the industrial structural changes, this study follows existing studies (i.e., Abeliansky and Prettner, 2021; Tang, 2006) and uses *the share of service's contribution to GDP* as the measurement of the industrial structure. In contrast to Wang et al., (2022), this paper excludes *the share of industry's (manufacturing, construction, etc.) contribution to GDP* from the model to avoid overfitting issues.

Urbanization: Some research on China (i.e., Li, 2016) have raised that urbanization is a featured process of China's historical development in witnessing population migration from rural areas to urban areas. It has led to the agglomeration of production resources, such that there are scale effects and spill over effects caused by the accumulation of concentrated human capital. The inclusion of the urbanization rate indicated by *the population of urban residents to the total population of each province* in Research Question 2 also allows to control for the process of Lewis turning point in China (i.e., Cai, 2004; 2006; 2009).

4.5.2 Data Source and Summary Statistics

1) Global Datasets for Research Question 1

i. Data Sources and Summary of Statistics

To create a dataset that allows for international comparisons, this study utilizes data from various sources. First, the "annual stock of industrial robots" data is obtained from the International Federation of Robotics (IFR), covering the period from 1993 to 2019. Second,

the total industrial employment data, adjusted for working hours, is sourced from Penn World Tables (PWT 10.0). Third, demographic structure estimations rely on data from the World Population Prospects of the United Nations, which provide information on the total population and population distribution across different age groups, including the elderly (aged 65 and above), children (aged 0-14), and the working-age population (aged 15-64).

In addition, the mediating variables, such as saving represented as a percentage of GDP and GNI, and human capital measured by HCI and life expectancy at birth, are obtained from Penn World Tables (PWT 10.0) and World Development Indicators (WDI) of the World Bank, respectively. Educational attainment measures related to human capital, including the proportion of the population with secondary education and above, average years of secondary schooling, and average years of secondary schooling for females, are collected from the Barro-Lee dataset. [50] Other covariates, including GDP per capita (2017 adjusted PPP), the labor force participation ratio (ILO: percentage of individuals aged 15 and above in the total population), the proportion of services to GDP, and the trade value-to-GDP ratio, are sourced from the WDI of the World Bank. Table 4.5.2A summarizes the source of the data, provides the first glimpse of their summary of statistics.

The analysis includes a list of 69 countries, as depicted in Figure 4.5.2A. Notably, Japan and Russia are excluded, aligning with Acemoglu and Restrepo (2021), due to changes in the definitions of industrial robots over time.

[50] The Barro-Lee Dataset gives a comprehensive picture of the distribution of education attainment and human capital among age groups and genders in 144 countries from 1970. See details in http://www.barrolee.com/

Table 4.5.2A: Summary of Statistics for Research Question 1

Sources	*Variable Descriptions*	*N*	*Mean*	*Std. dev.*	*Min*	*Max*
	Year	1917	2,006	7.8	1,993	2,019
IFR	Operational Robots Stock	1917	15,169.0	57,597.1	0	782,725.0
PWT 10.0	Number of persons engaged (in millions)	1917	33.3	103.4	0.1	799.3
	Average annual hours worked by persons engaged	1917	1,425.0	844.3	1,380.6	2,653.2
	Human capital index	1917	2.7	0.8	0	4.4
World Population Prospects UN	Population growth (annual %)	1917	1.0	1.6	-3.8	17.5
	Population ages 0-14 (% of total population)	1917	21.9	7.3	11.0	43.6
	Population ages 15-64 (% of total population)	1917	66.8	4.6	52.8	86.4
	Population ages 65 and above (% of total population)	1917	11.3	5.6	0.7	28.0
WDI World Bank	GDP per capita, PPP (constant 2017 international $)	1917	29,190.2	22,094.6	1,653.4	161,971.5
	Gross domestic savings (% of GDP)	1917	25.3	12.6	-25.5	75.5
	Gross savings (% of GNI)	1917	22.3	11.6	2.0	65.3
	Labor force participation rate, total (% of total population ages 15+)	1917	52.2	22.4	29.6	91.8
	Services, value added (% of GDP)	1917	56.7	10.4	28.5	96.2
	Trade (% of GDP)	1917	89.3	62.4	13.4	442.6
	Life expectancy at birth, total (years)	1917	75.0	6.7	0.0	85.1
Barro-Lee	Percentage of population age 15+ with secondary schooling, total	1917	47.2	18.7	0.0	89.0
	Average years of secondary schooling, age 15+, total	1917	3.3	1.4	0.0	6.8
	Average years of secondary schooling, age 15+, female	1917	3.2	1.4	0.0	6.6

Source: Created by author

Table 4.5.2B: Availability of Country Samples (N=69)

Argentina	China	Greece	Korea, Rep.	Netherlands	Romania	Tunisia
Australia	Colombia	Hong Kong SAR, China	Kuwait	New Zealand	Saudi Arabia	Turkey
Austria	Croatia	Hungary	Latvia	Norway	Serbia	Ukraine
Belarus	Czech Republic	Iceland	Lithuania	Oman	Singapore	United Arab Emirates
Belgium	Denmark	India	Macao SAR, China	Pakistan	Slovenia	United Kingdom
Bosnia and Herzegovina	Egypt, Arab Rep.	Indonesia	Malaysia	Peru	South Africa	United States
Brazil	Estonia	Iran, Islamic Rep.	Malta	Philippines	Spain	Uzbekistan
Bulgaria	Finland	Ireland	Mexico	Poland	Sweden	Venezuela, RB
Canada	France	Israel	Moldova	Portugal	Switzerland	Vietnam
Chile	Germany	Italy	Morocco	Qatar	Thailand	

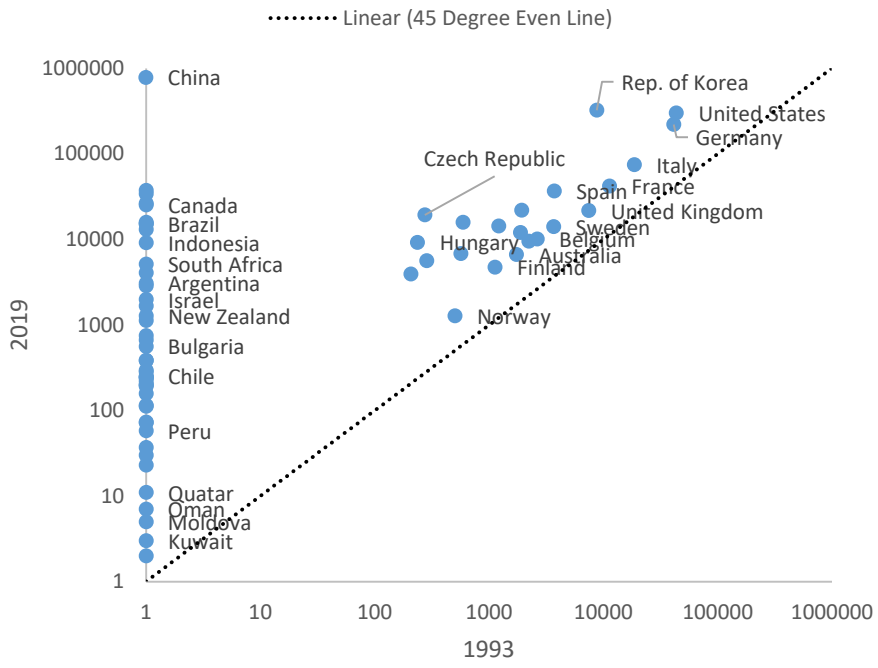
Source: International Federation of Robotics (2019)

Note: In line with Acemoglu and Restrepo (2021), the analysis excludes Japan and Russia due to significant revisions in the definitions and classification of industrial robots over time.

ii. Evolvement of Robots

The following figure depicts the progression of robot stock from the initial year of 1993 to the final observation period in 2019. Figure 4.5.2B illustrates the changes between the initial and end values, with the initial value plotted on the x-axis and the end value on the y-axis. Notably, all data points are positioned above the 45-degree line within the "inverted triangle area," indicating that all 69 countries included in the analysis have experienced significant expansions in the adoption and utilization of robots. It is particularly noteworthy that over 45 countries, which did not possess any robots in 1993, have gradually implemented and integrated automation technologies into their countries, where China ranks highest in its progression.

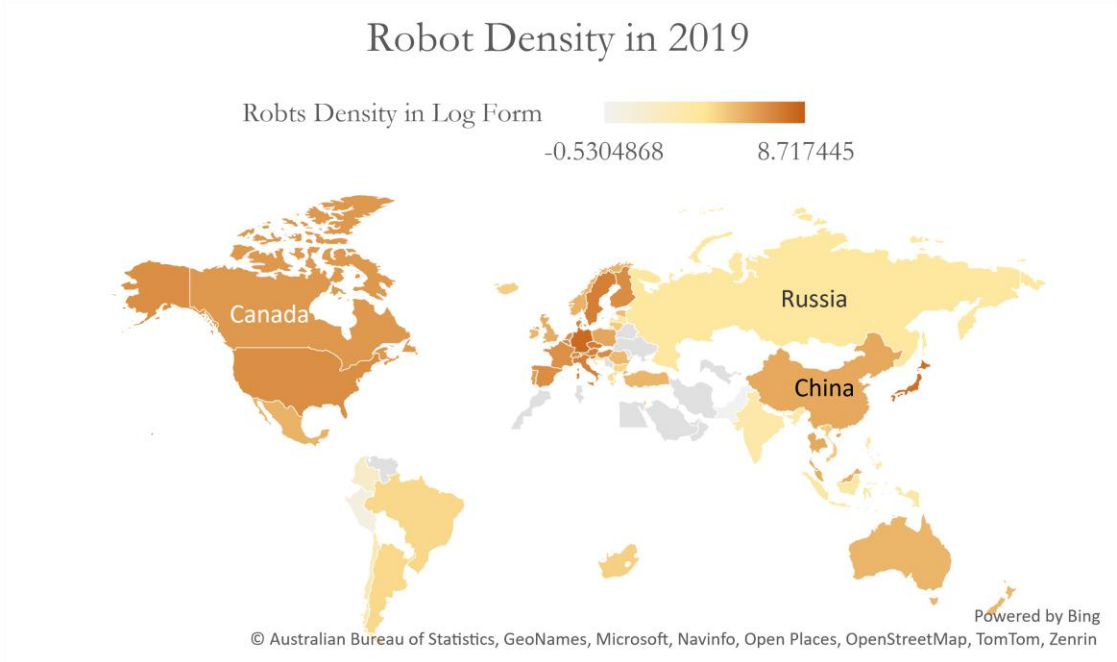
Figure 4.5.2B: Evolvement of Robots Stock from 1993 to 2019



Source: Created by author based on IFR (2019)

Figure 4.5.2C displays the robot density as of 2019, which is calculated by dividing the absolute robot stock data by the total number of workers, adjusted for their average hours of work. This figure provides an overview of the distribution of robot density across different regions worldwide, highlighting regions such as Europe, North America, and East Asia stand out with higher levels of robot density, indicating a greater prevalence and utilization of robots in these areas.

Figure 4.5.2C: Robots Density in 2019 across the World



Source: Created by author based on IFR (2020)

Note: Robots density represents the stock of robots per thousand industrial workers with adjustment by average hours worked.

2) Domestic Data for Research Question 2

i. Data Sources and Summary of Statistics

Research Question 2 is focused on the domestic context of China from the period of 1990 to 2020, and it combines the various official data reports to carry out the analysis. To estimate the primarily interested depend variable- TFP level based on DEA (including OLS and SFA) methods, the data series on nominal GDP, GDP deflator, capital inputs, and labor inputs are retrieved from China's Statistical Yearbook. In addition to the TFP level, two additional variables for the proximation of technological advancements including number of patent applications and R&D expenditure are obtained from China's Statistical Yearbook of Science and Technology. Equally importantly, estimations of demographic structures based on the total population and population by different age groups including the elderly (aged 65 and above), children (aged 0-14), and the working age population (aged between 15 and 64), are obtained from the China's Statistical Yearbook. The mediating variables of saving *s* proxied by the investment rate as a percentage of GDP is

obtained from Provincial National Accounts, and human capital *h* measured by the proportion of population with completed secondary education and above is collected from China's Population and Employment Statistical Yearbook. All other variables including birth rate, death rate, labor force participation rate, government's fiscal spending as a proportion of regional GDP, FDI as a proportion of regional GDP, proportion of services to GDP, and urbanization rate are estimated respectively based on raw data from China's Statistical Yearbook. The sectoral exercise in Research Question 2.3 is also employed by official data from China's statistics yearbook by combining with 1990, 2000, and 2010 census data to estimate the profile of labor force across sectors. Table 4.5.2B summarizes the source of the data and provides the first glimpse of the summary of statistics.

Table 4.5.2B: Summary of Statistics for Research Question 2

Source	**Variable Descriptions**	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Author's own estimation based on China's Statistical Yearbook	year	954	2005	9	1990	2020
	TFP Estimation based on OLS	954	162559.4	675801.0	0.0	4692545.0
	TFP Estimation based on SFA	954	33325.1	135966.6	0.0	1088191.0
	TFP Estimation based on DEA	954	66867.3	351123.4	0.0	4369409.0
China's Statistical Yearbook of Science and Technology	Number of patent applications accepted	954	37824.8	92833.8	2.0	967204.0
	Research and experimental development (R&D) internal expenditure (Billion yuan)	954	20.1	41.9	0.0	348.0
China's Statistical Yearbook	Population ages 0-14 (% of total population)	954	0.2	0.1	0.1	0.4

	Population ages 15-64 (% of total population)	954	0.7	0.0	0.6	0.8
	Population ages 65 and above (% of total population)	954	0.1	0.0	0.0	0.2
	Birth Rate (‰)	954	13.0	4.3	3.8	26.7
	Death Rate (‰)	954	6.2	0.8	4.2	8.8
	GDP (current, Billion Yuan)	954	1076.5	1544.2	2.8	11076.1
	GDP per capita (current, Yuan)	954	25059.5	27064.3	810.0	164889.5
	Labor force participation rate (% of total population)	954	0.5	0.1	0.4	0.8
	Foreign Direct Investment (Billion Yuan)	954	27.6	40.6	0.0	225.7
	Services, value added (% of GDP)	954	41.9	9.4	23.3	83.9
	Government Fiscal Expenditure (Billion Yuan)	954	181.1	247.3	0.0	1729.8
China' Population and Employment Statistics Yearbook	Percentage of population age 15+ with secondary schooling. Total	954	0.2	0.1	0.0	0.7
Provincial National Accounts	Capital Formulation Rate (%)	954	46.1	21.5	0.0	148.5

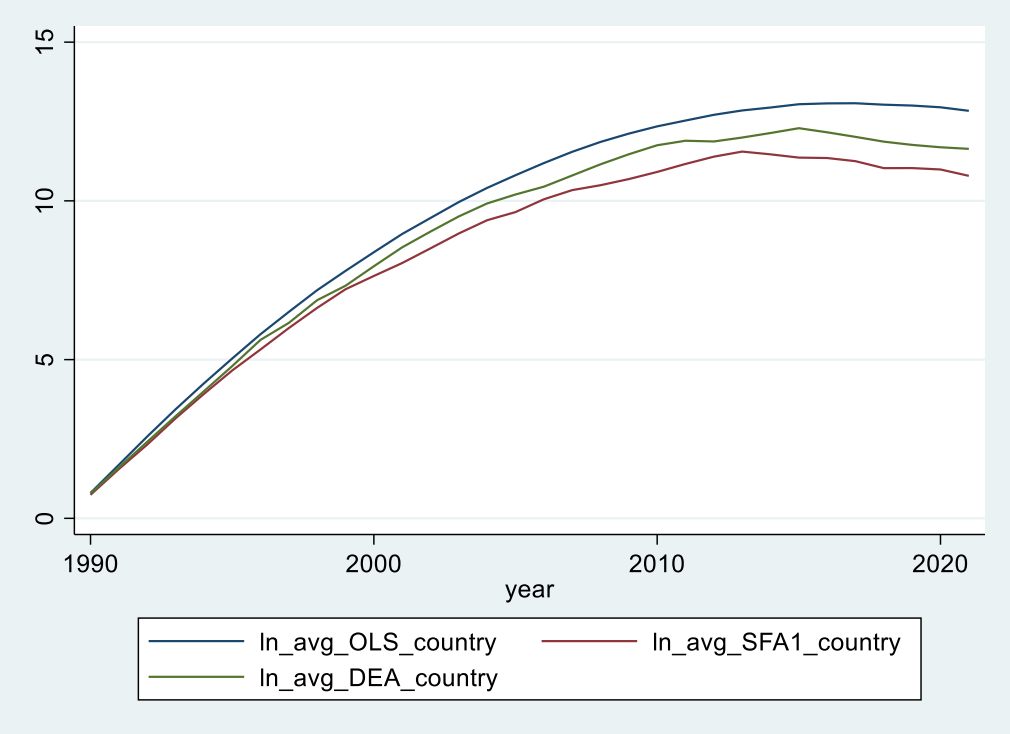
Source: Created by author

ii. Evolvement of TFP

This study calculated the actual level of TFP based on DEA, OLS, and SFA methods respectively in China from 1990 to 2020, and their logarithm transformations are conducted to reveal the growth rate of TFP as presented in Figure 4.5.2D. The results indicate that

during the period of transitioning to a market economy since 1990, China experienced a continuous increase in TFP, achieving a relatively high growth rate and peaking in 2015, but entered a deaccelerating period afterwards.

Figure 4.5.2D: China's Evolvement of Average TFP Growth from 1990 to 2020

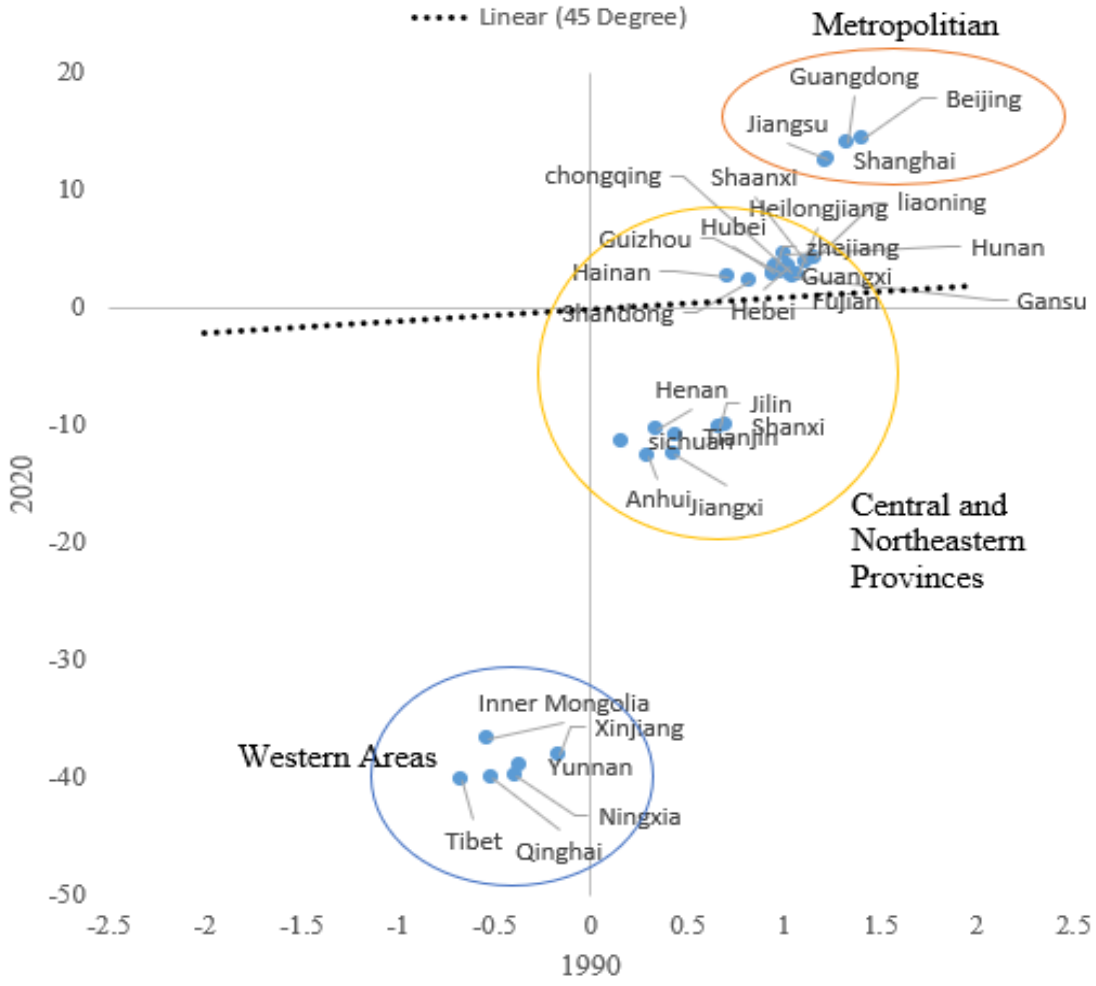


Source: Created by author based on estimations

Figure 4.5.2E depicts the growth rate in TFP measured by DEA for each province over the period of 1990 to 2020. The x-axis represents the initial value of TFP in 1990, while the y-axis represents the end value of TFP in 2020. The scatter plot in the figure reveals variations TFP across different provinces. Some provinces exhibit TFP growth above the 45-degree line, indicating a significant improvement in their technological advancements. Notably, they include metropolitan areas such as Beijing, Shanghai, Guangdong, and Jiangsu, with their values increasing by more than 10 times over the past 30 years. In contrast, several major western provinces including Inner Mongolia, Tibet, Xinjiang, Yunnan, Qinghai, and Ningxia have shown continuous and accelerated negative growth in TFP, indicating a decline in their technological advancements. Other regions in

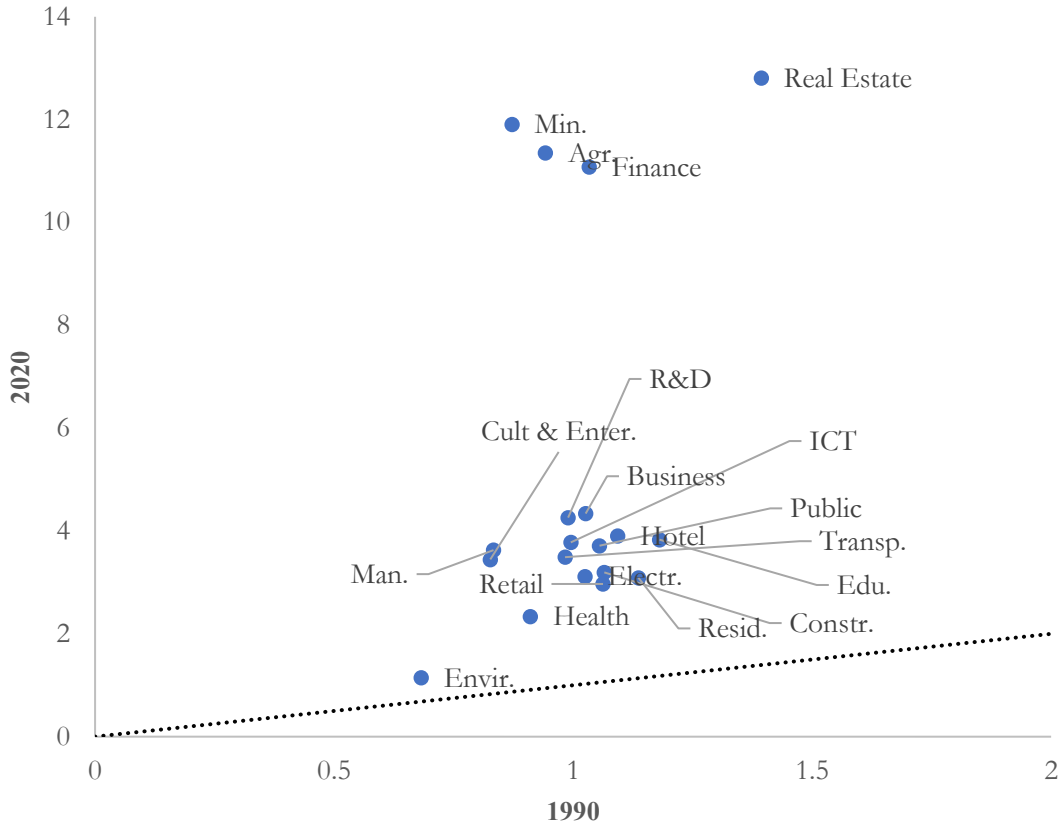
central and north-eastern China also display notable disparities in their progress of TFP growth.

Figure 4.5.2E: China's Evolvement of TFP Growth Across Regions from 1990 to 2020



Source: Created by author based on estimations

Figure 4.5.2F: China's Evolvement of TFP Growth Across Sectors from 1990 to 2020



Source: Created by author based on estimations

In addition to regional disparities, the progress of technological development across sectors also exhibits significant variations. Although the average growth of TFP is positive across all 19 broad sectors from 1990 to 2020 (above 45-degree line), the pace of growth differs considerably. Some sectors stand out as leaders in terms of TFP growth, including the Real Estate, Finance, Mining, and Agricultural sectors. These sectors have likely benefited from advancements in financial systems, technology adoption, and spill overs of know-how, leading to improved efficiency and productivity. On the other hand, certain sectors have shown slower growth in TFP, such as environment and health services, which likely have faced challenges in terms of structural transformation and government regulations over time. Factors such as regulatory constraints, limited investment in R&D, and complex operational dynamics may have contributed to the slower TFP growth in these sectors.

This chapter provides an overview of the theoretical foundations, analytical framework, hypotheses derived from previous research. The modelling approach and empirical data utilized in the analysis to examine the interactions between demographic structural changes and technological advancements are also displayed. A key focus of this study is to investigate whether savings and human capital serve as indirect channels through which the impact is transmitted, as suggested by the theory of demographic dividend. Understanding these channels is crucial for comprehending the overall effects of demographic structural changes on technological advancements in the post-demographic transition China. Furthermore, the chapter presents preliminary summary statistics and featured trends, highlighting substantial disparities observed across countries, regions, and sectors. These disparities emphasize the need for careful and detailed investigations to better understand the underlying factors contributing to variations in technological advancements. With the groundwork laid out in this chapter, the subsequent chapter will delve into the empirical analysis, employing rigorous econometric techniques to unravel the intricate relationship between demographic changes and technological advancements.

CHAPTER 5: RESULTS

This chapter of the dissertation presents main findings derived from the empirical estimations conducted in accordance with the model specifications and econometric techniques outlined in Chapter IV. The objective is to examine the implications of demographic structural changes on technological advancements, by investigating the dual indirect mechanisms of saving and human capital development.

The chapter is structured into two sections, with each corresponding to one of the main research questions raised in Chapter I. The first section examines the linkages between demographic changes and technological advancements in the global context. The second section provides complementary results specifically focused on the domestic context of China. Different outcome variables related to technological advancements are utilized in each section, including the growth rate in the adoption of automation robotics in the first section, and a set of indicators in the second section, such as the growth rate in the level of total factor productivity (TFP), the growth rate in patent application density per thousand employees, and the growth rate in R&D expenditure per thousand employees.

The key explanatory variables in the study are demographic structure variables, specifically the old-age support ratio and child dependency ratio of the population. These variables serve to capture the changes of demographic dynamics. Furthermore, mediation analyses and robustness checks using multiple methods (i.e., changing data samples, the inclusion of additional covariates, and utilizing different estimation methods) have been carried out to ensure the validity and the reliability of the findings.

5.1. IMPLICATIONS OF DEMOGRAPHIC STRUCTURAL CHANGES ON TECHNOLOGICAL ADVANCEMENTS IN THE GLOBAL CONTEXT

The regression results on the relationship between robot's density and demographic structural changes in the global context are presented in this section, along with an assessment of how advances in automation are facilitated by saving and human capital.

Additionally, towards the end of this section, comparisons between China and other peer countries on a global scale are provided.

5.1.1 The Indirect Mechanism Through Savings

Based on existing research, this analysis compares the extended Model 1 with the baseline Model 0, following the approach outlined in Chapter IV. Fixed-Effect (FE) estimation methods are utilized on all data samples. The objective is to investigate the intermediary role of savings in linking demographic structural changes and the development of automation technologies. Model 2 is estimated to assess changes in estimators. Both results from stepwise approach and the Sobel-Goodman test are presented. Furthermore, Model 3 and Model 4 examine the interactive effects between demographic changes and savings.

1) Demographic Structure and Automation

In Model 0, two independent variables are included: the growth rate in population (*pop_growth*) and saving rate (*s*). The results in column M0 indicates a negative relationship between robot's density and the population growth rate, and a positive relationship with the saving rate (Table 5.1.1A).

The findings consistently demonstrate a significant negative association between population growth in period t-1 and the growth rate of robot density in subsequent period *t*. Interestingly, contrary to the conclusions drawn by other researchers, a compelling result emerges in this study, indicating a significant positive effect of the growth of the saving rate in the preceding period on the advancement of automation. This outcome holds true across various measures, whether proxies such as domestic saving of GDP or total saving of GNI, as well as different sample intervals of 3-year or 5-year periods are considered.

In Model 1, the variable *s* is decomposed into the following components: OADR (*sup*), CDR (*dep*) [51], the GDP per capita growth rate (*lngdpc*), and the labor force participation ratio growth rate (*lnlfpc*). The results consistently reveal a significant negative

[51] In this study, three distinct specifications are employed to approximate demographic changes. The first specification considers the elderly support ratio and children's dependency ratio as separate variables. The second specification employs the total dependency ratio. Lastly, the third specification utilizes the growth rate of the proportion of working-age population. Additional results pertaining to these specifications can be found in the Appendix II.

correlation between the CDR (*dep*) and the growth rate in robot's density across all exercises. These findings support the initially posited hypotheses. However, the results regarding *sup* are not statistically significant. Furthermore, *lngdpc* as an indicator of economic condition demonstrates its pivotal role in driving advancements in automation.

Based on the analysis of the 1994-2018 and 1995-2019 samples, the results consistently indicate that a 1 percent slowdown in population growth leads to an average annual increase in robot density per thousand workers ranging from 0.05 to 0.10 percent. Additionally, a 1 percentage point decrease in the children's dependency ratio corresponds to an average annual growth in robot density of 1.2 percent. These findings not only support that incentives for automation are influenced by demographic structural changes but also emphasize the significant role of changes in demographic structure compared to population growth alone. In terms of the absolute magnitude, changes in demographic structure have a more pronounced impact on the growth of automation.

Table 5.1.1A: Demographic Structure and Automation
3-Year Interval Samples

Panel A: Gross domestic savings (% of GDP)

	1993-2017		1994-2018		1995-2019	
VARIABLES	**M0**	**M1**	**M0**	**M1**	**M0**	**M1**
pop_growth	-0.437***	-0.228***	-0.295***	-0.149**	-0.185***	-0.0678
	(0.0933)	(0.0857)	(0.0787)	(0.0633)	(0.0611)	(0.0473)
lnlfpc		-0.986		-2.015***		-1.038*
		(1.020)		(0.775)		(0.590)
lngdpc		1.913***		3.111***		2.890***
		(0.608)		(0.436)		(0.382)
sup		-0.956		2.401		0.621
		(3.774)		(2.903)		(2.487)
dep		-10.37***		-3.600*		-3.822**
		(2.497)		(1.947)		(1.718)
s	2.215***		1.425***		1.040***	
	(0.485)		(0.398)		(0.370)	
Constant	-2.619*	-7.400	0.148	-18.04***	1.517	-19.29***
	(1.570)	(7.941)	(1.289)	(5.659)	(1.200)	(4.894)
Observations	301	286	299	286	303	292
R-squared	0.920	0.933	0.933	0.951	0.940	0.962
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: Gross savings (% of GNI)

	1993-2017		1994-2018		1995-2019	
VARIABLES	**M0**	**M1**	**M0**	**M1**	**M0**	**M1**
pop_growth	-0.373***	-0.228***	-0.274***	-0.149**	-0.156**	-0.0678
	(0.0976)	(0.0857)	(0.0823)	(0.0633)	(0.0631)	(0.0473)
lnlfpc		-0.986		-2.015***		-1.038*
		(1.020)		(0.775)		(0.590)
lngdpc		1.913***		3.111***		2.890***
		(0.608)		(0.436)		(0.382)
sup		-0.956		2.401		0.621
		(3.774)		(2.903)		(2.487)
dep		-10.37***		-3.600*		-3.822**
		(2.497)		(1.947)		(1.718)
s	0.846***		0.877***		0.792**	
	(0.292)		(0.296)		(0.327)	
Constant	1.880**	-7.400	1.962**	-18.04***	2.359**	-19.29***
	(0.932)	(7.941)	(0.948)	(5.659)	(1.052)	(4.894)
Observations	283	286	283	286	288	292
R-squared	0.919	0.933	0.934	0.951	0.941	0.962
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

5-Year Interval Sample

Panel C: Gross domestic savings (% of GDP)

		1993-2018		1994-2019
VARIABLES	**M0**	**M1**	**M0**	**M1**
pop_growth	-0.340***	-0.208**	-0.375***	-0.127
	(0.0848)	(0.0838)	(0.108)	(0.0971)
lnlfpc		-1.794		-0.573
		(1.299)		(1.277)
lngdpc		2.147***		2.189***
		(0.683)		(0.775)
sup		-0.293		0.895
		(4.180)		(4.627)
dep		-7.034**		-12.50***
		(2.873)		(3.038)
s	1.386***		1.616***	
	(0.512)		(0.590)	
Constant	0.472	-7.258	-0.471	-11.25
	(1.657)	(8.887)	(1.901)	(9.915)
Observations	188	164	202	175
R-squared	0.936	0.955	0.916	0.950
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel D: Gross savings (% of GNI)

		1993-2018		1994-2019
VARIABLES	**M0**	**M1**	**M0**	**M1**
pop_growth	-0.313***	-0.208**	-0.365***	-0.127
	(0.0900)	(0.0838)	(0.111)	(0.0971)
lnlfpc		-1.794		-0.573
		(1.299)		(1.277)
lngdpc		2.147***		2.189***
		(0.683)		(0.775)
sup		-0.293		0.895
		(4.180)		(4.627)
dep		-7.034**		-12.50***
		(2.873)		(3.038)
s	0.280		1.040**	
	(0.275)		(0.411)	
Constant	4.080***	-7.258	1.424	-11.25
	(0.877)	(8.887)	(1.312)	(9.915)
Observations	173	164	188	175
R-squared	0.936	0.955	0.919	0.950
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates respectively. All independent variables are log transformed except *sup* and *dep*, and data represent the changes in lagged periods *t-1*.

2) Causal Stepwise Approach on the Indirect Channel of Saving

To examine the mediating role of saving between demographic structural changes and the development of automation technologies, this section presents estimation results from the casual stepwise approach in Table 5.1.1B (also refer to Appendix).

In Step 1 of regression analysis, the total effect (TE) of demographic structural changes on robot's density is estimated. Specifically, in Panel A and C, the growth rate of working-age population l*nwap* exhibits a significant positive TE at a 99 percent confidence level. However, in Panel B, the TE of the elderly support ratio (*sup*) is not statistically significant, indicating potential demographic heterogeneity.

The Step 2 involves regressing the mediator *s*on demographic variables while controlling for other factors. The coefficients on *lnwap, sup,* and *dep* are significant across all exercises, suggesting a viable mediating pathway.

In Step 3, the mediator *s* is added to the model in the first step. The results indicate that the direct effect (DE) on *lnwap* changes to insignificant and the magnitude of coefficients also reduces. Similarly, the DE on dep remains significant but decreases. However, for *sup*, the inclusion of the mediator *s* leads to a significant increase in magnitude. The coefficient on *sup* reverts from -2.75 to 7.389, remaining statistically significant. Furthermore, the positive and significant coefficients on *s* in all settings confirm a hypothesized viable pathway through saving. Sobel-Goodman tests support these findings, highlighting the existence of a mediating effect through saving, although the effects vary among OADR (*sup*), CDR (*dep*), and the growth in the proportion of working-age population (*lnwap)*.

The comparison between results in Step 1 to Step 3 indicates that *s* acts as a "complete mediation," explaining approximately 59.4 percent of the TE for the growth in the proportion of working-age population (*lnwap*). *s* also acts as a "partial mediation" on CDR (*dep*), explaining about 27.3 percent of the TE. However, a "suppression effect is observed on OADR (*sup*), as its coefficient magnitudes becomes larger by approximately 5.2 times with the inclusion of *s*. Please refer to Table 5.1.1B in the Appendix for more detailed information.

These analyses highlight the crucial role of saving in translating automation incentives into practical implementation within the context of demographic structural changes. However, the divergent results indicate heterogeneous implications for different population. As a result, it is necessary to conduct separate investigations that delve into the specific characteristics and dynamics of these population groups.

Table 5.1.1B: Mediating Effects Through Saving

Panel A: Independent Variable=Log Value of Share of Working Age Population			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=*s***	**Y=robot's density**
s			1.576***
			(0.363)
lnwap	8.829***	3.326***	3.586
	(2.140)	(0.340)	(2.401)
pop_growth	-0.315***	0.0635***	-0.415***
	(0.110)	(0.0175)	(0.109)
lnlfpc	-0.516	0.593***	-1.451*
	(0.792)	(0.126)	(0.797)
lngdpc	2.228***	0.0376	2.169***
	(0.145)	(0.0230)	(0.141)
Constant	-53.12***	-13.56***	-31.76***
	(8.925)	(1.418)	(9.960)
Observations	287	287	287
R-squared	0.573	0.353	0.600
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, s* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and saving rates respectively. All independent variables are log transformed and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	3.965***	0.00
Aroian	3.948***	0.00
Goodman	3.982***	0.00
Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	9.783***	0.00
b_coefficient	4.337***	0.00
Indirect_effect_aXb	3.965***	0.00
Direct_effect_c'	1.493	0.147
Total_effect_c	4.127***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: 0.594

3) Interaction Approach on the Indirect Channel of Saving

To gain further insights, an alternative approach is adopted by incorporating interaction terms in the regressions. Unlike mediating analysis, interactions do not establish a causal

relationship but offer flexibility in capturing joint effects between saving, overall demographic changes, and their impacts on different population groups. [52]

Model 2 replicates the regression model from Step 3 in the previous exercise, by separating OADR (*sup*) and CDR (*dep*). On the one hand, Models 3 incorporates synergistic interactions (*sav_int*) between saving and demographic structural changes. On the other, Model 4 further distinguishes the interaction terms for the aging burden (*sav_age_int*) and children dependency burden (*sav_chld_int*) respectively.

The main findings across various samples (Table 5.1.1C Panel A to Panel J) indicate strong negative associations between dep and robot density consistently, regardless of the inclusion of interactions. Moreover, positive and robust coefficients for *sav_int* and *sav_chld_int* suggest the presence of an "interaction effect." However, the contributions of *sup* to automation motivations vary, exhibiting significant heterogeneity among groups.

When comparing Model 2 to Model 3 and Model 4, the coefficients for *dep* significantly increase upon the inclusion of *sav_int* and *sav_chld_int*. In Panel A, for instance, the coefficient rises from 10.28 to 50.38 or 41.36. Furthermore, the inclusion of interactions results in a change on the sign of *s*, shifting from a positive value of 1.4 in Model 2 to a negative value at -5.4 in Model 3 in Panel A. Conversely, the coefficient for *sup* changes from 1.1 to 38.8 in Model 3 and 21.7 in Model 4. Overall, considering the coefficient of the interaction in Model 3 (12.6), the TE of *dep* is negative, and *s* exhibits a positive effect, while the effect of *sup* remains varying.[53] These findings align with the hypothesized expectations.

The results indicate a significant relationship between the decline in children's dependency ratio, an increase in the saving rate, and the density of robots. These factors interact with each other and influence the motivation for automation. Interestingly, these

[52] Corraini et al. (2017) delves into the nuances and contrasts between interaction and mediation, providing valuable insights into their respective roles and implications in research.

[53] The overall impact of saving on robots' density comprises two components: saving (s) and the interaction term (sav_int). Combining these components yields an estimated total effect of saving, which can be approximated as 7.224 (-5.366 + 12.59). Similarly, the total effects can be calculated for the child dependency ratio, resulting in negative values, such as -37.79 (-50.38 + 12.59). For the aged support ratio, the total effect is either negative (-26.22) or positive (15.00) depending on the model used (model 3 or model 4).

findings challenge Acemoglu and Restrepo (2020) by suggesting that automation is primarily driven by the anticipated labor shortage resulting from declining fertility (or lower CDR), rather than population aging. The explanation lies in the lower CDR reduces the childcare burden, enabling higher savings that can be allocated to long-term investments in robot adoption. This aligns with the concept of the DDT. On the other hand, although population aging (or a higher OADR) stimulates the adoption of robotics, it also results in increased pension expenditures and thus decreased savings. As a result, the overall impact of population aging on automation is not straightforward.

Table 5.1.1C: Interaction Approach

3-Year Interval Sample of 1993-2017

	Gross domestic savings (% of GDP) Panel A				Gross savings (% of GNI) Panel B			
VARIABLES	M1	M2	M3	M4	M1	M2	M3	M4
pop_growth	-0.228***	-0.259***	-0.223***	-0.224***	-0.228***	-0.170**	-0.140*	-0.146*
	(0.0857)	(0.0850)	(0.0838)	(0.0819)	(0.0857)	(0.0850)	(0.0830)	(0.0808)
lnlfpc	-0.986	-0.835	-0.729	-0.306	-0.986	-1.531	-1.600	-1.369
	(1.020)	(1.004)	(0.982)	(0.969)	(1.020)	(0.999)	(0.972)	(0.948)
lngdpc	1.913***	1.708***	2.167***	2.341***	1.913***	1.426**	1.768***	2.102***
	(0.608)	(0.601)	(0.604)	(0.593)	(0.608)	(0.596)	(0.587)	(0.579)
sup	-0.956	1.097	-38.81***	21.74	-0.956	-0.935	-42.42***	11.34
	(3.774)	(3.773)	(12.41)	(21.72)	(3.774)	(3.705)	(11.93)	(19.10)
dep	-10.37***	-10.28***	-50.38***	-41.36***	-10.37***	-12.35***	-55.24***	-45.31***
	(2.497)	(2.455)	(12.14)	(12.17)	(2.497)	(2.438)	(12.00)	(12.01)
s		1.361***	-5.366***	-1.082		0.565**	-6.199***	-2.218
		(0.455)	(2.046)	(2.373)		(0.249)	(1.871)	(2.140)
sav_age_int				-6.736				-4.031
				(6.813)				(6.064)
sav_chld_int				9.807***				10.45***
				(3.748)				(3.659)
sav_int			12.59***				13.36***	
			(3.738)				(3.663)	
Constant	-7.400	-10.72	5.681	-11.43	-7.400	-1.191	17.16*	0.106
	(7.941)	(7.884)	(9.119)	(10.27)	(7.941)	(7.813)	(9.110)	(10.09)
Observations	286	286	286	286	286	268	268	268
R-squared	0.933	0.936	0.939	0.942	0.933	0.941	0.944	0.947
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

3-year sample of 1994-2018

	Gross domestic savings (% of GDP) Panel C				Gross savings (% of GNI) Panel D			
VARIABLES	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
pop_growth	-0.149**	-0.161**	-0.148**	-0.147**	-0.149**	-0.126*	-0.114*	-0.112*
	(0.0633)	(0.0636)	(0.0617)	(0.0618)	(0.0633)	(0.0644)	(0.0622)	(0.0622)
lnlfpc	-2.015***	-2.033***	-1.630**	-1.603**	-2.015***	-2.358***	-2.052***	-2.036***
	(0.775)	(0.773)	(0.756)	(0.757)	(0.775)	(0.760)	(0.738)	(0.736)
lngdpc	3.111***	2.968***	3.361***	3.370***	3.111***	2.772***	3.137***	3.199***
	(0.436)	(0.445)	(0.442)	(0.443)	(0.436)	(0.441)	(0.435)	(0.437)
sup	2.401	2.873	-33.84***	-22.46	2.401	2.112	-35.38***	-21.67
	(2.903)	(2.913)	(9.695)	(15.94)	(2.903)	(2.878)	(9.692)	(14.29)
dep	-3.600*	-3.868**	-41.51***	-40.64***	-3.600*	-5.216***	-44.15***	-43.43***
	(1.947)	(1.950)	(9.697)	(9.749)	(1.947)	(1.953)	(9.826)	(9.825)
s		0.503	-5.602***	-4.803***		0.387	-5.683***	-4.766***
		(0.338)	(1.577)	(1.811)		(0.236)	(1.520)	(1.673)
sav_age_int				8.022				7.673*
				(4.940)				(4.475)
sav_chld_int				11.28***				11.77***
				(2.953)				(2.982)
sav_int			11.60***				12.03***	
			(2.930)				(2.980)	
Constant	-18.04***	-18.14***	-4.099	-6.814	-18.04***	-13.72**	0.727	-2.846
	(5.659)	(5.645)	(6.519)	(7.187)	(5.659)	(5.653)	(6.526)	(7.067)
Observations	286	286	286	286	286	270	270	270
R-squared	0.951	0.952	0.955	0.955	0.951	0.955	0.959	0.959
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

3-year sample of 1995-2019

	Panel E				Panel F			
VARIABLES	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
pop_growth	-0.149**	-0.161**	-0.148**	-0.147**	-0.149**	-0.126*	-0.114*	-0.112*
	(0.0633)	(0.0636)	(0.0617)	(0.0618)	(0.0633)	(0.0644)	(0.0622)	(0.0622)
lnlfpc	-2.015***	-2.033***	-1.630**	-1.603**	-2.015***	-2.358***	-2.052***	-2.036***
	(0.775)	(0.773)	(0.756)	(0.757)	(0.775)	(0.760)	(0.738)	(0.736)
lngdpc	3.111***	2.968***	3.361***	3.370***	3.111***	2.772***	3.137***	3.199***
	(0.436)	(0.445)	(0.442)	(0.443)	(0.436)	(0.441)	(0.435)	(0.437)
sup	2.401	2.873	-33.84***	-22.46	2.401	2.112	-35.38***	-21.67
	(2.903)	(2.913)	(9.695)	(15.94)	(2.903)	(2.878)	(9.692)	(14.29)
dep	-3.600*	-3.868**	-41.51***	-40.64***	-3.600*	-5.216***	-44.15***	-43.43***
	(1.947)	(1.950)	(9.697)	(9.749)	(1.947)	(1.953)	(9.826)	(9.825)
s		0.503	-5.602***	-4.803***		0.387	-5.683***	-4.766***
		(0.338)	(1.577)	(1.811)		(0.236)	(1.520)	(1.673)
sav_age_int				8.022				7.673*
				(4.940)				(4.475)
sav_chld_int				11.28***				11.77***
				(2.953)				(2.982)
sav_int			11.60***				12.03***	
			(2.930)				(2.980)	
Constant	-18.04***	-18.14***	-4.099	-6.814	-18.04***	-13.72**	0.727	-2.846
	(5.659)	(5.645)	(6.519)	(7.187)	(5.659)	(5.653)	(6.526)	(7.067)
Observations	286	286	286	286	286	270	270	270
R-squared	0.951	0.952	0.955	0.955	0.951	0.955	0.959	0.959
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

5-year sample of 1994-2018

	Panel G				Panel H			
VARIABLES	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
pop_growth	-0.208**	-0.227***	-0.206**	-0.209**	-0.208**	-0.166*	-0.152*	-0.154*
	(0.0838)	(0.0847)	(0.0851)	(0.0848)	(0.0838)	(0.0849)	(0.0845)	(0.0839)
lnlfpc	-1.794	-1.748	-1.429	-1.460	-1.794	-2.769**	-2.606**	-2.687**
	(1.299)	(1.295)	(1.301)	(1.296)	(1.299)	(1.299)	(1.291)	(1.283)
lngdpc	2.147***	2.073***	2.347***	2.381***	2.147***	1.878***	2.055***	2.265***
	(0.683)	(0.683)	(0.699)	(0.697)	(0.683)	(0.679)	(0.681)	(0.690)
sup	-0.293	1.182	-19.82	7.557	-0.293	1.134	-19.88	4.791
	(4.180)	(4.310)	(13.71)	(24.22)	(4.180)	(4.188)	(13.08)	(20.62)
dep	-7.034**	-6.892**	-27.64**	-22.62*	-7.034**	-8.629***	-30.21**	-25.49*
	(2.873)	(2.865)	(13.18)	(13.63)	(2.873)	(2.879)	(13.05)	(13.32)
s		0.674	-2.918	-0.801		0.139	-3.282	-1.399
		(0.504)	(2.282)	(2.750)		(0.232)	(2.032)	(2.359)
sav_age_int				-2.305				-1.340
				(7.614)				(6.584)
sav_chld_int				4.936				5.423
				(4.200)				(4.058)
sav_int			6.533				6.761*	
			(4.051)				(3.991)	
Constant	-7.258	-9.184	-1.773	-8.615	-7.258	-0.543	7.846	0.0599
	(8.887)	(8.973)	(10.02)	(11.17)	(8.887)	(8.995)	(10.20)	(11.32)
Observations	164	164	164	164	164	153	153	153
R-squared	0.955	0.956	0.957	0.958	0.955	0.960	0.961	0.962
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

5-year sample of 1995-2019

	Panel I				Panel J			
VARIABLES	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
pop_growth	-0.127	-0.148	-0.125	-0.120	-0.127	-0.0731	-0.0511	-0.0506
	(0.0971)	(0.0968)	(0.0943)	(0.0913)	(0.0971)	(0.0947)	(0.0908)	(0.0902)
lnlfpc	-0.573	-0.513	-0.205	0.0218	-0.573	-1.361	-1.208	-1.080
	(1.277)	(1.265)	(1.232)	(1.195)	(1.277)	(1.213)	(1.161)	(1.156)
lngdpc	2.189***	2.047***	2.605***	2.529***	2.189***	1.507**	1.874**	1.996***
	(0.775)	(0.771)	(0.773)	(0.749)	(0.775)	(0.747)	(0.722)	(0.722)
sup	0.895	2.628	-39.90**	15.41	0.895	-1.732	-47.34***	-17.93
	(4.627)	(4.674)	(15.36)	(23.50)	(4.627)	(4.533)	(14.15)	(23.43)
dep	-12.50***	-12.35***	-54.69***	-45.01***	-12.50***	-14.66***	-62.00***	-55.27***
	(3.038)	(3.009)	(14.90)	(14.76)	(3.038)	(2.947)	(14.27)	(14.81)
s		0.952*	-6.328**	-1.904		0.678**	-6.873***	-4.602*
		(0.510)	(2.560)	(2.873)		(0.319)	(2.252)	(2.664)
sav_age_int				-4.089				5.561
				(7.357)				(7.368)
sav_chld_int				10.36**				12.80***
				(4.641)				(4.562)
sav_int			13.55***				14.87***	
			(4.673)				(4.395)	
Constant	-11.25	-13.46	2.576	-11.45	-11.25	-1.829	17.66	8.611
	(9.915)	(9.888)	(11.08)	(11.67)	(9.915)	(9.542)	(10.79)	(12.17)
Observations	175	175	175	175	175	163	163	163
R-squared	0.950	0.951	0.954	0.958	0.950	0.958	0.962	0.963
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, sav_int, sav_age_int, sav_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, interaction between saving and total dependency ratio, interaction between saving and old-age support ratio, interaction term between saving and children dependency ratio respectively. All independent variables are log transformed except sup and dep, and data represent the changes in lagged periods t-1. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

4) Validation and Robustness Checks

To ensure the reliability of the findings, this study conducts additional tests using different estimation methods, including pooled OLS (POLS), random-effects (RE), and fixed-effects (FE) estimators. Additionally, two potentially omitted covariates, namely the openness of the economy and the service sector's contribution to GDP, are included to address biases. The rationales for including these variables are based on previous research suggesting that countries with open economies may have a stronger incentive to invest in advanced technologies, while those with a larger services sector may have less motivation to adopt robots due to the complexity of automating customized tasks. The results of these tests are summarized in Table 5.1.1D in the Appendix.

Table 5.1.1D: Validation and Robustness Check

Panel A: Five-Year Samples

	1993-2018				1994-2019			
VARIABLES	**POLS**	**RE**	**FE**	**FE**	**POLS**	**RE**	**FE**	**FE**
pop_growth	-0.199	-0.210**	-0.206**	-0.225**	-0.270*	-0.127	-0.125	-0.0722
	(0.137)	(0.0833)	(0.0851)	(0.0886)	(0.159)	(0.0914)	(0.0943)	(0.0907)
lnlfpc	-2.045**	-1.388	-1.429	-1.595	-1.036	-0.371	-0.205	-0.902
	(0.908)	(1.042)	(1.301)	(1.375)	(0.977)	(1.059)	(1.232)	(1.213)
lngdpc	1.399***	1.696***	2.347***	2.197***	1.564***	1.823***	2.605***	2.681***
	(0.271)	(0.345)	(0.699)	(0.747)	(0.265)	(0.387)	(0.773)	(0.779)
sup	20.74	-5.786	-19.82	-19.93	4.406	-26.64**	-39.90**	-38.62**
	(12.77)	(11.44)	(13.71)	(14.23)	(12.65)	(12.76)	(15.36)	(14.92)
dep	13.14	-9.940	-27.64**	-27.18*	-2.126	-31.34***	-54.69***	-46.24***
	(12.23)	(10.77)	(13.18)	(13.71)	(11.78)	(12.02)	(14.90)	(14.59)
s	4.326**	0.318	-2.918	-2.608	2.120	-2.682	-6.328**	-5.109**
	(1.917)	(1.818)	(2.282)	(2.396)	(1.878)	(2.031)	(2.560)	(2.476)
sav_int	-5.044	1.338	6.533	6.425	-0.449	7.015*	13.55***	11.20**
	(3.639)	(3.254)	(4.051)	(4.207)	(3.567)	(3.729)	(4.673)	(4.548)
lntrade				-0.128				0.873*
				(0.441)				(0.480)
lnservice				1.470				-0.710
				(1.563)				(1.507)
Constant	-14.37*	-5.840	-1.773	-5.955	-13.35*	-0.486	2.576	0.825
	(8.204)	(7.845)	(10.02)	(12.00)	(8.013)	(8.433)	(11.08)	(12.13)
Observations	166	166	164	160	179	179	175	169
R-squared	0.670		0.957	0.958	0.674		0.954	0.960
Country FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, sav_int, lntrade, lnservice* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, interaction term between saving and total dependency ratio, and share of trade respectively. All independent variables are log transformed except *sup* and *dep*, and data represent the changes in lagged periods *t-1*. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

Consistent with the hypotheses, the analysis reveals significant correlations between the growth of robot density and the decline in both the elderly and children's dependency ratios, the decline in population growth, growth in GDP per capita, the decline in the saving rate, and raises in interactions. The inclusion of other two covariates have minimal impact on the results, as there is no significant relationship found. These findings reinforce the validity of the analyses.

5.1.2 The Indirect Mechanism Through Human Capital

In this analytical exercise, the focus shifts to investigate the role of human capital as another indirect mechanism in the relationship between demographic changes and technological advancements. This analysis follows the methods described in section 5.1.1, ensuring consistency in the practical approach. The objective of this exercise is to examine how human capital influences the adoption and advancement of automation technologies.

1) Causal Stepwise Approach on the Indirect Channel of Human Capital

This analysis extends the previous causal stepwise approach by examining the role of human capital as a second mediator between demographic changes (measured by log values of the proportion of working age population, old-age support ratio, and child dependency ratio) and automation outcomes. Table 5.1.2A presents separate estimations using a 3-year interval dataset from 1995-2019, [54] considering three distinct mediating variables: overall human capital index, health represented by life expectancy at birth, and education indicated by the percentage of the population with secondary schooling.

Similar to previous findings, Step 1 regression indicates a significantly positive total effect (TE) of demographic changes on automation density, with significant effects observed for working age population *lnwap* and child dependency ratio *dep* in most cases, but not for the old-age support ratio *sup*. These results reinforce the notion that aging and low fertility have different implications for automation.

[54] The examination has been carried out across all 3-year interval and 5-year interval samples, and the results remain consistent in most cases. To save space, this paper does not report other results but can provide upon request.

In Step 2, regressing the mediator *h* (human capital index, life expectancy at birth, or education level) on demographic variables, controlling for other factors, estimates the proportion that human capital mediates for the demographic structural changes. The coefficients on OADR (*sup*), CDR (*dep*), and the growth in the proportion of working-age population (*lnwap)* are significant in most cases, indicating viable mediating pathways. Notably, the mediating effects differ across population groups and the selected proxies of human capital: the human capital index and life expectancy at birth mediate *lnwap* and *sup*, while the education level mediates *sup* and *dep*. This suggests that different dimensions of human capital play a role for different population groups.

In Step 3, the mediator *h* is added to the model in the first step. The results show that the direct effect (DE) of *lnwap* through the human capital index increases from 7.212 to 8.599, and the DE of *dep* through education decreases from -6.974 to -6.206. These coefficients remain significant throughout the three steps. With positively significant coefficients on *h* in all settings, Sobel-Goodman tests confirm a viable mediating pathway through human capital for CDR and the growth rate of the working-age population. However, the estimators for *sup* are mostly found to be insignificant, suggesting no apparent mediating effect of human capital between aging burdens (or OADR) and the adoption of automation technologies.

Comparing changes in coefficients from Step 1 to Step 3, it indicates that human capital serves as a "suppressing mediation," explaining approximately 19.2 percent of the total effects of automation incentives in observing declining working-age population and child dependency ratio. A "partial mediation" through education is also identified for *dep*, explaining approximately 11 percent of the total effects.

These analyses support the second hypothesis that human capital serves as another mediating channel in addition to saving, to transmit the automation incentives in the context of post-demographic transition. More importantly, it also highlights the multiplicity of the human capital implications from demographic dynamics owing to the structure of the population. For example, the increasing longevity of individuals is inherently linked to the ageing population. As people are healthier and live longer, the population composition shifts, with a larger proportion of older individuals. This ageing

population necessitates the implications on automation through the health dimension. On the other hand, human capital development through education and early childhood investment plays a crucial role for the children. It serves as a vital mechanism for equipping individuals with the necessary knowledge, skills, and capabilities to adapt to changing socio-economic conditions and contribute to technological advancements at early stage. Therefore, the demographic shifts to low fertility population necessitates the implications on automation through the education dimension.

Table 5.1.2A: Mediating Effects Through Human Capital Index
1995-2019 Sample

Panel A: Independent Variable=Log Value of Share of Working Age Population			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=hc**	**Y=robot's density**
hc			1.030***
			(0.273)
lnwap	7.212***	-1.346***	8.599***
	(1.864)	(0.392)	(1.859)
pop_growth	-0.293***	-0.0636***	-0.228***
	(0.0877)	(0.0184)	(0.0875)
lnlfpc	-1.013	0.993***	-2.036***
	(0.703)	(0.148)	(0.739)
lngdpc	2.078***	0.495***	1.568***
	(0.122)	(0.0258)	(0.180)
Constant	-42.55***	-0.543	-41.99***
	(7.722)	(1.624)	(7.553)
Observations	295	295	295
R-squared	0.586	0.597	0.606
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Note: *pop_growth, lnlfpc, lngdpc, lnwap, hc* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and human capital index respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	-2.539***	0.01
Aroian	-2.492***	0.01
Goodman	-2.589***	0.01

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	-3.433***	0.00
b_coefficient	3.773***	0.00
Indirect_effect_aXb	-2.539***	0.01
Direct_effect_c'	4.625***	0.00
Total_effect_c	3.87***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: -0.192

Panel B: Independent Variable=Old-age Support Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=hc**	**Y=robot's density**
hc			0.757***
			(0.283)
sup	1.913	1.409***	0.847
	(1.983)	(0.407)	(2.003)
pop_growth	-0.291***	-0.0190	-0.277***
	(0.102)	(0.0210)	(0.101)
lnlfpc	-0.458	0.959***	-1.184
	(0.713)	(0.146)	(0.756)
lngdpc	2.050***	0.383***	1.760***
	(0.179)	(0.0369)	(0.208)
Constant	-14.60***	-5.155***	-10.70***
	(3.290)	(0.676)	(3.568)
Observations	295	295	295
R-squared	0.566	0.597	0.577
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, hc* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and human capital index respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	2.116**	0.03
Aroian	2.063**	0.04
Goodman	2.174**	0.03

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	3.459***	0.00
b_coefficient	2.675***	0.01
Indirect_effect_aXb	2.116**	0.03
Direct_effect_c'	0.423	0.67
Total_effect_c	0.965	0.34

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: 0.557

Panel C: Independent Variable=Child Dependency Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=hc**	**Y=robot's density**
hc			0.891***
			(0.265)
dep	-6.974***	0.393	-7.324***
	(1.371)	(0.299)	(1.351)
pop_growth	-0.0907	-0.0690***	-0.0292
	(0.0984)	(0.0214)	(0.0984)
lnlfpc	-0.943	0.927***	-1.770**
	(0.685)	(0.149)	(0.717)
lngdpc	1.570***	0.510***	1.115***
	(0.168)	(0.0365)	(0.213)
Constant	-5.060	-6.211***	0.476
	(3.683)	(0.802)	(3.976)
Observations	295	295	295
R-squared	0.600	0.583	0.616
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, hc* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and human capital index respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	1.227	0.22
Aroian	1.182	0.24
Goodman	1.277	0.20

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	1.317	0.19
b_coefficient	3.364***	0.00
Indirect_effect_aXb	1.227	0.22
Direct_effect_c'	-5.42***	0.00
Total_effect_c	-5.086***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: -0.05

Table 5.1.2B: Mediating Effects Through Life Expectancy at Birth
1995-2019 Sample

Panel A: Independent Variable=Log Value of Share of Working Age Population			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y= lifeexp**	**Y=robot's density**
lifeexp			1.030***
			(0.273)
lnwap	7.212***	-1.346***	8.599***
	(1.864)	(0.392)	(1.859)
pop_growth	-0.293***	-0.0636***	-0.228***
	(0.0877)	(0.0184)	(0.0875)
lnlfpc	-1.013	0.993***	-2.036***
	(0.703)	(0.148)	(0.739)
lngdpc	2.078***	0.495***	1.568***
	(0.122)	(0.0258)	(0.180)
Constant	-42.55***	-0.543	-41.99***
	(7.722)	(1.624)	(7.553)
Observations	295	295	295
R-squared	0.586	0.597	0.606
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Note: *pop_growth, lnlfpc, lngdpc, lnwap, lifeexp* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and life expectancy at birth respectively. All independent variables are log transformed except for lifeexp, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	-2.539***	0.01
Aroian	-2.492***	0.01
Goodman	-2.589***	0.01

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	-3.433***	0.00
b_coefficient	3.773***	0.00
Indirect_effect_aXb	-2.539***	0.01
Direct_effect_c'	4.625***	0.00
Total_effect_c	3.87***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: -0.192

Panel B: Independent Variable=Old-age Support Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y= lifeexp**	**Y=robot's density**
lifeexp			0.757***
			(0.283)
sup	1.913	1.409***	0.847
	(1.983)	(0.407)	(2.003)
pop_growth	-0.291***	-0.0190	-0.277***
	(0.102)	(0.0210)	(0.101)
lnlfpc	-0.458	0.959***	-1.184
	(0.713)	(0.146)	(0.756)
lngdpc	2.050***	0.383***	1.760***
	(0.179)	(0.0369)	(0.208)
Constant	-14.60***	-5.155***	-10.70***
	(3.290)	(0.676)	(3.568)
Observations	295	295	295
R-squared	0.566	0.597	0.577
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, lifeexp* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and life expectancy at birth respectively. All independent variables are log transformed except for lifeexp, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	2.116**	0.03
Aroian	2.063**	0.04
Goodman	2.174**	0.03

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	3.459***	0.00
b_coefficient	2.675***	0.01
Indirect_effect_aXb	2.116**	0.03
Direct_effect_c'	0.423	0.67
Total_effect_c	0.965	0.34

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: 0.557

Panel C: Independent Variable=Child Dependency Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y= lifeexp**	**Y=robot's density**
lifeexp			0.891***
			(0.265)
dep	-6.974***	0.393	-7.324***
	(1.371)	(0.299)	(1.351)
pop_growth	-0.0907	-0.0690***	-0.0292
	(0.0984)	(0.0214)	(0.0984)
lnlfpc	-0.943	0.927***	-1.770**
	(0.685)	(0.149)	(0.717)
lngdpc	1.570***	0.510***	1.115***
	(0.168)	(0.0365)	(0.213)
Constant	-5.060	-6.211***	0.476
	(3.683)	(0.802)	(3.976)
Observations	295	295	295
R-squared	0.600	0.583	0.616
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, lifeexp* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and life expectancy at birth respectively. All independent variables are log transformed except for lifeexp, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	1.227	0.22
Aroian	1.182	0.24
Goodman	1.277	0.20

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	1.317	0.19
b_coefficient	3.364***	0.00
Indirect_effect_aXb	1.227	0.22
Direct_effect_c'	-5.42***	0.00
Total_effect_c	-5.086***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: -0.05

Table 5.1.2C: Mediating Effects Through Education
1995-2019 Sample

Panel A: Independent Variable=Log Value of Share of Working Age Population			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=edu**	**Y=robot's density**
edu			0.0272***
			(0.00662)
lnwap	7.212***	15.85	6.781***
	(1.864)	(16.10)	(1.818)
pop_growth	-0.293***	-2.856***	-0.216**
	(0.0877)	(0.757)	(0.0874)
lnlfpc	-1.013	-3.753	-0.911
	(0.703)	(6.077)	(0.685)
lngdpc	2.078***	4.916***	1.944***
	(0.122)	(1.058)	(0.124)
Constant	-42.55***	-51.59	-41.14***
	(7.722)	(66.71)	(7.527)
Observations			
R-squared	295	295	295
Country FE	0.586	0.157	0.609
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Note: *pop_growth, lnlfpc, lngdpc, lnwap, edu* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and percentage of population with secondary schooling respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	-2.263**	0.02
Aroian	-2.216**	0.03
Goodman	-2.314**	0.02

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	-2.766***	0.01
b_coefficient	3.937***	0.00
Indirect_effect_aXb	-2.263**	0.02
Direct_effect_c'	4.545***	0.00
Total_effect_c	3.87***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: -0.161

Panel B: Independent Variable=Old-age Support Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=edu**	**Y=robot's density**
edu			0.0282***
			(0.00682)
sup	1.913	35.59**	0.909
	(1.983)	(16.63)	(1.946)
pop_growth	-0.291***	-2.050**	-0.233**
	(0.102)	(0.858)	(0.101)
lnlfpc	-0.458	-1.311	-0.421
	(0.713)	(5.980)	(0.694)
lngdpc	2.050***	2.783*	1.972***
	(0.179)	(1.504)	(0.176)
Constant	-14.60***	20.53	-15.18***
	(3.290)	(27.59)	(3.205)
Observations			
R-squared	295	295	295
Country FE	0.566	0.167	0.591
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, edu* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and percentage of population with secondary schooling respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	2.442**	0.02
Aroian	2.398**	0.02
Goodman	2.489***	0.01

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	4.224***	0.00
b_coefficient	2.993***	0.00
Indirect_effect_aXb	2.442**	0.02
Direct_effect_c'	0.228	0.82
Total_effect_c	0.965	0.34

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: 0.759

Panel C: Independent Variable=Child Dependency Ratio			
	Step 1	**Step 2**	**Step 3**
VARIABLES	**Y=robot's density**	**Y=edu**	**Y=robot's density**
edu			0.0239***
			(0.00661)
dep	-6.974***	-32.10***	-6.206***
	(1.371)	(11.93)	(1.360)
pop_growth	-0.0907	-1.811**	-0.0474
	(0.0984)	(0.856)	(0.0972)
lnlfpc	-0.943	-4.588	-0.834
	(0.685)	(5.960)	(0.672)
lngdpc	1.570***	2.340	1.514***
	(0.168)	(1.457)	(0.165)
Constant	-5.060	55.32*	-6.383*
	(3.683)	(32.04)	(3.627)
Observations			
R-squared	295	295	295
Country FE	0.600	0.174	0.618
Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, lnwap, edu* stand for population growth rate, labor force participation rate, GDP per capita, share of working-age population, and percentage of population with secondary schooling respectively. All independent variables are log transformed except for hc, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**
Sobel	-2.159**	0.03
Aroian	-2.108**	0.04
Goodman	-2.214**	0.03

Indirect, Direct, and Total Effects	**z**	**P>z**
a_coefficient	-2.692***	0.01
b_coefficient	3.615***	0.00
Indirect_effect_aXb	-2.159**	0.03
Direct_effect_c'	-4.563***	0.00
Total_effect_c	-5.086***	0.00

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated: 0.11

2) Interaction Approach on the Indirect Channel of Human Capital

Following a similar approach, alternative model settings by including interaction terms in regressions is also provided. This allows the examination of the joint effects of human capital and demographic changes on the adoption of automation technologies, as well as the separate effects for different populations. The results from the interaction analysis shed light on how the growth of automation technologies respond to different population groups,

characterized by varying levels and dimensions of human capital. This allows for a more nuanced understanding of the complex dynamics and the interplay between demographic changes, human capital, and technological progress.

To start with the baseline Model 1, it replicates the regression model in 5.1.1, by adding three types of human capital indicators used in the previous stepwise analysis. It is worth mentioning that an addition human capital indicator- average years of total schooling of female aged 15+ is also added in Panel D, as inspired by Schultz (2002) and Psacharopoulos and Patrinos (2002) that girls' education is a key component of a country's human capital development. Similarly, these interaction models replace *lnwap* by *sup* and *dep.* Interaction terms between *h* and demographic changes being added in M2 and M3 means to reveal the overall and separate synergistic interplays, respectively.

The findings from the 5-year sample analysis are summarized in Table 5.1.2D, while the results from the 3-year sample analysis are presented in Table 5.1.2D (cont'd) in the Appendix. Across all exercises in Panel A to Panel D, the child dependency ratio *dep* consistently exhibits a strong negative correlation with robots' density, regardless of the inclusion of interaction terms. Furthermore, the coefficients associated with the interaction variables, such as *hc_int* and *hc_chld_int,* [55] are positive and statistically significant (Table 5.1.2D Panel A), indicating the presence of an "interaction effect." These findings support and reinforce the results obtained in the previous section on saving. However, the old-age support ratio *sup* does not consistently demonstrate a significant contribution to the motivation for automation, except in analyses conducted in Panel B focusing on life expectancy at birth and Panel C considering education.

Comparing Model 1 to Model 2 and Model 3, there is an evident increase in the coefficients on *dep* after the inclusion of *hc_int* and *hc_chld_int*. In Panel A, the coefficient rises from 8.681 in Model 1 to 31.62 and 27.27 in Model 2 and Model 3, respectively. In the meantime, the magnitude of coefficients on *hc* increased from 1.134 in M1 to 4.778 and 3.533 in Model 2 and Model 3 respectively, and the coefficients also turned into significant. The overall magnitude of marginal impact of *dep* on the growth of robot's

[55] The marginal effects are consistent for all other interactions in Panel B-Panel D as well.

density can be estimated being negative at -18.8 percent,[56] and the marginal impact of *hc* can be estimated as 4.19 percent,[57] which are in line with the hypotheses.

The results of this study provide further evidence supporting the relationship between the decline in children's dependency ratio, higher levels of human capital, and the increasing density of robots. Numerous studies have examined the relationship between low fertility rates and technological advancements, arguing that the demographic transition, characterized by declining fertility rates, has played a significant role in fostering technological advancements (i.e., Galor and Weil, 2000; Bloom, Canning and Sevilla, 2003). On the other hand, influential works by Barro and Sala-i-Martin (1995) and Romer (1990) had argued the prominent role of human capital in fostering technological advancements and productivity growth.

However, population aging, as indicated by a higher support ratio, does not bring consistently significant effect to the adoption of robotics. Many studies have demonstrated a complex relationship between population aging, human capital, and technological advancements, with mixed results observed in the literature. The impact of population aging on technological progress depends on several factors, including the specific age structure (i.e., Lindh and Malmberg, 1999), the level of human capital (i.e., Bloom, Canning, and Fink, 2010), investments in education and healthcare (i.e., Cervellati & Sunde, 2005), and the adaptability of the labour force (i.e., Acemoglu and Restrepo, 2017) to technological changes.

[56] The overall effects of 1 percentage point change in *dep* on the growth of robot's density -27.27+8.474= -18.796 when *hc* is 1 using Model 3 estimators in Panel A. Estimators from Panel B-D also show consistent results.
[57] The overall effects of 1 percentage point change in *hc* on the growth of robot's density 8.963-4.778=4.185 when *dep* is 1 using Model 2 estimators in Panel A. Estimators from other Panel B-D also show consistent results.

Table 5.1.2D: Interaction Approach
5-year sample

Panel A: Through Human Capital Index						
	1993-2018			1994-2019		
VARIABLES	M1	M2	M3	M1	M2	M3
pop_growth	-0.224***	-0.215***	-0.176**	-0.153	-0.147	-0.117
	(0.0840)	(0.0801)	(0.0817)	(0.0964)	(0.0897)	(0.0930)
lnlfpc	-1.379	-0.429	-0.827	-0.429	-0.191	-0.442
	(1.305)	(1.273)	(1.274)	(1.260)	(1.174)	(1.190)
lngdpc	2.143***	2.742***	2.602***	2.163***	2.860***	2.727***
	(0.679)	(0.669)	(0.665)	(0.772)	(0.735)	(0.742)
sup	0.992	-23.83***	14.10	2.492	-26.02***	-2.625
	(4.278)	(8.210)	(21.27)	(4.654)	(7.746)	(20.92)
dep	-8.681***	-31.62***	-27.27***	-13.72***	-38.04***	-36.41***
	(3.043)	(7.196)	(7.455)	(3.142)	(6.208)	(6.344)
s	0.586	0.338	0.429	0.874*	0.575	0.590
	(0.503)	(0.485)	(0.481)	(0.511)	(0.480)	(0.479)
hc	-1.134	-4.778***	-3.533**	-1.019	-4.825***	-4.103***
	(0.688)	(1.235)	(1.380)	(0.702)	(1.078)	(1.231)
hc_age_int			-2.665			3.099
			(6.543)			(6.398)
hc_chld_int			8.474***			10.30***
			(2.555)			(2.311)
hc_int		8.963***			10.28***	
		(2.574)			(2.315)	
Constant	-7.151	-7.061	-9.274	-11.25	-9.368	-9.934
	(8.990)	(8.567)	(8.539)	(9.959)	(9.278)	(9.273)
Observations	164	164	164	175	175	175
R-squared	0.957	0.961	0.963	0.952	0.959	0.959
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, hc, hc_int, hc_age_int, hc_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, human capital index, interaction between hc and total dependency ratio, interaction between hc and old-age support ratio, interaction term between hc and children dependency ratio respectively. All independent variables are log transformed except sup, dep, and hc, and data represent the changes in lagged periods t-1. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

Panel B: Through Life Expectancy at Birth

	1993-2018			1994-2019		
VARIABLES	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
pop_growth	-0.222**	-0.234***	-0.219**	-0.147	-0.170*	-0.188*
	(0.0850)	(0.0814)	(0.0878)	(0.0970)	(0.0903)	(0.0965)
lnlfpc	-1.786	-0.862	-0.878	-0.479	0.0252	0.0929
	(1.299)	(1.274)	(1.279)	(1.268)	(1.183)	(1.193)
lngdpc	1.954***	2.715***	2.608***	1.964**	3.212***	3.366***
	(0.701)	(0.709)	(0.751)	(0.781)	(0.777)	(0.829)
sup	0.536	-60.13***	-33.84	1.990	-79.17***	-112.1*
	(4.396)	(18.78)	(62.27)	(4.767)	(18.60)	(62.97)
dep	-6.894**	-68.67***	-65.95***	-12.30***	-93.43***	-96.85***
	(2.870)	(18.84)	(19.88)	(3.016)	(18.28)	(19.37)
s	0.696	0.646	0.659	0.929*	0.705	0.689
	(0.506)	(0.485)	(0.487)	(0.512)	(0.478)	(0.481)
lifeexp	0.0650	-0.364**	-0.332*	0.0581	-0.530***	-0.566***
	(0.0834)	(0.152)	(0.168)	(0.0811)	(0.151)	(0.165)
health_age_int			0.512			1.517*
			(0.774)			(0.780)
health_chld_int			0.813***			1.144***
			(0.259)			(0.255)
health_int		0.836***			1.112***	
		(0.252)			(0.248)	
Constant	-12.76	7.335	5.569	-17.05	12.00	13.51
	(10.10)	(11.41)	(12.13)	(11.11)	(12.18)	(12.52)
Observations	164	164	164	175	175	175
R-squared	0.956	0.960	0.960	0.952	0.958	0.959
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, lifeexp, health_int, health_age_int, health_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, life expectancy at birth, interaction between lifeexp and total dependency ratio, interaction between lifeexp and old-age support ratio, interaction term between lifeexp and children dependency ratio respectively. All independent variables are log transformed except sup, dep, and lifeexp, and data represent the changes in lagged periods t-1. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

Panel C: Through Education

	1993-2018			1994-2019		
VARIABLES	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
pop_growth	-0.225***	-0.233***	-0.246***	-0.133	-0.116	-0.149
	(0.0852)	(0.0804)	(0.0822)	(0.0974)	(0.0927)	(0.0957)
lnlfpc	-1.690	-0.519	-0.505	-0.450	-0.358	-0.343
	(1.312)	(1.275)	(1.277)	(1.264)	(1.201)	(1.198)
lngdpc	2.079***	3.138***	3.186***	2.094***	3.324***	3.360***
	(0.686)	(0.704)	(0.708)	(0.771)	(0.803)	(0.801)
sup	1.509	-9.185*	-13.67*	3.803	-7.778	-14.04*
	(4.434)	(5.030)	(7.697)	(4.770)	(5.492)	(7.287)
dep	-6.935**	-18.79***	-20.02***	-11.97***	-23.08***	-23.92***
	(2.879)	(4.122)	(4.424)	(3.021)	(4.134)	(4.172)
s	0.686	0.287	0.224	0.997*	0.506	0.446
	(0.508)	(0.490)	(0.498)	(0.511)	(0.503)	(0.503)
edu	-0.00344	-0.199***	-0.217***	-0.0123	-0.201***	-0.219***
	(0.0102)	(0.0520)	(0.0570)	(0.0104)	(0.0514)	(0.0531)
edu_age_int		0.381***				0.503***
		(0.0997)				(0.139)
edu_chld_int			0.474***			0.364***
			(0.156)			(0.101)
edu_int			0.378***		0.378***	
			(0.1000)		(0.101)	
Constant	-9.437	-17.87**	-16.97*	-14.18	-19.86**	-18.77*
	(9.040)	(8.808)	(8.900)	(9.890)	(9.521)	(9.530)
Observations	164	164	164	175	175	175
R-squared	0.956	0.961	0.962	0.952	0.957	0.957
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, edu, edu_int, edu_age_int, edu_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, percentage of population age 15+ with secondary schooling, interaction between edu and total dependency ratio, interaction between edu and old-age support ratio, interaction term between edu and children dependency ratio respectively. All independent variables are log transformed except sup, dep, and edu, and data represent the changes in lagged periods t-1. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

Panel D: Through Female's Education Attainment

	1993-2018			1994-2019		
VARIABLES	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
pop_growth	-0.222**	-0.241***	-0.221***	-0.140	-0.150	-0.135
	(0.0849)	(0.0808)	(0.0844)	(0.0969)	(0.0922)	(0.0946)
lnlfpc	-1.530	-0.405	-0.458	-0.440	-0.481	-0.506
	(1.322)	(1.293)	(1.296)	(1.264)	(1.202)	(1.205)
lngdpc	2.088***	2.810***	2.693***	2.084***	3.013***	2.922***
	(0.684)	(0.679)	(0.695)	(0.771)	(0.775)	(0.786)
sup	2.117	-4.379	-0.201	4.047	-3.162	0.106
	(4.453)	(4.593)	(6.884)	(4.826)	(4.983)	(6.694)
dep	-6.843**	-15.75***	-14.65***	-11.93***	-19.77***	-19.32***
	(2.869)	(3.671)	(3.917)	(3.027)	(3.569)	(3.627)
s	0.635	0.304	0.393	0.925*	0.571	0.595
	(0.507)	(0.490)	(0.503)	(0.510)	(0.494)	(0.496)
femedu	-0.159	-2.417***	-2.234***	-0.232	-2.276***	-2.181***
	(0.187)	(0.649)	(0.688)	(0.201)	(0.582)	(0.598)
femedu_age_int			3.285			3.502*
			(2.039)			(1.813)
femedu_chld_int			4.903***			4.818***
			(1.327)			(1.291)
femedu_int		4.587***			4.491***	
		(1.268)			(1.208)	
Constant	-9.898	-16.98*	-17.00*	-13.87	-18.76*	-18.53*
	(9.024)	(8.786)	(8.800)	(9.880)	(9.487)	(9.511)
Observations	164	164	164	175	175	175
R-squared	0.956	0.961	0.961	0.952	0.957	0.957
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, femedu, femedu_int, femedu_age_int, femedu_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, average years of total schooling of female aged 15+, interaction between femedu and total dependency ratio, interaction between femedu and old-age support ratio, interaction term between femedu and children dependency ratio respectively. All independent variables are log transformed except sup, dep, and femedu, and data represent the changes in lagged periods t-1. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

3) Validation and Robustness Check

Similarly, various robustness checks are also carried out to ensure the reliability of the findings. In addition to the fixed-effects (FE) estimations, pooled OLS (POLS) and random-effects (RE) estimators, as well as primary results with two potential covariates are also provided in the last column in Table 5.1.2E.[58]

The results reveal that significant correlations that align with the hypothesized relationships between the growth in robot density and the decline in child dependency ratio,

[58] Results using 5-year samples are provided in Table 5.1.2E: Robustness Check (cont'd) in the Appendix

positive in human capital, negative in population growth, positive in GDP per capita, negative in labor force participation rate, and positive in interaction effects. Nevertheless, the effects on old-age support ratio and saving becomes in consistent across different samples, model specifications, and estimation methods. The inclusion of additional variables has limited impact on the results, although significant effect is found on the openness, no significant relationship is observed for the contribution of the service sector. These findings provide further validation of the analyses.

Table 5.1.2E: Validation and Robustness Check
1995-2019 Sample

	Panel A: HCI				Panel B: Life Expectancy at Birth			
VARIABLES	POLS	RE	FE	FE	POLS	RE	FE	FE
pop_growth	-0.0484	-0.0625	-0.0484	-0.0287	-0.0831*	-0.0768	-0.0831*	-0.0625
	(0.0444)	(0.0452)	(0.0444)	(0.0445)	(0.0478)	(0.0487)	(0.0478)	(0.0478)
lnlfpc	-1.230**	-1.085**	-1.230**	-1.273**	-0.737	-0.736	-0.737	-0.764
	(0.544)	(0.540)	(0.544)	(0.544)	(0.576)	(0.568)	(0.576)	(0.576)
lngdpc	3.054***	2.213***	3.054***	3.214***	3.304***	2.380***	3.304***	3.490***
	(0.366)	(0.275)	(0.366)	(0.372)	(0.425)	(0.286)	(0.425)	(0.432)
sup	17.05	4.910	17.05	21.53*	-40.49	-14.04	-40.49	-23.52
	(12.04)	(10.37)	(12.04)	(12.23)	(36.24)	(28.96)	(36.24)	(36.74)
dep	-25.26***	-23.47***	-25.26***	-23.31***	-53.95***	-43.11***	-53.95***	-52.91***
	(3.862)	(3.678)	(3.862)	(3.948)	(11.14)	(10.42)	(11.14)	(11.03)
s	0.0133	0.375	0.0133	-0.245	0.0259	0.473*	0.0259	-0.287
	(0.272)	(0.263)	(0.272)	(0.309)	(0.293)	(0.274)	(0.293)	(0.332)
h	-2.615***	-2.464***	-2.615***	-2.277***	-0.311***	-0.294***	-0.311***	-0.306***
	(0.655)	(0.644)	(0.655)	(0.666)	(0.0920)	(0.0877)	(0.0920)	(0.0910)
h_age_int	-3.351	-0.942	-3.351	-5.462	0.575	0.205	0.575	0.336
	(3.623)	(3.040)	(3.623)	(3.710)	(0.447)	(0.353)	(0.447)	(0.456)
h_chld_int	9.015***	7.463***	9.015***	8.641***	0.671***	0.514***	0.671***	0.675***
	(1.326)	(1.259)	(1.326)	(1.336)	(0.144)	(0.136)	(0.144)	(0.142)
lntrade				0.750***				0.820***
				(0.254)				(0.274)
lnservice				0.0135				-0.0522
				(0.824)				(0.879)
Constant	-16.39***	-7.382*	-15.04***	-19.84***	-2.201	5.046	-1.889	-6.482
	(4.488)	(3.969)	(4.520)	(5.597)	(7.025)	(6.852)	(6.948)	(7.712)
Observations	295	295	292	288	295	295	292	288
R-squared	0.971		0.970	0.971	0.967		0.965	0.967
Country FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

	Panel C: Education				Panel D: Female's Education Attainment			
VARIABLES	POLS	RE	FE	FE	POLS	RE	FE	FE
pop_growth	-0.0976**	-0.0955**	-0.0976**	-0.0815*	-0.0775	-0.0754	-0.0775	-0.0573
	(0.0472)	(0.0476)	(0.0472)	(0.0475)	(0.0479)	(0.0485)	(0.0479)	(0.0478)
lnlfpc	-1.115*	-1.029*	-1.115*	-1.107*	-1.066*	-0.989*	-1.066*	-1.037*
	(0.567)	(0.557)	(0.567)	(0.569)	(0.576)	(0.567)	(0.576)	(0.574)
lngdpc	3.430***	2.381***	3.430***	3.618***	3.059***	2.191***	3.059***	3.250***
	(0.401)	(0.277)	(0.401)	(0.409)	(0.407)	(0.282)	(0.407)	(0.414)
sup	-9.471**	-11.57***	-9.471**	-10.93***	0.734	-2.577	0.734	-0.754
	(3.947)	(3.866)	(3.947)	(4.034)	(3.674)	(3.517)	(3.674)	(3.723)
dep	-13.31***	-11.49***	-13.31***	-13.01***	-9.168***	-8.777***	-9.168***	-8.779***
	(2.617)	(2.417)	(2.617)	(2.687)	(2.318)	(2.061)	(2.318)	(2.350)
s	-0.118	0.301	-0.118	-0.306	-0.000696	0.426	-0.000696	-0.278
	(0.296)	(0.277)	(0.296)	(0.333)	(0.300)	(0.280)	(0.300)	(0.337)
h	-0.143***	-0.104***	-0.143***	-0.143***	-1.264***	-1.014***	-1.264***	-1.291***
	(0.0298)	(0.0282)	(0.0298)	(0.0303)	(0.351)	(0.335)	(0.351)	(0.350)
h_age_int	0.326***	0.256***	0.326***	0.310***	1.723*	1.345	1.723*	1.441
	(0.0756)	(0.0734)	(0.0756)	(0.0771)	(1.024)	(0.953)	(1.024)	(1.020)
h_chld_int	0.240***	0.160***	0.240***	0.257***	2.888***	2.123***	2.888***	3.190***
	(0.0604)	(0.0569)	(0.0604)	(0.0615)	(0.778)	(0.729)	(0.778)	(0.787)
lntrade				0.711**				0.866***
				(0.275)				(0.275)
lnservice				0.476				0.157
				(0.890)				(0.889)
Constant	-19.12***	-10.50***	-19.04***	-25.27***	-19.63***	-11.77***	-19.14***	-24.55***
	(4.683)	(3.805)	(4.736)	(6.058)	(4.712)	(3.833)	(4.796)	(6.029)
Observations	295	295	292	288	295	295	292	288
R-squared	0.967		0.965	0.967	0.966		0.964	0.966
Country FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, h, h_age_int, h_chld_int, lntrade, lnservice* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, proxies for human capital, interaction term between the human capital proxy and old-age support ratio, interaction term between the human capital proxy and child dependency ratio, share of trade, and share of services respectively. All independent variables are log transformed except *sup, dep, and h,* and data represent the changes in lagged periods *t-1*. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

5.1.3 A Global Perspective from the Comparative Analysis

With the evidence presented in the global context, it is natural to question whether the implications of demographic structural changes on technological advancements are consistent across countries and how they specifically apply to China.

The reason is that while the overall findings suggest a significant relationship between demographic changes and technological advancements through dual indirect mechanism, it is important to consider the unique characteristics of different countries, including their stages in the demographic transition, the level of economic development stage, institutional factors, and policy frameworks as illustrated in Chapter 2.

For China specifically, the impact of demographic structural changes on technological advancements may exhibit some variations compared to other countries

because China has undergone significant demographic transitions with respect to its speed and magnitude. In addition, China has also witnessed rapid economic development, technological advancements, and human capital development in the past decades. The country is also known well for its high saving rates.[59] These unique features pertaining to China may have different implications for its technological advancements.

Therefore, this analytical piece means to further disentangle the complex interplay between demographic structural changes, technological advancements, and the two indirect mediating channels of saving and human capital with more granular analyses, and with specific research interests in the global comparison of China.

1) Comparison Across Income Groups

First and foremost, this paper divides the global sample according to their income groups as classified by the World Bank in 2019, in concordant with the latest year of the data. The classification categorizes countries into four groups: high-income countries (HIC), upper-middle income countries (UMIC), lower-middle income countries (LMIC), and low-income countries (LIC), based on their Gross National Income (GNI) per capita using the World Bank Atlas method. [60]

In this analysis, HIC countries are separated from the rest of the countries (Non-HIC) to ensure the sufficient sample size to carry out the investigation. The rationale behind this is that, as demonstrated in DMT, economic development is closely linked to the stages of demographic transition. Many high-income countries have already entered the post-demographic transition stage (Stage 4), characterized by low fertility rates and longer life expectancy. On the other hand, many middle-income and low-income countries (MIC and LIC) are still in the process of transitioning through the various stages of demographic transition at different paces. This classification allows for a comparative analysis that takes into account the specific characteristics and development stages of countries in different

[59] According to official data, China's household savings rate stood at approximately 32 percent in both 2018 and 2019. This rate is significantly higher than that of the EU and the US, which were approximately 12 percent and 7 percent, respectively, during the same period. (Data source: NBS, 2020; Eurostat, 2020; BEA; 2020).

[60] Details see link: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

income groups, providing complementary insights across the global landscape. Additional examination using Non-HIC sample without China data is also provided.

Table 5.1.3 provides the comparison of regression results using different country group samples based on Model 2 in 5.1.2, including world (full sample of 69 countries), HIC (40 countries), Non-HIC (29 countries), and Non-HIC (excluding China).[61] The results reveal that the coefficients of *dep* remain significantly negative across all samples, while the magnitude of the coefficients is largest for the Non-HIC. The aggregated impact of 1 percentage point decline in *dep* is estimated to bring about 27.34 percent growth in the robot density. When China is excluded from the sample, the total impact will decrease to 19.94. In contrast, the aggregated impact for HIC and the World is 19.72 and 16.25 respectively.

The coefficients of human capital *h* indicated by human capital index also remain significantly positive across all samples, depending on the level of population structure. For instance, for countries with 1/3 of children population (0-14), working-age population (15-64), and the elderly (65 and above) each, their *dep* and *sup* are equivalent to 1. It suggests that the aggregated impact of 1 percentage point increase in *h* is estimated to bring about 73.27 percent, 65.65 percent growth in the robot density for Non-HIC and without China respectively. In comparison, the aggregated impact for the World is estimated about 3.05, and even negative at 0.65 for HIC, implying significant variations across countries at different level of development.

One interesting finding worth mentioning is that, while the old-age support ratio *sup* is not significant when considering the world as a whole, it shows a positive association with technological advancements in high-income countries (HIC). The aggregated marginal impact of the old-age support ratio in HIC is estimated to be 37.68 percent with 1 percentage point change in *sup*, although not significant when applying a 5-year sample.

[61] The HIC group includes Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR China, Hungary, Iceland, Ireland, Israel, Italy, Korea Rep., Kuwait, Latvia, Lithuania, Macao SAR China, Malta, Netherlands, New Zealand, Norway, Oman, Poland, Portugal, Qatar, Saudi Arabia, Singapore, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, and United States. The Non-HIC group includes Argentina, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, mainland China, Colombia, Croatia, Egypt, Arab Rep., India, Indonesia, Iran, Islamic Rep., Malaysia, Mexico, Moldova, Morocco, Pakistan, Peru, Philippines, Romania, Serbia, South Africa, Thailand, Tunisia, Turkey, Ukraine, Uzbekistan, Venezuela, RB, and Vietnam.

However, *sup* has a significantly negative association with the growth of robots' density in Non-HIC, regardless of whether China is included in the analysis or not. The aggregated marginal impact of the *sup* in the Non-HIC exercise is estimated to be 105.86 percent and 88.53 percent, with and without China respectively, for each percentage point change in *sup*. These negative effects suggest a decrease in the old-age support ratio is associated with a promotion in robot's density for non-high income countries.

Table 5.1.3A: Global Comparison by Income Groups

	3-Year Sample (1995-2019)				5-Year Sample (1995-2019)			
VARIABLES	World	HIC	Non-HIC	Non-HIC (exl. China)	World	HIC	Non-HIC	Non-HIC (excl. China)
pop_growth	-0.0484	-0.0477	0.251	0.311	-0.117	-0.0817	-1.846*	-2.204**
	(0.0444)	(0.0441)	(0.460)	(0.450)	(0.0930)	(0.0875)	(0.975)	(1.023)
lnlfpc	-1.230**	-1.600***	0.266	0.101	-0.442	-1.624	-0.496	-0.780
	(0.544)	(0.600)	(1.976)	(1.905)	(1.190)	(1.410)	(2.649)	(2.654)
lngdpc	3.054***	2.551***	3.383***	5.788***	2.727***	3.959***	4.138***	5.453***
	(0.366)	(0.617)	(0.634)	(0.974)	(0.742)	(1.145)	(1.087)	(1.610)
sup	17.05	34.94**	-173.5***	-148.7***	-2.625	17.00	-181.4***	-188.9***
	(12.04)	(13.76)	(54.23)	(52.28)	(20.92)	(24.85)	(64.31)	(64.47)
dep	-25.26***	-29.58***	-46.93***	-37.05**	-36.41***	-36.69**	-67.36***	-64.53***
	(3.862)	(10.05)	(15.78)	(15.45)	(6.344)	(17.14)	(21.10)	(21.51)
s	0.0133	0.162	-0.648	-0.676	0.590	0.215	0.0355	-0.128
	(0.272)	(0.320)	(0.667)	(0.649)	(0.479)	(0.552)	(0.963)	(0.989)
h	-2.615***	-2.256**	-13.96***	-11.63***	-4.103***	-3.303*	-18.67***	-18.92***
	(0.655)	(0.921)	(4.258)	(4.158)	(1.231)	(1.719)	(5.889)	(5.900)
h_age_int	-3.351	-8.247**	67.64***	60.17***	3.099	-2.307	61.89**	62.68**
	(3.623)	(4.156)	(21.52)	(20.65)	(6.398)	(7.519)	(27.50)	(27.48)
h_chld_int	9.015***	9.856***	19.59***	17.11***	10.30***	11.25**	29.61***	30.00***
	(1.326)	(2.923)	(6.444)	(6.265)	(2.311)	(5.099)	(9.649)	(9.681)
Constant	-15.04***	-10.39	6.825	-23.15	-9.934	-21.52	13.16	1.962
	(4.520)	(7.705)	(13.84)	(16.32)	(9.273)	(14.24)	(18.11)	(21.41)
Observations	292	215	77	71	175	125	50	47
R-squared	0.970	0.948	0.975	0.979	0.959	0.940	0.978	0.979
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, h, h_age_int, h_chld_int* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, proxies for human capital, interaction term between the human capital proxy and old-age support ratio, and interaction terms between the human capital proxy and child dependency ratio respectively. All independent variables are log transformed except *sup, dep, and h,* and data represent the changes in lagged periods *t-1*. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

These findings highlight the heterogeneity in the relationship between the old-age support ratio and technological advancements across different groups of countries. While the positive relationship observed in high-income countries may reflect their relatively developed social security systems and higher capacity to invest in advanced technologies as suggested by Acemoglu and Restrepo (2020), the negative relationship in non-high-income countries could be attributed to their relatively less developed economic conditions

and human capital, that lower support-ratio suggests less old-age supporting burden and more societal resources can be mobilized for technological advancements.

It is worth noting that the significance and magnitude of these effects vary depending on the specific time period analysed and the inclusion/exclusion of China. Therefore, further research and analysis are needed to understand the potential variations in the relationship between the demographic structural changes and technological advancements across different contexts, and China.

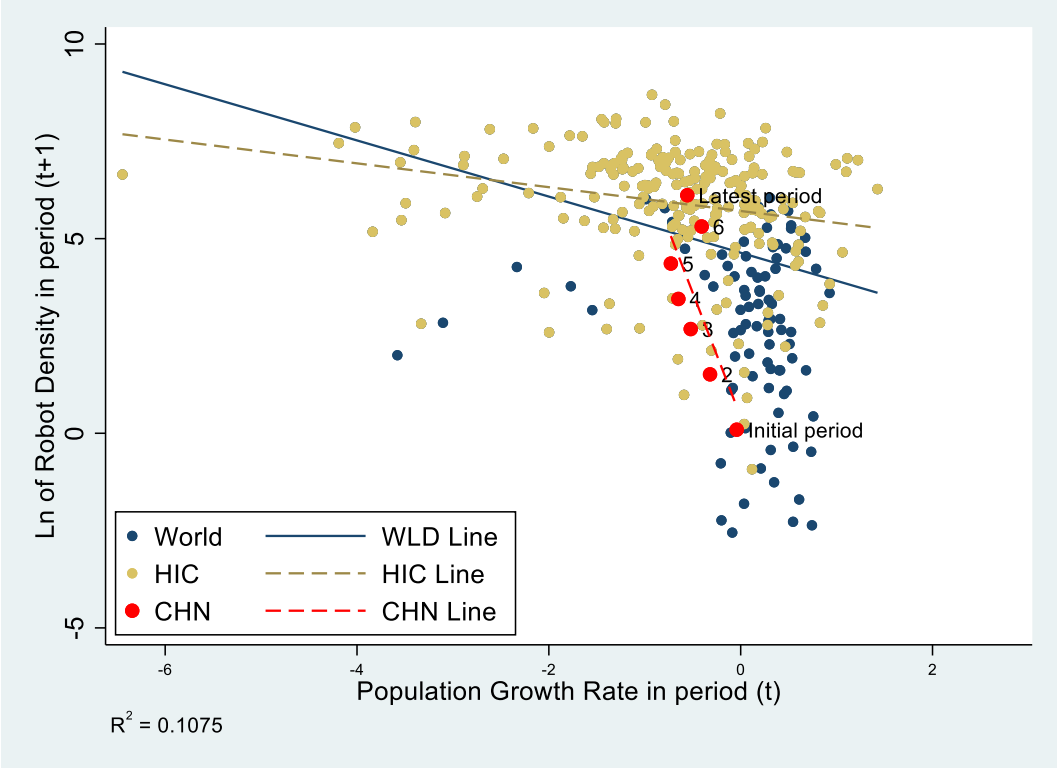
2) China in the Global Context

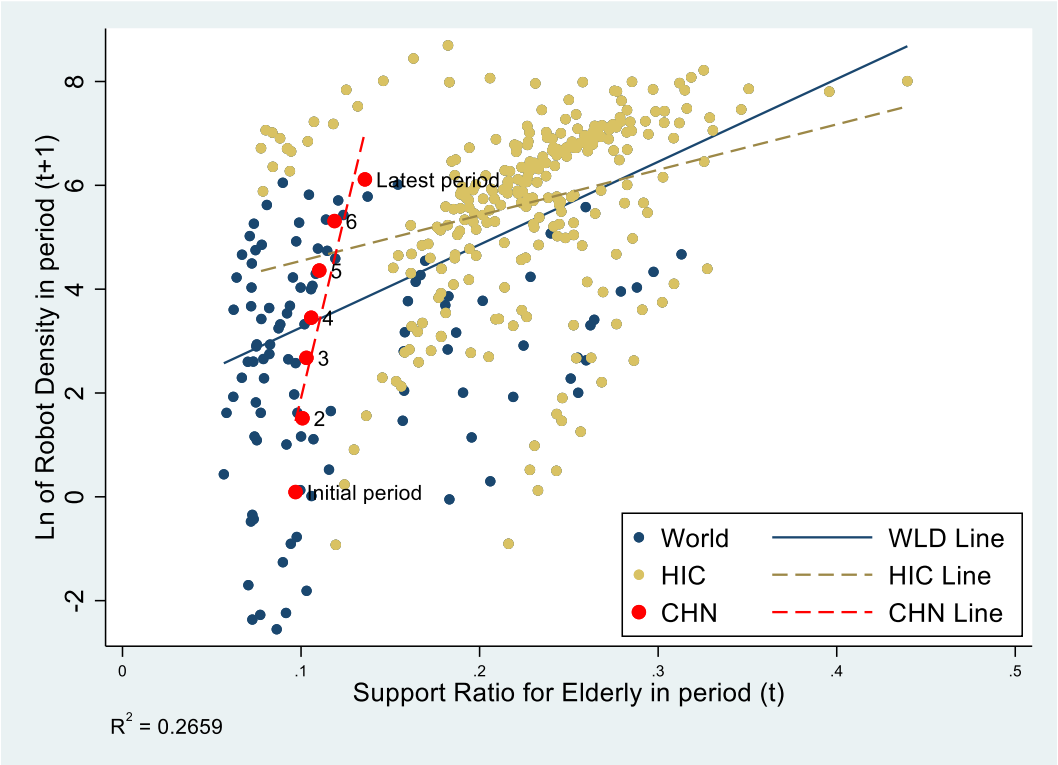
The following analysis provides additional insights by considering China as a separate group of samples in addition to the global, high-income countries (HIC), and non-high-income countries (Non-HIC). By examining China as a separate group, this analysis aims to explore the specific dynamics and different patterns of the relationship between demographic structural changes and technological advancements in the Chinese context when compared with other countries. It is important to note that due to the limitation of sample size, [62] the findings in this exercise should be interpreted with caution and primarily serve for illustrative purposes and conceptual understanding of the heterogeneity rather than establishing rigid causal relationships.

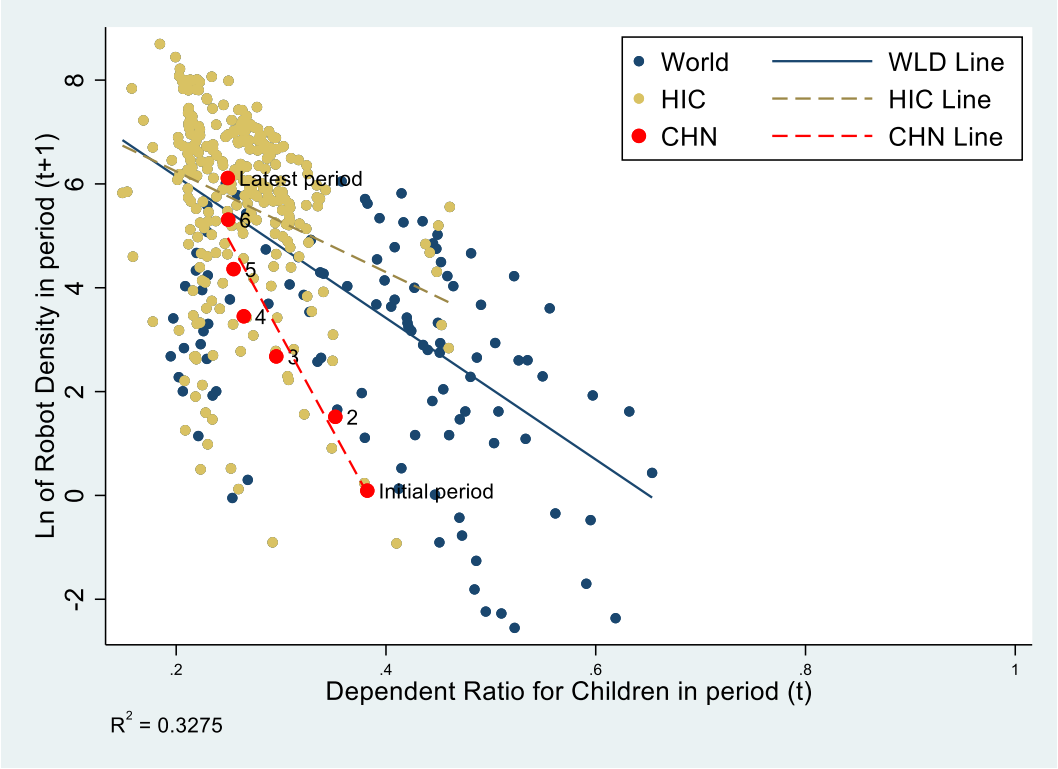
Figure 5.1.3 visually illustrates where China stands when comparing to other HIC and Non-HIC peers. The y-axis is set as the growth rate of robots' density in the leading period *(t+1)*, while different variables of interests at the period *t* are put in the x-axis, including *sup* and *dep* illustrating demographic structural changes, population growth rate, and various mediating variables including growth in the saving ratio *s* (Panel A), changes in the human capital index, life expectancy at birth, education attainment, and female's education attainment (Panel B), respectively.

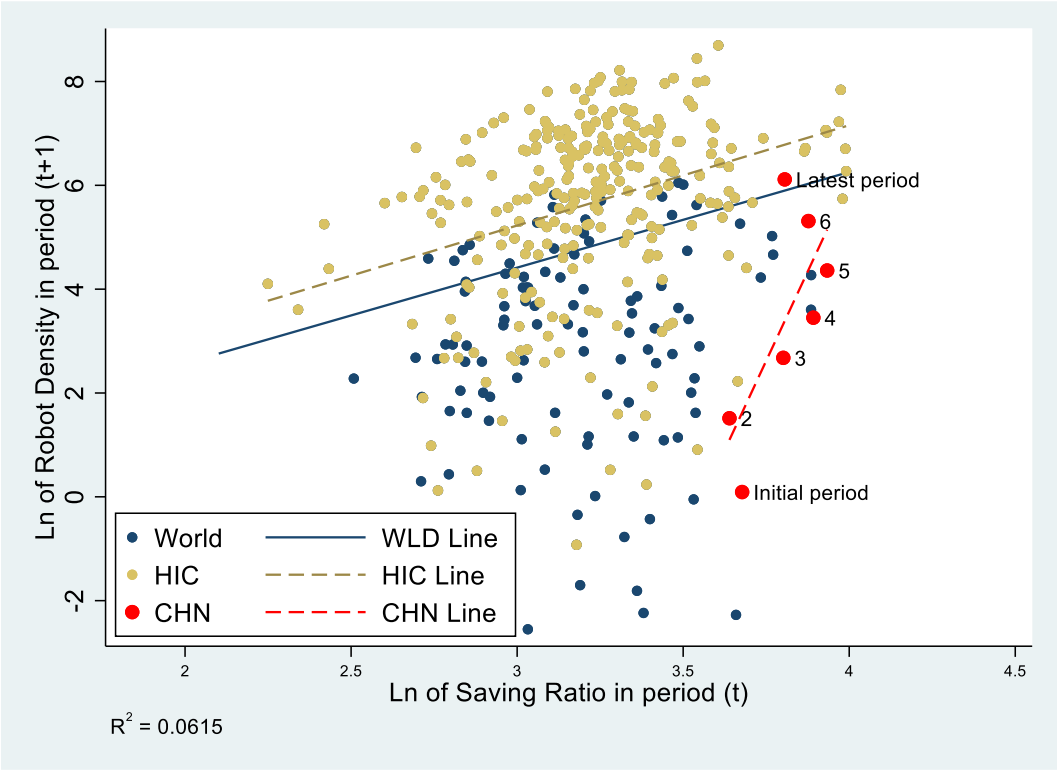
[62] 1995-2019 only contains 24 years, suggesting 8 observations for each country when building a 3-year interval sample. However, considering the time difference between leading period *t+1* and *t*, there will be only 7 observations left for the actual regression.

Figure 5.1.3A: International Comparison of China (Part A)



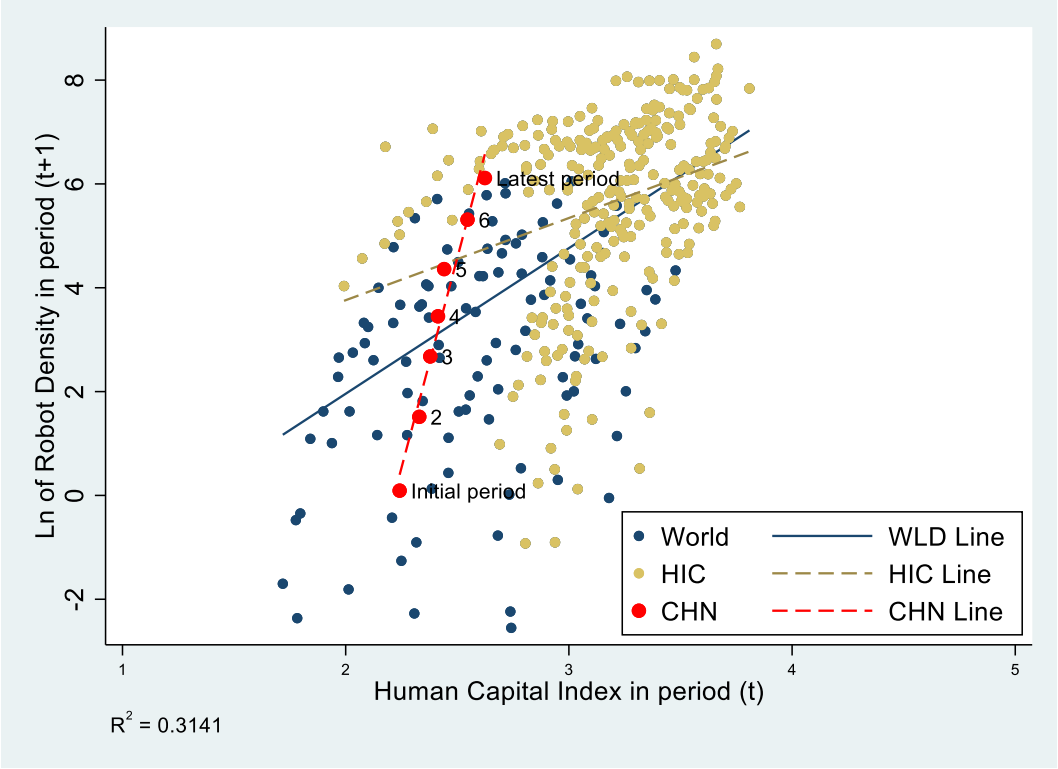


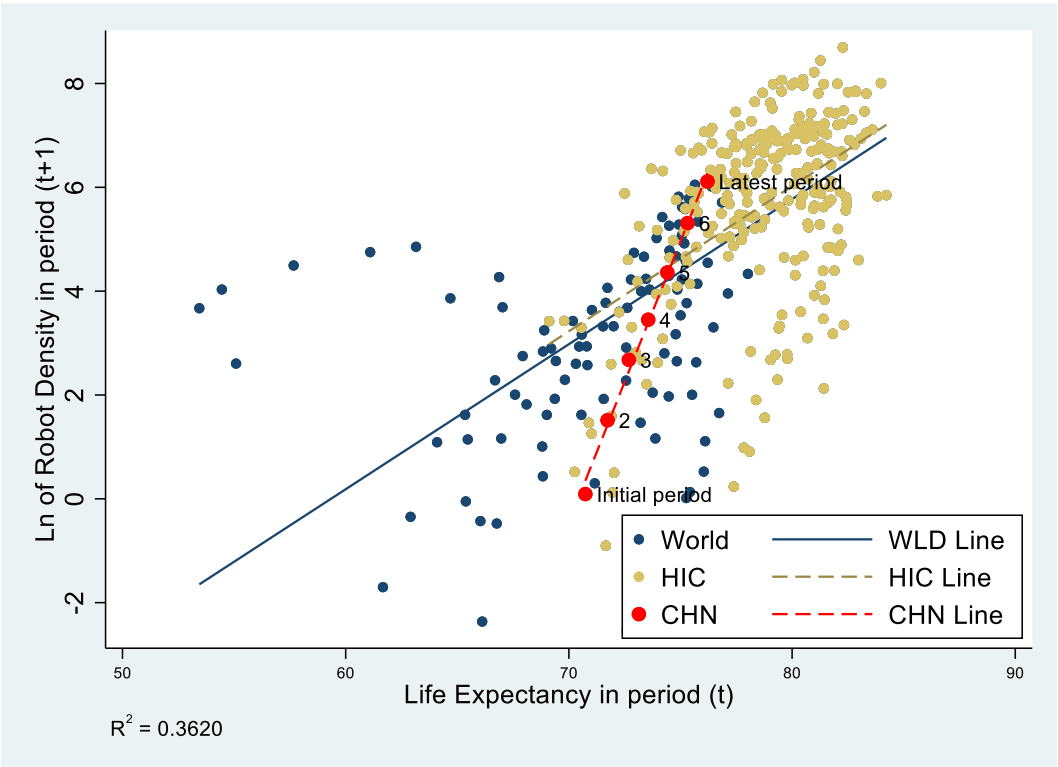


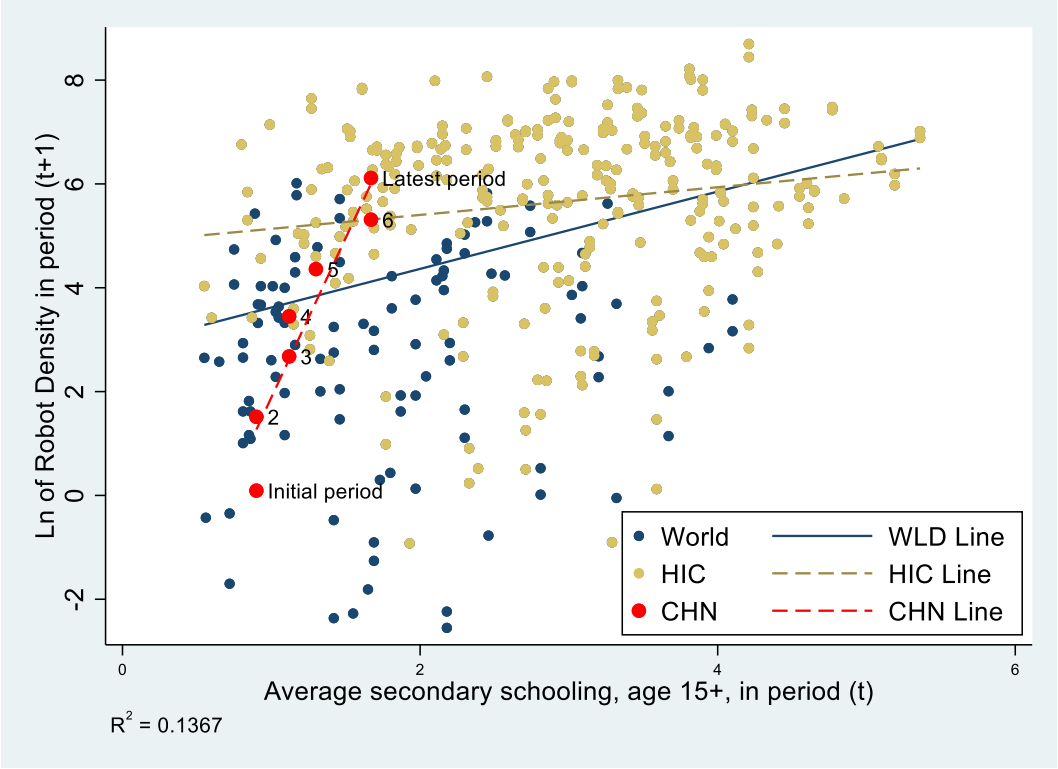


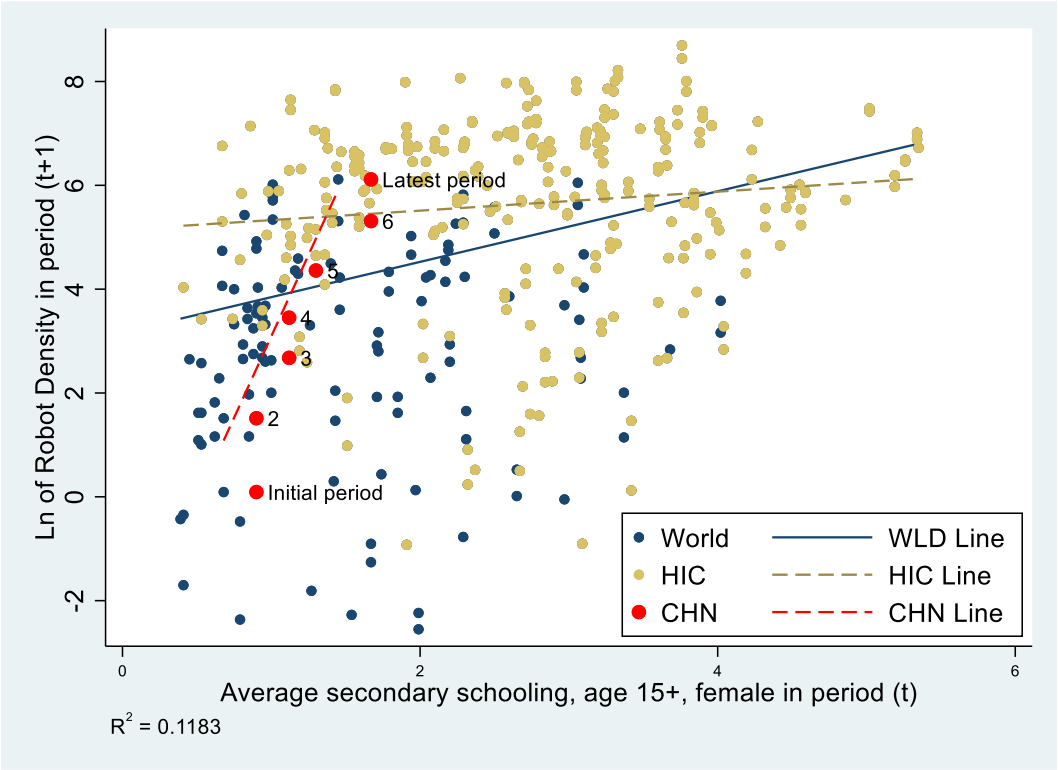
Source: Created by author based on estimation

Figure 5.1.3B: International Comparison of China (Part B)









Source: Created by author based on estimation

The results of the analysis indicate that the dynamics between demographic structural changes and technological advancements in China differ significantly from the global average and many high-income countries (HIC), and in particularly suggest that China is experiencing a faster momentum in terms of technological advancements compared to the global average and many high-income countries leaders. It is evident from the substantial deviation of the slope of the fitted lines for China, representing the magnitude of correlation, when compared to the fitted lines for the world and HIC.

The univariate regressions presented in Table 5.1.3B provide a summary of the correlation coefficients in quantity terms for the global comparison. In consistent with the visual displays, the regression results show that the magnitude of the estimators for China is remarkably higher compared to the estimators derived using the world, HIC, and Non-HIC samples for all variables. For instance, the marginal coefficients of the old-age support ratio *sup* for China are 143, which is significantly higher than the average level of the global, HIC, and Non-HIC samples. This indicates that the impact of the old-age support ratio *sup* on the growth in robot density is much more pronounced in China compared to its global peers. Similarly, the coefficient of the dependency ratio *dep* for China is 37.04, surpassing the average level of the global, HIC, and Non-HIC samples by 2.7, 4, and 4.3 times, respectively.

The higher magnitude of these coefficients suggests that the growth in robots' density is happening at a much more dramatic and faster pace in China compared to other countries. It indicates that demographic structural changes, specifically indicated by the old-age support ratio and dependency ratio, have a substantial impact on the adoption and development of robotics in China, while changes in the variables on the x-axis, such as the demographic factors and human capital proxies, are not prevailing over a relatively short timeframe.

The deviations in the global comparison of China indicate that China's trajectory in technological advancements is distinct from the rest of the world and many high-income countries. China is making significant progress in leveraging demographic structural changes to drive technological development. It also suggests China has unique factors at play, such as its demographic structure features, social-economic development levels such

as saving ratio and human capital, and specific policies and strategies aimed at fostering technological growth.

However, it is also important to consider the limitations of the data, methods used, and context-specific factors when interpreting these results. The smaller sample size of China compared to the global or regional samples indeed limits the statistical power and precision of the estimates. Therefore, these findings should be interpreted with caution and serve as a starting point for further investigation rather than definitive conclusions.

Table 5.1.3B: Correlation Coefficients of Univariate Regression

	Panel A: 3-Year Interval Sample (1995-2019)				**Panel B: 5-Year Interval Sample (1994-2019)**			
	China	World	HIC	Non-HIC	China	World	HIC	Non-HIC
sup	143.3***	15.68***	7.442**	8.034***	214.8**	17.50***	9.855**	8.639***
	(31.01)	(1.397)	(3.237)	(1.991)	(36.81)	(1.837)	(4.553)	(2.566)
dep	-37.04***	-13.67***	-9.229***	-8.694***	-37.16***	-14.87***	-11.26***	-11.38***
	(5.829)	(0.986)	(1.637)	(2.007)	(5.331)	(1.109)	(1.936)	(2.366)
pop_growth	-6.379*	-0.739***	-0.555	-0.248**	-7.288*	-0.894***	-0.83	-0.267*
	(2.964)	(0.125)	(0.428)	(0.0975)	(-2.406)	(-0.168)	(-0.504)	(-0.139)
s	13.76*	1.935***	1.441**	1.849***	17.60	2.316***	2.043***	2.056***
	(6.002)	(0.367)	(0.582)	(0.355)	(9.745)	(0.456)	(0.735)	(0.425)
hc	16.16***	2.782***	2.340***	1.471***	15.38***	2.981***	3.022***	1.519***
	(0.977)	(0.0949)	(0.294)	(0.0999)	(1.146)	(0.255)	(0.614)	(0.361)
lifeexp	1.082***	0.276***	0.0948**	0.265***	1.151***	0.307***	0.168***	0.256***
	(0.0361)	(0.0202)	(0.0425)	(0.0321)	(0.0830)	(0.0256)	(0.0571)	(0.0406)
edu	6.147***	0.774***	0.456	0.255**	7.078***	0.869***	0.877**	0.268**
	(0.977)	(0.0949)	(0.294)	(0.0999)	(0.878)	(0.122)	(0.388)	(0.126)
femedu	6.272***	0.703***	0.479*	0.173*	7.112***	0.804***	0.902**	0.191
	(0.833)	(0.0942)	(0.279)	(0.0980)	(0.727)	(0.121)	(0.365)	(0.123)

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *sup, dep, pop_growth, s, hc, lifeexp, edu, and femedu* stand for old-age support ratio, children dependency ratio, population growth rate, saving rates, human capital index average years of total schooling of total population aged 15+, and average years of total schooling of female aged 15+ respectively. *Pop_growth* is log transformed and data represent the changes in lagged periods *t-1*. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.

Yet, this exercise highlights the importance of understanding the specific context and dynamics within China when examining the relationship between demographic changes and technological advancements. Further research and analyses are in particular necessary to gain a more comprehensive understanding of factors driving China's rapid technological advancements in the context of its own demographic structural changes.

5.2. IMPLICATIONS OF DEMOGRAPHIC STRUCTURAL CHANGES ON TECHNOLOGICAL ADVANCEMENTS IN CHINA'S CONTEXT

The preceding section presents and validates the overarching concepts regarding the interplay between demographic structural changes and technological advancements. It explores the dual indirect mechanisms of saving and human capital in the global context, while the additional analysis comparing China with other countries provides insights into distinctive factors that contribute to its remarkable technological progress. However, the study also acknowledges the limitations posed by the sample size and cautions in the exercise when drawing conclusions from these findings. To address these limitations, this section aims to complement the earlier findings by incorporating larger samples from China via both regional and industrial lenses while employing more robust methodologies. The objective is to conduct a more comprehensive and detailed examination that offers a deeper understanding of the relationship between demographic structural changes and technological advancements within the Chinese domestic context.

5.2.1 The Dual Indirect Mechanisms Through Savings and Human Capital

In line with the methodology employed in the previous section, the analysis in China adopts a similar approach to examine the hypothesis regarding the dual indirect mediation role of saving and human capital in the relationship between demographic structural changes and technological advancements. Specifically, the study investigates whether saving and human capital act as mediators between demographic structural changes, represented by a group of indicators including the logarithm of the proportion of the working-age population, the level of the old-age support ratio, and the child dependency ratio, and the growth rate in technological advancements, measured by a set of indicators such as total factor productivity (TFP), patent applications per thousand employees, and research and development expenditure per thousand employees.

Table 5.2.1A reports estimations based on a 3-year interval data from 1990-2019,[63] with the application of three distinct mediating variables throughout Panel A to Panel C: growth rate in the saving ratio, education that indicated by the growth rate in the percentage of population with secondary schooling, and health that indicated by the growth rate in the proportion of government expenditure out of regional GDP.

The results of the step 1 regression analysis indicate that the increase in the old-age support ratio (*sup* on the left-hand side) has a significant and positive total effect (TE) on the growth in TFP level, at a confidence level of 99 percent across all exercises. On the other hand, the decrease in the child dependency ratio (*dep* on the right-hand side), which is indicative of low fertility, does not show a significant total effect on the development of TFP. These findings support the previous observations that ageing and low fertility have distinct implications for technological advancements in the global context.

In Step 2, the mediators such as saving, education, and health proxies are regressed on demographic variables, while controlling for other factors. This allows us to estimate the contributions of demographic changes on the growth in TFP that operate through these mediators. The coefficients on the old-age support ratio *sup* and child dependency ratio *dep* are significant on saving and many cases of human capital, indicating plausible mediating pathways. However, there are also variations observed among population groups when considering different human capital proxies. Specifically, education is found to be a significant mediating channel for the *dep*, but not for the *sup*, while health is found to be a significant mediating channel for the *sup*, but not for the *dep.* This suggests that changes in the child dependency ratio have a stronger relationship with education, while the old-age support ratio tend to have a stronger connection with the health aspect. This reinforces that different dimensions of human capital are at play for different population groups.

In Step 3, the mediators *s* (saving) and *health* (health) are added to the regression model used in Step 1. By comparing the results from Step 1 to Step 3, changes in the direct effect (DE) of the old-age support ratio *sup* through mediators can be observed. In Panel A, the direct effect of *sup* through the mediator *s* decreases from 150.2 to 49.3 and becomes

[63] The examination has been carried out on all dependent variables and 5-year interval sample as well, and the results remain consistent in most cases. To save space, this paper does not report other results but can provide upon request.

statistically insignificant. This suggests a "complete mediation" effect, where the mediator *s* explains about 67.5 percent of the total effects (TE) on the growth in TFP associated with the aging population. This result is consistent with the hypothesis that saving serves as a viable pathway through which the old-age support ratio influences TFP. The significance of the Sobel-Goodman tests further supports this mediating pathway through saving. Similar results are also observed in Panel C, where the health mediator *h* is added to the regression model. The direct effect of *sup* through *h* decreases, and a "complete mediation" effect is also observed, explaining about 52 percent of the total effects on the growth of TFP. This indicates that the health aspect also plays a significant mediating role in the relationship between the old-age support ratio and TFP.

In this analysis, an interesting finding emerges in the child dependency ratio *dep*. In Panel A, the right-hand side table shows that while the total effect (TE) of *dep* on TFP is initially insignificant and positive in the Step 1, it becomes significant when the mediator variable *s* is included in the Step 3. Furthermore, the coefficient of *s* becomes negative, indicating a "suppression effect." The significance of the Sobel-Goodman tests further supports this "suppression effect" through saving, which amplifies the total effect (TE) by more than 3.8 times. Similarly, in Panel B, the right-hand side table shows a "suppression effect" through the mediator *edu* (education). The inclusion of the mediator variable reveals a significant relationship between *dep* and the growth in TFP, and the coefficient of the mediator *edu* is negative. This implies that education amplifies the total effect (TE) of *dep* on TFP by more than 1.9 times. These mean that the relationship between *dep* and technological advancements is not apparent in the TE alone, but also depends on the inclusion of the mediator variables such as saving and education.

These analyses reinforce the hypotheses that both saving and human capital, at least partially, serve as indirect mediating channels to motivate technological advancements in the context of post-demographic transition in line with the findings in the global context. The inclusion of these mediators uncovers both "mediating effects" and "suppressed effects" for different population, highlighting the complex relationship between demographic dynamics and technological advancements. It also highlights the importance of considering different mediators and their varying effects in the examination.

It is important to acknowledge that findings obtained from the regression analysis using total factor productivity (TFP) as the dependent variable should be interpreted as indicative rather than conclusive. This is because the results may vary when alternative indicators of technological advancements are used, such as the growth rate in patent application density and research and development (R&D) expenditure per thousand employees. Different indicators may capture different aspects of technological advancements, and their inclusion allows for a more comprehensive assessment of the relationship under investigation. Therefore, detailed results of the regression analysis using these alternative indicators are provided in Table 5.2.1A in the Appendix.

Table 5.2.1A: Mediating Effects Through Saving and Human Capital

Panel A: The Saving Mechanism

	Panel A: Old-age Support Ratio			**Panel B: Child Dependency Ratio**		
	Step 1	**Step 2**	**Step 3**	**Step 1**	**Step 2**	**Step 3**
VARIABLES	**Y=**	**Y=*s***	**Y=**	**Y=**	**Y=*s***	**Y=**
	TFP-DEA		**TFP-DEA**	**TFP-DEA**		**TFP-DEA**
s			-27.09***			-28.72***
			(2.407)			(2.318)
sup	150.2***	-3.774***	49.30			
	(36.12)	(0.745)	(31.50)			
dep				5.661	0.727**	26.31*
				(16.91)	(0.350)	(13.77)
ln_birth	-10.55***	0.0667	-8.850***	-15.63***	0.0379	-14.58***
	(2.627)	(0.0542)	(2.200)	(3.930)	(0.0814)	(3.176)
ln_death	-8.230	0.369**	1.081	7.189	-0.0125	6.541
	(7.161)	(0.149)	(6.111)	(6.322)	(0.132)	(5.164)
lngdpc	-6.188***	0.207***	-0.660	-3.642***	0.177***	1.397
	(0.994)	(0.0206)	(0.971)	(1.079)	(0.0225)	(0.967)
lnlfpc	8.561	-0.0435	7.959	14.23**	-0.164	9.845*
	(6.225)	(0.130)	(5.252)	(6.270)	(0.132)	(5.151)
Constant	87.75***	1.519***	131.3***	67.83***	1.834***	121.7***
	(21.47)	(0.450)	(18.57)	(21.98)	(0.463)	(18.54)
Observations	290	289	289	290	289	289
R-squared	0.181	0.345	0.435	0.132	0.297	0.438

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *s, sup, dep, ln_birth, ln_death, lngdpc, lnlfpc* stand for saving rates, old-age support ratio, children dependency ratio, crude birth rate, crude death rate, GDP per capita, and labor force participation rate respectively. All independent variables except sup and dep are log transformed and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests

	z	**P>z**	**z**	**P>z**
Sobel	4.62	0.00***	-2.05	0.04**
Aroian	4.61	0.00***	-2.04	0.04**

Goodman	4.64	0.00***		-2.05	0.04**

Indirect, Direct, and Total Effects

a_coefficient	-5.07	0.00***		2.07	0.04**
b_coefficient	-11.25	0.00***		-12.39	0.00***
Indirect_effect_aXb	4.62	0.00***		-2.05	0.04**
Direct_effect_c'	1.57	0.12		1.91	0.06*
Total_effect_c	4.18	0.00***		0.32	0.75

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated:

		0.675			**-3.84**

Panel B: The Human Capital Mechanism (Education)

	Panel A: Old-age Support Ratio			**Panel B: Child Dependency Ratio**		
	Step 1	**Step 2**	**Step 3**	**Step 1**	**Step 2**	**Step 3**
VARIABLES	**Y=**	**Y=h**	**Y=**	**Y=**	**Y=h**	**Y=**
	TFP-DEA		**TFP-DEA**	**TFP-DEA**		**TFP-DEA**
edu			7.150**			6.856**
			(2.964)			(3.120)
sup	150.2***	-0.758	155.6***			
	(36.12)	(0.717)	(35.89)			
dep				5.661	-1.143***	13.50
				(16.91)	(0.319)	(17.17)
ln_birth	-10.55***	-0.447***	-7.349**	-15.63***	-0.222***	-14.11***
	(2.627)	(0.0521)	(2.923)	(3.930)	(0.0743)	(3.965)
ln_death	-8.230	-0.294**	-6.130	7.189	-0.385***	9.825
	(7.161)	(0.142)	(7.155)	(6.322)	(0.119)	(6.393)
lngdpc	-6.188***	0.334***	-8.573***	-3.642***	0.277***	-5.539***
	(0.994)	(0.0197)	(1.396)	(1.079)	(0.0204)	(1.376)
lnlfpc	8.561	-0.614***	12.95**	14.23**	-0.664***	18.78***
	(6.225)	(0.124)	(6.435)	(6.270)	(0.118)	(6.563)
Constant	87.75***	-3.537***	113.0***	67.83***	-3.176***	89.60***
	(21.47)	(0.426)	(23.73)	(21.98)	(0.415)	(23.98)
Observations	290	290	290	290	290	290
R-squared	0.181	0.851	0.198	0.132	0.857	0.146

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: h*, sup, dep, ln_birth, ln_death, lngdpc, lnlfpc* stand for proportion of population with completed secondary education and above, old-age support ratio, children dependency ratio, crude birth rate, crude death rate, GDP per capita, and labor force participation rate respectively. All independent variables except sup and dep are log transformed and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests

	z	**P>z**		**z**	**P>z**
Sobel	-0.97	0.33		-1.87	0.06*
Aroian	-0.91	0.37		-1.82	0.07*
Goodman	-1.05	0.30		-1.93	0.05**

Indirect, Direct, and Total Effects

a_coefficient	-1.06	0.29		-3.58	0.00***

b_coefficient	2.41	0.02		2.20	0.03**
Indirect_effect_aXb	-0.97	0.33		-1.87	0.06*
Direct_effect_c'	4.34	0.00***		0.79	0.43
Total_effect_c	4.16	0.00***		0.34	0.74

*** p<0.01, ** p<0.05, * p<0.1

Proportion of total effect that is mediated:

		-0.036			**-1.39**

Panel C: The Human Capital Mechanism (Health)

	Panel A: Old-age Support Ratio			**Panel B: Child Dependency Ratio**		
	Step 1	**Step 2**	**Step 3**	**Step 1**	**Step 2**	**Step 3**
VARIABLES	**Y=**	**Y=h**	**Y=**	**Y=**	**Y=h**	**Y=**
	TFP-DEA		**TFP-DEA**	**TFP-DEA**		**TFP-DEA**
health			-13.43***			-14.20***
			(1.293)			(1.272)
sup	150.2***	-5.798***	72.32**			
	(36.12)	(1.413)	(31.69)			
dep				5.661	-1.031	-8.977
				(16.91)	(0.658)	(14.17)
ln_birth	-10.55***	0.383***	-5.408**	-15.63***	0.724***	-5.347
	(2.627)	(0.103)	(2.293)	(3.930)	(0.153)	(3.407)
ln_death	-8.230	0.932***	4.283	7.189	0.327	11.83**
	(7.161)	(0.280)	(6.222)	(6.322)	(0.246)	(5.293)
lngdpc	-6.188***	0.439***	-0.288	-3.642***	0.309***	0.745
	(0.994)	(0.0389)	(1.020)	(1.079)	(0.0420)	(0.983)
lnlfpc	8.561	-0.875***	-3.189	14.23**	-1.110***	-1.532
	(6.225)	(0.244)	(5.425)	(6.270)	(0.244)	(5.421)
Constant	87.75***	-8.504***	-26.43	67.83***	-7.545***	-39.30*
	(21.47)	(0.840)	(21.35)	(21.98)	(0.856)	(20.71)
Observations	290	290	290	290	290	290
R-squared	0.181	0.353	0.407	0.132	0.321	0.397

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: h, *sup, dep, ln_birth, ln_death, lngdpc, lnlfpc* stand for proportion of population with completed secondary education and above, old-age support ratio, children dependency ratio, crude birth rate, crude death rate, GDP per capita, and labor force participation rate respectively. All independent variables except sup and dep are log transformed and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests

	z	**P>z**		**z**	**P>z**
Sobel	3.82	0.00		1.55	0.12
Aroian	3.80	0.00		1.55	0.12
Goodman	3.83	0.00		1.56	0.12

Indirect, Direct, and Total Effects

a_coefficient	-4.10	0.00		-1.57	0.12
b_coefficient	-10.39	0.00		-11.16	0.00
Indirect_effect_aXb	3.82	0.00		1.55	0.12
Direct_effect_c'	2.28	0.02		-0.63	0.53
Total_effect_c	4.16	0.00		0.34	0.74

*** p<0.01, ** p<0.05, * p<0.1		
Proportion of total effect that is mediated:	0.52	2.59

In addition to the stepwise analysis, alternative interaction models are employed to further explore the intricate relationship between demographic structural changes and technological advancements. The baseline model, which resembles Model 0 discussed in Section 5.1.1, examines the association between the old-age support ratio *sup* and child dependency ratio *dep* with various indicators of technological advancements as dependent variables, including the growth in TFP, patent application density, and research and development (R&D) expenditure density, as presented in Panels A to C. The baseline model has been examined by using pooled OLS, RE, and FE respectively, and the results are provided from column 1 through column 3 in Table 5.2.1B.

The baseline model incorporates important covariates such as the growth in birth rate and death rate (as a substitute for natural population growth rate), growth rate in GDP per capita, and growth rate in labour force participation rate. To account for the specificities of the Chinese context, three additional variables are included in the baseline model aligning with existing literature, namely the share of foreign direct investment (FDI) to GDP, the share of services' value added to GDP, and the urbanization rate of each province. The results are provided in column 4.

The subsequent interaction analysis explores the joint effect of demographic changes and mediators on technological advancements, as well as the distinct effects of saving, education, and health with the incorporation of interaction terms into the previous regression model. It also accounts for the heterogeneity across different population groups and dimensions of mediating variables, such that the results shed light on how technological advancements responds to different population groups characterized by varying levels and dimensions of mediating channels. The findings from the interaction analysis are presented in the column 5 through column 7 of Table 5.2.1B, providing complementary insights into the nuanced dynamics between demographic changes, mediators, and technological advancements in addition to the stepwise analysis.

The regression results in columns 1-3 replicate the baseline model used in the global analysis. In Panel A to Panel C, these results demonstrate significant negative associations between the child dependency ratio *dep* and technological advancements, as indicated by the growth rate in TFP, patent application density, and research and development (R&D) expenditure density. On the other hand, the old-age support ratio *sup* shows a significant positive relationship with technological advancements in most cases, except for the Random-Effect estimators in column 2 and the Fixed-Effect estimators in column 3 in Panel A. This suggests that regional and yearly variations should be carefully considered when analyzing the relationship. Besides, the inclusion of additional variables in column 4 provides further control of the variations but it does not change the significance and direction of previous estimations, indicating robust results.

Similar to the stepwise analysis, coefficients on the interactions between *dep* and saving and education present overall significant negative effects when taking both the marginal coefficients of *dep* and *med_chld_int* into account, implying that the decreases in child dependency ratio is correlated with the technological advancements, while depending on the level of saving and education. It implies the existence of dual indirect channels. The overall magnitude of marginal impacts of *dep* on the growth in TFP level, patent application density, and R&D expenditure density through saving can be estimated at negative -2.76 percent, -5.68 percent, and -14.1 percent respectively. Similarly, significant negative results can also be obtained for the education mechanism as well.

On the other hand, the old-age support ratio *sup*, however, does not reveal constant estimations except in the column 7 about health proxy (public spending as a proportion of GDP), indicating that the raise in old-age support ratio will motivate technological advancements through a higher public spending for a better healthcare system. The overall magnitude of marginal impact of *sup* on the growth in TFP level, patent application density, and R&D expenditure density through *health* can be estimated at positive 4.24 percent, 20.4 percent, and 6.934 percent respectively. However, the effect through saving shows an opposite negative marginal impact on the growth in TFP level, patent application density but R&D expenditure density, suggesting that the raise of old-age support ratio will hinder technological advancements through a lower national saving and capital resources.

Overall, findings of this study provide further evidence for the relationship between the decline in child dependency ratio, higher levels of saving and education, and technological advancements, aligning with the demographic dividends theory (DDT) proposed by Mason and Lee (2006). Previous studies have extensively discussed the positive link between lower fertility rates and higher human capital (e.g., Galor and Weil, 2000; Bloom, Canning, and Sevilla, 2003), and there are ongoing discussions on the relationship between lower fertility and increasing saving at the international level (e.g., Mason, 1988; Bloom, Canning, and Sevilla, 2003; Bloom and Finlay, 2009). Similar confirmatory findings are also observed in various developing countries' contexts, such as the Philippines and Chile (e.g., Orbeta Jr, 2005; Brito González, 2016). Therefore, the increasing saving rate and human capital resulting from lowering fertility rate are expected to play a crucial role in promoting technological advancements (i.e., Galor and Weil, 2000).

However, this study in the context of China sheds light on the mixed results regarding population aging, human capital, and technological advancements. Specifically, results demonstrate that an increase in the old-age support ratio can stimulate technological advancements through increased public spending, highlighting the importance of having a robust pension, long-term care, and social protection system. At the same time, technological advancements in the context of population aging imply a lower saving rate and reduced financial capacity available for mobilization in the capital market, which can impede technological advancements. This finding is consistent with the research of Batini, Callen, and McKibbin (2006), which suggests that population aging in industrialized countries and developing regions can lead to a decline in saving and a deterioration in their current account. However, these findings contrast with earlier discussions in many European contexts, where ongoing population aging was expected to result in rising aggregate private savings as a vehicle of retirement income in response to decreases in internal rates of return (e.g., Boersch-Supan and Winter, 2001).

Table 5.2.1B: Interaction Approach
Panel A: Dependent Variable= TFP-DEA

Column	1	2	3	4	5	6	7
VARIABLES	POLS	RE	FE	More Control	Saving	Edu	Health
ln_birth	-6.823	1.124	1.595	2.442	-5.761	4.408	0.585
	(4.335)	(2.328)	(2.231)	(4.606)	(3.990)	(4.678)	(3.930)
ln_death	-9.835	25.01***	27.24***	-2.693	3.014	0.628	4.377
	(7.312)	(5.003)	(4.861)	(7.426)	(6.492)	(7.731)	(6.352)
lngdpc	-7.139***	-1.479	-0.456	-8.837***	-2.694*	-9.200***	-4.413***
	(1.328)	(0.935)	(0.928)	(1.561)	(1.531)	(1.665)	(1.399)
lnlfpc	7.689	-18.77***	-22.88***	9.676	10.74**	12.79**	2.977
	(6.275)	(4.842)	(4.798)	(6.253)	(5.307)	(6.444)	(5.512)
lnopenness				2.933***	1.791***	2.863***	0.434
				(0.635)	(0.555)	(0.623)	(0.627)
lnservice				1.956	3.944	-5.399	12.15***
				(4.313)	(3.808)	(4.818)	(3.839)
urbanization				14.15**	4.696	4.155	9.770**
				(5.526)	(4.880)	(6.175)	(4.714)
sup	163.7***	-52.45**	-78.70***	148.8***	-1,318***	5.228	480.5***
	(38.23)	(25.10)	(24.47)	(38.23)	(414.4)	(100.5)	(96.19)
dep	-18.76	-25.80**	-21.15**	-42.29**	-369.2***	-125.1***	52.42
	(17.38)	(10.73)	(10.51)	(19.30)	(94.15)	(33.60)	(34.30)
Mediator					-90.62***	34.45***	-55.79***
					(15.86)	(12.33)	(9.569)
med_age_int					351.7***	-88.59	237.7***
					(106.7)	(61.50)	(55.36)
med_chld_int					93.03***	-52.04***	48.29***
					(23.75)	(15.78)	(15.89)
Constant	93.82***	-32.05**	-47.83***	81.61***	381.0***	162.3***	-109.7***
	(22.19)	(15.07)	(14.63)	(25.33)	(65.11)	(34.32)	(29.33)
Observations	290	290	290	270	269	270	270
R-squared	0.184		0.850	0.306	0.519	0.340	0.507
Province FE	NO	NO	YES	NO	NO	NO	NO

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Panel B: Dependent Variable= Patent Application Per Thousand Employees

Column	1	2	3	4	5	6	7
VARIABLES	POLS	RE	FE	More Control	Saving	Edu	Health
ln_birth	0.258	0.721***	0.942***	0.307	0.186	0.418**	0.251
	(0.210)	(0.178)	(0.172)	(0.213)	(0.211)	(0.206)	(0.208)
ln_death	-1.180***	-0.00688	0.449	-1.242***	-1.328***	-1.040***	-1.114***
	(0.354)	(0.365)	(0.376)	(0.344)	(0.343)	(0.341)	(0.337)
lngdpc	0.959***	1.086***	1.210***	0.839***	0.946***	0.796***	0.927***
	(0.0644)	(0.0655)	(0.0717)	(0.0722)	(0.0810)	(0.0735)	(0.0741)
lnlfpc	0.258	-0.153	-0.230	0.753***	0.773***	1.140***	0.685**
	(0.304)	(0.336)	(0.371)	(0.289)	(0.281)	(0.284)	(0.292)
lnopenness				-0.0346	-0.0466	-0.0384	-0.0765**
				(0.0294)	(0.0294)	(0.0275)	(0.0332)
lnservice				-0.307	-0.122	-0.938***	-0.112
				(0.200)	(0.201)	(0.213)	(0.203)
urbanization				1.890***	1.574***	1.076***	1.779***
				(0.256)	(0.258)	(0.273)	(0.250)
sup	8.385***	6.070***	4.118**	9.569***	-59.85***	4.822	22.04***
	(1.853)	(1.829)	(1.890)	(1.768)	(21.92)	(4.435)	(5.096)
dep	-2.380***	-2.278***	-1.407*	-1.576*	-7.284	-6.188***	0.980
	(0.842)	(0.779)	(0.812)	(0.893)	(4.980)	(1.483)	(1.817)
Mediator					-2.880***	2.061***	-1.616***
					(0.839)	(0.544)	(0.507)
med_age_int					17.41***	-2.605	8.306***
					(5.644)	(2.714)	(2.933)
med_chld_int					1.596	-3.203***	1.336
					(1.256)	(0.696)	(0.842)
Constant	5.551***	1.037	-1.599	6.730***	16.85***	12.62***	2.264
	(1.076)	(1.087)	(1.130)	(1.172)	(3.444)	(1.515)	(1.554)
Observations	290	290	290	270	269	270	270
R-squared	0.907		0.957	0.924	0.931	0.934	0.929
Province FE	NO	NO	YES	NO	NO	NO	NO

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Panel C: Dependent Variable= R&D Expenditure Per Thousand Employees

Column	1	2	3	4	5	6	7
VARIABLES	POLS	RE	FE	More Control	Saving	Edu	Health
ln_birth	-0.534**	0.134	0.221	-0.408*	-0.513**	-0.173	-0.546**
	(0.218)	(0.156)	(0.157)	(0.221)	(0.227)	(0.225)	(0.215)
ln_death	-1.232***	-1.025***	-1.038***	-1.003***	-0.828**	-0.807**	-0.810**
	(0.369)	(0.317)	(0.324)	(0.361)	(0.369)	(0.364)	(0.350)
lngdpc	0.954***	0.995***	1.035***	0.780***	0.829***	0.586***	0.880***
	(0.0739)	(0.0628)	(0.0662)	(0.0842)	(0.0961)	(0.0928)	(0.0848)
lnlfpc	0.749**	-0.0669	-0.212	1.062***	1.094***	1.514***	0.780***
	(0.304)	(0.302)	(0.325)	(0.297)	(0.296)	(0.307)	(0.296)
lnopenness				0.0243	0.00990	0.00802	-0.0205
				(0.0318)	(0.0323)	(0.0310)	(0.0357)
lnservice				0.575***	0.516**	0.138	0.701***
				(0.202)	(0.212)	(0.228)	(0.204)
urbanization				0.930***	0.911***	0.689**	0.903***
				(0.292)	(0.301)	(0.310)	(0.286)
sup	3.966**	4.153***	3.636**	3.637*	-17.73	3.189	8.523*
	(1.898)	(1.572)	(1.623)	(1.856)	(22.76)	(4.663)	(5.046)
dep	-3.127***	-3.724***	-3.436***	-3.399***	-17.89***	-3.804**	2.834
	(0.897)	(0.680)	(0.701)	(0.937)	(6.220)	(1.641)	(1.924)
Mediator					-1.870**	1.117*	-1.589***
					(0.887)	(0.601)	(0.505)
med_age_int					5.200	-0.643	3.676
					(5.853)	(2.914)	(2.921)
med_chld_int					3.798**	-0.654	3.148***
					(1.565)	(0.783)	(0.873)
Constant	1.242	-1.527	-2.217**	0.0209	7.038*	4.493**	-4.539***
	(1.147)	(0.955)	(0.979)	(1.253)	(3.691)	(1.782)	(1.621)
Observations	261	261	261	244	244	244	244
R-squared	0.915		0.973	0.926	0.929	0.932	0.933
Province FE	NO	NO	YES	NO	NO	NO	NO

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *ln_birth, ln_death, lngdpc, lnlfpc, lnopenness, lnservice, urbanization, sup, dep, mediator, med_age_in, and med_chld_int* stand for the crude birth rate, crude death rate, GDP per capita, labor force participation rate, proportion of FDI to regional GDP, proportion of services VA to regional GDP, urbanization rate, old-age support ratio, children dependency ratio, mediators including saving ratio, proportion of population with completed secondary education and above, and public expenditure to regional GDP respectively. All independent variables except sup and dep are log transformed and data represent the changes in lagged periods *t-1*.

5.2.2 Regional Disparities of the Implications

In light of the importance in considering variations across spaces as raised in the preceding discussions, the focus of this analysis then is zoomed in to the sub-regional level. In so doing, this exercise employs the same empirical models as in 5.2.1 but divides the provinces into the eastern, central, western, and north-eastern regions, to reflect their

diverse economic and social characteristics of different areas within the country.[64] However, due to the small number of provinces in the central and north-eastern places, this analysis practically combines the central and north-eastern regions into one cluster.

In a nutshell, the eastern region, characterized by high levels of economic development and urbanization, represents the most developed part of China. It includes major cities and coastal provinces that have experienced rapid industrialization and international trade and experienced rapid urbanization and a shift towards a more service-oriented economy. It is also characterized by a relatively high population density and a significant concentration of urban areas due to sizable immigrants from rural areas. Therefore, its demographic structure is relatively balanced, with a moderate proportion of elderly population compared to other regions, as described in Chapter 2.

The central region represents a transitional zone between the eastern and western regions by encompassing provinces with a mix of urban and rural areas, diverse economic activities, and emerging industries. It has a more diverse demographic structure and is characterized by substantial internal migration flows, with a significant number of rural residents moving to urban areas. This region is also experiencing emigration to the more developed eastern region. The north-eastern region was historically an important industrial base but has faced economic challenges and population decline in recent years. The region has a relatively older demographic structure with a higher proportion of elderly population, and the migration patterns in the north-eastern region have been influenced by economic restructuring, with many residents migrating to other regions.

The western region comprises provinces with relatively lower levels of economic development and is characterized by their challenges related to economic development and poverty reduction. It has a relatively sparse population and a lower population density compared to the other regions due to its a large land area. The demographic structure in the western region is typically younger, with a higher proportion of rural population. In recent years, the western region has witnessed a significant influx of migrants from rural areas as

[64] According to the official classification, Eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The Northeastern region includes Liaoning, Jilin and Heilongjiang.

well as interregional migration to seek employment opportunities in traditional production sectors such as mining, energy, and infrastructure development.

Although these demographic characteristics in each region are generalized, great variations can also be found within the region, and demographic patterns in China are dynamic and subject to change over time due to various economic, social, and policy factors, by considering the regional divisions, the analysis can help capture the variations in socio-economic development levels, industrial structures, and policy contexts across different parts of China, providing a more nuanced understanding of the relationship between demographic structural changes and technological advancements in the country.

Table 5.2.2 reports the empirical results on the relationship between demographic structural changes across three distinct regions, total factor productivity (TFP), Patent application density, and R&D expenditure in China from 1990 to 2019. In addition, three mediating variables including saving ratio, education, health, and their interactions are also employed for each individual region.

The findings suggest significant regional disparities in the relationship between the demographic structural changes, technological advancements, and the proposed mechanisms. In the eastern region, the old-age support ratio *sup* does not exhibit a significant relationship with technological advancements through the saving channel. However, in the western regions, the increasing old-age support ratio has led to declines in saving, which have negatively impacted technological advancements related indicators such as TFP, patent applications per thousand employees, and R&D expenditure per thousand employees.

On the other hand, declines in the child dependency ratio *dep* in the central and northeastern regions have positively influenced the growth in R&D expenditure through both increased saving and higher levels of public expenditure. Overall, the increasing level of public expenditure, driven by rises in the old-age support ratio *sup* and the child dependency ratio *dep*, plays a crucial role in promoting technological advancements in both central and western regions. Education, as another component of human capital, is identified as a significant driver for the growth in patent applications in both eastern and western regions during the low-fertility transition period.

Additionally, it is worth noting that other covariates including the urbanization rate, industrial structure of the economy, openness of the region, and economic conditions all play different roles in motivating the technological advancements. For instance, openness of the region is demonstrated to be a key player for the growth in R&D expenditure in the central region, while urbanization process has contributed significantly to the growing number of patent application across eastern, central, and western places of the country. In contrast, the urbanization in the eastern regions implies the outflow of migrations from central and western areas, leading to a negative correlation with the growth in TFP in these places. Similarly, the emigration feature from the western region to eastern places has also led to the service-oriented development phenomenon in the eastern area, which significantly contributes to its growth in TFP. Yet, the left-behind population in the western places have to bear with the less developed market such that the services' industry is negatively associated with technological advancements to the most extend.

Table 5.2.2: Regional Disparities of the Implications
Panel A: Dependent Variable= TFP-DEA

	Eastern			Central and North-Eastern			Western		
VARIABLES	Saving	Edu	Health	Saving	Edu	Health	Saving	Edu	Health
ln_birth	-7.525*	-5.680	3.431	-1.137	-0.897	1.258	-16.91*	-17.04*	-13.70
	(3.911)	(4.323)	(3.867)	(3.368)	(3.290)	(3.092)	(9.166)	(10.06)	(9.624)
ln_death	1.685	-11.50	-3.123	33.80***	26.82***	32.61***	5.749	13.99	3.137
	(7.492)	(7.480)	(6.665)	(7.033)	(7.340)	(5.931)	(10.67)	(10.62)	(10.71)
lngdpc	1.232	0.237	2.249*	-4.972***	-7.433***	-3.424***	-9.856***	-11.12***	-9.171***
	(1.412)	(1.579)	(1.326)	(1.380)	(1.634)	(1.042)	(3.257)	(2.708)	(2.949)
lnlfpc	1.114	-6.048	-20.55***	-8.373	-4.933	-15.30***	11.48	5.421	13.20
	(6.509)	(7.101)	(6.325)	(5.186)	(5.680)	(4.573)	(9.989)	(9.596)	(10.76)
lnopenness	-1.018	-0.914	-1.559*	2.072***	2.954***	1.303**	-1.043	-0.660	-1.393
	(0.888)	(1.027)	(0.818)	(0.739)	(0.748)	(0.643)	(1.029)	(1.006)	(1.114)
lnservice	5.973	14.61**	14.58***	-3.938	-3.401	-4.372	-19.12**	-14.90*	-11.62
	(4.462)	(6.721)	(4.249)	(4.340)	(4.698)	(3.640)	(9.047)	(8.907)	(9.996)
urbanization	-3.051	2.359	1.223	-9.673**	-18.81***	-2.461	1.876	-18.48*	-12.67
	(5.657)	(7.509)	(5.205)	(4.802)	(5.625)	(4.334)	(11.08)	(10.99)	(12.72)
sup	75.20	4.450	-124.4	-33.01	288.5***	-73.24	-1,167	399.7**	425.0**
	(579.7)	(92.79)	(114.9)	(352.6)	(105.5)	(96.77)	(713.5)	(189.1)	(174.6)
dep	-233.7*	9.434	46.55	-183.3*	-25.64	-85.93***	-505.0***	58.32	48.71
	(118.7)	(29.17)	(37.39)	(94.15)	(29.19)	(32.41)	(179.5)	(57.87)	(51.24)
mediator	-28.78	-10.19	-7.839	-13.86	-22.27	-1.056	-84.33***	-1.421	-27.41
	(24.73)	(14.45)	(11.30)	(13.08)	(14.01)	(9.169)	(27.53)	(18.68)	(16.58)
med_age_int	-26.30	-23.13	-76.20	13.63	166.5**	-70.46	348.3*	72.24	132.4
	(150.4)	(73.87)	(63.06)	(91.10)	(71.99)	(57.04)	(179.7)	(103.3)	(108.9)
med_chld_int	66.00**	9.768	21.47	30.09	26.86*	-4.209	131.5***	5.857	23.73
	(30.51)	(16.33)	(17.10)	(23.26)	(15.13)	(14.70)	(43.90)	(23.53)	(30.14)
Constant	95.52	-42.77	-111.4***	80.56	34.64	-3.630	497.5***	130.9***	88.17
	(96.54)	(42.40)	(38.28)	(56.45)	(40.40)	(23.09)	(115.2)	(48.69)	(56.23)
Observations	91	91	91	84	84	84	101	102	102
R-squared	0.368	0.237	0.466	0.651	0.669	0.746	0.669	0.664	0.655

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Panel B: Dependent Variable= Patent Application Per Thousand Employees

	Eastern			Central and North-Eastern			Western		
VARIABLES	**Saving**	**Edu**	**Health**	**Saving**	**Edu**	**Health**	**Saving**	**Edu**	**Health**
ln_birth	0.0130	-0.223	0.194	0.543*	0.588*	0.208	-0.00425	-0.0784	-0.209
	(0.378)	(0.376)	(0.426)	(0.292)	(0.305)	(0.291)	(0.447)	(0.427)	(0.445)
ln_death	-0.710	-1.486**	-0.975	-0.898	-0.702	-0.131	-1.106**	-0.196	-1.124**
	(0.724)	(0.650)	(0.735)	(0.610)	(0.679)	(0.557)	(0.521)	(0.451)	(0.495)
lngdpc	0.901***	0.999***	0.944***	0.883***	0.929***	0.571***	0.771***	1.043***	1.035***
	(0.137)	(0.137)	(0.146)	(0.120)	(0.151)	(0.0979)	(0.159)	(0.115)	(0.136)
lnlfpc	1.505**	1.207*	0.717	1.088**	1.229**	1.241***	0.374	0.493	0.372
	(0.629)	(0.617)	(0.697)	(0.450)	(0.526)	(0.430)	(0.488)	(0.407)	(0.498)
lnopenness	0.0228	-0.120	-0.0249	-0.115*	-0.105	-0.0263	-0.125**	-0.0912**	-0.0722
	(0.0859)	(0.0892)	(0.0902)	(0.0641)	(0.0693)	(0.0604)	(0.0502)	(0.0427)	(0.0515)
lnservice	0.0782	-1.441**	-0.149	-0.112	0.0965	-0.322	-2.006***	-1.660***	-1.935***
	(0.431)	(0.584)	(0.469)	(0.377)	(0.435)	(0.342)	(0.442)	(0.378)	(0.462)
urbanization	2.205***	1.570**	2.503***	1.339***	1.576***	0.442	1.268**	-0.0973	0.108
	(0.547)	(0.652)	(0.574)	(0.417)	(0.521)	(0.407)	(0.541)	(0.467)	(0.588)
sup	-46.00	-3.720	14.01	-57.98*	23.08**	32.81***	-73.43**	29.56***	37.61***
	(56.05)	(8.061)	(12.67)	(30.60)	(9.767)	(9.093)	(34.82)	(8.027)	(8.077)
dep	6.712	-6.805***	-1.698	3.008	-2.251	6.099**	-15.86*	4.213*	-2.963
	(11.48)	(2.534)	(4.123)	(8.171)	(2.702)	(3.045)	(8.760)	(2.457)	(2.369)
mediator	-1.908	2.539**	-0.852	-1.989*	-2.502*	-2.263**	-2.767**	-0.608	-0.849
	(2.391)	(1.255)	(1.246)	(1.135)	(1.296)	(0.862)	(1.344)	(0.793)	(0.767)
med_age_int	12.71	-6.355	5.322	16.87**	11.58*	14.57***	22.22**	10.59**	17.66***
	(14.54)	(6.417)	(6.953)	(7.906)	(6.664)	(5.361)	(8.772)	(4.388)	(5.034)
med_chld_int	-1.927	-4.612***	-0.355	-1.567	1.442	4.763***	3.857*	0.734	-2.288
	(2.950)	(1.418)	(1.886)	(2.019)	(1.400)	(1.381)	(2.143)	(0.999)	(1.394)
Constant	12.98	15.12***	3.598	12.83**	0.220	5.113**	23.72***	6.560***	10.04***
	(9.334)	(3.683)	(4.221)	(4.899)	(3.739)	(2.170)	(5.621)	(2.067)	(2.600)
Observations	91	91	91	84	84	84	101	102	102
R-squared	0.940	0.942	0.934	0.953	0.949	0.960	0.919	0.938	0.924

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Panel C: Dependent Variable= R&D Expenditure Per Thousand Employees

	Eastern			Central and North-Eastern			Western		
VARIABLES	Saving	Edu	Health	Saving	Edu	Health	Saving	Edu	Health
ln_birth	-0.194	-0.422	0.0268	0.140	0.0903	-0.0452	-1.455**	-1.298**	-1.263**
	(0.341)	(0.343)	(0.300)	(0.224)	(0.243)	(0.232)	(0.554)	(0.555)	(0.565)
ln_death	-0.000288	-0.966*	0.423	-1.479***	-1.616***	-1.406***	-0.698	-0.211	-0.783
	(0.598)	(0.543)	(0.500)	(0.457)	(0.525)	(0.468)	(0.710)	(0.646)	(0.694)
lngdpc	0.551***	0.566***	0.904***	0.950***	1.003***	1.013***	0.653***	0.666***	0.952***
	(0.155)	(0.167)	(0.146)	(0.0999)	(0.135)	(0.0975)	(0.228)	(0.172)	(0.203)
lnlfpc	1.119**	0.600	-0.147	-0.284	-0.240	-0.442	0.648	0.696	1.067
	(0.526)	(0.530)	(0.485)	(0.338)	(0.407)	(0.345)	(0.621)	(0.546)	(0.660)
lnopenness	-0.0334	-0.165	0.0591	0.139**	0.115*	0.0903*	-0.0358	-0.0154	-0.0452
	(0.0878)	(0.103)	(0.0799)	(0.0536)	(0.0582)	(0.0534)	(0.0677)	(0.0625)	(0.0711)
lnservice	0.428	-0.675	0.635*	0.522*	0.528	0.385	-0.725	-0.110	-0.0734
	(0.407)	(0.538)	(0.326)	(0.284)	(0.356)	(0.286)	(0.557)	(0.510)	(0.624)
urbanization	3.017***	2.654***	3.078***	-0.220	-0.220	0.0358	0.316	-1.167*	-0.546
	(0.574)	(0.587)	(0.477)	(0.349)	(0.432)	(0.362)	(0.696)	(0.630)	(0.790)
sup	-35.24	-10.67	22.28**	26.74	8.893	-3.300	-81.51*	13.79	13.23
	(45.82)	(7.001)	(8.634)	(23.78)	(7.652)	(7.394)	(43.56)	(10.97)	(10.71)
dep	5.171	-5.173**	2.311	-29.97***	2.657	4.417*	-28.11*	-1.960	1.019
	(11.66)	(2.236)	(3.094)	(6.699)	(2.221)	(2.508)	(14.60)	(3.270)	(3.045)
mediator	-1.224	2.423**	-3.242***	-1.020	-1.043	-0.293	-4.006**	0.824	-1.898*
	(1.931)	(1.120)	(0.885)	(0.846)	(1.027)	(0.700)	(1.869)	(1.062)	(1.000)
med_age_int	9.383	-11.72**	12.58**	-5.607	2.211	-5.569	21.80*	4.698	7.969
	(11.87)	(5.613)	(4.815)	(6.149)	(5.216)	(4.371)	(10.98)	(6.029)	(6.522)
med_chld_int	-2.560	-1.483	3.522**	7.072***	2.831**	3.248***	6.487*	-1.320	1.973
	(3.028)	(1.302)	(1.414)	(1.680)	(1.142)	(1.152)	(3.569)	(1.329)	(1.839)
Constant	4.736	8.185**	-12.12***	1.927	-4.169	-3.241*	23.35***	5.020*	-0.0937
	(7.604)	(3.705)	(3.177)	(3.642)	(3.078)	(1.787)	(7.950)	(2.841)	(3.681)
Observations	82	82	82	76	76	76	93	93	93
R-squared	0.962	0.962	0.971	0.973	0.969	0.974	0.876	0.896	0.878

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *ln_birth, ln_death, lngdpc, lnlfpc, lnopenness, lnservice, urbanization, sup, dep, mediator, med_age_in, and med_chld_int* stand for the crude birth rate, crude death rate, GDP per capita, labor force participation rate, proportion of FDI to regional GDP, proportion of services VA to regional GDP, urbanization rate, old-age support ratio, children dependency ratio, mediators including saving ratio, proportion of population with completed secondary education and above, and public expenditure to regional GDP respectively. All independent variables except sup and dep are log transformed and data represent the changes in lagged periods *t-1*.

These findings highlight regional disparities in China, indicating complex and context-specific nature of the relationship between demographic factors and technological advancements through different mechanisms across places. More importantly, the interpretation of these results requires careful consideration on its demographic features that particularly driven by migration, suggesting that variations in demographic structures and economic development levels can lead to varying mechanisms and the outcome in technological advancements.

5.2.3 Sectoral Disparities of the Implications

In the previous section, this paper has analysed and discussed the impact of demographic structural changes on technological implications in the population. However, it is also important to examine whether these implications remain similar when focusing on the demographic shifts within the workforce. To address this question, this analysis estimates the relationship between the demographic profile of the labour force in China using data from the 1990, 2000, and 2010 population censuses, and the corresponding growth in the level of TFP across 19 sub-industries in leading years at various intervals, including 3-year, 6-year, 9-year, and 12-year intervals, respectively.[65] This way allows for an examination of the effects over both short and long time horizons, taking into consideration that varying timeframes required for technological advancements to occur. It is also important to note that due to limited sample size used in this analysis, the results provided are only exploratory in nature and should not be considered as definitive findings.

Acemoglu and Restrepo (2018) argued that the responses of technological advancements (automation robots) to demographic change is more pronounced in industries that rely more on middle-aged workers, indicated by an increase in the ratio of older to middle-aged workers. However, two caveats exist in their analysis. Firstly, the study mentioned did not consider the potential impact of human capital, such as education attainment, on employment within different sectors and its relationship with technologies. Human capital, as demonstrated in preceding sections, plays a crucial role in driving technological advancements and innovation. The level of education and skills possessed by workers can significantly influence their ability to adapt to new technologies and contribute to technological developments in their respective sectors. Secondly, the analysis also did not account for the "spill over effects" that could arise from the burden of dependent populations in a specific time context, in particular prominent in a long-time horizon. The demographic structural changes in the population can have broader implications beyond the labour market. For example, the increasing demand for aged care time allocation within the household resulting from an aging population implies less opportunities in the labour market participation, particularly for women (i.e., Gaddis and

[65] For instance, the demographic data in 1990 is combined with growth in TFP data in 1993, 1996, 1999, and 2012 respectively.

Klasen, 2014; Jayachandran, 2021). Neglecting the broad demographic context may lead to an incomplete understanding of their implications.

Therefore, this paper follows their identification strategy but adding the interactions between the education level of employment and demographic structure factors including *sup* and *dep* in the corresponding year.

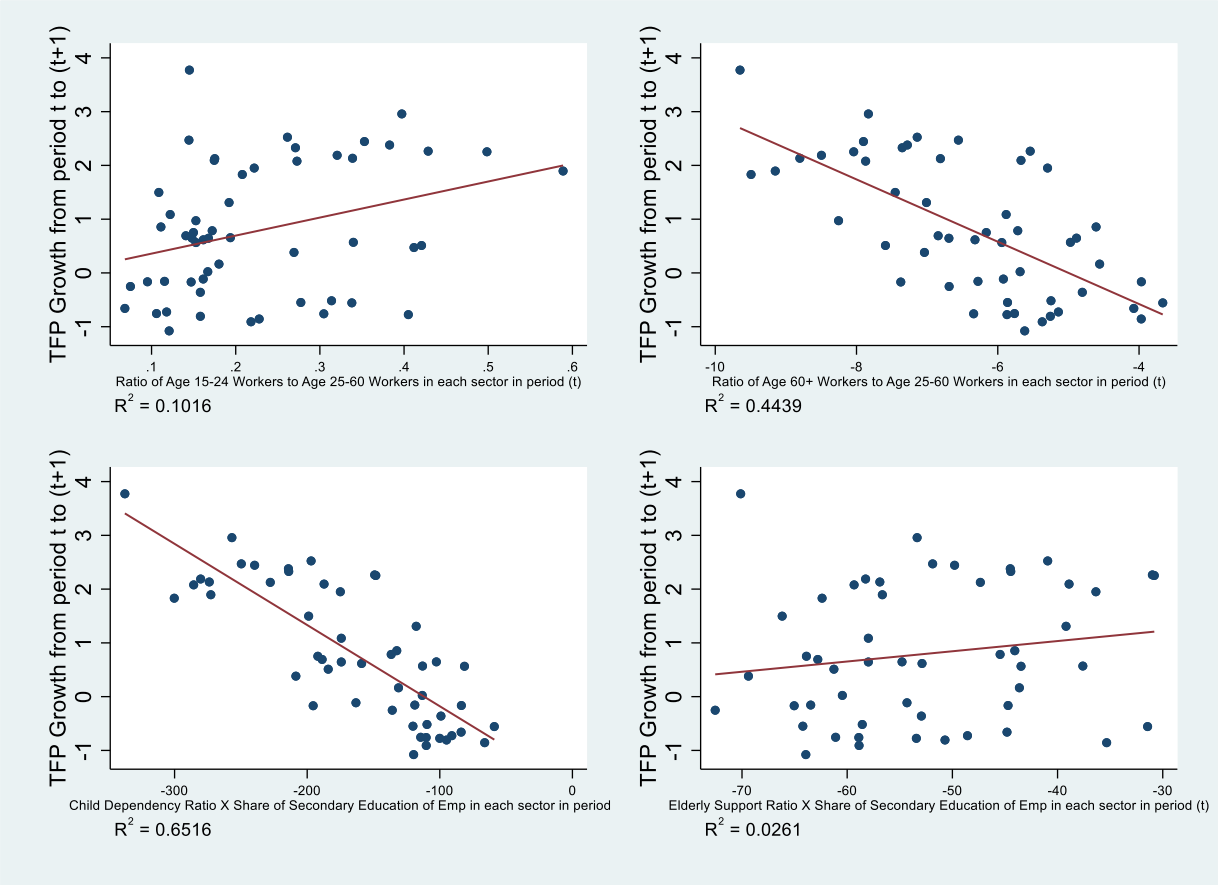
$$\frac{TFP_{i,t+1}}{TFP_{i,t}} = \beta_0 + \beta_1 Relevance\ on\ Younger\ Workers_{i,t} + \beta_2 Relevance\ on\ Older\ Workers_{i,t} + \beta_3 SUP_t * EDU_{i,t} + \beta_4 DEP_t * EDU_{i,t} + \varepsilon_{i,t} \quad (5.2.3)$$

where the left-hand side variable denotes the growth rate in TFP level from period *t* to *t+1*. The right-hand side variable captures various dimensions of demographic structural changes in the workforce: *relevance on younger-workers*$_{i,t}$ (hereafter *youngworker*) and *relevance on older-workers*$_{i,t}$ (hereafter *oldworker*) is estimated by the ratio of young-aged employment (15-24) to the working age employment (25-60), and the ratio of old-aged employment (60 and above) to the working age employment (25-59). $EDU_{i,t}$ represents the proportion of employment with completed secondary education, and its interactions with *SUP* and *DEP* are denoted as *edu_burden_age* and *edu_burden_chld* respectively. While *i* and *t* represent each sub-industry and time respectively.

Figure 5.2.3 visually presents the relationship between each demographic factor with technologically advancements. The y-axis is set as the growth rate in TFP level in the leading period *(t+1)*, while different variables of interests at the period *t* are put in the x-axis, including *youngworker, oldworker* to illustrate both demographic shifts in the workforce, and *edu_burden_age* and *edu_burden_chld* to capture the previously identified demographic dividend mechanism through education.

Specifically, results of the analysis indicate that there are strong correlations between demographic structural changes in the workforce and technological advancements in China, and the relationship varies depending on the employment profiles within different sectors. Sectors with a higher proportion of younger workers relative to the working-age employment tend to be positively correlated with technological advancements. On the other hand, sectors with a higher proportion of older workers show a negative correlation instead.

Figure 5.2.3: Relationship between Workforce Demography and Technological Advancements after 3-year



Source: Created by author based on estimation

Furthermore, the analysis reveals a clear declining trend in the growth in TFP in line with *edu_burden_chld*. This suggests that a decreasing dependency ratio, or a lower proportion of children in the population, is negatively associated with technological advancements, depending on the level of education among workforces. However, the relationship between technological advancements and *edu_burden_age*, which represents the burden of an aging population, is less clear.

Following the illustrative results, additional multivariate regression analysis has been conducted by following Equation 5.2.3. Initially, the regression included variables related to workforce demographics such as *youngworker* and *oldworker,* and the results are presented in the left-hand side of Table 5.2.3. Subsequently, two interaction terms, *edu_burden_chld* and *edu_burden_age* are added to the baseline model, and the results are

presented in the right-hand. Exercises have been carried out by using 3-year, 6-year, 9-year, and 12-year interval respectively, allowing for a deeper understanding of changes of the effects over time (Column 1-4). In addition, results using both POLS and FE methods are provided in Panel A and Panel B.

The regression results in Table 5.2.3 support and strengthen findings presented in the visual display by providing quantitative measures in the form of correlation coefficients. These results reaffirm the previous discussions and provide more precise insights into the relationships between workforce demographics, education, and technological advancements, although the small sample size[66] may have limited the statistical power and the precision of estimations, such that findings should be interpreted with caution, simply serving as a starting point for further investigations rather than definitive conclusions.

Consistent with earlier findings, regression results confirm a positive and significant relationship between a younger workforce and technological advancements across various sub-industries. This implies that sectors with a higher proportion of younger workers tend to experience greater pace in technological advancements. Additionally, the interaction between the child dependency ratio and the education level of the workforce also reveals a negative relationship, suggesting that sectors with a higher level of education among their workforce in the context of a lower burden of child dependency tend to exhibit positive effects on technological advancements. These findings are also in line with previous findings in this Chapter 5 on characterizing the role of low-fertility rate in promoting technological advancements through the indirect channel of human capital.

[66] There seems to be plausible ways to increase the sample size such as carrying out the exercise at 2-digits sub-sector levels. However, due to the continuous updates in the Industrial Classification for National Economic Activities over time, such that industrial classification of employment profile also changed constantly with sectors are dropped, changed, or reclassified. Because the population census in 1990 adopts the 1985 classification, the census in 2000 adopts the 1994 classification, and the 2010 census adopts the 2002 classification, it leads to significant inconsistencies over time when appending the employment profile together. To address these issues, this analysis has decided to use the broad 19 sub-industry classification to match against the TFP results. Due to three missing industries of "Retail" and "ICT" in 1990 and 2000 data, the final sample being employed in the exercise is 54.

Table 5.2.3: Workforce Demographics and Human Capital on Technological Advancements

Panel A: OLS Estimators

	Baseline Model				Inclusion of Human Capital Interactions			
VARIABLES	**3-Year**	**6-Year**	**9-Year**	**12-Year**	**3-Year**	**6-Year**	**9-Year**	**12-Year**
youngworker	3.153**	6.926**	8.961**	12.03**	-0.696	0.170	-0.536	0.0192
	(1.409)	(2.619)	(3.716)	(4.686)	(0.663)	(1.297)	(1.802)	(2.321)
oldworker	5.365	8.511	15.35	18.12	3.660	6.307	12.47	14.06
	(6.632)	(12.32)	(17.49)	(22.05)	(2.795)	(5.468)	(7.597)	(9.785)
edu_burden_chld					-0.0184***	-0.0337***	-0.0477***	-0.0599***
					(0.00117)	(0.00229)	(0.00318)	(0.00409)
edu_burden_age					0.0576***	0.0986***	0.143***	0.185***
					(0.00746)	(0.0146)	(0.0203)	(0.0261)
Constant	-0.0568	-0.564	-1.095	-2.153*	0.861*	0.660	0.805	0.552
	(0.370)	(0.687)	(0.975)	(1.230)	(0.430)	(0.841)	(1.168)	(1.504)
Observations	54	54	54	54	51	51	51	51
R-squared	0.113	0.141	0.129	0.139	0.864	0.854	0.858	0.853
Regional FE	No	No	No	No	No	No	No	no

Panel B: FE Estimators

	Baseline Model				Inclusion of Human Capital Interactions			
VARIABLES	**3-Year**	**6-Year**	**9-Year**	**12-Year**	**3-Year**	**6-Year**	**9-Year**	**12-Year**
youngworker	9.869***	19.47***	26.99***	35.02***	-0.433	0.665	0.338	0.596
	(1.954)	(3.508)	(4.930)	(6.146)	(1.223)	(1.965)	(2.565)	(3.107)
oldworker	38.77***	64.84**	91.76**	110.2**	1.798	-1.100	-0.982	-7.705
	(13.46)	(24.15)	(33.94)	(42.31)	(6.199)	(9.963)	(13.00)	(15.75)
edu_burden_chld					-0.0184***	-0.0333***	-0.0472***	-0.0589***
					(0.00142)	(0.00228)	(0.00298)	(0.00361)
edu_burden_age					0.0521***	0.100***	0.142***	0.206***
					(0.0172)	(0.0277)	(0.0361)	(0.0437)
Constant	-2.358***	-4.712***	-6.945***	-9.488***	0.558	0.893	0.942	2.222
	(0.609)	(1.092)	(1.535)	(1.913)	(1.078)	(1.732)	(2.261)	(2.738)
Observations	53	53	53	53	50	50	50	50
R-squared	0.526	0.571	0.572	0.587	0.935	0.953	0.959	0.963
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

However, results on the ageing workforce do not present consistent findings with the graphs. The regression results, contrary to the figures, indicate a positive relationship between an ageing workforce and technological advancements across various sub-industries, although the estimators are not significant using the POLS estimation method. In addition, demographic implications through the education mechanism also present a significantly positive effect, suggesting that sectors with a higher level of education among their workforce in the context of higher burden of child dependency are motivated to promote technological advancements. These varying results about ageing workforce also highlight a complex relationship between population aging, human capital, and technological advancements in line with mixed results observed in the literature (i.e., Lindh and Malmberg, 1999; Bloom, Canning, and Fink, 2010; Acemoglu and Restrepo, 2017).

In addition, it is also worth noting that the magnitude of the correlation coefficients increase overtime, for both *youngworker, edu_burden_chld*, and *edu_burden_age,* indicating that as time passes, the impact of these factors becomes more pronounced. This finding suggests that demographic structural changes and human capital accumulation are gradual processes that require a long timeframe to fully manifest their implications. The slow nature of demographic structural changes and human capital accumulation implies that their effects on technological advancements may not be immediately apparent, and it takes time for changes in the composition of the workforce and the accumulation of human capital to translate into visible improvements in technological capabilities and productivities.

Overall, these findings are in line with previous findings in Chapter 5 regarding the role of lower child-dependency in promoting technological advancements across various sectors over time, while underscoring the complex relationship between workforce ageing and technological advancements. Additionally, the sectoral analysis confirms the indirect channel through which human capital facilitates technological implications. By considering a longer time horizon, this analysis captures the cumulative effects of demographic structural changes and human capital accumulation on technological advancements. It highlights the importance in understanding that these slow variables operate over long periods. Therefore, policies and strategies aimed at promoting technological advancements should consider the cumulative effects of these slow variables and allow sufficient time for their implications to materialize.

CHAPTER 6: DISCUSSION AND CONCLUSION

This Chapter interprets and discusses the extensive analytical results in the preceding Chapter 5, in against with the hypotheses and existing studies on the technological consequences of demographic structural changes and their mechanisms based on the demographic dividends theory, as delineated in the Chapter 3 and Chapter 4. This Chapter also acknowledges the limitations and shortcomings of the analytical methods employed in this study and raises challenging issues that could not be fully addressed in the current analysis. Furthermore, this Chapter highlights potential avenues for future research in this field. This dissertation draws conclusions from key findings derived throughout the study and relates them to the real economic dynamics, consolidating the understanding of the relationship between demographic structural changes and technological advancements in the country's context, offering insights into the real societal implications and providing policy suggestions for China's reform.

6.1. DISCUSSION

This section focuses on the empirical results obtained from Chapter 5, and it compares these results with six hypotheses proposed in Chapter 4. Based on an extended theoretical framework and existing studies, this study explores the overall and separated implications of demographic structural changes on technological advancements in the post-demographic transition China by adopting wide-ranging model specifications and examination methods.

In response to research questions, discussions in this section are divided into two parts. The first part explores the general findings regarding the implications of demographic structural changes on automation robotics, where it also examines the hypothesized dual indirect mechanisms of saving and human capital in the global context, highlighting their role in transmitting the implications. The second part of the section shifts the focus to the specific country context of China. It delves deeper into the dual mechanisms discussed earlier and provides additional insights into disparities analysis across different regions and sectors within China. This analysis overall helps to uncover

the variations and specificities of the relationship between demographic structural changes and technological advancements in various contexts.

6.1.1 The Implications of Demographic Structural Changes on Technological Advancements in the Global Context

1) The Role of Saving in Facilitating the Impact of Demographic Structural Changes on Technological Advancements

The first research question explores the relationship between demographic structural changes and technological advancements, following the analytical framework derived from the demographic dividends theory (DDT). The DDT suggests that demographic changes not only have a direct impact on the labour force, but also lead to two types of indirect effects through changes in savings and human capital. Research Question 1.1 focuses on investigating the first indirect mechanism, namely the role of saving in facilitating the implications of demographic structural changes on technological advancements, proxied by the robot density in the global context. This study examines the Hypothesis 1.1, which posits that "*demographic structural changes driven by different age-specific dynamics have varying effects on the growth in robots' density while depending on the saving ratio.*"

To tests hypothesis 1.1, this study builds upon the extension of theoretical model setting by Abeliansky and Prettner (2017; 2021), and incorporates the key variable of interest, saving *s,* into the baseline model. This study also employs two approaches, namely the casual stepwise approach and the interaction analysis, to examine the mediation effect of saving *s* on the relationship between demographic structural changes and the growth in robots' density. To ensure the reliability and robustness of findings, the study replicates the examination using various samples with different initial years and spanning timeframes. Multiple estimation methods, including pooled ordinary least squares (POLS), random effects (RE), and fixed effects (FE), are employed. In addition, model specifications are expanded to include other control variables.

By utilizing these rigorous methods and extensive analyses, the study primarily finds that the child dependency ratio presents strong negative associations with the growth in robots' density, whilst the old-age support ratio does not reveal constant and significant

coefficients, confirming the hypothesis that demographic structural changes with specific population dynamics have varying effects on the growth in robots' density. In addition, results derived from the causal stepwise approach show that saving presents a "partial mediation" effect for changes in the child dependency ratio but a "suppressing effect" for changes in the old-age support ratio, suggesting saving's different effects in the interplay between demographic structural changes and technological advancements. These results have been further confirmed by the interaction analysis, where coefficients on the interactions between saving and the child dependency ratio are significantly positive and robust, while not always so for the interactions between saving and the old-age support ratio. Regression results, in the meantime, reveal that a lower population growth rate and an increasing share of working-age population can motivate the growth in robots' density.

More precisely, estimations reveal that a 0.1 percentage point decrease in the child dependency ratio is associated with a 0.12 percent increase in robots per thousand workers on average. This effect is driven by the reduced burden of child dependency, leading to a higher national saving and investment, and subsequently contributing to the adoption of robots in the labor market. The interaction between saving and the child dependency ratio also plays a significant role in promoting automation, particularly in a low-fertility context during the post-demographic transition period. These findings are in line with life-cycle theory (i.e., Mason, 1988; Modigliani & Cao, 2004), macroeconomic evidence (i.e., Mason, 1988), and microeconomic evidence in China (i.e., Bairoliya & Miller, 2021) and beyond (i.e., Loayza et al., 2000).

However, in contrast to Acemoglu and Restrepo (2020), regression results suggest that the impact of an increasing aged care burden on the growth in robots' density is not clear and significant. It is plausible because population aging leads to a decrease in national saving, as indicated by many existing studies (i.e., Loayza et al., 2000; Curtis, Lugauer, and Mark, 2017; Horioka, Suzuki, and Hatta, 2007), but a decrease in saving may counteract the positive effect of saving in promoting technological advancements, resulting in a less pronounced impact on the growth of robots' density. However, it is worth noting that some studies using micro-level data in developing contexts, such as ASEAN countries, reveal that population aging may not have profound negative effects on the aggregate

saving (Ong, 2022), in contrast to findings in developed economies like OECD countries (Xiong, Celebi, and Welfens, 2022).

Another complexity introduced by population aging is the changing behaviour related to the public saving scheme, such as pensions. For example, Boersch-Supan and Winter (2001) predicted that the saving rate in European countries would initially increase before 2025 but then decline due to the trade-off between private savings and public pension schemes in the context of population aging. As the expectation of living longer leading to an extension in the pensionable age, people intend to save more to finance a longer retirement (Gruber and Wise, 1998). Whilst Bloom et al., (2007) pointed out that ageing driven by increased longevity raised aggregate savings rates in countries with universal pension coverage, but not in countries with pay-as-you-go systems. These findings highlighted the importance in revisiting the pension system in light of the intricate relationship between population aging and saving.

The results of the analysis support the finding in Abelianisky and Prettner (2017 & 2021), indicating that a 1 percent slowdown in population growth is associated with an acceleration of robots per thousand workers by approximately 0.075 percent annually in the following period. Additionally, this study reveals that an increasing proportion of the working-age population and a higher initial level of GDP per capita have a significant impact on the growth of robots' density. On the other hand, variables such as labour force participation rate, country openness, and industrial structure are less clear in their relationship with the automation outcomes.

Overall, findings of the analysis align with previous research and provide support for hypothesis 1.1. Results indicate that demographic structural changes, such as low fertility, low population growth, and a shrinking working-age population, have varying impacts on technological advancements. However, the effect of population aging on technological advancements is not pronounced. Additionally, the analysis confirms that saving plays a positive mediating role in promoting the adoption of robotic technologies. These findings contribute to the understanding of the first indirect mechanism in the complex relationship between demographic changes and technological advancements.

2) The Role of Human Capital in Facilitating the Impact of Demographic Structural Changes on Technological Advancements

Research Question 1.2 shifts the focus to the investigation on the second indirect mechanism, namely the role of human capital in facilitating the implication of demographic structural changes on the growth in the adoption of robot in the global context. This study examines the Hypothesis 1.2, which posits that "*demographic structural changes driven by different age-specific dynamics have varying effects on the growth in robots' density while depending on the level of human capital.*"

In so doing, this study incorporates a group of plausible proxies for the variables of interest, human capital *h,* including into Human Capital Index (HCI), education level, life expectancy at birth, and female's education respectively into the model employed in the preceding analysis. Likewise, this study also employs two approaches (e.g., casual stepwise approach and interaction analysis) to examine the mediation effect of human capital *h* on the relationship between demographic structural changes and the growth in robots' density. This analysis also utilizes different samples, mixed estimation methods, and wide-ranging model specifications to examine the reliability and robustness of the findings.

The study primarily finds that the child dependency ratio still presents a strong negative association with the growth in robots' density, and different human capital proxies preserve varying effects. For instance, causal stepwise approach shows that HCI and life expectancy at birth presents a "supressing effect" for changes in the child dependency ratio, while the education attainment presents a "partial mediation effect". These results from the interaction analysis have provided further confirmation that coefficients on the interactions between various human capital indicators and the child dependency ratio are significantly positive and robust, suggesting that human capital serves as a pivotal role in the interplay between demographic structural changes and technological advancements.

There is a significant body of research that supports the significant negative relationship between the fertility rate and human capital in various theories (i.e, Becker and Lewis, 1973; Lee and Mason, 2011), and empirical analyses using various proxies: human capital index (i.e., Brixi, Rawlings, and Koechlein, 2021), education and schooling (i.e., Shiue, 2017; Murphy, Simon, and Tamura, 2008; Cochrane, 1979), health (i.e., Liu and

Liu, 2019;), life expectancy at birth (i.e., Cervellati and Sunde, 2015), and female's education level (i.e., Schultz, 2007). The underlying explanation by the Quantity-Quality trade-off theory has been discussed in Chapter 4, and the paralleled fertility falls and investments in human capital rise is "one of the most clear-cut correlations" that has been widely accepted in academia (Becker and Lewis, 1973).

In addition, results of this study provide further evidence supporting the relationship between the decline in the child dependency ratio, higher levels of human capital, and the increasing robots' density. Numerous studies have examined the relationship between low fertility rates and technological advancements, arguing that the demographic transition, characterized by declining fertility rates, played a significant role in fostering technological advancements (i.e., Galor and Weil, 2000; Bloom, Canning and Sevilla, 2003). On the other hand, the influential works by Barro and Sala-i-Martin (1995) and Romer (1990) argued the prominent role of human capital in fostering technological advancements and productivity growth.

On the other hand, regression results in the stepwise analysis consistently show insignificant coefficients for the old-age support ratio, and the inclusion of human capital proxies further diminishes the magnitude of these coefficients. Yet, complementary analyses using the alternative interaction approach reveal significant negative coefficients when considering the interactions of the old-age support ratio with education and life expectancy at birth. These results suggest that although there is no mediating channel through human capital between ageing burdens and the adoption of automation technologies, raises in the old-age support ratio do have a somewhat negative impact on the growth in robots' density. However, higher levels of education and longer life expectancy at birth may help mitigate these negative effects at a significant level.

A plausible reason to explain why population aging indicated by a higher support ratio does not bring consistently significant effect on the adoption of robotics, is its complicated relationship with human capital and technological advancements. Many studies have demonstrated their complex relationship with mixed results observed in the literature. For instance, from the supply side perspective, workforce ageing naturally implies a decline in human capital because older workers have lower level of skills,

cognitive abilities, and willingness to learn (i.e., Čiutienė and Railaitė, 2015; Czaja and Lee, 2007; Chomik and Piggott, 2021), such that it leads to a reduction in the average productivity of workers (i.e., Gu and Stoyanov, 2019).

However, from the demand side perspective, population ageing may lead to the replacement of older and less-educated workers by younger and more educated workers (Day and Dowrick, 2004), implying more opportunities for younger generations to invest in human capital formation. Fougère & Mérette (1999; 2009) and Han and Lee (2020) identified a positive relationship between population ageing, human capital, and productivity in OECD, Canada, and Korea respectively. Therefore, it explains the positive effect identified in the interaction term of the old-age support ratio and education, underscoring the important role of education in mitigating the negative impacts.

Besides, Mincer (1996) noted that population ageing is paralleled with raising life expectancy, suggesting a longer investment period to ensure the human capital development. As people are expected to live longer, they are also enforced to work longer before the pension access age (Gruber and Wise, 1998). David et al., (2011) and Lisenkova, Mérette, and Wright (2013) further complemented that population ageing would also induce behavioral responses such as greater female labor force participation, to mitigate the negative consequences. Therefore, these may explain the positive effects identified in the interaction term between the old-age support ratio and life expectancy at birth, and female's education, respectively.

In addition, many studies found that the impact of population aging on technological progress depends on several factors, including the specific age structure (i.e., Lindh and Malmberg, 1999), the level of human capital (i.e., Bloom, Canning, and Fink, 2010), investments in education and healthcare (i.e., Cervellati and Sunde, 2005), and the adaptability of the labour force (i.e., Acemoglu and Restrepo, 2017) to technological changes.

The declining growth in the working-age population is the flipside of the increasing child dependency ratio and old-age support ratio. As observed in previous analyses, the results consistently demonstrate a significant positive association between the growth in robots' density and the declining working-age population. This relationship holds true

alongside a higher initial level of GDP per capita. Additionally, the slowdown in population growth exhibits a notable correlation with the robots' density as identified in line with preceding analyses and findings in Abelianisky and Prettner (2017 & 2021). Meanwhile, other control variables such as labour force participation rate, openness, and industrial structure do not exhibit significant relationships with automation outcomes, further emphasizing the consistency with previous analyses.

These analyses provide support for the second hypothesized mechanism, indicating that human capital acts as an additional indirect mediating pathway, alongside saving, in transmitting automation incentives during the post-demographic transition. More importantly, it also highlights the multiplicity of the human capital implications from varying demographic dynamics with respect to the population structure. For example, the increasing longevity of individuals is inherently linked to an ageing population. As people are living healthier and longer, the population composition shifts, with a larger proportion of older individuals. This demographic shift towards an ageing workforce has implications for automation by considering the importance of both health and education dimensions: the ability to live longer and the need for lifelong learning. On the other hand, human capital development through education and early childhood investment will play a crucial role for the children. It serves as a vital mechanism for equipping individuals with the necessary knowledge, skills, and capabilities to adapt to changing socio-economic conditions and contribute to technological advancements at early stage. Therefore, demographic structural shifts to low fertility population necessitate the implications on automation through the education dimension.

3) Different Technological Implications with Respect to China Against the World

The presented evidence on the relationship between demographic structural changes and technological advancements in the global context prompts the question of whether these implications hold true across countries and how they are specifically applicable to China. Therefore, Research Question 1.3 attempts to revisit the technological implications of demographic structural changes by using sub-samples in considering the unique pace and characteristics of the demographic transition across countries. This hypothesis 1.3 posits

that "*demographic structural changes have varying effects on the growth in robots' density, but the effects are more significant in China compared to the global average.*"

In addition to regression analysis by using sub-samples according to country's income classification, this analysis extends the investigation by examining the correlation coefficients between technological advancements and key variables of interest using visual and quantitative methods. The variables of interest include the old-age support ratio, child-dependency ratio, population growth ratio, saving, Human Capital Index (HCI), education level, life expectancy at birth, and female's education respectively, which are consistent with earlier analyses. Both visual representations and numerical measures of the correlations are reported in Chapter 5.

Results show that the old-age support ratio has a positive association with technological advancements in high-income countries (HIC) but a negative association in non-high-income countries (Non-HIC). In HIC, a 1 percentage point increase in old-age support ratio leads to a 37.68 percent growth in robots' density, which is consistent with findings in Acemoglu and Restrepo (2020). While in Non-HIC, its decrease is associated with an increase in robot density. These findings suggest strong heterogeneity in the relationship between population ageing and technological advancements across different country groups, reflecting the influence of factors such as social security systems and economic conditions. These findings are partially endorsed by the previous studies in Acemoglu and Restrepo (2017) and Park, Shin, and Kikkawa (2022) that coefficients of population ageing on the technological progresses are weaker for OECD countries- namely HIC in this study.

In addition, aligning to the hypothesis 1.3, this analysis confirms significant differences between China and the global average, as well as high-income countries (HIC), regarding the overall relationship between demographic structural changes and technological advancements. China shows a faster momentum in technological advancements compared to its global and HIC counterparts, as indicated by higher magnitudes of the correlation coefficients. The impact of variables such as the old-age support ratio and the child dependency ratio on the growth in robots' density is more pronounced in China. Chomik and Piggott (2021) also underscored a more prominent

effects of population ageing on technology, innovation, and productivity in China when compared to other Asia countries.

The potential explanation for China's distinctive trajectory in technological advancements lies in its unique features that have been identified as crucial drivers throughout the previous analysis. These features include rapid and substantial demographic transitions (i.e., Fang et al., 2015; He, Goodkind, and Kowal, 2016) and its significant economic growth (i.e., Jorgenson and Vu, 2016). The development of human capital (i.e., Li, Fraumeni, Liu, and Wang, 2009; Lee and Francisco, 2012) and China's high saving rates (i.e., Ma, Yi, 2010; Kuijs, 2005; He and Cao, 2007; Yang, Zhang, and Zhou, 2012) have all provided important resources for the momentum in technological growth. These factors collectively contribute to China's unique position in the global comparison.

6.1.2 The Implications of Demographic Structural Changes on Technological Advancements in the China Context

Previous exercises validate the fundamental linkages between demographic structural changes and technological advancements, considering dual indirect mechanisms of saving and human capital globally. Comparing China with other countries also highlights its favourable position for remarkable technological progresses. However, limitations in the sample size pause caution in drawing conclusions. To overcome this issue, the following Research Question 2 incorporates larger samples across provinces from China, exploring a comprehensive examination of the relationship between demographic structural changes and technological advancements within China's domestic context.

1) To what extend do these mechanisms facilitate technological advancements in China?

To start with, this exercise examines the Hypothesis 2.1, which posits that "*demographic structural changes driven by age-specific dynamics have varying effects on the growth in technological advancements while depending on the saving ratio and human capital*" in line with the findings drawn from Research Question 1.

To tests hypothesis 2.1, the analysis in China follows a similar methodology to explore the mediation role of saving and human capital in the relationship between demographic structural changes and technological advancements. A group of proxies are used to measure the technological advancements in China including the growth in TFP level, patent application per thousand employees, and R&D expenditure per thousand employees. In addition, a group of plausible proxies for the mediating variables of interest, saving ratio *s* and human capital *h,* such as education level and healthcare conditions respectively are also incorporated into the model. Likewise, this study also employs two approaches (e.g., casual stepwise approach and the interaction analysis) to examine the mediation effects on the relationship between demographic structural changes and technological advancements. This analysis also utilizes different samples, mixed estimation methods, and wide-ranging model specifications to examine the reliability and robustness of findings.

The study reveals a significant negative association between the child dependency ratio and various measures of technological advancements, including TFP, patent applications per thousand employees, and R&D expenditure per thousand employees. Additionally, the stepwise analysis indicates "suppression effects" from saving and the education level, which is further supported by the interaction analysis. These findings suggest that a decrease in the child dependency ratio is linked to the development of technological advancements, but this relationship is influenced by factors such as saving and the education level, which is in line with findings from Research Question 1.

On the other hand, the old-age support ratio demonstrates a significant positive correlation with technological advancements in most instances, while the inclusion of mediating variables such as saving and health reduce the magnitude of the coefficients, indicating "complete mediating effects." Moreover, the subsequent interaction analysis reinforces the positive impact of the interactions between the old-age support ratio and saving and health, suggesting viable mediating pathways through these dimensions for the aging population, despite an insignificant result for saving in the context of R&D expenditure per thousand employees. Findings suggest that an increase in the old-age support ratio is associated with the development of technological advancements in China.

However, this relationship is influenced by factors such as saving and health. Specifically, higher levels of saving and better health care conditions are important for the growth in technological advancements in the ageing context of China.

The inclusion of mediators in the analysis uncovers both "mediating effects" and "suppressed effects" for different age-specific structural dynamics, confirming the hypothetical varying and complex relationship between demographic structural changes and technological advancements. In addition, both saving and human capital, to a great extent, are confirmed to serve as indirect mediating channels to motivate technological advancements in the context of post-demographic transition in China, which is also in line with the findings in the global context.

Overall, findings of this study provide further evidence for the relationship between the declining child dependency ratio, higher levels of saving and education, and technological advancements, aligning with the demographic dividends theory (DDT) proposed by Mason and Lee (2006). Previous studies have extensively discussed the positive link between low fertility rates and higher human capital (e.g., Galor and Weil, 2000; Bloom, Canning, and Sevilla, 2003), and there has been ongoing discussions on the relationship between low fertility and increasing saving at the international level (e.g., Mason, 1988; Bloom, Canning, and Sevilla, 2003; Bloom and Finlay, 2009).

Similar confirmatory findings are also observed in various developing country contexts, such as the Philippines and Chile (e.g., Orbeta Jr, 2005; Brito González, 2016). Li (2020) confirmed the effects of low fertility on human capital in China's country context, and human capital had significant and positive effects on TFP in China (i.e., Wei and Hao, 2011). Li and Zhao (2022) further clarified that the negative relationship between falls in fertility and human capital are realized before it is too low in China, and the human capital accumulation could help promote the growth in TFP. Therefore, the increasing saving rate and human capital resulting from a low-fertility rate are expected to play a crucial role in promoting technological advancements (i.e., Galor and Weil, 2000).

However, this study in the context of China sheds light on the mixed results regarding population aging, human capital, and technological advancements. Specifically, results demonstrate that an increase in the old-age support ratio can stimulate technological

advancements through increased public spending, highlighting the importance of having a robust pension, long-term care, and social protection system. The result is well aligned to previous findings in Liu (2019) that the increasing elderly dependency ratio promoted the growth in TFP through social security in China. At the same time, technological advancements in the context of population aging imply a lower saving rate and reduced financial capacity available for mobilization in the capital market, which could impede technological advancements. This finding is consistent with Batini, Callen, and McKibbin (2006), which suggested that population aging in industrialized countries and developing regions could lead to a decline in saving and a deterioration in their current account. The increasing old-age support ratio and falls in saving ratio also holds true in China (i.e., Chen, Guo, and Yao, 2014; Yang and Zhang, 2013; Wang, Cai, and Zhang, 2004).

Nevertheless, several papers have empirically challenged the presumption that dissaving occurs in retirement (see, e.g., Hamermesh, 1984, Banks et al., 1998). These findings also contrast with earlier discussions in India (i.e., Curtis, Lugauer, and Mark, 2017) and many European contexts, where ongoing population aging was expected to result in rising aggregate private saving as a vehicle of retirement income in response to decreasing internal rate of return (e.g., Boersch-Supan and Winter, 2001). Focusing on China, it is observed that high levels of precautionary household saving can be attributed to the longer life expectancy at birth and the absence of a comprehensive social security system. As a result, individuals have been motivated to accumulate high levels of precautionary household savings (i.e., Pettis, 2021). Additionally, Chamon et al. (2013) demonstrated that income uncertainty and pension reforms, which led to a decrease in pension levels relative to local average wages, could explain a significant portion of the increase in Chinese household savings from 1989 to 2009. Curtis et al. (2015) also found that demographic structural changes and the aging population contributed about half of the Chinese saving rate's increase during 1955–2009 in a long term.

Findings in parallel align with many previous studies on the role of control variables in the growth of TFP in China, including FDI (i.e., Liu and Wang, 2003) and labour force participation rate (i.e., Hicks, Basu, and Sappey, 2010), as well as the role of urbanization in driving TFP and R&D progress in China (i.e., Dai, Li, and Lu, 2017; Zhang, Wan, Luo,

and Wang, 2019). However, in contrast to Li and Zhao (2022), the current analysis does not find a significant role of birth rate, possibly due to the confounding effect of the child dependency ratio. Industrial structure does not demonstrate significant associations with technological advancements as well.

In summary, analyses provide support for hypothesis 2.1 that demographic structural changes influenced by different age-specific dynamics have diverse impacts on the growth of technological advancements in China. The decline in the child dependency ratio is found to facilitate technological advancements through increased levels of saving and education. Conversely, the impact of increase in the old-age support ratio is mixed, by facilitating technological advancements through improved health conditions but at the same time changing the saving portfolio of a country. These findings underscore the complex relationship between demographic factors and technological progresses, emphasizing the need for careful policy considerations to address different challenges. By understanding the interplay and mechanisms between demographics and technological advancements, policymakers can design targeted policies to maximize the positive effects while mitigate any potential negative consequences.

2) Heterogeneous Technological Implications Across Regions in China

To account for regional variations within China, the analysis narrows its focus to the sub-regional level to test the hypothesis 2.2, posits at "*Significant heterogeneity are found across provinces, and demographic implications on technological advancements are more significant in regions with higher capital and human capital endowments.*"

Using same empirical models as in the previous section, the sample is divided into the eastern, central and north-eastern, and western regions, representing diverse social-economic characteristics and policy contexts across different areas in the country.

Results demonstrate significant regional disparities in the relationship between demographic changes, technological advancements, and their underlying mechanisms, but significant results are found in regions with different favourable capital and human capital conditions. In the eastern region, the old-age support ratio shows no significant impact on

technological advancements through saving. However, in the western regions, an increasing old-age support ratio leads to a decline in saving, negatively affecting indicators of technological advancements such as TFP, patent applications, and R&D expenditure. On the other hand, in the central and north-eastern regions, a decrease in the child dependency ratio has a positive influence on the growth of R&D expenditure, depending on both higher levels of saving and public expenditure. Education emerges as a significant driver of patent applications in both the eastern and western regions during the low-fertility transition.

Additionally, this study finds that various other factors play distinct roles in motivating technological advancements across regions through different ways. The openness of a region, which refers to the degree of integration with global markets as a recipient of Foreign Direct Investment (FDI), is identified as a key driver for the growth of R&D expenditure in the central region, similar to Liu and Wang (2003). This suggests that technological developments in the central region significantly depend on the inflow of foreign capital and additional resources, such that relevant policies such as promoting engagements with global markets, attraction of foreign investments, and leveraging external resources to foster its technological developments.

While urbanization process, which represents the proportion of the population living in urban areas, significantly contributes to the increasing number of patent applications in the eastern, central, and western regions, in line with many existing studies (i.e., Dai, Li, and Lu, 2017; Zhang, Wan, Luo, and Wang, 2019). Higher levels of urbanization rate are associated with increased access to infrastructure, education, and innovation centres, which foster the development and application of new technologies. This is evident in the growing number of patent applications across the eastern, central, and western regions, where urbanization has created favourable conditions for innovation and knowledge exchange. Such that a negative correlation between urbanization and the growth in TFP is found in these regions. In the meantime, economic conditions, including factors such as GDP per capita, income levels, and investment rates, can also impact technological advancements. Higher level of economic development and investment rates generally create a more conducive environment for the innovation and technological progress.

The overall results are consistent with previous studies in China. For instance, Qi (2015) conducted a study in China and revealed similar disparities across regions. The author noted that increases in the old-age dependency ratio in the eastern region will lead to a relatively small contribution to the growth in TFP, compared to the western and central regions.

The regional disparities can be attributed to several factors. Firstly, different initial conditions imply varying levels of development potential. The eastern region has already established favourable capital and educational conditions earlier than other regions, resulting in less pronounced effects of demographic changes on technological progress. In contrast, the central and western regions have experienced more significant changes in their demographic structure due to migration, leading to a higher capital-labour ratio and more emphasis on investment and human capital, which in turn have created greater potential for technological advancements.

Secondly, skills demand across regions generates diverse preferences in inputs requirements. In more developed eastern regions, a larger proportion of the labour force is engaged in knowledge-intensive works, which is less affected by the capital decline and technological ceilings. The ageing workforce can still utilize their accumulated human capital in terms of technological skills and continue contributing to technological progresses and overall productivity. On the other hand, in less developed western regions, where a larger proportion of the labour force is engaged in labour-intensive works, such that productivity is closely tied to capital conditions. This leads to a stronger tendency towards saving in western regions.

Thirdly, prominent internal migration is another driving force in explaining these disparities. Urbanization rate also reflects the migration process of the country, where a higher urbanization rate in the eastern region has led to significant outflow of migrants from central and western areas, leading to a negative correlation with the growth in TFP.

On the flipside, the industrial structure of the economy also depicts the phenomenon of migration. Different regions in China have distinct industrial profiles. The development of a service-oriented economy in the eastern regions, driven in part by the migration inflows from the western region at low labour costs, has contributed to its technological

advancements indicated by the growth in TFP. However, the left-behind population in western regions must cope with a less balanced labour market structure and a less developed services market, leading to a negative association between the level of services' sector and technological advancements in those areas to a significant extent.

In short, these findings confirm the hypotheses and emphasize the presence of regional disparities across China, highlighting the complex and context-specific nature of the relationship between demographic factors and technological advancements through different mechanisms in different regions.

3) Heterogeneous Technological Implications Across Sectors in China

The last Research Question 2.3 attempts to investigate the heterogeneity across sectors, against the hypothesis 2.3 that "*Significant heterogeneity are found across sectors, and demographic implications on technological advancements are more significant in sectors with higher human capital endowments.*"

Considering the shift of focus from the population demographic dynamics to the labour forces dynamics, this analysis explores the technological implications in China using a new set of census data from 1990, 2000, and 2010 combined with Total Factor Productivity (TFP) growth rate across 19 sub-industries over different time intervals. The study also considers both the short and long-time horizons to capture varying timeframes for technological advancements. Both visual representations and numerical measures of the correlation are reported in Chapter 5.

The results are confirmative to the hypothesis that demographic structural changes in the workforce are correlated with technological advancements in China, with varying relationships across different sectors. Sectors with a higher proportion of younger workers show a positive correlation, indicating that sectors with a higher proportion of younger workers experience faster technological progress. Whilst sectors with a higher proportion of older workers exhibit a negative correlation. The interaction between the child dependency ratio and the education level of the workforce also shows a negative relationship, suggesting that sectors with higher education levels and lower child

dependency burdens have positive effects on technological advancements. However, the relationship between technological advancements and the burden of an aging population is less clear.

These findings align with previous discussions on the role of low fertility rates in promoting technological advancements through the indirect channel of human capital (i.e., Wei and Hao, 2011; Li and Zhao, 2022), and are partially confirmed by previous studies in China. For instance, Li (2016) found that the age of the labor force has a significant impact on the growth of TFP, with young and middle-aged (40-49 years old) workers contributing the most to its increase compared to other age groups. On the other hand, the varying results about ageing workforce also highlight a complex relationship between population aging, human capital, and technological advancements in line with mixed results observed in the literature (i.e., Lindh and Malmberg, 1999; Bloom, Canning, and Fink, 2010; Acemoglu and Restrepo, 2017).

In addition, the analysis also indicates that the correlation between demographic structural changes, human capital, and technological advancements in China become more pronounced over time. As time progresses, the influence of factors such as the composition of the workforce and the level of education on technological advancements becomes more significant. This highlights the importance of considering the long-term effects of demographic changes and human capital development on technological advancements, as their implications may not be immediately apparent such that it requires patience and a broader perspective.

6.2. LIMITATION OF THE STUDY

This study provides a comprehensive analysis of the relationship between demographic structural changes and technological advancements in and beyond China based on available data. However, there are limitations and areas should be borne in mind for further improvements.

6.2.1 Definitional and Measurement Issues

This study aims to comprehensively investigate the relationship between demographic structural changes and technological advancements by considering various variables such as robots, total factor productivity (TFP), patent applications, and research and development (R&D). However, it is important to note that there is no universally agreed-upon definition of "technological advancements" in existing studies, but the limitation of data availability also adds complexities to the analysis.

In a broader context, technological advancements are global megatrends undergoing, with increasing presences of various digital technologies. The advancement of technology, driven by factors such as increased computational power, the widespread use of connected devices for data collection, and the rapid progress of self-learning algorithms, has experienced an exponential growth. Among emerging technologies, machine learning, artificial intelligence (AI), and robotics have become widespread globally.

However, it is important to understand that new technologies are not monolithic entities, as their dynamics vary based on the underlying source of efficiency gains. A study by Hallward-Driemeier, Nayyar, and Fengler (2020) categorized digital technologies into three distinct types: transactional, informational, and operational. Transactional technologies focus on enhancing market transactions by reducing information asymmetries, such as through digital e-commerce platforms and blockchain. Informational technologies leverage the abundance of data and computing power to enable tasks like business management software, cloud computing, big data analytics, and machine learning. Operational technologies integrate data and physical automation to optimize production processes and reduce costs, including smart robots, 3D printing, and the Internet of Things (IoT).

Therefore, the non-monolithic nature of various technologies introduced two limitations in this study.

Firstly, the study focused on industrial robots, neglecting the broader range of technologies and their heterogeneous effects. This analysis employs the industrial robot's data from IFR, which is defined as programmed machines to replace manual operations on assembly lines, contribute to higher productivity and efficiency in manufacturing. However,

it is noteworthy that service robots[67], characterized by their ability to interact with humans, also becomes increasingly prevalent, in reshaping the society in various areas, including home care, logistics, healthcare, education, and specialized operations. The continuous expansion of service robot applications, accelerated by the COVID-19 pandemic, presents great demands in areas such as intelligent reception, delivery, retail, surgery and healthcare assistance, and cooking and companionship. Estimations show that the service robot's market in China is projected to surpass the industrial robot market in size by 2023.[68]

Apart from China, similar trends have been observed in numerous economies. For example, Japan has pioneered the use of "Carerobots" to address the shortage of human caregivers for the elderly (The Economist, 2017). This adoption of robotic nurses and caregivers has had a profound impact on elderly care in rapidly aging countries like Japan, South Korea, Singapore, Germany, and various European nations (The Economist, 2016; 2017; 2019). Robotics not only assist with physical tasks such as lifting and monitoring, but also play active roles in communication, companionship, and other aspects of aged care services.

As the service robot industry continues to evolve, it is also poised significant economic and social consequences (Prettner and Bloom, 2020). In the long run, if robot nurses become capable substitutes for human caregivers, older adults could receive their aged care in their own homes without burdening close family members with intimate care responsibilities. Similarly, advancements in childcare could transform the way children are taken care of. Another example is the application of translation programs and voice recognition technology through automation and artificial intelligence (AI). The significant process made in this regard suggests that international communication may become less reliant on learning foreign languages and translators, which could lead to enhanced global connectivity and collaboration. Therefore, by solely examining the effects of industrial robots, the study may have overlooked the multifaceted implications of other technological advancements on industries and their structural transformations.

[67] The International Organization for Standardization defines a "service robot" as a "robot in personal use or professional use that performs useful tasks for humans or equipment". (ISO 8373)
[68] "2022 Special Research Report on the Development of China's Robot Industry" by iMedia Consulting

Secondly, different technological developments are disrupting value chains and industries, fundamentally transforming the nature of work, generating complex linkages with the society (i.e., Mondolo, 2022). It is equally important to acknowledge that the disruption brought by technological advancements will "spill-over" and be complicated. For instance, Acemoglu et al. (2017) demonstrated that industrial robots enhance labour productivity in manufacturing, and they stimulated the development of the service industry within the same production chain through the "scale-productivity" effect. Wang et al., (2020) confirmed that the use of industrial robots is an important driving force for the structural upgrading of the service industry. In addition, Lu et al (2021) found that industrial robots lead to the displacement effect on manufacturing labour, causing displaced workers to transition into the service industry, thereby promoting the development of services' trade.

In summary, this study acknowledges the limitations of focusing solely on industrial robots and highlights the potential ambiguities and variations in interpreting the results due to spill-over effects and heterogenous changes in other areas. These limitations call for future research to address definitional challenges and explore a broader range of technologies to achieve a more comprehensive understanding of the intricate relationship between demographic structural changes and technological advancements and industrial changes, to enhance the generalizability and comparability of findings in the field.

6.2.2 Limitations in the Analysis

There are several limitations in this analysis that should be addressed for future improvements. Firstly, the current general equilibrium model used assumes a closed economy and does not consider the influence of international connectivity through migration and capital flows. However, countries such as Japan and European nations that experiencing demographic transition often rely on foreign workers to address labor shortages (e.g., Parsons, 2018; Seol, 2015). Additionally, in an open market, national savings tend to flow outward in search of higher returns. Considering these factors would provide a more dynamic and comprehensive understanding of the subject.

Secondly, the analysis does not examine the differentiated impact of automation incentives between urban and rural areas in the context of China, although the study acknowledges the significance of migration in shaping the demographic structure. As the country experienced rapid urbanization and economic development, large numbers of people migrated from rural to urban areas in search of better opportunities and living conditions. However, the study falls short in thoroughly exploring the spillover effects and endogenous issues related to labor mobility. For instance, factors such as the hukou policy have a significant impact on labor mobility, as individuals with rural hukou face administrative barriers when attempting to move and work in urban areas. The study acknowledges the presence of this policy but does not delve deeply into how it affects migration patterns and labor allocation. In addition to the hukou policy, family dynamics, housing availability, and access to quality education resources also impose incentives and constraints on labor mobility in China. Unfortunately, due to data limitations, the study relies solely on provincial-level economic development data, which might not provide enough granularity to capture the distinctions between populations with different hukou statuses and the disparities between urban and rural areas within specific regions. Understanding the disparities between urban and rural areas is vital for formulating effective policies to reduce regional inequalities. By prioritizing future research on investigating the impact on both urban and rural areas of China, a more comprehensive perspective can be gained on the root causes of regional disparities in the country. This knowledge can inform targeted interventions aimed at reducing regional disparities.

In conclusion, a thorough investigation into the factors affecting labor mobility and regional disparities is crucial for a comprehensive understanding of the demographic transition and technological advancements in China. By addressing these limitations of the current study and prioritizing research on these critical aspects, research can provide valuable insights that inform policy decisions and contribute to the country's sustainable and equitable development.

6.3. CONCLUSIONS AND IMPLICATIONS

The impact of demographic changes on economics is widely studied. Departing from the existing literature, this study takes a different perspective by examining the relationship between demographics and technological advancements - a crucial factor in economic development and societal progress.

This dissertation provides an overview of demographic structural changes and technological advancements at the global and the national level, followed by a thorough literature review on the relationship between these two factors. It then proposes and investigates two mediating pathways, focusing on saving and human capital, to understand how demographic structural changes influence technological advancements. The study expands on the theoretical framework and conducts comprehensive empirical analyses to test hypotheses. Based on the theoretical and empirical findings, the main conclusions of this dissertation are as follows:

In summary, this study reveals significant impacts of demographic structural changes on technological advancements in China's post-demographic transition phase, while changes in the child-dependency ratio and the old-age support ratio have distinct effects. The relationship between demographics and technological advancements is influenced by dual indirect mechanisms and contingent on various factors.

The decline in the child dependency ratio has a positive impact on technological advancements through two mechanisms. Firstly, it leads to higher savings rates as households have fewer dependents to support. This surplus of saving can be directed towards investments in research and development, technological infrastructure, and innovation, driving the adoption of automation technologies. Secondly, it leads to higher level of human capital accumulation. As fertility rates decline, there is a greater emphasis on improving the quality of human capital, including education and health. With the expectation of a shrinking workforce, there is a shift towards investing in education and skills' development. Highly educated and skilled individuals can drive technological advancements through innovation, research, and the adoption of new technologies like robotics.

However, the implications of the raising old-age support ratio on technological advancements are multifaceted. On the one hand, the saving mechanism suggests that as the old-age support ratio increases, the need for healthcare, pension, and social services for the elderly may reduce the public saving and lead to private precautious saving. This can potentially hinder technological progress. On the other hand, the human capital mechanism highlights that the rising old-age support ratio and the extension of working lives can motive technological advancements through the increased demand of new technologies for improving efficiency in healthcare and aged-care services. In the meantime, the increasing healthy life expectancy alongside longer life expectancy will lead to intergenerational knowledge transfer and the utilization of diverse skill sets from more experienced older workers, driving technological advancements. Recognizing the importance of a skilled workforce will also incentivize investments in human capital development and upskilling, leading to enhanced adaptability of new technologies and productivity growth.

In addition, this study also acknowledges that the demographic structural changes on technological advancements is complex and context dependent. This study reveals significant differences across countries, regions in China, and sectors. China exhibits a faster pace of technological growth compared to other global and high-income countries, which can be attributed to specific factors such as rapid demographic transitions, economic growth, human capital development, high saving rates, government policies, and institutional arrangements. Additionally, regional and sectoral disparities in technological advancements within China are subject to factors such as capital and human capital conditions, skills-demand, and migration patterns.

While demographic shifts are often viewed as challenges for the global economy, this study highlights potential positive effects on technological advancements. It is important to maintain an optimistic perspective when considering the "headwinds" caused by demographic changes. The findings emphasize the importance of saving and human capital accumulation as essential factors in mitigating challenges and navigating opportunities posed by demographic shifts, both for China and the world. Additionally, it is important to focus on the changing structure rather than the overall size of the population.

To well prepare for exceptional demographic changes, the Chinese Central Committee and the State Council has issued *"Opinions of Strengthening the Work on Aging in the New Era"*[69] in November 2021 (Appendix I). On top of that, this study suggests the government to consider three more comprehensive and long-term demographic policy measures and institutional reforms to guarantee the technological benefits of demographic structural can be realized.

1) Pension System Reform

The raise in the old-age support ratio puts significant pressure on public expenditure, including healthcare, pensions, and aged-care services. To release the public financing pressure, the government should consider a systematic approach for the reform of pension system, including (1) upgrading pension fund management strategy and promoting their active participation in capital market; (2) leveraging differentiated tax deduction incentives to expand the second and third pillars; and (3) introducing labor market policies to delay the pension accessible age and encourage labor market participation rate.

Specifically, China's existing pension system is ill-suited to meet the increasing pension demands, which is characterized by significant imbalance among three pillars. The 1st pillar (a public PAYG pension) covers more than 80 percent of the total labor force population, while the 2nd pillar (voluntary enterprise annuity and occupational annuity for urban workers) only covers less than 10 percent of the total labor force. The 3rd pension pillar (individual-based commercial pension) is not piloted and rolled out until 2022, with a much smaller pensioner size and coverage rate. Therefore, the government could consider introducing differentiated tax incentives for the contribution to the second and third pillars to reshape the uneven pension system.

Moreover, the underdeveloped pension scheme and the insufficient capital market participation of pension assets in China implies low rate of return and prominent issues of adequacy and sustainability in the longer term. In order to achieve a higher and diversified

[69] The original title in Chinese is "中共中央 国务院关于加强新时代老龄工作的意见." See link: https://www.gov.cn/xinwen/2021-11/24/content_5653181.htm

investment returns, the government should consider relaxing the regulatory restrictions imposed on pension funds in China and promoting a more diverse investment portfolio such as funds, bonds, and bank wealth management products like the United States and Japan.

Thirdly, the retirement age is currently relatively low in China compared to other developed countries. Given people are living longer and healthier, flexible retirement age could be an option, which allows individuals to choose to work beyond the traditional retirement age. It can be achieved through incentives such as pension bonuses or adjusting pension eligibility criteria based on the number of years worked rather than a specific age. There are also labour market policy options could be considered, including encouraging longer workforce participation, such as providing tax refunds or subsidies incentives for employers to employers to retain older workers and female workers.

2) Human Capital and Early Childhood Investment

The reduction in the child dependency burden implies positive effects on saving and human capital accumulations, and the government should leverage these benefits and prioritize the continuous development of human capital. This can be achieved through the efficient allocation of public resources, with a particular focus on investing in early childhood education and rural areas. Similar to investments in physical capital, investments in human capital yield diminishing returns over time. Hence, it is essential for the government to prioritize sectors and regions that offer higher social returns on education, with early childhood education being a key area according to education economics. Additionally, addressing disparities in educational resources across regions, urban and rural areas, and different educational levels is vital to ensure equitable access to education for all individuals. Considering the inclusion of early childhood education as part of compulsory education can be a feasible strategy. The changing demographic structure implies a significant reduction in the burden of compulsory education in the future and allows for increased educational resources. Therefore, leveraging these resources to improve the quality of education, particularly in the early childhood, is both possible and necessary to ensure China's sustainable and high-quality development.

3) Hukou Policy Reform

Another labor market policy option to address challenges posed by an aging society is the reform of the hukou system. Currently, a significant portion of China's labor force remains in the rural agricultural sector. By relaxing the hukou system and allowing rural migrant workers to obtain urban household registration, they can become full-fledged citizens with equal access to social services and benefits in urban areas. By implementing hukou reform and fostering the development of the urban labor market, migrant workers can be successfully transitioned from agriculture to non-agricultural industries, leading to a significant increase in the available labor supply. This reform offers various opportunities, including ensuring a stable labor supply for urban non-agricultural sectors, stimulating consumption in urban areas, and providing avenues for human capital investment such as education and on-the-job training programs for migrant workers. However, careful consideration must be given to regional disparities to ensure the equitable distribution of benefits and sustainable development across different areas.

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APPENDIX

Appendix I: Opinions of the Central Committee of the CPC and the State Council on Strengthening the Work on Aging in the New Era

1. General requirements and Working Principles	(1) Strengthen the Party's overall leadership of the work on aging, and adhere to People-centred, integrate the development of the cause of aging into the overall plan to promote the "five in one" overall layout and coordinate the promotion of the "four comprehensive" strategic layout, implement the national strategy to actively respond to the aging of the population, and integrate the positive outlook on aging and the concept of healthy aging into the economy and society (2) Working principles: Adhere to the leadership of the party committee and the participation of all parties; Insist on systematic planning and comprehensive implementation of policies; Insist on integrating resources and coordinated development; Insist on highlighting key points and consolidating the grassroots.
2. Improve the elderly care service system	(3) Innovate the service model for the elderly in the home community. (4) Further standardize the development of pension institutions. (5) Establish a list system for basic elderly care services. (6) Improve the multi-level old-age security system.
3. Improve the health support system for the elderly	(7) Improve the health service and management level of the elderly. (8) Strengthen long-term care services and guarantees for disabled elderly people. (9) Deepen the integration of medical care and nursing care.
4. Promote the social participation of the elderly	(10) Expand the supply of education resources for the elderly. (11) Improve the quality of cultural and sports services for the elderly. (12) Encourage the elderly to continue to play a role.
5. Focus on building an elderly-friendly society	(13) Strengthen the protection of the rights and interests of the elderly. (14) Create a liveable environment for the elderly. (15) Strengthen social respect for the elderly.
6. Actively cultivate the silver-haired economy	(16) Strengthen planning and guidance. (17) Develop industries suitable for the elderly.
7. Strengthen work protection for the elderly	(18) Strengthen the construction of talent team. (19) Strengthen the supply of facilities for the elderly. (20) Improve relevant support policies. (21) Strengthen scientific research and international cooperation.
8. Strengthen organization and implementation	(22) Strengthen the party's leadership over the work on aging. (23) Implement work responsibilities. (24) Extensively mobilize social participation.

Source: State Council of China (2021)

Appendix II: Additional Results

Table 5.1.1B: Mediating Effects Through Saving (cont'd)

Panel B: Independent Variable=Old-age Support Ratio				*Panel C: Independent Variable=Children Dependency Ratio*			
VARIABLES	**Step 1 Y=robot's density**	**Step 2 Y=*s***	**Step 3 Y=robot's density**	**VARIABLES**	**Step 1 Y=robot's density**	**Step 2 Y=*s***	**Step 3 Y=robot's density**
s			2.248***	s			1.511***
			(0.336)				(0.322)
sup	1.201	-2.752***	7.389***	dep	-7.910***	-1.431***	-5.748***
	(2.382)	(0.393)	(2.401)		(1.574)	(0.281)	(1.587)
pop_growth	-0.385***	-0.0492**	-0.274**	pop_growth	-0.0625	0.0890***	-0.197
	(0.128)	(0.0211)	(0.120)		(0.127)	(0.0227)	(0.126)
lnlfpc	-0.0462	0.631***	-1.465*	lnlfpc	-0.314	0.711***	-1.389*
	(0.815)	(0.134)	(0.787)		(0.776)	(0.138)	(0.783)
lngdpc	2.299***	0.277***	1.676***	lngdpc	1.643***	-0.0387	1.702***
	(0.214)	(0.0353)	(0.220)		(0.201)	(0.0359)	(0.195)
Constant	-18.95***	-1.739***	-15.04***	Constant	-8.267**	1.173	-10.04**
	(3.746)	(0.618)	(3.534)		(4.146)	(0.739)	(4.017)
Observations	287	287	287	Observations	287	287	287
R-squared	0.548	0.262	0.610	R-squared	0.585	0.207	0.615
Country FE	YES	YES	YES	Country FE	YES	YES	YES
Year FE	YES	YES	YES	Year FE	YES	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, saving* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates respectively. All independent variables are log transformed except *sup* and *dep*, and data represent the changes in lagged periods *t-1*.

Sobel-Goodman Mediation Tests	**z**	**P>z**		**z**	**P>z**
Sobel	-4.839***	0.00	Sobel	-3.452***	0.001
Aroian	-4.814***	0.00	Aroian	-3.417***	0.001
Goodman	-4.865***	0.00	Goodman	-3.488***	0.00
Indirect, Direct, and Total Effects	**z**	**P>z**		**z**	**P>z**
a_coefficient	-7.01***	0.00	a_coefficient	-5.099***	0.00
b_coefficient	6.689***	0.00	b_coefficient	4.69***	0.00
Indirect_effect_aXb	-4.839***	0.00	Indirect_effect_aXb	-3.452**	0.001
Direct_effect_c'	3.077**	0.002	Direct_effect_c'	-3.622***	0.00
Total_effect_c	0.504	0.614	Total_effect_c	-5.026***	0.00
Proportion of total effect that is mediated:	**-5.152**		**Proportion of total effect that is mediated:**	**0.273**	

Table 5.1.1D: Validation and Robustness Check (cont'd)

Panel B: Three-Year Samples

	1993-2017				1994-2018				1995-2019			
VARIABLES	**POLS**	**RE**	**FE**	**FE**	**POLS**	**RE**	**FE**	**FE**	**POLS**	**RE**	**FE**	**FE**
pop_growth	-0.223***	-0.220***	-0.223***	-0.245***	-0.223***	-0.220***	-0.223***	-0.245***	-0.0616	-0.0658	-0.0616	-0.0541
	(0.0838)	(0.0841)	(0.0838)	(0.0908)	(0.0838)	(0.0841)	(0.0838)	(0.0908)	(0.0458)	(0.0466)	(0.0458)	(0.0462)
lnlfpc	-0.729	-0.814	-0.729	-0.995	-0.729	-0.814	-0.729	-0.995	-0.981*	-0.950*	-0.981*	-1.013*
	(0.982)	(0.872)	(0.982)	(1.040)	(0.982)	(0.872)	(0.982)	(1.040)	(0.566)	(0.557)	(0.566)	(0.572)
lngdpc	2.167***	1.652***	2.167***	2.120***	2.167***	1.652***	2.167***	2.120***	3.231***	2.264***	3.231***	3.362***
	(0.604)	(0.324)	(0.604)	(0.641)	(0.604)	(0.324)	(0.604)	(0.641)	(0.387)	(0.273)	(0.387)	(0.399)
sup	-38.81***	-25.18**	-38.81***	-40.67***	-38.81***	-25.18**	-38.81***	-40.67***	-35.90***	-28.01***	-35.90***	-34.58***
	(12.41)	(10.92)	(12.41)	(12.90)	(12.41)	(10.92)	(12.41)	(12.90)	(8.048)	(7.709)	(8.048)	(8.251)
dep	-50.38***	-31.17***	-50.38***	-51.51***	-50.38***	-31.17***	-50.38***	-51.51***	-41.58***	-30.88***	-41.58***	-37.78***
	(12.14)	(10.33)	(12.14)	(12.75)	(12.14)	(10.33)	(12.14)	(12.75)	(8.070)	(7.427)	(8.070)	(8.345)
s	-5.366***	-2.340	-5.366***	-5.444**	-5.366***	-2.340	-5.366***	-5.444**	-5.931***	-3.712***	-5.931***	-5.595***
	(2.046)	(1.722)	(2.046)	(2.138)	(2.046)	(1.722)	(2.046)	(2.138)	(1.314)	(1.208)	(1.314)	(1.332)
sav_int	12.59***	7.273**	12.59***	13.05***	12.59***	7.273**	12.59***	13.05***	11.66***	8.043***	11.66***	10.64***
	(3.738)	(3.150)	(3.738)	(3.907)	(3.738)	(3.150)	(3.738)	(3.907)	(2.449)	(2.257)	(2.449)	(2.525)
lntrade				-0.259				-0.259				0.522*
				(0.434)				(0.434)				(0.275)
lnservice				1.176				1.176				0.0559
				(1.385)				(1.385)				(0.883)
Constant	5.577	0.756	5.681	3.783	5.577	0.756	5.681	3.783	-4.211	-0.676	-3.946	-8.511
	(9.034)	(7.330)	(9.119)	(10.98)	(9.034)	(7.330)	(9.119)	(10.98)	(5.667)	(5.161)	(5.683)	(6.817)
Observations	287	287	286	277	287	287	286	277	295	295	292	288
R-squared	0.939		0.939	0.939	0.939		0.939	0.939	0.967		0.965	0.966
Country FE	YES	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5.1.2D: Interaction Approach (cont'd)

3-year sample

	Panel A: Through Human Capital Index								
	1993-2017			1994-2018			1995-2019		
VARIABLES	M1	M2	M3	M1	M2	M3	M1	M2	M3
pop_growth	-0.259***	-0.240***	-0.151*	-0.172***	-0.156***	-0.0951	-0.0774	-0.0867*	-0.0484
	(0.0847)	(0.0808)	(0.0824)	(0.0635)	(0.0598)	(0.0604)	(0.0478)	(0.0441)	(0.0444)
lnlfpc	-0.680	-0.387	-1.200	-1.736**	-1.096	-1.768**	-0.960	-0.829	-1.230**
	(1.007)	(0.960)	(0.962)	(0.786)	(0.747)	(0.749)	(0.591)	(0.546)	(0.544)
lngdpc	1.754***	2.627***	2.439***	3.009***	3.438***	3.215***	2.859***	3.288***	3.054***
	(0.601)	(0.599)	(0.585)	(0.443)	(0.423)	(0.416)	(0.394)	(0.369)	(0.366)
sup	1.024	-30.65***	35.79*	2.743	-24.57***	25.46*	0.586	-23.36***	17.05
	(3.764)	(7.363)	(19.61)	(2.898)	(5.615)	(14.64)	(2.486)	(4.369)	(12.04)
dep	-11.70***	-40.92***	-33.47***	-5.202**	-30.49***	-26.39***	-4.992***	-27.63***	-25.26***
	(2.629)	(6.441)	(6.599)	(2.068)	(4.944)	(4.938)	(1.835)	(3.901)	(3.862)
s	1.314***	0.873**	0.912**	0.467	0.146	0.224	0.146	-0.0275	0.0133
	(0.455)	(0.442)	(0.431)	(0.337)	(0.322)	(0.314)	(0.301)	(0.279)	(0.272)
h	-0.932	-5.686***	-3.320**	-0.834*	-4.388***	-2.880***	-0.595*	-3.752***	-2.615***
	(0.629)	(1.136)	(1.283)	(0.448)	(0.765)	(0.850)	(0.351)	(0.587)	(0.655)
hc_age_int			-9.008			-5.442			-3.351
			(6.065)			(4.410)			(3.623)
hc_chld_int			10.79***			9.675***			9.015***
			(2.275)			(1.677)			(1.326)
hc_int		11.47***			9.584***			8.744***	
		(2.328)			(1.723)			(1.358)	
Constant	-8.427	-4.974	-9.174	-16.72***	-13.40**	-15.07***	-17.61***	-14.06***	-15.04***
	(8.014)	(7.663)	(7.551)	(5.665)	(5.356)	(5.231)	(4.975)	(4.625)	(4.520)
Observations	286	286	286	286	286	286	292	292	292
R-squared	0.936	0.942	0.946	0.953	0.958	0.961	0.962	0.968	0.970
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

	Panel B: Through Life Expectancy at Birth								
	1993-2017			1994-2018			1995-2019		
VARIABLES	M1	M2	M3	M1	M2	M3	M1	M2	M3
pop_growth	-0.0699	-0.0860*	-0.0831*	-0.141**	-0.148**	-0.127**	-0.257***	-0.256***	-0.167*
	(0.0481)	(0.0461)	(0.0478)	(0.0644)	(0.0606)	(0.0629)	(0.0854)	(0.0814)	(0.0873)
lnlfpc	-1.059*	-0.723	-0.737	-2.053***	-1.052	-1.185	-0.833	-0.265	-0.561
	(0.593)	(0.572)	(0.576)	(0.770)	(0.747)	(0.754)	(1.006)	(0.966)	(0.960)
lngdpc	2.802***	3.338***	3.304***	2.758***	3.282***	3.098***	1.659***	2.757***	2.151***
	(0.401)	(0.399)	(0.425)	(0.459)	(0.442)	(0.467)	(0.615)	(0.628)	(0.662)
sup	0.467	-48.74***	-40.49	1.292	-68.56***	-19.67	0.695	-82.44***	54.26
	(2.541)	(10.63)	(36.24)	(3.035)	(13.08)	(41.88)	(3.910)	(17.50)	(54.94)
dep	-3.904**	-54.59***	-53.95***	-3.553*	-74.14***	-69.57***	-10.25***	-94.16***	-78.86***
	(1.749)	(10.79)	(11.14)	(1.949)	(13.03)	(13.54)	(2.461)	(17.41)	(18.15)
s	0.171	0.0192	0.0259	0.475	0.230	0.263	1.357***	1.064**	1.104**
	(0.302)	(0.291)	(0.293)	(0.337)	(0.320)	(0.321)	(0.456)	(0.439)	(0.433)
h	0.0241	-0.319***	-0.311***	0.114*	-0.332***	-0.269**	0.0305	-0.544***	-0.372**
	(0.0477)	(0.0855)	(0.0920)	(0.0646)	(0.102)	(0.114)	(0.0759)	(0.139)	(0.152)
hc_age_int			0.575			0.340			-0.543
			(0.447)			(0.518)			(0.682)
hc_chld_int			0.671***			0.905***			1.000***
			(0.144)			(0.174)			(0.237)
hc_int		0.676***			0.940***			1.139***	
		(0.142)			(0.172)			(0.234)	
Constant	-20.67***	-1.511	-1.889	-24.36***	0.242	-3.234	-12.49	17.19	8.750
	(5.662)	(6.750)	(6.948)	(6.637)	(7.697)	(8.193)	(9.048)	(10.57)	(10.92)
Observations	292	292	292	286	286	286	286	286	286
R-squared	0.962	0.965	0.965	0.952	0.958	0.958	0.936	0.942	0.944
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

	Panel C: Through Education								
	1993-2017			1994-2018			1995-2019		
VARIABLES	M1	M2	M3	M1	M2	M3	M1	M2	M3
pop_growth	-0.246***	-0.243***	-0.216**	-0.160**	-0.157***	-0.122*	-0.0681	-0.0844*	-0.0976**
	(0.0853)	(0.0815)	(0.0837)	(0.0641)	(0.0600)	(0.0623)	(0.0480)	(0.0462)	(0.0472)
lnlfpc	-0.822	-0.701	-0.674	-2.035***	-1.905***	-1.848**	-1.034*	-1.117*	-1.115*
	(1.002)	(0.957)	(0.956)	(0.775)	(0.726)	(0.722)	(0.591)	(0.568)	(0.567)
lngdpc	1.751***	3.184***	3.150***	2.975***	3.862***	3.853***	2.835***	3.428***	3.430***
	(0.601)	(0.647)	(0.647)	(0.447)	(0.446)	(0.443)	(0.395)	(0.402)	(0.401)
sup	2.395	-9.500**	-3.456	3.012	-7.576**	-0.577	1.353	-5.969**	-9.471**
	(3.881)	(4.463)	(6.291)	(3.007)	(3.364)	(4.884)	(2.562)	(2.952)	(3.947)
dep	-10.22***	-22.70***	-21.19***	-3.860**	-16.62***	-15.14***	-3.999**	-13.02***	-13.31***
	(2.451)	(3.507)	(3.674)	(1.955)	(2.878)	(2.956)	(1.740)	(2.612)	(2.617)
s	1.428***	0.834*	0.868*	0.505	-0.0109	0.0563	0.181	-0.101	-0.118
	(0.457)	(0.453)	(0.453)	(0.339)	(0.330)	(0.329)	(0.302)	(0.297)	(0.296)
h	-0.0118	-0.225***	-0.204***	-0.00144	-0.196***	-0.176***	-0.00638	-0.137***	-0.143***
	(0.00855)	(0.0454)	(0.0479)	(0.00747)	(0.0347)	(0.0360)	(0.00576)	(0.0296)	(0.0298)
hc_age_int			0.301**			0.240**			0.326***
			(0.130)			(0.101)			(0.0756)
hc_chld_int			0.441***			0.419***			0.240***
			(0.0900)			(0.0690)			(0.0604)
hc_int		0.429***			0.388***			0.262***	
		(0.0897)			(0.0675)			(0.0582)	
Constant	-11.21	-18.33**	-19.77**	-18.17***	-20.09***	-22.24***	-19.16***	-19.78***	-19.04***
	(7.877)	(7.667)	(7.726)	(5.660)	(5.307)	(5.385)	(4.900)	(4.711)	(4.736)
Observations	286	286	286	286	286	286	292	292	292
R-squared	0.936	0.942	0.943	0.952	0.958	0.959	0.962	0.965	0.965
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

	Panel D: Through Female's Education Attainment								
	1993-2017			1994-2018			1995-2019		
VARIABLES	M1	M2	M3	M1	M2	M3	M1	M2	M3
pop_growth	-0.251***	-0.258***	-0.196**	-0.158**	-0.174***	-0.102	-0.0701	-0.0881*	-0.0775
	(0.0846)	(0.0822)	(0.0845)	(0.0637)	(0.0612)	(0.0638)	(0.0478)	(0.0469)	(0.0479)
lnlfpc	-0.757	-0.527	-0.564	-2.039***	-1.698**	-1.686**	-1.022*	-1.049*	-1.066*
	(0.999)	(0.973)	(0.960)	(0.774)	(0.746)	(0.730)	(0.591)	(0.576)	(0.576)
lngdpc	1.793***	2.571***	2.261***	2.995***	3.407***	3.122***	2.826***	3.164***	3.059***
	(0.600)	(0.618)	(0.622)	(0.446)	(0.438)	(0.437)	(0.394)	(0.396)	(0.407)
sup	2.937	-3.100	7.230	3.529	-2.249	8.069*	1.603	-1.979	0.734
	(3.874)	(4.093)	(5.623)	(3.025)	(3.167)	(4.407)	(2.585)	(2.713)	(3.674)
dep	-9.873***	-17.41***	-14.52***	-3.730*	-12.02***	-9.411***	-3.903**	-9.474***	-9.168***
	(2.450)	(3.111)	(3.259)	(1.959)	(2.617)	(2.680)	(1.739)	(2.302)	(2.318)
s	1.350***	0.946**	1.034**	0.488	0.110	0.255	0.153	-0.0304	-0.000696
	(0.452)	(0.453)	(0.448)	(0.339)	(0.335)	(0.331)	(0.302)	(0.299)	(0.300)
h	-0.320*	-2.310***	-1.864***	-0.117	-1.996***	-1.594***	-0.144	-1.324***	-1.264***
	(0.169)	(0.553)	(0.572)	(0.145)	(0.436)	(0.444)	(0.110)	(0.347)	(0.351)
hc_age_int			0.739			0.433			1.723*
			(1.726)			(1.371)			(1.024)
hc_chld_int			5.097***			5.182***			2.888***
			(1.157)			(0.930)			(0.778)
hc_int		4.233***			3.968***			2.533***	
		(1.124)			(0.872)			(0.707)	
Constant	-11.57	-16.03**	-15.80**	-18.22***	-19.25***	-19.68***	-19.00***	-19.59***	-19.14***
	(7.852)	(7.724)	(7.624)	(5.650)	(5.422)	(5.309)	(4.897)	(4.781)	(4.796)
Observations	286	286	286	286	286	286	292	292	292
R-squared	0.937	0.940	0.942	0.952	0.956	0.958	0.962	0.964	0.964
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5.1.2E: Validation and Robustness Check (cont'd)

1994-2019 Sample

	Panel A: HCI				Panel B: Life Expectancy at Birth			
VARIABLES	**POLS**	**RE**	**FE**	**FE**	**POLS**	**RE**	**FE**	**FE**
pop_growth	-0.176**	-0.204**	-0.176**	-0.168*	-0.219**	-0.201**	-0.219**	-0.224**
	(0.0817)	(0.0801)	(0.0817)	(0.0867)	(0.0878)	(0.0870)	(0.0878)	(0.0912)
lnlfpc	-0.827	-0.962	-0.827	-0.791	-0.878	-0.957	-0.878	-1.040
	(1.274)	(1.058)	(1.274)	(1.337)	(1.279)	(1.041)	(1.279)	(1.340)
lngdpc	2.602***	1.811***	2.602***	2.522***	2.608***	1.967***	2.608***	2.576***
	(0.665)	(0.380)	(0.665)	(0.703)	(0.751)	(0.368)	(0.751)	(0.799)
sup	14.10	-12.99	14.10	10.73	-33.85	-26.88	-33.85	-30.49
	(21.27)	(15.86)	(21.27)	(22.30)	(62.27)	(45.10)	(62.27)	(63.70)
dep	-27.27***	-24.14***	-27.27***	-30.09***	-65.95***	-49.65***	-65.95***	-69.80***
	(7.455)	(6.630)	(7.455)	(7.822)	(19.88)	(17.23)	(19.88)	(20.74)
s	0.429	0.759*	0.429	0.645	0.659	0.998**	0.659	0.895
	(0.481)	(0.433)	(0.481)	(0.550)	(0.487)	(0.427)	(0.487)	(0.563)
h	-3.533**	-3.124**	-3.533**	-3.927***	-0.332*	-0.347**	-0.332*	-0.371**
	(1.380)	(1.288)	(1.380)	(1.421)	(0.168)	(0.143)	(0.168)	(0.176)
h_age_int	-2.665	4.182	-2.665	-2.382	0.512	0.367	0.512	0.447
	(6.543)	(4.761)	(6.543)	(6.886)	(0.774)	(0.553)	(0.774)	(0.794)
h_chld_int	8.474***	6.808***	8.474***	9.380***	0.813***	0.592***	0.813***	0.871***
	(2.555)	(2.224)	(2.555)	(2.655)	(0.259)	(0.225)	(0.259)	(0.271)
lntrade				0.439				0.323
				(0.427)				(0.449)
lnservice				2.173				2.023
				(1.474)				(1.527)
Constant	-10.36	-1.649	-9.274	-18.32*	5.595	13.00	5.569	-0.683
	(8.469)	(6.655)	(8.539)	(10.15)	(12.30)	(11.32)	(12.13)	(13.08)
Observations								
R-squared	166	166	164	160	166	166	164	160
Country FE	0.965		0.963	0.964	0.962		0.960	0.961
Year FE	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

	Panel C: Education				Panel D: Female's Education Attainment			
VARIABLES	**POLS**	**RE**	**FE**	**FE**	**POLS**	**RE**	**FE**	**FE**
pop_growth	-0.246***	-0.231***	-0.246***	-0.260***	-0.221***	-0.210**	-0.221***	-0.226**
	(0.0822)	(0.0809)	(0.0822)	(0.0860)	(0.0844)	(0.0831)	(0.0844)	(0.0876)
lnlfpc	-0.505	-0.915	-0.505	-0.619	-0.458	-0.821	-0.458	-0.454
	(1.277)	(1.043)	(1.277)	(1.335)	(1.296)	(1.054)	(1.296)	(1.360)
lngdpc	3.186***	1.877***	3.186***	3.104***	2.693***	1.863***	2.693***	2.601***
	(0.708)	(0.361)	(0.708)	(0.746)	(0.695)	(0.386)	(0.695)	(0.734)
sup	-13.67*	-13.10*	-13.67*	-17.21**	-0.201	-7.262	-0.201	-2.741
	(7.697)	(7.072)	(7.697)	(8.217)	(6.884)	(6.077)	(6.884)	(7.418)
dep	-20.02***	-14.88***	-20.02***	-21.32***	-14.65***	-12.47***	-14.65***	-16.25***
	(4.424)	(3.775)	(4.424)	(4.640)	(3.917)	(3.135)	(3.917)	(4.155)
s	0.224	0.713	0.224	0.542	0.393	0.744*	0.393	0.768
	(0.498)	(0.436)	(0.498)	(0.562)	(0.503)	(0.443)	(0.503)	(0.575)
h	-0.217***	-0.136***	-0.217***	-0.231***	-2.234***	-1.766***	-2.234***	-2.486***
	(0.0570)	(0.0487)	(0.0570)	(0.0584)	(0.688)	(0.602)	(0.688)	(0.716)
h_age_int	0.474***	0.293**	0.474***	0.512***	3.285	3.041*	3.285	3.729*
	(0.156)	(0.138)	(0.156)	(0.159)	(2.039)	(1.729)	(2.039)	(2.074)
h_chld_int	0.378***	0.249***	0.378***	0.415***	4.903***	3.516***	4.903***	5.669***
	(0.1000)	(0.0866)	(0.1000)	(0.106)	(1.327)	(1.113)	(1.327)	(1.424)
lntrade				0.222				0.328
				(0.433)				(0.424)
lnservice				2.509				2.541*
				(1.513)				(1.517)
Constant	-16.50*	-5.729	-16.97*	-26.96**	-17.03*	-7.880	-17.00*	-28.26***
	(8.773)	(5.771)	(8.900)	(10.88)	(8.651)	(5.975)	(8.800)	(10.73)
Observations								
R-squared	166	166	164	160	166	166	164	160
Country FE	0.964		0.962	0.963	0.963		0.961	0.963
Year FE	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: *pop_growth, lnlfpc, lngdpc, sup, dep, s, h, h_age_int, h_chld_int, lntrade, lnservice* stand for population growth rate, labor force participation rate, GDP per capita, old-age support ratio, children dependency ratio, and saving rates, proxies for human capital, interaction term between the human capital proxy and old-age support ratio, interaction term between the human capital proxy and child dependency ratio, share of trade, and share of services respectively. All independent variables are log transformed except *sup, dep, and h,* and data represent the changes in lagged periods *t-1*. Domestic saving as a percentage of GDP is used by default in this empirical analysis, while the other proxy does not skew the results.