Population Aging, Structural Change, and Economic Growth: The Case of China

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Thesis submitted to the Department of Economics in partial fulfilment of the requirements for the degree of

Doctor of Philosophy in Economics

University College London

London

September 11, 2025

Declaration

‘I, Yimeng Zhang, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.'

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Abstract

Population aging is a worldwide phenomenon. However, there is limited consensus regarding the effects of aging. China is an interesting case because of its enormous size, impressive economic development, and rapid population aging. In this thesis, we present five studies on population aging, structural change, and economic growth in China.

In the first two studies, we approach the topic from the supply side. We compile data for China's sectoral factor inputs, including sectoral capital services and age-specific sectoral effective labour. Using said data, we conduct sectoral growth accounting for China. Our results show that factor accumulation and productivity growth are both important drivers of China's aggregate economic growth. While growth in services was overwhelmingly due to factor accumulation, growth in agriculture was due to productivity growth. Compared to young workers, older workers had lower employment per capita, falling labour productivities, and greater tendencies to work in agriculture. Resultantly, aging may have impeded structural change and economic growth in China.

In the third and fourth studies, we focus on the demand side. We estimate time series of China's age-consumption profiles by type. We then estimate aggregate and age-specific sectoral demand functions. We find that compared to youth, elderlies prefer agricultural consumption and disprefer service consumption. Through counterfactual analyses, we find that relative price effect and income effect played important roles in driving China's structural change. The effects on elderlies' consumption were stronger than others due to elderlies' relatively low elasticities of demand.

Building on the previous studies, the fifth study calibrates and simulates a three-sectors and six-generations overlapping-generations model of China. Through counterfactual analyses, we find that aging impedes China's structural change towards services through preferences, capital deepening, and government spending. Although aging boosts per capita output by raising per capita savings, aging lowers aggregate output by diminishing effective labour input.

Impact Statement

In this thesis, we contribute to the knowledge about population aging, structural change, and economic growth by bringing forward evidence from China. Our findings can help policymakers worldwide adapt policies to population aging and facilitate economic development.

In Chapter 2, we discuss various issues in China's capital measurement. On that basis, we compile and analyse China's sectoral capital stock and capital services data. These pave the way for future studies that require China's sectoral capital data. We find that capital accumulation in China had run into diminishing returns as a driver of economic growth. Policymakers should pay particular attention to the secondary sector where returns were falling drastically.

There is a long-standing 'perspiration versus inspiration' debate about China's economic growth. Our results from Chapter 3 show that factor accumulation and productivity growth were both important drivers of China's economic growth. As factor accumulation runs out of steam, policymakers should consider boosting productivity growth in order to sustain China's rapid economic growth. Our findings indicate that structural change can be a main source of productivity growth in the future. Aging's adverse effects on structural change and growth are expected to intensify in the future. To alleviate such effects, policymakers can raise the retirement ages and provide transferable skills training to elderlies.

In Chapter 4, we reconcile China's sectoral supply side and demand side data using Input-Output Tables. Through demand estimation, we determine the ideal utility function that explains China's sectoral consumption patterns. Adding to the debate about the drivers of structural change, our evidences show that both relative price effect and income effect played major roles in driving China's structural change. In the future, however, income effect will be negligible.

In Chapter 5, we find China's age-consumption profiles to be consistently hump-shaped over time. This means population aging undermines China's transition towards a consumption-oriented economy. In response, policymakers can raise elderlies' propensity to consume by improving elderlies' access to markets and imposing inheritance taxes. Elderlies in China prefer agricultural consumption and disprefer service consumption compared to youth. This implies that population aging impedes China's structural change, especially towards services. As agricultural prices surge, elderlies' low consumption and low price elasticities of demand not only make them vulnerable but also exacerbate aging's impediment to structural change. To protect elderlies' welfare and facilitate structural change, policymakers can consider improving social security and controlling agricultural prices.

Building on our work from the previous chapters, we calibrate and simulate a three-sectors and six-generations overlapping-generations model of China in Chapter 6. Our counterfactual analyses show that aging raises savings per capita in China, thereby fostering per capita GDP growth. This partially explains the Great Savings Puzzle in China. Through preferences, capital deepening, and government spending, population aging impedes China's structural change towards services. As remedies, policymakers can stimulate elderlies' service consumption and raise per capita education spending. According to our results, the biggest challenge posed by population aging in China will be that of plummeting effective labour input which is predicted to hamper economic growth.

Acknowledgements

I would like to thank my primary supervisor, Franck Portier, for his unwavering support, enlightening advice, thoughtful guidance, and consistent positivity throughout my PhD journey. I would also like to thank my secondary supervisor, Ian Preston, for his constructive feedback, and for his tireless help and encouragement during the hardest times. Through their expertise, wisdom, and kindness, my supervisors guided me as a researcher and nurtured me as a person. This endeavour would not have been possible without them. I would like to thank them from the bottom of my heart.

I would like to express my gratitude to Wendy Carlin, Mariacristina De Nardi, and Wei Cui for mentoring or supervising me at various phases of my education at UCL, beginning at the undergraduate level. Their help, support, and teaching inspired me and my research profoundly.

I am grateful to UCL for providing a supportive, comfortable, and inspiring space for me to learn and grow, for teaching me invaluable knowledge and skills, and for providing the best resources and tools available for me to conduct research.

Finally, I would like to thank my parents for everything. My parents have taken care of me with the utmost love and attentiveness. For decades, they sacrificed themselves to support me, my education, and my research. I would not be here without their unconditional love and faith.

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List of Abbreviations

CE	Consumption Expenditure
CFPS	China Family Panel Studies
CHIP	China Household Income Project
CPI	Consumer Price Index
CST	Capital Stock
CSV	Capital Services
CVA	Consumption Value Added
FOC	First Order Condition
FPC	Finite Population Correction
FU	Final Use
GCF	Gross Capital Formation
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
ICST	Index of Capital Stock
ICSV	Index of Capital Services
IDGCF	Implicit Deflator of Gross Capital Formation
IFGNLS	Iterative Feasible Generalised Non-linear Least Squares
IOT	Input-Output Table
IVAD	Implicit Value-Added Deflator
LHS	Left Hand Side
MPS	Material Product System
MRPK	Marginal Revenue Product of Capital
MRPKS	Marginal Revenue Product of Capital Services
MRPL	Marginal Revenue Product of Labour
MSOLG Model	Multi-Sector Overlapping Generations Model
NBS	National Bureau of Statistics
Obs	Number of Observations
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PBC	People’s Bank of China

PIFA	Price Index for Investment in Fixed Assets
PIM	Perpetual Inventory Method
PPI	Producer Price Index
RHS	Right Hand Side
RMSE	Root Mean Squared Error
SNA	System of National Accounts
SOE	State Owned Enterprise
SWLS	Survey Weighted Least Squares
TFP	Total Factor Productivity
TFPG	Total Factor Productivity Growth
TIFA	Total Investment in Fixed Assets
UHS	Urban Household Survey
VA	Value Added
VICS	Volume Index of Capital Services
WTO	World Trade Organization

Chapter 1: Introduction

In the past few decades, China has experienced impressive economic growth and structural change. These changes propelled China to the forefront of economic and political discussions. At the same time, China's population has been aging rapidly. In recent years, China's population aging accelerated while economic growth slowed. Understanding population aging's effects on structural change and economic growth have profound implications for how China and aging economies worldwide adapt to them. In this thesis, we investigate these effects in the case of China. In the process, we study and contribute to knowledge about China's population aging, structural change, and economic growth.

Between 1981 and 2020, China's economy grew by an average of 9% per year in real terms (National Data, 2025) and lifted 900 million Chinese people out of extreme poverty (World Bank Open Data, 2025). Uncovering the drivers, mechanisms, and challenges behind China's growth would contribute to the knowledge about economic development and inspire growth policies in other economies. In 2020, China occupied 18% of the world's real GDP (World Bank Open Data, 2025). China's large size and rapid growth mean it has been a major driver of global economic growth. Given the interconnectedness in the global economy, events in the China can impact economies worldwide. Investigating China's economic growth would shed light on the sustainability of China's growth and allow policymakers in China and around the world to adapt their policies accordingly.

China's economic growth has been accompanied by rapid structural change. Between 1981 and 2020, the output shares of primary, secondary, and tertiary sectors changed respectively from 31%, 46%, and 23% to 8%, 38%, and 55% (National Data, 2025). Structural change has played important roles in China's economic growth. However, the extents, drivers, and contributions of structural change in China are yet to be fully quantified and understood. In this thesis, we study structural change in China and make a number of contributions in the process. We are particularly interested in the interactions between structural change, population aging, and economic growth.

One distinguishing feature of China's economy is its 1.4 billion population. Such population has meant a massive pool of labour and low labour costs which have enabled

China to become one of the world's largest economies. However, China's population has been aging rapidly. Population aging is generally defined as an increase in the share of elderlies in the population. According to the United Nations' World Population Prospects 2022 (United Nations, 2024), the share of elderlies aged 61 and above in China's population increased form 7% in 1990 to 17% in 2020 and will reach 37% in 2050. If such forecast turns out to be true, China will be older than the US and most Northern European countries in 2050. In recent years, population aging in China has accelerated while economic growth has slowed down. This coincidence spurred intense interest in aging's effect on the Chinese economy. Although population aging has been a global phenomenon, there is limited consensus in the literature regarding the direction and magnitude of aging's effects. While existing studies have focused on developed countries, limited attention has been paid to developing countries. In this thesis, we contribute by investigating the effects of aging on structural change and growth in China.

The rest of this thesis is divided into 6 chapters. In Chapters 2 and 3, we approach our topic from the supply side perspective. In Chapter 2, we compile and analyse measures of China's sectoral capital inputs and returns. In Chapter 3, we compile sectoral effective labour input data and conduct sectoral growth accounting for China. In the process, we investigate the effects of population aging through the effective labour channel. In Chapters 4 and 5, we shift our focus to the demand side. In Chapter 4, we investigate the demand-side drivers of structural change in China. In Chapter 5, we investigate aging's effects through the channels of consumption and consumption structure. In Chapter 6, we bring supply and demand sides together in a multisector overlapping generations model to investigate the effects of aging on structural change and economic growth in China. In addition to the aforementioned channels of aging effects, Chapter 6 studies the channels of savings and government spending. Throughout our investigations, we treat aging as exogenous, meaning that other variables do not influence aging. Although Chapters 2 to 5 can each be read as a self-contained essay, they all contribute to our work in Chapter 6. Chapter 7 concludes this thesis by summarising our main results and their implications. In the rest of this chapter, we briefly introduce the five essays.

Capital input is a fundamental variable in macroeconomic analyses. This is particularly true in our case for several reasons. First, capital input is an important channel through which aging affects the economy. Second, changes in the sectoral structure of capital input can be both drivers and results of structural change. Third, since China devoted on average an extraordinary 41% of its annual GDP to capital accumulation between 1978 and 2020 (National Data, 2025), capital accumulation has been regarded as the key driver of China's economic development. Unfortunately, there is neither official nor consensus capital input measurement for China, especially at the sectoral level. In Chapter 2, we contribute by compiling and analysing the levels and returns of two measures of sectoral capital input for China: sectoral capital stock and sectoral capital services. Capital stock measures the value of accumulated capital goods whereas capital services measure the value of services provided by the capital stock. The compiled capital data will be used throughout the thesis. Our results show that in China, structural change in capital was at a more advanced stage compared to those in labour and output. Capital accumulation, especially that in the secondary sector, ran into diminishing returns in the late 2000s. There were substantial and growing gaps in returns between sectors, suggesting that there could be frictions in China's factor markets. Compared to the capital stock measure, the capital services measure shows higher industrial capital share, slower structural change, and smaller cross-sector differences in returns.

In Chapter 3, we conduct growth accounting for China and study the supply-side forces behind China's structural change and growth. We contribute by exploring the implications of our compiled measures of sectoral effective factor inputs. We find that factor accumulation and Total Factor Productivity (TFP) growth both played important roles in driving China's growth. As capital accumulation runs into diminishing returns and labour input shrinks, China will increasingly have to rely on TFP growth. Structural change contributed to a large share of TFP growth and hence has the potential to be an important source of China's growth in the future. At the sectoral level, growth in agriculture was driven almost entirely by TFP growth while growth in services was driven almost entirely by factor accumulation. These raise doubts about the sustainability and benefits of China's ongoing structural change towards services. In particular, China's rapid structural change towards services could be a symptom of Baumol's cost disease (Baumol, 1967). Labour participation rate, employment rate, and productivities can vary across age, time, and sector. We use household survey data to construct a measure of effective sectoral labour input that accounts for such variations. We then use this measure to study the effects of aging. To our knowledge, we are the first to do these. Our results show that older workers had higher tendencies to work in agriculture, lower employment per capita, and falling labour productivities compared to young workers. Population aging thus impeded China's structural change and economic growth through the effective labour channel. Despite decades of marketisation reforms, substantial factor market frictions remain in China. We contribute by using our own data to compute and analyse China's factor price wedges. We compute the wedges as ratios of marginal revenue products between sectors. We find that the wedges were higher in industry than in services and were higher for labour than for capital. We find that the wedges can partially be explained by variations in factor input effectiveness across sectors.

Although consumption occupies the majority of China's GDP, existing literature on China's structural change has paid limited attention to it. In Chapter 4, we study China's structural change in terms of consumption. We start by acknowledging the distinction between sectoral expenditure data on the demand side and sectoral value-added data on the supply side. To reconcile data from the two sides, we compile and analyse sectoral consumption expenditure and sectoral consumption value added data for China using official Input-Output-Tables. Next, we contribute to the debate about drivers of structural change by bringing the Chinese case forward. Using the two sets of consumption data, we estimate China's sectoral demand functions. We analyse the functions and investigate the roles played by income effect and relative price effect in driving China's structural change. To our knowledge, we are the first to do these. Our estimation results show that a non-homothetic utility function is the most suitable for explaining China's sectoral consumption patterns. We find that in China, price elasticities of sectoral demands are low. This means sectoral consumption shares tend to move in the same directions as their corresponding sectoral relative prices. Our results also confirm the presence of subsistence agricultural consumption and endowment service consumption in China. While both relative price and income effects played vital roles in lowering industrial and raising service consumption shares, income effect was the key driver behind the drop in agricultural consumption share over time. Income effect will be small in the future, however, as the shares of subsistence and endowment consumption in total consumption had become tiny by 2018. The results of Chapter 4 reveal the important roles played by preferences in China's structural change. These results inspire us to investigate the links between aging, preferences, and consumption structure in Chapter 5.

As people age, their preferences change, causing them to demand different consumption bundles and react differently to changes in prices and incomes. Population aging can therefore affect structural change and economic growth through private consumption. Currently, there is no literature consensus regarding the direction and magnitude of such aging effects, especially in the case of China. In Chapter 5, we first contribute by estimating and analysing individual-level age profiles of consumption categories for China at numerous points between 1981 and 2020 using household survey data. To investigate aging's effects on structural change, we use the age-consumption profiles to breakdown China's sectoral consumption by age group. We propose that China's age-specific sectoral consumption patterns can be explained by a three-sectors overlapping generations model with age-specific preferences. We then estimate and analyse such preferences. Following similar steps to Chapter 4, we investigate the relative price and income effects behind the structural change of age-specific consumption. We analyse how these effects differ across age due to age-varying preferences. To our knowledge, we are the first to conduct these estimations and analyses. Our results show that age profiles of total consumption are consistently hump-shaped rather than smooth. This means population aging can reduce consumption in China. Older age groups have greater preference for agricultural and industrial consumption but less preference for service consumption compared to younger age groups. Aging can therefore impede structural change towards services in the long term. Relative price and income effects both played important roles in driving age-specific sectoral consumption shares. The effects intensify over age because older age groups have lower elasticities of demand than younger age groups.

In Chapters 3 and 5, we investigate population aging's effects on the supply side and demand side separately under the ceteris paribus assumption. In reality, as the population ages, there are interactions between supply side and demand side forces, and variables such as prices and incomes can change. In Chapter 6, we construct, calibrate, and simulate a three-sectors-and-six-generations overlapping-generations model of China with both supply and demand sides. In doing so, we use our work from previous chapters as building blocks. Through counterfactual analyses, we investigate the effects of aging on China's structural change and growth via the channels of preferences, savings, labour, and government expenditures. In the model, aging is driven by both falling fertility and rising longevity while structural change is driven by both supply side and demand side forces. To investigate the preferences channel, we incorporate age-specific preferences as in Chapter 5 into the model. To account for aging's effects through the effective labour channel, we adopt the effective labour input measure from Chapter 3. To our knowledge, we are the first to do these. We find that population aging impedes China's structural change towards services via preferences, savings, and government expenditure channels. Population aging boosts per capita output growth by raising per capita savings and productivity growths. At the aggregate level, aging lowers China's economic growth by reducing effective labour input. The adverse aging effect acting through the effective labour channel strongly dominates the positive effects from other channels. As such, the effective labour channel is the main channel of concern for policymakers.

Chapter 2: China's Sectoral Capital Measurement and Structural Transformation

2.1 Introduction

Capital consists of accumulated investment from the demand side and is used as a factor of production on the supply side. As such, capital is a key variable in macroeconomic analyses. However, there is no official capital input data for China. Past studies of China's economy have had to start with constructing their own capital input data, giving rise to a wide variety of results. To this day, there is no consensus on the measurement of China's capital input, especially at the sectoral level. In fact, little attention has been paid to sectoral capital in the literature of China's capital input and structural change. In this chapter, we compile and analyse sectoral capital input and capital return data for China. These data are not only fundamental to our thesis but are also interesting on their own. We contribute to the capital measurement literature for China mainly by compiling sectoral capital services data and comparing them with sectoral capital stocks data for China.

Between 1981 and 2020, China devoted over 40% of annual GDP to investment (National Data, 2025). This is very high compared to the international norm. In the same period, China underwent rapid economic growth. Unsurprisingly, capital accumulation has been considered a key driver of China's economic growth. A number of studies, including Chow (1993), Zhang and Shi (2003), and Zhu (2012), have attempted to quantify the role of capital in China through growth accounting analyses. The growth accounting literature confirms that capital has contributed significantly to China's growth. However, there is no consensus about the magnitude of capital's contribution, especially relative to that of Total Factor Productivity (TFP).

Along with rapid capital and output growths, China also experienced rapid structural change. Capital is a fundamental building block of dynamic general equilibrium models of structural change. Capital goods are produced overwhelmingly in the secondary sector. As a result, capital accumulation can facilitate structural change towards the secondary sector. An increase in capital-labour ratio, referred to as capital deepening, can reduce costs and hence prices of capital-intensive sectors. This allows said sectors to expand in real terms relative to other sectors (Acemoglu and Guerrieri, 2008).

Another major change experienced by China over the past decades is population aging. Capital is a key channel through which population aging affects the economy. Population aging affects savings, which is the source of capital accumulation. On the one hand, more elderlies mean more retirees who are de-savers (Modigliani and Brumberg, 1954). On the other hand, as people expect to live longer, they save more to finance for their extended retirement (Mason and Lee, 2006). Population aging can also reduce labour supply and hence facilitate capital deepening. As people get older, their preferences change. Aging can therefore affect capital accumulation by changing the demand for capital intensive goods. In this thesis, we seek to investigate these aging effects in the case of China.

Past studies of growth accounting, structural change, and population aging have produced wildly different results. This is partially due to their use of different capital data. The absence of official data and the sensitivity of empirical results to capital data have given rise to studies dedicated entirely to measuring capital in China. Huang (2002), Zhang et al (2004), and Dan (2008) are among the most notable works. The literature on China's capital input focuses on capital stocks and agrees that China's capital stock should be computed using the Perpetual Inventory Method (PIM). However, the literature disagrees over the determination of the four elements used in the PIM: investment, investment deflator, depreciation, and initial capital stock. What's more, according to the international literature, capital stock is not the most ideal measure of capital input.

The ultimate goal of our project is to explore the interactions between population aging, structural change, and economic growth in China. To this end, we will conduct growth accounting and simulate a Multi-Sector Overlapping Generations (MSOLG) Model of China. As mentioned earlier, capital is a crucial element in growth accounting and general equilibrium models but there is no consensual capital data for China. Constructing sectoral capital series for China is therefore an important and necessary task for us to undertake.

In this chapter, we start by discussing various issues in China's capital measurement. On that basis, we construct, analyse, and compare two measures of China's sectoral capital input: sectoral capital stock and sectoral capital services. Capital stock is relatively easy to compute and use for a variety of purposes. These are perhaps why capital stock is used by the existing literature on China's capital. Theoretically, however, capital input into production should be measured by the amount of capital services supplied by capital stock (Organisation for Economic Co-operation and Development, 2009). Even if capital stock increases, capital services could fall because, for example, each unit of capital is used for less hours. In addition, capital services per unit differs across different types of capital stocks. The capital stock measure is unable to capture changes in capital productivity resulting from changes in the composition of capital stock. Therefore, we also construct sectoral capital services for China in this chapter. In Chapter 3, we will use both capital stock and capital services data in growth accounting and compare the two sets of results. To the best of our knowledge, we are the first to construct and analyse sectoral capital services and use them in growth accounting for China. Based on our results in this chapter and the next, we will determine the capital measure that is the most appropriate for the other chapters.

Sectoral capital data are interesting and worth exploring in their own right. Using our capital data, we analyse China's structural transformation in terms of capital. The literature has so far paid little attention to sectoral capital patterns as it has focused on China's structural change in terms of labour and output. In the process of our capital construction, we compute sectoral capital returns. These returns provide insights into the sustainability of capital-driven economic growth in China and to the frictions in China's factor markets. We compute and analyse returns using both measures of sectoral capital input. Our comparison of the two sets of results reveals major causes of the frictions. As far as we know, we are the first to make such comparisons.

Chinese data have faced their fair shares of doubts and criticisms. Many of the concerns are reasonable given the facts that China is a unique and rapidly developing country. Recognising the concerns about Chinese data, we take extra care in selecting, scrutinising, and adjusting Chinese data in our project. This chapter dedicated to capital measurement demonstrates our attitude and efforts regarding Chinese data. In the methodology and data section, we review the literature on China's capital input and the available data sources and methods. On the basis of such review, we explain our choices of data and methodology for computing capital data for China.

Our results in this chapter show that China's capital underwent rapid structural change between 1981 and 2020. The structural change in China's capital input was mostly from industry to services. This was different to the structural changes in China's labour and output which were mostly from agriculture to the modern sectors. Capital accumulation, especially that in the secondary sector, ran into diminishing returns around 2008. There were substantial and growing gaps in capital returns between sectors, suggesting there could be frictions in China's factor markets. Compared to the capital stock measure, the capital services measure shows higher industrial capital share, slower structural change, and smaller cross-sector differences in returns. The gaps in returns across sectors can thus partially be explained by the fact that the modern sectors use more productive compositions of capital stocks than agriculture.

The rest of this chapter is organised as follows. Section 2.2 discusses our methodology and data choices for constructing capital stock and capital services. Section 2.3 presents and analyses the results. Section 2.4 concludes.

2.2 Methodology and Data

In this study, we first compute real capital stock by sector using the Perpetual Inventory Method (PIM). This is the conventional measure of sectoral capital input that can be readily used in economics models.

For the purpose of growth accounting, however, capital service is the theoretically ideal measure of capital input. This is mainly because capital service accounts for the productivity differences of different types of assets. To compute sectoral capital services, we first compute real capital stock by sector by type using the PIM. Then, we compute sectoral capital services as the user-cost-weighted average of different types of assets within each sector.

For the computation of capital services, we rely on the Organisation for Economic Co-operation and Development (OECD) Capital Measurement Manual (OECD, 2009) as our primary guide for consensus theory and methodology. Inevitably, we have to adapt the methodology to suit the Chinese case and the purposes at hand. Specifically, we have to account for China's data limitations and for the common practices in the literature for Chinese capital input. We have to ensure that our capital measure can be used in the contexts of growth accounting and models of China in later chapters.

In this thesis, we are interested in the division of China's economy into the primary, secondary, and tertiary sectors following the NBS's Regulations for Three-Sector Classification (NBS, 2018). The primary sector is composed of agriculture, forestry, animal husbandry, and fishing. The secondary sector is composed of industry and construction. The tertiary sector refers to services. For brevity, we often refer to the three sectors respectively as agriculture, industry, and services. Additionally, we sometimes refer to the secondary sector and the tertiary sector as the modern sectors and sometimes collectively as the modern sector.

2.2.1 Computation of sectoral capital stock

Under the assumption of geometric depreciation profile, there is a simple stock and flow relation between real capital stocks of adjacent periods:

$$K_{t+1} = (1 - \delta)K_t + I_t$$

where K_t denotes real capital stock, I_t denotes real investment, and δ denotes depreciation rate. This is the formula for the Perpetual Inventory Method (PIM) first introduced by Goldsmith (1951). The formula shows that if we know capital stock in the initial period, we can construct the time series of capital stock by accumulating investment and depreciation.

We use the PIM to compute sectoral real capital stock. From the formula, we can see that the computation uses four ingredients: real capital stock in the initial period, annual nominal investment, price index to deflate nominal investment, and depreciation rate. In the following subsections, we describe the data and computation for these ingredients.

2.2.1.1 Choice of the initial period

In studies of China's capital measurement and economy in general, 1952 and 1978 are the most common choices for the initial period. Although the People's Republic of China was formally established in 1949, 1952 was the first year for which basic macroeconomic data for China became available. Unfortunately, most of the sectoral level data relevant to our thesis are not available for the 1952-1977 period. The quality of data for this period is also highly questionable given the concurrent economic and political instabilities. This period also saw China transitioning from using the Material Product System (MPS) to the modern System of National Accounts (SNA). This transition inevitably led to errors and incompatibility between historical and modern data. All of these mean that a lot of assumptions have to be made to construct sectoral data between 1952 and 1977 (see, for example, Chow (1993)). The errors incurred by such assumptions are too great to justify using 1952 as the initial year.

After the turmoil of the Cultural Revolution, 1978 marked the beginning of a new era of political leadership and economic policy in China. The government implemented comprehensive and profound reforms to marketize and open up the Chinese economy. After 1978, sectoral level data become much more available. Although sectoral investment data are available from 1978, data for several other key variables for our thesis only became available years later. To ensure comparability and consistency across all chapters, we choose 1981 to be the initial year.

2.2.1.2 Annual investment data

2.2.1.2.1 Indicators of Investment

The National Bureau of Statistics (NBS) publishes three main indicators of investment for China: Gross Capital Formation (GCF), Gross Fixed Capital Formation (GFCF), and Total Investment in Fixed Assets (TIFA). All three indicators are frequently used in the Chinese capital input literature to construct capital input.

In this study, we use GCF as the measure for investment. GCF consists of GFCF and change in inventory. The reason for choosing GCF over GFCF is that GCF is more suited for the dynamic models and analyses in our thesis. Afterall, GCF is a component of expenditure approach GDP along with consumption, government spending, and net exports.

TIFA data are the basis on which the NBS constructed GFCF and GCF data. The main advantage of TIFA data is that it features rich breakdowns by sector and by type. When GCF data at lower-level breakdowns are not available, we use TIFA data to breakdown GCF data. While this is a common practice in the literature, some studies have tried to construct their own GCF and GFCF data based on TIFA data. According to Xu (2009), GFCF is linked to TIFA as follows:

$$GFCF = TIFA + investment\ under\ 500000\ Yuan +$$
$$+value\ increase\ of\ commercial\ properties - expediture\ on\ land +$$
$$+ - investment\ in\ second\ handed\ capital$$

The availability of data for variables on the right-hand side of the equation above is severely lacking. As a result, construction of GCF data using the equation likely introduces more errors than it tries to resolve. There has also been no evidence that such constructed data give rise to different results. Therefore, we do not construct GCF using TIFA and the equation above in this study.

2.2.1.2.2 Investment by sector data

Aggregate GCF data from 1981 to 2020 are available from NBS's China Statistical Yearbooks (NBS, 1981-2020). We use aggregate GCF data as control totals for sectoral breakdowns.

We obtain provincial sectoral GCF data between 1981 and 1995 from China's National Income, 1952-1995 (Hsueh and Li, 1999) and Data of GDP of China 1952-1995 (NBS, 1997). We obtain provincial sectoral GCF data between 1995 and 2002 from Data of GDP of China: 1996-2002 (NBS, 2004). These are all official NBS data sources.

For the provinces of Guangdong, Jiangxi, and Tibet, aggregate GCF data are available but sectoral GCF data are missing for the 1981-1990 period. For these provinces, we assume their sectoral GCF shares for 1981-1990 are constant at the 1991-1995 average levels. We then estimate their sectoral GCF data for the 1981-1990 period by using these shares to breakdown their aggregate GCF data.

Due to fears of overreporting in the pre-2000s, the NBS applied downward scaling to provincial data. Years later, the NBS verified the accuracy of original data submitted by provinces. The data sources mentioned earlier are published before the verification. Therefore, we have to undo the NBS's downward adjustment manually. Following common practice, we scale provincial GCF data so that the sum-provincial GCF values are consistent with the latest version of national aggregate data.

After 2002, sectoral GCF data cease to be available. Instead, the NBS started to publish sectoral TIFA data. For 2002-2020, we use sectoral TIFA shares to breakdown aggregate

GCF data. We obtained sectoral TIFA data for the 2002-2020 period from Statistical Yearbooks of the Chinese Investment in Fixed Assets (NBS, 1987-2018).

2.2.1.3 Price index to deflate investment

Using the index of GCF from China Compendium of Historical GDP data (NBS, 2022), we compute the Implicit Deflator of GCF (IDGCF). This is the ideal price index for deflating GCF. We are among the first to use this index as the data source was published only recently and is not well known.

Past studies typically used the Price Index for Investment in Fixed Assets (PIFA). A few studies computed IDGCF for 1978-2004 using GCF index from Data of GDP of China 1952-2004 (NBS, 2007) and then used PIFA for the post 2004 period.

Sectoral investment price index data are not available for China. It is therefore unknown whether investment prices vary much or not across sectors. Several studies such as Xu et al (2007) tried to infer sectoral investment price index using aggregate investment price index and sectoral value-added deflator. Some studies used sectoral producer price indices to deflate sectoral investment. Such estimations and approximations would inevitably lead to errors. More importantly, sector-specific investment prices are inconsistent with the models we use in later chapters. All in all, we choose to use one price index, the IDGCF, to deflate investment of all sectors.

2.2.1.4 Depreciation rate

For our sectoral capital stock measure, we use a single depreciation rate for all three sectors. This makes the measure more suitable for use in our models in later chapters. We also assume that the depreciation rate stays constant over time, as time-varying depreciation rate is not consistent with geometric depreciation. The determination of China's depreciate rate is controversial. Given the lack of official data and of empirical studies for economic depreciation rate, the literature presents three approaches. In this subsection, we survey the approaches and discuss the reasons behind our choices.

The first approach is to assume a depreciation rate without computations. Hu and Khan (1997), for example, assumed a depreciation rate of 3.6%. Perkins (1998), Wang and Fan

(2000), and Wang and Yao (2001) assumed the depreciation rate to be 5%. Young (2003) assumed a rate of 6%. Indeed, most of the assumed rates are around 5%. Gong and Xie (2004), on the other hand, assumed a relatively high rate of 10%. With such a wide range, the assumed depreciation rate can seem arbitrary and subjective.

Assumptions about depreciation rate are often drawn from international experiences and domestic accounting rules. Since China is a unique economy, depreciation rates from other countries may not be applicable to China. The official accounting depreciation rates in China are based on linear depreciation profiles and thus cannot represent geometric depreciation profiles. In addition, accounting depreciation is based on the original value of capital. This is different to economic depreciation which is based on the replacement value of capital.

The second approach is to use data on depreciation. Chow (1993), for example, computed depreciation as: $GDP - national\ income + subsidy - indirect\ taxes$. Xu et al (2007) and Xue and Wang (2007) used Depreciation of Fixed Assets from income approach GDP. Unfortunately, these are essentially depreciation values computed using linear depreciation profiles. China does not yet have the capacity to compile sufficient replacement price data. As a result, national account depreciation value is still computed based on the original value of capital.

The third approach is to compute geometric depreciation rate using data on service lives of capital goods. While service life of the average capital good is elusive, information about service lives by type of capital goods are available. There is more consensus about the service lives than about the depreciation rates. Compared to arbitrary assumptions and accounting depreciation, service lives are the most solid foundation on which to derive depreciation rates. Therefore, we follow the third approach in this study.

The NBS divides China's investment in fixed asset into three types: Construction and Installation, Equipment and Machinery, and Others. For brevity, we shall refer to them respectively as construction, machinery, and others. We obtain investment in fixed assets by type data from China Statistical Yearbooks (NBS, 1981-2020). We use this data to break down aggregate investment by type. Official definition shows that spending on the 'Others' category of capital goods is directly linked to spendings on construction and machinery capital. We therefore follow the common practice of dividing 'Others' capital into construction and machinery capital according to the relative sizes of the latter two.

In the literature, service lives for China's capital are typically sourced from the Ministry of Finance of China, the Chinese Industrial Association, and international experience. Maddison (1994) suggested a construction service life of 40 years and machinery service life of 16 years for China. The same values were later adopted by Ye (2010) and Sun and Ren (2014). Huang et al (2002) estimated the service lives to be 38 and 20 years but eventually also adopted values of 40 and 16 in their computation of capital. Wang and Wu (2003) obtained service lives of 38 and 12 which were adopted later by Bai et al (2006). Dan (2008) set service lives to be 38 and 16.

In summary, service life in the literature is typically taken to be 38 to 45 years for Construction and Installation and 12 to 20 years for Equipment and Machinery. Through experimentation, we find that changing the service lives within the common ranges of values have very small impacts on the computed depreciation rates. In our study, we choose the service life of Construction and Installation to be 40 and the service life of Equipment and Machinery to be 16. These are the most common values in the literature.

Given service lives, depreciation rates can be computed using two methods. The first method uses the equation of geometric age-efficiency or age-price profile:

$$d = (1 - \delta)^T$$

where δ is depreciation rate, T is service life, and d is the efficiency of a unit of capital at the end of its service life. Studies in the literature typically use the official rate of residual value of 3-5% for the value of d. This, together with data on service life, can be used to compute depreciation rate using the equation above.

The second method is that of declining balance as in Wykoff and Hulten (1979, 1981). In this method, depreciation boils down to a simple formula:

$$\delta = \frac{R}{T}$$

where T is the service life and R is the declining balance rate. The most commonly adopted value of R is two. When R is set to be two, the method is referred to as the double declining balance method. Due to the lack of empirical studies estimating the value of R for China, studies following this method typically set R to be two or values from other countries. Wang and Wu (2003) and Wu (2015), for examples, used the declining balance rates from the U.S. Bureau of Economic Analysis with some adjustments.

The declining balance method is widely used across the world and is recommended by the OECD manual. Therefore, we use the double declining balance method to compute depreciation rates for China. Given the service lives of 40 and 16 years, we obtain depreciation rates of 5.0% and 12.5% for construction and machinery assets, respectively. Using the computed type-specific depreciation rate and type-specific investment data (data sources will be described in Section 2.2.2), we compute type-specific capital stock using the PIM. Next, we compute annual aggregate depreciation rate as a weighted average of type specific depreciation rates. The weights are the shares of the two types of capital in aggregate capital stock. Finally, we compute the average annual aggregate depreciation rate between 1981 and 2020, obtaining a value of 7.16%. This is the long-term average depreciation rate that we use to compute sectoral capital stocks.

2.2.1.5 Initial Capital Stock

The closest official data for initial capital stock in China are those of original value of fixed assets and net value of fixed assets. These were used for initial capital stock in the seminal paper of Chow (1993). Unfortunately, NBS's original and net value of fixed assets are constructed using investments in original prices without deflation. Therefore, original and net value of fixed assets are not ideal measures of capital stock.

Some studies made assumptions about the relationship between capital and other variables. They then estimated initial capital using data on these variables. Perkins (1998), Ye (2010), and Sun and Ren (2014) use output data and an assumed capital-output ratio to estimate initial capital stock. The assumed capital-output ratios range from 0.05 to 3.5, generating a wide range of results. The assumed ratios can seem arbitrary and subjective. Long and Herrera (2016) assumed China's national capital-output ratio was equal to that of Shanghai's. Then, using data on Shanghai's capital-output ratio, they estimated initial capital stock for China. Shanghai has been one of the richest cities in China and is hence unlikely to be representative of the nation. Furthermore, Shanghai's GDP was only 5% of China's GDP in 1952. Long and Herrera (2016)'s assumptions are thus questionable.

Another approach to estimate initial capital for China is the growth rate approach used by studies including Zhang et al (2004), Dan (2008), and Wu (2016). Following the growth rate approach, initial capital K_0 can be estimated using the equation:

$$K_0 = \frac{I_0}{g + \delta}$$

where g stands for growth rate of investment, capital, or GDP. As can be seen from the equation, the approach assumes that investment serves to counteract depreciation and maintain a certain rate of capital growth.

The growth rate approach is the most widely used approach in the literature. Although assumptions under the growth rate approach can only hold approximately, they are more convincing than the assumptions required for the other approaches. In addition, the growth rate approach is the only one that is consistent with standard dynamic models in economics. All in all, we choose the growth rate approach to estimate initial capital stock for China.

Table 2.1: Initial capital stock values from the literature

Past Studies	1981 Capital Stock in 1981 Prices (100 million Yuan)
Chow (1993)	13485
Zhang and Zhang (2003)	10757
Zhang et al (2004)	8750
Sun and Ren (2005)	7347
Holz (2006)	11699
Dan (2008)	8490
Wang et al (2009)	9151
Chen (2014)	10489
Sun and Ren (2014)	7532
Long and Herrera (2016)	11434
Average	9913
This study	9520

Previously, we have described our choices for investment and depreciation. To compute initial capital stock for each sector using the above equation, we set g to be the 5-year average sectoral output growth rate between 1979 and 1983. This prevents initial capital stock from being skewed by anomalous growth rate from a single year. We obtain the real sectoral value-added growth rates from China Statistical Yearbooks (NBS, 1981-2021).

Using the growth rate approach, we obtain an initial aggregate capital stock value of 952 billion Yuan for China in 1981. To check our capital stock value in 1981, we compare it in Table 2.1 with values from other studies in the literature. All capital stocks in Table 2.1 are 1981 values measured in 1981 prices. As the table demonstrates, there is a wide range of values in the literature. Our 1981 capital stock is close to the average in Table 2.1.

2.2.2 Computation of sectoral capital services

2.2.2.1 Capital stock and capital services

Theoretically, capital input into production should be measured by the amount of capital services provided by capital stock rather the capital stock. Even if capital stock increases, total capital services could fall because, for example, each unit of capital stock is used for less hours. Different types of capital goods provide different amounts of capital services per unit. Measuring capital input using capital services allows us to account for the productivity effects of varying composition of capital goods across sectors and across time.

Computing the volume of capital services per unit of capital is unrealistic. The common practice is to assume that the volume of capital services is proportional to the capital stock and the proportion is fixed over time. After normalisation, the total volume of capital services is indicated by the capital stock.

The value of capital services is conceptually equivalent to the rental price and marginal revenue product of capital. In reality, producers usually own capital goods so that no actual rents are paid and recorded. To estimate the value of capital services, rental prices have to be imputed based on the costs incurred to producers for using the capital. This gives rise to the alternative phrase for such imputed rents—user costs. For firms to be willing to use capital, the marginal revenue product of capital has to be enough to cover these costs.

The unit user cost f_t can be computed using the equation:

$$f_t = P_t(r_t + \delta - i_t + \delta i_t)$$

where P_t denotes the price of an asset, δ denotes the depreciation rate, i_t denotes capital gains (revaluation), and r_t denotes the net rate of return.

This equation shows that the user cost has three components, each expressed as a share of the asset's price. The net return r_t is the opportunity cost of using the asset. If the owner did not hold capital but instead made investments elsewhere, he would earn the net return r_t. r_t can also represent the interest rate the owner would have to pay if he borrowed money to use the asset.

In each period, the asset loses value through depreciation and devaluation. Such losses would not be incurred if the owner did not hold the asset. Therefore, depreciation and devaluation are costs to the owner for using the asset.

As mentioned earlier, the ideal measure of capital input should capture heterogenous capital marginal productivities across different types of capital goods. Such a measure can be constructed by aggregating capital services from different types of assets using weights that are computed using type-specific user costs.

Market prices of capital goods are used as weights to aggregate different types of capital goods in order to compute capital stock measures. However, such market prices cannot be used to aggregate different types of capital services. This is because the price of a capital good in period t does not measure the value of its capital services in t. Instead, the price can be interpreted as measuring the discounted sum of the value of capital services provided by the capital good over its lifetime.

In this study, we compute capital stock and user costs for different types of capital in the three sectors using respectively the PIM and the equation above. We then compute sectoral capital services (K_{it}^{s}) by aggregating across types of capital stocks (K_{ikt}'s) using base year user costs (f_{ik0}) as weights:

$$K_{it}^{s} = \sum_{k} K_{ikt} f_{ik0}$$

We also compute sectoral Volume Index of Capital Services (VICS) in the form of a Laspeyres index Q_{Lit}:

$$Q_{Lit} = \frac{\sum_k f_{ikt-1} K_{ikt}}{\sum_k f_{ikt-1} K_{ikt-1}}$$

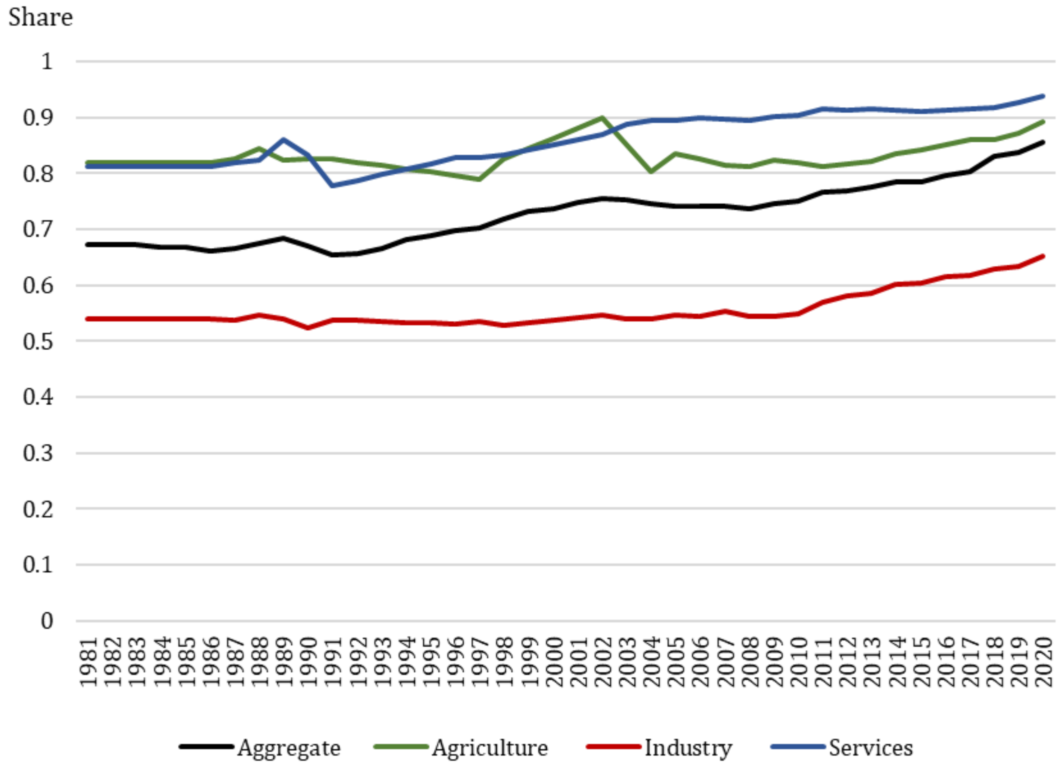
In the following subsections, we describe the methodology and data for the variables used to compute the index.

2.2.2.2 Investment by sector by type of asset

As mentioned previously, we divide capital goods in China into two types: Construction and Installation, and Machinery and Equipment. For brevity, we shall sometimes refer to the two types of capital as construction capital and machinery capital, respectively.

We use fixed assets investment by sector by type data to breakdown aggregate investment. We obtain fixed asset investment by sector by type data for the 2003-2017 period from NBS's National Data website (National Data, 2025). For the 2018-2020 period, growth rates of fixed asset investment by sector by type are available from China Statistical Yearbooks (NBS, 1981-2021). We use the growth rates for 2018-2020, along with the levels data for 2017, to compute fixed asset investment by sector by type for the 2018-2020 period. The aforementioned NBS data between 2003 and 2020 are collected from all units except rural households. On average, non-rural-household investment in fixed assets accounted for 92% of annual total investment in fixed assets in this period.

Figure 2.1: Share of construction and installation in nominal investment



For the periods of 1986-1991, 1996-1998, and 2002, we obtain fixed asset investment by sector by type data of State-Owned Enterprises (SOEs) from Statistical Yearbook of the Chinese Investment in Fixed Assets (NBS, 1987-2018). We interpolated type shares for the years with missing data. The state played a major role in the economy, especially in investment. In the 1986-2002 period, SOE fixed asset investment accounted for 65% of annual total fixed asset investment on average.

Figure 2.1 above plots type-specific shares in fixed asset investment in each of the three sectors. We can see that type-specific shares change little over time, especially in the early years. We therefore assume that the shares from 1981 to 1985 are constant at 1986 levels. The figure also shows that there is no break when the data source changes from SOE investment to non-rural-household investment.

2.2.2.3 Price indices by type of asset

To deflate nominal investment by type, we need price index of investment by type data. We obtain price index of fixed asset investment by type data from 1990 to 2019 from China Statistical Yearbooks (NBS, 1981-2021). For the pre-1990 period, the literature typically uses replacements. Huang (2002) used retail price indices of construction and machinery goods. Wang and Wu (2003) obtained Investment in Fixed Assets (IFA) price index by type for 1985-1990 from the NBS. Through comparison, we find Wang and Wu (2003)'s machinery price index to be the same as NBS's machinery PPI. Bai et al (2006) used construction industry's implicit value-added deflator and machinery industry's PPI. Sun and Ren (2014) used construction industry PPI and Wang and Wu (2003)'s index for equipment.

Consumer and retail price indices are not suitable for our purposes because they measure prices of goods purchased by consumers which are very different to goods used by producers. In this study, we use construction industry's implicit value-added deflator in place of construction IFA price index for the pre-1990 period and for 2020. We use machinery industry PPI from 1981 to 1989 and manufacturing PPI from 2020 to fill the missing data for machinery IFA price index. We choose these replacement indices over others because they are commonly used in the literature and because they track their IFA price index counterparts better in the 1990-2019 period. In the 1990-2019 period, construction industry implicit value-added deflator (previous year=1) and machinery industry PPI (previous year=1) deviate from their IFA price index counterparts by 0.68 and 0.58 percentage points on average, respectively.

2.2.2.4 Depreciation rate

Following the same reasoning as that for aggregate depreciation rate, we assume that type specific depreciation rates do not vary across sector. Therefore, we can use the same methodology and results from Section 2.2.1 for type-specific depreciation rates. Given service lives of 40 and 16 years, we use the double declining method to compute depreciation rates, obtaining 5.0% and 12.5% for construction and machinery assets, respectively.

2.2.2.5 Initial capital

Initial capital stock by sector by type is computed using the growth rate approach given the aforementioned investment by sector by type, depreciation rate by type, and average output growth rate by sector.

2.2.2.6: User cost

The unit user cost formula for an asset is:

$$f_t = P_t(r_t + \delta - i_t + \delta i_t)$$

where P_t denotes cumulative price index and δ denotes depreciation rate. The values for these are taken directly from the previous subsections. The revaluation rate i_t is computed using the price index P_t:

$$i_t = \frac{P_{t+1} - P_t}{P_t}$$

To estimate the net rate of return, there are two main approaches: the endogenous ex post approach and the exogenous ex ante approach. The exogenous approach involves assuming constant net rates of return for the two types of assets. This would be arbitrary and subjective, especially given the lack of relevant data and empirical analysis in China.

In addition, the gross return computed under the exogenous approach would not be consistent with income data from national accounts. We therefore adopt the more commonly used endogenous approach.

The endogenous approach to return is based on the assumption that the total user cost of capital services should be equal to total capital income in a competitive market:

$$U_t = G_t + T_{Kt} = \sum_{k=1}^{N} P_{kt}[r_t + \delta_k(1 + i_{kt}) - i_{kt}]K_{kt}$$

In the equation above, G_t denotes gross operating surplus, T_{Kt} denotes taxes on capital, U_t denotes total user costs of capital, $P_{kt}K_{kt}$ is the value of productive capital stock of type k, δ_k is the depreciation rate of type k capital, i_{kt} is the revaluation rate of type k, r_t is the real net rate of return.

The net return does not vary across asset types. Therefore, r_t is the only unknown in the equation above. This allows us to solve for r_t. In this study, we apply the equation to solve for r_t for each of the three sectors.

In China, GDP by income approach breaks GDP into compensation of employees, depreciation of fixed assets, net taxes on production, and (net) operating surplus. Capital income can be computed as gross operating surplus plus net taxes associated with capital. We assume that the share of net taxes on capital is equal to the share of capital income in the rest of national income. In other words, our capital income is computed by multiplying national income by the following capital income share:

$$Capital\ income\ share = \frac{Fixed\ asset\ depreciation + Net\ operating\ surplus}{Total\ income - Net\ taxes\ on\ production}$$

We obtain China's income approach GDP by sector data between 1978 and 1995 from Hsueh and Li (1999). Data for the 1995-2004 period are obtained from Data of GDP of China 1952-2004 (NBS, 2007). For the post-2004 period, we obtain data for 2005, 2007, 2010, 2012, 2015, 2017, and 2020 from the corresponding issues of Input-Output Tables (IOTs) of China (NBS, 1991-2022). These are all official NBS data sources. For the years with missing data, we linearly interpolate capital income shares.

2.3 Results

In this section, we present and compare our two sectoral capital input measures for China. The first measure, which we refer to as capital stock for brevity, is the most commonly reported and used measure. This is largely due to its ease of computation and use for a variety of purposes, including for growth accounting and for dynamic economic models. The second measure, capital services, is the ideal capital input measure for growth accounting but is not easily usable in the context of dynamic models.

2.3.1 Capital stock

Figure 2.2 shows the levels of China's real sectoral and aggregate capital stocks between 1981 and 2020. Aggregate capital stock is computed as the sum of sectoral capital stocks. As can be seen in the figure, capital stocks in all three sectors rose rapidly. This was achieved through consistently high annual capital growth rates which are shown in Figure 2.3. On average, China's aggregate capital stock grew at an annual rate of 10.6% between 1981 and 2020.

While structural transformation is usually discussed in terms of sectoral output and labour, less attention has been paid to the structural transformation of capital. In the case of China, the sectoral composition of capital stock underwent rapid changes. Figure 2.4 plots the evolution of sectoral capital stock shares in China. Agriculture already had the lowest share of 12% in 1981, after which it continued to fall, reaching 3% in 2020. Industrial capital stock share started off at 54%, which was much higher than the concurrent service share of 34%. However, industrial share fell while service share rose over time. In 1999, service share overtook industrial share to become the highest of the three. In 2020, industrial and service shares reached 38% and 59%, respectively. Overall, between 1981 and 2020, China's structural change in terms of capital mainly involved shifts from agriculture and industry to services. This is unlike the structural change of labour and output which were mostly from agricultural to industry and services. Capital stock was therefore at a more advanced stage of structural change compared to labour and output.

Figure 2.2: Real capital stocks

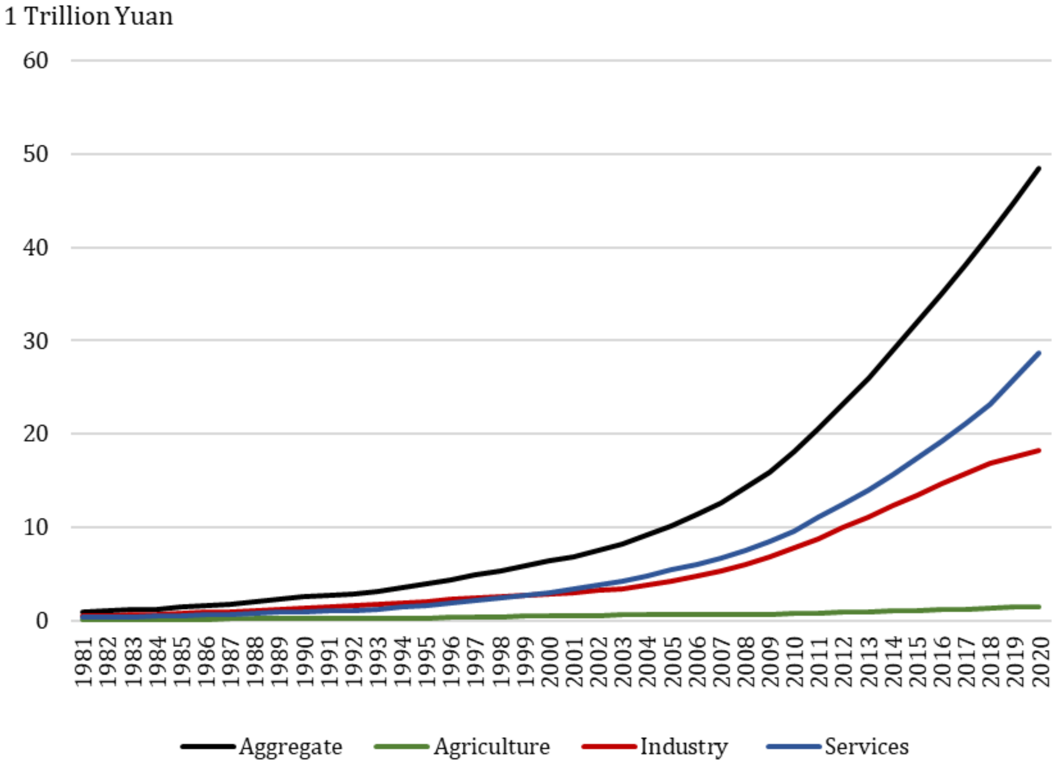


Figure 2.3: Real capital stock growth rate

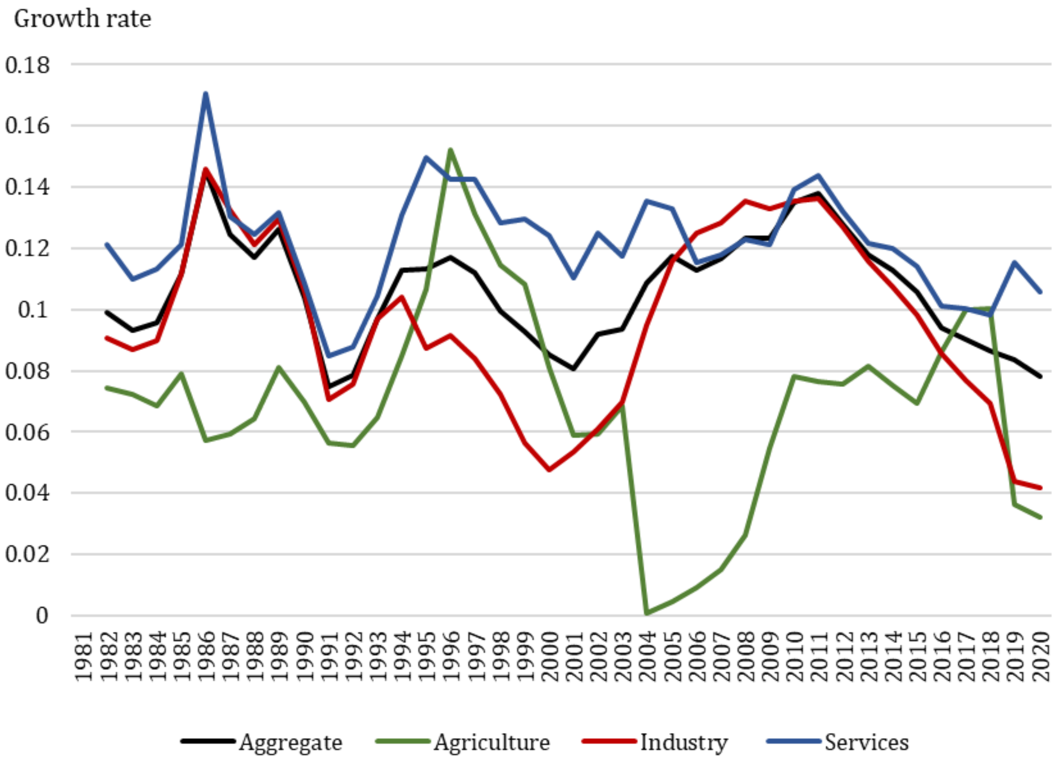


Figure 2.4: Sectoral capital stock shares

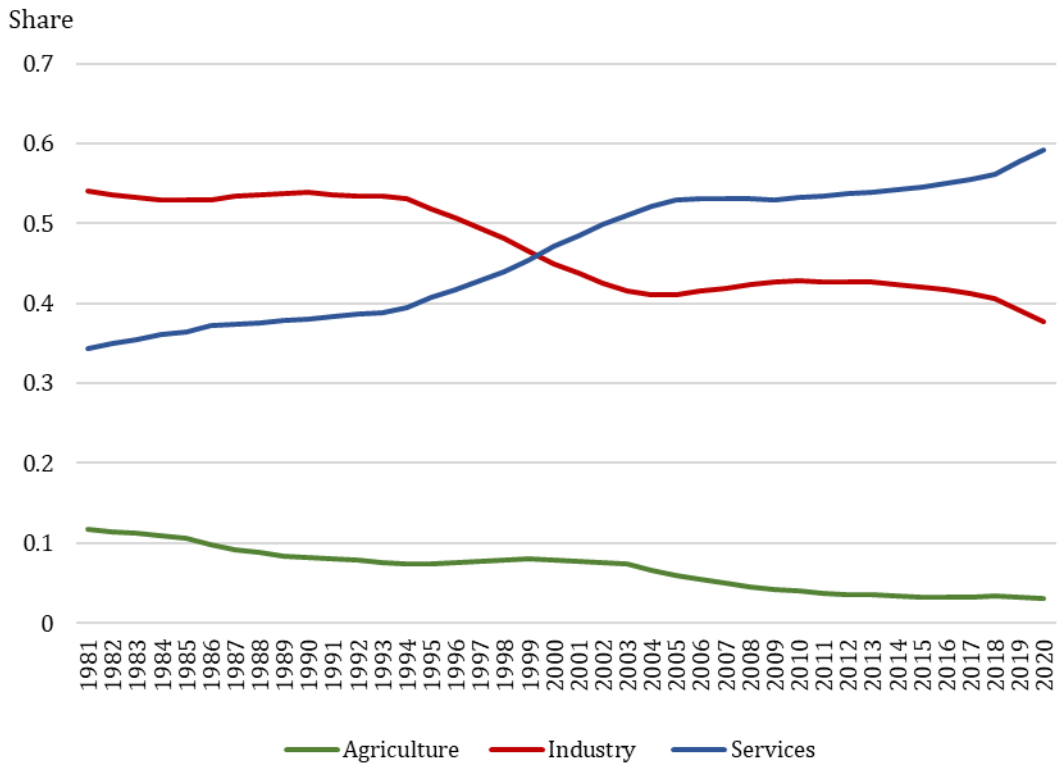


Figure 2.3 plots the growth rates which lie behind the observed aggregate and sectoral capital stock patterns. The surge in aggregate capital stock growth in the early 1980s reflects the effects of reforms and stimuli adopted by the new leadership from 1978. However, inflation started to rise sharply, peaking at 28% in 1989. Partially due to inflation, social stability deteriorated, eventually resulting in crisis. These events forced capital accumulation to be cut down around 1989. Throughout the 1980s, capital accumulation in agriculture was slow compared to those in the modern sectors.

Inflation and political instability were quickly brought under control by 1992 and investment was increased again. High inflation soon returned, reaching 20% in 1995. Policymakers were determined to break the cycle of growth and inflation. The People's Bank of China (PBC) was restructured into a true central bank responsible for monetary policy. The PBC restricted credit and imposed other harsh borrowing constraints on SOEs. These measures allowed China to transition to a low inflation regime in a few years. While fundamental institutional reforms were taking place in China, the Asian financial crisis hit. These factors together can explain the fall in capital growth in the late 1990s.

In 2001, China was acceded into the World Trade Organization (WTO). China's comparative advantage in manufacturing meant net export expanded rapidly. Investment was poured into manufacturing to cease the opportunities in world trade. The expansions in net exports and investment were facilitated by China's surging saving rate in the 2000s. As investment moved to manufacturing, agricultural capital growth was brought to a halt. The government soon adopted policies to support agriculture, including the abolition of agricultural taxes. As a result, agricultural capital growth started to pick up in 2005.

In 2008, the world was hit by the Global Financial Crisis. In response, China implemented massive stimulus packages which kept capital growth rate high until the early 2010s. These packages focused on infrastructure, industry, and real estate. As a result, capital growth in industry exceeded that in services.

After years of over-investment, manufacturing and real estate industries were left with excess productive capacity and unsold stocks in the 2010s. Resultantly, capital accumulation rate in industry fell relative to that in services. Policymakers tried to steer the economy away from investment driven growth and towards consumption driven growth. Simultaneously, many countries adopted protectionist policies which constrained China's net export expansion. These, along with many other factors, contributed to the declines in capital growth rates in the 2010s.

2.3.2 Capital services

Figure 2.5 shows that capital services in China rose rapidly over the sample period. Service sector capital services grew faster than industrial capital services, which grew faster than agricultural capital services. These patterns are similar to those in the case of capital stock. However, unlike in the case of capital stocks, service sector capital services never overtook industrial capital services over the sample period. In fact, capital service in the service sector was still 25% lower than that in industry in 2020.

To uncover the factors behind the patterns of capital service levels, we plot cumulative growth (1981=1) Indices of Capital Services (ICSV) and Indices of Capital Stocks (ICST) in Figure 2.6. Agricultural capital service growth and capital stock growth were almost the same. Service sector capital services grew relative to industrial capital services. However, such relative growth is slower than that for capital stocks. In 2020, the cumulative growth of service sector capital service was 14% lower than that of service sector capital stock.

In the same year, the cumulative growth of industrial capital service was 23% higher than that of industrial capital stock.

Figure 2.7 shows annual growth (previous year=1) Index of Capital Services (ICSV) and Index of Capital Stock (ICST) for the economy as a whole and for the three sectors. We can see that the annual growth rates of capital services and capital stocks are similar. The gaps between cumulative indices in Figure 2.6 are due to accumulations of small differences in annual growth rates over time rather than to large differences in growth rates at any particular point in time.

Although capital services grew faster in services than in industry, capital service level in services was still lower than that in industry in 2020. This is because the industrial sector, by choosing capital types more productively, started off with much larger capital services than the service sector. As can be seen in Figure 2.8, in 1981, industrial share in China's capital services was 67%, which was more than twice the services share of 29%. In contrast, industrial and service capital stock shares were 54% and 34%, respectively.

Figure 2.5: Real capital services

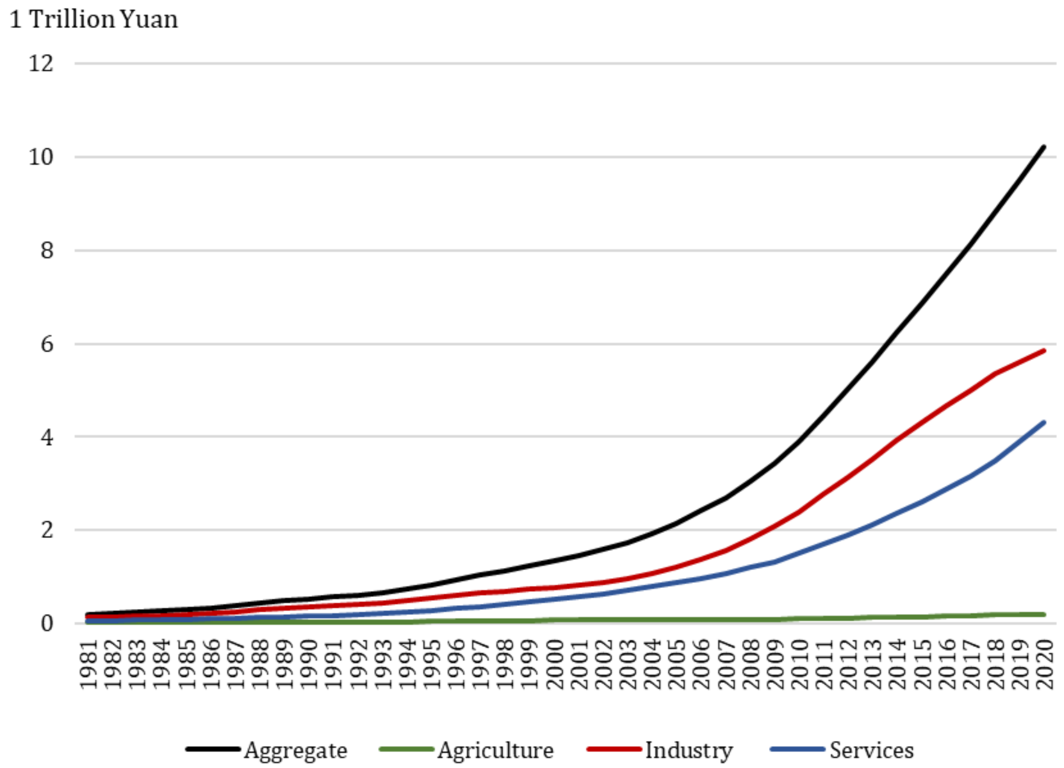


Figure 2.6: Indices (1981=1) of Capital Stock (ICST) and Indices of Capital Services (ICSV)

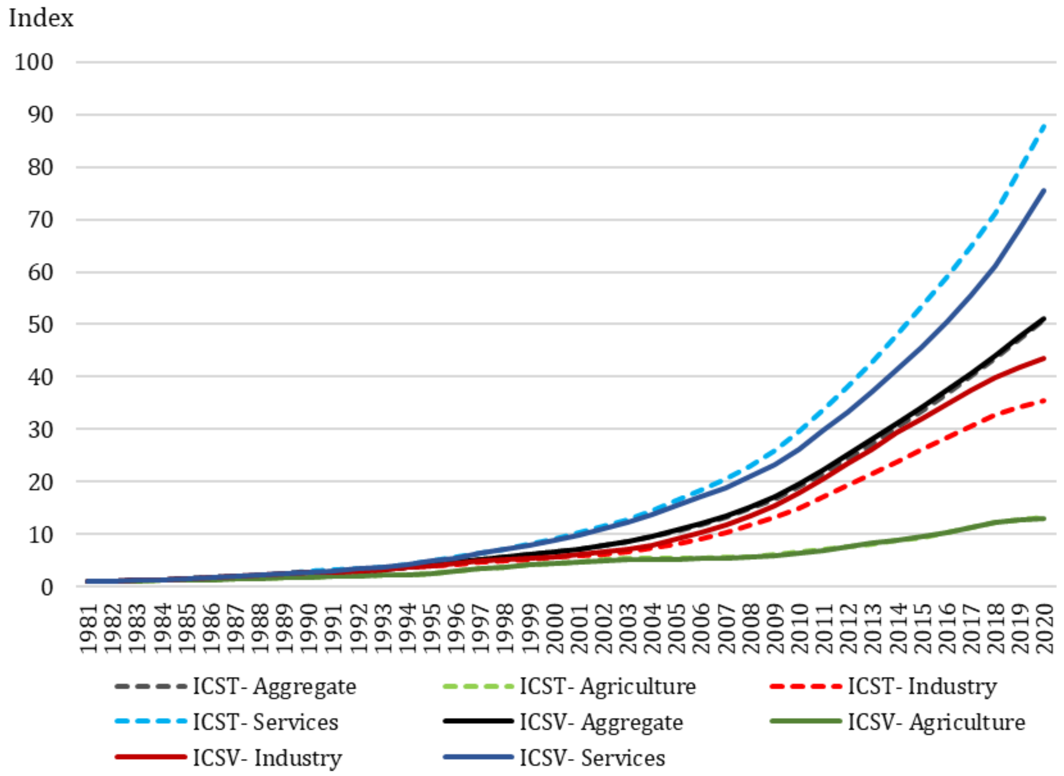


Figure 2.7: Indices (previous year=1) of Capital Stock (ICST) and Indices of Capital Services (ICSV)

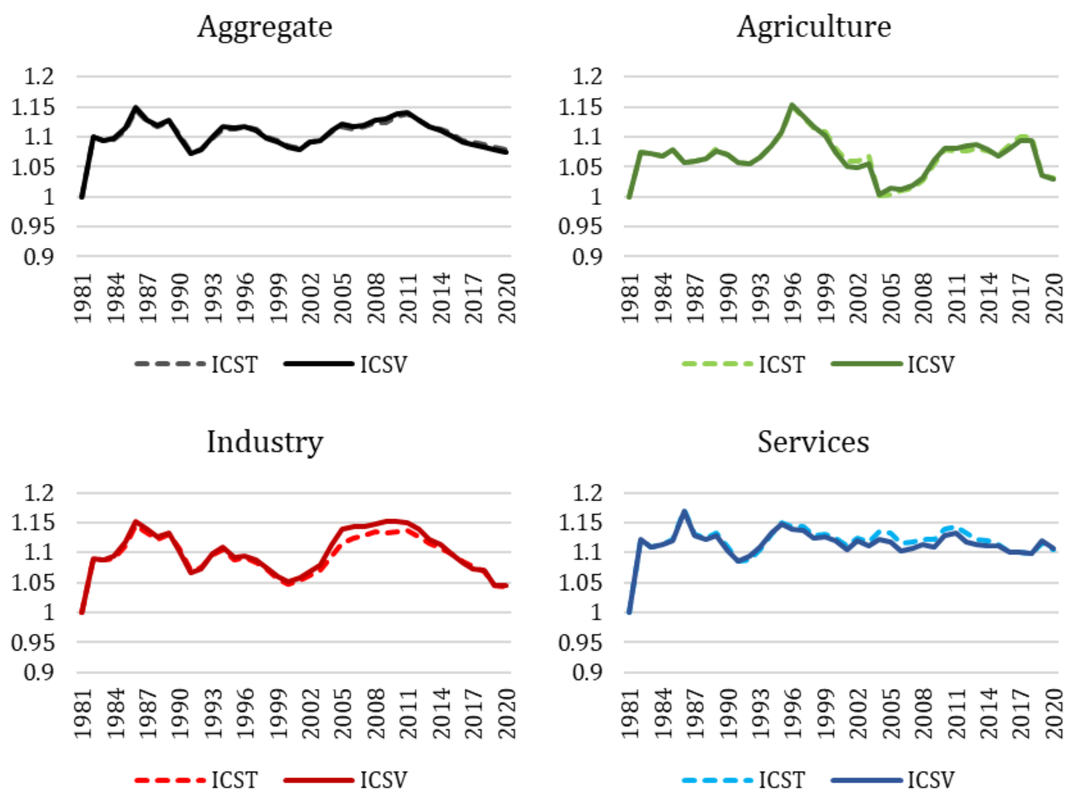
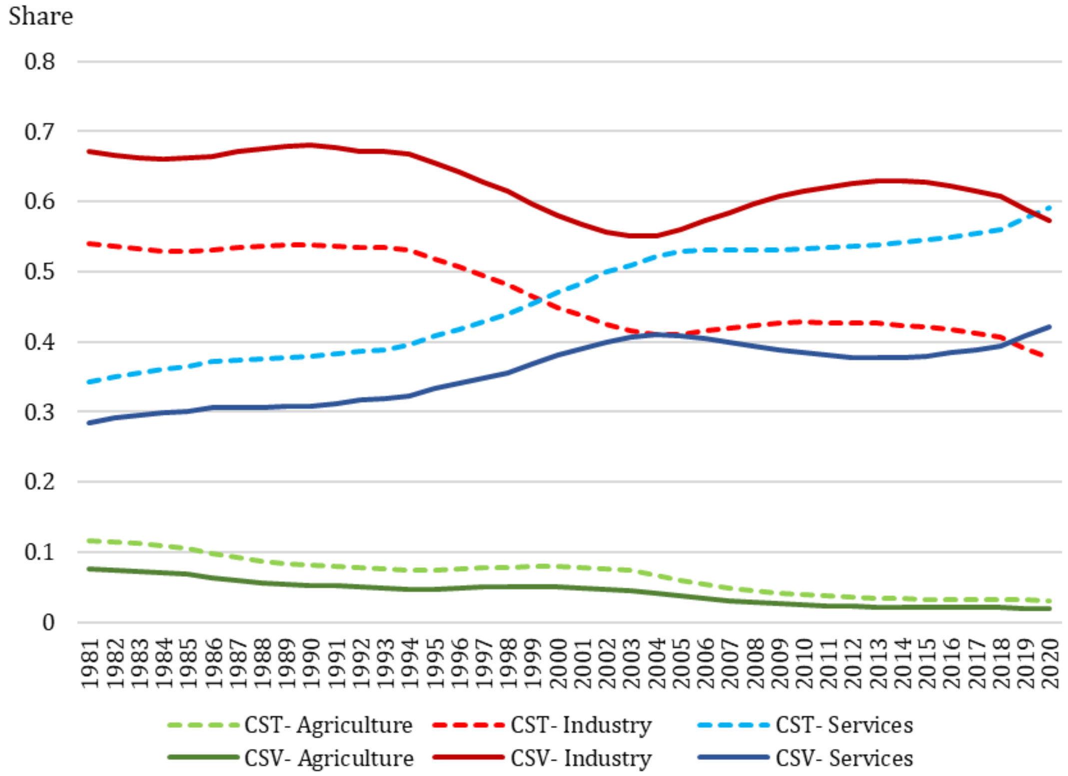


Figure 2.8: Sectoral shares of capital services (CSV) and capital stock (CST)

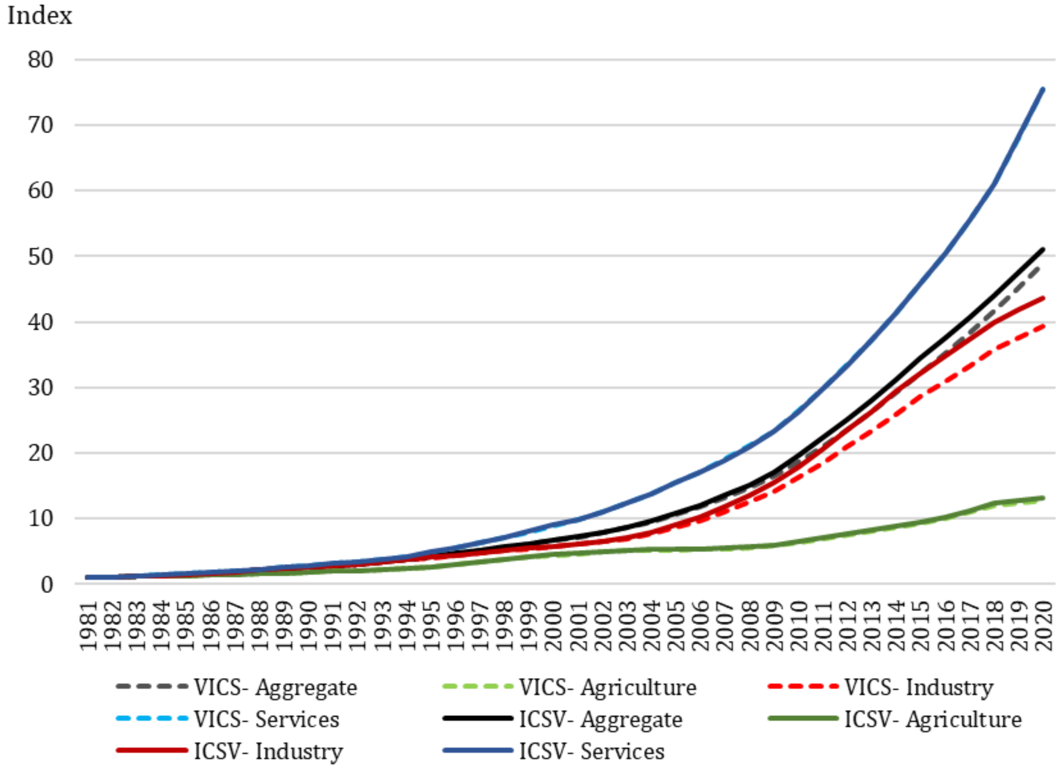


2.3.3 Volume Index of Capital Services (VICS)

The VICS is a commonly used capital input measure for growth accounting and is recommended by the OECD manual. The difference between VICS and ICSV is that VICS uses changing weights while ICSV uses constant weights to aggregate capital services across types. Figure 2.9 shows that VICS and ICSV are almost the same in agriculture and services. In industry, VICS grew slower than ICSV over the sample period. By 2020, industrial VICS was about 10% smaller than industrial ICSV.

Overall, the differences between VICS and ICS are small. This is not surprising as VICS and ICSV are both fundamentally measures of changes in the volume of capital services. In Chapter 3, we will examine if they lead to significant differences in growth accounting results.

Figure 2.9: Cumulative Indices (1981=1) of Capital Services (ICSV) and Volume Index of Capital Services (VICS)



<u>2.3.4 Return to capital stock</u>

In the rest of this chapter, we analyse China's capital returns at the aggregate and sectoral levels. In Sections 2.3.4 and 2.3.5, we analyse Marginal Revenue Product of Capital Stock (MRPK) and Marginal Revenue Product of Capital Services (MRPKS), respectively. The marginal revenue products are theoretically ideal measures of capital returns. In Appendix 2.1, we present our results for capital-output ratios which are commonly used as indicators of capital returns.

As mentioned previously, MRPK is conceptually equivalent to user cost per unit of capital stock. Figure 2.10 plots per capital stock user costs for the aggregate economy and for the three sectors. As can be seen in the figure, aggregate capital productivity rose steadily till 2008, after which it fell. The explanation could be that the massive investment projects adopted by the government to stimulate the economy during the Great Recession were not carried out efficiently, causing capital productivity to fall. However, capital productivity continued to fall long after the Great Recession. It seems undeniable that capital accumulation had run into diminishing returns in China. As a factor of production, capital has long been considered a key driver of China's economic growth. The diminishing returns to capital can partially explain the slowdown in China's economic growth in recent years.

Agricultural MRPK initially grew at similar rates to modern sector MRPK but it plummeted in the late 1990s and then stagnated. Throughout the 1981-2020 period, agriculture had the lowest capital productivity among the three sectors. This is consistent with the relatively slow agricultural capital accumulation observed in the data.

Industrial MRPK was neck and neck with service MRPK from 1981 to 1993. Industrial MRPK then grew faster and stayed higher than service MRPK. Since 2008, industrial MRPK fell rapidly, eventually converging with service MRPK in the late 2010s. As service MRPK stagnated between 2008 and 2020, it is clear that the fall in aggregate MRPK was driven by the sharp fall in industrial MRPK.

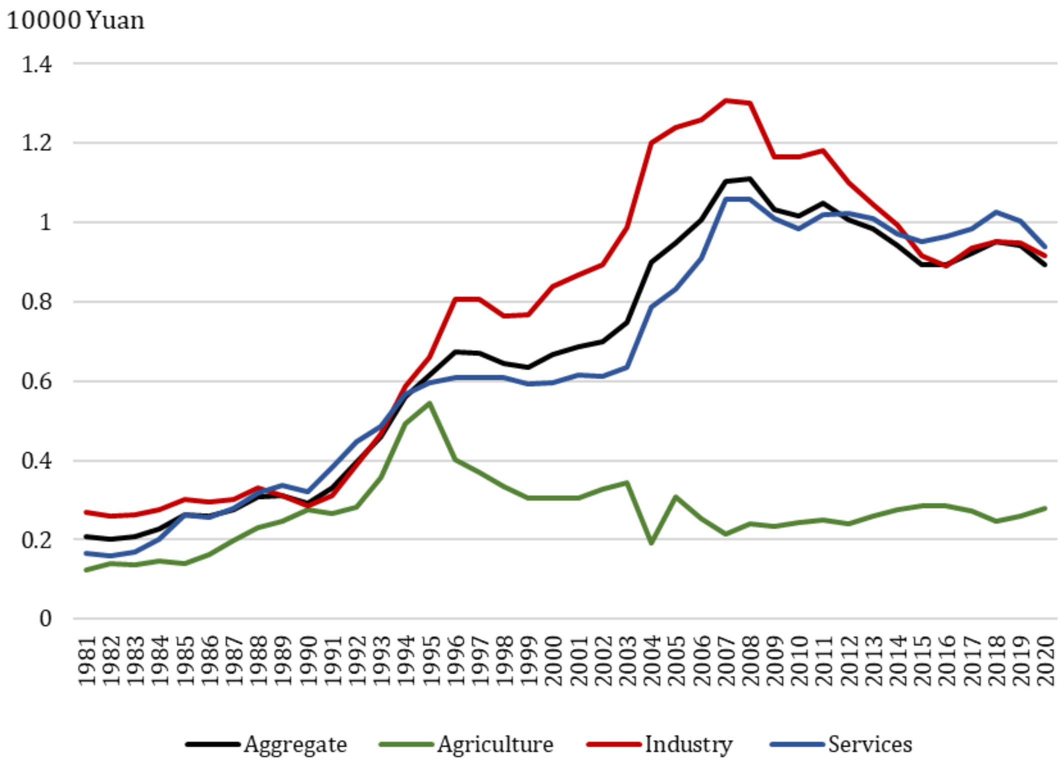
In a competitive economy, resources would flow to sectors with higher returns. This flow would cause sectoral returns to converge as a result of diminishing returns. Our results suggest that capital stock was not allocated entirely according to sectoral returns in China. Over the 1981-2020 period, the industrial sector had higher or similar capital returns to the service sector but it had lower capital accumulation than the service sector. As the least productive sector, agriculture did have the least capital accumulation compared to the modern sectors. Before 1995, there were signs of convergence in capital productivity between agriculture and the modern sectors. After 1995, however, agricultural MRPK diverged from modern sector MRPKs.

The relatively fast capital growth in services and the large gaps between agricultural and modern sector MRPKs point to the presence of frictions which interfered with the free movement of factor inputs across sectors. One example of such frictions is the state's influence on the financial industry which distorted the allocation of investment. Another example is the household registration system which impeded the movement of households and their capital between rural and urban areas.

An alternative explanation for the gaps in capital productivities is that there are limitations in the MRPK measure of sectoral capital productivity. In the next subsection, we investigate China's sectoral capital productivities using the alternative measure:

Marginal Revenue Product of Capital Services (MRPKS).

Figure 2.10: Marginal revenue product (user cost per unit) of capital stock

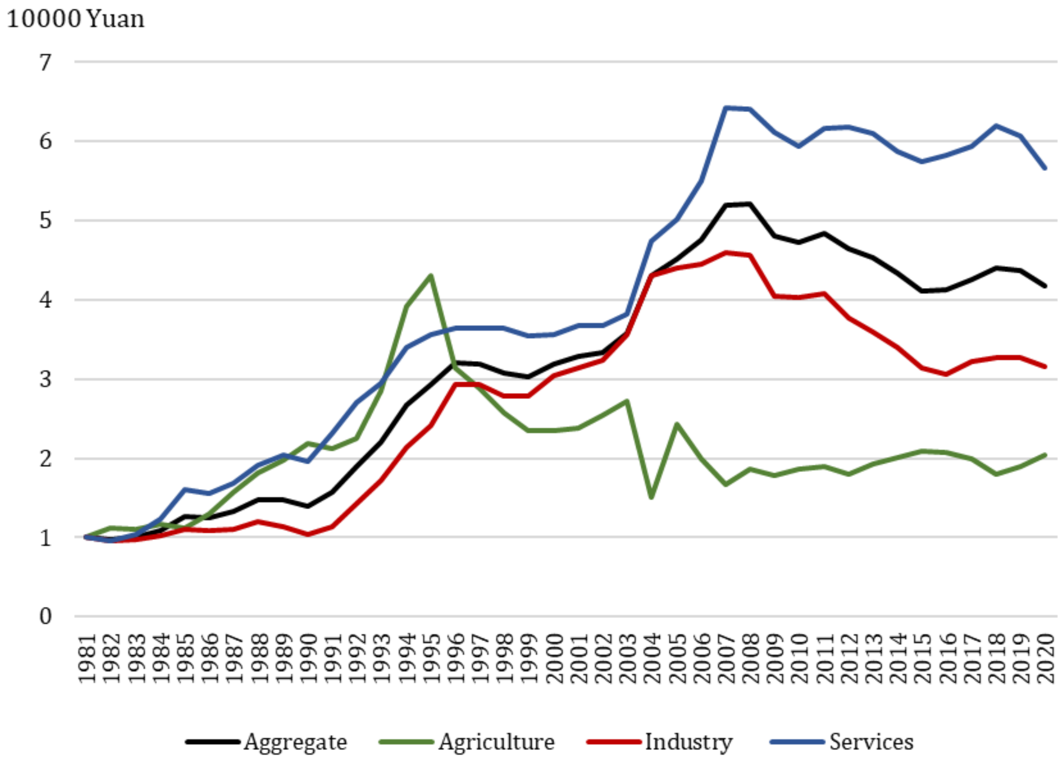


2.3.5 Return to capital services

In the case of capital services, the analogous productivity measure to MRPK is the Marginal Revenue Product of Capital Services (MRPKS). We estimate the MRPKS by dividing capital income by capital services. As can be seen in Figure 2.11, aggregate MRPKS peaked in 2008 and fell thereafter. This is similar to the pattern of aggregate MRPK, confirming the presence of diminishing returns to capital in China. Like in the case of MRPK, the fall in aggregate MRPKS was driven mainly by the sharp fall in industrial MRPKS.

Like before, agricultural capital productivity failed to keep up with those of modern sectors after 1995. In 2020, the service to agriculture MRPKS ratio and industry to agriculture MRPKS ratio were 1.5 and 2.8, respectively. These were much smaller than their MRPK ratio counterparts, which were respectively 3.3 and 3.4. The larger-than-one marginal productivity ratios indicate capital price wedges between sectors. These capital price wedges measure the capital market frictions which impede the movement of capital across sectors. The results show that capital stock wedges can partially be explained by variations in the composition of capital across sectors and time. In particular, modern sectors' capital stocks had higher productivities partially because these sectors used more productive compositions of capital stocks than agriculture.

Figure 2.11: Marginal revenue product (user cost per unit) of capital services



In Figure 2.11, service MRPKS is consistently higher than industrial MRPKS. This is opposite to the MRPK results in Figure 2.10 and can explain the observation that capital input growth was faster in services than in industry. However, the relative capital service growth between services and industry appears slow given the rapidly diverging MRPKS's of the two sectors after 2004.

2.4 Conclusion

In this chapter, we compiled, analysed, and compared China's sectoral capital stock and sectoral capital services, and their corresponding returns. We based our compilation on the best practices in the literature, availability of data, and applicability in the other chapters.

Our compiled data show that between 1981 and 2020, China's aggregate capital input grew faster than GDP. Therefore, capital accumulation likely played important roles in China's economic growth. China's capital input underwent rapid structural change. Unlike those in labour and output, structural change in capital was mostly from industry to services rather than from agriculture to the modern sectors. This is partially due to the facts that in 1981, 90% of China's capital was already in the modern sector and only 10% was in agriculture. These imply that capital was at a more advanced stage of structural change and had less potential for further structural changes than labour and output.

The return to capital in China rose steadily till 2008, after which it started to fall. This fall was mainly driven by the rapid fall in industrial capital return. After 1995, the gaps in returns between agriculture and the modern sectors expanded. This suggests there could be factor market frictions which impeded the free movement of capital into the modern sectors where capital returns were higher.

Compared to capital stocks data, capital services data show higher industrial capital share and slower structural change towards services. These mean that although more capital stock had been accumulated in services than in industry, the composition of capital stock accumulated in services was less productive than that in industry.

Our results show that the return to capital services in the service sector was higher than that in the industrial sector. This is consistent with the observation that capital growth in services was faster than that in industry. In contrast, capital stocks data show lower returns in services than in industry.

The gaps in capital return between agriculture and the modern sectors computed using capital services are smaller than those computed using capital stocks. This means capital stock wedges can partially be explained by the varying productivity across different types of capital goods and the changing type composition of capital stocks across sectors and across time. More specifically, modern sectors' capital stocks had higher productivities partially because these sectors used more productive compositions of capital stocks than agriculture.

Our results imply that capital accumulation, especially those in construction and industry, will be less reliable as drivers of economic growth in China due to diminishing returns. The sharp fall in industrial capital return, if continued, will make it harder for China to expand its advantage in the international trade of manufactured goods. China will have to explore other sources of economic growth. Given that the service capital share was 40% in 2020, there is still plenty of room for the structure of capital to transform towards services where return is the highest. The government can facilitate such transformation by finding and reducing frictions in the capital market.

Theoretically, it is more rigorous to use capital services rather than capital stock as the measure of capital input, especially for analyses at the sectoral level. However, this study shows that the differences between capital services and capital stock results are small. In addition, capital services required more data and assumptions to compute. Perhaps more importantly for our project, capital services are harder to use in dynamic general equilibrium models compared to capital stocks. The choice of measurement for capital input in our later chapters therefore depends on the level of precision required, the purposes at hand, and the practicality of using capital services. In Chapter 3, we will conduct growth accounting for China using both measures of capital input. This will allow us to gauge the impact of using alternative capital measures in dynamic economic models.

Our constructed capital data are far from perfect. We had to make assumptions in order to compute China's initial capital and depreciation rate. Data for some variables are not available for the entire sample period, so that we had to fill the missing data by estimating them or approximating them by substitutes. Due to data availability, we had to assume that asset prices are the same across sectors. Although these are common assumptions in the capital measurement literature, it is undeniable that they could have led to errors in our results. Nevertheless, until the NBS publishes more data about China's capital, our constructed capital data are the best we can get for our thesis.

Appendix 2.1 Capital-output ratios

In this appendix, we present results for an alternative measure of capital return: capital-output ratio. Figures 2.12 and 2.13 show the ratios of capital stocks to output and the ratios of capital services to output, respectively.

As can be seen in the figures, aggregate capital-output ratios increased between 1981 and 2020, indicating that the returns to capital accumulation decreased over time. The increases in aggregate capital-output ratios accelerated in the late 2000s. These suggest that capital accumulation as a driver of China's economic growth was running out of steam.

Agricultural and service capital-output ratios both increased over the sample period. Although industrial capital-output ratios also increased since the late 2000s, they underwent substantial reductions in the 1990s and early 2000s. These mean that overall, industrial capital-output ratios stagnated over the sample period.

The figures show wide gaps in capital-output ratios between sectors. Over the 1981-2020 period, agriculture had the lowest capital-output ratios and services had the highest capital-output ratios. These are puzzling as agriculture had the least capital accumulation and services had the most capital accumulation. The low capital-output ratios in agricultural can largely be explained by the fact that agriculture in China is far more labour-intensive than the modern sector. The high service capital-output ratios indicate that there could be market frictions which distort the allocation of capital. The counter-intuitive results could also be due to limitations of capital-output ratios as measures of capital returns.

Figure 2.12: Capital stock-output ratios

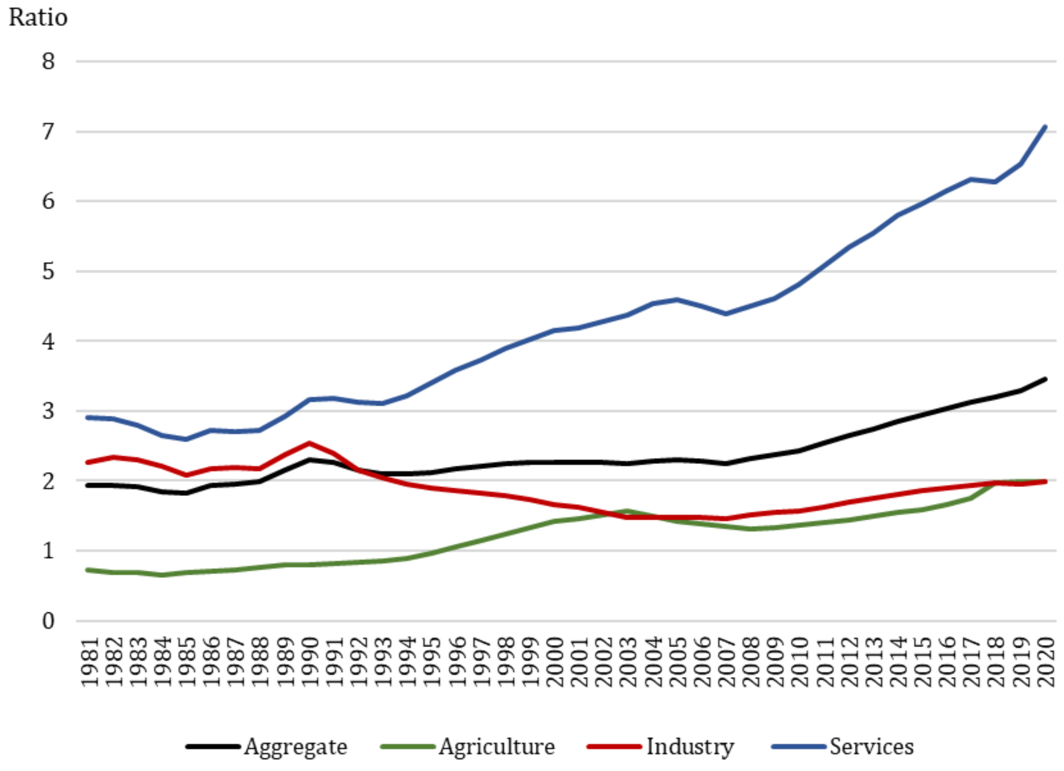
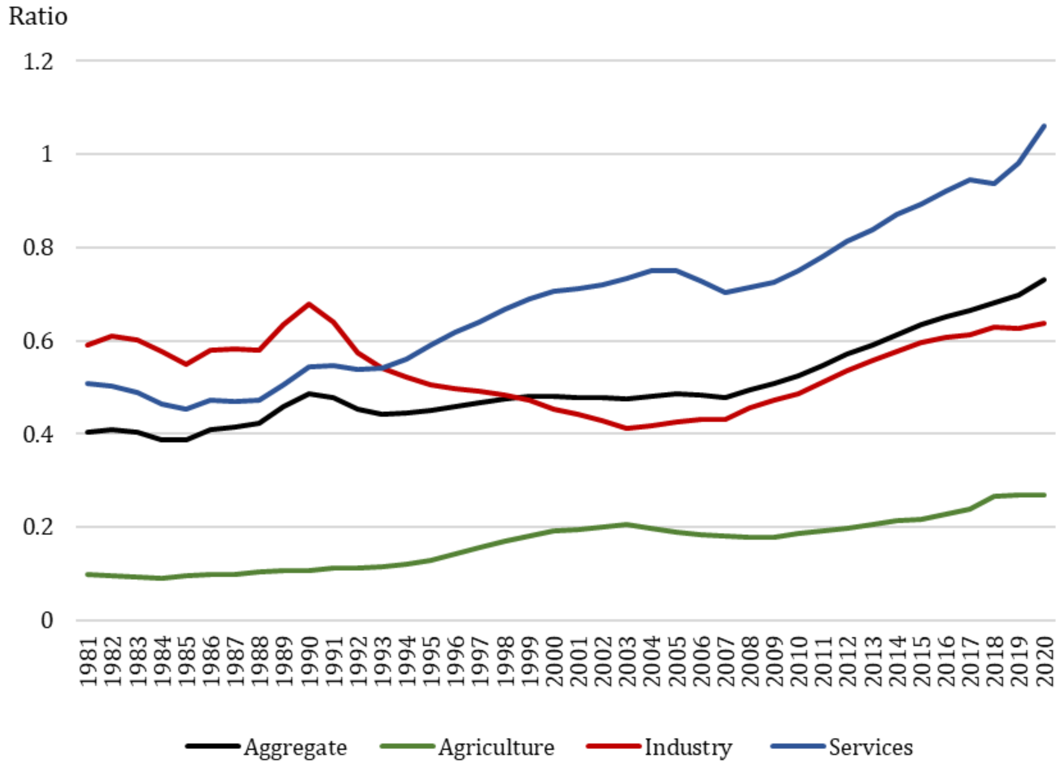


Figure 2.13: Capital services-output ratios



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Chapter 3: Accounting for China's Growth at the Sectoral Level: Factor Accumulation, Productivity, Structural Change, Population Aging, and Factor Market Frictions

3.1 Introduction

Between 1981 and 2020, China's economy grew at an average rate of 9% per year (National Data, 2025) and lifted over 900 million Chinese people out of extreme poverty (World Bank Open Data, 2025). Uncovering the sources of China's growth would contribute to the knowledge about economic development and potentially inspire growth policies in other developing economies. China's large size and rapid growth mean it occupied 18% of the world's GDP in 2020 and has been a major driver of global economic growth (World Bank Open Data, 2025). As such, China has taken centre stage in economic and political discussions. On the ground, the average Chinese person is still relatively poor compared to those in developed economies. In 2020, real GDP per capita in China was respectively 17%, 30%, and 30% of those in the US, the Euro area, and Japan (World Bank Open Data, 2025). China therefore has ample room to grow. However, China's growth has slowed in recent years, suggesting that China might be entering the middle-income trap. Accounting for China's economic growth would shed light on the sustainability of China's growth and allow policymakers in China and around the world to devise policies accordingly. Despite decades of lively debates, there is no consensus in the literature accounting for China's growth. In this chapter, we compile supply-side data for China and account for China's growth at sectoral and aggregate levels. We contribute to the growth accounting literature for China mainly by exploring the implications of our own measures of sectoral factor inputs, including sectoral capital services and sectoral effective labour input.

China's enormous population has been the backbone of its economy. In 2020, China's 1.4 billion population supplied a labour force of 784 million (National Data, 2025), which accounted for 23% of the world's labour force (World Bank Open Data, 2025). However, China's population has been aging rapidly due to demographic transition and population policies. The population share of elderlies aged 61 and above increased from 7% in 1990 to 17% in 2020 (United Nations, 2024). As people get older, their labour participation rates, employment rates, and productivities change. Such changes can vary across sectors and time. In this chapter, we use time series of household survey data to construct age-specific effective labour input by sector by time. We then use the constructed data in growth accounting to study the impacts of population aging through the labour input channel. To our knowledge, we are the first to do these. Some studies such as Young (2003), Wu (2014), and Cheng (2019) incorporated human capital into China's growth accounting. However, they did not explore the impact of aging as it cannot be separately identified from the effects of human capital.

China's economic growth has been accompanied by rapid structural transformation. Between 1981 and 2020, the output shares of primary, secondary, and tertiary sectors changed respectively from 31%, 46%, and 23% to 8%, 38%, and 55% (National Data, 2025). As factor inputs move to more productive sectors, aggregate productivity increases and the economy grows. The growth accounting literature for China, however, has focused on the aggregate economy. In this chapter, we compile and analyse sectoral data for China. On that basis, we examine the drivers of growth across the three sectors and the contribution of structural change to aggregate economic growth in China.

Since the adoption of wide-reaching reforms from 1978, China has been transitioning from a planned economy to a more market-oriented economy. However, many institutional and policy-related frictions still remain in China's factor markets. For example, the Hukou (household registration) system has prevented the free movement of labour. The state-dominated financial sector has favoured State-Owned Enterprises (SOEs) in capital allocation. These factor market frictions impede structural change and hence economic growth. There have been a number of studies on factor market frictions in China including: Brandt and Zhu (2010), Zhu (2012), Cao and Birchenall (2013), and Cheremukhin et al (2015). In this chapter, we contribute by using our own data to compute and analyse China's factor price frictions across sectors. Using our effective capital and labour measures, we examine how much of the frictions can be explained by the changing age composition of labour and type composition of capital.

At the centre of debates in China's growth accounting literature is the relative importance of capital accumulation versus Total Factor Productivity (TFP) growth to China's economic growth. Studies such as Young (2003), Zhang and Shi (2003), and Cheng et al (2019) have found that China's growth is driven primarily by capital accumulation. If so, growth in China is nothing special, as it is just like those experienced by other Newly Industrialised Countries in Asia. Furthermore, such growth is not sustainable because capital accumulation will inevitably run into diminishing returns. Other studies have disagreed, arguing that the role of TFP growth in driving China's growth is no less important than that of capital accumulation (Dekle and Vandenbroucke, 2010; Bosworth and Collins, 2007; Zhu, 2012).

The differences in results across studies are largely attributable to the use of different data. This is no surprise given the data-oriented nature of growth accounting analysis. The most contentious data issues are those of capital stock. Since there is no official capital data for China, studies have had to construct their own, leading to a wide variety of capital data in the literature. In Chapter 2, we discussed the relevant data issues in detail and constructed sectoral capital input data for China. In this chapter, we use our constructed data to conduct growth accounting for China. We compare results computed using different measures of capital input. To our knowledge, we are the first to do these.

China is a developing country with a unique history and a relatively young national accounting system. Understandably, many have questioned the accuracy and consistency of official data published by the National Bureau of Statistics (NBS) of China. Meng and Wang (2000), Young (2003), and Wu (2014) are among the growth accounting studies that have been highly critical of official Chinese data. Some of the data issues pointed out by such studies deserve attention. However, the alternative data proposed by these studies are also subject to various issues. As such, there is no consensus about the construction of alternative data. The rest of the literature, such as Chow (1993) and Bosworth and Collins (2007), and most studies in Chinese language, have conducted analyses using official data. In this study, we conduct growth accounting for China using official data. Considering the doubts about official data, we collect them carefully and make adjustments wherever there is consensus for doing so. When multiple options are present, we follow the best practices in the literature.

Our main findings include that factor accumulation and TFP growth both played important roles in driving China's growth. A large share of China's aggregate TFP growth was due to structural change. At the sectoral level, growth in agriculture was driven almost entirely by TFP growth while growth in services was driven almost entirely by factor accumulation. Older people had lower labour participation rates, employment rates, and diminishing wage premium compared to younger people. Resultantly, population aging had negative effects on effective labour input since the late 2000s. Older people were more likely to work in agriculture than younger people. As a result, population aging impeded structural change in China. We expect these adverse aging effects acting through the effective labour channel to intensify in the future as China's population aging accelerates. There were substantial factor price wedges between the modern sectors and agriculture. The wedges were higher in industry than in services and were higher for labour than for capital. The wedges can partially be explained by the fact that different sectors used different types of capital and labour.

The rest of this chapter is organised as follows. Section 3.2 describes our methodology for growth accounting and for computing factor price wedges. Section 3.3 describes our compilation of data and presents graphical analyses of data. These data will be used throughout this thesis. Section 3.4 presents our growth accounting results. Section 3.5 investigates the effects of population aging through the effective labour input channel. Section 3.6 computes and analyses factor price wedges across sectors. Section 3.7 concludes.

3.2 Methodology

In this section, we start by defining our measurements for real and nominal output. We then describe our methodology for growth accounting and for computing factor price wedges.

In this thesis, we are interested in China's structural change across the three sectors: primary, secondary, and tertiary. For brevity, we often refer to the three sectors respectively as agriculture, industry, and services. Additionally, we sometimes refer to the secondary sector and the tertiary sector as the modern sectors and sometimes collectively as the modern sector. In mathematical expressions, unless stated otherwise, subscript i is the general indicator for sector and can be a for agriculture, d for industry, and s for services. The subscript t refers to time.

3.2.1 Real and nominal output

Let cumulative implicit value-added deflator (base year=1) of sector i in period t be denoted by P_{it}. We obtain period-t real sectoral value-added measured in 1981 prices, which we denote by Y_{it}, by deflating period-t nominal sectoral value-added by P_{it}. This means nominal GDP of sector i in t can be written as:

$$Nominal\ GDP_{it} = P_{it}Y_{it}$$

Aggregate nominal GDP and real GDP are the sums of their sectoral counterparts:

$$Nominal\ GDP_t = \sum_i P_{it}Y_{it}$$

$$Real\ GDP_t = Y_t = \sum_i Y_{it}$$

Aggregate implicit value-added deflator P_t can then be computed as:

$$P_t = \frac{\sum_i P_{it}Y_{it}}{\sum_i Y_{it}}$$

3.2.2 Growth accounting

We assume that real output of sector i in period t, Y_{it}, is a Cobb-Douglas production function of Total Factor Productivity A_{it}, capital income share α_i, capital input K_{it}, and labour input L_{it}:

$$Y_{it} = A_{it}K_{it}^{\alpha_i}L_{it}^{1-\alpha_i} \tag{3.1}$$

Taking natural logarithms of both sides, we obtain:

$$lnY_{it} = lnA_{it} + \alpha_i lnK_{it} + (1-\alpha_i)lnL_{it}$$

First differencing:

$$\Delta lnY_{it} = \Delta lnA_{it} + \alpha_i \Delta lnK_{it} + (1-\alpha_i)\Delta lnL_{it}$$

Most studies in China's growth accounting literature used this equation with log-differences replaced by percentage changes. Given percentage changes of output and factor inputs, the percentage change of TFP can be backed out.

Log-difference and percentage change are approximations of each other. In the case of China, growth rates of inputs and output are often large. As a result, the approximation might lead to large errors in estimated TFP growths. Since the assumptions associated with the Cobb-Douglas production function are to be made anyway, and since we are interested in the levels of TFPs, we use the function directly to compute TFP and TFP Growth (TFPG). In other words, we use equation (3.1) to back out the value of A_{it} given data on Y_{it}, K_{it}, L_{it}, and α_i. We do this for the three sectors and for the aggregate economy.

We compute the annual contributions to real GDP growth of factor inputs and TFP as:

$$Contribution\ of\ capital\ in\ t = \left(\frac{K_{t+1}}{K_t}\right)^{\alpha} - 1$$

$$Contribution\ of\ labour\ in\ t = \left(\frac{L_{t+1}}{L_t}\right)^{1-\alpha} - 1$$

$$Contribution\ of\ TFP\ in\ t = \frac{A_{t+1}}{A_t} - 1$$

Note that real GDP growth in t is equal to the product of gross contributions:

$$\frac{Y_{t+1}}{Y_t} = \frac{A_{t+1}K_{t+1}^{\alpha}L_{t+1}^{1-\alpha}}{A_t K_t^{\alpha} L_t^{1-\alpha}}$$

Aggregate output Y_t is approximately the sum of sectoral outputs:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \approx \sum_i A_{it} K_{it}^{\alpha_i} L_{it}^{1-\alpha_i}$$

The equation above shows that aggregate economic growth is driven by aggregate TFP growth and aggregate factor input growths. Aggregate TFP growth is driven by sectoral TFP growths and the reallocation of factor inputs across sectors (structural change).

To compute the contribution of structural change to China's economic growth in each period, we start by computing output growth under a counterfactual scenario in which sectoral TFPs stay constant. By comparing actual output growth with the counterfactual, we obtain $G_t^{sectoral\ TFPG}$, the part of output growth that is due to sectoral TFP growths:

$$G_t^{sectoral\ TFPG} = \frac{\frac{\sum_i A_{it+1} K_{it+1}^{\alpha_i} L_{it+1}^{1-\alpha_i}}{\sum_i A_{it} K_{it}^{\alpha_i} L_{it}^{1-\alpha_i}}}{\frac{\sum_i A_{it} K_{it+1}^{\alpha_i} L_{it+1}^{1-\alpha_i}}{\sum_i A_{it} K_{it}^{\alpha_i} L_{it}^{1-\alpha_i}}} = \frac{\sum_i A_{it+1} K_{it+1}^{\alpha_i} L_{it+1}^{1-\alpha_i}}{\sum_i A_{it} K_{it+1}^{\alpha_i} L_{it+1}^{1-\alpha_i}}$$

By similar logic, we can compute the contribution to output growth of aggregate TFP growth, denoted by $G_t^{agg\ TFPG}$:

$$G_t^{agg\ TFPG} = \frac{A_{t+1}}{A_t}$$

The economy's growth that is due to structural change, G_t^{SC}, can then be obtained by deducting the contribution of sectoral TFP growths from that of aggregate TFP growth:

$$G_t^{SC} = \frac{G_t^{agg\ TFPG}}{G_t^{sectoral\ TFPG}}$$

3.2.3 Factor price wedges

If factor markets are frictionless, factor inputs would move to sectors with higher factor prices, causing sectoral factor prices to converge. Variations in factor prices across sectors therefore reflect factor market frictions that impede the free movements of factor inputs across sectors. In this study, we measure factor market frictions using factor price wedges.

To compute factor price wedges for each sector, we first obtain per unit factor incomes by dividing each sector's total factor incomes by their corresponding factor inputs. Note that under the assumption of perfectly competitive markets, the profit maximisation problem of sector i's rational representative firm leads to the result that factor payments are equal to their marginal revenue products:

$$Rent_{it} = \frac{Total\ capital\ income_{it}}{Capital\ input_{it}} = MRPK_{it} = P_{it} \alpha_{it} A_{it} K_{it}^{\alpha_{it}-1} L_{it}^{1-\alpha_{it}}$$

$$Wage_{it} = \frac{Total\ labour\ income_{it}}{Labour\ input_{it}} = MRPL_{it} = P_{it}(1-\alpha_{it}) A_{it} K_{it}^{\alpha_i} L_{it}^{-\alpha_i}$$

We then compute factor price wedges as ratios of the modern sectors' factor payments to agricultural factor payments minus ones:

$$Capital\ wedge_{it} = \frac{Rent_{it}}{Rent_{at}} - 1$$

$$Labour\ wedge_{it} = \frac{Wage_{it}}{Wage_{at}} - 1$$

3.3 Data

3.3.1 Time span

Our analyses cover the period of 1981-2020. As explained in Chapter 2, we choose 1981 to be the initial year in our analyses to account for data availability and quality issues and to ensure consistency across all chapters. Real variables in our project are therefore measured in 1981 prices.

3.3.2 Sectoral classifications

According to the NBS's Regulations for Three-Sector Classification (NBS, 2018), China's economy can be divided into three sectors: primary, secondary, and tertiary. The primary sector is composed of agriculture, forestry, animal husbandry, and fishing. The secondary sector is composed of industry and construction. The tertiary sector refers to services. For brevity, we will often refer to the three sectors respectively as agriculture, industry, and services.

The sectoral classification of economic activities has gone through a number of updates over the years. The updates included reallocations, relabelling, and introduction of new sub-industry categories. Fortunately, reallocations across sectors have been few. The changes in general have been so small that sectoral data are approximately compatible across the classifications.

The NBS regularly updates and revises data to ensure adherence to the latest classification. In our project, we therefore use the latest NBS data whenever we can to ensure consistency in sectoral classification. When we have to use data from old publications, we make adjustments to account for the changes in sectoral classification as much as we can. The bottom line is that the changes across classifications and the adjustments we make are so small that they have little impact on our results.

3.3.3 Output

In our project, we choose Value-Added (VA) GDP as the measure of output. China's value-added data at sectoral and aggregate levels are available annually. In contrast, data for gross output, an alternative measure of output, are available every 2 to 3 years since 1987. Unlike gross output data, value added data are adjusted regularly by the NBS to account for data issues that emerge.

We obtain nominal sectoral value-added data for China from China Statistical Yearbooks (NBS, 1981-2021). The yearbooks also provide indices of real sectoral value-added, which allow us to compute sectoral implicit value-added deflators. Given sectoral nominal value-added and sectoral implicit value-added deflators, we compute real sectoral value-added data as described in Section 3.2.1.

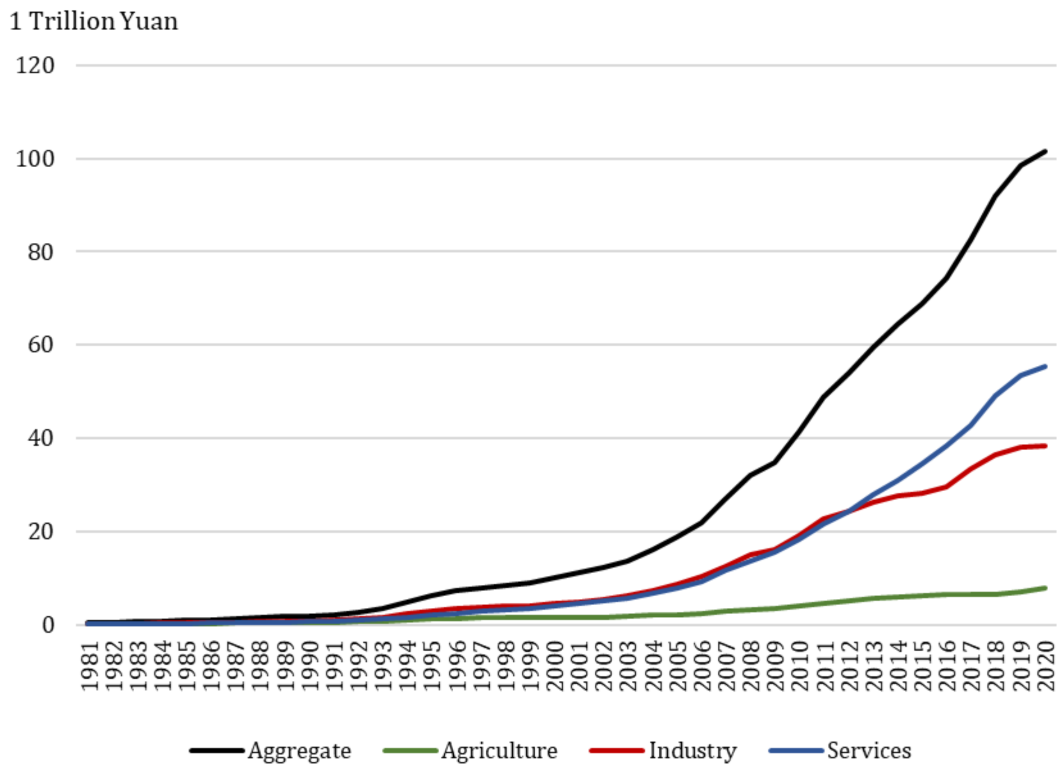
A number of studies, including Wu (2014), Young (2003), and Maddison (1998) have argued that China's real GDP growth is overreported due to overreporting of nominal GDP growth and underreporting of inflation figures. The NBS, however, seems impervious to these studies. In fact, the NBS adjusted China's GDP figures upwards in recent rounds of adjustments, citing, for example, the discovery and inclusion of economic activities that were previously unaccounted for.

A detailed discussion about the accuracy and consistency of China's GDP figures is beyond the scope of our study. Currently, there is no consensuses in the literature regarding the issues with China's official GDP data and the construction of alternative data. In this thesis, we follow the majority of studies on China and use official GDP data from the NBS.

Figures 3.1 and 3.2 below show that nominal and real GDP of China grew rapidly between 1981 and 2020. On average, China's real GDP grew by 9% per year. At the sectoral level, agricultural output stagnated relative to the other two. In nominal terms, service output had exceeded industrial output since 2012. In contrast, real service output never caught up with real industrial output over the sample period.

The structural change of China's output can be seen more clearly in Figures 3.3 and 3.4 which show sectoral nominal GDP and sectoral real GDP shares. In 1981, secondary sector had the highest nominal output share, followed by agriculture, and then services. Over time, agriculture's share in nominal GDP plummeted from 31% in 1981 to 8% in 2020. The structural change in nominal GDP was mostly between agriculture and services, as nominal service share increased from 23% to 55% between 1981 and 2020. The nominal industrial share stagnated at around 45% and then declined steadily in the 2010s, reaching 38% in 2020.

Figure 3.1: Aggregate and sectoral nominal GDP



In real GDP, agriculture's share fell even more drastically from 31% in 1981 to 5% in 2020. As agricultural share fell, industrial share and service share in real GDP both increased. Industrial share rose rapidly, from 46% in 1981 to 67% in 2014 and then stabilised. Service share increased from 23% in 1981 to 28% in 1989 but then stagnated, ending the sample period at 29%.

The different patterns of structural change between nominal GDP and real GDP are attributable to the patterns of sectoral implicit value-added deflators. As can be seen in Figure 3.5, service sector had the fastest increases in prices at 7.1% per year on average. Agricultural inflation also averaged at a high rate of 6.5% per year and was more volatile than service inflation. Secondary sector inflation was much lower compared to the rest, at an average annual rate of 3.9%. The increase in service price relative to industrial price explains why the growth of service output relative to industrial output in nominal terms was much faster than that in real terms.

Figure 3.2: Aggregate and sectoral real GDP in 1981 prices

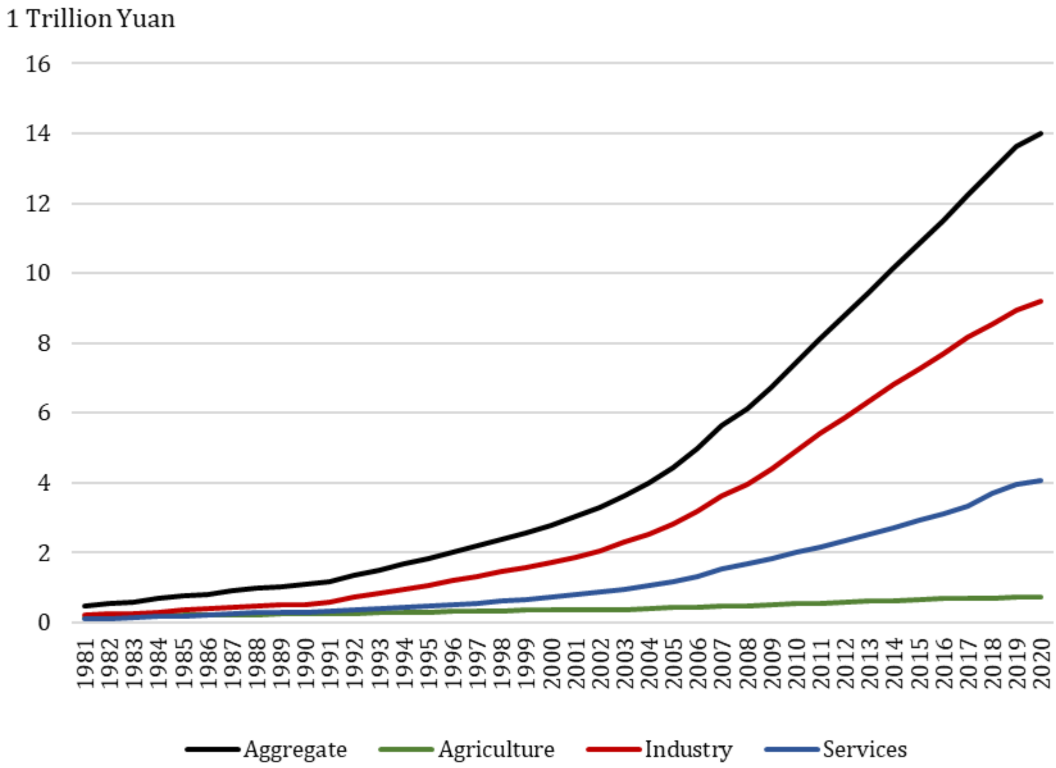


Figure 3.3: Sectoral nominal GDP shares

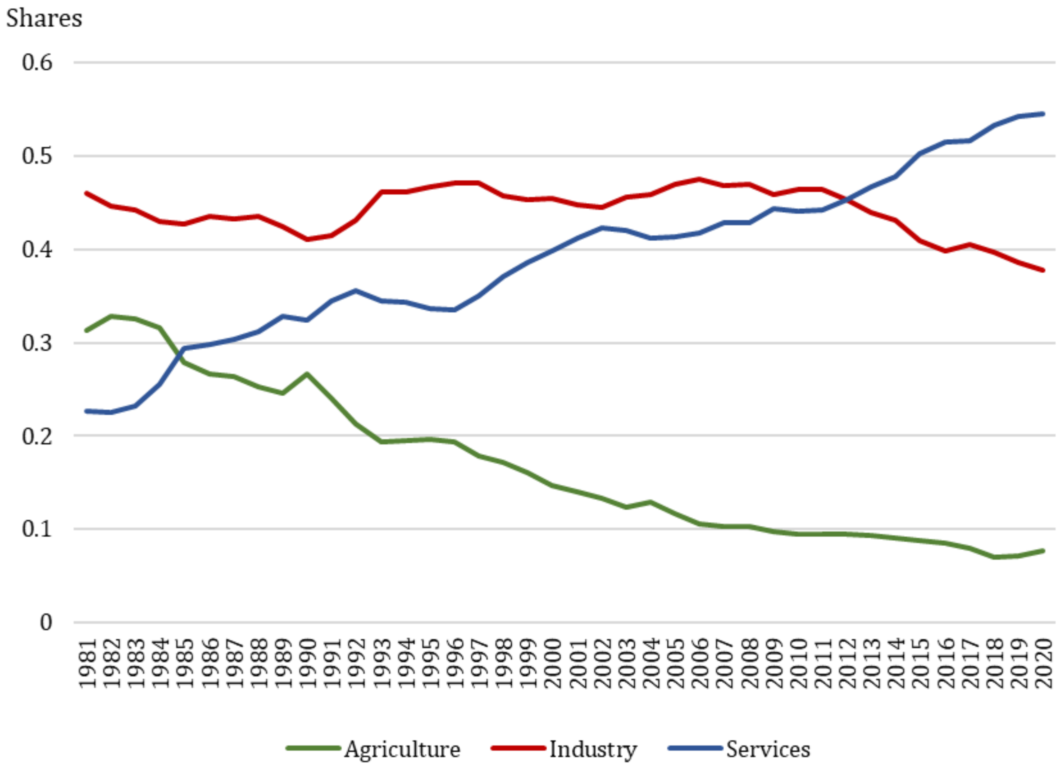


Figure 3.4: Sectoral real GDP shares

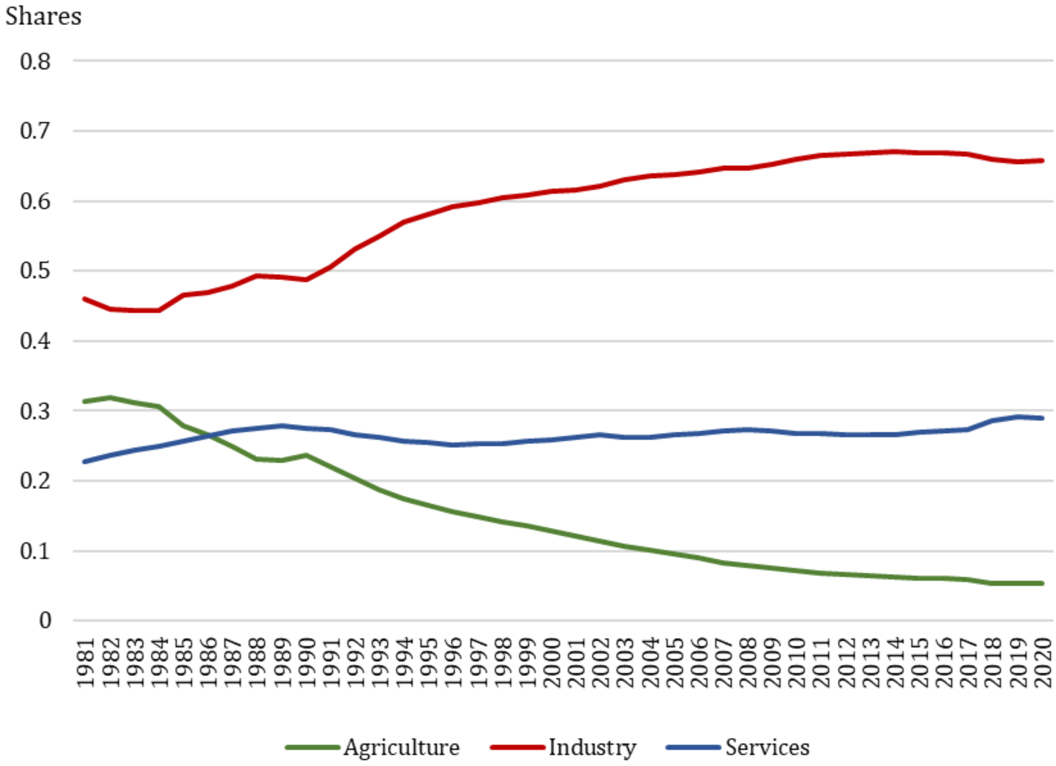
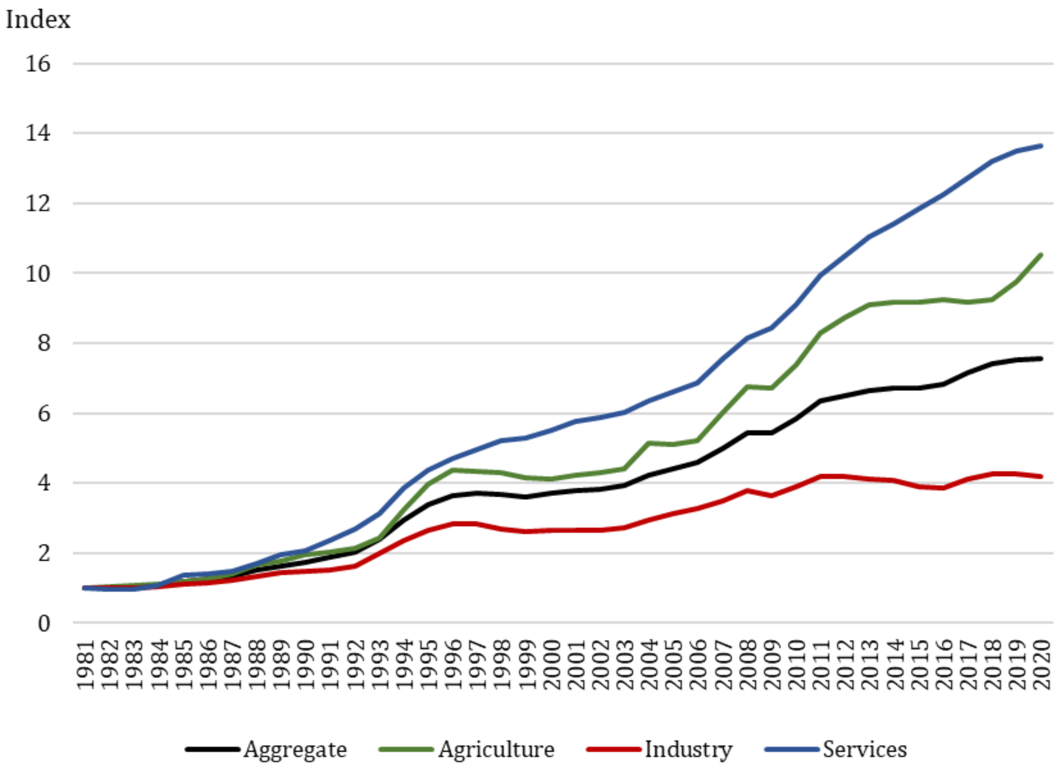


Figure 3.5: Aggregate and sectoral implicit value-added deflators



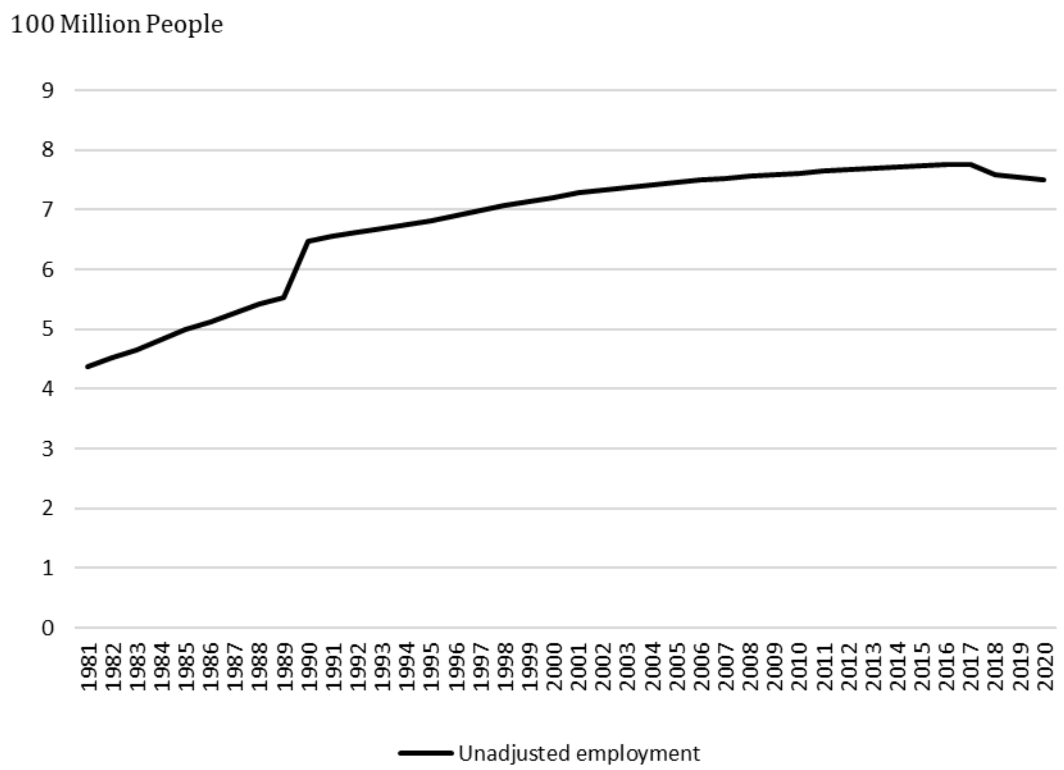
3.3.4 Labour and population

3.3.4.1 Employment

The NBS publishes aggregate and sectoral employment data annually through China Statistical Yearbooks (NBS, 1981-2021). However, the data should not be put to use without adjustments. As can be seen in Figure 3.6, China's official national employment data jumped by 17% between 1989 and 1990. Fortunately, among studies that address the issue, there is consensus regarding its causes and solution. In this section, we briefly summarise the causes of the issue and present the solution we adopt to address it. More detailed accounts of the issue can be found in Yue (2005), Holz (2005), and Wu (2011).

China's official employment data come broadly from two sources: population censuses and annual surveys. In China, a population census takes place approximately every 10 years since 1982. The older censuses of 1953 and 1964 do not contain the employment by age by sector data that we need for our project. Indeed, this is among the reasons why we chose 1981 to be the initial period in our analyses. Between two main censuses, the NBS typically carries out a mini-census using a smaller sample of about 1% of China's population. For simplicity, we will often refer to the mini-censuses as censuses.

Figure 3.6: National employment (unadjusted)



The annual surveys are carried out annually and therefore can better capture short term movements of China's demographic patterns than population censuses. On the downside, the annual surveys use much smaller samples and are therefore arguably less accurate and reliable than population censuses.

Annual surveys differ to censuses in data collection and measurement. The differences allow the two sources of data to act as complements and verifications for each other. However, they can also lead to inconsistencies in official data. The break in aggregate employment data in 1990 is an example of such inconsistency. China's employment data before 1990, as shown in Figure 3.6, are annual survey data. The employment data after 1990, however, have been adjusted by the NBS to be consistent with population censuses in 1990 and beyond.

The census-based data from 1990 onwards are higher than the annual survey data before 1990 for two main reasons. First, census and annual survey follow different definitions for the 'employed'. Census data determine employment status using the workers' actual (or current) status: if a person received income for work in the past week, the person is employed. Annual survey data defines employment by usual status: if working was a person's main activity in the past year (indicated by having a contract with a unit), then he is employed. As a result, population census data has a wider coverage than annual survey data.

The second reason lies in the difference in sampling unit. Census data are collected from household surveys while annual survey data are collected from work units. Resultantly, annual survey data do not capture informal employees who do not have formal contracts with anyone. This again means population censuses have a wider coverage and hence tend to produce larger employment figures than annual surveys.

To ensure consistency of employment data over time, we adjust the pre-1990 employment data using the 1982 and 1990 population census data (NBS, 1985; 1993). We do so in the same way the NBS adjusted post 1989 employment data. Our adjustment follows the procedure in Holz (2005) which is widely used in the literature.

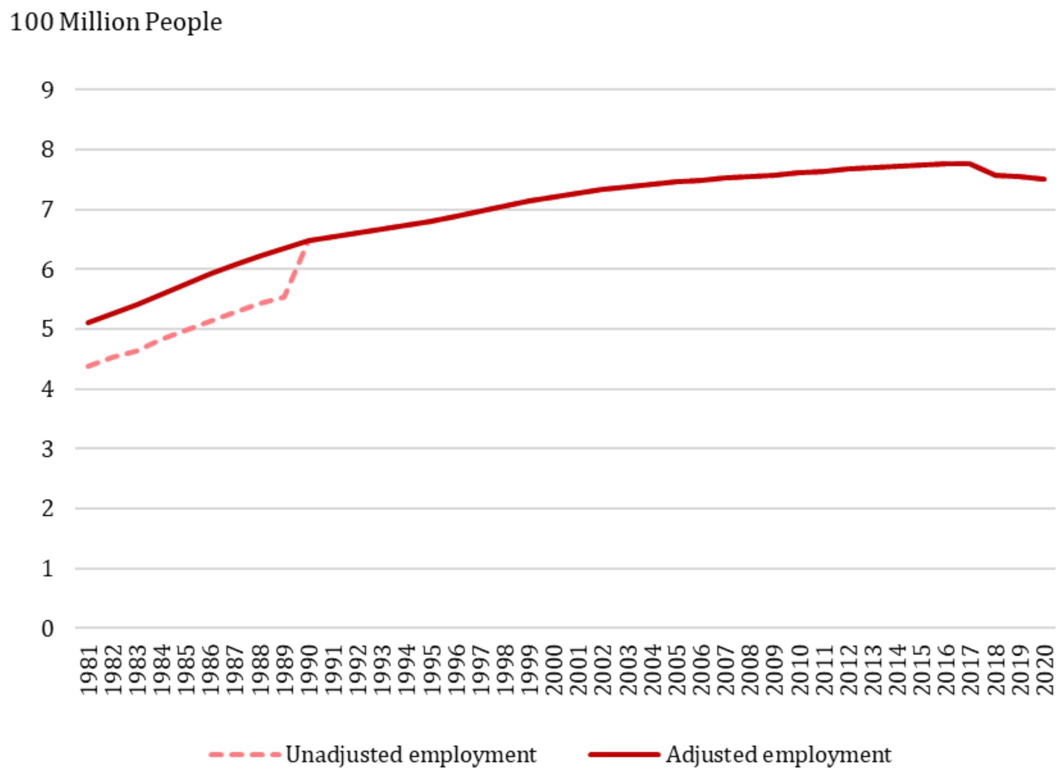
To adjust annual survey data using censuses data, we need to account for several other differences between the two. Unlike population census data, annual survey data are end-year values, include military personnel, and exclude the 15-year age group. To reconcile the differences between the two datasets, we exclude the 15-year-olds from and add military personnel to the 1982 and 1990 census data.

Since we don't have data to turn census data into end year values, we instead turn annual survey data into midyear values. We estimate midyear value as the arithmetic average of two adjacent end-year values.

Now that the two sets of data are comparable, we compute adjusted employment for 1983-1989 by, in each year, covering the same proportion of the distance between the 1982 and 1990 census employment as the annual survey employment does. For employment in 1981, we divide 1982 census employment by the 1981-1982 employment growth rate from annual survey data.

So far, the adjusted pre-1990 employment data are mid-year values. To be consistent with official data, we turn them into end year values. We compute end-year value as the arithmetic average of two adjacent mid-year values.

Figure 3.7: Unadjusted and adjusted national employment



Our adjusted employment data are shown alongside the unadjusted data in Figure 3.7 above. As can be seen in the figure, China's employment grew over much of the sample period. However, such growth decelerated over time. Between 1981-1990, China's employment grew at an average annual rate of 2.7%. As such, employment was clearly an important driver of China's economic growth in these early years. In the 2001-2010 period, average employment growth fell to only 0.5% per year. After 2017, China's employment started to fall and became a drag on economic growth.

3.3.4.2 Sectoral employment

There are some differences in the sectoral breakdown of employment between population census data and annual survey data. In terms of measurement, the sectoral breakdown from population census is not considered superior or inferior to that from annual survey data. We obtain sectoral employment data by applying sectoral employment shares from annual surveys to our adjusted aggregate employment data. Like the vast majority of studies of China's economy, we use annual survey data for sectoral employment breakdown mainly because of its annual nature.

Figure 3.8: Sectoral employment shares

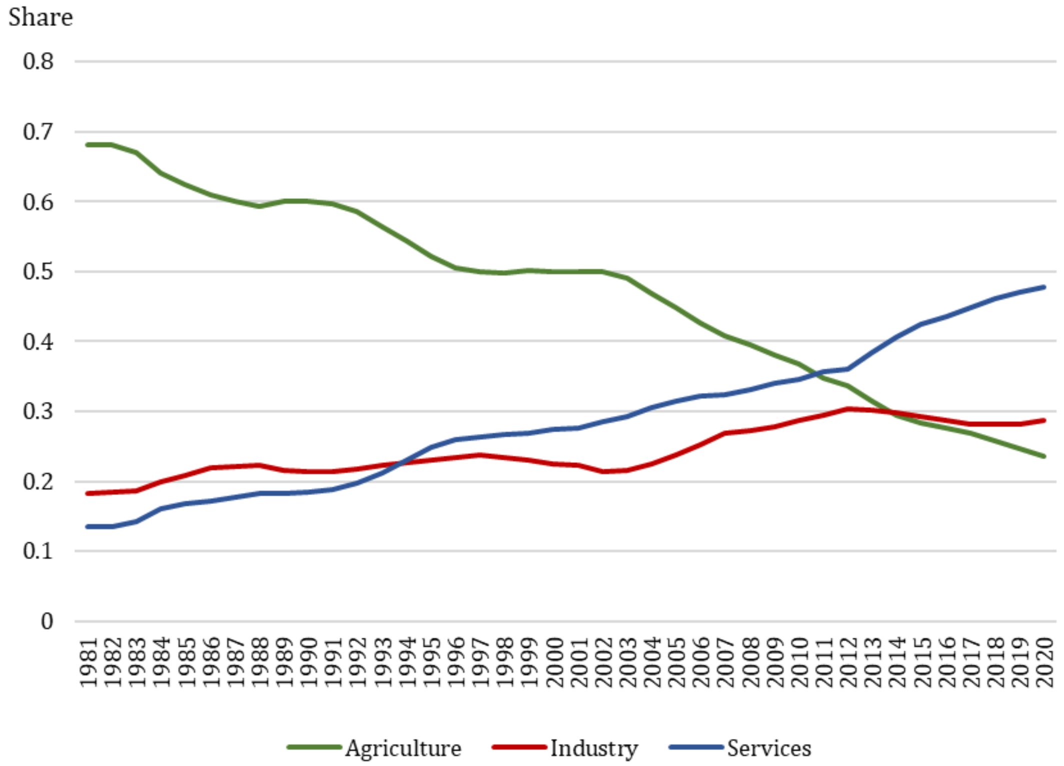


Figure 3.8 above shows the evolutions of China's sectoral employment shares. In 1981, agriculture's share in China's employment was 68%. In comparison, industry's share of 18% and service's share of 14% were very low. Note that in the same year, agriculture

occupied 31% of China's output while industry occupied 46%. These data suggest that productivity in industry was much higher than that in agriculture.

Over time, agricultural employment share fell while industrial and service employment shares rose. Despite the rapid fall, by 2020, 23.6% of China's employment was still in agriculture. There was thus still ample room for further structural change in China. Service employment share started off as the lowest but increased at the fastest rate. In 2020, service employment share reached 47.7% and was the highest among the three. The industrial share saw increases in the 1981-1988 and 2002-2012 periods but stagnated in the rest. By 2020, industrial employment share had increased by about 11% to 28.7%.

3.3.4.3 Employment by sector by age

To investigate the effects of population aging on sectoral labour supply and in turn on structural change and economic growth, we breakdown China's employment data by sector by age. Data for such breakdown is only available from population censuses.

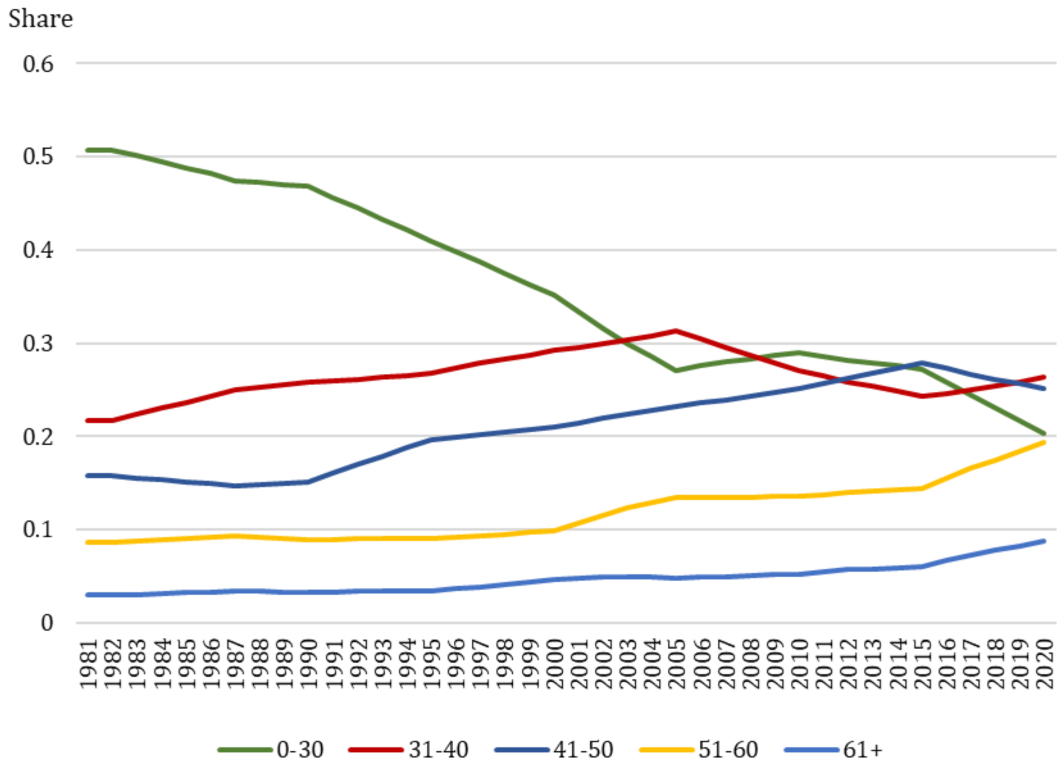
We compile sectoral employment data by 10-year age groups. Data of one-year age groups can be noisy. Grouping data of multiple ages together alleviates the effect of such noises. Later in this thesis, we will use micro-level data to investigate how characteristics such as wages and preferences vary across age groups. Estimating these characteristics for groups of 10 ages rather than groups of one age means we have larger samples and hence more accurate and reliable results for each group. In addition, the patterns across age and time are clearer and more tractable when we have a smaller number of age groups. For brevity, we often use the terms 'age group' and 'age' interchangeably.

For each sector, we obtain the share of each age group in employment from the censuses of 1982, 1987, 1990, 1995, 2000, 2005, 2010, 2015, and 2020 (NBS, 1985-2022). We use interpolation for years without data. We then multiply sectoral employment from the previous section by the age employment shares to obtain sectoral employment by age data.

Figure 3.9 plots the age composition of China's aggregate employment. Between 1981 and 2020, employment share of the 0-30 age group fell rapidly from 51% to 20%. The 31-40 and 41-50 shares increased initially but started to fall after 2005 and 2015, respectively.

The 51-60 and 61+ shares increased from 9% and 3% in 1981 to 19% and 9% in 2020, respectively. The decreases in young workers' shares and increases in older workers' shares mean that China's employment had been aging. The rate of aging accelerated first in the early 2000s and then again in the late 2010s.

Figure 3.9: Shares of age groups in employment



Figures 3.10 to 3.12 below show employment shares of age groups in the three sectors. Employment in all three sectors aged during the sample period, albeit at very different rates. Initially, the differences in age-employment shares across sectors were small. In 1981, the shares of relatively young workers aged between 16 and 40 in the primary, secondary, and tertiary sectors were 72%, 77%, and 69%, respectively. The shares of relatively old workers aged 51 and above started off as 13%, 7%, and 12%. Over time, wide gaps in age composition emerged between sectors. Employment in agriculture aged the most. By 2020, agricultural youth share had fallen to 22% and elderly share had risen to 56%. In comparison, industrial sector aged much less as its youth share fell to 50% and elderly share rose to 22% in 2020. Service sector aged the least, with its youth share falling to 57% and its elderly share reaching 18% in 2020.

Figure 3.10: Shares of age groups in agricultural employment

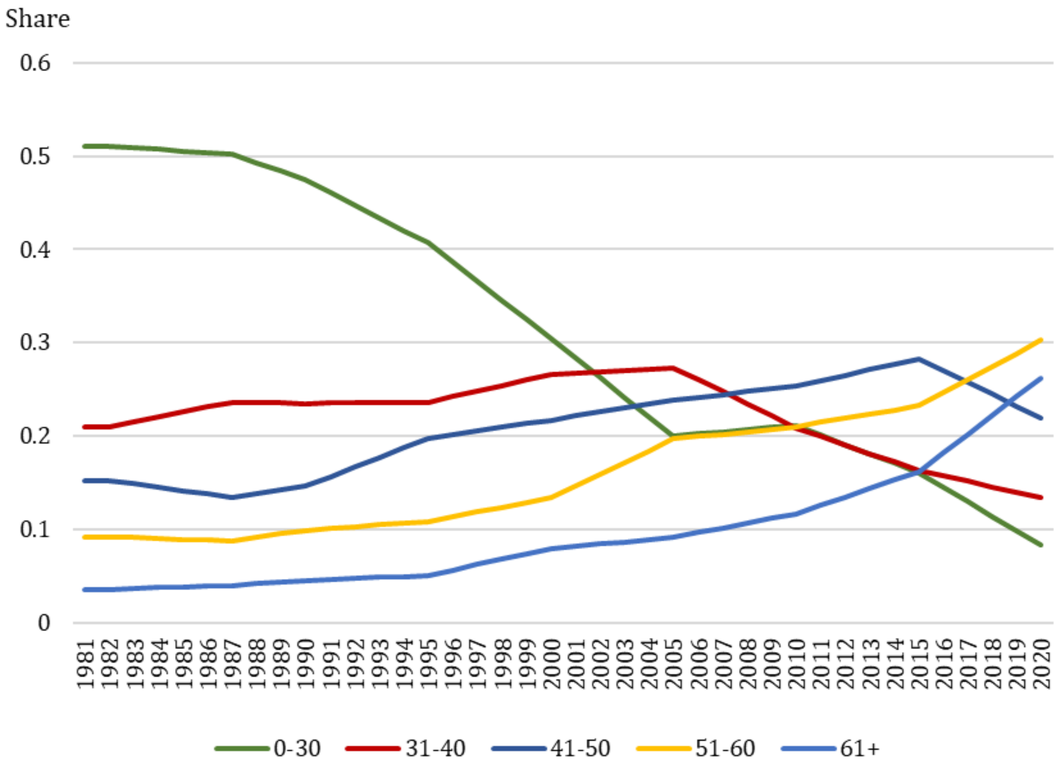


Figure 3.11: Shares of age groups in industrial employment

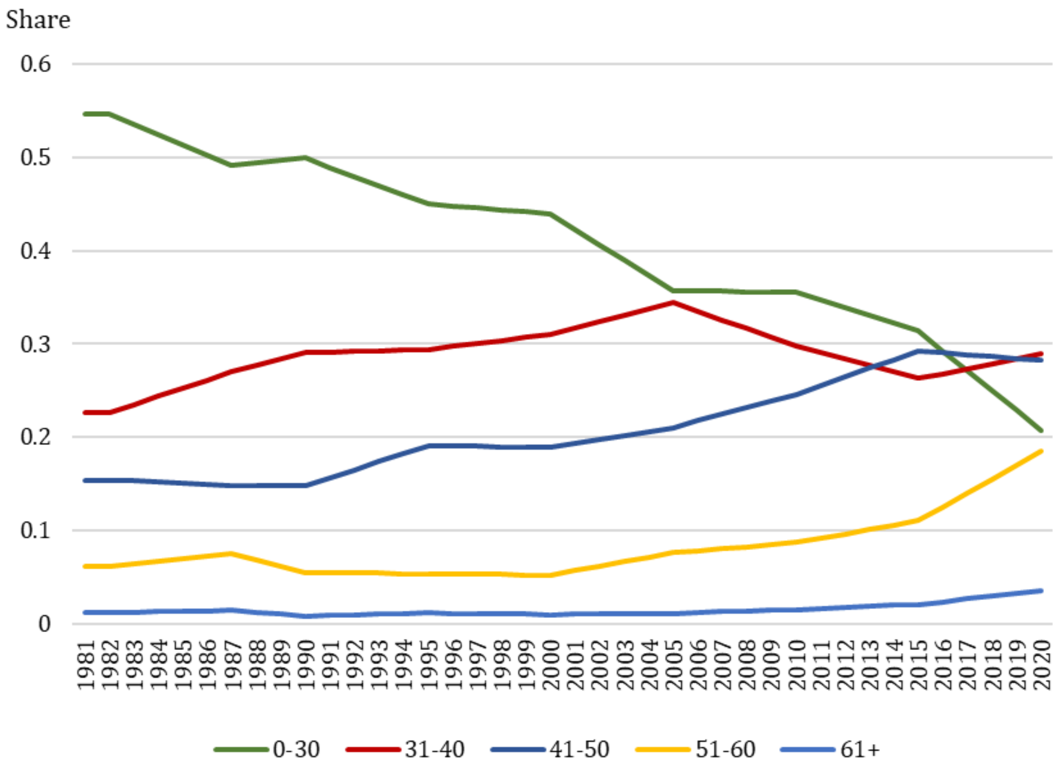
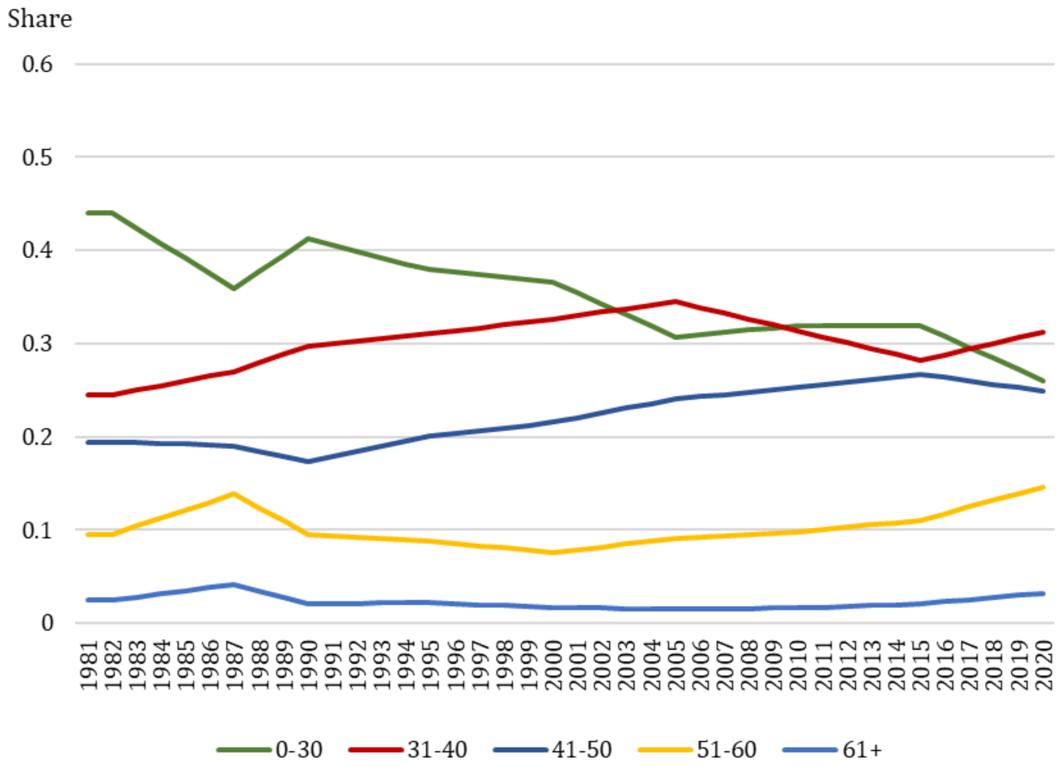


Figure 3.12: Shares of age groups in services employment



3.3.4.4 Wage by age by sector

Labour productivity can vary across age, sector, and time. Population aging can therefore affect structural change and economic growth through the effective labour input channel. This is particularly true given the drastic changes in the age composition of employment across time and across sectors in China. In this section, we compile effective labour input by age by sector data for China. Later in this study, we will use said data to investigate the effects of aging.

Labour productivity can be proxied by wage. To estimate wage by age by sector, we need individual level wage, age, and sector of employment data. Such data are only publicly available from survey projects. There are a number of survey projects that report such data. When choosing among the survey datasets, we consider their sample sizes, representation, and reputation in the literature. Since we will use the datasets for other investigations in later chapters, we need datasets that suit our purposes throughout the thesis. We will use the datasets to construct micro-foundations for our macroeconomic models. As such, we would like to use survey projects that are the most consistent with aggregate data compiled by the NBS. Since we are interested in the long-run patterns of effective labour and consumption, we choose datasets to cover the 1981-2020 period as much as possible. All in all, we choose data from China Household Income Project (CHIP) and China Family Panel Studies (CFPS).

In this section, we start by introducing the household survey datasets. We describe our methodology which accounts for the sampling designs. Finally, we present our measure of age-and-sector-specific per worker effective labour input for China. In Appendix 3.1, we describe our cleaning and processing of the household survey datasets.

3.3.4.4.1 CHIP

We obtained household survey data for 1988, 1995, 2002, and 2007 from China Household Income Project (CHIP). CHIP is a national-wide household survey project conducted jointly by China Institute for Income Distribution of Beijing Normal University, the National Bureau of Statistics (NBS), Chinese Academy of Sciences, and others. The household survey data consist of data not only at household level but also data of individuals within the sampled households. CHIP is the only publicly accessible source of comprehensive and nationally representative household income and expenditure data for the pre-2008 period.

CHIP's samples are subsamples of NBS's household survey samples. Since 1981, the NBS has been conducting urban household surveys and rural household surveys annually, collecting data on household characteristics including demographics, income, and expenditures. NBS's Urban Household Survey (UHS) and rural household survey samples are large and nationally representative but are generally not publicly accessible. Through collaborations with the NBS, CHIP drew a subsample from NBS's UHS sample and a subsample from NBS's rural household survey sample in each of CHIP's survey years. CHIP then surveyed the households in its samples with the assistance of the NBS. Inevitably, many questions regarding incomes and expenditures in CHIP's survey questionnaires are the same as those in NBS's household surveys. In some cases, NBS directly supplied the relevant answers to CHIP. In the other cases, households had to show CHIP the data they supplied to the NBS. Since NBS exerts great efforts working with the households to ensure the reliability and accuracy of its household survey data, the collaboration with NBS is a feature of strength of CHIP.

CHIP has a multi-stage sampling design. CHIP divides China into two areas: rural and urban. Each area is divided into four regions: west, central, coastal, and special municipalities. Within each region, a representative set of provinces is selected. Within each province, a set of households is selected through a multi-stage process designed to ensure representation.

In each of the survey years, CHIP collected data on province, age, industry of work, and income of each individual within each household. In Appendix 3.1, we describe our cleaning and processing of data for these variables.

Like the NBS's household surveys, CHIP surveyed rural and urban areas separately following slightly different sampling designs and survey methods. To prevent these differences from adversely affecting our results, we estimate weighted average labour income by age by sector or sectoral age-income profiles separately for rural and urban areas. We then estimate national profiles as weighted averages of profiles from the two areas. The weights are area-and-sector-specific employment shares.

Among household survey projects, it is common for strata sample sizes not to be proportional to their populations. In such cases, sampling weights are needed to ensure the representativeness of the samples. CHIP's sample sizes from the four regions are not proportional to their shares in the national population. Furthermore, within each region, the sample sizes from selected provinces are not proportional to their shares in the region population. We therefore construct weights at the provincial level following CHIP's instructions (Song et al, 2013) as:

$$weight_A = \frac{Province\ A's\ population}{Province\ A's\ sample\ size} \times \\ \times \frac{Population\ of\ region\ that\ contains\ province\ A}{Population\ of\ selected\ provinces\ in\ the\ region\ that\ contains\ province\ A}$$

In essence, the weight reflects the number of people in the population that is represented by each person in the sample. To construct the weights, we use sample sizes from CHIP and population data at various levels from NBS's population censuses and China Population and Employment Statistical Yearbooks (NBS, 1988-2020). The constructed weights are used in the estimation of average labour income by sector by age.

3.3.4.4.2 CFPS

We obtained household survey data for 2010, 2012, 2014, 2016, and 2018 from China Family Panel Studies (CFPS). CFPS is a nationally representative survey project conducted by the Institute of Social Science Survey at Peking University. In 2010, CFPS surveyed a baseline sample of households. Since then, the household members have been tracked and surveyed every 2 years. Like CHIP, CFPS also collects and provides both household and individual datasets. In this chapter, we use the individual dataset which contains age, industry of work, and income data for all individuals within the sampled households.

CFPS has a multi-stage complex sampling design that involves both stratification and clustering. The sampling design divides China into 6 strata: 5 large provinces and 1 set of small provinces. From each stratum, a set of counties is selected. Within each county, a set of communities is selected. Within each community, a set of households is selected.

For every wave of its data, CFPS provides cross-sectional weights designed to account for misrepresentation, non-responses, and post-stratification adjustment. We use these weights directly in our computation of average labour income by sector by age.

3.3.4.4.3 Average wage by sector by age and effective labour

Using household survey data from each of the survey years, we compute weighted average wage by sector by age group. The numbers of workers aged below 21 and workers aged above 60 are small so we group them together respectively with the 21-30 group and 51-60 group. Since the legal minimum working age in China is 16, we shall refer to the under-30 age group as the 16-30 age group.

We compute effective labour input of an age g worker in sector i as the ratio of age g average wage in i to young workers' (16-30 age group's) average wage in i:

$$l_{git} = \frac{w_{git}}{w_{1it}}$$

In the equation above, w_{git} refers to the average wage of age group g in sector i in period t. This effective labour measure is in units of young workers. Since wage is an indicator of productivity, l_{git} is also a measure of the relative productivity of age g workers to young workers. We interpolated the relative productivities to obtain continuous time series between 1981 and 2020.

Figures 3.13 to 3.15 show effective labour per worker by age group in the primary, secondary, and tertiary sectors, respectively. In industry and services, older workers were initially more productive than young workers aged under 30, as their relative productivities exceeded ones. Over time, the relative wages of older workers fell. In agriculture, relative wages of older workers first surged above that of young workers but then also started to fall sharply after 1995.

The fall in relative wages of older employees was likely due to drastic changes in labour allocation and wage determination in China. Initially, employment and wages were heavily controlled by the state. Workers were assigned to work units where they typically stayed for life. Wages at that time depended heavily on seniority. In the 1990s, labour allocation and wage determination were marketized rapidly. Resultantly, wages became less dependent on seniority and more dependent on other variable such as education (Gustafsson and Wan, 2020).

In the 2010s, the 41+ age groups became less productive than younger age groups and increasingly so over time. The relative wage shortfalls of the 41+ age groups were the largest in agriculture, followed by those in industry, and then by those in services. In 2020, the 51+ age group was only about 60% as productive as the 16-30 age group in agriculture. The same figures in industry and services were about 70% and 90%, respectively. The 31-40 age group generally maintained their productivity advantage over the 16-30 group and emerged as the most productive group in the late 2010s.

3.3.4.5 Population by age

In this section, we describe our compilation of data and projections for China's population by age. Population by age data is fundamental to our study of population aging and will be used throughout our project. Later in this chapter, we will use population by age data to construct labour input under various scenarios, which will enable us to investigate the effect of aging on labour input and hence economic growth.

Figure 3.13: Age specific effective labour per worker in agriculture

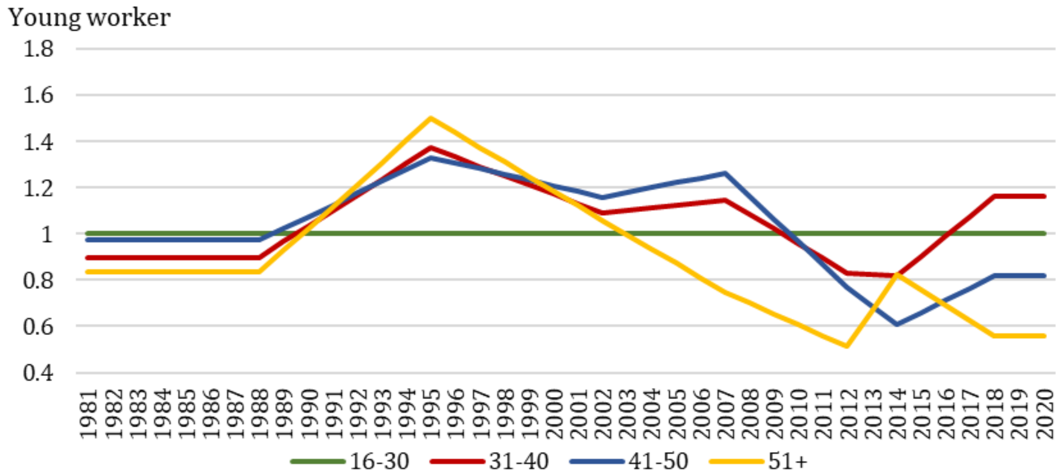


Figure 3.14: Age specific effective labour per worker in industry

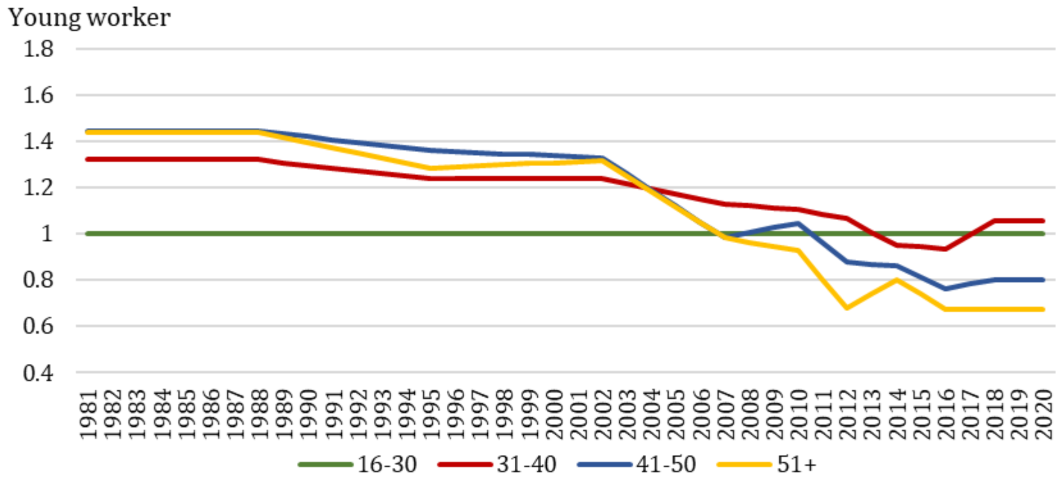
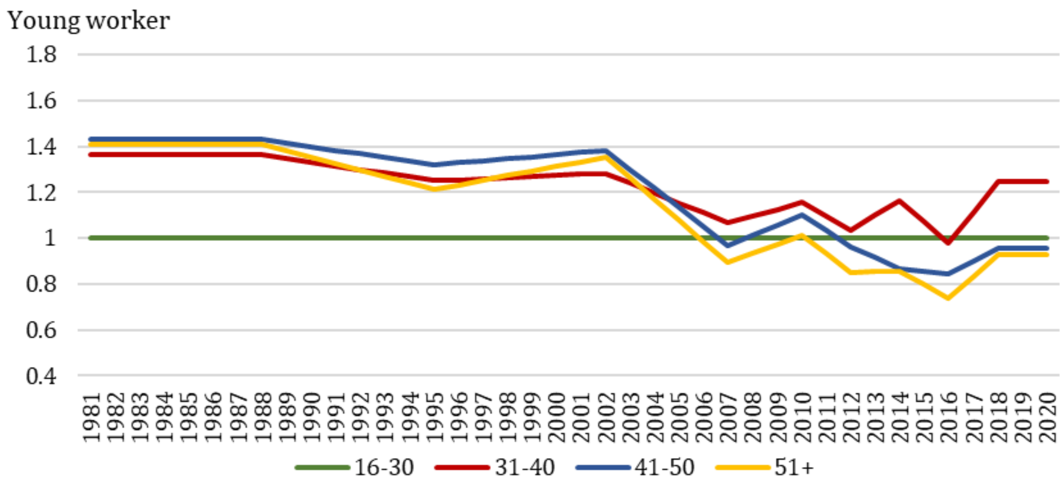


Figure 3.15: Age specific effective labour per worker in services



China's official population by age data are derived from population censuses and from annual surveys. We obtained annual survey data from China Population and Employment Statistical Yearbooks (NBS, 1988-2020). Data from the censuses and data from the yearbooks are consistent with each other. However, we find major inconsistencies in China's official population by age data across time. In particular, population of cohorts increase over time, suggesting survival probabilities exceed ones, which cannot be true in reality. This issue is highly prevalent in the data.

If there is underreporting of some age groups and overreporting of others, grouping data of multiple ages together could help by averaging out the noises. Table 3.1 shows the survival probabilities of 10-year age groups over the 1981-2020 period, with incidences of larger-than-one survival probabilities highlighted in yellow. As can be seen in the table, abnormal survival probabilities remain prevalent. They occur even in recent years, at which point China had well established statistical systems. Furthermore, the vast majority of the abnormal survival probabilities are substantially above one. These raise serious questions about the accuracy and reliability of China's official population by age data.

There is a lively literature, including the studies of Qiao and Li (1995), Zhang and Cui (2003), Goodkind (2004), and Tao and Zhang (2013), that is dedicated to the issue. The literature points to the underreporting of births and children and the overreporting of young working age people as causes of the inconsistencies in China's population by age data.

The underreporting of births is largely attributable to China's population control policies. After the surge in births in the 1960s, the Chinese government implemented a series of population control policies, including the One Child Policy in 1980. Compliance with these policies was rewarded while incompliance was punished. In response, some families concealed their children and some local officials manipulated data. These unreported children would eventually be registered and appear in the statistics when they started working and got married, causing recorded cohort population to rise over time.

The overreporting of young workers is attributable to mismeasurement of floating population. Floating population refer to people who live and or work in areas that are different to their household registration areas. The overwhelming majority of these people are young rural household registration holders who work in urban areas. Many of them move back and forth between rural and urban areas to take advantage of job opportunities. According to the 2020 census, there were 376 million floating population in China in 2020. The massive floating population brings about significant double counting issues. In particular, the floating population can be counted once at the address of their household registration and then a second time at their urban residence or place of work. Such errors were intensified by the introduction of systematic recording of floating people in both addresses in the 2000s.

Survival probabilities are vital for projecting future population by age and for models of population aging. The aforementioned data issue therefore means we cannot use China's official population by age data without making adjustments. However, adjusting the data would involve a massive amount of data work which are beyond the limit of our study. We therefore seek to use existing alternatives to official data. Some studies in the literature show their adjusted data. However, these data are lacking in time coverage, reliability, and comprehensiveness. All in all, we decide to use population by age data and projection from United Nations' (UN) World Population Prospects (WPP) 2022 (World Population Prospects, 2024). UNWPP adjusted China's historical population by age data to address the issue and to ensure consistency with the rest of official Chinese data. UNWPP produces projections under numerous scenarios. In this thesis, we use UNWPP 2022's projected population for the medium scenario.

Figure 3.16 shows China's population data from the WPP. We can see that China's population increased from about 1.00 billion in 1981 to 1.42 billion in 2020. The increase took place at a decreasing rate. This can be seen more clearly in Figure 3.17, which shows that China's annual population growth rate fell from 1.6% in 1981 to 0.2% in 2020.

Figure 3.18 and 3.19 show China's projected population and population growth rate from UNWPP 2022. As mentioned earlier, we use the medium variant of UNWPP 2022's population projections. Due to falling birth rate, China's population is projected to fall from 1.43 billion in 2021 to 0.77 billion in 2100. The rate of reduction increases over time, reaching -0.6% in 2050 and -1.2% in 2100. Such rapid reductions in population, if realised, will have large impacts on China's economy.

Table 3.1: Survival rates of 10-year age groups

	Survival probability between age groups							
Year	0-10 to 11-20	11-20 to 21-30	21-30 to 31-40	31-40 to 41-50	41-50 to 51-60	51-60 to 61-70	61-70 to 71-80	71-80 to 81+
1991	0.91	0.95	1.00	0.96	0.94	0.87	0.64	0.34
1992	0.88	0.97	0.99	0.97	0.95	0.87	0.64	0.35
1993	0.88	0.99	1.00	0.98	0.97	0.87	0.63	0.35
1994	0.88	0.98	0.99	0.99	0.96	0.88	0.64	0.35
1995	0.85	0.95	**1.01**	**1.04**	0.99	0.90	0.66	0.36
1996	0.85	0.95	**1.01**	**1.04**	1.00	0.91	0.68	0.37
1997	0.87	0.93	**1.02**	**1.03**	**1.03**	0.91	0.67	0.38
1998	0.88	0.88	**1.04**	**1.09**	**1.05**	0.94	0.70	0.38
1999	0.89	0.94	**1.00**	**1.05**	**1.03**	0.94	0.69	0.37
2000	0.95	1.00	**1.03**	0.98	0.98	0.87	0.66	0.38
2001	0.89	0.97	**1.03**	**1.06**	**1.01**	0.93	0.68	0.37
2002	0.92	0.93	**1.05**	**1.04**	**1.05**	0.93	0.70	0.40
2003	0.92	0.92	**1.05**	**1.02**	**1.06**	0.94	0.71	0.41
2004	0.91	0.90	**1.03**	**1.08**	**1.08**	0.95	0.71	0.41
2005	0.88	0.89	**1.04**	**1.06**	**1.05**	0.95	0.73	0.43
2006	0.93	0.87	**1.00**	**1.07**	**1.07**	0.95	0.72	0.42
2007	0.92	0.88	**1.00**	**1.06**	**1.07**	0.94	0.72	0.42
2008	0.93	0.88	**1.00**	**1.05**	**1.07**	0.94	0.71	0.43
2009	0.92	0.88	**1.02**	**1.05**	**1.05**	0.94	0.72	0.43
2010	**1.00**	0.98	0.99	0.96	0.94	0.89	0.71	0.46
2011	0.97	**1.05**	**1.06**	0.96	0.90	0.85	0.66	0.43
2012	0.98	**1.04**	**1.09**	0.95	0.89	0.83	0.66	0.42
2013	0.96	**1.06**	**1.11**	0.96	0.89	0.82	0.64	0.43
2014	0.95	**1.06**	**1.12**	0.97	0.89	0.81	0.65	0.44
2015	0.90	**1.08**	**1.18**	1.00	0.89	0.80	0.64	0.42
2016	0.91	**1.06**	**1.19**	**1.02**	0.88	0.78	0.64	0.43
2017	0.92	**1.06**	**1.19**	**1.02**	0.88	0.78	0.65	0.44
2018	0.93	**1.04**	**1.19**	**1.04**	0.89	0.78	0.66	0.44
2019	0.94	**1.05**	**1.17**	**1.03**	0.90	0.79	0.66	0.45
2020	0.96	0.94	0.97	0.96	0.96	0.91	0.79	0.58

Figure 3.16: China's population

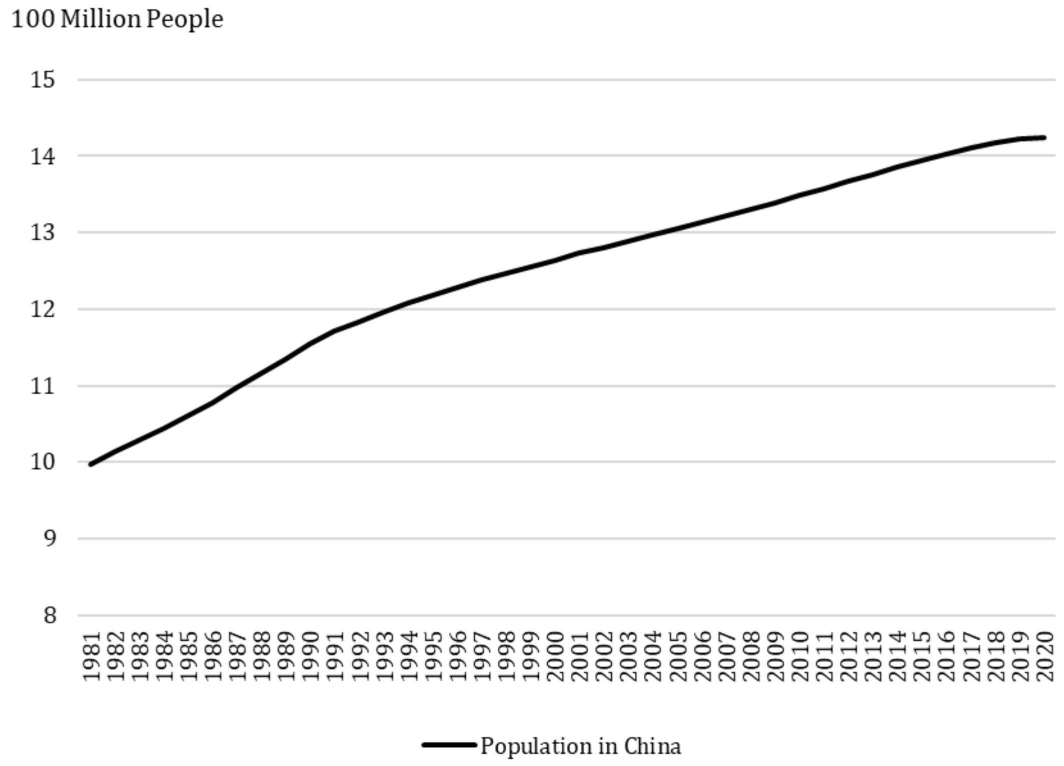


Figure 3.17: China's population growth rate

Figure 3.18: China's projected population

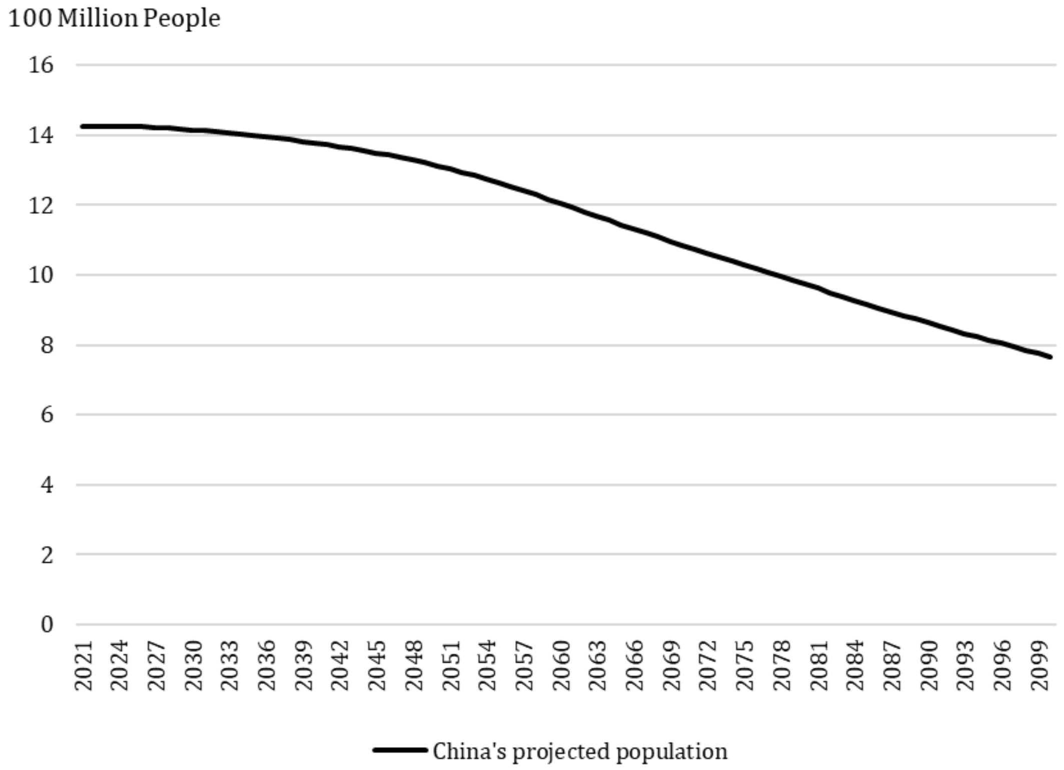


Figure 3.19: China's projected population growth

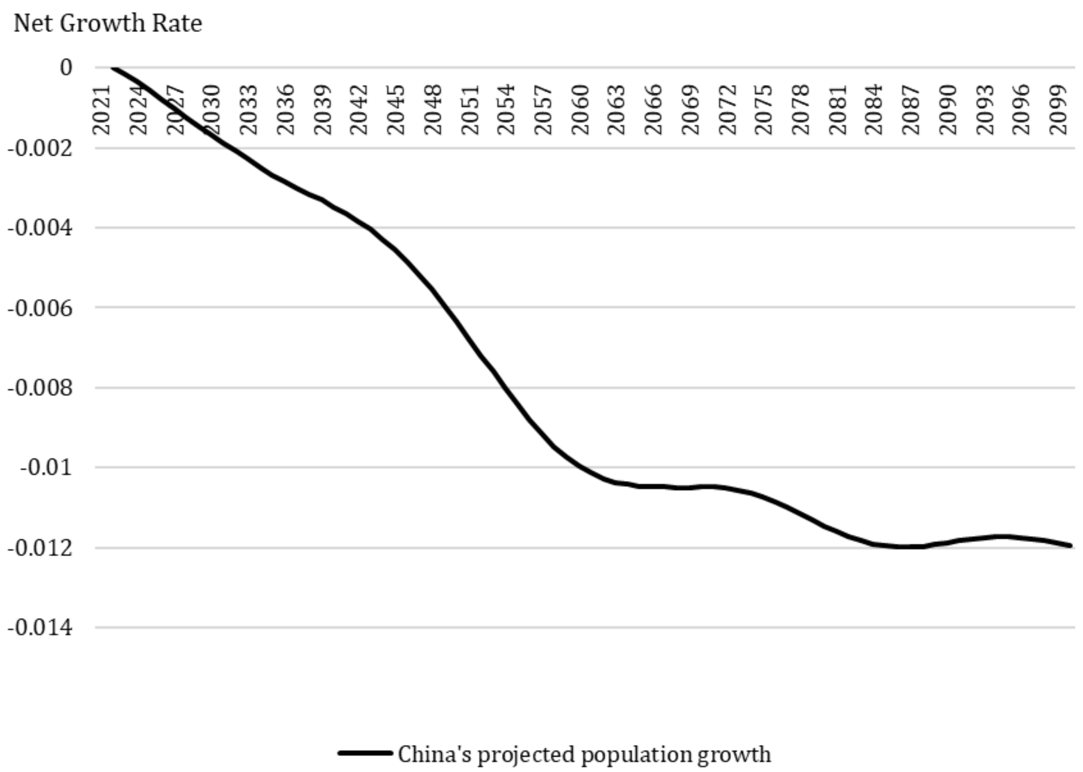


Figure 3.20 shows the shares of 20-year age groups in China's population. As can be seen in the figure, falling shares of young population and rising shares of old population mean China's population aged rapidly. Between 1981 and 2020, the shares of 41-60 and 61+ age groups increased from 15.8% and 6.4% to 29.4% and 17.0%, respectively. Over the same period, the population shares of 0-20 and 21-40 age groups fell respectively from 48.5% and 29.2% to 24.7% and 28.9%. Initially, due to the entry of baby boom generations of the 1950s and 1960s, the share of 21-40 age group increased. As the effects of plummeting births in the 1970s and 1980s fed through, the 21-40 age group's share started to decrease in 2003. As more young age groups started to shrink and as old age groups continued to expand, China's population aging accelerated.

Figure 3.20: Shares of 20-year age groups in China's population

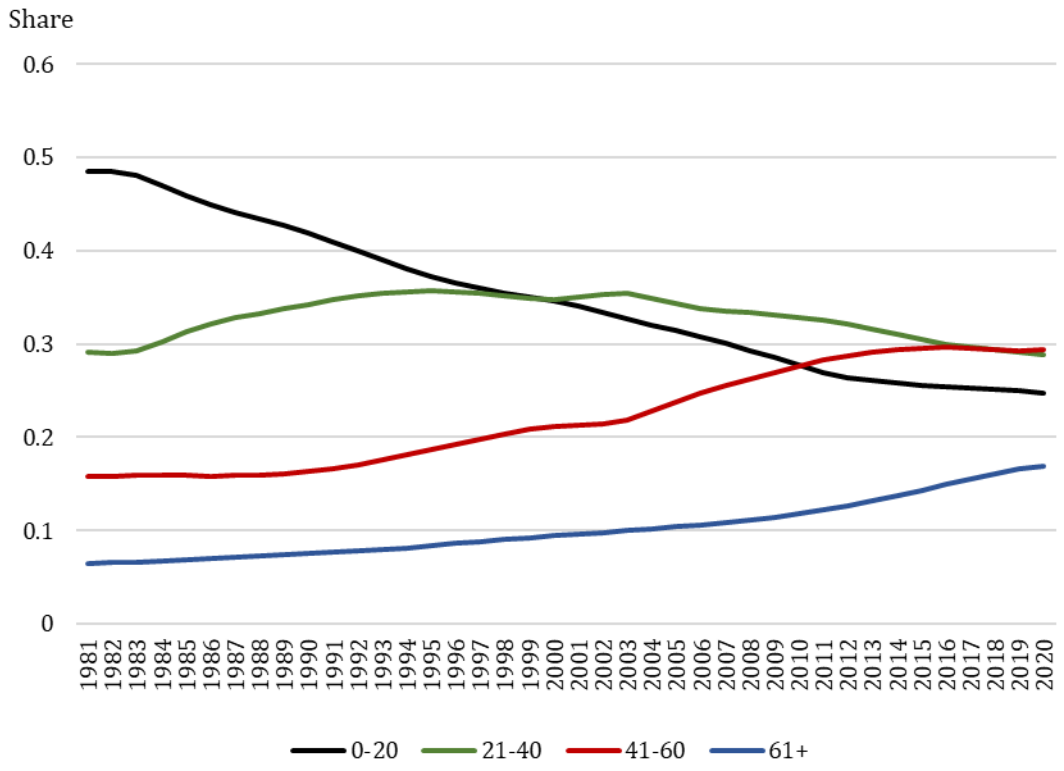
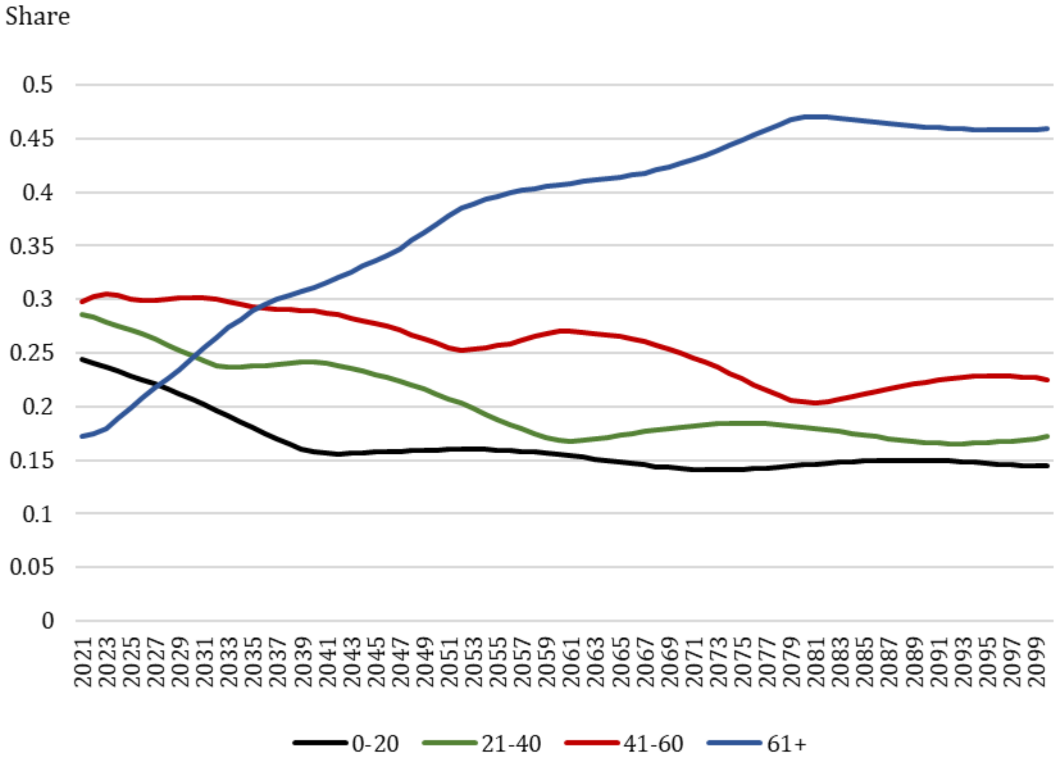


Figure 3.21 shows UNWPP 2022's projected age population shares. According to the projection, the share of elderly population aged 61 and above will rise, reaching a maximum of 47% in 2081, after which it will fall. Conversely, the shares of younger age groups aged between 0 and 60 are projected to fall till around 2080, after which they are projected to either remain stable or increase. By definition, these mean China's population aging is expected to continue till the early 2080s and then reverse.

Figure 3.21: Shares of 20-year age groups in China's projected population



3.3.5 Factor income shares

According to the NBS, GDP by income approach breaks China's GDP into: compensation of employees, depreciation of fixed assets, net taxes on production, and net operating surplus. We obtain labour's share in national income as:

$$Labour\ Income\ Share = \frac{Compensation\ of\ Employees}{GDP - Net\ Taxes\ on\ Production}$$

We obtain capital income share as:

$$Capital\ Income\ Share = \frac{Fixed\ Asset\ Depreciation + Net\ Operating\ Surplus}{GDP - Net\ Taxes\ on\ Production}$$

Our sectoral income approach GDP data are obtained from a number of NBS publications. From Hsueh and Li (1999), we obtain data between 1978 and 1995. From Data of GDP of China 1952-2004 (NBS, 2007), we obtain data between 1995 and 2004. Data from the two aforementioned sources are provincial level data. We aggregate across provinces to obtain data at the national level, using which we compute factor income shares. For the post-2004 period, we obtain data for 2005, 2007, 2010, 2012, 2015, 2017, and 2020 from

Input-Output Tables of China (NBS, 1991-2022). We compute factor income shares for these years and use interpolation to fill the missing data in between.

Figure 3.22 below shows labour income shares in China changed little over time. Industrial and service labour income shares fluctuated around constant trend values. Labour income share in agriculture shifted to a higher trend value in the late 2000s but the shift was small. These patterns mean that the assumptions of constant factor income shares and Cobb-Douglas production function and are justifiable. Taking long term averages, we obtain the constant labour income shares. Table 3.2 shows the constant factor income shares that will be used in this study.

Figure 3.22: Labour income shares

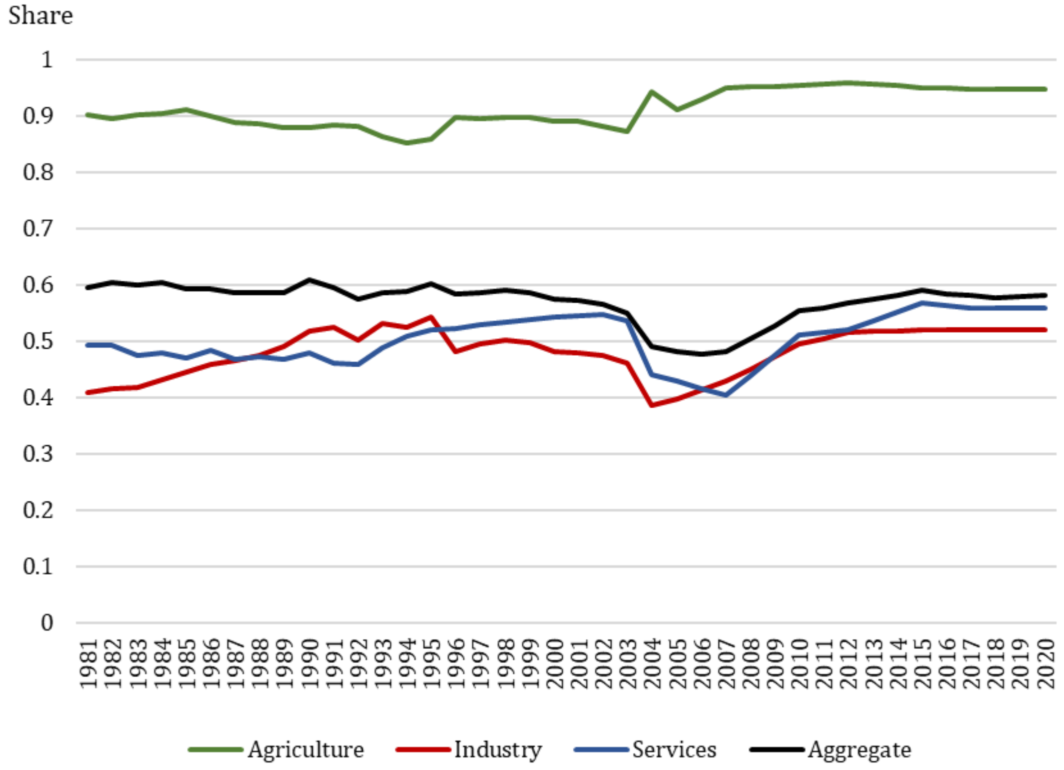


Table 3.2: Long-term average factor income shares

	Aggregate	Agriculture	Industry	Services
Labour income share	0.57	0.91	0.48	0.50
Capital income share	0.43	0.09	0.52	0.50

One feature that stands out from the observations is the overwhelming labour intensity of China's agricultural sector. A number of studies have raised doubts about China's income approach GDP data. However, their evidence and alternative data are yet to convince the literature.

China's high agricultural labour income share can partially be explained by several characteristics of China's economy. Although China's land area is large, only a small fraction of it is arable. According to the World Bank, arable land constituted 12% of China's total land area on average between 1961 and 2022 (World Bank Open Data, 2025). At the same time, China has hundreds of millions of farmers. As such, China's agriculture has evolved over a long history to utilize the relative abundance of labour. Land means security for farmers as it provides food and shelter. Historically, the ownership of land has been a major source of tension in Chinese society. One way or another, land ends up being distributed across the vast number of farmers. This means land of each farmer is small in scale, making the use of capital less cost-effective.

3.4 Growth accounting results

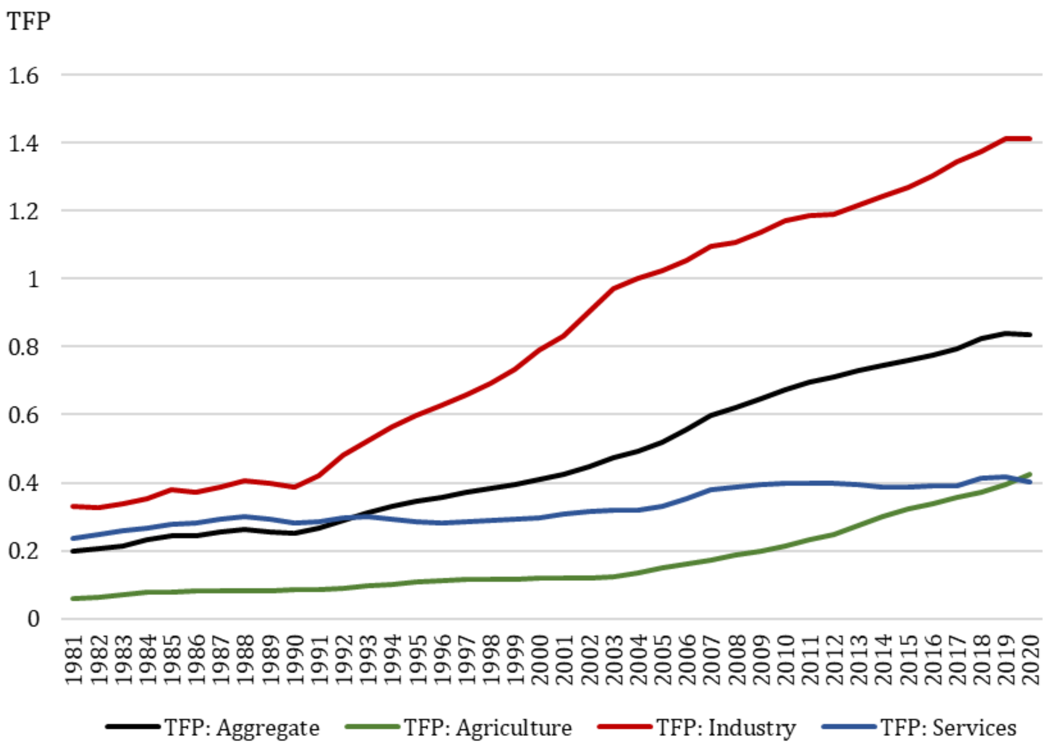
In this section, we present our growth accounting results for China. We first present our results for China's Total Factor Productivity (TFP) at aggregate and sectoral levels. We then compare the contributions of factor inputs and TFP to China's sectoral and aggregate output growths. Finally, we analyse the contribution of structural change to China's economic growth.

Our baseline results are computed using capital stock as the measure for capital input and employment as the measure for labour input. In this section, we compare the baseline results with two variants of results, referred to as variant 2 and variant 3. Variant 2 uses capital services data that we constructed in Chapter 2 as capital input. Variant 3 uses Volume Index of Capital Services (VICS) from Chapter 2 as capital input. The comparisons in this section focus on the variant TFP levels and structural change contributions which are found to be substantially different to their baseline counterparts. The variant TFP growth and contribution results are similar to the baseline. As such, these results are shown in Appendix 3.2 for brevity.

3.4.1 TFP results

Figures 3.23 and 3.24 present respectively China's TFP levels and TFP Growths (TFPGs) in our baseline. Table 3.3 shows baseline TFP growths by period. In the baseline, capital input is measured by capital stock and labour input is measured by employment.

Figure 3.23: Baseline TFP level results



Between 1981 and 2020, China's TFP grew at an annual average rate of 3.8%. Considering China's average real GDP growth rate of 9% over said period, our results support the view that TFP growth played an important role in China's economic growth. Although factor accumulation was the more important driver of China's growth, its importance relative to TFP growth was not overwhelming.

Table 3.3 shows TFP growths by 10-year periods. Between 1981 and 1990, China had a moderate TFP growth of 3%. In this period, China underwent early stages of marketisation and opening up reforms while battling macroeconomic and social instability. In the 1991-2000 period, due to rapid institutional reform and privatisation, TFP growth surged, averaging at an annual rate of 4.9%. In the wake of the WTO membership, China's trade expanded drastically after 2001. This, together with policies that promoted urbanisation and technological progress, gave rise to an impressive average annual TFP growth of 5% in the 2001-2010 period. In response to the Great Recession in the late 2000s, the Chinese government adopted massive stimulus packages. In the 2010s, the long-term costs of these packages emerged in the forms of debt, inefficiency, and excess capacity. The 2010s was also a challenging time for China's net exports as international demand fell due to the aftermath of the Great Recession and due to geopolitical tension. These were the backdrops behind China's relatively low average TFP growth rate of 2.1% between 2011 and 2020.

Figure 3.24: Baseline TFP Growth results

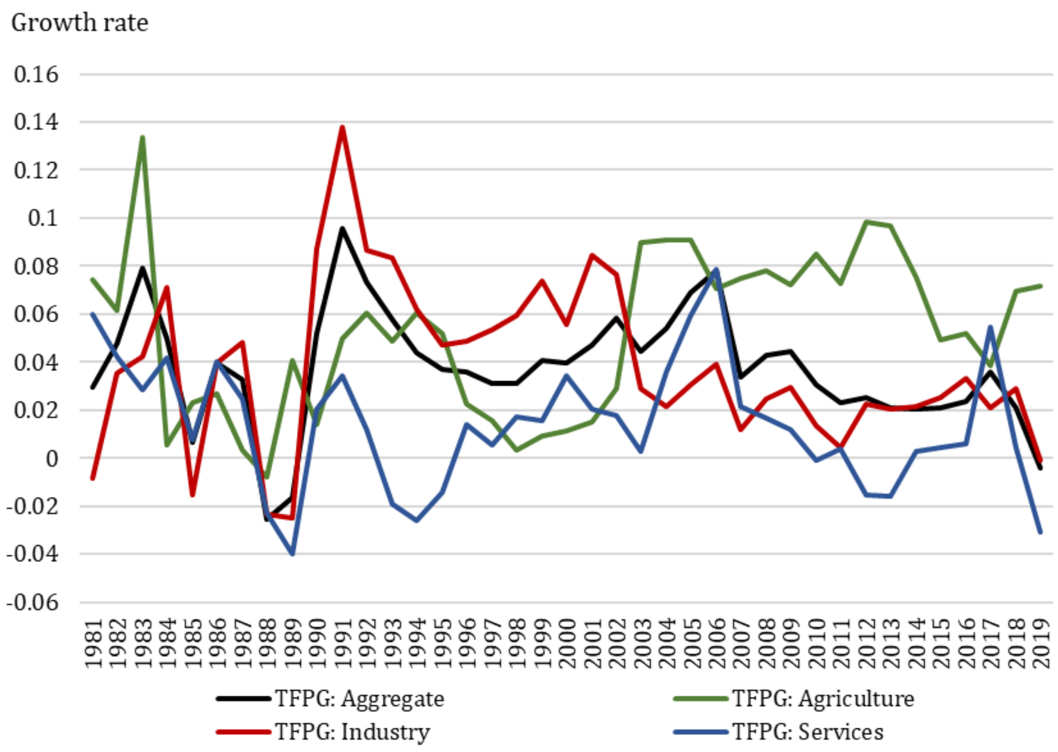


Table 3.3: Average annual TFPG (Baseline)

Baseline: K=capital stock, L=employment				
	Aggregate	Agriculture	Industry	Services
1981-2020	0.038	0.052	0.038	0.014
1981-1990	0.030	0.038	0.025	0.020
1991-2000	0.049	0.033	0.071	0.007
2001-2010	0.050	0.070	0.036	0.026
2011-2020	0.021	0.069	0.020	0.002

At the sectoral level, Figure 3.23 shows that industrial TFP was higher than service TFP, which was higher than agricultural TFP. Therefore, structural change from agriculture to industry and services had positive impacts on China's economic growth. In 1981, industrial TFP and service TFP were respectively 5.5 and 3.9 times the size of agricultural TFP. Over time, TFP in all three sectors grew. Between 1981 and 2020, agriculture had the highest average TFP growth rate of 5.2%, industry had a moderate rate of 3.8%, and services had the lowest rate of 1.4%. Resultantly, the gaps between agricultural TFP and the rest shrunk. By 2020, industrial TFP and service TFP were respectively 3.3 and 0.95 times the size of agricultural TFP. The low TFP growth in services deserves policymakers' attention. If service TFP continues to fall behind the others, China's rapid transition towards services can actually dampen its economic growth.

Figure 3.25: Variant 2 TFP level results

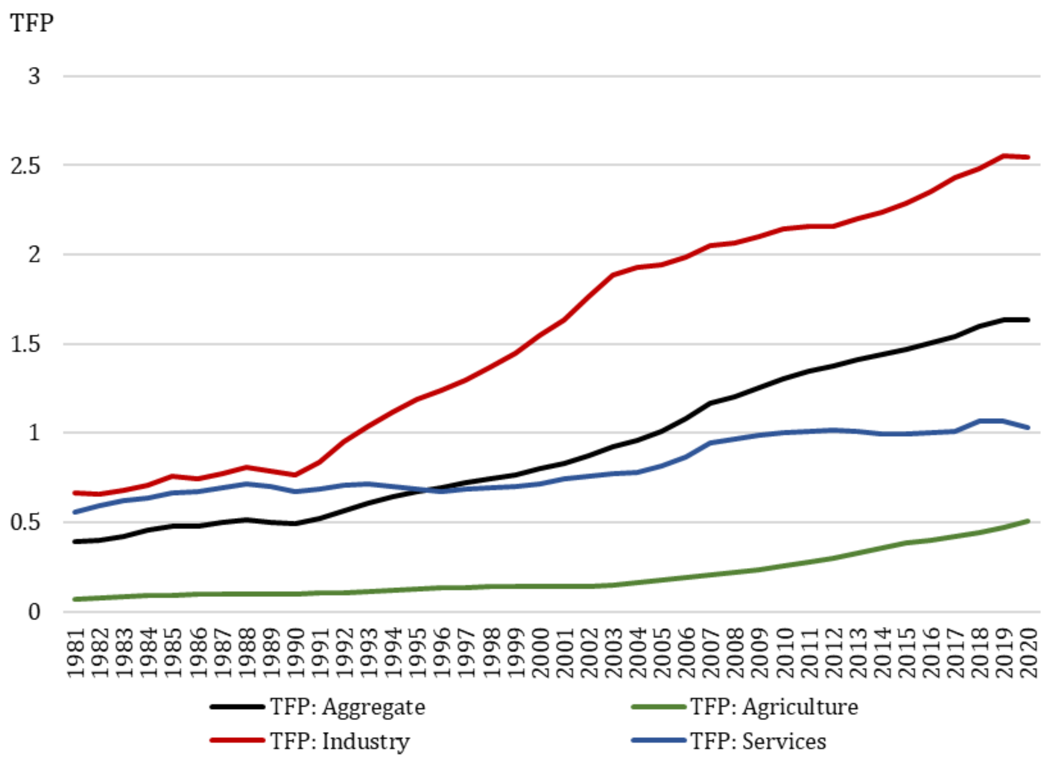


Figure 3.25 above shows variant 2 TFP level results which are computed with capital services as capital input. The figure shows that variant 2 relative TFP levels between sectors are different to their baseline counterparts. Variant 2 results show that in 1981, industrial TFP and service TFP were respectively 9.3 and 7.9 time the size of agricultural TFP. These numbers are much larger than their baseline counterparts which are 5.5 and 3.9, respectively. Over time, sectoral relative TFPs fell as agricultural TFP grew relative to

the other two. However, due to the large initial levels, variant 2 relative TFP of industry to agriculture and relative TFP of services to agriculture remained large in 2020, reaching 5.1 and 2.1, respectively. Variant 2 results therefore suggest that structural change from agriculture to services still had potential to grow China's economy. However, if service TFP growth continues to lag behind agricultural TFP growth, service TFP will at some point be overtaken by agricultural TFP.

3.4.2 Growth contributions of factor inputs and TFP

Figures 3.26 to 3.29 plot annual contributions of capital, labour, and TFP to output growth in the aggregate economy and in the three sectors. Table 3.4 shows the average shares of the contributions in aggregate and sectoral growths. Our results show that between 1981 and 2020, 38% of China's economic growth was due to TFP growth. This supports the view that TFP growth played an important role in China's growth. However, the biggest driver of China's economic growth was capital accumulation, which on average accounted for 56% of aggregate growth. Labour input growth had the least contribution, which averaged at only 6% of aggregate growth. This was not always the case. Figure 3.26 shows that in the early years, labour's contribution share was much higher, at about 20%. Over time, as there was less and less spare labour that could be utilised, labour's contribution fell. In the late 2010s, labour's contribution turned negative as China's employment started to fall.

Figure 3.26 also shows that TFP's contribution was more volatile compared to the factor inputs' contributions. In fact, TFP's contribution was the main source of volatility in China's economic growth over the sample period. Between 1981 and 2007, the average contribution of TFPG was similar to that of capital accumulation. A persistent and large gap between the contributions of TFPG and capital accumulation only opened up after the 2007-2008 crisis.

The contribution shares varied across sectors. Between 1981 and 2020, factor accumulation was the main driver of economic growth in industry and services. In services, the average capital contribution share was an overwhelming 71%. The service sector also had the highest average labour contribution share of 23%. These together mean 94% of service sector's growth between 1981 and 2020 was driven by factor input growths, leaving only 6% for the contribution of TFP growth. In industry, contribution shares of capital, labour, and TFP averaged at 58%, 9%, and 33%, respectively. These are not far from the average contribution shares in the aggregate economy. Growth in agriculture, unlike the others, was driven primarily by TFP growth. As can be seen in Figure 3.27, in agriculture, labour contribution was mostly negative and capital contribution was consistently small, leaving TFP as the dominant driver of growth. The observed variations in factor input contribution shares across sectors reflect the reallocation of factor inputs from agriculture to industry and services.

Table 3.4: Average shares of contributions to growth (Baseline)

Baseline: K=capital stock, L=employment				
	Aggregate	Agriculture	Industry	Services
K	0.56	0.14	0.58	0.71
L	0.06	-0.20	0.09	0.23
A	0.38	1.06	0.33	0.06

Figure 3.26: Contributions to aggregate economic growth (Baseline)

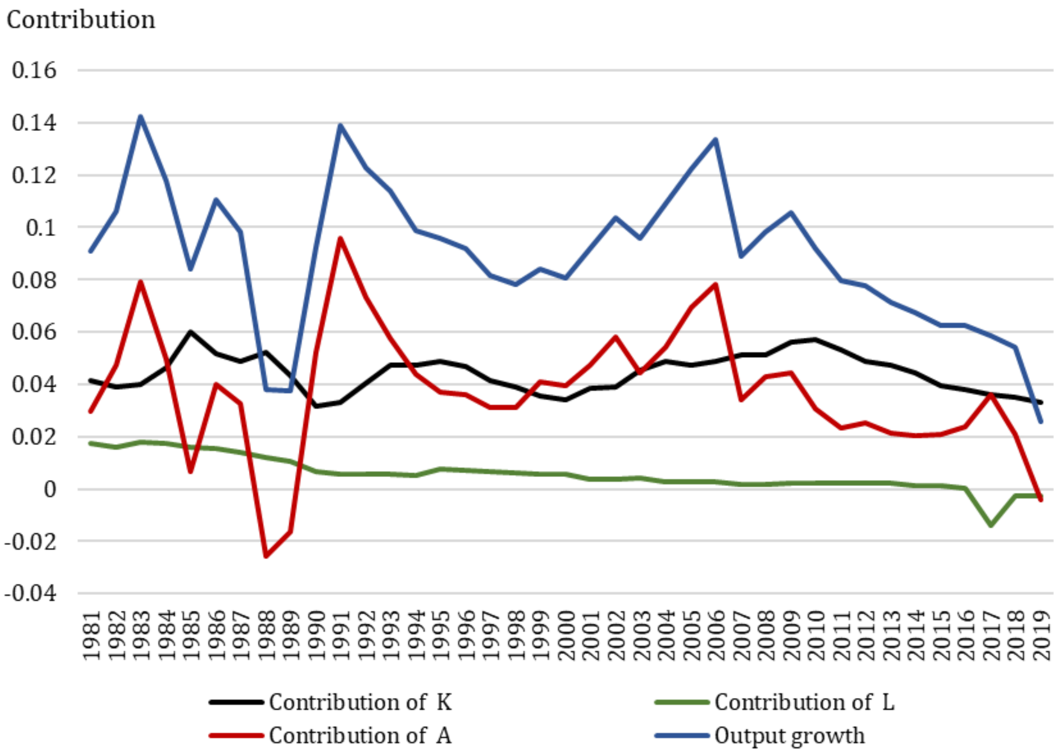


Figure 3.27: Contributions to agricultural economic growth (Baseline)

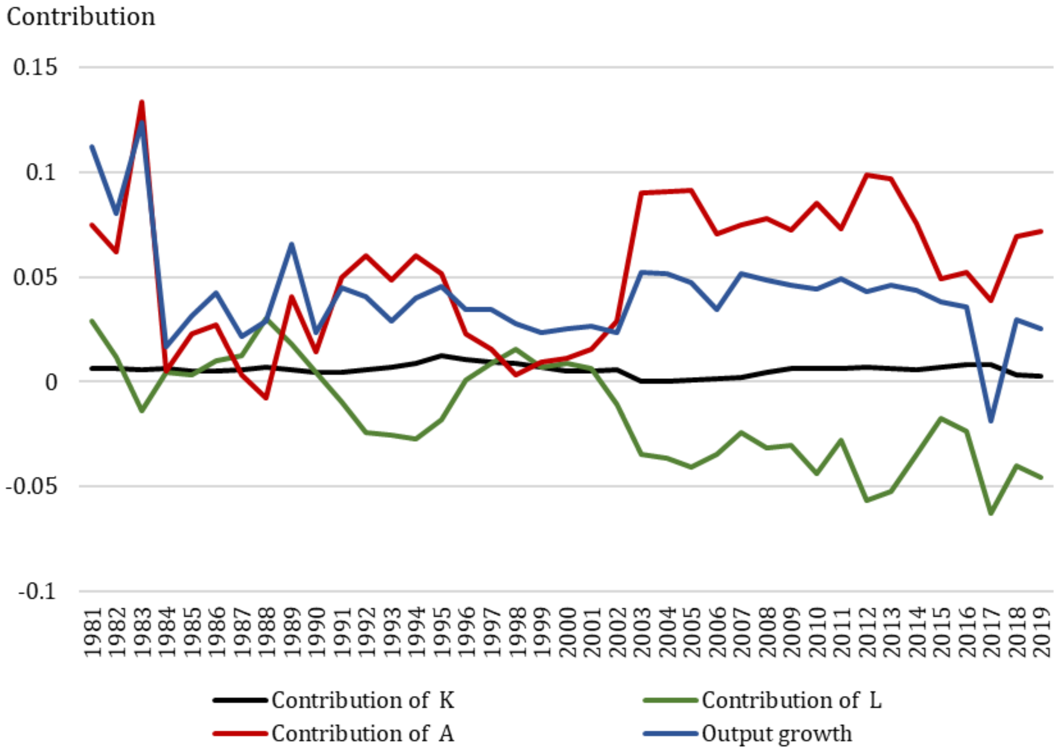


Figure 3.28: Contributions to industrial economic growth (Baseline)

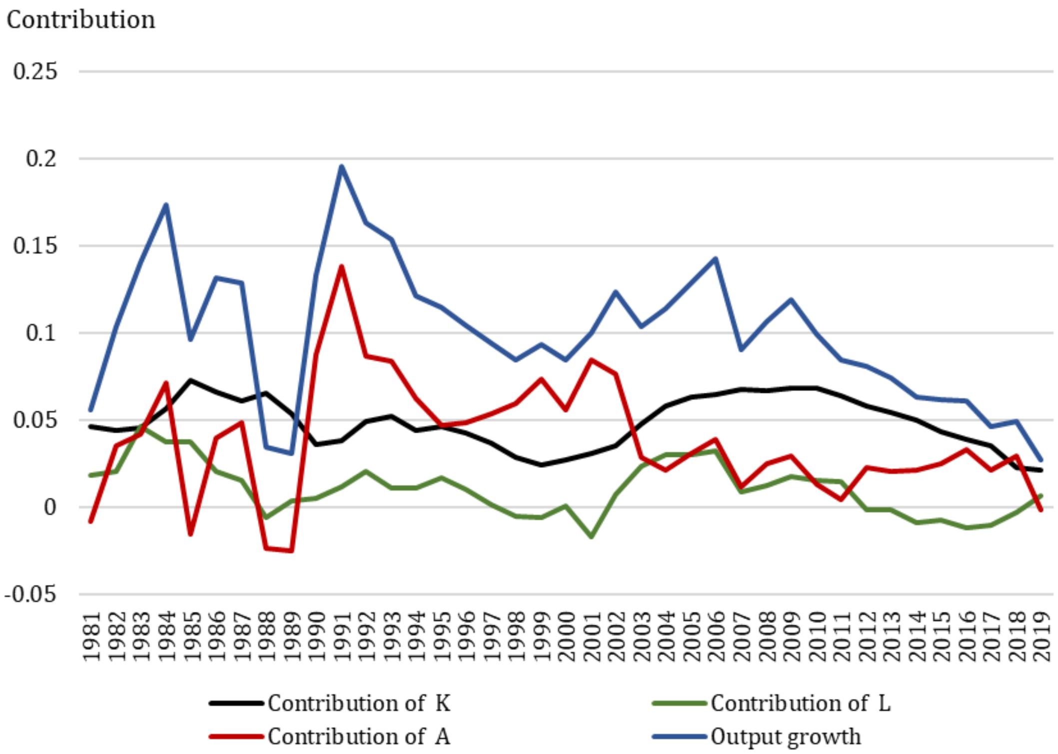
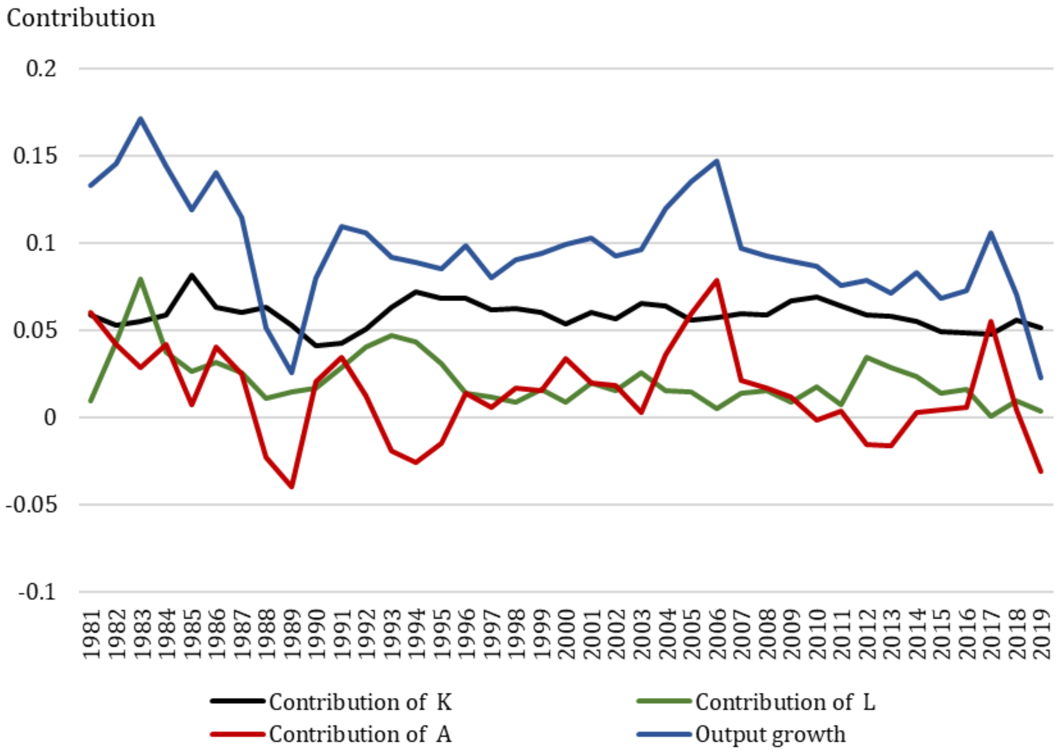


Figure 3.29: Contributions to service economic growth (Baseline)



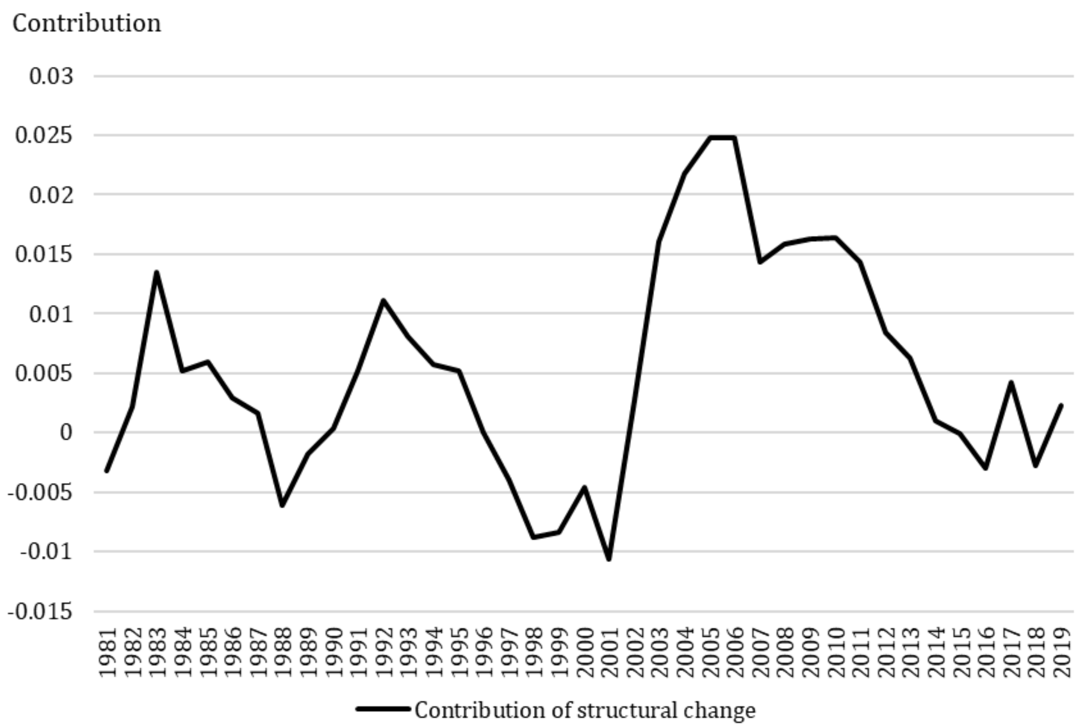
3.4.3 Contribution of structural change

Structural change refers to the shift of factor inputs and output across sectors. As inputs relocate to more productive sectors, the economy's productivity increases, boosting economic growth. Our baseline results show that on average, structural change generated 0.52 percentage points of economic growth each year. This amounts to 13.8% of China's annual average TFP growth between 1981 and 2020.

Figure 3.30 plots the contribution of structural change to annual economic growth between 1981 and 2020. The structural change contribution seems to follow a cyclical pattern. The contribution plummeted during the social-economic crises in the late 1980s, the Asian financial crises in the late 1990s, and the Great Recession in the late 2000s. It could be that these crises paralysed the economy and impeded the efficient movement of factor inputs. It could also be that government interventions during the crises did not direct resources to their best uses. In the early 2000s, there was an unusually large increase in contribution. This can be explained by the rapid shift of resources into the secondary sector following China's accession into the WTO.

While variant 3 results for structural change's contribution are very similar to the baseline results, variant 2 results are substantially larger than the baseline results. In particular, variants 2 results show that structural change added on average 0.63 percentage points to China's economic growth each year. This was 16.8% of TFPG's average contribution in the sample period. Relative to the capital stock measures of capital inputs, the capital services measures better capture the shifts of capital input from services to industry. Since industry was more productive than the service sector, structural change's contributions computed using capital services are greater than those computed using capital stocks.

Figure 3.30: Contribution of structural change to economic growth (Baseline)



3.5 Population aging's effects through the effective labour input channel

There are differences in labour participation rate, employment rate, and labour productivity across age groups. Such differences vary across sector and time. In this section, we investigate population aging's effects on the economy through the channel of effective labour. In Section 3.5.1, we show the impacts of accounting for age-varying sectoral labour productivities on the measurement of labour input and on growth accounting. In Section 3.5.2, we investigate the effects of population aging on effective labour input and economic growth through counterfactual analyses.

3.5.1 Accounting for age-specific labour productivity

In Section 3.3, we compiled data for a measure of effective labour input per worker of age g in sector i, which is denoted by l_{git}. Using this measure and data on age-specific sectoral employment Emp_{git}, we compute a measure of sectoral effective labour input L_{it} as:

$$L_{it} = \sum_g Emp_{git} l_{git}$$

We measure aggregate effective labour input L_t as:

$$L_t = \sum_i L_{it}$$

Figure 3.31 compares indices (base year=1) of employment and effective labour input at the national level. Initially, the 31 to 50 age groups saw the most rapid increases in employment shares. At the same time, these age groups were more productive than others. These explain why effective labour initially rises faster than employment in Figure 3.31. Over time, the 31-50 age groups' shares started to fall while the increases in 51+ groups' shares accelerated. In addition, the relative productivity of older workers fell. Resultantly, effective labour fell relative to employment since the late 1990s.

On average over the sample period, effective labour grew 0.3 percentage points less than employment each year. This implies that even less of China's economic growth was due to labour input growth than previously understood. In fact, since 2002, effective labour input has acted as a drag on economic growth by falling at an average annual rate of 1.0%. Assuming a Cobb-Douglas production function for the aggregate economy and ceteris paribus, the fall in effective labour reduced China's annual average economic growth by 0.6 percentage points.

Figure 3.31: Indices of labour (1981=1)

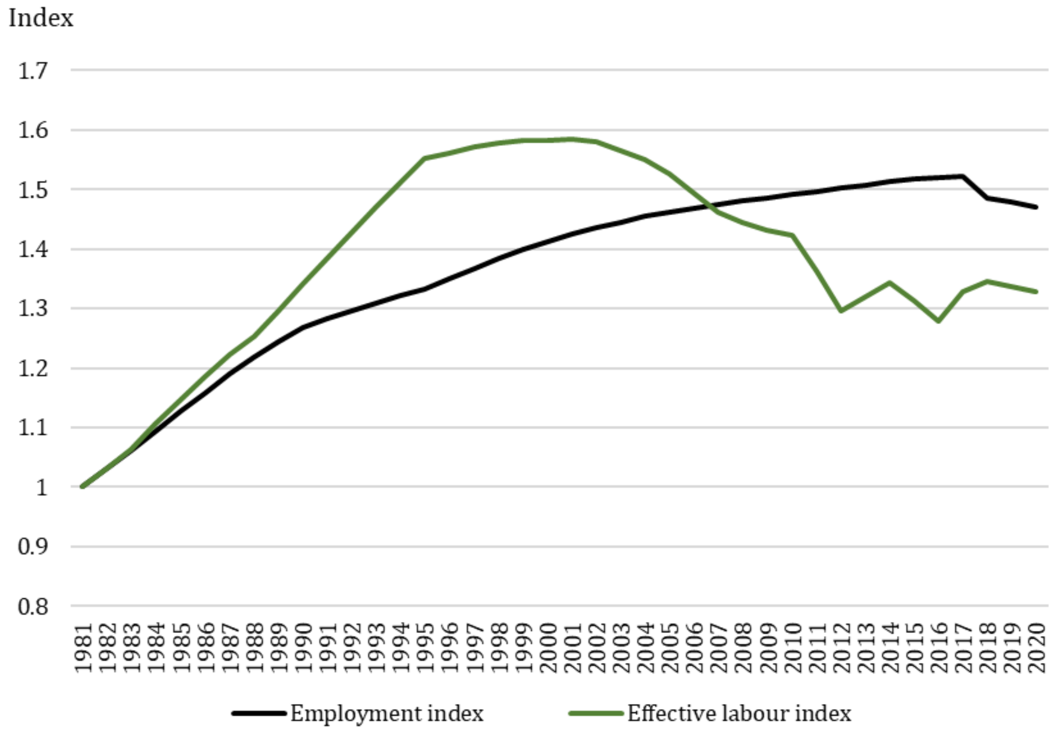
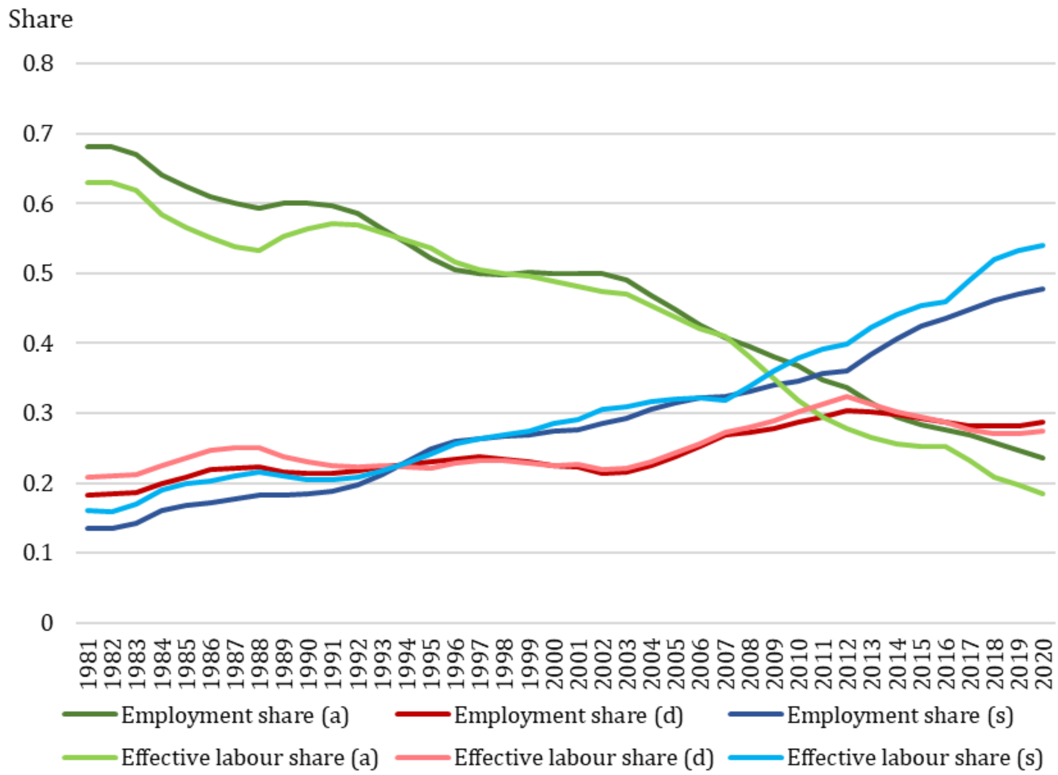


Figure 3.32: Sectoral employment and effective labour shares



In Section 3.3, we learned that the aging of employment and the falls in older workers' relative productivities in agriculture were faster than those in industry, which were faster than those in services. As a result, the negative aging effect on labour productivity was the most acute in agriculture, followed by that in industry, and then by that in services. These aging effects are captured by our sectoral effective labour measures. As can be seen in Figure 3.32, effective labour share of agriculture was smaller and effective labour shares of industry and services were larger than their employment share counterparts. In 2020, effective labour share in agriculture was 5.1 percentage points smaller and effective labour share in services was 6.4 percentage points larger than their employment share counterparts. These results show that structural change in labour input took place not only through the movement of labour away from agriculture but also through the aging of agricultural labour relative to modern sector labour.

Using effective labour and capital stock data, we compute a new set of growth accounting results which we refer to as variant 4. As can be seen in Table 3.5, variant 4 results show larger TFP growths than baseline results. This is because the negative aging effect on labour productivity has been relocated from TFP growth to labour input growth. Compared to the baseline results, variant 4 average TFP growths in the aggregate economy, agriculture, industry, and services were respectively 0.16, 0.72, 0.35, and 0.20 percentage points higher.

Table 3.5: Average annual TFP growths (Variant 4)

Variant 4: K=capital stock, L=effective labour				
	Aggregate	Agriculture	Industry	Services
1981-2020	0.039	0.059	0.042	0.016
1981-1990	0.025	0.028	0.025	0.021
1991-2000	0.047	0.029	0.071	0.007
2001-2010	0.062	0.103	0.044	0.035
2011-2020	0.021	0.079	0.026	0.000

Table 3.6 below shows the variant 4 average annual contribution shares of the drivers of China's growth. Relative to baseline results, variant 4 results show a shift from labour

contribution share to TFP contribution share of 1 percentage point at the aggregate level. The shifts in agriculture, industry, and services are 1.8, 4.1, and 2.5 percentage points, respectively. Despite these shifts, capital accumulation remains the dominant driver of growths in China. Variant 4 results for structural change contribution are similar to the baseline results. Therefore, we do not repeat the description for brevity.

Table 3.6: Average shares of contributions to growth (Variant 4)

Variant 4: K=capital stock, L=effective labour				
	Aggregate	Agriculture	Industry	Services
K	0.56	0.13	0.58	0.71
L	0.05	-0.21	0.05	0.21
A	0.39	1.07	0.38	0.09

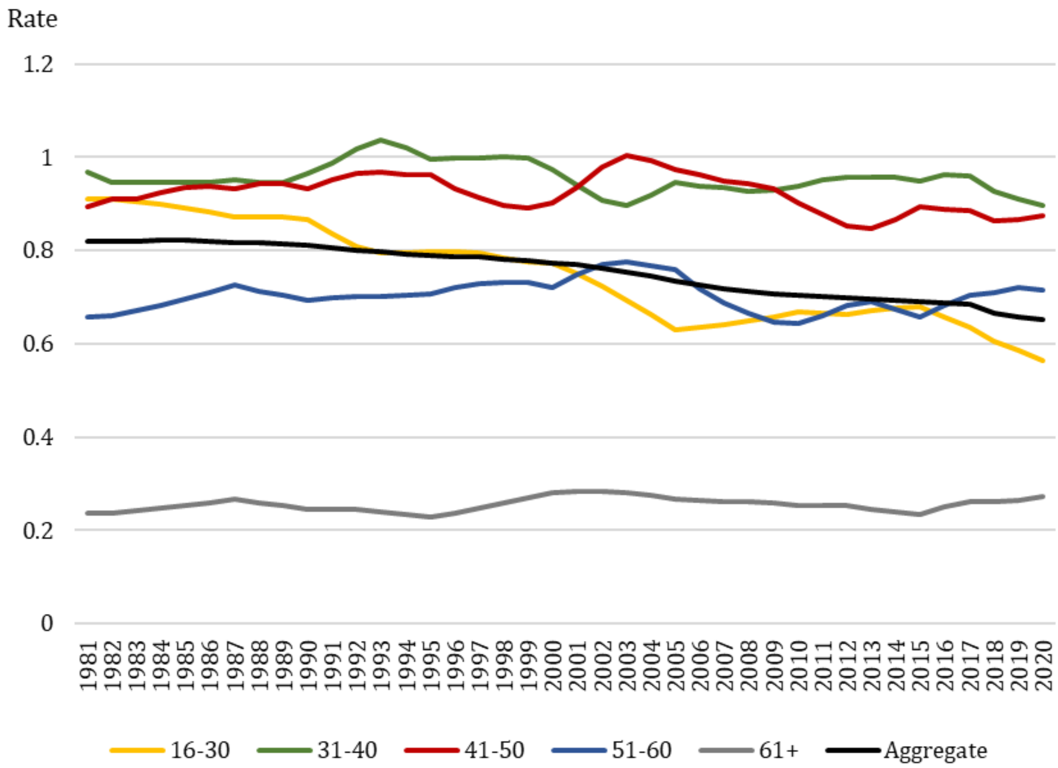
3.5.4 Age effect on aggregate labour input and economic growth

In the previous section, we compared results computed using effective labour with those computed using employment. Such comparison partially revealed aging's effect through labour productivity. In this subsection and the next, we quantify the effects of aging on effective labour input via labour participation rate, employment rate, and labour productivity by comparing effective labour inputs constructed under scenarios with aging and without aging.

Figure 3.33 shows employment per person by age in China between 1981 and 2020. Note that employment per person is a product of labour participation rate and employment rate. As can be seen in the figure, per capita employment generally fell with age. The differences between age groups were large. The most active groups were those aged between 31 and 50, who had per capita employments close to ones. Elderlies aged 61 and above had the lowest per capita employment of about 0.25.

Age-specific per capita employments seem to follow constant trend values. The exception to this was the per capita employment of the 16-30 age group which fell from 91% in 1981 to 56% in 2020. This is attributable to the rapid expansions of high school and university enrolments in China. According to data from Educational Statistics Yearbooks of China (Ministry of Education, 1996; 2022), gross enrolment rates of high school and higher education in China increased respectively from 22% and 3% in 1990 to 91% and 54% in 2020.

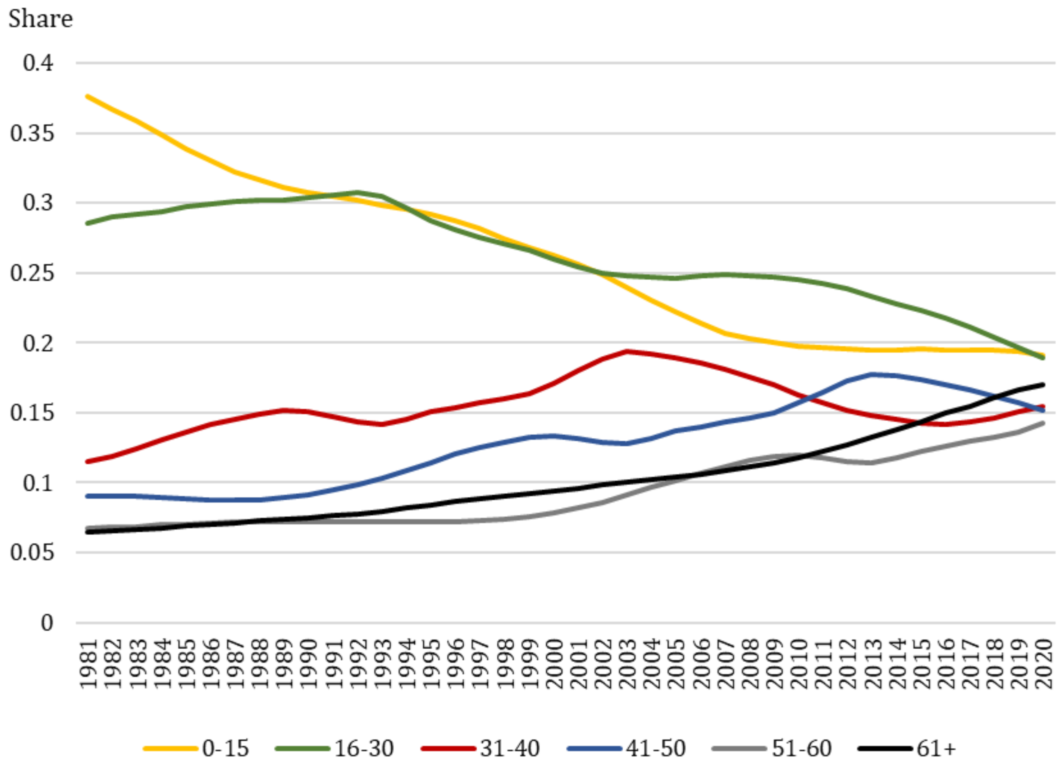
Figure 3.33: Employment per person by age group



Some economists argue that aging's negative effects on labour supply can be mitigated if people retire later. In the case of China, per capita employment of elderlies aged 61 and above remained low and stable. This is in spite of the increase in elderlies' population share from 6.5% to 17.0% between 1981 and 2020, and the increase in life expectancy from 44 to 78 between 1950 and 2020 (World Population Prospects, 2024). Therefore, population aging has had and will likely continue to have negative impacts on China's labour input. As remedies, policymakers can attempt to raise elderly per capita employment by, for example, raising the retirement ages.

Since per capita employment and effective labour vary across age, changes in population age structure can affect aggregate effective labour input. Figure 3.34 shows the evolutions of age specific population shares over the sample period. Initially, the shares of people aged 16 to 50 rose rapidly while the shares of people aged 51 and above rose slowly. These changes raised aggregate effective labour as the 16-50 age groups had higher per capita employment than the others. Over time, the 16-50 age groups' shares started to fall and the 51+ age groups' shares rose more rapidly, dragging aggregate employment downwards. Furthermore, older workers became less and less productive relative to younger workers. These caused aging's effect on effective labour input to turn negative over time.

Figure 3.34: Shares of age groups in population



To quantify aging's effect on effective labour, we start by constructing population by age under a counterfactual scenario in which there is no aging. We assume that the shares of age groups stay constant at 1981 levels and use them to breakdown total population data between 1981 and 2020. Therefore, population aging affects the age structure but not the level of population in this exercise. We compute age g per capita effective labour $\tilde{l}_{gt}$ as aggregate age g effective labour L_{gt} divided by age g population Pop_{gt}:

$$\tilde{l}_{gt} = \frac{\sum_i Emp_{git} l_{git}}{Pop_{gt}} = \frac{L_{gt}}{Pop_{gt}}$$

Next, we multiply counterfactual age-specific population Pop_{gt}^{c} by age-specific per capita effective labour to obtain counterfactual age-specific effective labour L_{gt}^{c}:

$$L_{gt}^{c} = Pop_{gt}^{c} \cdot \tilde{l}_{gt}$$

Finally, we aggregate effective labour across age to obtain counterfactual aggregate effective labour L_{t}^{c}:

$$L_{t}^{c} = \sum_{g} L_{gt}^{c} = \sum_{g} Pop_{gt}^{c} \cdot \frac{\sum_{i} Emp_{git} l_{git}}{Pop_{gt}}$$

As can be seen in the equation above, aging's effect on aggregate effective labour stems from the differences across age in sectoral employment per capita and sectoral labour productivity.

Figure 3.35 below plots the ratio of actual effective labour to counterfactual effective labour which reveals the effects of aging. Population aging initially had positive effects on effective labour. Between 1981 and 2007, population aging raised effective labour growth by 1.0 percentage points per year on average. By 2007, actual effective labour was 1.3 times the counterfactual. Deducing from the aggregate Cobb-Douglas production function under the ceteris paribus assumption, aging's effect on effective labour caused GDP to grow by an extra 0.6 percentage points per year. Everything else the same, actual GDP would be 16.0% larger than the counterfactual in 2007.

Our results in Figure 3.35 show that aging's effect on labour started to turn negative in 2007. To fully gauge such negative aging effects both within sample and in the future, we conduct a similar counterfactual analysis for the 2007-2100 period using 2007 as the base year. In both baseline (aging) and counterfactual (no-aging) scenarios, we compute age-specific effective labour by multiplying age-specific population and age-specific per capita effective labour. We then aggregate effective labour across age to obtain aggregate effective labour. Age-specific per capita effective labours are the same in the two scenarios. For the 2007-2020 period, age-specific per capita effective labours are the same as before. For the 2021-2100 period, we assume age-specific per capita effective labours stay constant at 2020 levels. With regard to age-specific population between 2007 and 2100, we use UNWPP's data and forecast for the baseline. We compute age specific population in the counterfactual by using constant 2007 age-population shares to breakdown total population data and forecast between 2007 and 2100.

Figure 3.35: Age effect between 1981 and 2020: Ratio of actual effective labour to counterfactual effective labour

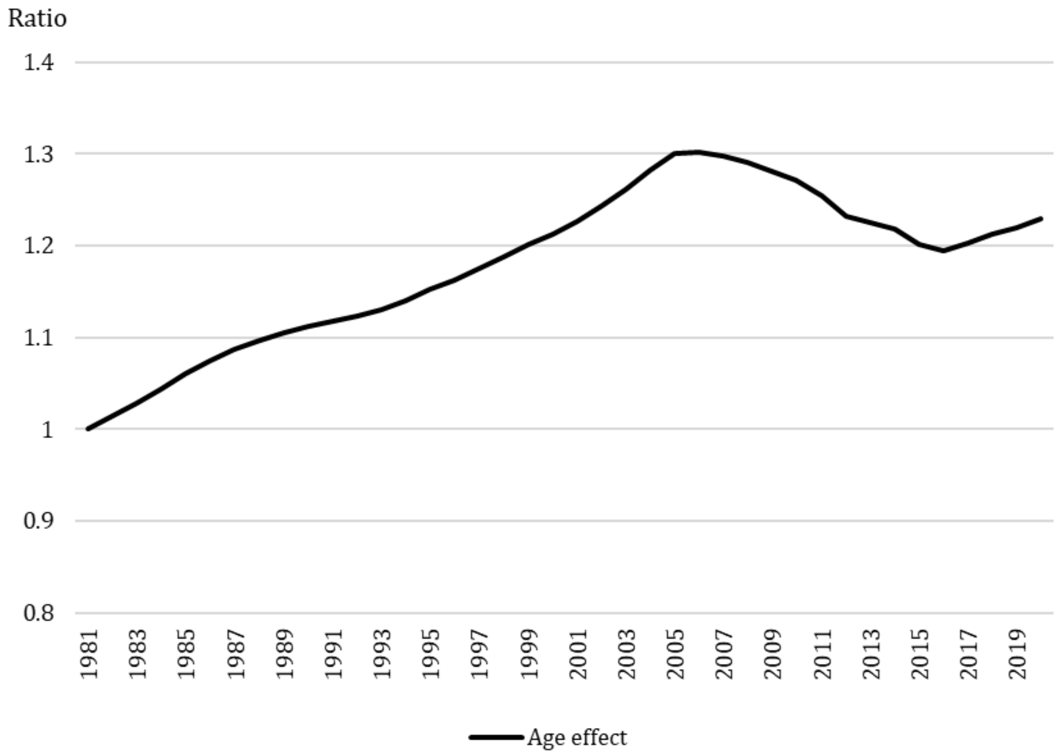
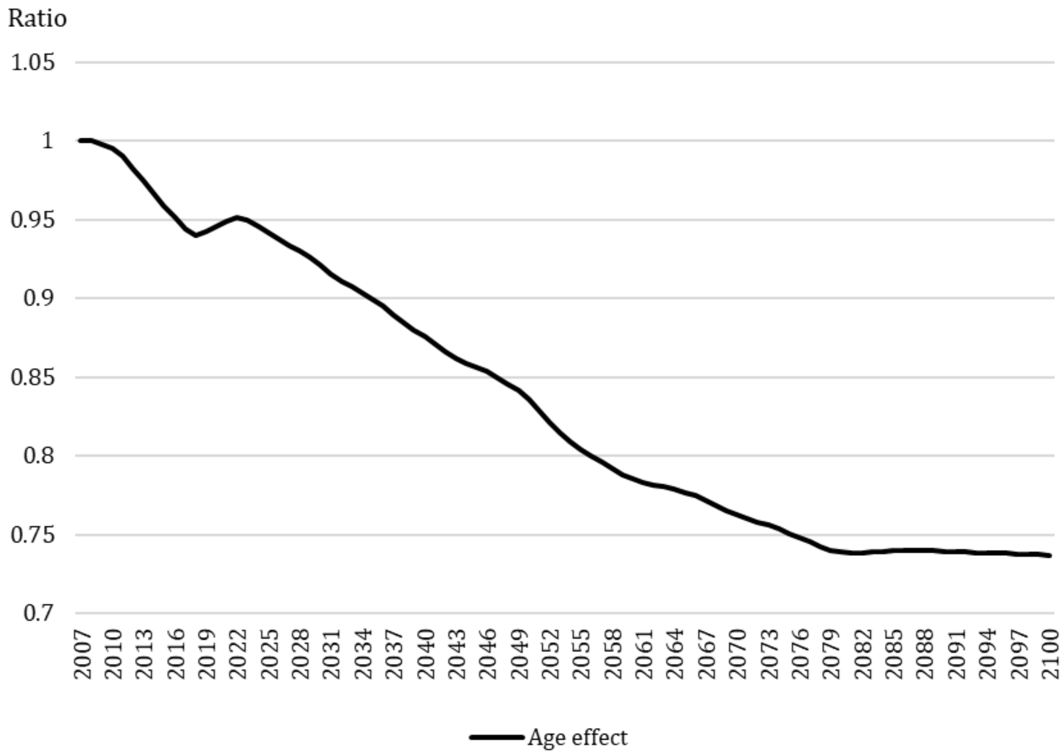


Figure 3.36 reveals the negative aging effect by comparing actual effective labour with the counterfactual. As China's population is forecast to age till the early 2080s, we focus on the 2007-2080 period. Between 2007 and 2080, aging causes annual effective labour growth to fall by 0.4 percentage points on average, thereby lowering annual GDP growth by 0.2 percentage points. By 2080, effective labour is predicted to be 26% smaller than it otherwise would be if there were no population aging. Through the channel of effective labour, aging is therefore expected to cause China's GDP to be 16% smaller than the counterfactual in 2080.

In addition to the analyses above, we conduct another set of analyses following the same procedures except that age-and-sector-specific per worker effective labour l_{git} for all ages and sectors are assumed to be equal to ones. The results can be interpreted as aging's effect on employment or as aging's effect on effective labour through labour participation rate and employment rate. By comparing the two sets of results, we find that aging's negative effect on employment explains about two-thirds of aging's negative effect on effective labour. For brevity, we do not present the results from this additional set of analyses.

Figure 3.36: Age effect between 2007 and 2100: Ratio of actual effective labour to counterfactual effective labour



3.5.5 Age effect on sectoral labour input

In this section, we investigate aging's effects on the sectoral allocation of effective labour input and hence structural change. Structural change, in turn, can affect aggregate output through productivity.

In Section 3.5.4, we computed China's age-specific population in two scenarios: baseline and counterfactual. In the baseline scenario, China's population age structure between 1981 and 2100 follows UNWPP's data and forecast. In the counterfactual scenario, age-population shares stay constant at base year levels. In both scenarios, total population follows UNWPP's data and forecast.

In this section, we construct China's sectoral effective labour under the baseline and counterfactual scenarios. We first estimate age-g per capita sectoral effective labour $\tilde{l}_{git}$ as:

$$\tilde{l}_{git} = \frac{Emp_{git} l_{git}}{Pop_{gt}}$$

For the 1981-2020 period, we use data to compute $\tilde{l}_{git}$. For the 2021-2100 period, we assume age-g per capita sectoral effective labours stay constant at 2020 levels. Next, we compute age-specific sectoral effective labour by multiplying age-specific sectoral effective labour per capita and age-specific population. Finally, we add up age-specific sectoral effective labour across age to obtain sectoral effective labour. The differences in age structure give rise to different sectoral effective labour patterns in the two scenarios.

Note that the aforementioned computation procedure is equivalent to applying age-specific sectoral effective labour shares to baseline and counterfactual age-specific effective labours computed in Section 3.5.4. Age-specific sectoral effective labour shares depend on age-specific sectoral effective labour per worker shown in Figures 3.13-3.15 and on age-specific sectoral employment shares shown in Figure 3.37. These figures plot data for the 1981-2020 period. For the 2021-2100 period, our computation assumes age-specific sectoral employment shares and age-specific sectoral effective labour per worker stay constant at 2020 levels.

As can be seen in Figure 3.37, older workers were more likely to be employed in agriculture and less likely to be employed in industry and services. Therefore, population aging can raise agriculture's share and reduce modern sectors' shares in aggregate effective labour. The gaps in employment shares across age in Figure 3.37 are large and their effects on effective labour dominate any opposing effects arising from differences in sectoral labour productivity across age.

Figure 3.37: Sectoral employment shares by age group

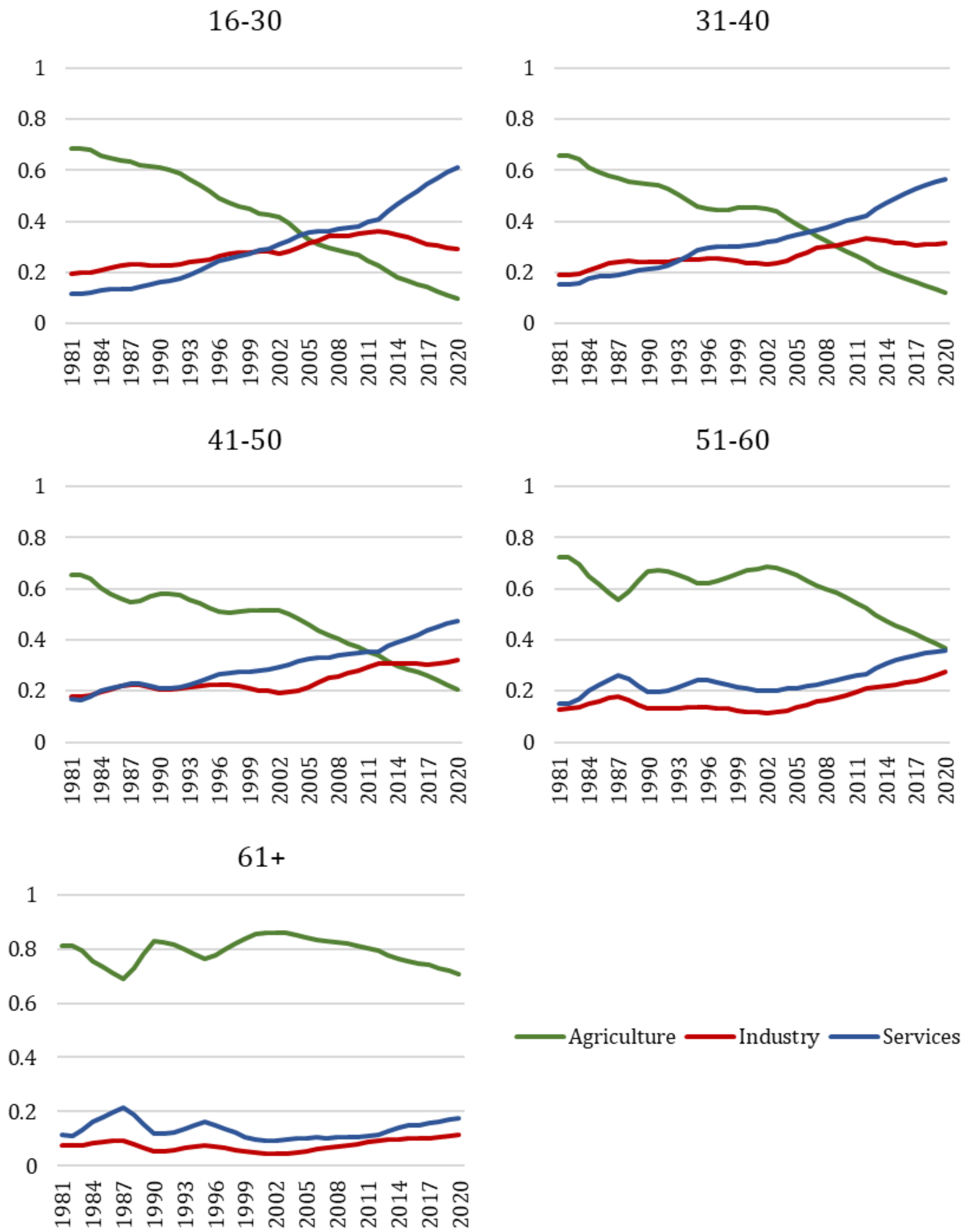
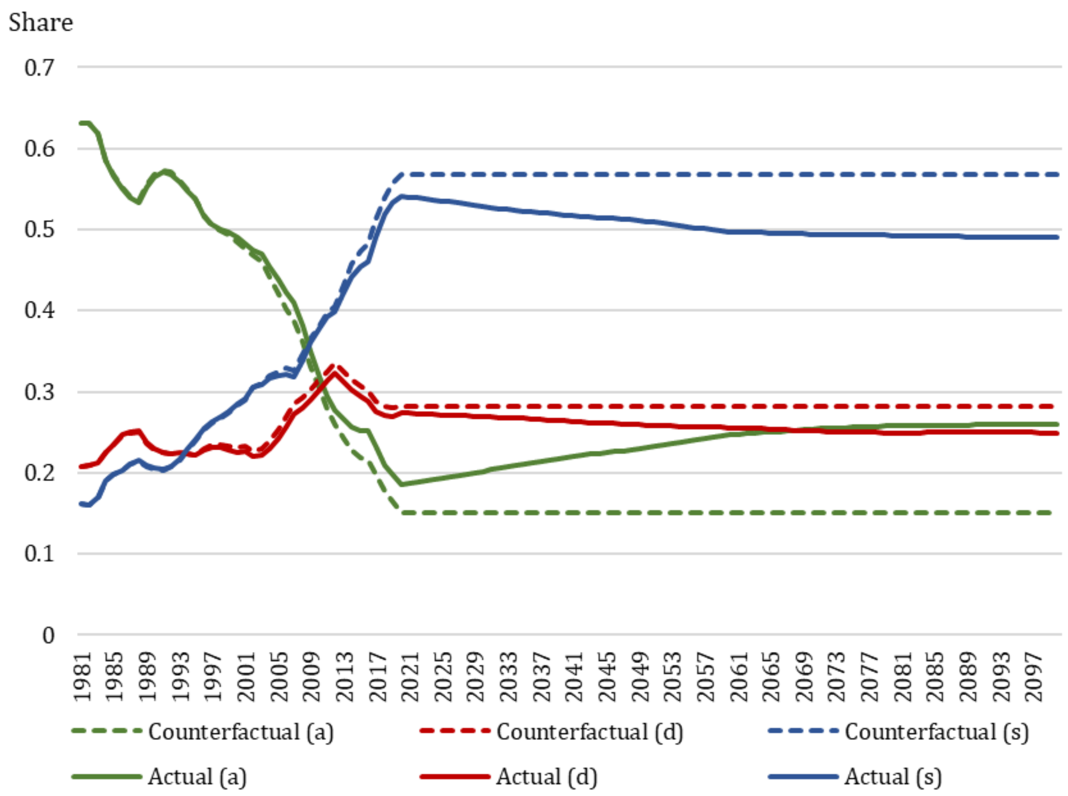


Figure 3.38 shows counterfactual and actual sectoral effective labour shares. The baseline (aging) scenario shows larger agricultural share and lower industrial and service shares than the counterfactual. By 2080, aging is predicted to raise the agricultural share by 10.8 percentage points, reduce the industrial share by 3.3 percentage points, and reduce the service share by 7.5 percentage points. Population aging therefore impedes China's structural change in terms of effective labour input.

By impeding structural change, population aging lowers aggregate productivity and economic growth. To quantify such effects, we need to predict each sector's weight in aggregate output under the two scenarios. This is beyond the scope of this study.

Figure 3.38: Baseline and counterfactual sectoral effective labour shares



3.6 Factor price wedges

3.6.1 Factor price wedges in the baseline

In this section, we investigate frictions in China's factor markets which impede the efficient allocation of factors across sectors. We measure such frictions using factor price wedges as described in Section 3.2. Figures 3.39 and 3.40 show that there were substantial employment and capital stock price wedges in China throughout the 1981-2020 period. Sectoral employment wedges were on average 1.5 times the sizes of sectoral capital stock wedges. The wedges in industry were on average about 44% higher than those in services.

Figure 3.39: Labour price wedges in industry and services

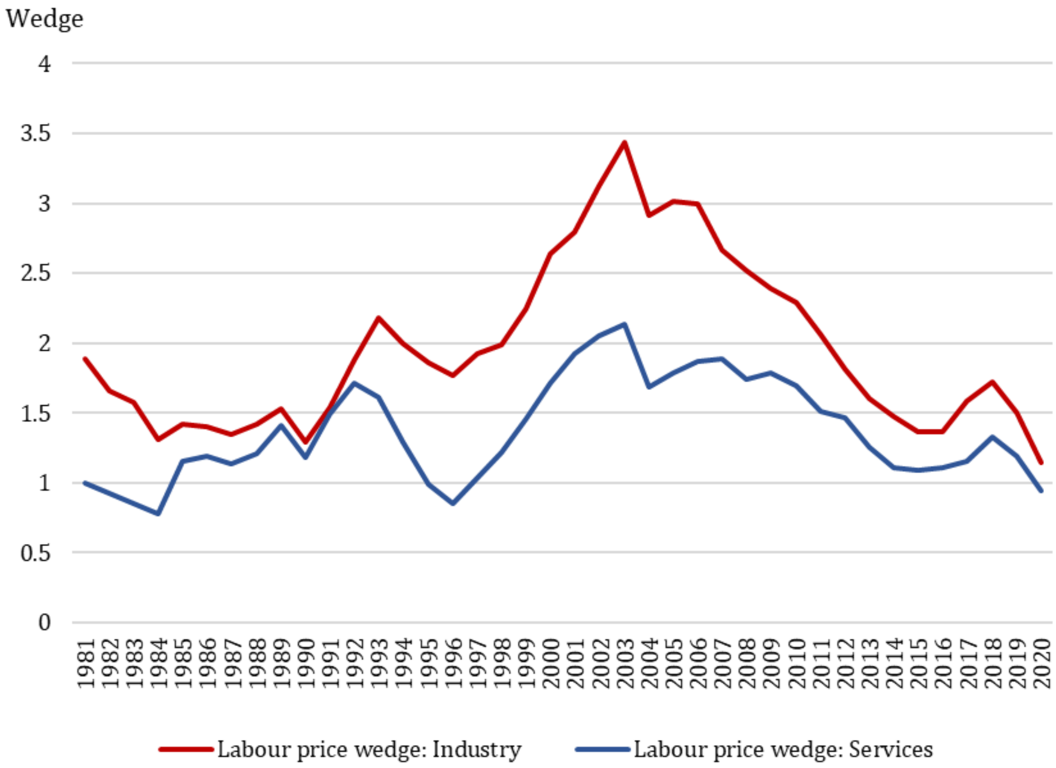
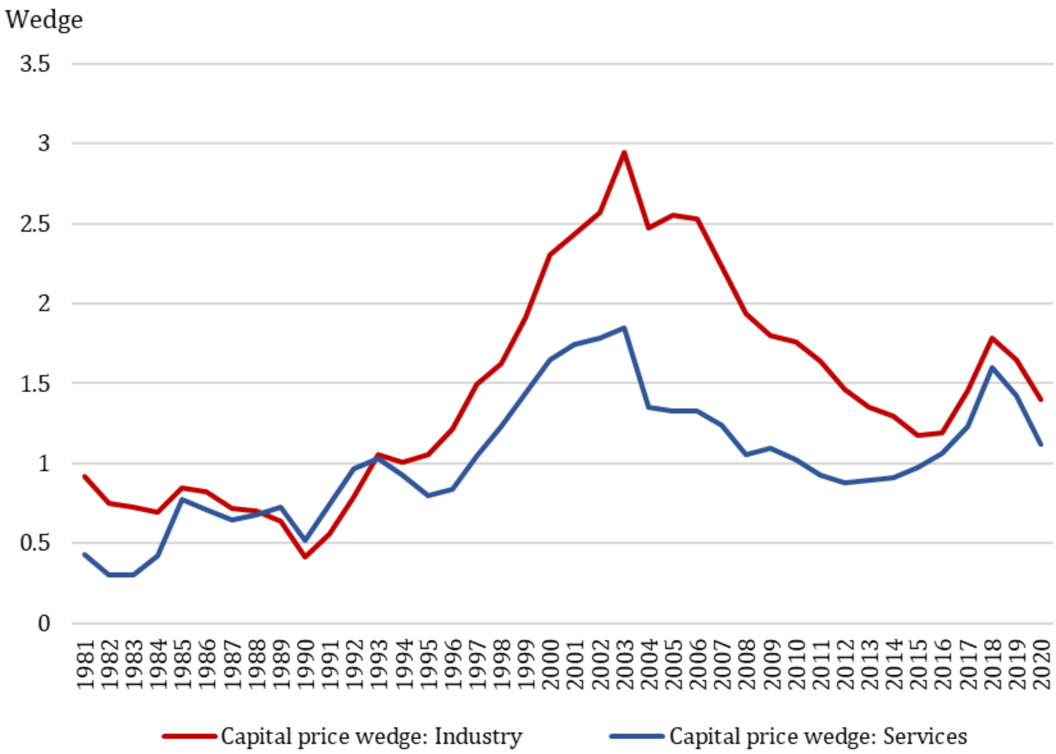


Figure 3.40: Capital price wedges in industry and services



In 1981, employment price wedges in industry and services were 1.9 and 1.0, respectively. In the same year, capital price wedges in industry and services were 0.9 and 0.4, respectively. Between 1993 and 2003, the wedges expanded rapidly, especially in industry. After 2003, the wedges fell and the gaps between industrial and service wedges shrunk. By the end of the sample period, employment wedges in industry and services were respectively 1.1 and 0.9, which were lower than those in 1981. Capital wedges, on the other hand, increased relative to their 1981 levels, reaching 1.4 and 1.1 in industry and services, respectively.

3.6.2 Aging and labour wedges

Different types of capital stocks and employees have different productivities. The type compositions of capital stock and employment change over time. These differences and changes can be captured by effective measures of capital and labour inputs. In this subsection and the next, we compare wedges computed using effective factor inputs with those computed using standard factor input measures.

Figures 3.41 compares employment wedge and effective labour wedge in industry. Figure 3.42 does so for services. As can be seen in the figures, effective labour wedges are smaller than employment wedges. This is due to interactions between changes in age structure of sectoral employment and age-specific sectoral labour productivity. For brevity, we shall refer to this as the age effect on wedges. By 2020, the age effect can explain 33% of industrial labour wedge and 63% of service labour wedge

In a perfectly competitive market, factors would move to sectors with higher payments. Results from Figure 3.41 and 3.42 show that in China, some of this movement was achieved through changes in the age compositions of sectoral employment in China. In particular, the modern sector employed more productive age groups of workers than agriculture. This explains why the modern sector's share in effective labour was higher than that in employment, and partially explains why employee wage in the modern sector was higher than that in agriculture.

Figure 3.41: Industrial labour price wedges computed using employment and effective labour

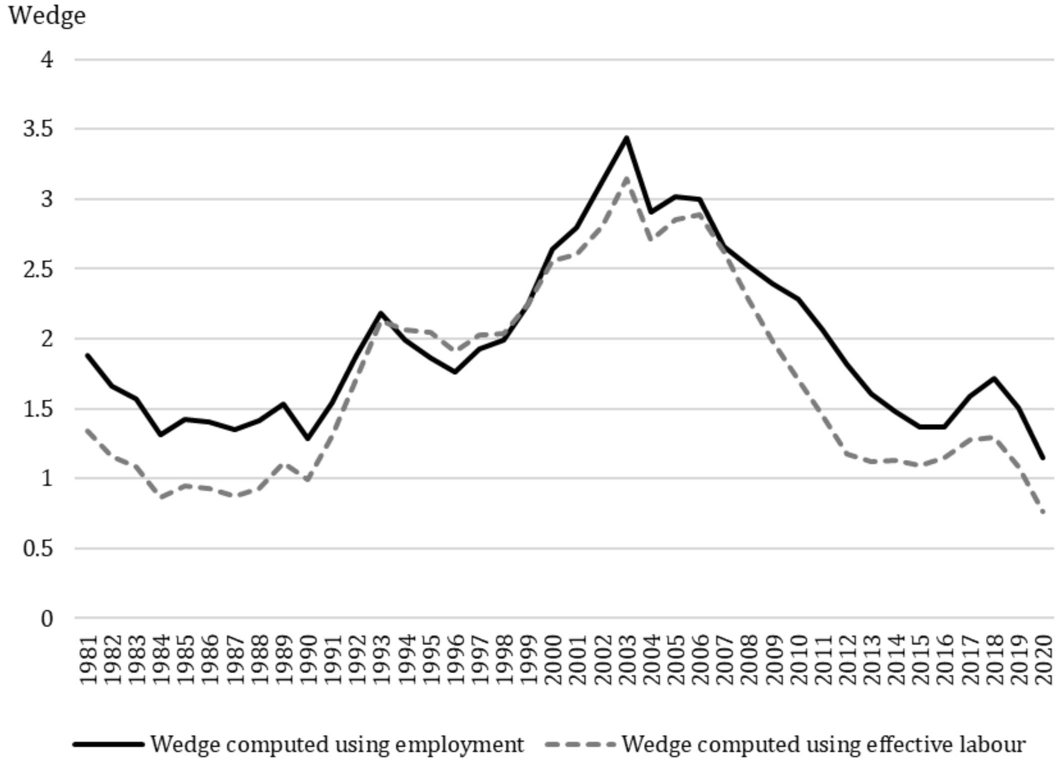


Figure 3.42: Service labour price wedges computed using employment and effective labour

3.6.3 Capital composition and capital wedges

In this section, we compute effective capital using a similar method to effective labour. Let subscripts c and m refer to construction capital and machinery capital, respectively. Real sector i capital stock K_{it} is the sum of sector i construction capital stock K_{ict} and machinery capital stock K_{imt}:

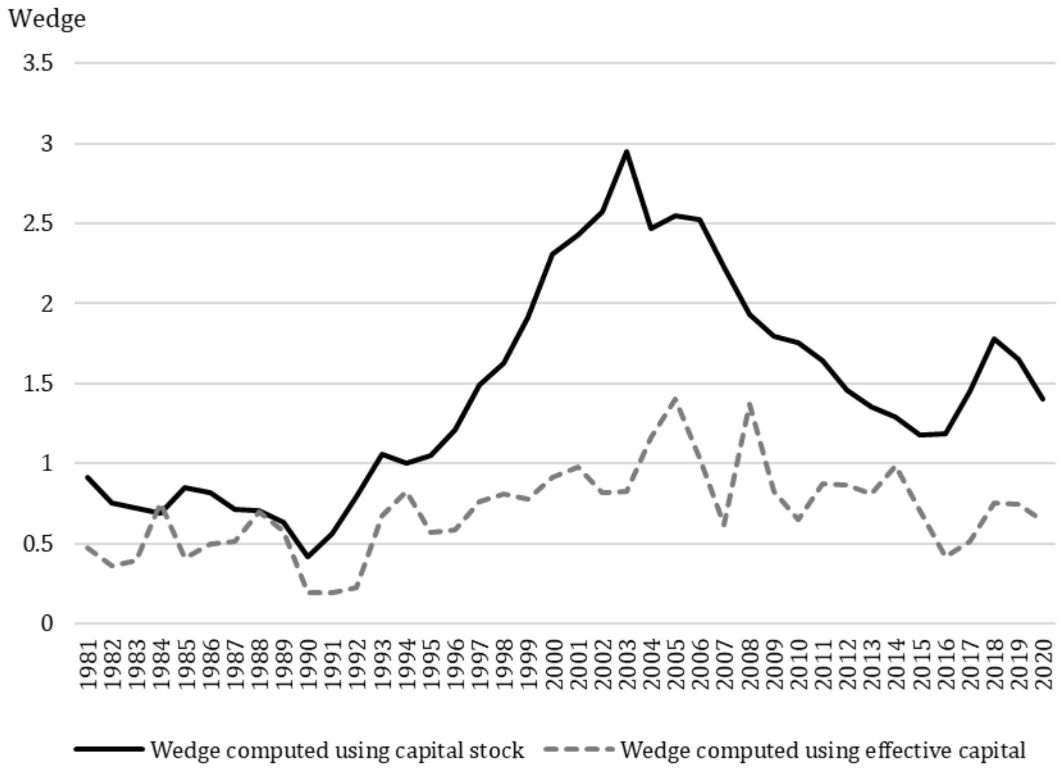
$$K_{it} = K_{ict} + K_{imt}$$

Since sector-and-type-specific capital productivities can be approximately measured by rents R_{ict} and R_{imt}, we compute sectoral effective capital input K_{it}^{e} as:

$$K_{it}^{e} = \frac{R_{ict}}{R_{imt}} K_{ict} + K_{imt}$$

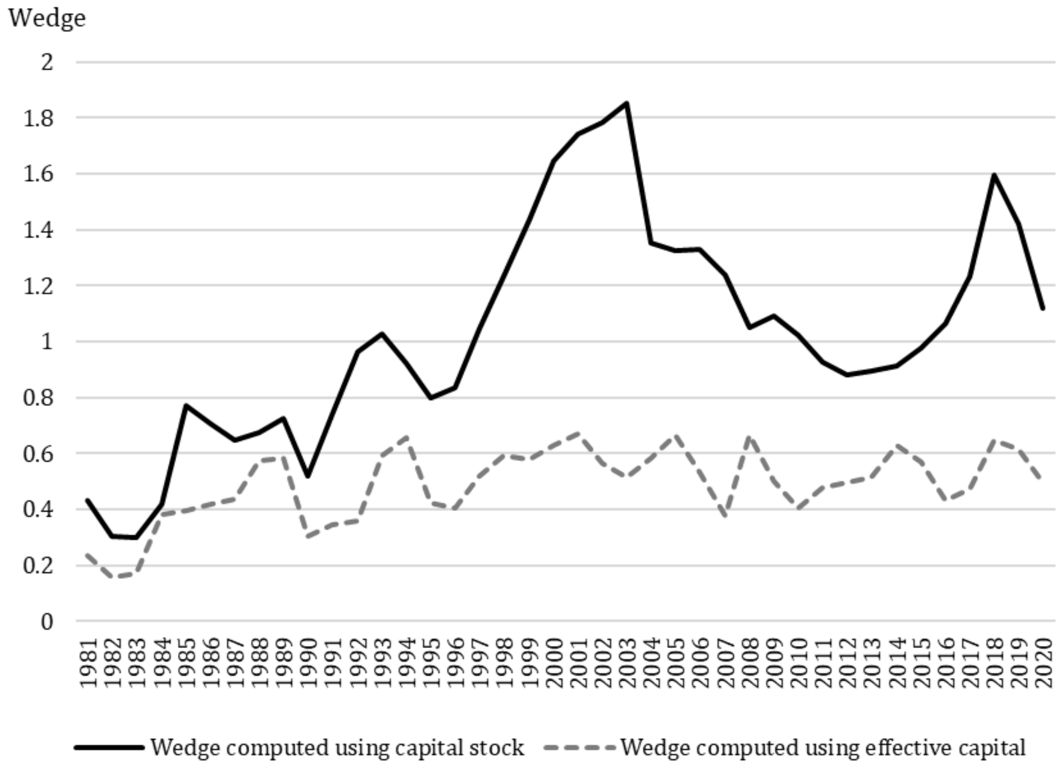
The data for sector and type specific capital stock and rent are taken from Chapter 2. Once we have computed sectoral effective capital, we compute sectoral capital price wedges following the method in Section 3.2.

Figure 3.43: Industrial capital wedges computed using capital stock and effective capital



Figures 3.43 and 3.44 show that capital wedges computed using effective capital are smaller than those computed using capital stocks. On average, capital composition can explain 46% and 48% of capital stock wedges in industry and services, respectively. These results imply that differences in rent between modern sectors and agriculture can partially be explained by the fact that modern sectors used more productive compositions of capital stocks than agriculture.

Figure 3.44: Service capital wedges computed using capital stock and effective capital



3.7 Conclusion

In this chapter, we compiled supply-side data for China between 1981 and 2020. Using the data, we accounted for the supply-side sources of China's structural change and economic growth. Specifically, we conducted growth accounting for China at sectoral and aggregate levels. We analysed the contribution of structural change to China's economic growth. We compared results computed using various measures of factor inputs. We estimated age-and-sector-specific effective labour input per worker series for China. Using said series, we investigated the effects of population aging through the effective labour channel. Finally, we estimated and analysed factor price wedges in China.

Our results suggest that 'inspiration' and 'perspiration' both played important roles in China's economic growth. Between 1981 and 2020, China's TFP grew at an annual average rate of 3.8%, accounting for 38% of China's economic growth. Capital accumulation was the biggest growth driver, accounting for 56% of China's growth. Labour's contribution was the smallest, at only 6% of China's growth. In fact, labour's contribution had been negative since 2017. As capital accumulation runs into diminishing returns, China needs to elevate its TFP growth and contain the shrinkage of its labour input in order to maintain its rapid economic growth.

TFP growth in China was the fastest in agriculture (5.2%), followed by that in industry (3.8%), and then by that in services (1.4%). As such, growth in agriculture was driven almost entirely by TFP growth while growths in the modern sectors were driven primarily by factor accumulation. In recent years, TFP growth in agriculture accelerated while TFP growth in services decelerated. If these patterns continue, rapid structural change towards services will impede rather than facilitate China's economic growth.

Our data and results are consistent with the presence of the Baumol cost disease (Baumol, 1967) in China. In particular, low service relative productivity growth led to increases in service relative price. Due to low price elasticity of demand, high income elasticity of demand, or government intervention, real service output share remained stable and nominal service out share surged. These caused factor inputs to structurally change towards the service sector. These changes can ultimately contribute to slowing down China's aggregate economic growth. As remedies, policymakers can attempt to facilitate productivity growth in services and or influence the elasticities which determine the patterns of service output shares. In Chapter 4, we will learn more about the elasticities by estimating preference for China.

Our results show that TFPs in the modern sectors were higher than that in agriculture over the sample period. Resultantly, structural change generated about 0.6 percentage points of economic growth in China each year, accounting for about 15% of China's annual TFP growth. The contribution of structural change tracked China's economic cycle and was the largest in the early 2000s following China's privatisation reforms and WTO accession. Data show that there is ample room for further structural change in China.

Therefore, structural change can potentially be an important driver of growth for China in the future.

At the aggregate level, our growth accounting results computed using capital services data are almost the same as those computed using capital stocks data. At the sectoral level, industrial TFP growth and its contribution to industrial output growth computed using capital services are smaller than those computed using capital stocks. The opposites are true for service TFP growth and its contribution to service output growth. Finally, the growth contribution of structural change computed using capital services is larger than that computed using capital stocks. In general, the differences between results computed using alternative factor input measures are small. Considering the small impacts of using alternative capital input measures on the results in this chapter, and the difficulties of incorporating capital services into models, we shall measure capital input using capital stock rather than capital services in later chapters.

Our estimated age-specific sectoral labour productivity series show that initially, older workers were more productive than young workers. Over time, productivities of older workers decreased relative to those of young workers. The relative labour productivities of older workers in agriculture were lower than those in industry, which were lower than those in services. The decreases in older workers' relative labour productivities were the fastest in agriculture, followed by those in industry, and then those in services. By 2020, workers aged above 50 were about 60%, 70%, and 90% as productive as workers aged below 31 in agriculture, industry, and services, respectively.

Using our estimated age-specific sectoral labour productivity series, we constructed sectoral effective labour input data for China. Population aging and the decline of elderly relative labour productivity mean that despite initial increases, aggregate effective labour fell relative to aggregate employment overall. This suggests that even less of China's growth was due to labour input growth. In fact, aggregate effective labour fell between 2003 and 2020 at an annual average rate of 0.6%, hindering China's economic growth. Since the decline in elderly labour productivity was the most rapid in agriculture, effective labour in China shifted from agriculture to the modern sectors more quickly than employment. Therefore, structure change in China's labour input involved not only shifts in employment but also changes in age composition of employment across sectors.

By comparing effective labour constructed under the aging and no-aging scenarios, we investigated aging's effects through age-varying labour participation rate, employment rate, and labour productivity. We found that aging's effect on China's effective labour was positive before 2007 but turned negative afterwards. Between 1981 and 2007, aging raised China's annual effective labour growth by 1.0 percentage point on average, adding 0.6 percentage points of growth to China's economy each year. Between 2007 and 2080, however, aging reduces annual effective labour growth by 0.4 percentage points, thereby deducting annual GDP growth by 0.2 percentage points. Out of the negative aging effects on effective labour, about two thirds can be attributed to aging's negative effects on aggregate labour participation rate and employment rate.

Compared to younger workers. older workers were more likely to work in agriculture and less likely to work in the modern sectors. Therefore, population aging impedes China's structural change in terms of effective labour input. By 2080, China's agricultural effective labour share in the aging scenario is predicted to fall by 10.8 percentage points less than that in the no-aging scenario. Within the modern sector, aging is predicted to lower service effective labour share growth by 7.5 percentage points and industrial effective labour share growth by 3.3 percentage points.

To alleviate the aforementioned adverse aging effects, attempts can be made to improve participation rate, employment rate, and productivity of elderlies. One potential solution would be to raise the retirement ages. Despite having a life expectancy of 78 in 2020, which was similar to that in the US, China had retirement ages that were among the lowest in the world: 60 for male workers, 55 for white-collar female workers, and 50 for other female workers. Policies to raise China's retirement ages had been proposed numerous times. In late 2024, the government finally committed to a plan to slowly increase the retirement ages to 63, 58, and 55 over a 15-year period. Our results lend support to these policies as the costs of aging effects through labour are high. While debates about the ideal retirement ages go on, other policies, such as promoting elderly training, tackling age discrimination, and improving elderly health care, can be considered.

In order to investigate factor market frictions in China, we estimated factor price wedges for China. Our results show that there were substantial factor price wedges in China. The wedges were higher in industry than in services and were higher for labour than for capital. Using our effective labour measure, we found that on average, 20% of employment wedges can be explained by the age composition of employment. Similarly, using our effective capital measure, we found that 47% of capital stock wedges can be explained by the composition of capital stock. In 2020, labour wedges were slightly lower while capital wedges were larger than their counterparts in 1981. These suggest there is ample room to improve the sectoral allocation of factors and hence aggregate productivity in China by dismantling factor market frictions.

This study is not without limitations. For example, the assumptions about Cobb-Douglas production function might hold only approximately, especially given China's unique history and economy. This study focuses only on the supply side and ignores the demand side. In reality, demand side forces play important roles in the economy and interact with supply side forces. In the next chapter, we will shift our focus to the demand side. Some of the results in this chapter are computed based on the ceteris paribus assumption. In reality, changes in one variable can induce changes in others. In Chapter 6, we will build a general equilibrium model that account for the important interactions between variables and use it to investigate population aging, structural change, and economic growth in China.

In this chapter, we did not estimate and analyse the contributions of international trade to China's structural change and economic growth. International trade has exposed China to international competition and allowed China to specialise in manufacturing where it has a comparative advantage. Through imports and through working with multi-national corporations, Chinese firms have gained technology and expertise. These have helped raise China's productivity. International demand for Chinese products has not only helped raise China's production but also provided a beneficial channel to utilise China's excess savings over investment. Accounting for the contributions of trade therefore represents an important avenue for future research. Our main conclusions from this chapter would likely still hold if we accounted for trade, however, because net exports constituted a small share of China's GDP, averaging at 2.2% over the 1981-2020 period.

Appendix 3.1 Cleaning and processing of household survey data

A3.1.1 CHIP

We use the province variable to construct and assign weights. In several datasets, there are a very small number of people who reported non-existent or incorrect province codes. We replace their province codes by the closest code. For example, one individual reported an unrecognisable province code of 25 and we replace it by the closest code that exists, which is 23 for Heilongjiang province. We drop sample individuals for whom provincial codes cannot not be assigned.

Age data is reported by almost everyone. For the few who did not, we try to use their spouses' ages to approximate their ages. If their spouses' ages are not available, we drop them from the dataset.

In the 2007 wave of CHIP, age is not directly reported but can be computed using the reported date, month, and year of birth. Everyone reported year of birth. There are about 50 people who did not report month or day of birth. For people without month of birth, we assume they were born in June. For people without day of birth, we assume they were born on the 15th.

We use the industry of work variable to sort individuals into the three sectors according to NBS's Regulations for Three-Sector Classification (NBS, 2018). There are a small number of workers who responded to the industry of work question with 'do not know', 'others', or no answer. We try to sort these people into sectors using other variables including occupation, source of income, hours worked in agriculture, and nature of work unit. We drop people for whom sector of work cannot be figured out.

CHIP datasets either report individual income directly or report a breakdown of individual income into components. In the latter case, we compute individual labour income by aggregating the components. For CHIP's 1988 data sets, we compute the in-kind income component as the reported market value of the goods minus the value paid by the recipients. We drop employees who reported zero income.

When cleaning the datasets, we find a small number of extremely large wages that are likely due to misreporting. To prevent extreme values from affecting our results, we trim the workers who constitute the top one percentile of wages.

On average, CHIP's rural survey covers 38,963 individuals and CHIP's urban survey covers 22,210 individuals between 1988 and 2007. After data cleaning and processing, the average CHIP sample size for rural and urban areas are respectively 6670 and 11724 individuals.

The cleaned and processed rural samples seem small compared to the original samples. This is because the overwhelming majority of workers in rural areas worked in agriculture, and the overwhelming majority of workers in agriculture were self-employed workers working on their own farms. For these workers, no wages were paid and recorded. Only workers who were employees and hence received wages in agriculture feature in our final sample. Across the four survey waves, the final sample sizes of agricultural employees average at 1183 and 148 for the rural area and urban area, respectively. In the urban area, very few workers work in agriculture. This means the final sample sizes for urban agricultural employees are small and that the weights of urban average agricultural wages are small.

A3.2.2 CFPS

To compute average labour income by age by sector, we use the variables of weight, age, industry of work, and labour income from CFPS's datasets for individuals.

Our cleaning and processing of CFPS data are similar to those for CHIP. For the small number of people with missing data, we try our best to figure out their data using other variables. For those with missing age data, we use spouses' ages to fill the missing ages. To fill missing industry of work, we primarily use occupational data. Occupation data in CFPS are quite detailed. There are about 500 hundred occupation categories and most of them are sector specific. People with missing data that cannot be filled are dropped from the sample. Like for CHIPs, we trim workers who constitute the top one percentile of wages to prevent extreme values from skewing our results. Across the five survey waves between 2010 and 2018, the average CFPS final sample that we use for computations after data cleaning and processing contains 11724 individuals.

In CFPS 2012, for some of the individuals who engaged in multiple activities, there is no data on their main job. We compare their incomes from the different activities and determine their main job as the activity from which they earned the most income.

Like in the CHIP's case, in agriculture, only employees who received wages reported their wages. The agricultural workers who owned their farms and hence did not receive wages do not feature in our final samples. On average, the final sample size of agricultural employees is 748.

Appendix 3.2 Variants of growth accounting results

In Section 3.4, we presented our baseline growth accounting results which were computed using capital stocks as the measures of capital inputs. In this appendix, we present variant 2 and variant 3 growth accounting results which are computed respectively using capital services and VICS's as the measures of capital inputs.

Tables 3.7 to 3.8 show that TFP growth results from variants 2 and 3 are very similar to those from the baseline. As mentioned in Chapter 2, capital services grew faster than capital stocks in industry while the opposite is true in services. It is therefore not surprising that the variant 2 results show slower TFP growths in industry and faster TFP growths in services than the baseline. The differences, however, are small. Since VICS's are very similar to the growth rates of capital services, variant 3 results are very similar to variant 2 results.

Table 3.7: Average annual TFPG (Variant 2)

Variant 2: K=capital services, L=employment				
	Aggregate	Agriculture	Industry	Services
1981-2020	0.038	0.052	0.036	0.016
1981-1990	0.029	0.038	0.024	0.021
1991-2000	0.049	0.033	0.069	0.008
2001-2010	0.049	0.069	0.029	0.031
2011-2020	0.022	0.069	0.018	0.003

Tables 3.9 and 3.10 show that variant 2 and variant 3 contribution shares results are similar to the baseline results. For industry, the alternative results show slightly larger capital contribution shares and smaller TFP contribution shares than the baseline. For

services, the opposites are true.

Table 3.8: Average annual TFPG (Variant 3)

Variant 3: K index=VICS, L=employment				
	Aggregate	Agriculture	Industry	Services
1981-2020	0.038	0.052	0.037	0.016
1981-1990	0.030	0.038	0.025	0.021
1991-2000	0.049	0.034	0.070	0.008
2001-2010	0.051	0.069	0.034	0.031
2011-2020	0.021	0.070	0.018	0.003

Table 3.9: Average shares of contributions to growth (Variant 2)

Variant 2: K=capital services, L=employment				
	Aggregate	Agriculture	Industry	Services
K	0.56	0.14	0.61	0.69
L	0.06	-0.20	0.09	0.23
A	0.38	1.06	0.31	0.08

Table 3.10: Average shares of contributions to growth (Variant 3)

Variant 3: K index=VICS, L=employment				
	Aggregate	Agriculture	Industry	Services
K	0.56	0.14	0.60	0.69
L	0.06	-0.20	0.09	0.23
A	0.38	1.06	0.32	0.08

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Chapter 4: Two Perspectives on Preferences and Structural Transformation in China

4.1 Introduction

China's structural change has typically been analysed through supply side variables such as output and labour. Limited attention has been paid to the rapid structural change taking place on the demand side of China's economy. In this chapter, we compile China's sectoral consumption expenditure and sectoral consumption value added data. These data enable us to estimate utility and sectoral demand functions for China. Using the estimation results, we analyse the demand-side drivers of structural change in China.

Between 1981 and 2018, agriculture's share in China's GDP fell from 31% to 7% (National Data, 2025). According to our compiled data in this chapter, agriculture's share in China's consumption expenditure fell from 32.1% to 5.6% over the same period. Demand side forces have clearly played important roles in China's structural change. The connection between sectoral GDP and sectoral expenditure cannot be made directly, however, as they are different measurements. Expenditure on goods produced in one sector can contain value added from all three sectors. As a result, expenditure on a sector is not equal to value added of the sector. In this thesis, we aim to construct and simulate a general equilibrium multi-sector model of China. The distinction between supply-side and demand-side data is particularly relevant to a project like ours (Herrendorf et al, 2014). Unlike most studies in the past, we tackle this issue explicitly. In this chapter, we use official Input-Output Table (IOT) data to break down China's consumption expenditure into sectoral value-added components. We compare and analyse sectoral consumption expenditure and sectoral consumption value added data. We are among the first to do these for China.

The structural change literature provides two broad types of explanations for structural change: demand side and supply side. The demand side explanations, such as those in Echevarria (1997), Kongsamut et al (2000), and Boppart (2014), emphasize the role of varying income elasticities of demand across sectors due to non-homothetic preferences.

As income grows, the demand for goods that are more income elastic expand relative to the others. For brevity, we shall refer to this as the income effect following the terminology in Herrendorf et al (2013). The supply side explanations, such as those in Baumol (1967), Ngai and Pissarides (2007), and Acemoglu and Guerrieri (2008), hinge on the differences in productivity growths and factor intensities across sectors. These differences influence relative sectoral prices which in turn influence the allocation of expenditure across sectors. We shall refer to the effect of relative sectoral price changes on sectoral allocation of expenditure as the relative price effect.

To this day, there is no consensus on the relative importance of income effect and relative price effects as drivers of structural change. China is an interesting and important case due to its enormous size and rapid economic growth. In this chapter, we contribute to the literature by bringing the Chinese case to light. We estimate China's sectoral demand functions. We then use them to analyse and compare the roles played by income effect and relative price effect in driving China's structural change following a similar approach to that in Herrendorf et al (2013). We conduct the estimation and analyses using both sectoral consumption expenditure and sectoral consumption value added data. We analyse the two sets of results comparatively. To our knowledge, we are the first to conduct such estimations and analyses for China.

Our results show that price elasticities of sectoral demands are low in China. This means sectoral consumption shares move with their respective relative prices. Relative price effect can therefore explain the observed fall in industrial consumption share and rise in service consumption share with their corresponding relative prices in China. However, only the income effect acting through non-homotheticity terms can explain the fall in agriculture consumption share in spite of increases in agricultural relative price. As such, a utility function with non-homotheticity terms is the most suitable for explaining China's sectoral consumption patterns.

Our work in this chapter lay the groundwork for the construction and simulation of our Multi-Sector Overlapping Generations (MSOLG) model in Chapters 5 and 6. The demand side data we compile in this chapter will be used directly. The importance of preferences discovered in this chapter inspire us to explore the implications of age-specific preferences in Chapters 5 and 6. The estimation results in this chapter help us determine the type of utility function that is most suitable for our MSOLG model of China.

Past studies on the composition of China's consumption have used micro-level consumption by categories data from household surveys (Zheng et al, 2013; Sun and Jiang, 2019; Qi and Liu, 2020). Each of these categories can contain products from multiple sectors. Since there are long time intervals between publicly accessible household survey data, past studies have used either data from one year or pooled data from a few survey waves. In this chapter, we study China's annual aggregate consumption of agriculture, industry and construction, and services between 1981 and 2018. These are the three sectors by which structural change is defined. In terms of approach, past studies have typically written and estimated linear regression models of consumption categories with a wide range of controls. In our study, we derive sectoral demand functions from a standard multi-sector model and estimate them directly.

The rest of this chapter is organised as follows. In Section 4.2, we explain the differences between sectoral value added and sectoral expenditure data and present our approach to reconcile the two sets of data. In particular, we present the methodology we use to break down consumption expenditure into sectoral value-added components. In Section 4.3, we compile and analyse data of sectoral consumption expenditure and sectoral consumption value added, and of their corresponding price indices. In Section 4.4, we present and analyse a standard three-sectors model of demand and derive our empirical specification. Section 4.5 presents our results for preference parameters and for the drivers of structural change estimated using sectoral consumption expenditure data. Section 4.6 presents results obtained using sectoral consumption value added data. Section 4.7 concludes. In Appendix 4.1, we conduct some robustness checks for our results.

4.2 Reconciliation of supply side and demand side data

4.2.1 Sectoral value added and sectoral expenditure (final use)

In economics, supply is typically measured by value added and demand is typically measured by expenditure (final use). At the aggregate level, value-added GDP equals expenditure GDP as all final goods produced by firms are used by individuals. At the sectoral level, however, value added is not equal to expenditure. Note that as always, we focus on the three production sectors: primary (agriculture), secondary (industry), and tertiary (services). Although the secondary sector contains industry and construction, we refer to it as industry for brevity. For brevity, we sometimes refer to the secondary sector and the tertiary sector as the modern sectors and sometimes collectively as the modern sector.

To explain the differences between sectoral expenditure and sectoral value added, we start with a simple example. A bag of potato chips is categorised as a processed food and is hence a secondary sector product. The spending on a bag of chips is therefore expenditure on a secondary sector product. However, a bag of chips is made using output from all three sectors. For examples, raw potatoes from agriculture, processing from manufacturing, and marketing from services. Resultantly, the market value of a bag of chips contains value added from all three sectors.

The connections between sectoral final use and sectoral value-added are captured by Input-Output Tables (IOTs). We use a hypothetical IOT in Table 4.1 below to explain the differences between sectoral final use and sectoral value added in more detail. As in a typical IOT, the yellow quadrant is a matrix of intermediate inputs. Along the horizontal direction, the yellow quadrant shows the amount of each sector's output used as intermediate inputs in different sectors. Along the vertical direction, the yellow quadrant shows, for each sector, the amounts of intermediate inputs from various sectors that it uses in production.

The yellow and green quadrants, along the horizontal direction, show how the gross output of each sector is allocated across intermediate uses and final use. The yellow and orange quadrants, along the vertical direction, show how each sector's gross input, which is equal to gross output, is split between intermediate inputs and value added.

The arbitrary numbers in the IOT in Table 4.1 present an example of how sectoral value added can differ from sectoral expenditure. We can see that modern sector production uses lots of intermediate inputs from agriculture but modern sector output is overwhelmingly used for expenditure (final use). Resultantly, modern sector expenditure exceeds modern sector value added. This difference indicates that modern sector expenditure contains lots of primary sector output, which consists mostly of primary sector value added. The opposite is true for the primary sector. Primary sector output and hence value added are mostly used to make goods in the modern sector rather than for expenditure. Resultantly, agricultural expenditure is less than agricultural value added.

Table 4.1: A simple example of an Input-Output Table

		Intermediate Use		Final Use	Gross Output
		Primary Sector	Modern Sector		
Intermediate inputs	Primary Sector	20	60	20	100
	Modern Sector	20	20	160	200
	Value Added	60	120		
	Gross Input	100	200		

In Chapters 2 to 5, we study the supply side and demand side of China's economy separately. In reality, there are important interactions between the two sides. Therefore, we would eventually like to study population aging, structural change, and growth in China using a three-sectors model in which supply and demand side forces operate and interact with each other. This will be our task in Chapter 6. The differences between sectoral expenditure and sectoral value-added present challenges when we construct general equilibrium models with multiple sectors. In a standard three-sectors model, market clearing means sector i supply equals sector i demand:

$$supply_{it} = A_{it}K_{it}^{\alpha_i}L_{it}^{1-\alpha_i} = C_{it} + I_{it} + G_{it} + NX_{it} = demand_{it}$$

The equation above shows sector i supply in period t is produced using primary inputs of capital K_{it} and labour L_{it}. A_{it} refers to total factor productivity. Sectoral demand is composed of household consumption C_{it}, investment I_{it}, government consumption G_{it}, and net exports NX_{it}. The issue, as described earlier, is that sector i supply as measured by value added is not equal to sector i demand as measured by expenditure.

One might be tempted to define both sectoral supply and sectoral demand in the model as sectoral expenditure. However, this leads to inconsistency between output data and factor inputs data on the side, since sectoral inputs in the data by definition are ones used to produce sectoral value added.

The solution we adopt is to measure both sectoral supply and sectoral demand by sectoral value added. To this end, we break down expenditures into their sectoral value-added components. These components correspond to the demand side variables in our model in Chapter 6. In Section 4.2.2, we detail the methodology for deriving these components.

In this chapter, we are interested in China's sectoral consumption. We compute the sectoral value-added components of consumption, which we shall refer to as sectoral consumption value added following Herrendorf et al (2013). We then estimate demand functions and investigate the demand side drivers of structural change in China using both sectoral consumption expenditure and sectoral consumption value added.

An alternative approach to reconcile the differences between sectoral value added and sectoral expenditure is to use multi-sector models with input-output structures. In such models, sectoral supply would be defined as sectoral gross output and intermediate inputs would be used in production. Needless to say, these models are harder to build, calibrate, simulate, and analyse. Our main goal in this project is to simulate a multi-sector model with overlapping generations to study the interactions between aging, structural change, and economic growth. Incorporating input-output structure explicitly into our model would add a layer of complexity that is unnecessary for our purposes. Furthermore, the data requirement for such exercise is huge. The limitations in China's IOT data would lead to a lot of noises if we were to use such models. Therefore, for simplicity, tractability, and reliability, we leave the exercise of incorporating input-output structure explicitly into an overlapping generation model of China to future projects.

4.2.2 Breaking down sectoral expenditures into sectoral value-added components

In this subsection, we present the procedure for breaking down expenditures into sectoral value-added components using Input-Output Tables (IOTs). This procedure is standard but rarely used, especially in the Chinese case. In this chapter, we apply the procedure to compile China's sectoral consumption value added data.

A typical Chinese IOT is shown in Table 4.2, which is sourced from Input-Output Table of China (NBS, 1991-2022). Along the horizontal direction, quadrants I and II show the amounts of each industry's gross output used as intermediate inputs and final uses, respectively. Quadrants I and III, along the vertical direction, show the amounts of each industry's gross input that are intermediate inputs from different industries and value added of the industry itself, respectively. At both industrial and aggregate levels, gross output and gross input are equal to each other. The industries can be classified into the three sectors following NBS's classification (NBS, 2018).

Table 4.2: Structure of 2007 Input-Output Table of China

2007 Input-Output Tables of China

(At Producers' Prices in 2007) 10000 yuan

INPUT \ OUTPUT		Intermediate Use				Final Use											Imports	Errors	Gross Output
						Final Consumption Expenditure					Gross Capital Formation								
						Household													
		Agriculture	…	Public Management and Social Organization	Total	Rural	Urban	Sub-Total	Government	Total	Gross Fixed Capital Formation	Change in Inventories	Sub-Total	Exports	Total				
Intermediate Inputs	Agriculture																		
	⋮	I				II													
	Public Management and Social Organization																		
	Total Intermediate Inputs																		
Value Added	Compensation of Employees																		
	Net Taxes on Production																		
	Depreciation of Fixed Capital	III																	
	Operating Surplus																		
	Total Value Added																		
Total Inputs																			

Quadrants I and II of IOT can be represented in matrix form as:

$$Total\ Intermediate\ Use + Total\ Final\ Use = Gross\ Output$$

where $Total\ Intermediate\ Use$ is a vector of total intermediate uses of the three sectors, $Total\ Final\ Use$ is a vector of total final uses minus imports of the three sectors, and $Gross\ Output$ is a vector of gross outputs of the three sectors. Entry i of $Total\ Intermediate\ Use$ represents the total amount of sector i's output used as intermediate inputs. Entry i of $Total\ Final\ Use$ represents the total amount of i's output allocated to final use. By excluding imports, $Total\ Final\ Use$ in the above equation represents total domestic final use (expenditure). Entry i of $Gross\ Output$ is the gross output of sector i.

We can write $Total\ Intermediate\ Use$ as:

$$Total\ Intermediate\ Use = A \times Gross\ Input$$

where $Gross\ Input$ is a vector of gross inputs of the sectors and A is the transaction matrix. The transaction matrix can be computed using data in the IOT. Entry ij of A shows the share of sector i's intermediate input in total input of sector j. Since $Gross\ Input$ is equal to $Gross\ Output$, entry ij of A also show the amount of output of sector i used as intermediate input to produced one unit of output of sector j.

We can then write $Gross\ Output$ as:

$$Gross\ Output = A \times Gross\ Input + Total\ Final\ Use$$

Rearranging:

$$(I - A) \times Gross\ Output = Total\ Final\ Use$$

where I is the identity matrix. This equation provides the relation between $Gross\ Output$ and $Total\ Final\ Use$. Given a vector of $Gross\ Output$, matrix $(I - A)$ applies the mapping which leads us to the vector $Total\ Final\ Use$ that can be achieved. Rearranging further:

$$Gross\ Output = (I - A)^{-1} \times Total\ Final\ Use$$

where $(I - A)^{-1} = R$ is called the total requirement matrix. Entry ij of R shows the amount of sector i's output that is required to deliver one unit of output of j to final uses.

Let v denote the vector of sectoral value added per unit of sectoral output, which is computed by dividing sectoral value added by sectoral output. Let $< v >$ denote the diagonal matrix with vector v in its diagonal. The value-added vector associated with the domestically produced final expenditure (Total Final Use) vector can be computed as:

$$Value\ added = < v > \times R \times Total\ Final\ Use$$

For brevity, we will refer to the matrix $< v > R$ as the 'extraction matrix' as it extracts sectoral value-added components from sectoral final uses. Entry ij of the extraction matrix shows the amount of sector i's value-added that is required to deliver one unit of output of j to final use. Therefore, like the requirement matrix, the extraction matrix is a representation of the economy's production process.

In this study, we apply the above formula to the final consumption expenditure vector to obtain the associated consumption value added vector:

$$Consumption\ Value\ Added = < v > \times R \times Final\ Consumption\ Expenditure$$

While Total Final Use excludes imports, Final Consumption Expenditure includes both domestically produced goods and imported goods. We do not know the share of imports in Final Consumption Expenditure. When we apply the above formula to obtain China's consumption value added, we are therefore assuming that imported goods are produced with the same input requirements as in China.

4.3 Data

4.3.1 Consumption expenditure

4.3.1.1 Consumption expenditure by sector

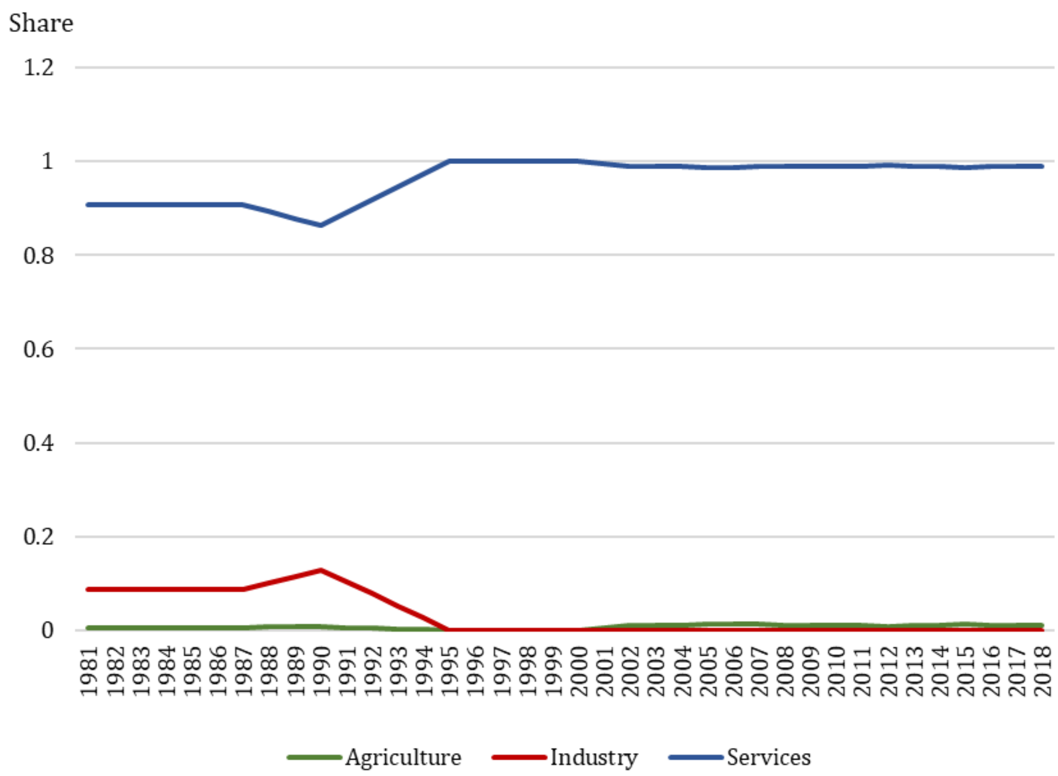
In this section, we construct consumption expenditure by sector data for China. To do so, we use a combination of China's official IOTs, expenditure approach GDP, and household survey data. In this chapter, unless stated otherwise, consumption refers to the sum of household consumption and government consumption.

As can be seen in Table 4.2, quadrant II of IOTs contain consumption expenditure data at the industrial level. We sort industries into the three sectors following the NBS's Regulations for Three-Sector Classification (NBS, 2018) and Industrial Classification for National Economic Activities (NBS, 2017). We obtain sectoral consumption expenditures by aggregating consumption expenditures of industries within each sector. Variables in China's IOTs are measured in producer prices. This means the demand side data constructed using IOT data are consistent with output data on the supply side.

Official expenditure approach GDP, along with its consumption expenditure components, have been adjusted over the years. To ensure consistency, we scale IOT sectoral consumption expenditure data so that they add up to the latest consumption expenditure data. This is equivalent to obtaining sectoral consumption expenditures by applying sectoral consumption expenditure shares from IOTs to the latest aggregate consumption expenditure data. We do so separately for household consumption and government consumption.

We obtain annual expenditure approach GDP data, of which household consumption expenditure and government consumption expenditure are components, from the 2020th edition of China Statistical Yearbook (NBS, 2020). We obtain China's IOT data from China Statistical Yearbooks (NBS, 1988-2021) and Input-Output Table of China (NBS, 1991-2022). China's IOT data are available every 2 to 3 years since 1987.

Figure 4.1: Sectoral shares in government consumption expenditure



Government consumption expenditure, as shown in Figure 4.1 above, is almost entirely on services and change little over time. For the years without IOT, we apply interpolated sectoral government consumption shares to the latest official aggregate government consumption.

For household consumption, we use household survey data to estimate data for the years without IOT data. Each year, the NBS conducts household surveys, collecting data on household characteristics, including consumption expenditure and income. The NBS uses annual household survey data to compute the household consumption expenditure data in expenditure approach GDP. The NBS also uses the household survey data to compute sectoral household consumption expenditure data. However, such sectoral household consumption expenditure data are only published at intervals of two to three years through the IOTs.

We obtain household survey consumption data for the 1981-2018 period from China Yearbook of Household Survey (NBS, 2011-2020), China Statistical Yearbooks (NBS, 1981-2021), China Yearbook of Price and Urban Household Income and Expenditure Survey (NBS, 1996-2005), China Urban Life and Price Yearbook (NBS, 2006-2012), China Urban Household Income and Expenditure Survey Data (NBS,1988-1994), National Urban Household Income and Expenditure Survey Data during the Six-Five Period (NBS, 1988), and NBS's National Data website (National Data, 2025).

Household survey consumption expenditure data are reported in per capita terms and are divided into various categories. The household survey data can be used to break down expenditure approach household consumption expenditure. We start by classifying the consumption categories roughly into the three sectors following NBS's Regulations for Three-Sector Classification (NBS, 2018). As an example, Table 4.3 below shows the consumption categories of survey data for the 2013-2019 period. The categories highlighted in green contain a mixture of primary and secondary sector products. The red categories contain secondary sector products. The purple categories contain a mixture of secondary sector and tertiary sector products. the blue categories contain services only.

For each year for which both IOT data and household survey data are available, we take a ratio of IOT agricultural household consumption to household survey approximate agricultural (the green categories) household consumption. This ratio extracts agricultural consumption out of the green categories of household survey consumption. For the years without IOT data, we estimate the ratios by linear interpolation and then multiply household survey approximate agricultural consumption by these ratios to estimate agricultural household consumption expenditures.

Table 4.3: Consumption expenditure categories of household survey data

Consumption Expenditure
1. Food, tobacco, and liquor
Food
Tobacco
Beverages
Food services
2. Clothing and footwear
Clothing
Footwear
3. Housing
Rent
Housing repair and management
Water, electricity, fuel, and others
Imputed rent of own house
4. Household equipment, furnishings, and services
Furniture and indoor decorations
Equipment and instruments for household use
Textile products for household use
Miscellaneous goods for household use
Personal care products
Household services
5. Transport and communications
Transport
Communications
6. Education, culture, and recreation
Education
Culture and recreation
7. Healthcare and medical services
Healthcare equipment and medicine
Healthcare services
8. Miscellaneous goods and services
Miscellaneous goods
Miscellaneous services

The residual part of the approximate agricultural household consumption, together with household survey consumption belonging to the red and purple categories, constitute consumption categories containing industrial products. We refer to consumption of these categories collectively as approximate industrial (secondary sector) consumption. For each year for which both IOT data and household survey data are available, we compute the ratio of IOT industrial household consumption to household survey approximate industrial household consumption. For the years without IOT data, we interpolate the ratios and estimate industrial household consumption expenditures by multiplying the ratios and the approximate industrial household consumption expenditures.

Finally, we subtract primary and secondary sector household consumption expenditure from total household consumption to obtain tertiary sector household consumption expenditure.

Although consumption categories of household surveys differ across periods and sometimes differ between rural and urban areas, the way we construct sectoral household consumption expenditure data for the years without IOTs is the same as above. We sort survey consumption categories into the three sectors. We compare the survey breakdowns of consumption with the IOT breakdowns from the same years to obtain parameters which allow us to estimate sectoral household consumption in years for which IOT data are unavailable.

The constructed sectoral household consumption expenditure data are shown in Figure 4.2. As can be seen in the figure, consumption expenditure of all three sectors increased. By 2018, household consumption expenditure in services had increased more than that in industry, which had increased more than that in agriculture. The pattern of structural change is more apparent in Figure 4.3 which plots sectoral household consumption shares. In 1981, industry occupied the highest share of 42.5%, agriculture occupied a middling 40.0%, while services occupied the smallest share of 17.5%. Over time, service share in household consumption expenditure surged, surpassing agricultural share in 1999 and industrial share in 2002, and reaching 55.3% in 2018. Industrial share fell slowly and agricultural share fell sharply, reaching 37.0% and 7.6% in 2018, respectively.

Figure 4.2: Aggregate and sectoral nominal household consumption expenditure

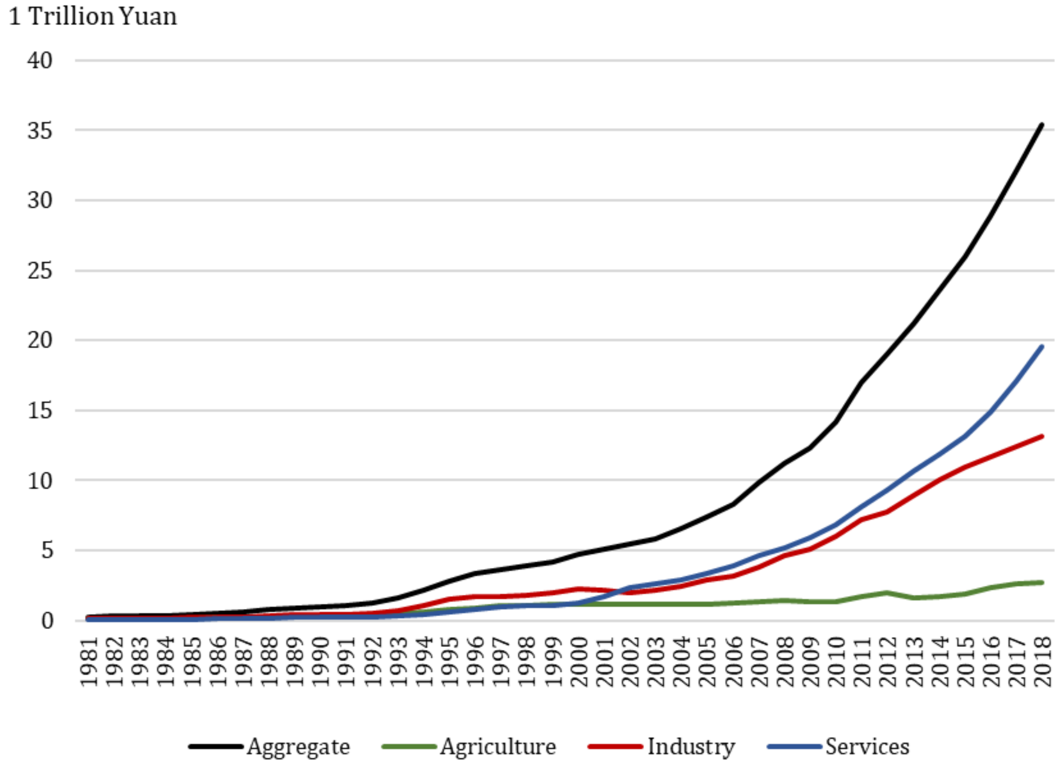


Figure 4.3: Sectoral shares in household consumption

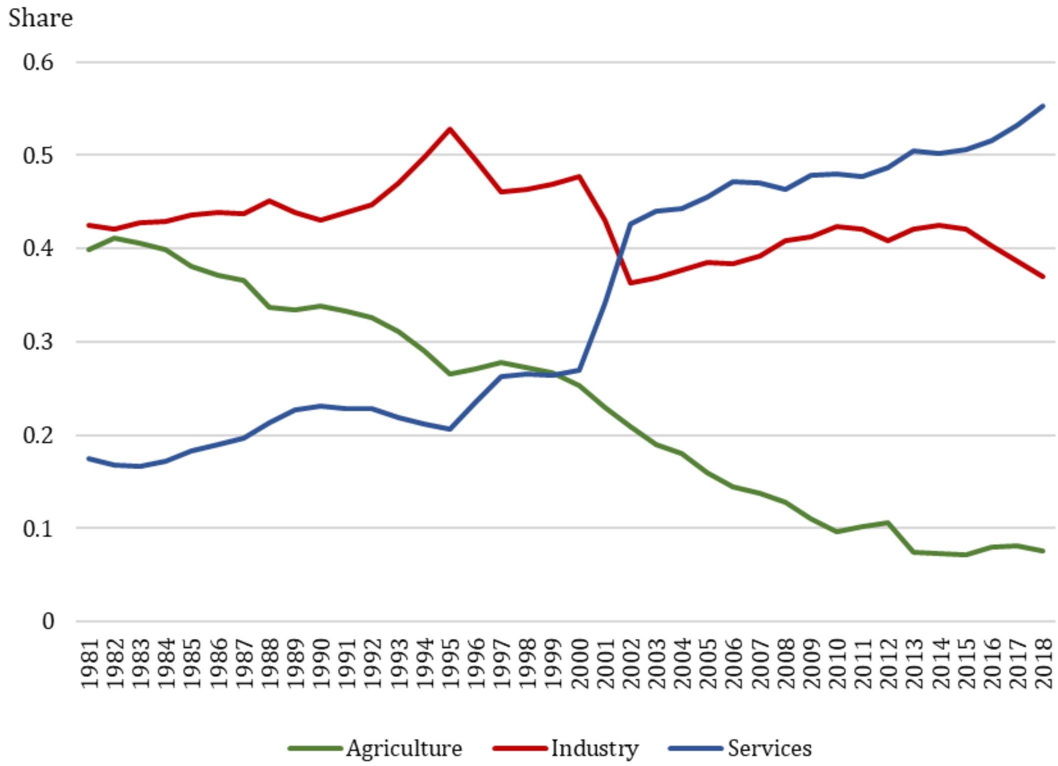


Figure 4.3 shows there were large changes in industrial and service shares between 1992 and 2002. From Figure 4.2, we can see that there is nothing abnormally large about the changes in sectoral household consumption in said period. In the next subsection, we will see that the shifts in shares can be explained by drastic changes in relative prices between 1992 and 2002.

Figure 4.4 plots sectoral shares in China's total consumption. With the inclusion of government consumption, service share in Figure 4.4 is generally higher than that in Figure 4.3. Between 1981 and 2018, China's consumption expenditure experienced rapid structural change towards services. As can be seen in Figure 4.4, service consumption share increased from 32.1% in 1981 to 68.4% in 2018. This was accompanied by reductions in both agricultural and industrial consumption shares. Agricultural share fell the most, from 32.1% to 5.6%. Industrial share fell moderately, from 35.8% to 25.9%.

Figure 4.4: Sectoral shares in total consumption

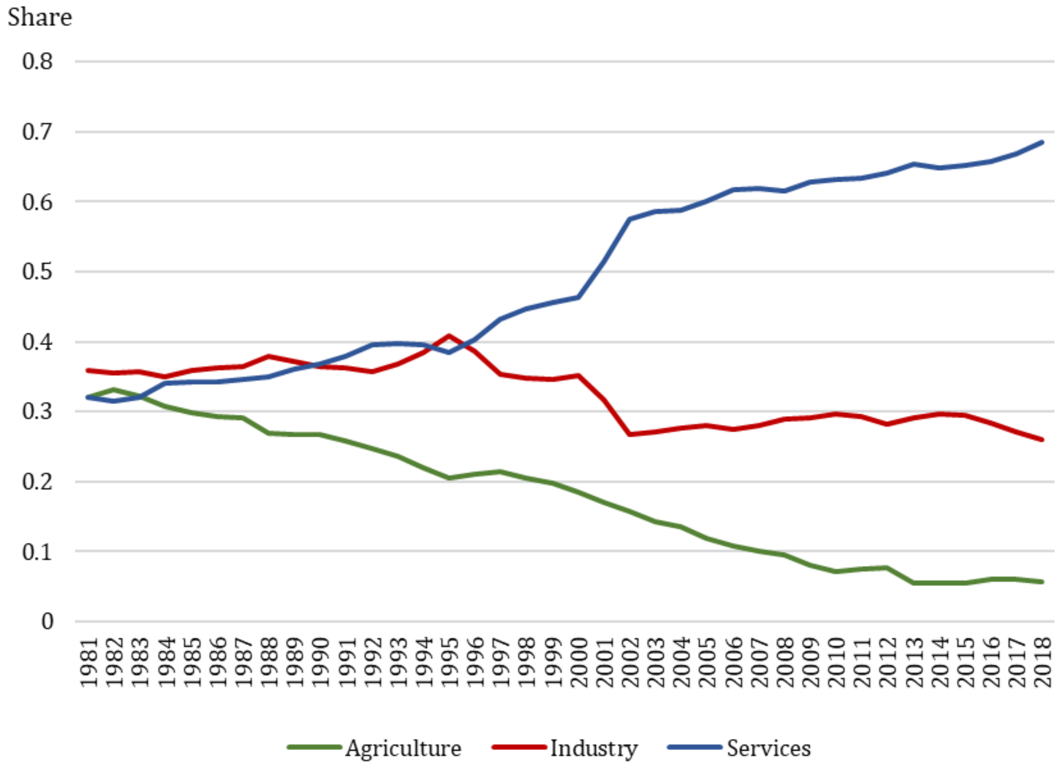
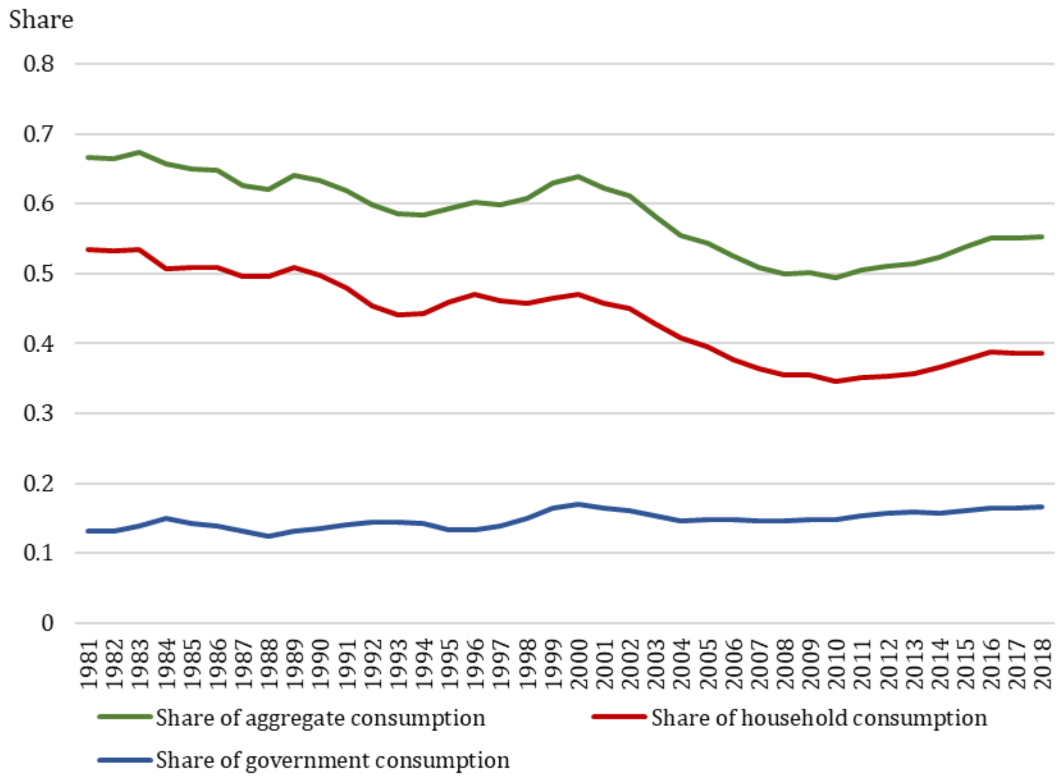


Figure 4.2 shows that China's household consumption increased rapidly between 1981 and 2018. The increase in consumption expenditure, however, was slower than that in GDP and that in government consumption. Figure 4.5 shows that household consumption's share in GDP decreased from 53% to 39% and government consumption's

share in GDP increased from 13% to 17% over the 1981-2018 period. The rise in government consumption share was not nearly enough to offset the fall in household consumption share. Resultantly, total consumption's share in GDP decreased from 67% in 1981 to 55% in 2018.

Although China's low and falling consumption share was unusual judging by the international experience, the data shows that it still constituted the majority of China's GDP. There have been hot debates about the sustainability and welfare implications of China's investment driven growth strategy. In recent years, the government has placed increasing emphasis on consumption driven growth. Understanding the structural change patterns in consumption is therefore key to our understanding of China's structural change and economic growth.

Figure 4.5: Consumption expenditure shares in GDP



4.3.1.2 Price indices for sectoral expenditure

To indicate the price of agricultural expenditure P_{at}, we use Producer Price Index (PPI) for agricultural products. According to the NBS, the secondary sector can be divided into two categories: industry and construction. We estimate the price index of secondary sector expenditure P_{dt} as a weighted average of PPI for industrial products and PPI for construction materials. The weights are shares of industry and construction in gross output from the IOTs. The aforementioned PPIs are published annually by the NBS through China Statistical Yearbooks (NBS, 1981-2021).

For the service sector, official PPI is not available. We estimate China's service PPI using the following relationships between aggregate expenditure and sectoral expenditures:

$$P_t Y_t = P_{at} Y_{at} + P_{dt} Y_{dt} + P_{st} Y_{st}$$

$$Y_t = Y_{at} + Y_{dt} + Y_{st}$$

Since aggregate expenditure is equal to aggregate value added, we use implicit value-added deflator to measure price index of aggregate expenditure P_t. Since we have data on nominal sectoral expenditures, this leaves us with P_{st} and Y_{st} as the two unknowns in the two equations. We estimate Y_{st} and P_{st} as:

$$\hat{Y}_{st} = Y_t - Y_{at} - Y_{dt}$$

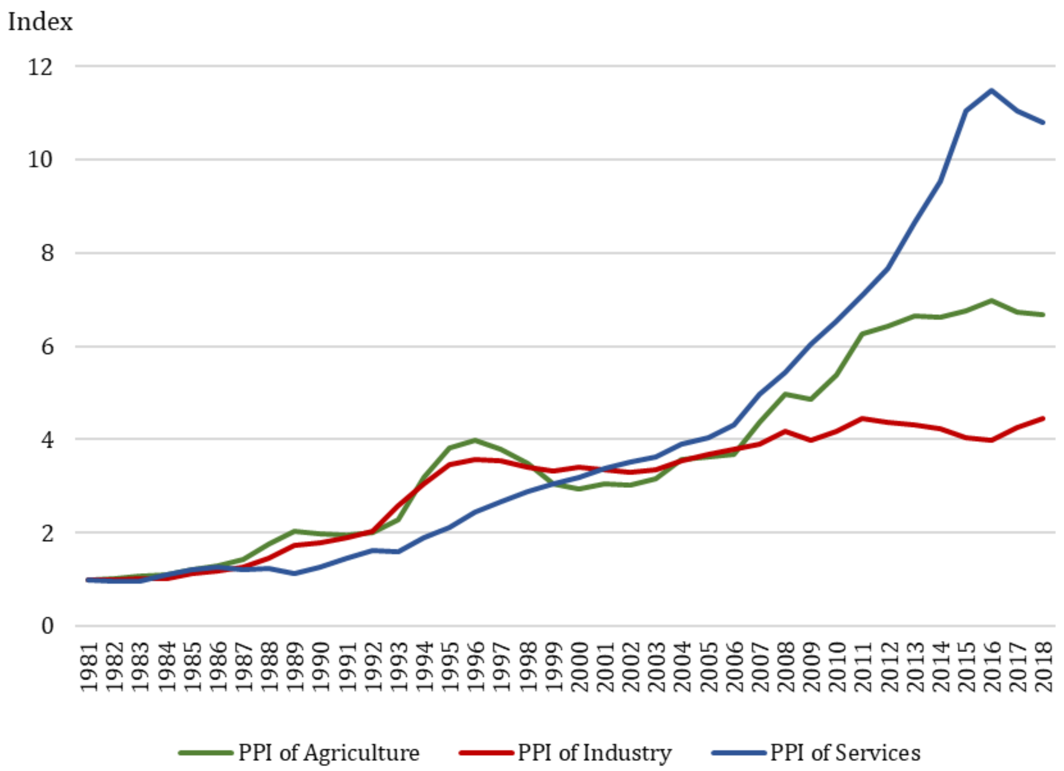
$$\hat{P}_{st} = \frac{P_{st} Y_{st}}{\hat{Y}_{st}} = \frac{P_{st} Y_{st}}{Y_t - Y_{at} - Y_{dt}}$$

It is not feasible to compute sectoral price indices for consumption, investment, and net exports separately. Although official aggregate Consumer Price Index (CPI) is available annually since 1985, CPI by sector is not. Official CPI is only available by household consumption goods categories. However, each category can contain goods from multiple sectors. Without knowing the prices of goods and services within each category, estimating sectoral CPIs using categorical CPIs would incur errors. Furthermore, IOT sectoral consumption expenditures are measured in producer prices. Sectoral producer prices are different to sectoral purchaser prices in the treatment of distribution costs such as those incurred in transportation, retail services, and wholesale services. Therefore, price indices from purchasers' perspective such as consumer price indices (CPIs) are not suitable for measuring price changes of IOT sectoral consumption expenditure. Finally, CPI measures price changes of household consumption but not government consumption. Since we are primarily interested in total consumption, CPI is not a suitable price index for our case.

Figure 4.6 below shows the evolution of price indices (base year=100) for China's sectoral expenditures. We can see that service price increased the most, followed by agricultural price, followed by industrial price. This ordering is the same as that for sectoral implicit value-added deflators.

Between 1992 and 2002, industrial price first surged and then fell while service price increased steadily. Our results from later sections will show that demand in China is inelastic and hence sectoral consumption shares move with their respective relative prices. These price changes can therefore explain the drastic changes in sectoral household consumption shares between 1992 and 2002 in Figure 4.3. Although agricultural price also surged and fell in the 1992-2002 period, agricultural consumption share fell due to income effects.

Figure 4.6: Sectoral Producer Price Indices (1981=1)



4.3.1.3 Sectoral real consumption expenditure

Using the producer price indices described in the previous subsection, we deflate nominal consumption expenditures. Figure 4.7 shows the resulting aggregate and sectoral real consumption expenditures. As can be seen in the figure, aggregate real consumption increased rapidly over the sample period. Figure 4.8 shows that consumption's share in GDP fell much more in real terms than in nominal terms. While nominal consumption's GDP share fell by 11% between 1981 and 2018, real consumption's GDP share fell by 22%. This is because service's share in consumption was much larger than service's shares in other components of expenditure GDP.

Figure 4.7 also shows that in real terms, industrial and service consumption both grew rapidly over the sample period while agricultural consumption increased by relatively little. These are confirmed by Figure 4.9 which shows sectoral shares in real consumption. Unlike industrial share in nominal consumption, industrial share in real consumption increased and caught up with service share. The structural change patterns in real and nominal terms are different due to the surging service and agricultural prices, and due to the stagnating industrial price.

Figure 4.7: Aggregate and sectoral real consumption expenditure

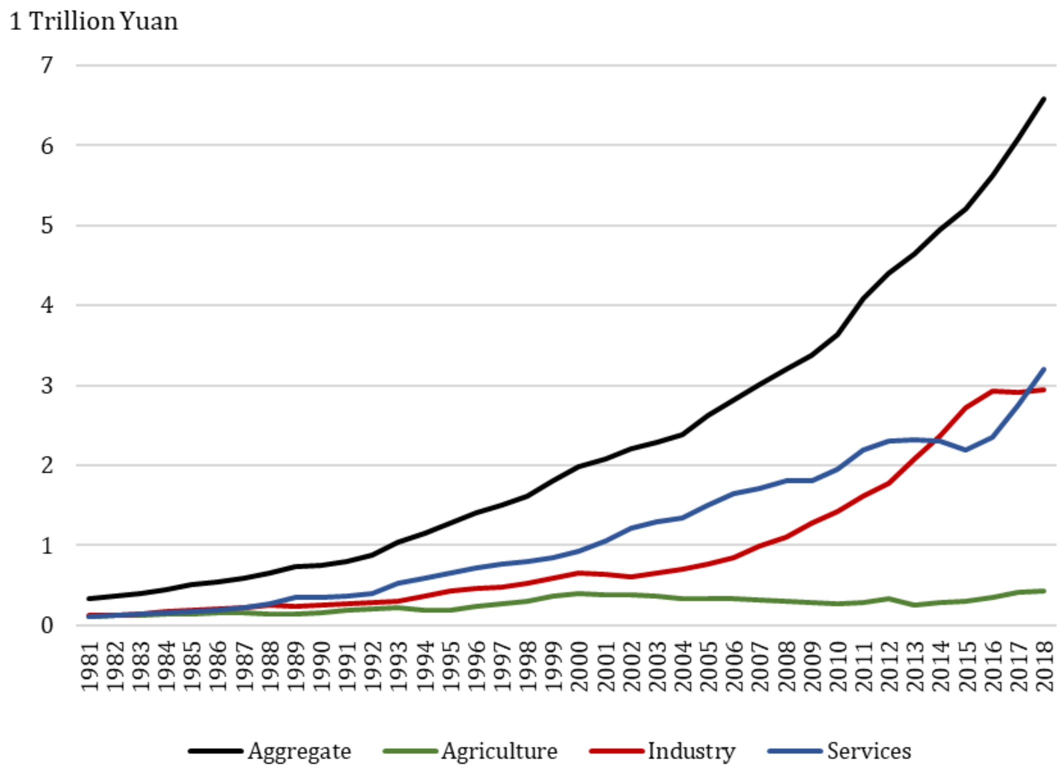


Figure 4.8: Real consumption shares in GDP

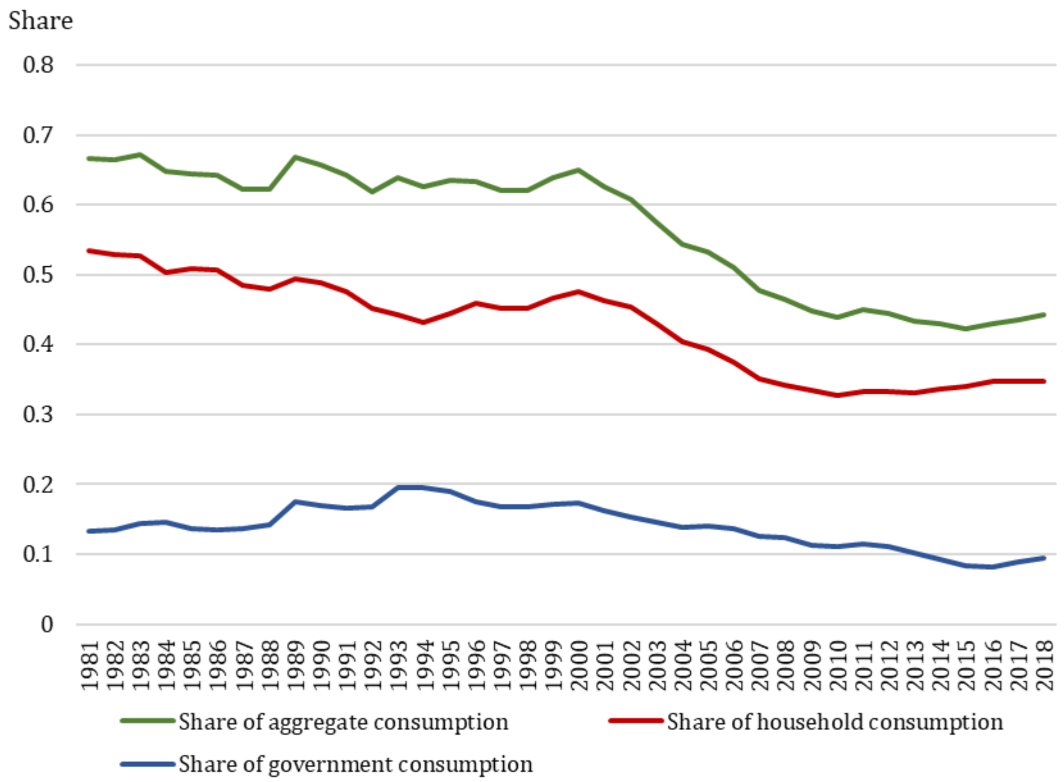
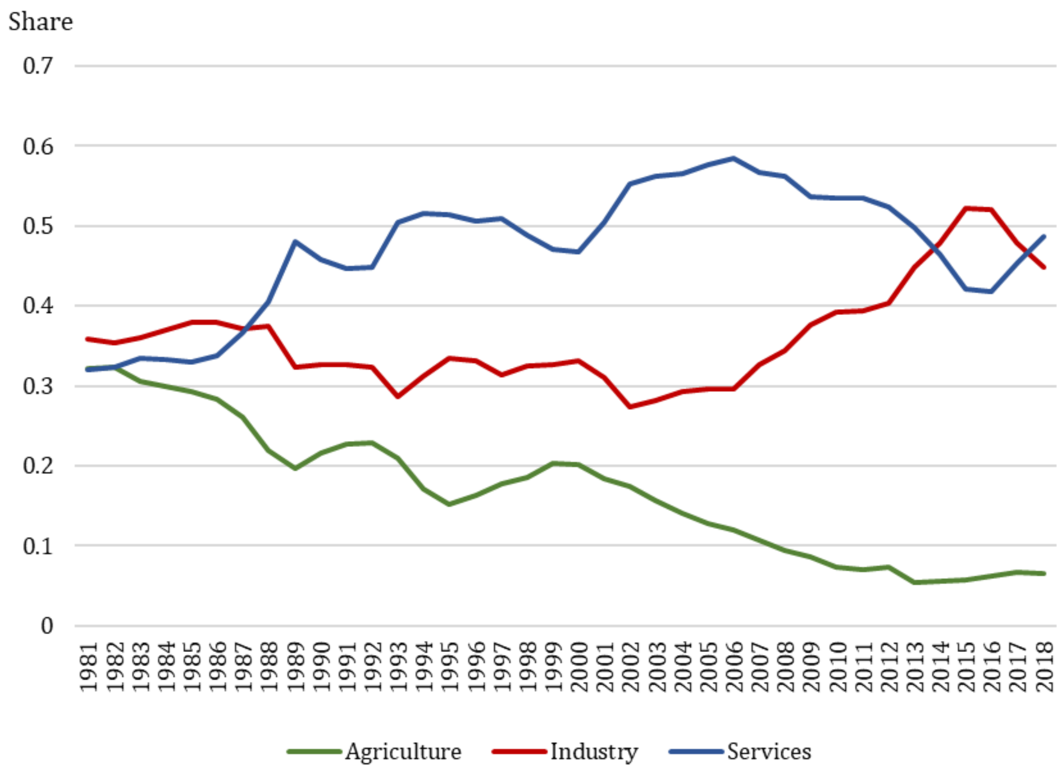


Figure 4.9: Sectoral real consumption shares



4.3.2 Consumption value added

4.3.2.1 Consumption value added by sector

Following the procedure described in Section 4.2, we compute consumption value-added vector for each year by pre-multiplying consumption expenditure vector by the extraction matrix. The extraction matrix is computed using China's IOTs. For the years without IOTs, we interpolated the extraction matrices.

In Figure 4.10, we plot our consumption value added together with consumption expenditure data. As can be seen in the figure, consumption value added of services rose the most, followed by that of industry, and then by that of agriculture. The differences between consumption value added data and consumption expenditure data are significant but small. By 2018, agricultural consumption value added was 28.7% higher than agricultural consumption expenditure. Relative to consumption expenditure data, consumption value added data show less structural change towards services. By 2018, consumption value added in services and industry were 3.9% smaller and 5.6% larger than their consumption expenditure counterparts.

Figure 4.11 shows sectoral shares in the two measures of consumption. As can be seen in Figures 4.10 and 4.11, the long-term patterns of structural change of consumption value added are similar to those of consumption expenditure. Initially, consumption value added share of agriculture was the highest (38.1%), followed by that of industry (36.4%), and then by that of services (25.5%). Over time, service share rose rapidly while agricultural and industrial shares fell. At the end of the sample period, agricultural, industrial, and service shares in consumption value added were respectively 7.2%, 27.2%, and 65.5%. For the 1981-2018 period as a whole, the shifts away from agriculture and towards services were slightly slower in terms of consumption value added than that in terms of consumption expenditure.

Figure 4.11 also shows substantial differences in short term movements between the two measures of sectoral consumption shares. Service share in consumption value added grew faster than that in consumption expenditure between 1981 and 1995, and then slower between 1995 and 2005, and then faster again after 2005. The opposites were true for industrial share in consumption value added.

In the previous chapter, we learnt that in China, total factor productivity in industry was higher than that in services, which was higher than that in agriculture. While the structural change of consumption away from agriculture raises aggregate productivity, the structural change from industry to services does not. Given that consumption is overwhelmingly composed of service value added and investment is overwhelmingly composed of industrial value added, raising investment would lead to more productivity gains than raising consumption. This is therefore an argument against the transition from investment-driven growth towards consumption-driven growth. Things might change, however, if China's industrial consumption share increases and or if China's service productivity growth accelerates in the future.

In Figure 4.12, we show sectoral shares in household consumption value added and household consumption expenditure. Again, the two sets of shares display similarities in the long-term pattern of structural change but large short-term differences in sectoral shares.

Figure 4.10: Aggregate and sectoral Consumption Value Added (CVA) and Consumption Expenditure (CE)

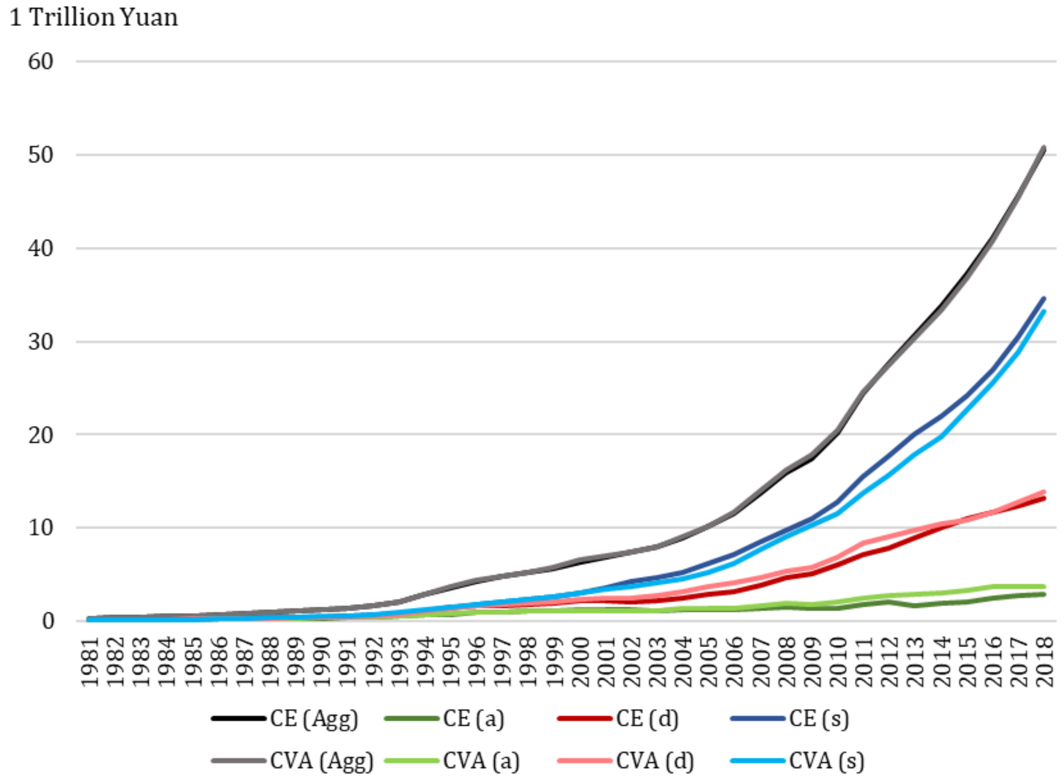


Figure 4.11: Sectoral shares in Consumption Value added (CVA) and Consumption Expenditure (CE)

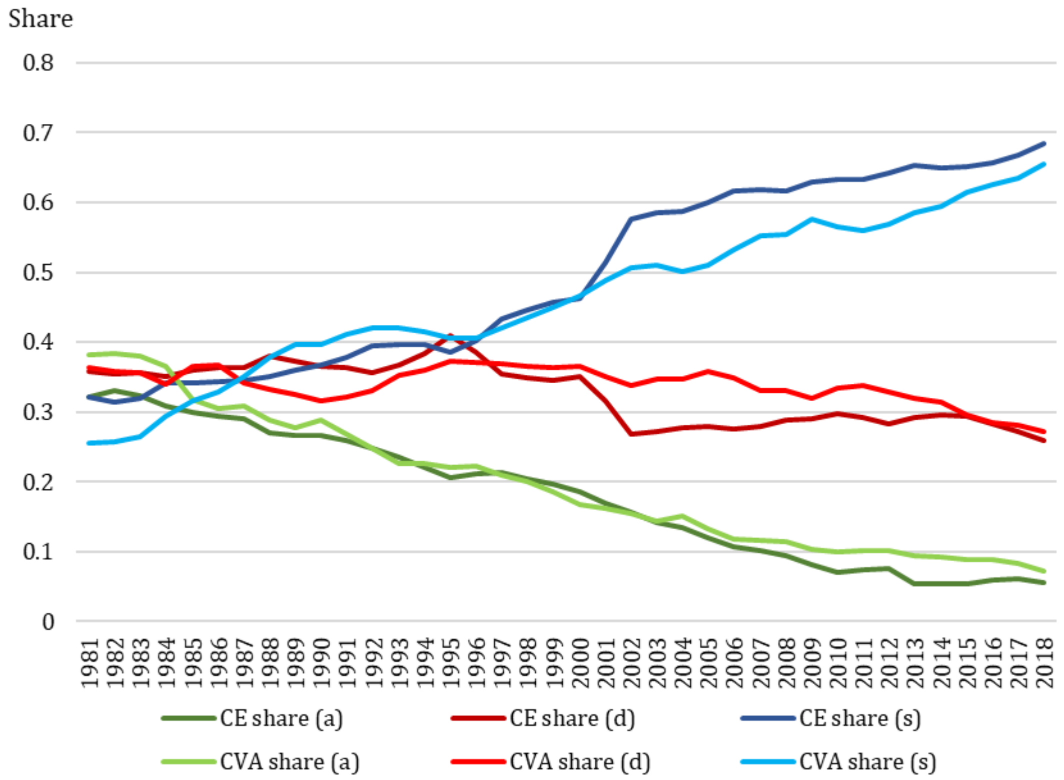
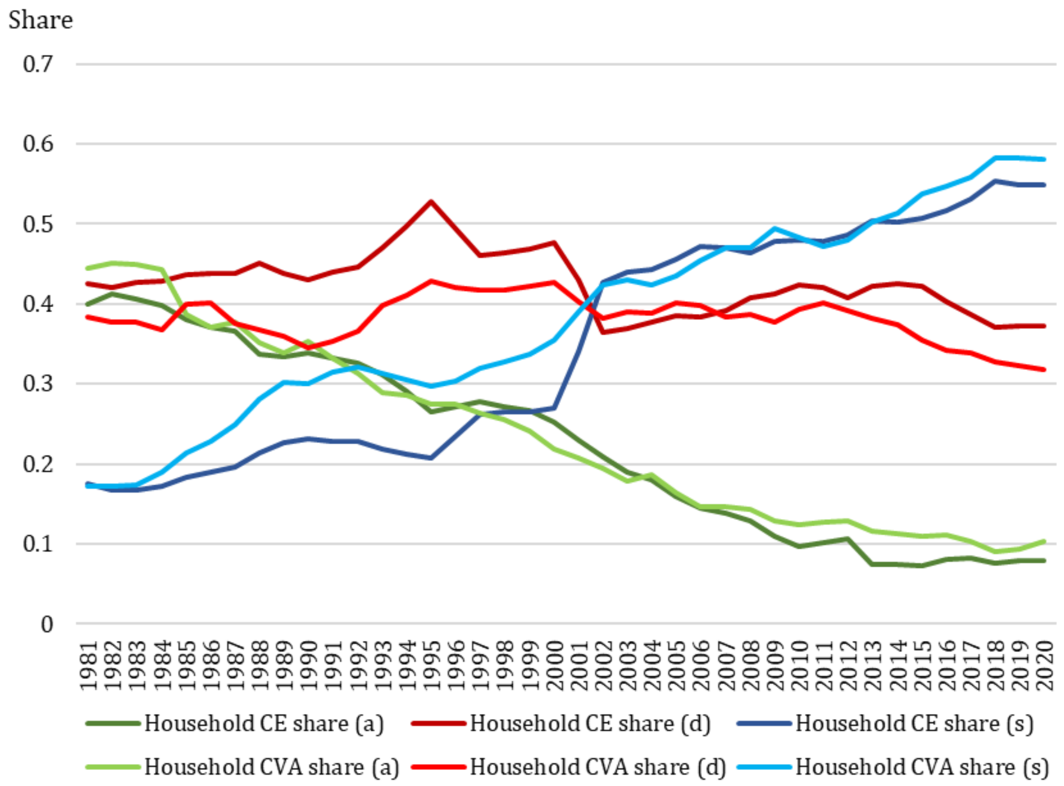


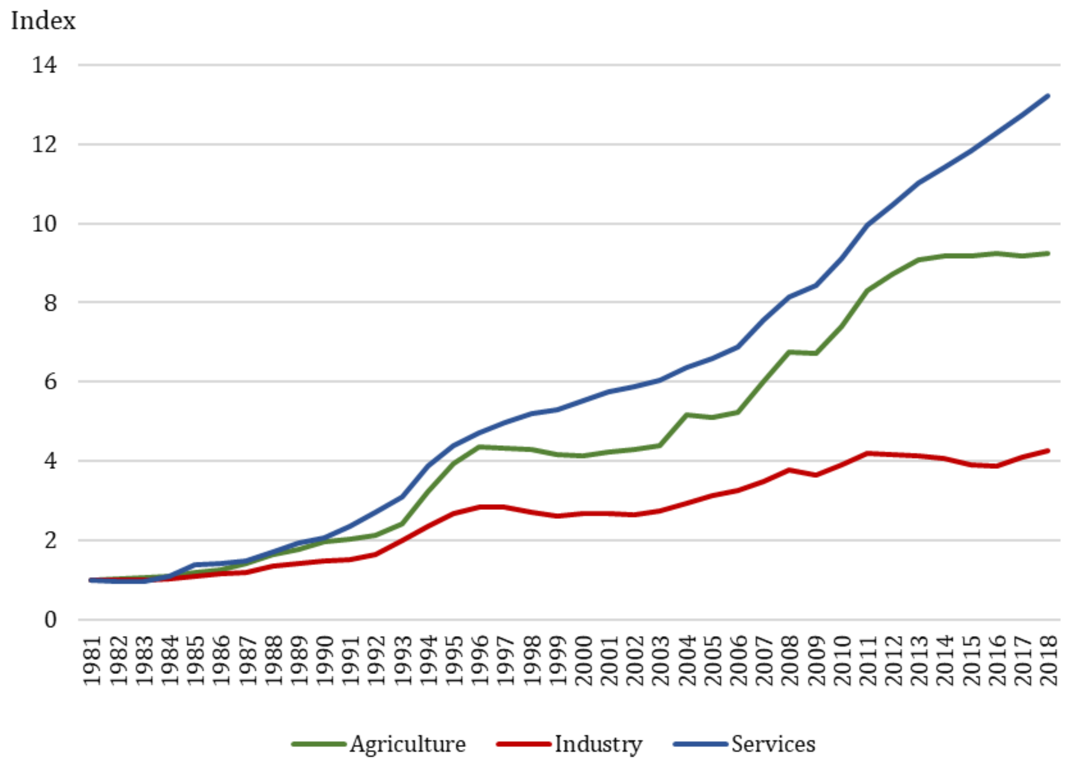
Figure 4.12: Sectoral shares in household Consumption Value Added and household Consumption Expenditure



4.3.2.2 Price indices for sectoral consumption value added

Consumption value added of a sector measures the value added of a sector that is used for consumption. To deflate sectoral consumption value added, we can therefore use the same price indices that we use to deflate sectoral value added—sectoral Implicit Value-Added Deflators (IVAD). Figure 4.13 below shows sectoral implicit value-added deflator data that we compiled in Chapter 3. Between 1981 and 2018, service price rose more rapidly than agricultural price, which rose more rapidly than industrial price. This explains why the secondary sector shrunk in nominal terms relative to the tertiary sector despite having faster real growths than the tertiary sector in the past decades. The relative IVAD of agriculture to industry increased by much more than the relative PPI of agriculture to industry. This is because the share of industrial value added in agricultural output was much smaller than the share of agricultural value added in industrial output.

Figure 4.13: Sectoral implicit value-added deflator (1981=1)



4.4 Model analysis and empirical strategy

In this section, we present a standard consumer problem on the demand side of a three-sectors model. The model nests a number of commonly used models and is frequently used in the literature. We then derive sectoral demand shares as functions of prices and total consumption. These functions constitute our empirical specifications in this chapter.

In the model economy, there is an infinitely lived representative individual. In each period, the individual derives utility from consumptions of the primary (agriculture), secondary (industry), and tertiary (services) sectors. The individual consumer's problem is to maximise expected present value of lifetime utility:

$$\sum_{t=1}^{\infty} \beta^t \frac{u(c_{at}, c_{dt}, c_{st})^{1-\rho} - 1}{1-\rho}$$

where

$$u(c_{at}, c_{dt}, c_{st}) = \left[\sum_{i=a,d,s} \omega_i^{\frac{1}{\sigma}} (c_{it} - \bar{c}_i)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

The consumer's optimisation problem is subject to a budget constraint:

$$z_t = \sum_{i=a,d,s} P_{it} c_{it} + s_t$$

As usual, the subscripts a, d, and s refer to agriculture, industry, and services, respectively. The parameter ρ determines the intertemporal elasticity of substitution of consumption. We refer to ω_i as preference weight for i. ω_i satisfies $\sum_i \omega_i = 1$ and is the key determinant of sector i's share in total consumption in the long term. σ is a parameter that determines the elasticities of demand.

$\bar{c}_i$ is a constant which can be thought of as subsistence sectoral consumption if it is positive and endowment sectoral consumption if it is negative. $\bar{c}_i$'s are the source of non-homotheticity to the periodic utility function. As such, $\bar{c}_i$'s are referred to as non-homothetic terms. If $\bar{c}_i$'s are all zeros, then periodic utility function $u(c_{at}, c_{dt}, c_{st})$ is homogeneous to the degree of 1.

In the budget constraint, z_t denotes the consumer's total resource in period t. z_t can include the individual's wage income, rent income, and depreciated savings from past periods. P_{it} denotes the price index of sector i and s_t denotes savings.

The solution for the consumption problem can be divided into two parts. First, we find the optimal rule for allocating total consumption across sectors within each period, given prices and the choice of total consumption. Second, given the optimal allocation rule, we choose total consumption and savings to maximise the individual's lifetime utility. In this study, we abstract away from the determination of prices, total income, and total consumption. We focus on the first part of the solution and analyse sectoral allocation of consumption in China, taking prices and total consumption as exogenously given.

The sectoral allocation of within-period total consumption is a static problem and can be written as:

$$\max_{c_{at}, c_{dt}, c_{st}} u(c_{at}, c_{dt}, c_{st})$$

$$s.t. \sum_{i=a,d,s} P_{it} c_{it} = P_t c_t$$

where c_t denotes real total consumption and P_t denotes the aggregate price index. Given the observed nominal total consumption $P_t c_t$ and sectoral price indices P_{it}'s, the representative individual optimally allocates total consumption across the three consumption categories.

c_t is the real income available for consumption in period t and increases with real total income. In the setting above, the effect of a rise in income is captured by a rise in total consumption. We refer to the effect of real total consumption change as income effect. For brevity, we often refer to total consumption as income in this chapter.

The first order conditions of the static problem can be rearranged to obtain:

$$\frac{\omega_i}{\omega_j} \frac{c_{jt} - \bar{c}_j}{c_{it} - \bar{c}_i} = \left(\frac{P_{it}}{P_{jt}}\right)^{\sigma}$$

The equation shows that sector i consumption is increasing in the preference weight of i and decreasing in the relative price of i. The elasticity of substitution parameter σ determines how strongly sectoral consumption reacts to relative price changes. Higher σ means greater responsiveness to relative price changes. Sectoral consumption is increasing in sectoral subsistence consumption. In addition, larger subsistence consumption of i reduces the reaction of c_{it} to a change in relative price.

After some algebra, we can obtain the sectoral demand function:

$$P_{it}c_{it} = P_{it}\bar{c}_i + \frac{\omega_i P_{it}^{1-\sigma}}{\sum_j \omega_j P_{jt}^{1-\sigma}}\left(P_t c_t - \sum_i P_{jt}\bar{c}_j\right)$$

Sectoral real consumption is therefore:

$$c_{it} = \bar{c}_i + \frac{\omega_i P_{it}^{-\sigma}}{\sum_j \omega_j P_{jt}^{1-\sigma}}\left(P_t c_t - \sum_i P_{jt}\bar{c}_j\right)$$

Since we are primarily interested in structural change, we divide both sides of the sectoral nominal consumption equation by total consumption to obtained the sectoral consumption share function:

$$s_{it} = \frac{P_{it}c_{it}}{P_t c_t} = \frac{P_{it}\bar{c}_i}{P_t c_t} + \frac{\omega_i P_{it}^{1-\sigma}}{\sum_j \omega_j P_{jt}^{1-\sigma}}\left(1 - \frac{\sum_i P_{jt}\bar{c}_j}{P_t c_t}\right) \tag{4.1}$$

Let p_{it} denote the relative price of sector i:

$$p_{it} = \frac{P_{it}}{P_t}$$

Sectoral consumption share can then be written as:

$$s_{it} = \frac{p_{it}c_{it}}{c_t} = \frac{p_{it}\bar{c}_i}{c_t} + \frac{\omega_i p_{it}^{1-\sigma}}{\sum_j \omega_j p_{jt}^{1-\sigma}}\left(1 - \frac{\sum_i p_{jt}\bar{c}_j}{c_t}\right) \tag{4.2}$$

Equation (4.2) is the empirical specification that we use to estimate preference parameters (ω_i's, $\bar{c}_i$'s, and σ) for China given data on relative prices (p_{it}'s), real total consumption per capita (c_t), and sectoral consumption shares (s_{it}'s). This is also the specification that we will use to estimate preferences by age group in Chapter 5.

The functions of sector i demand have two terms. The first term corresponds to subsistence consumption or endowment consumption of sector i. The second term is a share of consumer's excess income over subsistence consumption. This share depends on preference weight, relative prices, and elasticity of demand. Intuitively, the consumer uses his total consumption to satisfy subsistence consumption first. If there is any income for consumption left, he then allocates them across sectors according to his preferences.

To explain the relative price effect, let us first assume that non-homotheticity terms are zeros and focus on the second term of the demand functions. This term shows that real consumption of sector i falls when price of i increases. The responsiveness of real consumption depends on the parameter σ. If σ is less than one, then real consumption falls less than proportionately to a rise in price. Resultantly, sector i nominal consumption and share increase following an increase in its price. If σ is greater than one, a rise in sectoral price would cause sectoral real consumption to fall more than proportionately, causing sectoral nominal consumption and share to fall.

If non-homotheticity terms are positive, their presence would reduce relative price elasticity of demand, so that sectoral nominal consumption and share are more inclined to increase with sectoral relative price. Intuitively, this is because the consumer cannot substitute away from subsistence consumption. If sector i's price increases, subsistence consumption of i becomes more expensive and sector i's share in nominal consumption increase. The opposites are true if non-homotheticity terms are negative.

Without subsistence consumption, the utility function is homothetic and sectoral consumption shares depend on prices but not on income. In addition, sectoral real consumption must move in opposite direction to sectoral relative price. Such utility functions on their own have struggled to explain observed structural changes, especially in developing countries.

The presence of non-homotheticity terms in the form of subsistence consumption allows the model to capture a channel through which income affects sectoral consumption shares. When income is low, consumption income is almost entirely spent on subsistence consumption. Such subsistence consumption is typically agricultural as foods are necessary for survival. As income rises, the consumer has more and more spare income that can be spent on products for which he has higher preference weights. These products are typically from secondary and tertiary sectors. Therefore, the presence of subsistence consumption means rising income would induce consumption to structurally shift from agriculture to industry and services.

Aside from the pure relative price and income effects, there are interactions between them. For clarity and relevance, we explain the interactions using specifically the sectoral consumption share equations. As can be seen in the equations, if sector i's relative price rises, the cost of sector i subsistence consumption increases. If real income c_t remains constant, the share of income that can be allocated according to preference weights falls. Resultantly, the relative price effect acting through the second term in the equation diminishes. If real income increases, the consumer can afford the higher subsistence consumption whilst having the same or higher spare income share. Therefore, some of the relative price effect associated with the spare income share can only occur if real income increases.

As mentioned earlier, we use equation (4.2) to estimate preference parameters for China. Throughout our project, we experimented with restricting various combinations of $\bar{c}_i's$ to zeros. To make comparisons of results across sectors, measures of sectoral consumption, and age groups meaningful, we need to use the same restrictions across all estimations. We eventually settled with the specification in which only $\bar{c}_d$ is restricted. The estimates for this specification are statistically significant in all cases and deliver the best fit of data in the vast majority of cases. This specification is also one that is most commonly used in the literature.

We estimate the system of sectoral consumption share equations using Iterative Feasible Generalised Nonlinear Least Squares (IFGNLS). Since the expenditure shares sum to one, one of the equations has to be dropped. Note that the results are not affected by which equation we drop. The empirical specification and estimation strategy presented above are frequently used in the literature and are also the ones used by Herrendorf et al (2013) to estimate preferences for the US. More details can be found in Deaton (1986), Greene (2012), and StataCorp (2025). In our case, our estimates for σ and ω_i all turn out to be positive. It is therefore unnecessary in our case to ensure the positivity of estimates by transforming and or restricting parameters.

The utility function in the above model is a general one that nests a range of utility functions in the literature. Kongsamut et al (2001) provided an explanation of structural change emphasizing the role of income elasticities of demand resulting from non-homothetic preferences. They used a Stone-Geary utility function shown below which is a special case of the general model in which $\sigma = 1, \bar{c}_a > 0$, and $\bar{c}_s < 0$.

$$u(c_{at}, c_{dt}, c_{st}) = \omega_a \ln(c_{at} - \bar{c}_a) + \omega_m \ln(c_{mt}) + \omega_s \ln(c_{st} - \bar{c}_s)$$

Ngai and Pissarides (2007) emphasized the role of sectoral Total Factor Productivity (TFP) growths and factor intensities in structural change. Their homothetic preferences are the special case in which $\sigma < 1, \bar{c}_a = 0$, and $\bar{c}_s = 0$:

$$u(c_{at}, c_{dt}, c_{st}) = \left[\sum_{i=a,d,s} \omega_i^{\frac{1}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

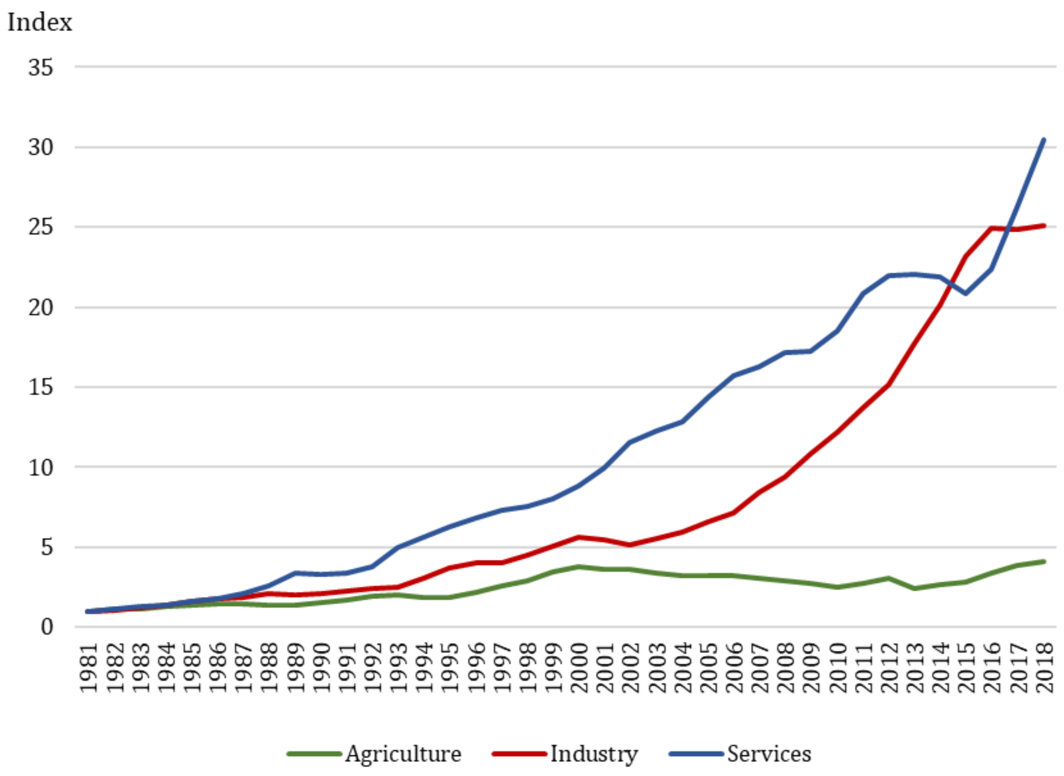
Our estimated preference parameters will shed light on what type of utility function can best explain Chinese data. The estimated preferences will also allow us to investigate the extents to which changes in income and changes in relative prices drove China's structural change.

4.5 Results with consumption expenditures

4.5.1 Preference estimation results

In this section, we present our estimation results for equation (4.2) using sectoral consumption expenditure and producer price index data.

Figure 4.14: Quantity indices of sectoral consumption expenditure (1981=1)



Looking at the price indices in Figure 4.6 and cumulative indices (base year=1) of real sectoral consumption expenditures in Figure 4.14, we can already form some predictions about the results based on the properties of the utility function. The price of services relative to that of agriculture and the quantity of services relative to that of agriculture both increased. As mentioned earlier, relative price effects always drive real relative quantities and relative prices in opposite directions. The observations therefore suggest that structural change in China's consumption was driven not only by relative price effects but also by income effects originating from the non-homotheticity terms. Specifically, the observations are consistent with the presence of subsistence agricultural consumption ($\bar{c}_a > 0$) and or endowment service consumption ($\bar{c}_s < 0$). The observed patterns maybe facilitated by σ being small so that the relative price effect was small and hence more easily dominated by the income effect.

The agriculture to industry relative price increased while the agriculture to industry quantity index decreased. These are consistent with the relative price effect and with the income effect resulting from agricultural subsistence consumption. For the relative price effect to play an important role, σ cannot be too small.

The industrial price fell relative to the services price. This raised the quantity of industry to services. However, the increase in industrial quantity relative to service quantity was quite slow considering the rapid divergence of the industrial price from the service price. This points to the presence of income effects associated with endowment service consumption ($\bar{c}_s < 0$).

Table 4.4 shows the estimation results for equation (4.2). As can be seen in the table, all estimates are highly significant at the 1% significance level. The point estimate for non-homotheticity term $\bar{c}_a$ is positive. This is consistent with the fact that there are subsistence agricultural consumption expenditures that the consumer needs in order to survive. The negative $\bar{c}_s$ estimate can be interpreted as endowment of services such as home-produced services. The significance of non-homotheticity terms' estimates suggest that non-homotheticity terms and hence income effects are crucial in explaining China's structural change.

The preference weight (ω_i) estimates show that consumers strongly prefer modern sector consumption to agricultural consumption. This facilitates the rise of modern sector consumption shares over time as income increases. Among modern sector products, consumers strongly prefer services to industrial products. While structural change towards the modern sector can boost economic growth, structural change from industry to services might not. This is because productivity in industry tends to be higher than that in services in China according to our results in Chapter 3.

Table 4.4: Preference estimation results with consumption expenditure

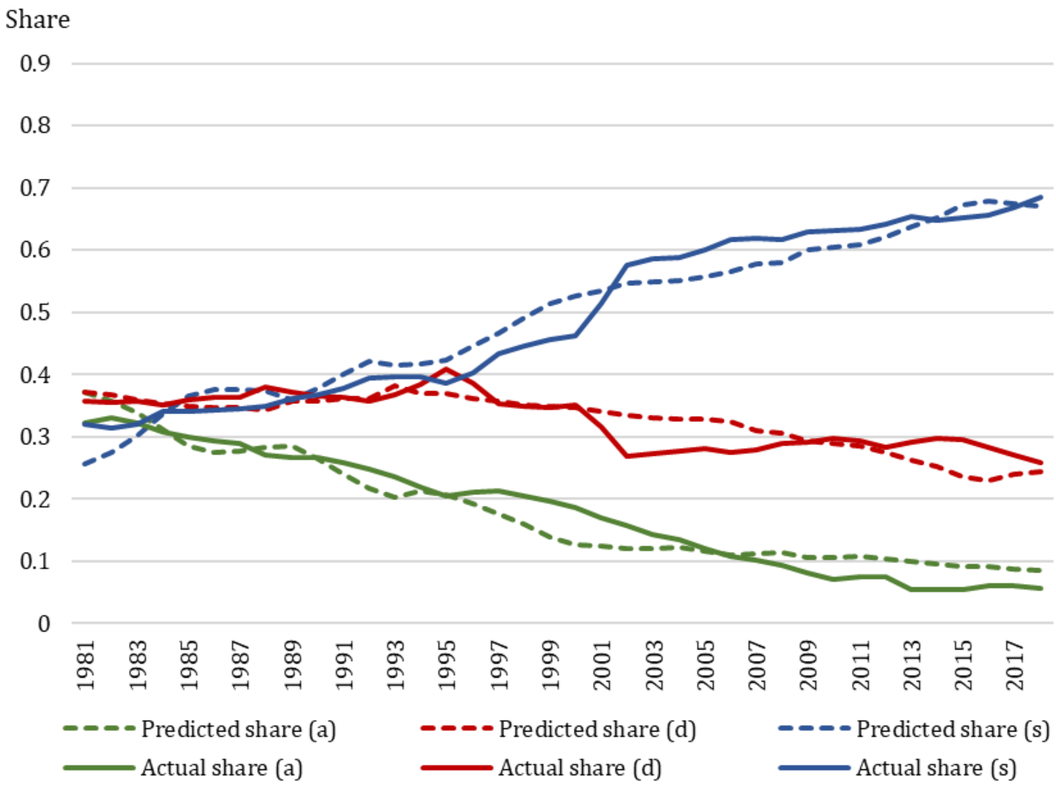
σ	0.48***
	(0.056)
ω_a	0.072***
	(0.0081)
ω_d	0.33***
	(0.0090)
ω_s	0.60***
	(0.010)
$\bar{c}_a$	95.42***
	(6.85)
$\bar{c}_s$	-139.56***
	(19.04)
R_a^2	0.978
R_s^2	0.996
$RMSE_a$	0.030
$RMSE_d$	0.029
$RMSE_s$	0.033

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

σ is estimated to be 0.48. This means neither a Stone-Geary utility function which features a σ of 1 nor a Leontief utility function which features a σ of zero is suitable for the Chinese case. Instead, a utility specification with an explicit substitution elasticity parameter should be used. The size of σ has important implications for the effect of relative price changes on sectoral consumption shares.

Figure 4.15 shows actual and model predicted paths of sectoral consumption expenditure shares. The predicted shares are computed by inserting data prices and income into the estimated sectoral consumption share functions. The model predictions fit sectoral consumption expenditure shares data well with an average Root Mean Squared Error (RMSE) of 0.03.

Figure 4.15: Actual and predicted sectoral consumption expenditure shares



<u>4.5.2 Relative price effect</u>

We would like to investigate the relative importance of relative price effect and income effect in explaining China's sectoral consumption shares following the approach in Herrendorf et al (2013). Since price and income effects are determined by preference parameters, the investigation would provide further evidence on the ideal form of utility function for studying the Chinese economy.

To study the effects of changing relative prices, we compute model predicted paths of sectoral consumption expenditure shares using equation (4.2) under the counterfactual scenario in which income is held constant at the 1981 level while relative prices are allowed to change following the data. Figure 4.16 shows the actual and counterfactual shares of sectoral consumption expenditures. The changes of counterfactual shares over time reflect relative price effects. To facilitate our analyses, we plot relative prices of the three sectors in Figure 4.17.

Figure 4.16: Sectoral consumption expenditure shares: actual shares versus counterfactual shares computed by holding income constant at the 1981 level

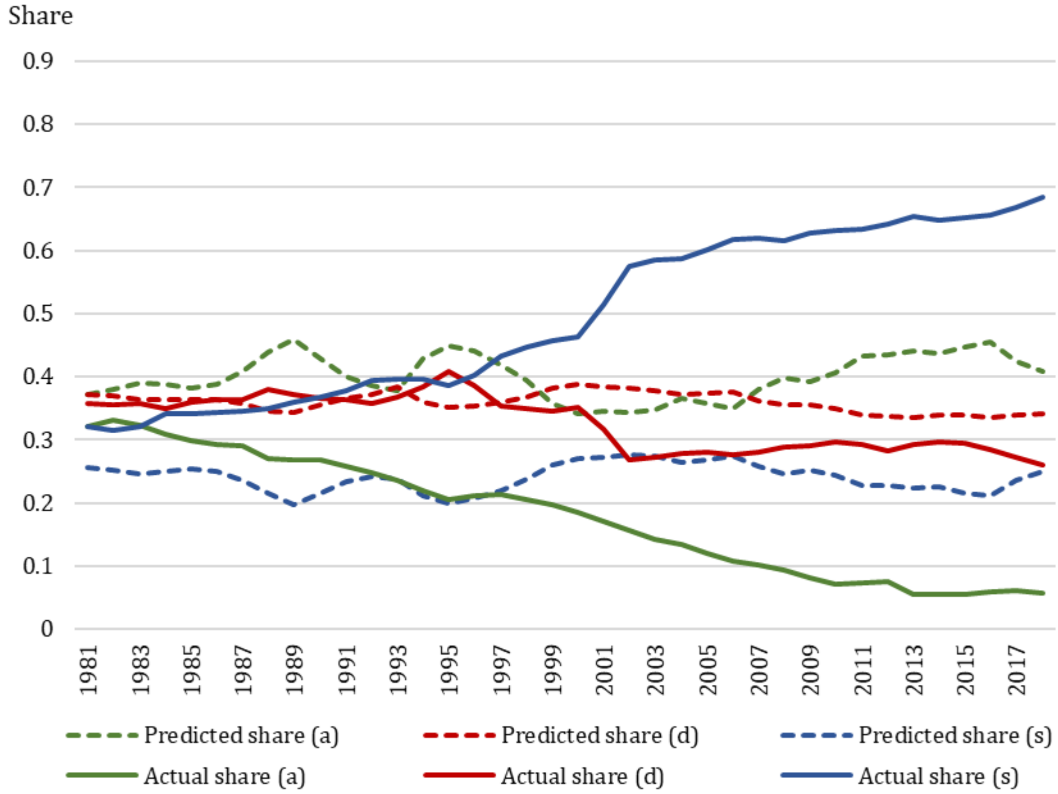
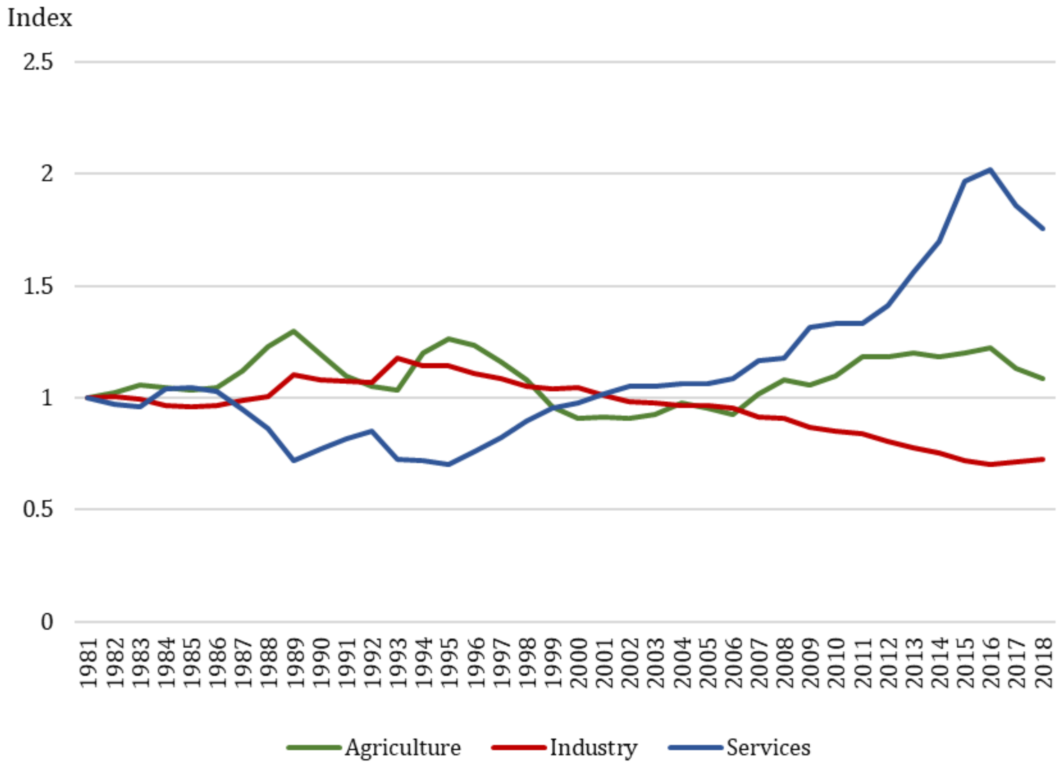


Figure 4.17: Sectoral relative PPI



Comparing Figure 4.16 and Figure 4.17, we can see that the predicted sectoral consumption expenditure shares move with their respective relative prices. This can be explained by the small value of σ. Since our estimated σ is between 0 and 1, sectoral real consumption is relative price inelastic. Resultantly, as sectoral relative price rises, real sectoral consumption falls less than proportionately, causing nominal sectoral consumption to rise.

As can be seen in Figure 4.16, counterfactual industrial share rises and then falls. These changes are in the same directions as those of the actual shares. Counterfactual service share fluctuates around a constant level while actual service share rises rapidly over time. Following the agricultural relative price, counterfactual agricultural share increases slightly over the sample period. This is in sharply contrast with actual agricultural share which decreases over time. While the relative price effect can explain a third of the observed decrease in industrial consumption expenditure share, it fails to explain the observed increase in service share and decrease in agriculture share. This points to the importance of income effect in explaining China's structural change.

4.5.3 Income effect

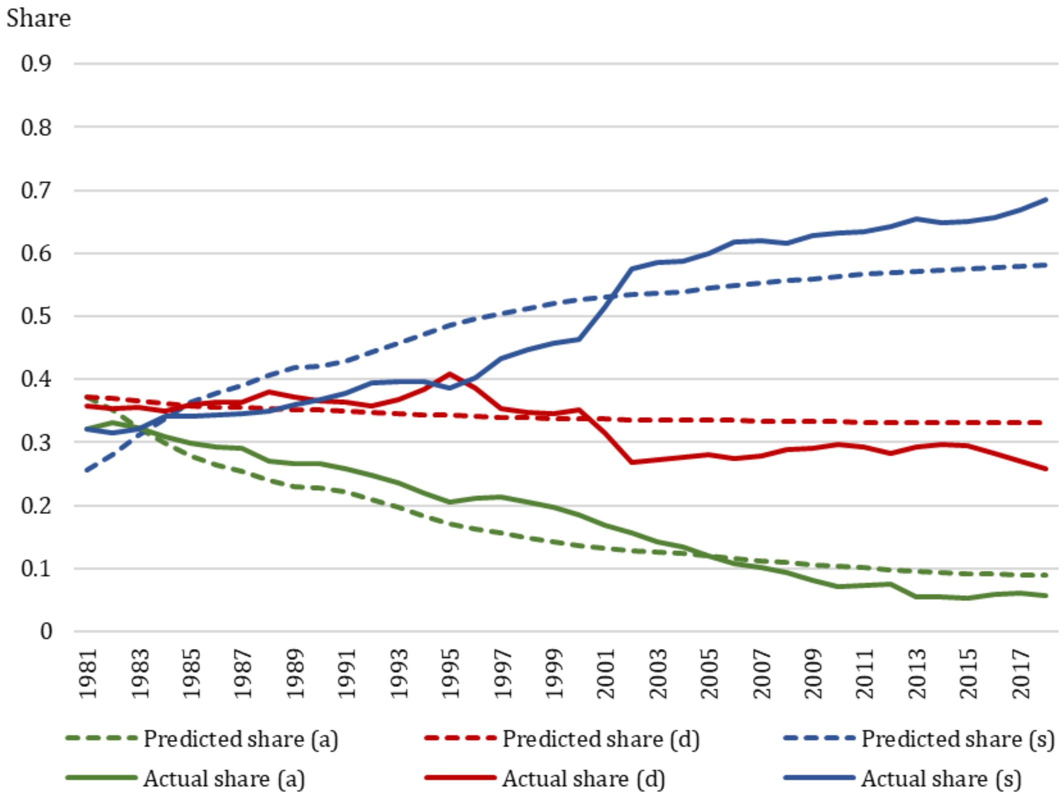
Next, we investigate the effects of real income changes. In Figure 4.18, we plot sectoral consumption shares in the data and in the counterfactual scenario in which prices are held constant at 1981 levels while real income follows the actual path.

Given constant prices, subsistence agricultural consumption and endowment service consumption stay constant over time. As income rises, subsistence agricultural consumption's share and endowment service consumption's share in total consumption fall. The rising income in excess of subsistence consumption is spent overwhelmingly on services because service preference weight is much higher than the others. The rise in service consumption share is facilitated by the fall in endowment service consumption share.

As can be seen in Figure 4.18, income effect is the key to explaining the observed shifts in agricultural and service consumption expenditure shares over the sample period. In Appendix 4.2 of this chapter, we provide some further evidence about the importance of income effects by estimating and analysing a specification without non-homotheticity terms.

Figure 4.18 shows that income effect can only partially explain the observed fall in industrial consumption expenditure share. In addition, income effects seem smooth and hence are unable to explain the short-term movements of sectoral consumption expenditure shares. Therefore, China's sectoral consumption expenditure patterns are driven by a combination of income and relative price effects rather than by income effect alone.

Figure 4.18: Sectoral consumption expenditure shares: actual shares versus counterfactual shares computed by holding relative prices constant at 1981 levels



4.6 Results with consumption value added

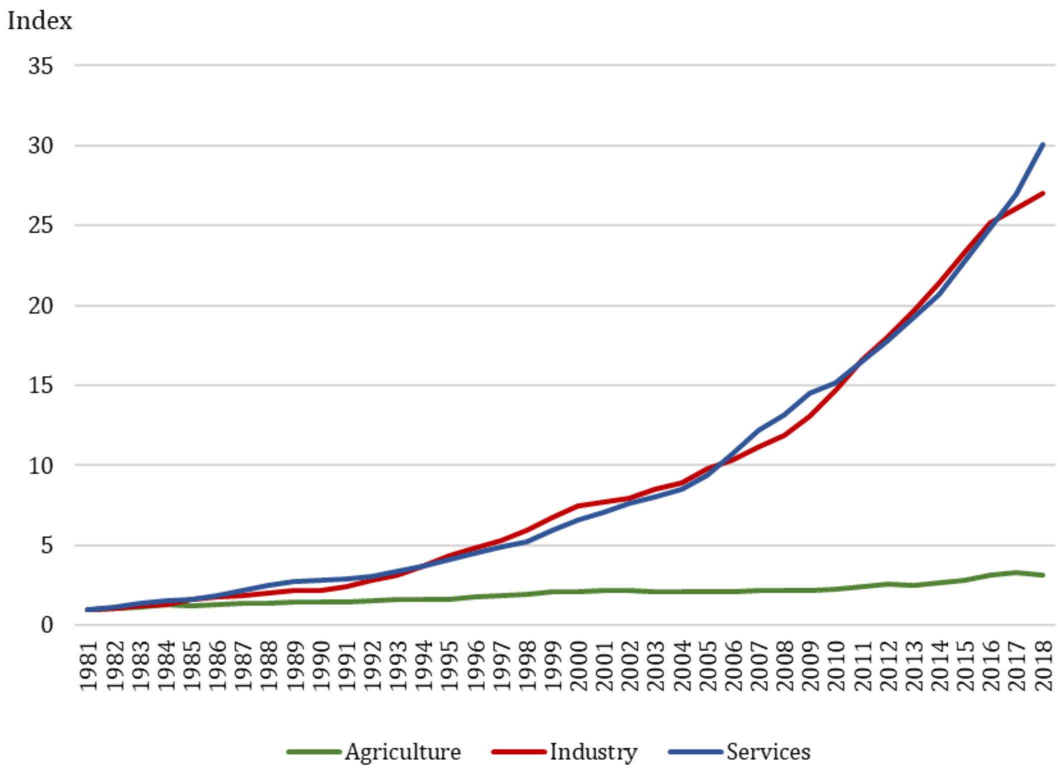
In this section, we estimate equation (4.2) using sectoral consumption value added and sectoral implicit value-added deflator data and analyse the results.

4.6.1 Preference estimation results

We start by inspecting the sectoral price indices in Figure 4.13 and quantity indices for sectoral consumption value added in Figure 4.19. As can be seen in the figures, the price and quantity of services relative to the other sectors both increased. These indicate that there were income effects resulting from subsistence agricultural consumption ($\bar{c}_a > 0$) and or endowment service consumption ($\bar{c}_s < 0$). For income effects to dominate relative price effects, σ is likely to be small.

The industry to agriculture relative price decreased while the corresponding relative quantity increased. This is consistent with the relative price effect and with the income effect associated with subsistence agricultural consumption. For the relative price effect to have played a significant role, σ is unlikely to be zero.

Figure 4.19: Quantity indices of sectoral consumption value added



The estimation results for equation (4.2) are shown in Table 4.5. All estimates are significant. The positive estimate of $\bar{c}_a$ is consistent with the fact that agricultural value added are necessities for consumers. The negative estimate of $\bar{c}_s$ points to consumers' endowment of services. The statistical significance of non-homotheticity terms suggests that a non-homothetic utility function is more suitable for explaining sectoral consumption shares in China than a homothetic utility function.

Table 4.5: Preference estimation results with consumption value added

σ	0.42***
	(0.14)
ω_a	0.051***
	(0.0039)
ω_d	0.46***
	(0.037)
ω_s	0.49***
	(0.036)
$\bar{c}_a$	128.02***
	(3.00)
$\bar{c}_s$	-41.11*
	(23.86)
R_a^2	0.996
R_s^2	0.998
$RMSE_a$	0.014
$RMSE_d$	0.017
$RMSE_s$	0.023

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

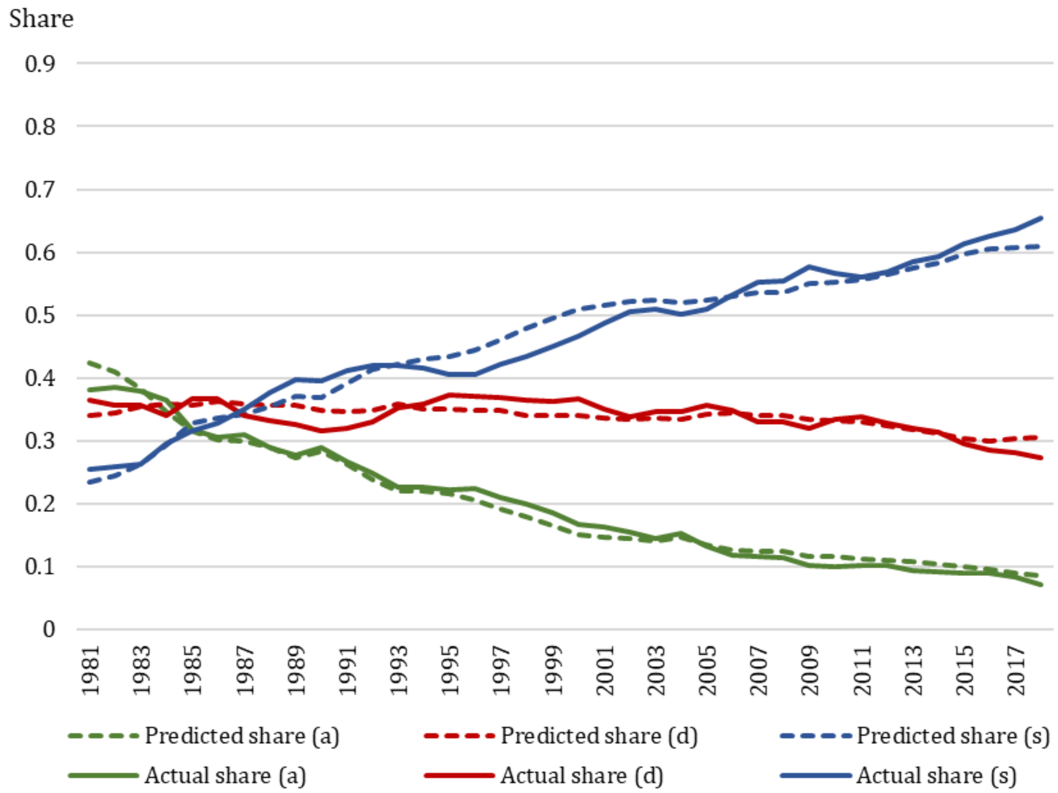
While subsistence consumption plays a major role in early stages of development, preference weights are the key to determining sectoral consumption shares as income grows over time. Table 4.5 shows the preference weights for industry and service are higher than that for agriculture. The estimated consumption value added preference weights for agriculture, industry, and service are respectively lower, higher, and lower than their consumption expenditure counterparts. Unlike in the case of consumption expenditure, industrial weight is about the same size as service weight in the consumption value added case.

The estimated preference weights in Table 4.5 suggest that as income increases over time, consumption value added would shift from agriculture to the modern sectors. The estimated preferences weights for industry and services are close to each other. This is unlike in the consumption expenditure case where service preference weight is much higher than industrial preference weight. Since productivity is the highest in industry, the results for consumption value added paint a more optimistic picture for China's future growth compared to those for consumption expenditure.

The estimated σ is less than one and significantly different from zero. This is similar to that in the consumption expenditure case. However, the value of σ estimated using consumption value added is smaller than that estimated using consumption expenditure. Herrendorf et al (2013) also found σ to be smaller for consumption value added than for consumption expenditure in the case of the US. Their results are more extreme, as they found σ to be close to one for consumption expenditure and to be zero for consumption value added. These results suggest that it is easier to substitute away from a sector's products than from a sector's value added. This can be explained using an example. Consumption expenditures on plane tickets, hotel rooms, and tourism packages are counted as consumption expenditures on services. However, these services have primary sector value added contents because food, snacks, and beverages are provided. If the prices of these services increase, people can substitute away from them. To make up for the lost meals provided by the service packages, consumers can consume ready meals or potato chips from supermarkets which are products of the secondary sector. If these secondary sector products become too expensive, households can substitute away from them and instead consume unprocessed food such fruits and vegetables which are primary sector products. In essence, while consumers can easily shift their consumption expenditure across products of different sectors to satisfy their need for calories and nutrients, they cannot substitute away from primary sector value added which is a fundamental source of calories and nutrients.

Figure 4.20 shows that the model predicted sectoral consumption value added shares fit data very well. This is confirmed by results from Table 4.5. In particular, the R-squareds are almost equal to ones and the average root mean squared errors is 0.019.

Figure 4.20: Sectoral consumption value added shares: actual VS predicted



4.6.2 Relative price effect

To analyse the effects of relative price changes, we compute the paths of counterfactual sectoral consumption value added shares holding income constant at the 1981 level. These counterfactual shares are plotted alongside actual data shares in Figure 4.21. The changes in counterfactual shares in Figure 4.21 are driven by changes in relative prices. In Figure 4.22, we plot relative prices of the three sectors.

Over time, service and agricultural relative prices rose and industrial relative price fell (Figure 4.22). Since the estimated σ lies between 0 and 1, demand is price inelastic. Resultantly, counterfactual agricultural and industrial consumption value added shares in Figure 4.21 move in the same directions as their corresponding relative prices. Comparing counterfactual shares with actual shares, we can see that relative price effects overpredict the fall in the industrial share and fails to predict the observed fall in agricultural share.

Figure 4.21: Sectoral consumption value added shares: actual VS counterfactual shares holding income constant at 1981 level

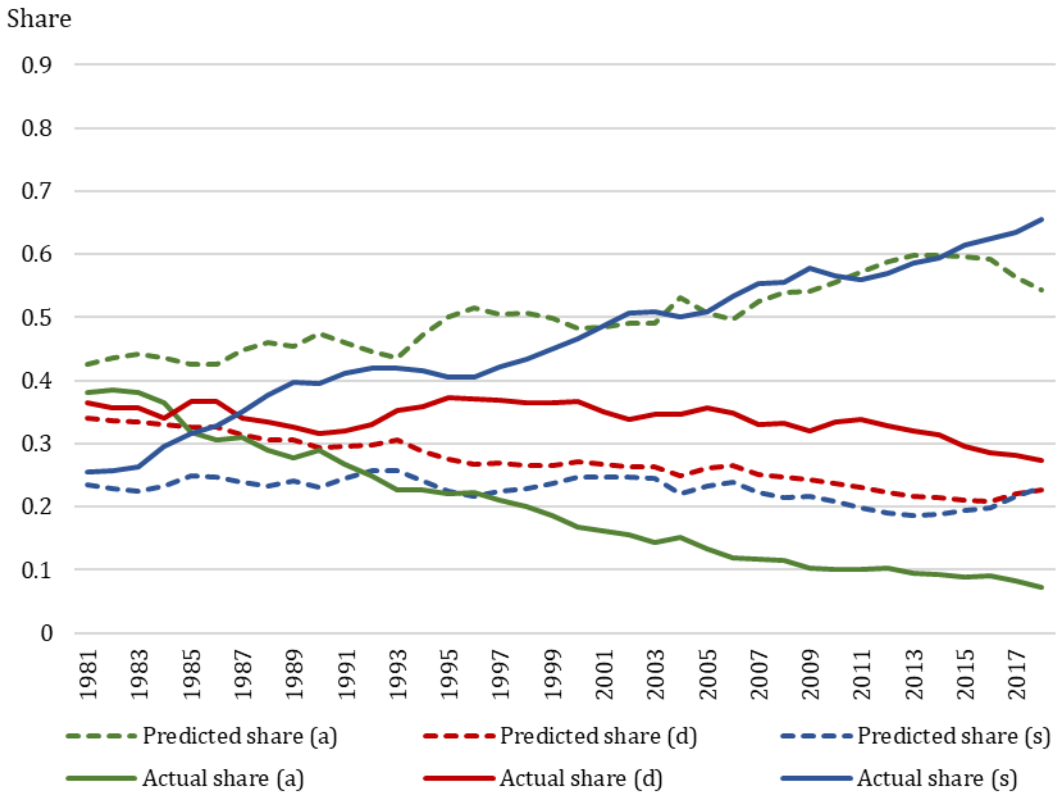
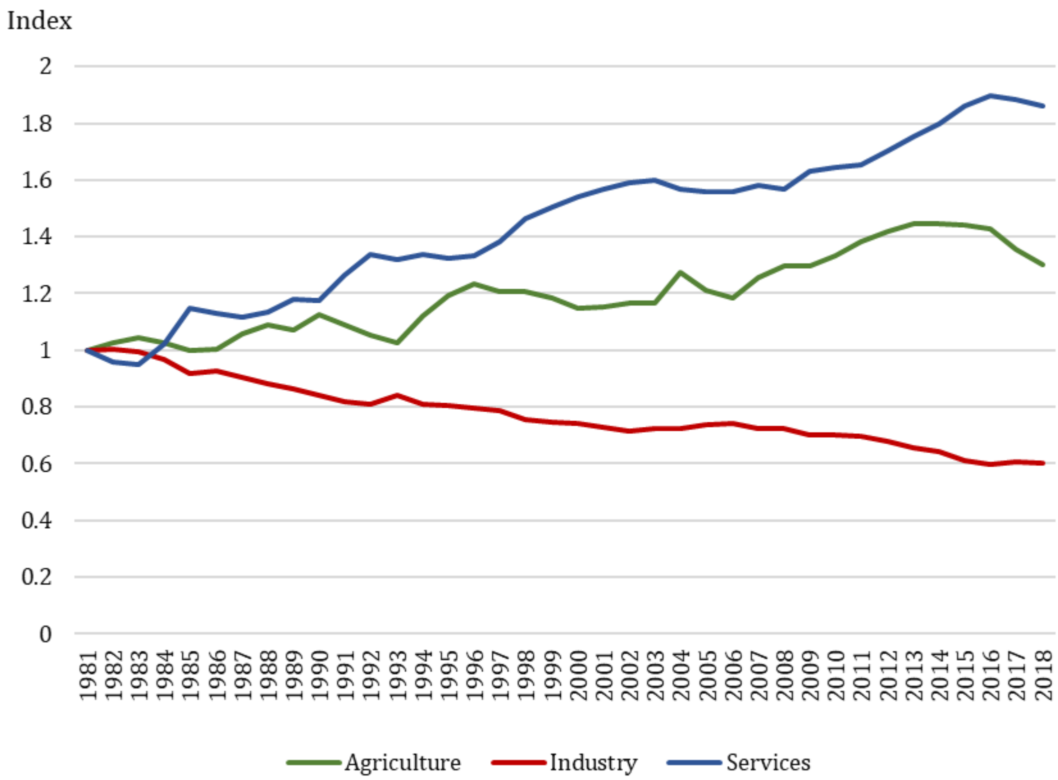


Figure 4.22: Sectoral relative implicit value-added deflators (1981=1)



As can be seen in Figures 4.21 and 4.22, service relative price increases rapidly but counterfactual service share stagnates rather than increases. This is due to the interaction between relative prices and non-homotheticity terms. The increase in agricultural relative price causes subsistence agricultural consumption to occupy a greater share of total consumption, thereby constraining the increases in service consumption share. Similarly, the rise in service relative price raises endowment service's share in total consumption, discouraging the consumer from allocating more income to services. These negative effects on the service share just about cancel out the positive effects associated with the second term in equation (4.2), causing service's share in consumption to stagnate.

Comparing Figure 4.21 and Figure 4.16, we can see that the relative price effect is worse at explaining consumption value added shares than at explaining consumption expenditure shares. This is because of two reasons. First, the paths of relative prices differ between the two cases. While agricultural price fluctuated around a roughly constant value in the consumption expenditure case, it increased in the consumption value added case. Second, σ estimate for consumption value added is smaller than that for consumption expenditure. This means consumption value added shares move more closely with relative prices than consumption expenditure shares.

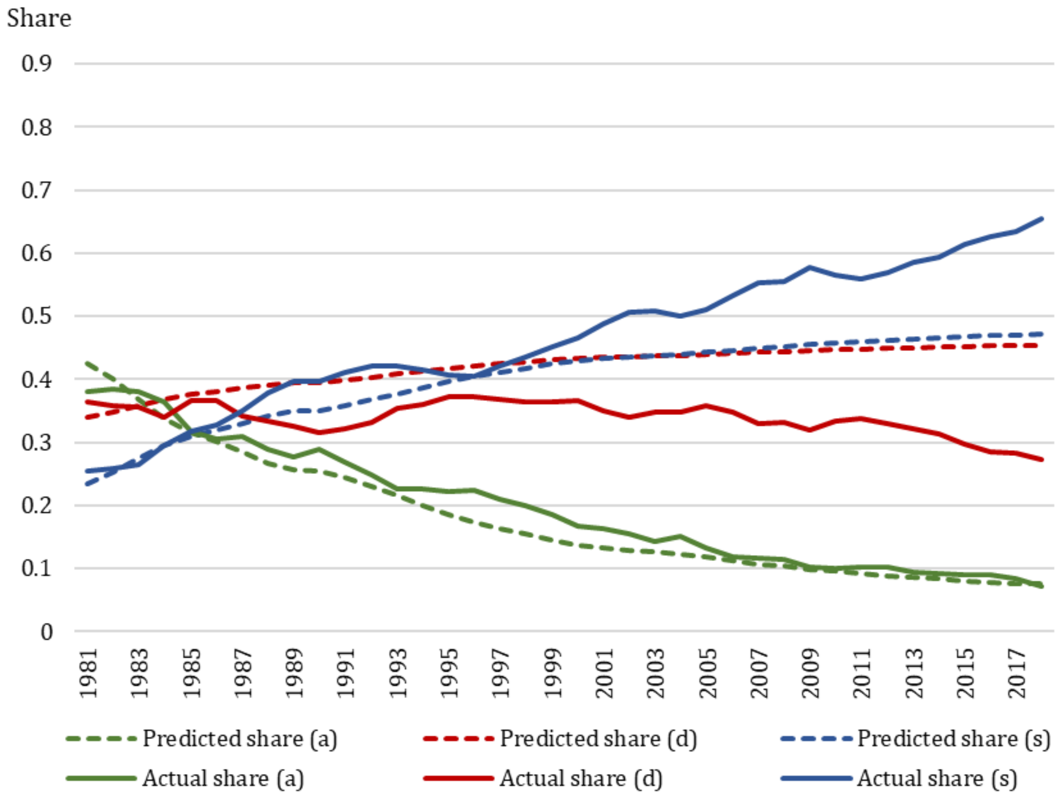
4.6.3 Income effect

Figure 4.23 below plots counterfactual sectoral consumption value added shares computed by holding relative prices constant at 1981 levels while allowing real income to change following the data, along with data shares. As income rises, the representative consumer has more income left after spending on subsistence consumption. The spare income is allocated overwhelmingly to industrial and service consumption in accordance with preferences. The shift in consumption towards services is facilitated by the fall in endowments services' share in total consumption.

As can be seen in Figure 4.23, income effect is the key driver of the observed increase in service consumption share and decrease in agricultural consumption share. The importance of income effect is further evidenced in Appendix 4.2 where we estimate and analyse a specification without non-homotheticity terms. Figure 4.23 shows that income effects are smooth and consistently act in the same direction over time. Relative price effect is therefore the key driver of short-term movements in shares. These conclusions are similar to those for the consumption expenditure case.

The relative price effects and income effects in Figure 4.21 and Figure 4.23 can explain about half of the observed increase in service consumption share. The rest can be explained by interactions between the two effects. Specifically, if real income were to rise as in the data, subsistence and endowment consumption would fall and quickly become negligible relative to income. In the environment of rising service and agricultural relative prices, this would magnify the positive relative price effect on service consumption share associated with the second term in equation (4.2) and diminish the negative effects associated with the rising subsistence and endowment consumption. Therefore, some of the positive effects on service consumption share would only occur if both real income and relative prices were allowed to change according to the data. Such effects can partially explain the observed increase in service share but are not captured by Figures 4.21 and 4.23.

Figure 4.23: Sectoral consumption value added shares: actual versus counterfactual shares computed by holding relative prices constant at 1981 levels



The observed industrial consumption value added share is explained by a combination of relative price effect and income effect. Unlike in the consumption expenditure case, income effect and price effect operate in opposite directions in the consumption value added case. As income rises, the consumer would like to allocate a greater share of income to industrial consumption value added. As industrial price falls, real industrial consumption value added rises less than proportionately, putting downward pressure on nominal industrial consumption value added share. The negative price effect is slightly bigger than the positive income effect, explaining the observed decline in industrial consumption value added share.

4.7 Conclusion

In this chapter, we started by compiling and analysing sectoral consumption data for China. We estimated a three-sectors model which explains the historical patterns of China's sectoral consumption. We used the model to analyse the demand side mechanisms behind China's structural change following the approach in Herrendorf et al (2013).

In the economics literature, sectoral demand is typically measured by sectoral expenditure (final use). On the supply side, sectoral production is typically measured by sectoral value added. We presented our approach to reconcile the two sets of data in the context of general equilibrium models. We used IOT data to breakdown China's consumption expenditure into sectoral value-added components. Our compiled data show that sectoral consumption expenditure and consumption value added data follow similar long-term patterns of structural change. However, the two measures of sectoral consumption differ wildly in terms of short-term movements.

We estimated a three-sectors model of demand and analysed demand-side drivers of structural change using both sectoral consumption expenditure and sectoral consumption value added data. We found price elasticities of sectoral consumption to be low in China. This means nominal sectoral consumption shares move with their corresponding sectoral relative prices. The observed fall in industrial consumption share and rise in service consumption share can therefore partially be explained by the fall in industrial relative price and rise in service relative price. The significance of relative price effect implies that factors that can influence relative prices, such as price controls, price distortions, and relative TFP growths, can influence structural change in China. However, relative price effect cannot explain China's structural change on its own. In particular, relative price effect cannot explain the observed decreases in agricultural consumption share following increases in agricultural relative price.

Our preference estimation results confirm the presence of subsistence agricultural consumption and endowment service consumption in China. Our results also show that preference weights for industry and services are much higher than that of agriculture. In the early years of development, promoting rapid structural transformation while meeting the population's needs for agricultural consumption was a major challenge for China. Over time, as income grew, the representative consumer had more and more spare income after subsistence consumption. The spare income was allocated overwhelmingly to services and industrial consumption in accordance with the preference weights. Therefore, income effect played key roles in driving the fall in agricultural consumption share and the rise in service consumption share in China. Today, however, the non-homotheticity terms constitute tiny shares of income in China. This implies that income effect as a driver of structural change has run out of steam. China will have to reply on other drivers of structural change in the future.

We found service preference weight to be higher than industrial preference weight. This means that over time, consumption tends to shift towards services. There has been a heated debate about consumption versus investment as drivers of China's economic growth. Many argue that China's investment-driven growth has not only run into diminishing returns but also sacrificed the population's utility. In recent years, China has attempted to pursue consumption-driven economic growth. Our results suggest that replacing investment by consumption can lead to a shift of economic activity from industry to services. This is because services' share in consumption is much higher than that in investment. In Chapter 3, we found the industrial sector to have higher productivity than the service sector in China. Therefore, the shift from investment to consumption can lead to structural changes that hamper China's growth.

Our results in this chapter provide inspirations and lay the foundation for our work in Chapters 5 and 6. This chapter revealed that preferences played important roles in China's structural change and hence economic growth. This inspires us to investigate how population aging can affect China's economy through preferences in Chapters 5 and 6 by estimating age-specific preferences and incorporating such preferences into an MSOLG model. Our results in this chapter suggest that a utility function with non-homotheticity terms and a substitution elasticity parameter can best explain China's structural change. Such utility function will therefore be adopted the models of Chapters 5 and 6. The sectoral consumption value added data constructed in this chapter will be used as data for the demand side of our MSOLG model. Since both relative price effect and income effect drove structural change in China, we will pay close attention to the mechanisms through which aging interacts with relative prices and income.

A number of studies have recently argued that traditional non-homothetic preferences such as the generalised Stone-Geary preferences that we use are flawed and some have put forth novel classes of preferences that arguably can better explain the long-term patterns of structural change (Buera and Kaboski, 2009; Comin et al, 2021; Alder et al, 2022). In our study, we found that the generalised Stone-Geary preferences can explain China's data well. In the future, as more data become available for China, we can reassess our model's fit to the data and consider experimenting with other classes of preferences.

In this chapter, we estimated preferences and studied the drivers of structural change taking prices and income data as given. The prices and income observed in the data were partially determined by China's interactions with international markets. As such, our results from this chapter can still hold in the context of a simple open economy model of China. A comprehensive account of international trade's roles in driving China's structural change represents a promising area for our future research.

Appendix 4.1 Robustness checks

In Sections 4.5 and 4.6, we presented our baseline results. In this appendix, we examine how alternative data and model assumptions affect our results. For each alternative scenario, we will present the preference estimation results. The relative price effect and income effect are determined by the estimated parameters. So long as the general patterns of consumption shares and prices remain unchanged, and the estimated parameters satisfy $0 < \sigma < 1$, $\bar{c}_a > 0$, and $\bar{c}_s < 0$, the qualitative results regarding relative price effect and income effect would remain unchanged. For brevity, we do not discuss relative price and income effects in detail in this appendix.

A4.1.1 Alternative price index for industrial consumption expenditure

Previously, we used a weighted average between industrial PPI and construction material PPI to estimate secondary sector PPI. Construction material PPI may not be a perfect approximation of construction PPI, the data for which are not available. We experiment with an alternative and frequently adopted approach of using industrial PPI to approximate secondary sector PPI. Figure 4.24 below shows the two alternative secondary sector PPIs. Table 4.6 shows the results estimated using industrial PPI as secondary sector price index. Given the similarity between the two sets of prices as shown in Figure 4.24, it is no surprise that the results in Table 4.6 are similar to those in the baseline. The model predictions continue to match data well as the R^2's are very close to ones and the average RMSE increases only a little from 0.030 to 0.032.

Figure 4.24: Alternative PPIs for the secondary sector

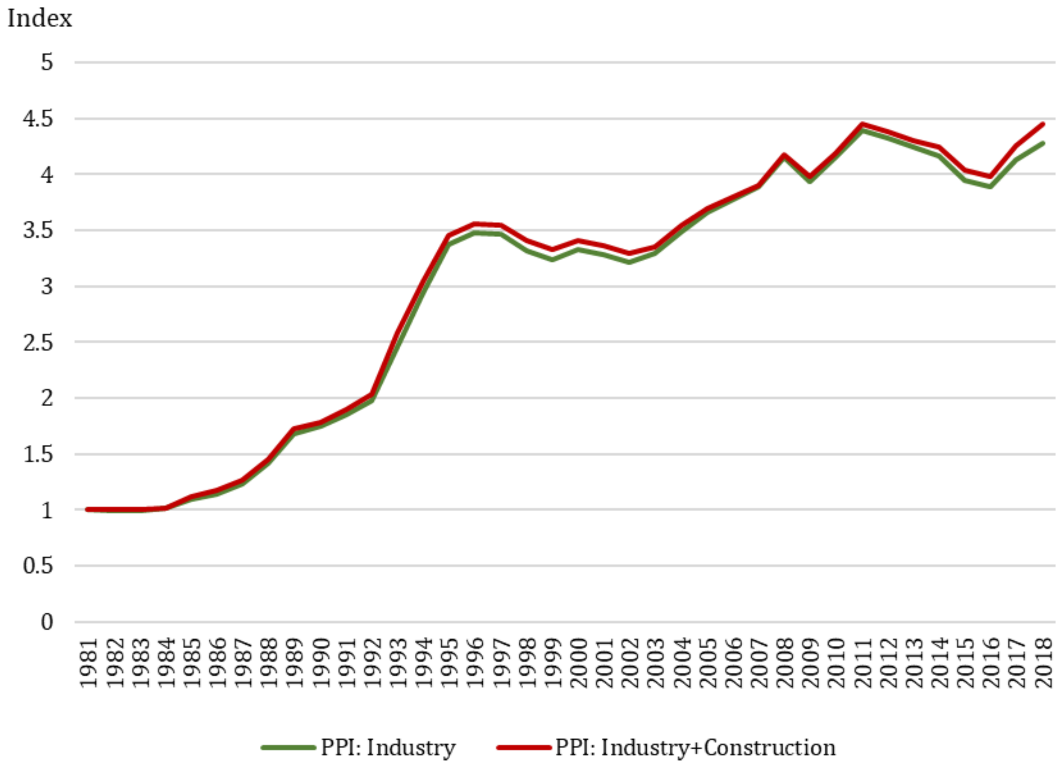


Table 4.6: Preference estimation results with consumption expenditure

σ	0.53***
	(0.060)
ω_a	0.072***
	(0.0081)
ω_d	0.33***
	(0.0095)
ω_s	0.60***
	(0.011)
$\bar{c}_a$	95.15***
	(6.73)
$\bar{c}_s$	-144.20***
	(20.06)
R_a^2	0.978
R_s^2	0.995
$RMSE_a$	0.030
$RMSE_d$	0.029
$RMSE_s$	0.036

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

A4.1.2 Government consumption as an endowment

In the baseline, we assumed that there is a representative individual in the economy who chooses total consumption, which includes both household consumption and government consumption, to maximise utility. In the process, we assumed that household consumption and government consumption are perfectly substitutable and enter the utility function in the same way. In reality, however, household and government have different considerations and mechanisms for choosing their respective consumption bundles. For instance, when allocating their respective resources, households are mostly interested in maximising their welfare while the government might place more emphasis on generating economic growth.

In this section and the next, we examine if the qualitative results from the baseline still hold for household consumption. To do so, we separate the choice of household consumption from that of government consumption. We assume that the representative individual of China's economy solves the constrained utility maximisation problem in Section 4.4 by choosing sectoral household consumption, given prices and total household consumption.

Following the example in Herrendorf et al (2013), we assume that government consumption is an exogenously determined and time-varying component of the individual's endowed consumption. This means the non-homotheticity term now has a time-varying component and a constant component:

$$\bar{c}_{it} = \bar{c}_i - g_{it}$$

Unlike Herrendorf et al (2013), we do not assume that government consumption expenditure is entirely on services. Therefore, g_{it} can be positive for all sectors.

Table 4.7: Preference estimation results with consumption expenditure

σ	0.50***
	(0.056)
ω_a	0.069***
	(0.0080)
ω_d	0.33***
	(0.0091)
ω_s	0.60***
	(0.010)
$\bar{c}_a$	97.84***
	(7.02)
$\bar{c}_s$	-143.55***
	(20.18)
R_a^2	0.975
R_s^2	0.985
$RMSE_a$	0.041
$RMSE_d$	0.040
$RMSE_s$	0.044

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

The individual's sectoral consumption share function is now:

$$s_{it} = \frac{p_{it}c_{it}}{c_t} = \frac{p_{it}\bar{c}_{it}}{c_t} + \frac{\omega_i p_{it}^{1-\sigma}}{\sum_j \omega_j p_{jt}^{1-\sigma}}\left(1 - \frac{\sum_i p_{jt}\bar{c}_{jt}}{c_t}\right)$$

where c_{it} denotes real sector i household consumption per capita and c_t denotes real household consumption per capita. We obtain results for household consumption in the same way as we did for total consumption.

Table 4.7 and Figure 4.25 show preference estimation results and model's fit with data for household consumption expenditure. Table 4.8 and Figure 4.26 show the results for household consumption value added. Similar to the findings in Herrendorf et al (2013), the RMSE's increase slightly relative to the baseline. The differences in estimation results between the alternative and the baseline are generally small. As such, the qualitative results from the baseline continue to hold.

Table 4.8: Preference estimation results with consumption value added

σ	0.39***
	(0.14)
ω_a	0.049***
	(0.0037)
ω_d	0.47***
	(0.035)
ω_s	0.48***
	(0.034)
$\bar{c}_a$	129.29***
	(2.94)
$\bar{c}_s$	-37.46*
	(22.58)
R_a^2	0.996
R_s^2	0.994
$RMSE_a$	0.018
$RMSE_d$	0.023
$RMSE_s$	0.031

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

Figure 4.25: Sectoral household consumption expenditure shares: actual VS predicted

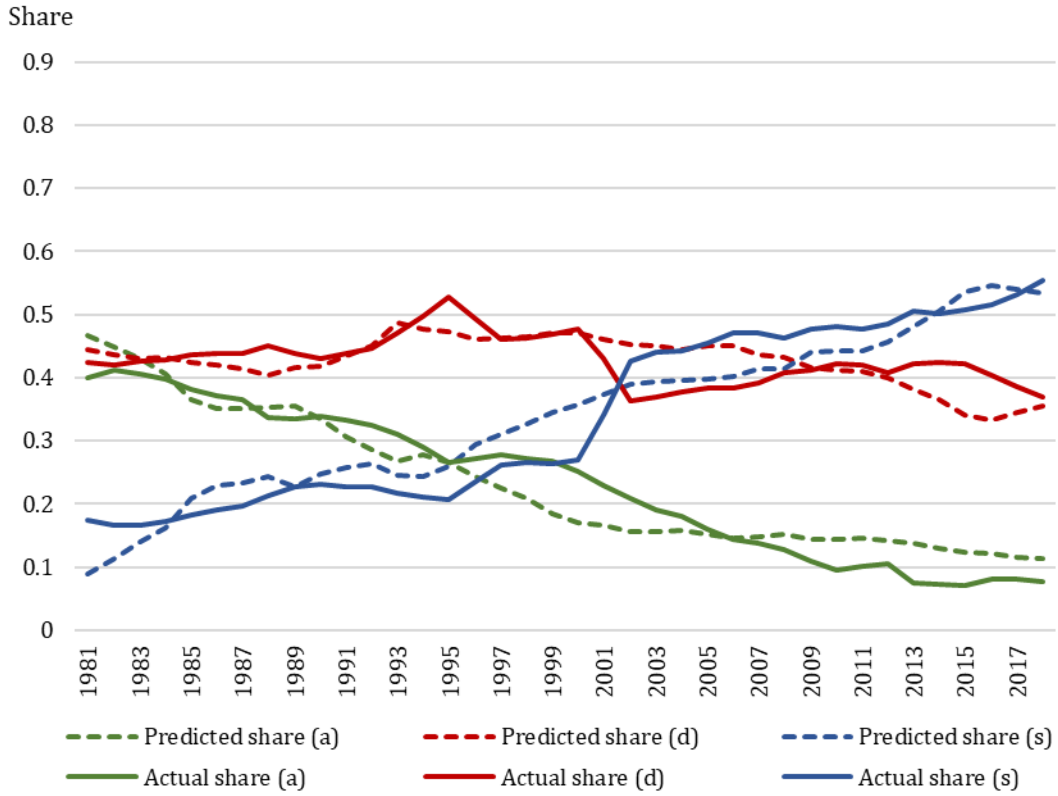
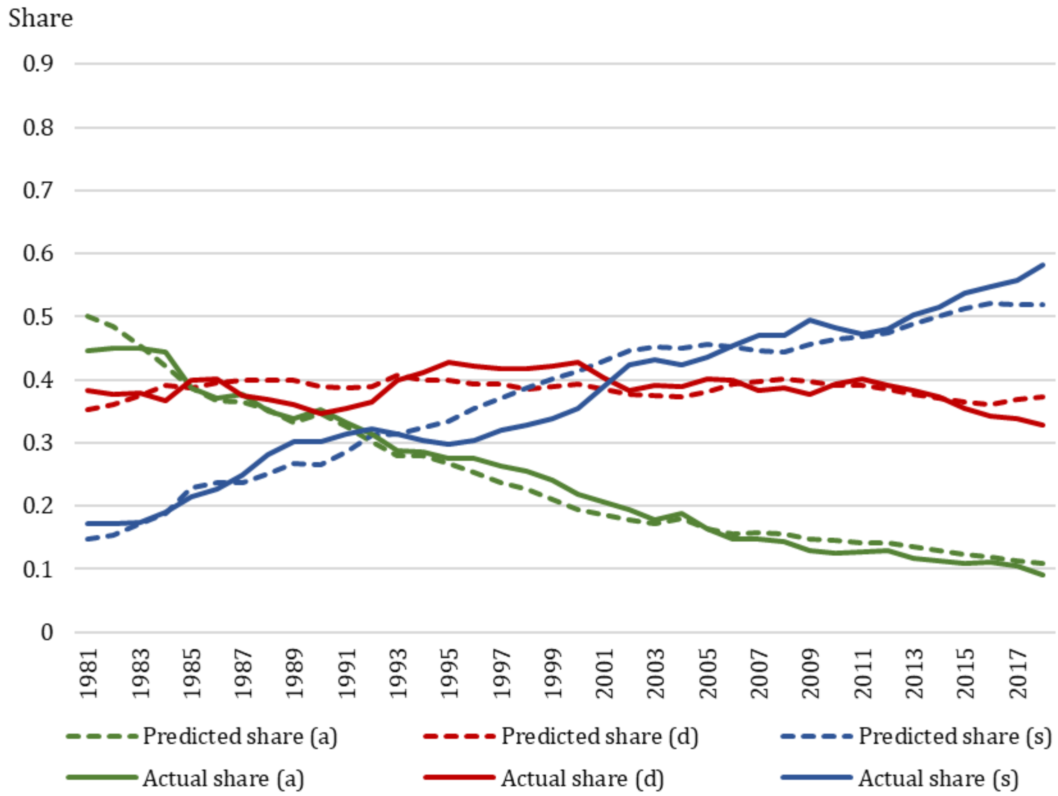


Figure 4.26: Sectoral household consumption value added shares: actual VS predicted



A4.1.3 Government consumption does not enter household utility

In the previous section, we conducted a robustness check following Herrendorf et al (2013) in which we assumed government consumption enter household utility as time-varying components of non-homotheticity terms. In reality, however, the presence of government consumption in subsistence and endowment consumption do not necessarily cause them to change over time. A reduction in the government expenditure component of subsistence consumption may incur increases in other components, so that the individual's total subsistence consumption remains stable over time.

In reality, sectoral government consumptions are different to sectoral household subsistence consumption and endowment consumption. For example, government service consumption is mainly on education, healthcare, Research and Development (R&D), and transportation, while household's service endowment can consist mainly of home-produced services such as housework, cooking, and childcare. Therefore, it can be argued that government consumption should not enter the individual's utility function in the same way as subsistence and endowment consumption. Government spending such as those on education and R&D do not increase utility immediately but can improve human capital and raise household's future income. It can therefore be argued that government consumption does not enter periodic utility function at all.

In this subsection, we experiment with an alternative treatment of government consumption. Like in the previous subsection, the representative individual maximises utility by choosing sectoral private consumption given prices and income for consumption. This time, we assume that government consumption is exogenous and does not explicitly enter the individual's utility function. The individual's consumption-savings choices are affected by government taxation and spending. However, since we take the individual's total consumption in each period as given, our specification for sectoral consumption choice becomes independent from government consumption. The specification for this subsection is:

$$s_{it} = \frac{p_{it}c_{it}}{c_t} = \frac{p_{it}\bar{c}_i}{c_t} + \frac{\omega_i p_{it}^{1-\sigma}}{\sum_j \omega_j p_{jt}^{1-\sigma}}\left(1 - \frac{\sum_i p_{jt}\bar{c}_j}{c_t}\right)$$

where c_{it} denotes real sector i household consumption per capita, $\bar{c}_i$ denotes real sector i household subsistence or endowment consumption per capita, and c_t denotes real household consumption per capita.

Table 4.9 and Figure 4.27 show the results for household consumption expenditure. Table 4.10 and Figure 4.28 show the results for household consumption value added. The results are similar to the baseline results with a few exceptions. The estimated service preference weights are lower than the baseline estimates as government consumption, which consists overwhelmingly of service consumption, is no longer chosen by the household. Like in the cases of the previous subsection and Herrendorf et al (2013), RMSE increases when we focus on household consumption. These changes, however, do not change the qualitative results from the baseline. Since the results show that σ lies between 0 and 1, and that there are substantial subsistence agricultural consumption and endowment service consumption, we can infer that relative price effect and income effect were both important in driving China's structural change. This means a homothetic utility function is not suitable for explaining China's sectoral consumption patterns.

Table 4.9: Preference estimation results with consumption expenditure

σ	0.53***
	(0.070)
ω_a	0.091***
	(0.0113)
ω_d	0.46***
	(0.012)
ω_s	0.45***
	(0.014)
$\bar{c}_a$	100.30***
	(6.87)
$\bar{c}_s$	-87.36***
	(13.48)
R_a^2	0.974
R_s^2	0.984
$RMSE_a$	0.042
$RMSE_d$	0.037
$RMSE_s$	0.046

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

Like in the baseline, the estimated σ for consumption expenditure is lower than that for consumption value added, suggesting that it is harder for individuals to substitute across sectoral value added than across sectoral products.

This way of modelling household and government consumption is particularly relevant to our project. In Chapters 5 and 6, we will construct a three-sectors value-added model with multiple generations of individuals for China. We are interested in how variations in preferences across age can affect structural change. To investigate this channel of effect, we need to breakdown consumption by age and estimate preferences by age. While we can breakdown household consumption by age using survey data, we have no realistic way of allocating government consumption across age. In addition, we would like to investigate the effects of aging on government consumption of education and healthcare. Given the absence of government consumption by age data, this can only be done by separating the determination of government consumption from that of household consumption. For the aforementioned reasons and others, we will adopt this subsection's treatment of government consumption in Chapters 5 and 6.

Table 4.10: Preference estimation results with consumption value added

σ	0.37**
	(0.16)
ω_a	0.054***
	(0.0053)
ω_d	0.54***
	(0.040)
ω_s	0.40***
	(0.038)
$\bar{c}_a$	125.48***
	(2.88)
$\bar{c}_s$	-33.44**
	(16.32)
R_a^2	0.996
R_s^2	0.995
$RMSE_a$	0.018
$RMSE_d$	0.019
$RMSE_s$	0.028

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

Figure 4.27: Sectoral household consumption expenditure shares: actual VS predicted

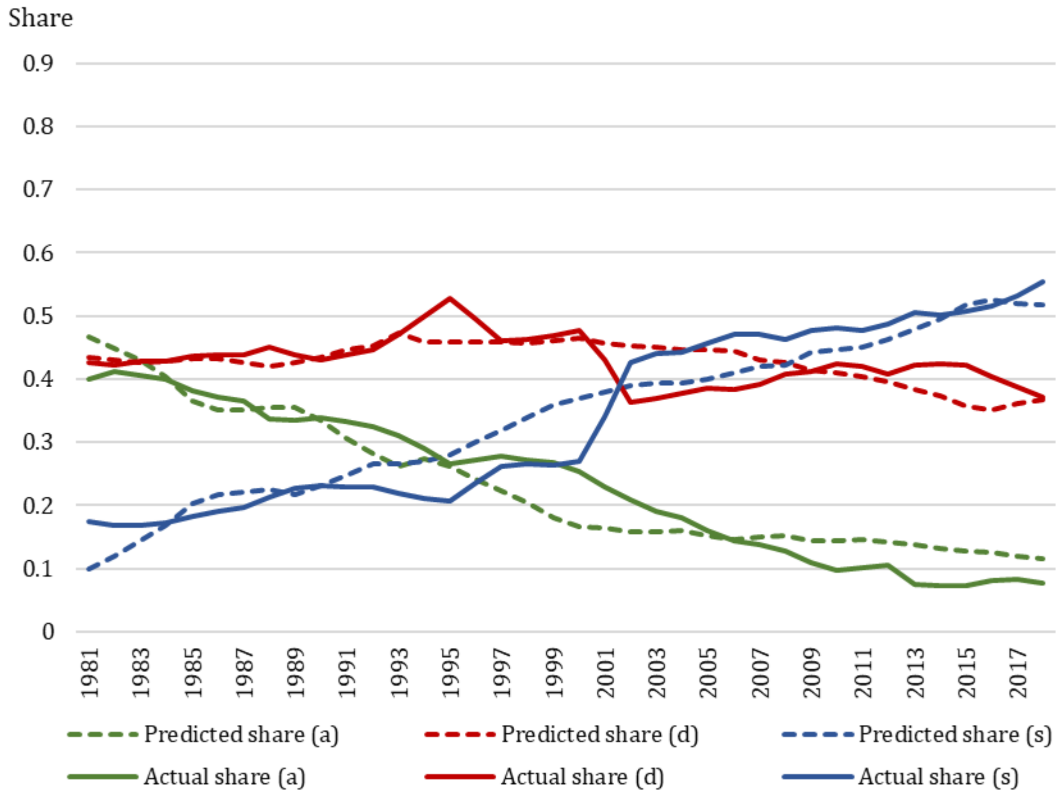
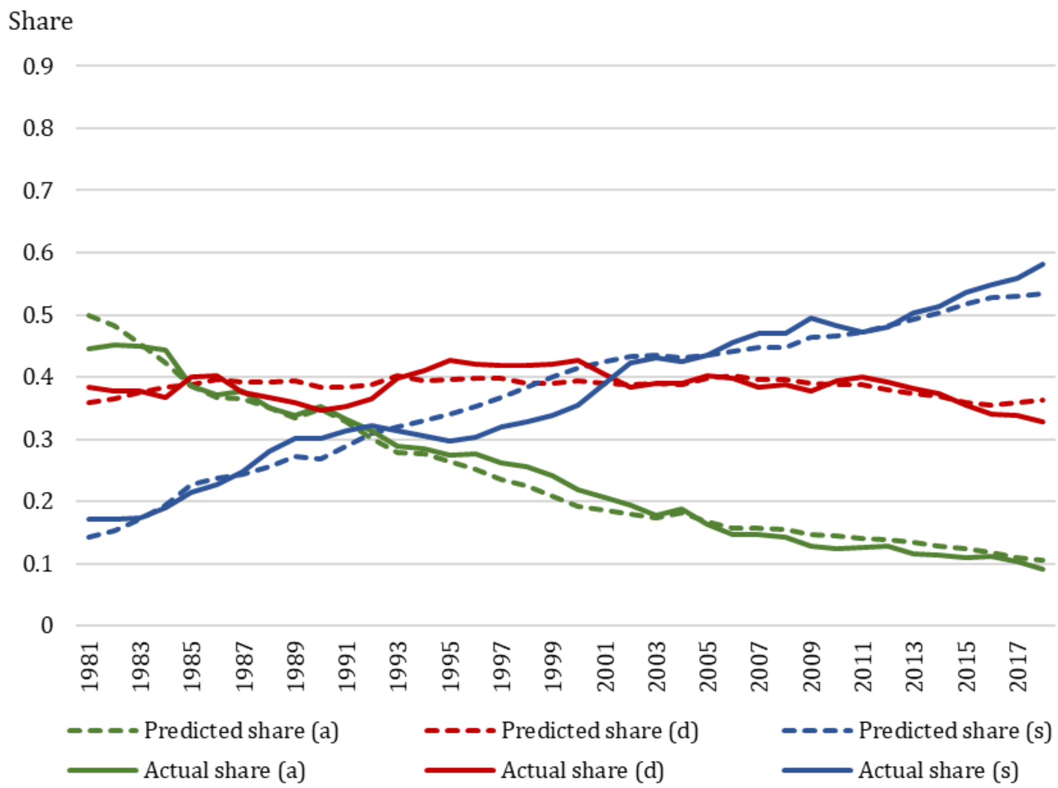


Figure 4.28: Sectoral household consumption value added shares: actual VS predicted



A4.1.4 Trend in home production

The estimated endowment service consumption $\bar{c}_s$ can contain home-produced services. The assumption that the real value of home-produced services stays constant is questionable. On the one hand, home produced services may follow a positive time trend due to improvements in productivity. On the other hand, home produced services may follow a negative time trend due to societal changes. For example, in traditional Chinese society, women tended to provide cooking, housework, and childcare at home. Over time, as women participated more in the labour force, their home production of services likely fell.

Table 4.11: Preference estimation results with consumption expenditure

σ	0.46***
	(0.066)
ω_a	0.065***
	(0.0207)
ω_d	0.30***
	(0.086)
ω_s	0.64***
	(0.11)
γ	0.029
	(0.053)
$\bar{c}_a$	95.34***
	(6.90)
$\bar{c}_s$	-167.12*
	(99.44)
R_a^2	0.978
R_s^2	0.996
$RMSE_a$	0.030
$RMSE_d$	0.029
$RMSE_s$	0.031

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

In this subsection, we investigate if there was a time trend in endowment service consumption and how such trend affects our results following the approach in Herrendorf et al (2013). In particular, we assume the service non-homotheticity term has a time trend:

$$\bar{c}_{st} = \exp(\gamma t)\, \bar{c}_s$$

In the equation above, t refers to time and γ is a parameter that determines the constant annual growth of home-produced services. We estimate equation (4.2) with $\bar{c}_s$ replaced by the $\bar{c}_{st}$ above. Tables 4.11 and 4.12 show results estimated with consumption expenditure and consumption value added, respectively. As can be seen in the tables, γ turns out to be statistically insignificant. This suggests there was no time trend in endowment service consumption in China. The rest of the estimation results are similar to the baseline. Therefore, imposing a time trend for endowment service consumption does not change our main conclusions.

Table 4.12: Preference estimation results with consumption value added

σ	0.58***
	(0.16)
ω_a	0.048***
	(0.0075)
ω_d	0.38***
	(0.069)
ω_s	0.58***
	(0.075)
γ	0.037
	(0.02)
$\bar{c}_a$	125.41***
	(3.32)
$\bar{c}_s$	-91.07*
	(53.32)
R_a^2	0.997
R_s^2	0.998
$RMSE_a$	0.013
$RMSE_d$	0.018
$RMSE_s$	0.021

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_a regression and R_s^2 is for the s_s regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

Appendix 4.2 Additional evidence for the non-homotheticity terms

A4.2.1 Results with consumption expenditures

The strong income effects shown in Sections 4.5 and 4.6 suggest that a utility function with non-homotheticity is ideal for explaining China's structural change. To confirm the importance of non-homotheticity terms and income effects, we estimate equation (4.2) restricting all non-homotheticity terms to 0. Table 4.13 shows the estimation results. As can be seen in the table, the root mean squared errors have increased drastically and the R-squared's have fallen. These suggest that the fit of the model has deteriorated. The deterioration of fit can be seen in Figure 4.29 which plots the actual and model-predicted sectoral consumption expenditure shares.

Table 4.13: Preference estimation results with consumption expenditure holding non-homotheticity terms at zeroes

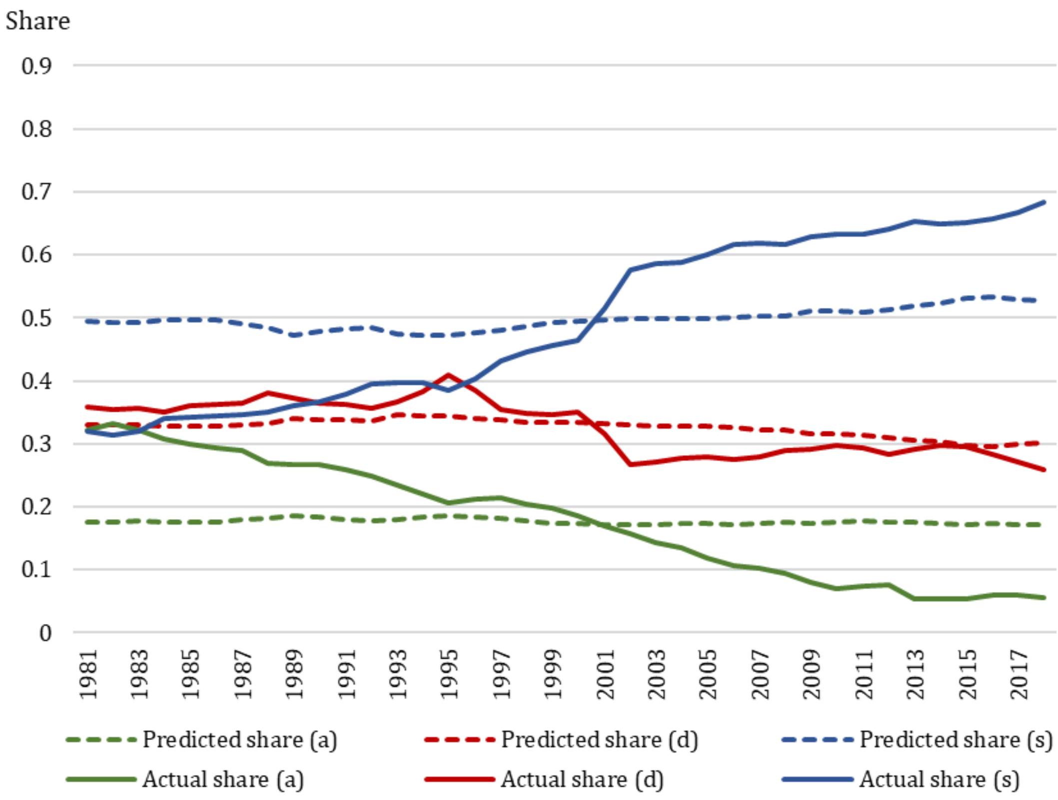
σ	0.82***
	(0.052)
ω_a	0.18***
	(0.014)
ω_d	0.33***
	(0.0057)
ω_s	0.49***
	(0.019)
R_a^2	0.800
R_s^2	0.948
$RMSE_a$	0.090
$RMSE_d$	0.034
$RMSE_s$	0.117

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_{ga} regression and R_s^2 is for the s_{gs} regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

From equation (4.2), we can see that without the non-homotheticity terms, income changes have no effect on sectoral consumption expenditure shares. The paths of sectoral shares in Figure 4.29 are therefore results of relative price effects. Since σ is smaller than 1, sectoral demand is inelastic and therefore sectoral consumption expenditure share moves in the same direction as sectoral relative price. The estimate of σ for the specification without non-homotheticity terms is 0.82, which is much larger than the baseline estimate. This explains why the counterfactual shares in Figure 4.29 move less with prices and are less volatile compared to the those in Figure 4.16.

As can be seen in Figure 4.29, without the non-homotheticity terms, predicted agricultural share starts off much lower and predicted service share starts off much higher than their actual counterparts. The relative price effect alone is unable to explain the rapid fall in agricultural share and the rise in service share over the sample period. In fact, the predicted shares are flat and hardly match the data at all. The specification without subsistence and or endowment consumption is therefore not suitable for explaining structural change in China.

Figure 4.29: Sectoral consumption expenditure shares: actual VS predicted



Generally, it is impossible for the specification without non-homotheticity terms to match the following two observations at the same time. The first observation is that modern sector shares move in the same directions as modern sector relative prices. The second observation is that agricultural share moves in opposite direction to agricultural relative price. Since relative price effects can drive sectoral consumption shares to move either in the same directions or in the opposite directions as sectoral relative prices, the specification without non-homotheticity terms cannot explain both observations in China.

A4.2.2 Results with consumption value added

In this section, we repeat the exercise in Section A4.2.1 using consumption value added data. Table 4.14 shows the estimation results for equation (4.2), holding all non-homotheticity terms at zeroes. As can be seen in the table, average root mean squared errors has increased and the R-squared's have fallen, suggesting that the fit of model has deteriorated.

Table 4.14: Preference estimation results with consumption value added holding non-homotheticity terms at zeroes

σ	0.55***
	(0.047)
ω_a	0.19***
	(0.015)
ω_d	0.40***
	(0.0074)
ω_s	0.41***
	(0.014)
R_a^2	0.796
R_s^2	0.969
$RMSE_a$	0.099
$RMSE_d$	0.027
$RMSE_s$	0.083

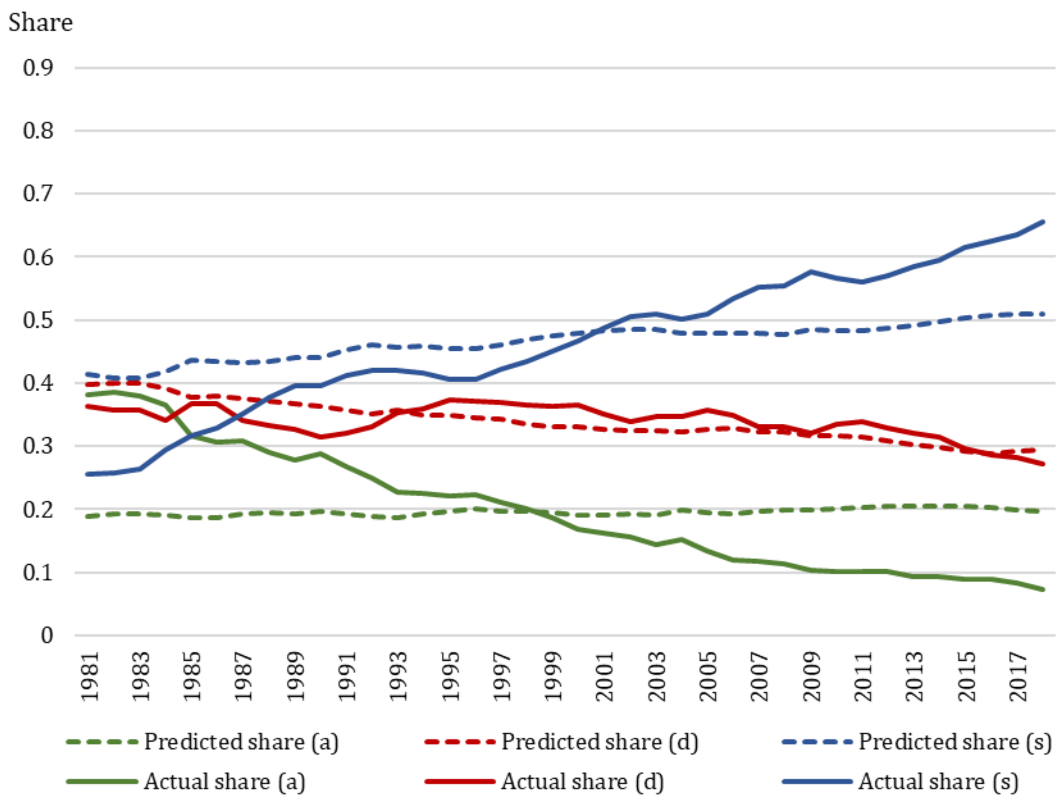
Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R_a^2 is for the s_{ga} regression and R_s^2 is for the s_{gs} regression. $RMSE_i$ refers to Root Mean Squared Errors of sector i.

Figure 4.30 below illustrates that the model without non-homotheticity terms does not fit the data. Given that the estimated σ is less than one, sectoral shares move in the same directions as sectoral relative prices. The movements are slower than the price effects in Section 4.6 because the estimate for σ has increased. Without the non-homotheticity terms, predicted agricultural share starts off much lower and predicted service share starts off much higher than their actual counterparts. In addition, relative price effect acting through the second term in equation (4.2) dominates, so that service share rises with service price, unlike in the baseline case.

Although the model without non-homotheticity terms is able to explain the overall decrease in observed industrial share, it can only explain a small fraction of the observed rise in service share. The model predicts slow increases in agricultural share but in reality, agricultural share fell rapidly over time.

Despite the presence of relative price effects, the predicted shares are almost linear and hence are unable to match the short-term movements in actual shares. This is because the estimated σ for the specification without non-homotheticity terms is higher than that for the baseline specification.

Figure 4.30: Sectoral consumption value added shares: actual VS predicted



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Chapter 5: Population Aging, Consumption Structure, and Age-specific Preferences in China

5.1 Introduction

For decades, China relied on capital accumulation and exports as main drivers of economic growth. In recent years, capital accumulation has run into diminishing returns and China has been engulfed in international trade disputes. As a result, China has been shifting its focus towards domestic consumption. According to China Statistical Yearbook 2021 (NBS, 2021), private consumption constituted 38.7% of China's GDP in 2016, which was low compared to the international norm. Unlike capital investment, which is composed overwhelmingly of industrial products, consumption has a more transformable structure. These mean consumption-driven economic growth has great potential in China. However, China's population, who carries out consumption, has been aging rapidly. As people get older, their preferences change, causing them to change their consumption bundles and react differently to changes in prices and incomes. Population aging can therefore have profound effects on consumption and hence on structural change and economic growth. In this chapter, we study these aging effects in the case of China.

Population aging can affect the consumption-savings choice through several channels. The Life Cycle Hypothesis (Modigliani and Brumberg, 1954) suggests that people smooth consumption over their lifetimes. To do so, individuals accumulate savings during mid-age when their incomes are high and dissave during youth and old-age when incomes are low. Since aging raises the population share of elderlies, it can lower the national saving rate. Aging can also raise the saving rate, however, as it can mean a fall in the youth population share. In addition, as people expect to live longer, they might accumulate more savings precautionarily to finance for their retirement. In this sense, population aging can bring about a Demographic Dividend by raising savings (Mason and Lee, 2006). The exact direction and magnitude of aging's effect on the consumption-savings choice have to be determined empirically and can vary wildly across countries.

To this day, aging's effect on consumption-savings choice in China is still a puzzle. Studies in the literature have typically used aggregate data at the national or provincial levels (Modigliani and Cao, 2004; Wang, 2008; Meng et al, 2019). Due to differences in methodology, measurement, and time span, the studies have produced mixed results. A small number of studies have analysed aging effects on consumption and savings using household survey data. Most of these studies, including Chamon and Prasad (2010), Liu and Hang (2013), and Lugauer et al (2019), have found aging to lower consumption and raise savings in China. The existing studies using aggregate and household level data have typically indicated age by elderly population share or dependency ratios. This approach obscures the variations in consumption across age groups and can therefore lead to misleading results.

While the literature has focused on aging's effects on total consumption and savings in China, little attention has been paid to the links between aging and the composition of consumption. Most of the existing works, such as Ni et al (2014), Wang and Liu (2017), and Liu (2020) have investigated the links between aging and consumption composition at the household level. To this end, they have typically measured the age of a household by the age of the household's head and or the elderly population share within the household. These measures do not account for the age composition of members within the household, leading to errors in results. These errors are likely to be large in the Chinese case as multigenerational co-residence is common in China. A few studies, including Mao and Xu (2014), Zhu and Wei (2016), and Yue (2018) have estimated age-consumption profiles. Such studies have typically analysed data at one point in time and often focused on either the urban or rural area. Implicitly, the studies have assumed that age-consumption patterns are constant across area and time. Such assumptions are unrealistic considering the systematic rural-urban divide and the rapid socio-economic changes in China.

In our study, we use household survey data to estimate age-consumption profiles for total consumption and consumption categories. We analyse the profiles to gain insights into how aging affects consumption-savings choice and consumption structure. We estimate age-consumption profiles at the individual level following an approach first put forth by Mankiw and Weil (1989). We contribute by estimating and analysing age-consumption profiles for China as a whole and at numerous points in a wide time span (1987-2016). Doing so improves the reliability of results and allows us to study changes in age-consumption profiles over time.

Structural transformation is typically defined in terms of the three sectors: primary, secondary, and tertiary. To investigate aging's effects on structural change, we use the estimated age-consumption profiles to breakdown the 1981-2016 sectoral consumption expenditure and sectoral consumption value added data from Chapter 4 by age group. We analyse how sectoral consumption varies across age and time. The differences in the evolutions of sectoral consumption shares across age groups suggest that preferences might differ across age groups. If so, population aging can affect China's structural change by changing the population's preferences. In Chapter 4, we found that preferences play major roles in driving China's structural change. We also learned that a non-homothetic utility function is the most suitable for explaining Chinese data. Inspired by these results, we propose that a Multi-Sector Overlapping Generations (MSOLG) model with non-homothetic age-specific preferences can explain the patterns of sectoral consumption by age in China. In this chapter, we estimate such preferences for China using age-specific sectoral consumption data. We analyse the differences in preferences across age and their implications for structural change in China. Following similar steps to those in Chapter 4, we investigate the roles played by relative price and income effects in explaining age-specific sectoral consumption patterns. We analyse how differences in age-specific preferences cause price and income effects to differ across age groups. To our knowledge, we are the first to conduct these estimations and analyses.

The estimated age-consumption profiles following Mankiw and Weil (1989)'s method reveal how consumption vary across age. They allow us to breakdown China's aggregate consumption by age and estimate age-specific preferences that can explain age-specific consumption in the context of an overlapping generations model. In this study, we often refer to the variations in consumption along the age-consumption profiles as age effects. Such age effect is not the ceteris paribus effect of age on consumption. As we move from one age to another, other variables can change which affect consumption. In particular, the age effect can contain a combination of the ceteris paribus age, cohort, and time effects. The intrinsic links between age, cohort, and time effects mean it is difficult to isolate them from each other. This Age-Period-Cohort (APC) identification problem means the ceteris paribus age effect can only be identified under assumptions (Deaton and Paxson, 2000; Chamon and Prasad, 2010; Deaton, 2018). Although we comment on the ceteris paribus age effects by comparing the profiles across time, we do not statistically confirm and identify the ceteris paribus age effects in this study.

Our main findings in this chapter include that age profiles of per capita consumption are consistently hump-shaped in China. This implies population aging can reduce per capita consumption in China. We find that older age groups have greater preference for agricultural consumption and less preference for service consumption compared to younger age groups. Population aging can therefore impede structural change towards services. We also find that older age groups have lower price elasticities of demand and higher subsistence consumption shares. These mean the magnitudes of relative price effect and income effect on nominal consumption structure increase over age.

In this chapter, we focus on aging's effects on the demand-side of China's economy and ignore the interactions between demand side and supply side. In Chapter 6, we will simulate and analyse an MSOLG model of China in which both demand side and supply side forces operate. To this end, our estimation and analyses in this chapter focus on the consumption value added measure of sectoral consumption. This is because sectoral consumption value added data are compatible with sectoral value added data on the supply side of the model economy. Our works in this chapter lay the foundation for our construction, calibration, and analyses of the demand side of the MSOLG model in Chapter 6.

The rest of this chapter is organised as follows. In Section 5.2, we first describe Mankiw and Weil (1989)'s method for estimating age-consumption profiles. We then present an MSOLG model from which we derive the specification for estimating age-specific preferences. Section 5.3 provides details about the household survey data used for our estimations, including details about sampling designs which determine our empirical methodology. Section 5.4 presents and discusses our estimated age-consumption profiles. Section 5.5 presents age-specific preference estimation results and analyse the relative price and income effects by age. Section 5.6 concludes.

5.2 Model and empirical specification

In this section, we derive the empirical specifications used in this chapter. In Section 5.2.1, we describe the specification for estimating age-consumption profiles which was first presented by Mankiw and Weil (1989). In Section 5.2.2, we present the demand side of a multi-sector overlapping generations model from which we derive the specifications for estimating preferences by age group.

5.2.1 Age-consumption profile estimation

Age-consumption profiles demonstrate how consumption vary by age and are hence crucial to the understanding of how aging affects consumption. Ideally, age-consumption profiles should be plotted using individual data on age and consumption. In reality, such data are hard to come by. While household surveys collect age data at the individual level, they collect consumption data at the household level. Age consumption profiles are therefore typically estimated at the household level, with household age indicated by household head's age. Using such a measure of age ignores the age composition of members within each household and can thus lead to errors. This is particularly a concern in the Chinese case where multigenerational co-residence is common due to cultural reasons and due to high population density in populated areas.

More importantly, in the context of MSOLG models, household age-consumption profiles cannot be easily reconciled with population and labour data measured at the individual level on the supply side. Since we would like to analyse the effects of aging using a general equilibrium MSOLG model in our project, we should ideally estimate age-consumption profiles at the individual level. To do so, we follow Mankiw and Weil (1989)'s method. The method delivers estimated individual-level age-consumption profiles that can be used directly in our models.

Mankiw and Weil (1989)'s method is designed to obtain the best estimate of an individual's consumption given only the individual's age, using data on household level consumption and on household members' ages. Specifically, they assume that consumption c_{hi} of individual i in household h is a function of age and can be written as:

$$c_{hi} = \alpha_0 D_{0,hi} + \alpha_1 D_{1,hi} + \cdots + \alpha_{81} D_{81,hi} + e_{hi}$$

where $D_{g,hi}$ is the dummy variable indicating whether or not the individual is of age g. α_g is the expected consumption of a person of age g. It is unlikely that the error e_{hi} between the expected consumption of age g and actual consumption of age g is correlated with age.

The consumption c_h of household h is modelled as the sum of consumptions of its N individual members:

$$c_h = \sum_{i=1}^{N} c_{hi}$$

Substituting the expression for individual consumption into that of household consumption, we obtain:

$$c_h = \alpha_0 \sum_{i=1}^{N} D_{0,hi} + \alpha_1 \sum_{i=1}^{N} D_{1,hi} + \cdots + \alpha_{81} \sum_{i=1}^{N} D_{81,hi} + u_h$$

where $\sum_{i=1}^{N} D_{g,hi}$ is the number of members of age g in household h. The equation above is Mankiw and Weil (1989)'s empirical specification that can be used to estimate consumption by age α_g.

Estimating consumption for each age using the equation above can lead to inaccuracies for some ages that have little consumption and for ages that constitute small shares of the population and hence of the sample. These are true in China's case for people aged below 16 and those above 70. In addition, the fluctuations in consumption across each age can make age-consumption patterns hard to discern. To improve the accuracy of our results and make age-consumption patterns clearer, we group the 0 to 15 ages into one group, the above 70 ages into another group, and the 16 to 70 ages into 5-year groups. The equation that we use to estimate age-consumption profiles is therefore:

$$\begin{aligned} c_h = {} & \alpha_{0-15} \sum_{i=1}^{N} D_{0-15,hi} + \alpha_{16-20} \sum_{i=1}^{N} D_{16-20,hi} + \alpha_{21-25} \sum_{i=1}^{N} D_{21-25,hi} + \cdots \\ & + \alpha_{66-70} \sum_{i=1}^{N} D_{66-70,hi} + \alpha_{70+} \sum_{i=1}^{N} D_{71+,hi} + u_h \end{aligned} \tag{5.1}$$

where $D_{g,hi}$ is the dummy variable indicating whether or not the individual is from age group g. α_g is the expected consumption of a person from age group g.

If we have a randomly selected sample that is representative of China's population, then a simple OLS estimator can be used to estimate the parameters in equation (5.1) above. In practice, the complex sampling design elements of household surveys such as stratification and clustering mean that the samples are not perfectly representative. In

Section 5.3, we will describe the sampling designs of the household survey data used to estimate equation (5.1) and our empirical strategy that accounts for them.

Since the goal is to obtain the best estimate of an individual's consumption based only on household level consumption and ages of members within each household, variables other than consumption and age are excluded from the regression equation. In this study, we will often refer to the variations in consumption across age along the estimated profiles as age effects. It is worth emphasizing that such age effects can contain cohort and time effects and hence are not the ceteris paribus effects of age on consumption. When we estimate preferences in Section 5.5, we will partially account for the cohort effect and the price effect. However, statistically and comprehensively addressing the APC problem is beyond the scope of this study.

In this thesis, we would like to study how consumptions change as people age. In addition, we would like to breakdown aggregate consumption by age in order to study aging's effects on aggregate consumption. Therefore, we are interested in the expected consumption of an age-g person, irrespective of the type of household he is from. This expected consumption is what Mankiw and Weil (1989)'s method estimates. The expected age g consumption α_g accounts for consumption of age-g people who live alone and for consumption of age-g people who live in multi-membered households. As such, α_g can contain private consumption and public consumption.

In this thesis, we do not explicitly consider public goods in the household and collective models of households. Given that we would like to construct and use a macroeconomic model with multiple generations and sectors, the aforementioned considerations would add additional layers of complexities and make our analyses intractable.

5.2.2 Model and specification for age-specific preference estimation

As people grow older, their preferences change. In particular, their tastes for different types of goods and services change. They also react differently to changes income and prices. Population aging can therefore affect the level and structure of aggregate consumption through the channel of preferences.

In this study, we would like to quantify and analyse age-specific preferences in China. To this end, we write a parsimonious consumption model for each age and derive age-specific demand functions. We then use the demand functions, along with data on prices and age-specific consumption, to estimate age-specific preference parameters.

When investigating the effects of aging in this chapter, we focus on the demand side. In reality, there are interactions between demand and supply sides. We would eventually also like to investigate the aging effects through age-specific preferences in a general equilibrium model with both demand and supply sides. The ideal model for such investigation would be a Multi-Sector Overlapping Generations (MSOLG) model. In this chapter, we formulate age-specific demand in the context of an MSOLG model. This chapter's model and results will be used in Chapter 6 where we construct and simulate a general equilibrium MSOLG model of China to study aging's effects on structural change and growth.

We now present the demand side of a three-sectors OLG model from which we derive the specification for age-specific preference estimation. At any given point in time, there are G age groups corresponding to G generations of individuals alive. The representative individual of a new generation entering the economy in period t faces the following dynamic problem of maximising lifetime utility U_t by choosing the paths of sectoral consumption $c_{gi,t+g-1}$ and savings s_{gt}:

$$\max_{c_{gi,t+g-1},\ s_{gt}} U_t = \sum_{g=1}^{g=G} \beta_g \left(\prod_{j=1}^{j=g} \pi_{j,t+j-1} \right) \frac{\left[\left(\sum_{i=a,d,s} \omega_{gi}^{\frac{1}{\sigma_g}} \left(c_{gi,t+g-1} - \bar{c}_{gi} \right)^{\frac{\sigma_g - 1}{\sigma_g}} \right)^{\frac{\sigma_g}{\sigma_g - 1}} \right]^{1-\rho}}{1-\rho}$$

In Chapter 4, we found that a utility function with non-homotheticity terms and an explicit substitution elasticity parameter is the most suitable for explaining China's sectoral consumption data. We therefore assume that utility functions of all ages take this form in this chapter. The new feature in this chapter is that the parameters of the utility function vary across age. As such, the parameters have subscripts g to indicate age group.

In each period, the individual derives utility from consumptions ($c_{gi,t+g-1}$'s) of the three sectors. As always, we use subscripts a, d, and s to denote primary (agriculture), secondary (industry), and tertiary (services) sector, respectively. For brevity, we sometimes refer to the secondary sector and the tertiary sector as the modern sectors and sometimes collectively as the modern sector. ρ denotes the inverse of intertemporal elasticity of substitution. β_g denotes age g's subjective discount factor. $\pi_{g,t+g-1}$ denotes the survival probability from age $g-1$ to age g in period $t+g-1$. β_g and $\pi_{g,t+g-1}$ are key determinants of the individual's consumption-savings choice.

$\bar{c}_{gi}$'s are the non-homotheticity terms. When they are positive, they represent subsistence consumption that the individual needs. When they are negative, they represent endowed consumption.

ω_{gi}'s are the preference weight parameters which satisfy $\sum_i \omega_{gi} = 1$. When income is low in early stages of development, consumption is overwhelmingly spent on subsistence. Over time, as productivity and income grow, subsistence consumption's share in total consumption falls. Consequently, the role of ω_{gi}'s in determining sectoral consumption shares grows. In the long term, when subsistence consumption shares are negligible, ω_{gi}'s are the key determinants of sectoral consumption shares.

σ_g is a parameter that determines within-period price elasticities of demand. Our results from Chapter 4 suggest that σ for China lies between 0 and 1. Therefore, in this chapter, we estimate σ_g rather than directly adopting Leontief or log utility functions which assume σ to be zero or one, respectively.

The individual's optimisation problem is subject to period-by-period budget constraints:

$$z_{g,t+g-1} = \sum_{i} P_{i,t+g-1} c_{gi,t+g-1} + P_{k,t+g-1} s_{g,t+g-1}$$

where $P_{i,t+g-1}$ denotes the price index of sector i, $P_{k,t+g-1}$ denotes the price index of capital goods, and $s_{g,t+g-1}$ denotes savings of age g in period $t+g-1$. $z_{g,t+g-1}$ denotes the individual's total resource at age g. The individual's total resource can consist of wages, depreciated savings, rent, and bequests.

The solution to the individual's optimisation problem can be divided into two steps. First, given prices and the choice of total consumption in each period, we find the optimal allocation rule of total consumption across the three sectors within each period. Second, given the optimal allocation rules, we maximise the individual's lifetime utility subject to constraints by choosing total consumption and savings for each period.

The sectoral allocation of within-period total consumption in the first step is a static problem and can be written as:

$$\max_{c_{gi,t+g-1}} u_{g,t+g-1} = \left(\sum_{i=a,d,s} \omega_{gi}^{\frac{1}{\sigma_g}} \left(c_{gi,t+g-1} - \bar{c}_{gi} \right)^{\frac{\sigma_g - 1}{\sigma_g}} \right)^{\frac{\sigma_g}{\sigma_g - 1}}$$

$$s.t. \sum_{i=a,d,s} P_{i,t+g-1} c_{gi,t+g-1} = P_{t+g-1} c_{g,t+g-1} = z_{g,t+g-1} - P_{k,t+g-1} s_{g,t+g-1}$$

where $c_{g,t+g-1}$ denotes real total consumption. P_{t+g-1} is a composite price index for all goods and services. Given the observed total consumption and price indices, the representative individual optimally allocates total consumption across the three consumption categories.

The static problem and its solution for the individual representing age g population is similar to those of the individual representing the entire population in Chapter 4. We therefore do not repeat detailed expositions about the model derivations and mechanisms as they are similar to those in Chapter 4.

Solving the static problem yields the following functions for sector i consumption $c_{gi,t+g-1}$ and consumption share $s_{gi,t+g-1}$ of age g in period $t+g-1$:

$$c_{gi,t+g-1} = \bar{c}_{gi} + \frac{\omega_{gi} P_{i,t+g-1}^{-\sigma_g}}{\sum_j \omega_{gj} P_{j,t+g-1}^{1-\sigma_g}} \left(P_{t+g-1} c_{g,t+g-1} - \sum_i P_{j,t+g-1} \bar{c}_{gj} \right)$$

$$s_{gi,t+g-1} = \frac{P_{i,t+g-1} c_{gi,t+g-1}}{P_{t+g-1} c_{g,t+g-1}} = \frac{P_{i,t+g-1} \bar{c}_{gi}}{P_{t+g-1} c_{g,t+g-1}} + \frac{\omega_{gi} P_{i,t+g-1}^{1-\sigma_g}}{\sum_j \omega_{gj} P_{j,t+g-1}^{1-\sigma_g}} \left(1 - \frac{\sum_i P_{j,t+g-1} \bar{c}_{gj}}{P_{t+g-1} c_{t+g-1}} \right)$$

Let $p_{i,t+g-1}$ denote the relative price of sector i:

$$p_{i,t+g-1} = \frac{P_{i,t+g-1}}{P_{t+g-1}}$$

Sectoral consumption share can then be written as:

$$s_{gi,t+g-1} = \frac{p_{i,t+g-1} c_{gi,t+g-1}}{c_{g,t+g-1}} = \frac{p_{i,t+g-1} \bar{c}_{gi}}{c_{g,t+g-1}} + \frac{\omega_{gi} p_{i,t+g-1}^{1-\sigma_g}}{\sum_j \omega_{gj} p_{j,t+g-1}^{1-\sigma_g}} \left(1 - \frac{\sum_i p_{j,t+g-1} \bar{c}_{gj}}{c_{t+g-1}} \right) \tag{5.2}$$

The solution above determines sectoral demand for age group g in period $t+g-1$. The same age groups, along with their representatives, are present in every period but correspond to different cohorts. Our setup assumes that the preferences of age groups stay constant over time. For each age group, sectoral consumption shares change across time in response to changes in prices and total consumption. Given time series data on prices and each age group's sectoral and total consumption, we estimate age specific preference parameters using equation (5.2).

The cohort effects on sectoral consumption are partially attributable to the differences in income across people from different cohorts. Such differences can be due to differences in education, life experiences, and beliefs. The time effects are partially due to time-specific shocks to incomes and prices. By incorporating age-specific income and relative prices as key determinants of sectoral consumption, our model can therefore partially account for cohort and time effects. However, there is a lot more to cohort and time effects.

A comprehensive account of cohort and time effects are beyond the scope of our study.

In this chapter, we sort people into three 20-year age groups: young (21-40), middle-aged (41-60), and old (61 and above). This makes the analyses and comparisons across groups clearer and more tractable. In addition, grouping improves the accuracy of results by raising the sample size for each group.

5.3 Data

Following the practice of the NBS, household consumption expenditure data in China are typically classified into 8 categories: food, clothing, daily, housing, healthcare, Transport and Communications (TRCO), Education and Entertainment and Culture (EEC), and others. The 'others' category is a very small category containing residual consumption after deducting other categories from total consumption. It is an unknow mixture of goods and services. For our purposes, we focus on total consumption and the 7 categories.

To estimate age-consumption profiles using Mankiw and Weil (1989)'s specification, we need national household survey data on household consumption and within-household age composition. There are a number of household survey projects in China that report such data. When choosing among the datasets, we take into consideration their sample sizes, representation, and reputation in the literature. Since we will use household data as micro-foundations of our macroeconomic model, we choose survey projects that are the most consistent with aggregate data compiled by the NBS. Since we are interested in the long-run patterns of consumption, we choose datasets to cover the 1981-2020 period as much as possible. All things considered, we choose data from the China Household Income Project (CHIP), Urban Household survey (UHS) of the NBS, and China Family Panel Studies (CFPS) for our study.

We have introduced CHIP and CFPS datasets in Chapter 3. In this section, we provide some details relevant to this chapter about the household survey data and discuss our econometric methodology based on the sampling designs. In Appendix 5.1, we present details about the cleaning and processing of household survey data for this chapter.

5.3.1 CHIP

As mentioned in Chapter 3, we use China Household Income Project (CHIP)'s data for 1988, 1995, 2002, and 2007 in our project. CHIP's data are essentially sub-samples of NBS's household survey data. In fact, the CHIP's surveys we use were all conducted by the NBS. These mean CHIP is closely aligned with NBS's household surveys in terms of measurements, methodology, and representation.

CHIP's surveys were conducted through interviews. In the interviews, surveyors helped households to complete a questionnaire. The questionnaire contains questions for the household as a whole and for individual household members. As such, each CHIP survey gave rise to two datasets: a household dataset and an individual dataset. The individual dataset reports age of each household member and the household dataset reports household consumption data. To ensure the completeness and accuracy of consumption data, households were asked to keep records of their incomes and expenses. Enumerators from the NBS interviewed households periodically to assist them in this process.

Like the NBS, CHIP provides separate datasets for urban and rural areas. The two datasets were compiled through slightly different sampling designs and questionnaires. As such, we estimate age-consumption profiles separately for rural and urban areas. We then obtain national profiles as weighted averages of profiles from the two areas. The weights are age specific and are computed as the shares of area-and-age-specific population in national age-specific population. We obtained such population by age by area data from China Population and Employment Statistical Yearbooks (NBS, 1988-2020).

From 2002, CHIP also collected a separate migrant sample independently. Unfortunately, due to the absence of data on the population of migrant households, CHIP's migrant sample is subject to representation issues. Migrants are already contained in CHIP's rural and urban samples. According to Song et al (2013), the only migrants that might be underrepresented in CHIP's rural and urban samples are those who are referred to by CHIP as long-term stable migrants. These are rural-urban migrants who live in urban areas for more than six months in the survey year but do not have close economic relationships with their rural household. Unfortunately, CHIP does not report data about migrants' economic relationship with their rural households. As a result, we cannot reliably identify the long-term stable migrants from CHIP's migrant sample. Furthermore, the absence of population data on long term stable migrants means we cannot sort CHIP's migrant households into rural and urban areas or weight them. For these reasons, we cannot incorporate CHIP's migrant samples into the national sample. It can be argued that the long-term stable migrants behave similarly to urban residents and hence their preferences are already captured by the urban sample.

CHIP has a multi-stage sampling design. Each area is divided into four regions (strata): west, central, coastal, and special municipalities. Within each region, a representative set of provinces is selected. Within each province, a set of households is selected through a multi-stage process designed to ensure representation.

In CHIP's samples, a province's share in the regional sample is different to the province's share in the regional population. Furthermore, a region's share in the national sample is different to the region's share in the national population. To ensure the sample data's representativeness, we follow CHIP's instructions in Song et al (2013) to compute provincial level weights. The formula for computing the weight of a household from province A is:

$$weight_A = \frac{Province\ A's\ population}{Province\ A's\ sample\ size} \times \frac{Population\ of\ region\ that\ contains\ province\ A}{Population\ of\ selected\ provinces\ in\ the\ region\ that\ contains\ province\ A}$$

The weight reflects the number of households in the population that is represented by each household in the sample. We obtain the number of households by area by province data from China Population and Employment Statistical Yearbooks (NBS, 1988-2020).

Given CHIP's sampling design, we use Survey Weighted Least Squares (SWLS) estimator as in Wooldridge (2001) to estimate age-consumption profiles. By using the provincial level weights we compiled, the SWLS estimator resolves potential consistency issues with point estimates and standard errors that may arise due to the misrepresentation of the unweighted sample.

5.3.2 UHS

The CHIP samples described in the previous subsection are sub-samples of NBS's household survey samples. In CHIP's 1988 urban dataset, several categories of consumption are missing. Fortunately, we obtain complete sample data of NBS's 1988 Urban Household Survey (UHS) from the Database for China Studies at the Chinese University of Hong Kong (2022). The dataset contains data on age of household members and on household consumption of the eight consumption categories.

The NBS is not fully transparent about the details of its household surveys' sampling designs. However, there is no doubt that the NBS's household survey data are the best household survey data for China. The NBS's UHS data are nationally representative and are used by the NBS to construct China's national accounts data. We therefore use Ordinary Least Squares (OLS) to estimate the 1988 urban age consumption profiles with UHS data.

5.3.3 CFPS

We use China Family Panel Studies (CFPS) data from 2010, 2012, 2014, and 2016. At the time of this study, CFPS was the only project that offered nation-wide household survey data that suit our purposes for the post-2010 period. CFPS is a nationally representative survey project conducted by the Institute of Social Science Survey of Peking University. CFPS's 2010 baseline sample was drawn from 25 provincial level administrations which represented over 95% of China's population. The baseline sample of households was followed and surveyed every two years. The surveys collected data on household consumption classified into NBS's eight consumption categories and on ages of household members.

CFPS provides details about its methodology and procedures through the CFPS User's Manual (Xie et al, 2017) and technical reports. CFPS exerted great efforts and experimented with new methods and technologies to improve the quality of its results. For examples, CFPS sampled China as a whole rather than rural and urban areas separately, interviewed every household member rather than just the household head, and used audio recordings and follow-up phone calls to help verifying and revising answers that were in doubt.

CFPS has a multi-stage complex sampling design. The sampling design divides China into 6 strata: 5 large provinces and 1 set of 20 small provinces. From each stratum, CFPS selects a set of counties which constitute the primary sampling units. Within each county, CFPS selects a set of communities which are the secondary sampling units. Within each community, a set of households is selected.

In accordance with the sampling design, CFPS provides weights for its datasets. The weights account for misrepresentation, non-responses, and post-stratification adjustment. The weights were adjusted to avoid extreme weight values. We use the household level weights directly to estimate age-consumption profiles through SWLS. When computing standard errors and test statistics, we account for the stratification and for clustering at county and community levels. We also apply Finite Population Correction (FPC) at the county level. We do not apply FPC at other levels for two reasons. First, such corrections are unnecessary due to the samples' shares in the corresponding populations being tiny. Second, the data required to compute FPC variables at the community level and the household level are not available.

5.4 Age profile estimation results

5.4.1 Age profile of consumption

In this section, we present age-consumption profiles estimated using Chinese data from the eight household surveys. Unlike existing studies in the literature which have typically studied profiles at the household level in China, we estimate age-consumption profiles at the individual level. Existing studies have focused on profiles at particular points in time. Implicitly, they have assumed that age-consumption profiles are constant across time. In this study, we compute profiles over a wide span of time. We then analyse and compare the profiles across time.

For each survey, we estimate age-consumption profiles of the consumption categories using Maniw and Weil (1989)'s specification (equation (5.1)). As mentioned in Section 5.3, we account for the sampling designs and use SWLS estimation. We report the estimation results in Tables 5.2 to 5.13 in Appendix 5.2 of this chapter. In general, the estimates are highly significant. A small number of estimates for the very young and very old are insignificant due to the facts that their consumptions are very small. We keep these estimates in the rest of this chapter because they nevertheless contain some information about individual consumption. Besides, setting them to zero have negligible impacts on our results because the estimates are already very close to zeros.

To account for any adjustments that the NBS has made to household consumption data over the years, we scale the profiles so that the national consumption implied by the profiles are consistent with the latest NBS data. Figure 5.1 plots the age profiles of real consumption and consumption categories in 1988 prices. The aggregate and category specific Consumer Price Indices (CPIs) that we use to deflate the nominal profiles are shown in Figure 5.16 in Appendix 5.2. These category-specific price indices are constructed using price data from China Price Statistical Yearbooks (NBS, 2013-2021) and Price Yearbooks of China (Editorial Board of Price Yearbook of China, 1989-2013), and within-category consumption composition data from China Statistical Yearbooks (NBS, 1981-2021).

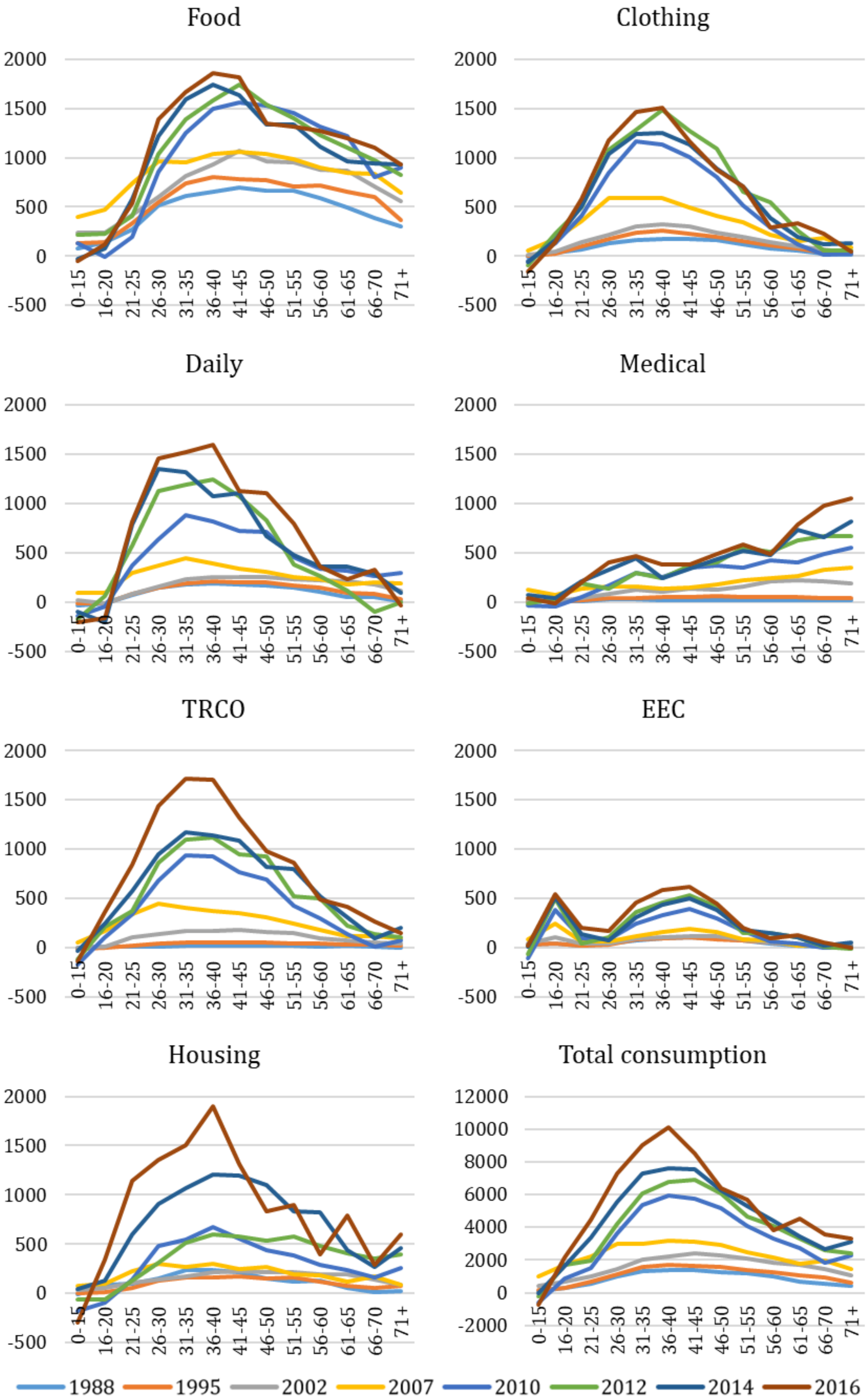
As can be seen in Figure 5.1, age-consumption profiles shift upwards over time. This reflects increases in consumption in China brought about by rapid income growth. For each category, profiles from the eight surveys show that consumption of different age groups change differently across time despite there being some similarities in the general curvatures of the profiles. It is therefore unrealistic to assume that age-consumption profiles stay constant over time.

Figure 5.1 shows that total consumption first increases with age, peaks at around 40 years of age, and then falls. The hump-shaped profiles are at odds with the life-cycle hypothesis which suggests that people smooth consumption over the life cycle. Since income typically rises in early stages of career and peak around mid-age, the profiles in Figure 5.1 suggest that consumption moves with income over the life cycle.

A verdict on traditional theory cannot be drawn easily by observing the profiles in Figure 5.1 as they capture not only age effects but also cohort effects and time effects. Elderlies likely have lower incomes and lower propensity to consume because they lived through turbulent times in China's history. Elderlies likely have lower incomes also because their skills and knowledge are outdated. These can partially explain the relatively low consumption of elderlies but not the low consumption of children and youth. The facts that the profiles are persistently hump-shaped and that they are not simply shifted versions of each other suggest that the age effect plays important roles in shaping them.

As can be seen in Figure 5.1, age-consumption profiles of all categories except for healthcare are hump-shaped. Past mid-age, clothing and EEC consumption drop the most while food consumption drops the least.

Figure 5.1: Real age-consumption profiles (unit=Yuan)



Profiles of the EEC category have an additional peak between 16 and 20 years of age. China's education system provides free but compulsory nine-year education from primary to middle school. High school and university education are heavily subsidized but students have to pay increasingly more after middle school. These explain why individual education consumption in Figure 5.1 surges after about 15 years of age and then drops after about 20 years of age. The drops got smaller over time as enrolments into masters and doctoral degrees surged in China.

As people age, they are more likely to experience serious health issues that demand treatment. Resultantly, medical consumption increases with age. The upward sloping shapes of medical age-consumption profiles were not enough to change the hump-shapes of total consumption profiles. This is because medical consumption's share in total consumption was small, averaging at 5.5% between 1988 and 2016.

People's preferences are what give rise to the profiles. Figure 5.1 shows that there are variations in consumption across age and such variations differ across categories. These suggest that preferences vary across age. We cannot easily make specific comments about the preferences by inspecting age profiles of consumption alone, however, as preferences determine the shares of categories in total consumption. We will learn more about how preferences vary across age in the upcoming sections by analysing age-consumption-share profiles and by estimating age-specific preferences.

5.4.2 Age profile of consumption share

To learn more about how preferences vary across age, we plot age profiles of consumption shares in Figure 5.2. Each age-consumption-share profile in Figure 5.2 shows how a category's share in total consumption changes across age groups in a particular survey year. The shares do not make sense in the presence of negative consumption levels and shares. When we plot consumption shares in Figure 5.2, we therefore exclude the 0-15 age group which has numerous negative values and set the few negative values that remain to zeroes. Such practices have small impacts on the patterns shown in Figure 5.2 as the negative values are close to zeros.

As can be seen in Figure 5.2, the share of total consumption spent on food increases with age. The upward slope becomes steeper over time as young people's shares fall relative to the others. One explanation for the upward slopes lies in the differences in income. Compared to younger people, older people tend to have less income because they belong to older cohorts and or because they have lower productivity. Since food is a necessity, people cannot reduce food consumption below subsistence. As a result, food occupies greater shares of the total consumption of older people. Similar forces lie behind the downward shifts in food profiles over time: as income rises, the share of total consumption dedicated to subsistence falls.

The aforementioned income effect is unlikely to be the only explanation for the upward sloping food profiles, however, as food consumption had risen way above subsistence in China. Another explanation is that older people have less wants and needs for other categories of consumption and would rather make savings than to spend on them. There have been ample evidence that elderlies in China save more than others. Other factors may also contribute. Elderlies may buy higher quality food because they are more conscious about the health risks and benefits of food. Elderlies are less physically able to shop ingredients and cook meals, causing them to rely more on pre-prepared, restaurant, and canteen food which are more expensive. In Section 5.5, our estimation results for age specific preferences will shed more light on the determinants of age specific demand.

Figure 5.2: Real age-consumption-share profiles

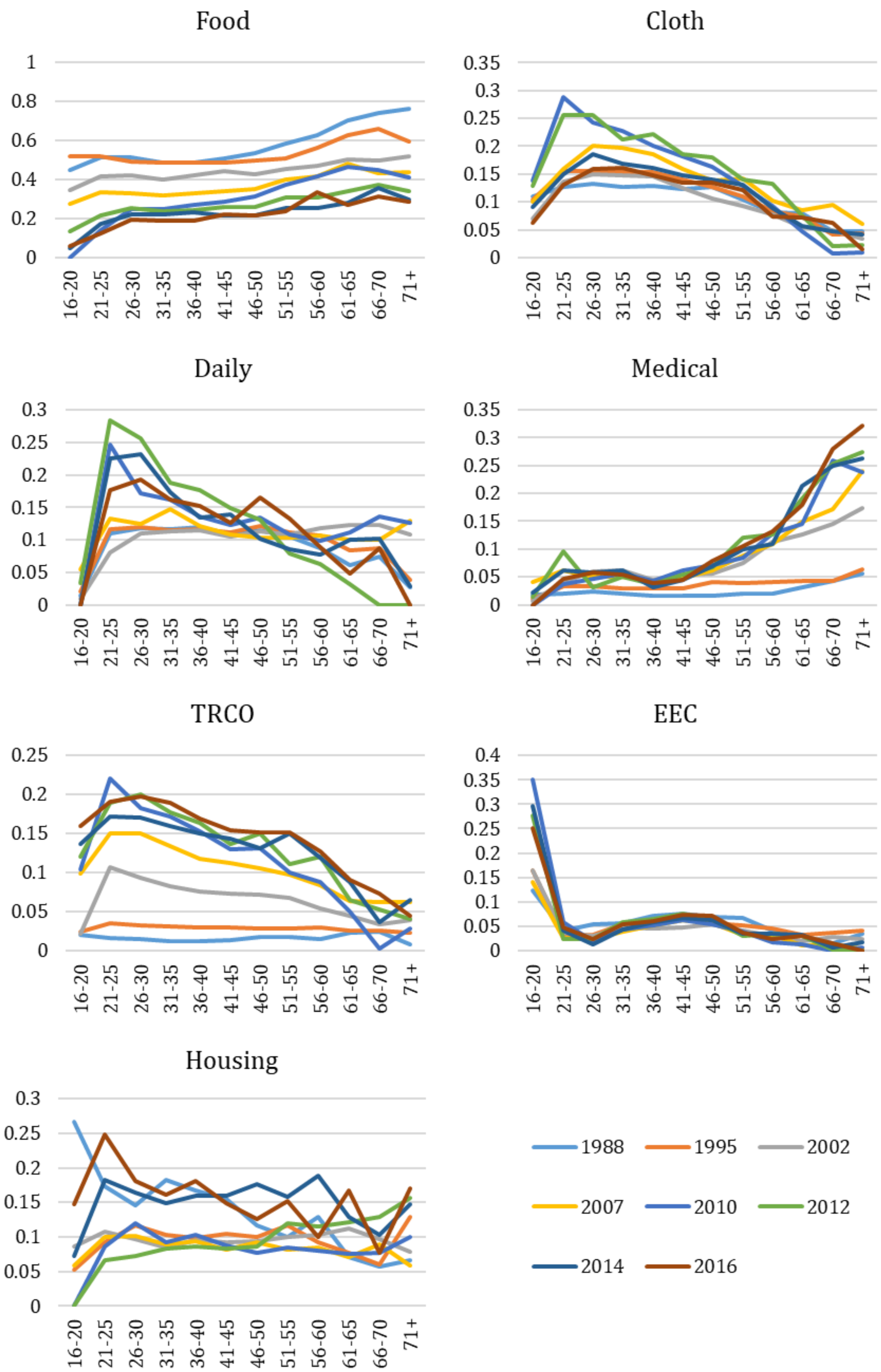


Figure 5.2 shows that age-consumption share profiles for clothing and transport and communications are hump-shaped. As people reach adulthood, they start to form families and participate more in social and work activities. Since clothing, transport, and communications are necessary for these activities, their consumption shares increase between the ages of 16 and 30. As people's family and work lives stabilise, consumption shares of clothing, transport, and communications stabilise and then start to decrease. The explanation could be that as people get older, they pay less attention to their looks. It could also be that older people travel less because they are busier with work and or because they are less adventurous. Past the age of about 50, the decreases accelerate. This is attributable to the reduction in work-related expenditures as people retire.

There were large upward shifts in Transport and Communications (TRCO) consumption shares between 1988 and 2007. These shifts were likely due to the introduction of new and expensive products such as vehicles, flights, and mobile phones to Chinese consumers. Such products were previously either non-existent or centrally planned. Throughout the sample period, increases in TRCO consumption were also facilitated by China's massive infrastructure projects.

Education, Entertainment, and Culture (EEC) consumption share for the 16 to 20 age group increased from 12% in 1988 to 35% in 2010, and then fell and fluctuated around 27%. The surge in EEC's share over the sample period reflects the rapid expansion in high school and university education in China. Data from Educational Statistics Yearbook of China (Ministry of Education, 1996; 2022) show that gross enrolment rates of high school and higher education increased respectively from 22% and 3% in 1990 to 91% and 54% in 2020. EEC's share in the 16-20 age group's consumption is very high compared to the shares of other categories. This suggests that the 16-to-20-year-olds disprefer the other categories relative to EEC. Another explanation is that China's public education system subsidizes students' consumption by providing cheap or free meals, accommodation, school buses, and uniforms, to name just a few, so that the 16-to-20-year-olds have limited unmet wants and needs when they are attending school. For the rest of the age groups, the EEC profiles are hump shaped. This is because entertainment and culture consumption are closely related to people's social activities which first increase and then decrease in life.

As people age, their health deteriorates at an increasing rate. Resultantly, they spend increasing shares of their income on healthcare. Over time, healthcare consumption shares of older people increased faster than those of younger people. The explanation could be that older people had more spare income to spend on healthcare as their incomes grew. It could also be that as China's healthcare system developed, healthcare became more accessible and new treatments became available for elderlies to consume.

Age-consumption-share profiles for the daily category are hump-shaped, peaking between 20 and 30 years of age. The daily category is also termed 'household equipment, furnishings, and services.' As the names suggest, the category covers a variety of products for household use. People carry out consumption of these household products in bulk when they move to new homes. Since the 20 to 30 age groups are more likely to move to new homes, they allocate higher shares of consumption to the daily category than others. The majority of daily consumption are spent on durable products such as refrigerators, washing machines, and ovens. Once people have bought these products, they seldom need to replace these products. This can partially explain the downward slope of daily consumption past the age of 30. Another explanation for the downward slope is that some daily products, such as jewelleries, makeup, and furniture, are luxuries. Since older age groups have lower incomes, they allocate smaller shares of total consumption to these products. In fact, clothing, TRCO, and EEC categories also contain luxuries. Luxury goods can therefore also help explain why profiles of these categories are humped shaped.

Housing consumption share rises between the ages of 16 and 25, which is consistent with the fact that people start to form new households as they reach adulthood. After the initial surge, the housing consumption shares either stabilise or decrease. Housing in China was initially centrally planned. Following marketisation reforms in the 1990s, the housing market boomed, eventually prompting the government to try to cool the market down in the 2010s. These events meant uncertainty and volatility in individual housing consumption behaviour which are likely behind the volatile patterns in the figure.

We can use the results to make some simple predictions about how increases in the share of elderlies, which we refer to as aging, will affect household consumption structure. As mentioned earlier, older people consume less than younger people. In addition, elderlies spend higher shares of their incomes on food and healthcare but lower shares on other categories. If these patterns remain in the future, population aging will reduce consumption per capita, raise the shares of food and healthcare in aggregate household consumption, and reduce the shares of other categories in aggregate household consumption. In this chapter, we refer to these as aging effects. Since the age-consumption-share profiles can depend on non-age factors such as cohort and time, our predictions about the future effects of aging should not be interpreted as the ceteris paribus effects of aging.

To quantify aging's effects on future consumption, we first forecast age-and-category-specific per capita consumption by assuming the categories' shares in age-specific consumption will stay constant at 2016 levels and that age-specific per capita consumptions will grow at the average annual rates between 2013 and 2016. We then forecast aggregate age-and-category-specific consumptions by multiplying predicted age-and-category-specific per capita consumption by predicted population by age. We predict aggregate consumptions under two scenarios: the aging scenario and the no-aging scenario. In the aging scenario, population by age data follow UNWPP 2022's forecasts. In the no-aging scenario, population by age data are computed by multiplying UNWPP 2022's forecast aggregate population and constant 2016 age population shares.

According to UNWPP's forecast, China's population will keep aging until the early 2080s. We reveal the effects of aging by comparing the changes in consumption shares between 2016 and 2085 in the aging scenario with those in the no-aging scenario.

Our results show that aging will cause consumption per capita to fall by 0.12% annually. By 2085, consumption per capita in the aging scenario is predicted to be 92.0% of that in the no aging scenario. At the category level, aging is predicted to cause food's share in total consumption to increase by 6.5 percentage points but all other categories' shares except healthcare's share to fall. Since primary sector products are food products, population aging can raise primary sector's share in output and hence impede structural change. The predicted falls in clothing and daily shares due to aging are smaller, both at 1.8 percentage points. Although aging is predicted to raise healthcare share by 3.9 percentage points, it is predicted to lower TRCO, EEC, and housing shares by 3.4, 2.1, and 1.3 percentage points, respectively. Since these four categories contain overwhelmingly service consumption, aging is expected to hinder structural change towards services.

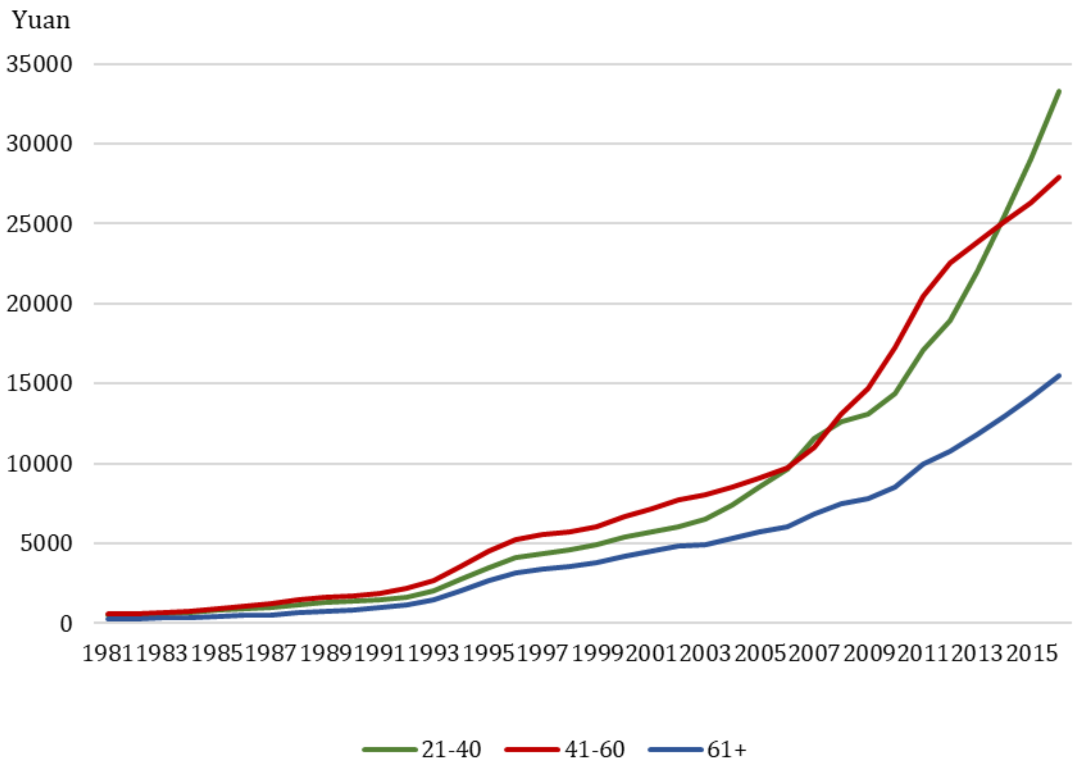
5.5 Age-specific preference estimation results

5.5.1 Sectoral consumption expenditure by age

In the MSOLG model presented in Section 5.2, each individual enters the economy as he or she starts to work and exits when he or she dies. In any given period, there are three generations or age groups of individuals alive in the economy: young, mid-aged, and old. We define the young age group as people aged between 21 and 40, the mid-aged group as people aged between 41 and 60, and the old age group as those aged 61 and above. In this set up, the consumption of people aged 0 to 20 are absorbed into the consumption of those aged 21 and above. We took into consideration life expectancy and retirement age when choosing 61 as the starting age for the elderly group. Although the minimum working age in China is 16, few people actually start working before 21.

To estimate preferences for each age group using equation (5.2), we need to construct per capita consumption by sector by age data. In Section 5.4, we estimated individual age-consumption profiles by category for 1988, 1995, 2002, 2007, 2010, 2012, 2014, and 2016. The profiles, together with population by age data from the UNWPP, allow us to compute aggregate age-consumption profile by category for the survey years. Next, we map the consumption categories into the three sectors following the same process as those in Chapter 4, obtaining the age profiles of aggregate consumption for each sector. For each sector, we compute the shares of the three age groups in consumption (the 0-20 age group is excluded). We interpolate these shares for the years for which survey data are not available. For 1981-1987, we assume the shares are the same as those in 1988. Finally, for each sector, we apply the shares of age groups to sectoral consumption expenditure data constructed in Chapter 4 to obtain sectoral consumption expenditure by age for the 1981-2016 period.

Figure 5.3: Per capita consumption by age group



For each age group, per capita total consumption is computed as the age group's aggregate consumption divided by the age group's population. As can be seen in Figure 5.3, per capita consumption expenditures of all three age groups grew over time. The growths were the fastest in the 1992-1996 and 2006-2016 periods. Before 2003, per capita consumption of the middle-aged grew faster than that of the young. Afterwards, the growth of youth per capita consumption accelerated. In the years to follow, per capita consumption of youth moved closely with that of the middle aged. Consumption per capita of the elderly started off as the lowest of the three and consistently had the slowest growth. The per capita consumption of elderlies never accelerated in the 2000s like the others. Resultantly, the gaps between per capita consumption of the elderly and those of the young and mid-aged widened over time. These suggest that cohort effect cannot be the only explanation for the low elderly consumption in China.

In Figure 5.4, we plot the time series of sectoral consumption shares for the three age groups. As can be seen in the figure, age-specific sectoral consumption shares move in similar directions as the aggregate sectoral consumption shares in Chapter 4. In particular, over the 1981-2016 period, agricultural shares fell, service shares rose, and industrial shares stagnated.

Figure 5.4: Sectoral consumption expenditure shares by age group

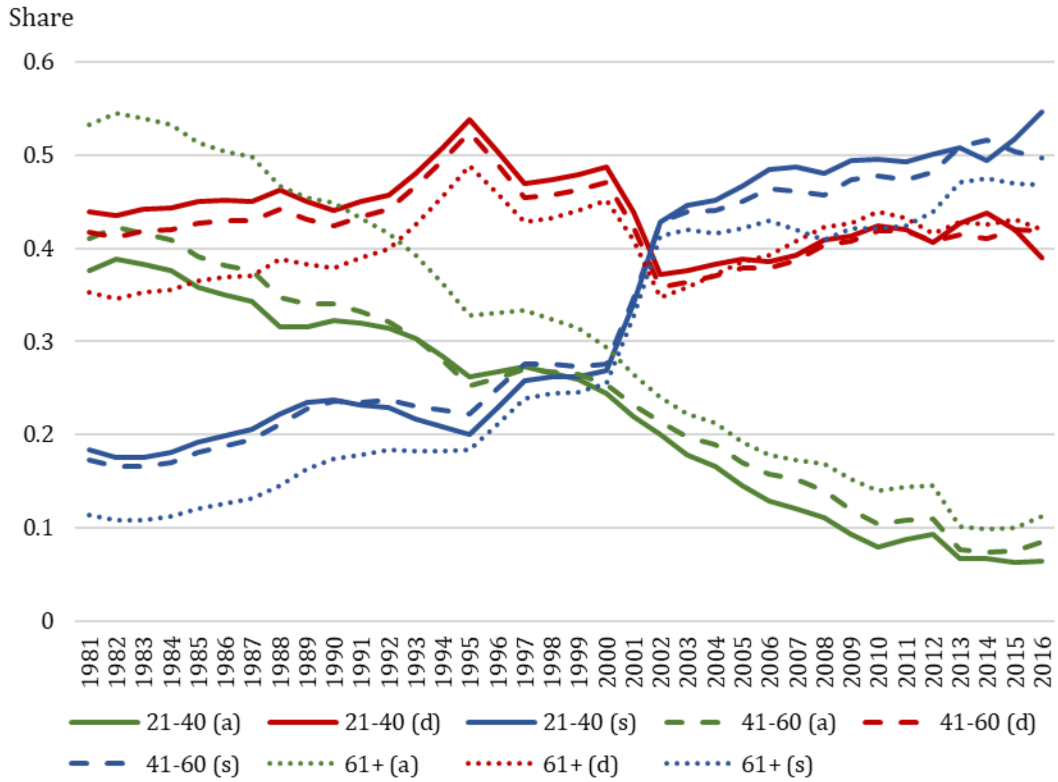


Figure 5.4 shows that the share of total consumption allocated to agriculture increased with age. The explanation could be that subsistence consumption occupied a higher share

of elderly total consumption. It could also be that elderlies did not have much taste for non-agricultural consumption. Over time, the gaps in agricultural share between age groups shrunk. In 1981, agriculture consumption share of elderlies was 15.7 percentage points higher than that of youths. By 2016, the number had shrunk to 4.7 percentage points.

Service consumption share of elderlies was consistently lower than that of youths. As mentioned earlier, although older people spent relatively more on healthcare, they spent relatively less on other services. The gap between elderly service share and youth service share shrunk till 2002 but expanded afterwards. Middle-aged service share was lower than youth service share in most periods but the two stayed close to each other throughout the sample period. In 2016, service consumption share of elderlies was 7.7 percentage points lower than that of youths and 2.9 percentage points lower than that of the mid-aged.

In 1981, industrial consumption share of elderlies was 6.4 percentage points lower than that of the mid-aged, which was 2.3 percentage points smaller than that of the young. Over time, industrial consumption share of elderlies grew relative to that of the mid-aged, which grew relative to that of the young. The ranking of industrial share by age started to change in 2005. By 2016, elderly industrial share was 3.0 percentage points higher than youth industrial share.

From these differences in sectoral shares across age groups, we can deduce that population aging can raise the aggregate consumption shares of agriculture and industry and reduce the aggregate consumption share of services. To quantify the aging effects on future consumption, we extend the analyses at the end of Section 5.4. We start by assuming that consumption patterns stay the same as those in 2016, and that per capita consumption of age groups will grow at the 2013-2016 average rates. We then forecast aggregate consumption by age by sector under the aging and no aging scenarios. Finally, we deduce the effects of aging by comparing the changes in consumption shares between

2016 and 2085 under the two scenarios. Our results show that by 2085, aging will have reduced service consumption share by 2.7 percentage points and raised agricultural and industrial shares by 1.6 and 1.1 percentage points, respectively.

5.5.2 Consumption value added results

5.5.2.1 Sectoral consumption value added by age

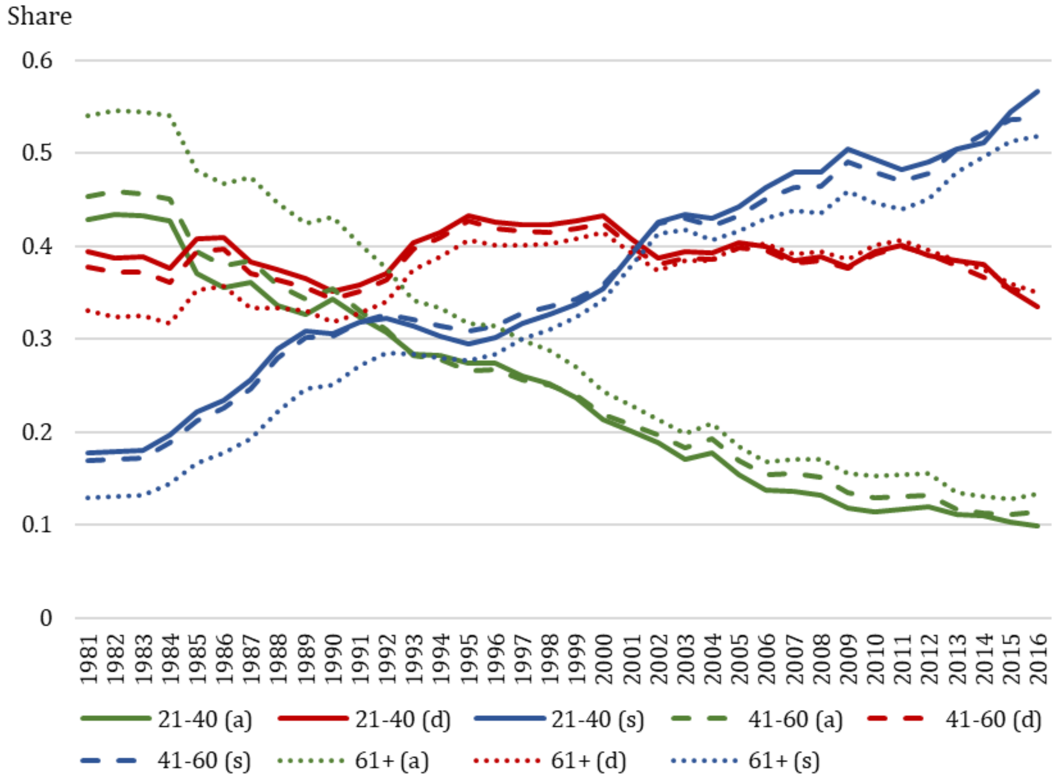
For each age group, we use the extraction matrices from Chapter 4 to map sectoral consumption expenditure to sectoral consumption value added. Figure 5.5 below shows sectoral consumption value added shares for the three age groups. Like before, agricultural shares fell, service shares rose, and industrial shares stagnated over the sample period.

Older age groups had higher agricultural consumption shares, but lower service consumption shares compared to younger groups. The gaps in agricultural and service shares across age shrunk from 1981 to 2002, after which they expanded slightly. In 1981, elderly agricultural and service shares were respectively 11.2 percentage points higher and 4.8 percentage points lower than their youth counterparts. By 2016, these numbers had changed to 3.4 and 4.9. Elderly industrial share started off the sample period being 6.4 percentage points lower than youth industrial share. Over time, elderly industrial share grew relative to youth industrial share. By 2016, elderly industrial share was 1.5 percentage points higher than youth industrial share.

The variations in sectoral consumption shares across age groups mean that population aging can affect the structure of China's consumption. To quantify the aging effect, we extend the analyses at the end of Section 5.4 again, this time comparing predicted changes in Chinese consumption value added shares under the aging and no-aging scenarios. The counterfactual analysis shows that aging will reduce per capita consumption by 0.12 percentage points per year. If the predicted reduction in consumption means an increase in savings and hence capital investment, aging can lead to a structural shift towards the industrial sector. This is because investment is composed overwhelmingly of industrial value added. At the sectoral level, aging is predicted to raise agricultural consumption value added share by 1.2 percentage points by 2085, thereby impeding structural change. Regarding the modern sector, aging is predicted to raise industrial consumption value added share by 0.5 percentage points but to reduce service consumption value added share by 1.7 percentage points.

The differences in sectoral consumption across age groups originate from differences in preferences across age groups. In this study, we are interested in finding out what these age-specific preferences are and how they differ across age. We therefore estimate age-specific preferences in the next step.

Figure 5.5: Sectoral consumption value added shares by age group



The estimated age-specific preferences will help us not only to better understand the observed patterns of sectoral consumption by age but also to make more realistic predictions about the effects of aging. The comparison of future scenarios above assumes that age-specific sectoral consumption shares in the future are exogenous and constant.

In reality, population aging can affect variables such as income and prices which can in turn influence age-specific sectoral consumption shares. By incorporating age-specific preferences into our general equilibrium MSOLG model, we will be able to account for these interactions when exploring the effects of aging in Chapter 6.

5.5.2.2 Age-specific preference estimation results

Using age-specific sectoral consumption value added shares and per capita consumption series, together with the implicit value-added deflators presented in Chapter 3, we estimate age-specific preference parameters in equation (5.2):

$$s_{gi,t+g-1} = \frac{p_{i,t+g-1}c_{gi,t+g-1}}{c_{g,t+g-1}} = \frac{p_{i,t+g-1}\bar{c}_{gi}}{c_{g,t+g-1}} + \frac{\omega_{gi}p_{i,t+g-1}^{1-\sigma_g}}{\sum_j \omega_{gj}p_{j,t+g-1}^{1-\sigma_g}}\left(1 - \frac{\sum_i p_{j,t+g-1}\bar{c}_{gj}}{c_{t+g-1}}\right) \tag{5.2}$$

Our estimation of age-specific preferences in this chapter follows the same steps as those of aggregate preferences in Chapter 4. Like before, our estimates for ω_{gi}'s and σ_g's all turn out to be positive. We therefore do not have to impose non-negativity restrictions on said parameters. Throughout our project, we experimented with restricting various combinations of $\bar{c}_{gi}$'s to zero. To make comparisons of results meaningful, we need to use the same restrictions across all estimations. We eventually settled with the specification in which only $\bar{c}_{gd}$ is restricted. The estimates for this specification are statistically significant in all cases and deliver the best fit of data in the vast majority of cases. This specification is also one that is most commonly used in the literature.

We show the estimation results for the specification in which only $\bar{c}_{gd}$ is restricted to zero for the young, mid-aged, and old in Table 5.1. As can be seen in the table, all estimates are highly significant. For all age groups, preference weight estimates for industry are higher than those for services, which are higher than those for agriculture. These mean people prefer industrial value added to service value added, and service value added to agricultural value added.

The σ_g's are estimated to lie between zero and one. This suggests that demands are relative price inelastic. An increase in sectoral relative price would induce a less than proportionate fall in sectoral real consumption, resulting in an increase in sectoral nominal consumption. The σ_g estimates also confirm that even at the age group level, neither a Leontief utility function nor a log utility function are suitable for explaining Chinese data.

Table 5.1: Age-specific preference estimation results

	Age group		
	21-40	41-60	61+
σ_g	0.50***	0.43**	0.32***
	(0.19)	(0.19)	(0.12)
ω_{ga}	0.012**	0.013**	0.034***
	(0.0050)	(0.0059)	(0.0084)
ω_{gd}	0.53***	0.55***	0.58***
	(0.056)	(0.053)	(0.028)
ω_{gs}	0.46***	0.44***	0.38***
	(0.056)	(0.053)	(0.028)
$\bar{c}_{ga}$	239.83***	296.30***	173.15***
	(4.40)	(6.06)	(4.26)
$\bar{c}_{gs}$	-91.39**	-82.63**	-24.60**
	(45.79)	(46.54)	(9.86)
R^2_{ga}	0.997	0.996	0.993
R^2_{gs}	0.995	0.996	0.994
$RMSE_{ga}$	0.015	0.017	0.029
$RMSE_{gd}$	0.020	0.019	0.015
$RMSE_{gs}$	0.027	0.024	0.028

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R^2_{gi} is for the s_{gi} regression. $RMSE_{gi}$ refers to Root Mean Squared Errors for the s_{gi} regression.

The positive point estimates for $\bar{c}_{ga}$ are consistent with the fact that some agricultural consumptions are necessary for survival. The negative estimates for $\bar{c}_{gs}$ confirm that individuals are endowed with some services. Examples of such endowment services include home-produced services and government provided services.

When incomes were low, people devoted the vast majority of their total consumption to subsistence consumption. As incomes grew over time, people had more spare income to spend on products according to their preference weights. The non-homotheticity terms, high service preference weights, and low agricultural preference weights can therefore explain the observed rises in service consumption shares and falls in agricultural consumption shares. Despite the high industrial preference weights, industrial consumption shares stagnated between 1981 and 2016. This can partially be explained by the fact that industrial shares were already high at the beginning of the sample period, so that they had less room to increase compared to service shares. Since σ_g's are estimated to be between zero and one, relative price effects induce sectoral consumption shares to move in the same directions as their corresponding relative prices. Therefore, the fall in industrial relative price played an important role in driving industrial shares down. In the next subsection, we will quantify the income and price effects and analyse them in more detail.

Comparing the estimates across age groups, we can see that older age groups have higher preference weights for agriculture and industry, and lower preference weights for services compared to younger age groups. These are consistent with the observations in Figure 5.5 which show that older age groups had higher agricultural and industrial consumption shares but lower service consumption shares than younger age groups.

Subsistence agricultural consumption of elderlies is estimated to be the lowest of the three. This is understandable as elderlies are physically the least active. Compared to younger age groups, elderlies devoted higher shares of their total consumption to subsistence. Therefore, subsistence consumption played bigger roles in determining the consumption structure of elderlies than in that of other age groups. The estimated agricultural subsistence consumption of the mid-aged is higher than that of youths. This suggests that the need for food can be related to work.

The estimated service endowment and its share in total consumption decrease with age. The difference in endowed service consumption between the mid-aged and the elderly is much larger than that between the mid-aged and the young. Such results refute the argument that service consumption share of elderlies is lower because they produce and or enjoy more home-produced services. Although elderlies have more free time after retirement, they do not necessarily spend the time on home production. Older people may be physically weaker or may want to retire from home production, causing them to engage less in home production than others.

The results show that σ_g decreases with age, with a particularly sharp drop between mid-age and old-age. These suggest that as people get older, they become less responsive to changes in relative prices. In the event of changing relative prices, sectoral nominal consumption shares of elderlies would move more closely with sectoral relative prices compared to those of younger age groups. One potential explanation for the relatively low elderly elasticity is that older people are physically less mobile and hence shop around less compared to younger people. Another explanation could be that people develop loyalty to products over time that discourages them from product substitution.

Figures 5.6 to 5.8 show the actual and model predicted paths of sectoral consumption value added shares for the three age groups. The model predicted shares are computed by plugging data values of income and prices into the estimated equation (5.2). As can be seen in the figures, the model predictions fit the data well. The good fit is confirmed by statistics from Table 5.1 which show that the average root mean squared errors for the regressions of the young, mid-aged, and old are 0.020, 0.020, and 0.024, respectively. Furthermore, the R^2's for the regressions are very close to 1's.

Figure 5.6: Actual and predicted sectoral Consumption Value Added (CVA) shares of the 21-40 (young) age group

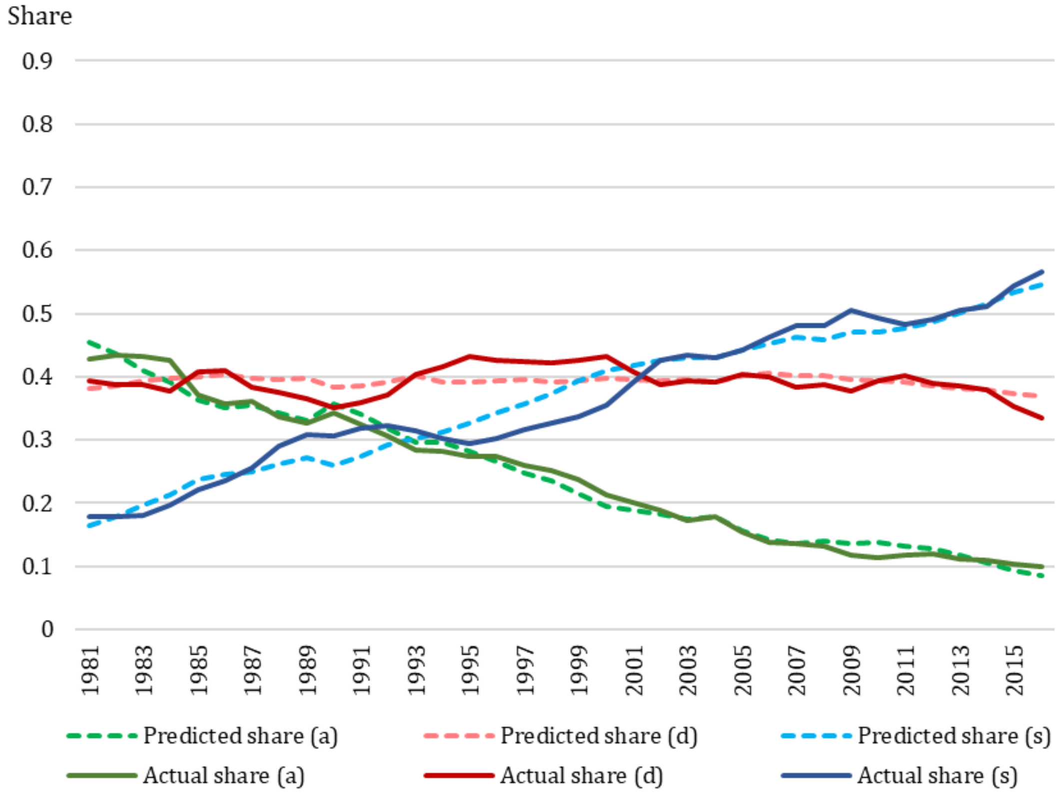


Figure 5.7: Actual and predicted sectoral CVA shares of the 41-60 (mid) age group

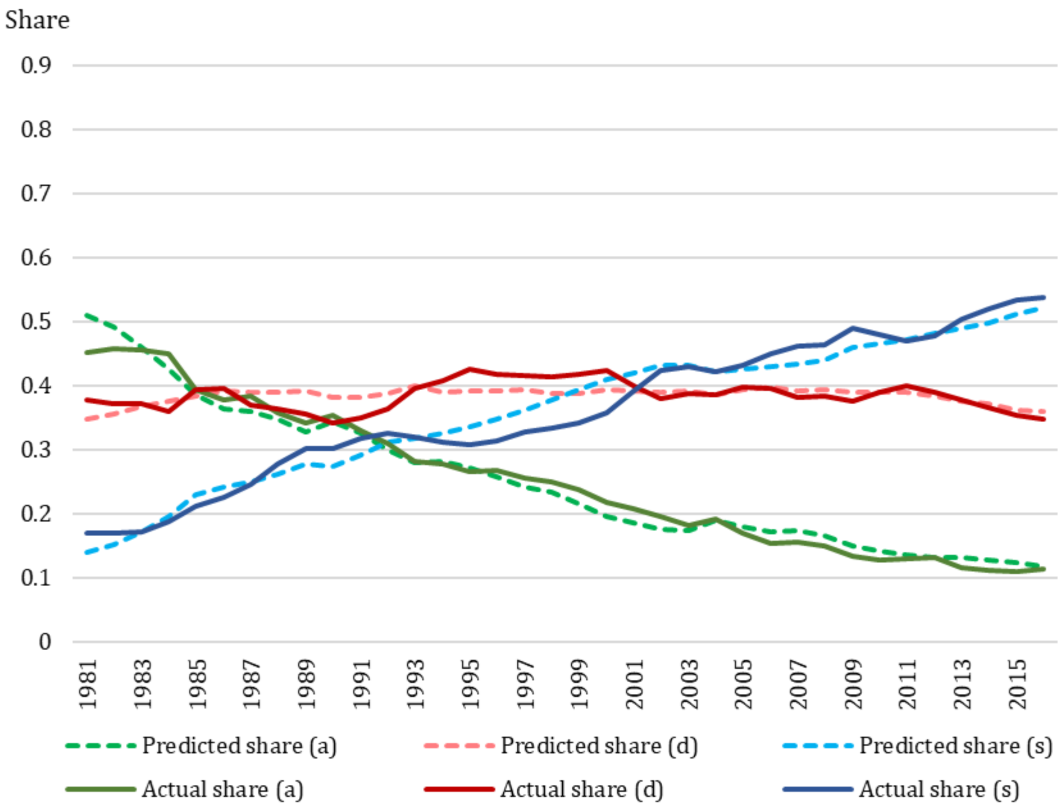
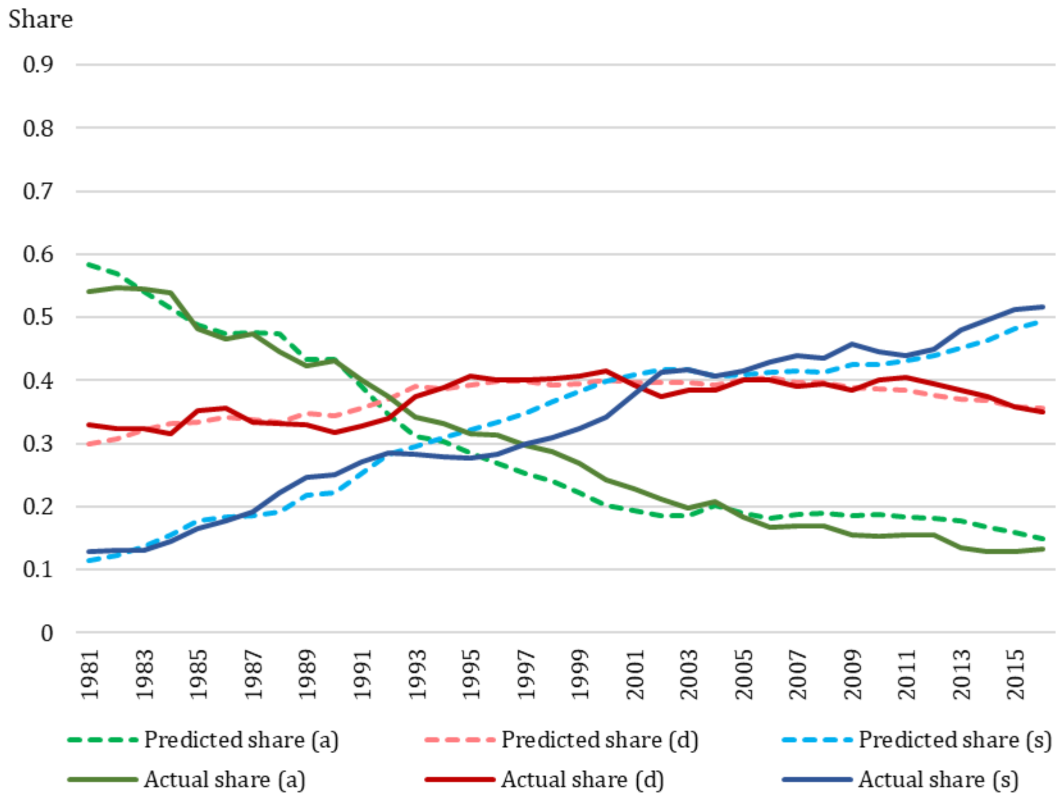


Figure 5.8: Actual and predicted sectoral CVA shares of the 61+ (old) age group

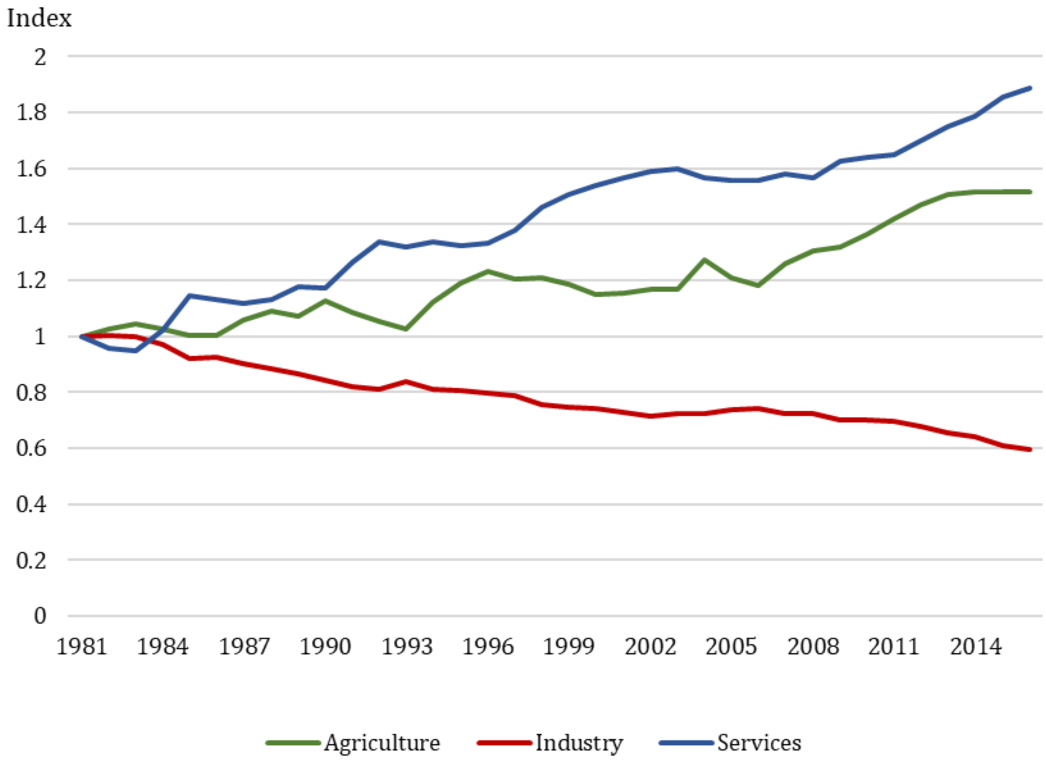


5.5.2.3 Relative price effect

In this section and the next, we investigate the roles played by relative price effect and income effect in driving the structural change of age-specific consumption. In doing so, we follow the same steps that we did for the investigation at the aggregate level in Chapter 4. Due to the differences in preferences, different age groups react differently to changes in income and prices. Therefore, the effects differ across age groups.

In Figure 5.9, we plot the time series of relative prices of the three sectors. As can be seen in the figure, agricultural and service relative prices rose while industrial relative price fell between 1981 and 2016. Overall, service relative price increased relative to agricultural relative price.

Figure 5.9: Sectoral relative prices



To study the relative price effect, we plot sectoral consumption shares data along with model predicted sectoral consumption shares under a counterfactual scenario in Figures 5.10 to 5.12. In the counterfactual scenario, incomes are held constant at 1981 levels while relative prices change according to data. The evolutions of counterfactual shares therefore represent the relative price effects.

Figures 5.10 to 5.12 show that in the counterfactual, agricultural shares increase and industrial shares decrease with their respective relative prices. These can be explained by the two components of relative price effect. First, since σ_g's are estimated to be between zero and one, real sectoral demands of all age groups are relative price inelastic. This means nominal sectoral consumption move in the same directions as their corresponding sectoral relative prices. Second, the increase in agricultural price causes subsistence consumption to become more expensive and hence occupy higher shares of total consumption over time.

Figure 5.10: Actual and counterfactual sectoral CVA shares of the young age group

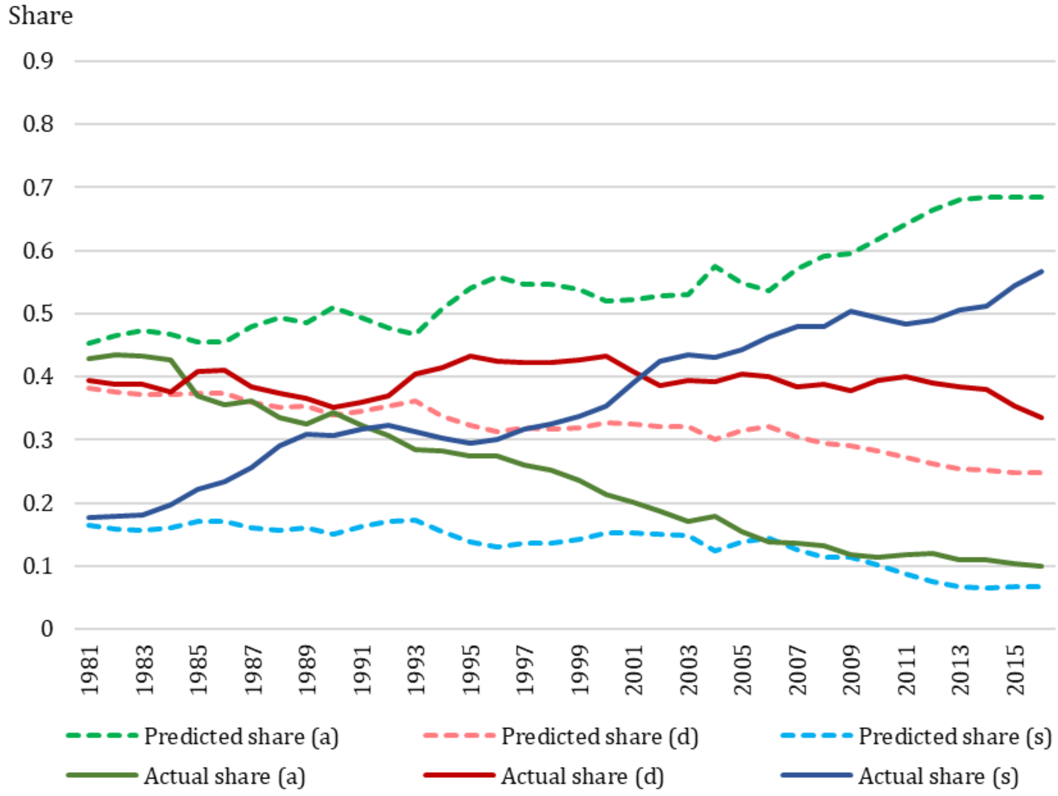


Figure 5.11: Actual and counterfactual sectoral CVA shares of the middle-age group

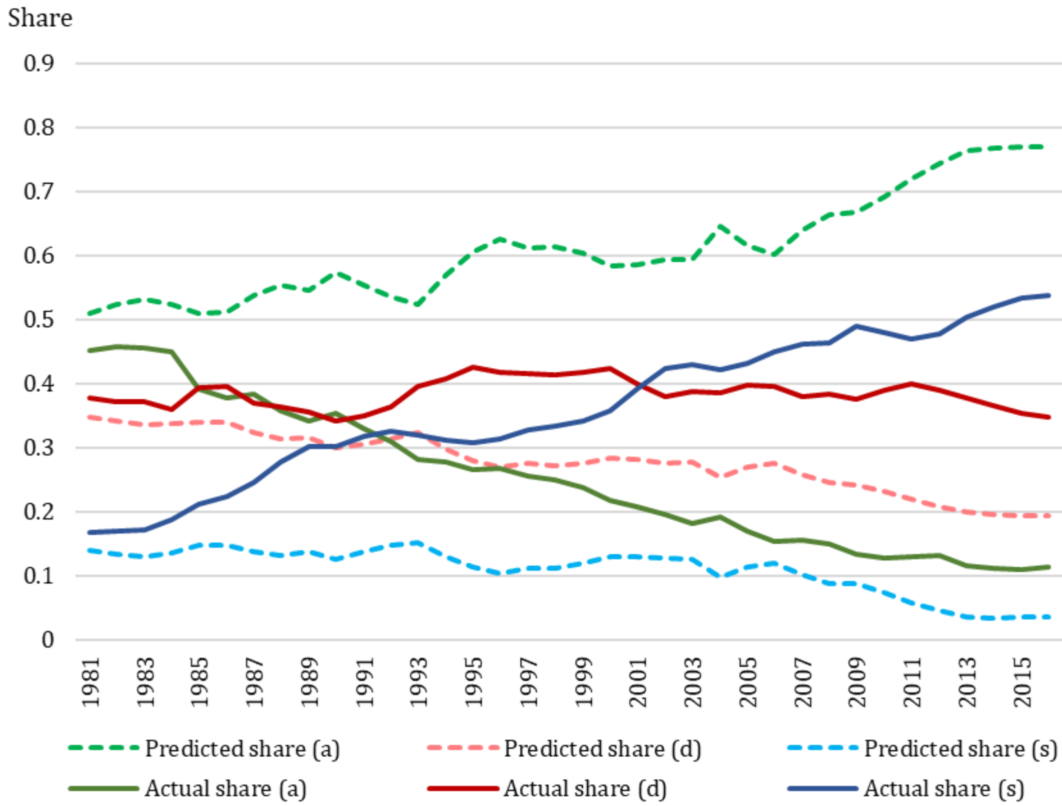
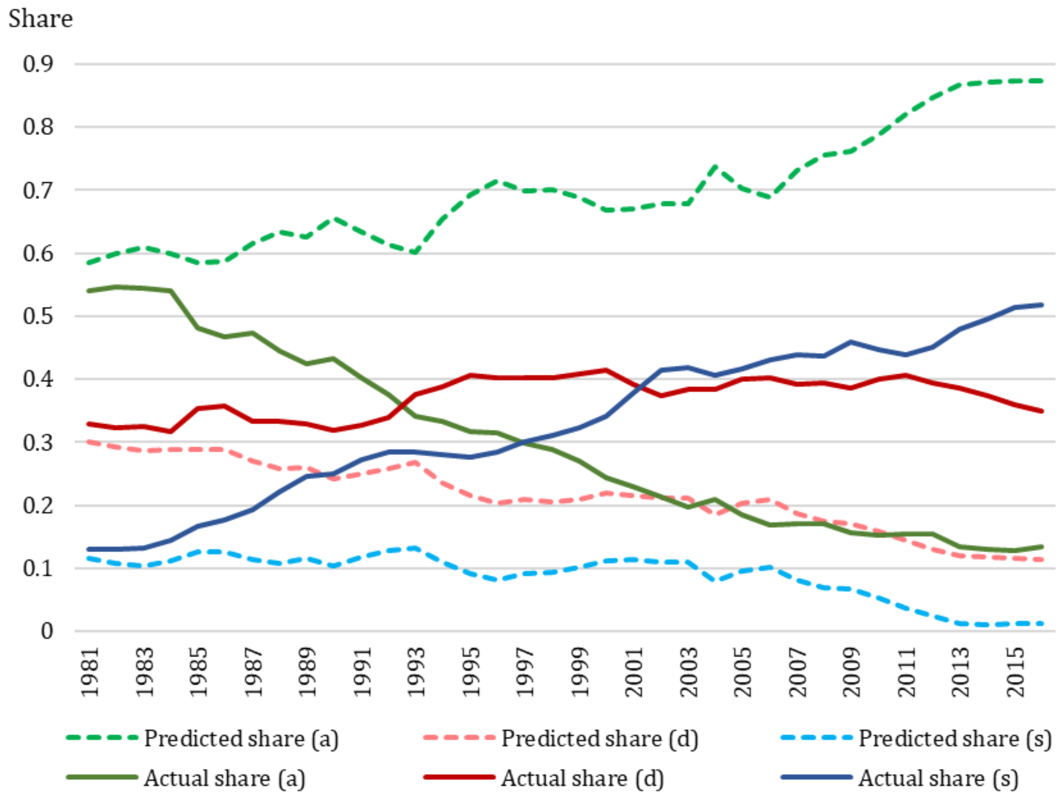


Figure 5.12: Actual and counterfactual sectoral CVA shares of the old age group



Comparing across age groups, we find that relative price effects are stronger on older age groups. In particular, relative price effects raise agricultural share of elderlies by 5.8 percentage points more than that of youths and reduce industrial share of elderlies by 5.2 percentage points more than that of youths. There are two explanations for these findings. First, older age groups have lower σ_g's and hence their sectoral consumption shares move more closely with prices. Second, subsistence consumption's share in total consumption increases with age. As such, the higher cost of subsistence due to rising agricultural relative price affects older age groups more.

Despite the increases in service relative price, counterfactual service shares decrease over time. This is mainly due to the interactions between sectoral relative prices and the non-homotheticity terms. As agricultural and service relative prices rise, subsistence agricultural consumption and endowment service consumption occupy greater shares in total consumption, causing service consumption shares to fall. Older age groups see larger falls in service shares because they have higher subsistence consumption shares and lower preference weights for services than others.

As can be seen in Figures 5.10 to 5.12, relative price effects can explain the short-term fluctuations of sectoral consumption shares and the fall in industrial consumption share. However, relative price effects cannot explain the fall in agricultural share and the increase in service share over time. Like in the aggregate case, the seemingly poor performance of relative price effects in explaining sectoral consumption value added shares in Figures 5.10 to 5.12 is partially due to the fact that the figures do not capture the interactions between relative price effects and income effects. In the counterfactual scenario, subsistence and endowment consumption occupy increasing shares of total consumption, forcing agricultural shares to increase and service shares to fall. If incomes were to increase like in the data, service consumption shares would move more closely with service relative price.

5.5.2.4 Income effect

In this subsection, we investigate the role of income effects in driving age-specific sectoral consumption patterns. In Figures 5.13 to 5.15, we plot actual consumption value added shares and counterfactual consumption value added shares. The counterfactual shares are model predicted shares under the scenario in which prices are constant at 1981 levels while real incomes change according to data. As such, changes in counterfactual shares capture income effects.

As people's incomes rise, subsistence agricultural consumption and endowment service consumption occupy smaller shares of their incomes, allowing them to spend greater shares of their incomes according to their preference weights. Since people of all ages have greater preference weights for modern sector consumption than for agricultural consumption, they allocate the spare incomes overwhelmingly to the modern sector. These explain why income effects cause agricultural shares to fall and industrial and service shares to rise in Figures 5.13 to 5.15.

The negative income effects on agricultural shares are stronger for older age groups. By 2016, income effect lowers agricultural share of elderlies by 8.4 percentage points more than that of youth. This is the result of subsistence agricultural consumption occupying greater shares in older age groups' total consumption. By similar logic, the positive income effect on service consumption share falls with age because service endowment consumption share falls with age. The faster drops in agricultural shares and slower increases in service shares cause industrial shares of older age groups to increase more rapidly than those of younger age groups. By 2016, income effect raises elderly industrial share by 12 percentage points more and raises elderly service share by 3.4 percentage points less than their youth counterparts.

Compared to relative price effects, income effects are steadier and hence are less able to explain the short-term movements of sectoral consumption. Income effect is the key to explaining the observed reductions in agricultural consumption shares. As shown in Figures 5.10 to 5.15, income effects on industrial shares are positive and roughly cancel out the negative relative price effects. The observed stagnant industrial consumption shares are therefore explained by a combination of income and price effects.

In isolation, income effect and price effect each under-predicts the rise in service consumption shares. This points to the importance of interaction effects between income and relative price effects which only occur when relative prices and income (real) are both allowed to change. The increases in agricultural and service relative prices cause subsistence consumption and endowment consumption to increase over the sample period. If real incomes were fixed, these would cause service consumption shares to fall. If real incomes were allowed to increase as in the data, subsistence and endowment consumption would quickly become negligible as shares of total incomes, allowing service consumption shares to increase more with service relative price.

Figure 5.13: Actual and counterfactual sectoral CVA shares of the young age group

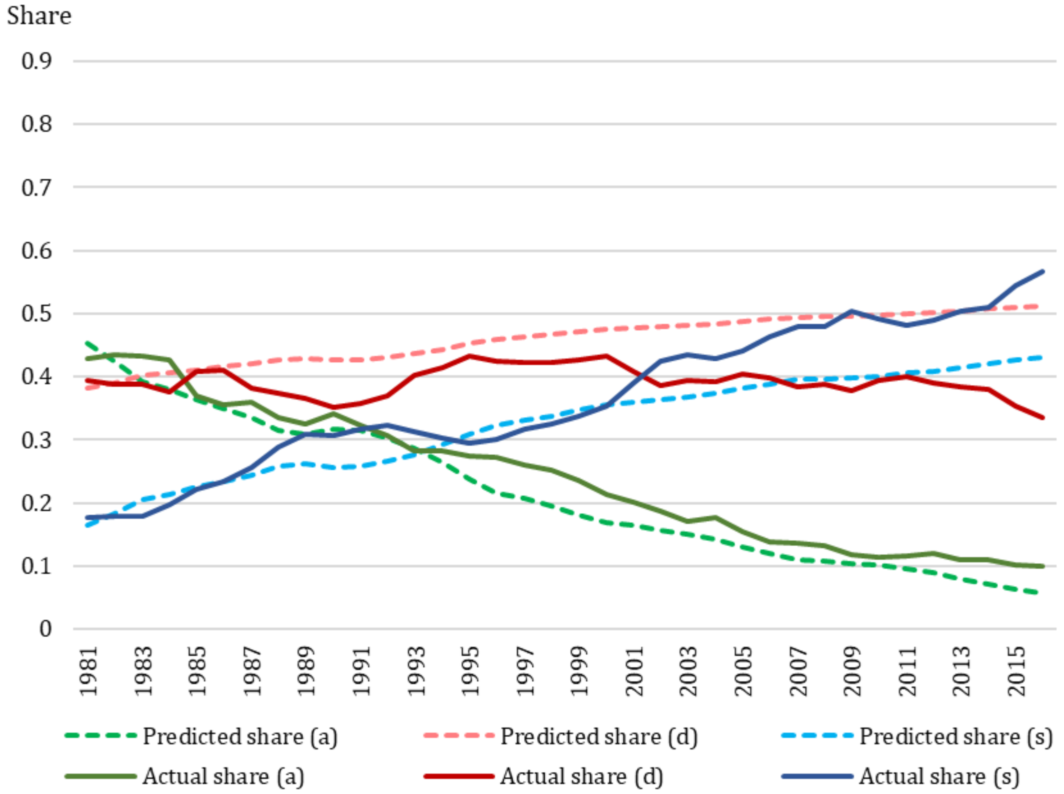


Figure 5.14: Actual and counterfactual sectoral CVA shares of the middle age group

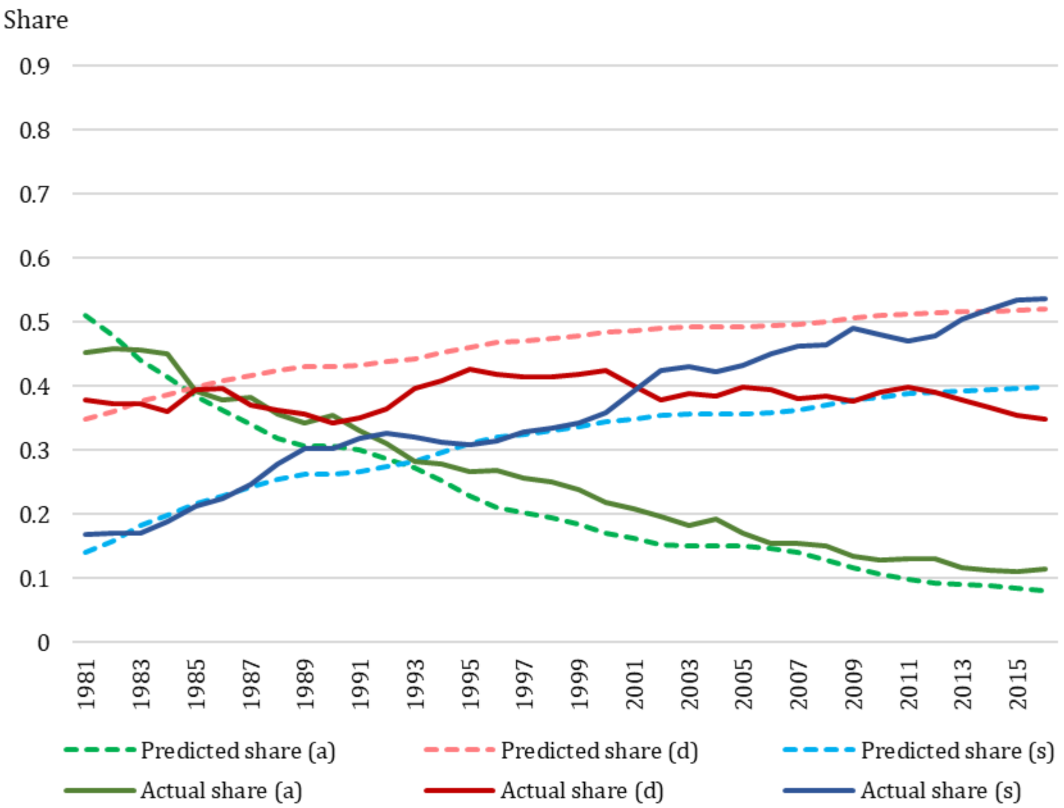
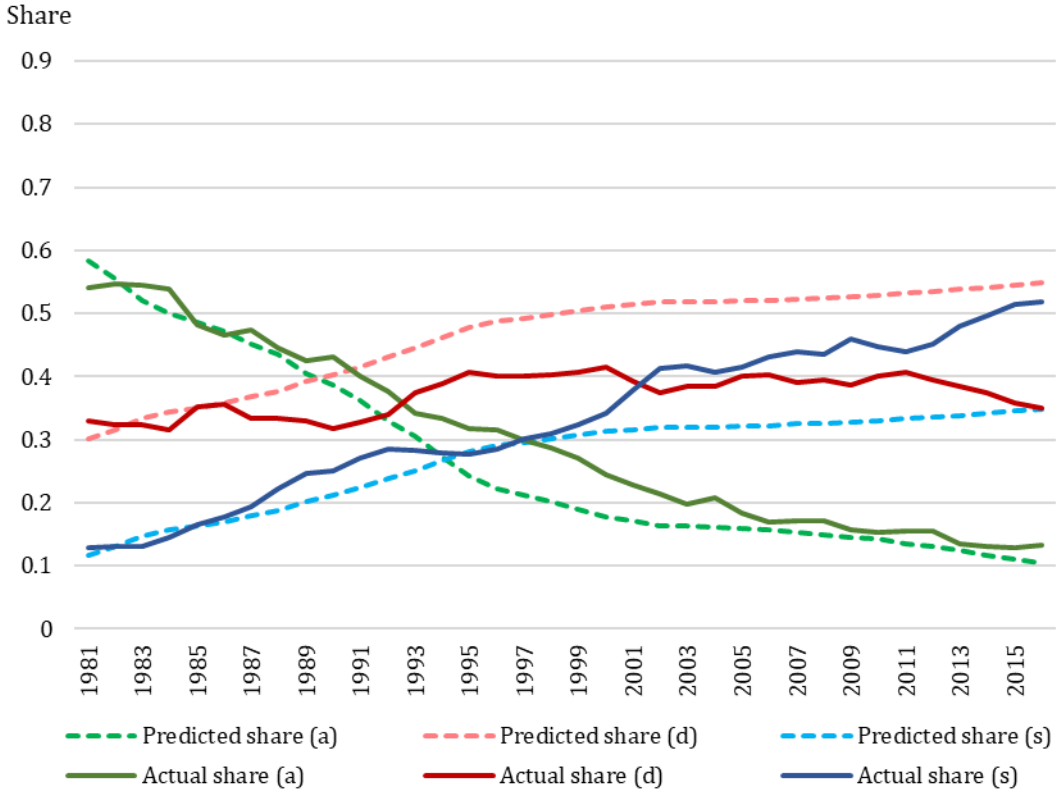


Figure 5.15: Actual and counterfactual sectoral CVA shares of the old age group



5.6 Conclusion

In this study, we first estimated individual level age-consumption profiles for eight selective years between 1988 and 2016. We found age profiles of per capita consumption to be consistently hump-shaped. This is at odds with the life-cycle hypothesis which suggests that consumers smooth consumption over their lifetimes. Our result implies that population aging can lower per capita consumption in China and thereby undermine China's transition towards a more consumption-oriented economy. If the elderlies' propensity to consume could be increased, the aforementioned adverse aging effect would be alleviated. One potential solution would be to improve social security so that elderlies can release some of their precautionary savings for consumption. Policymakers can also attempt to improve elderlies' access to products by adapting transport and communications systems to elderlies' needs.

Our results at the category level show large variations in age-consumption profiles across categories and across time. This invalidates the assumption that age-consumption patterns are constant across time. Compared to younger age groups, older age groups allocated greater shares of their consumption to food and healthcare but similar or smaller shares to other categories. By comparing predicted consumption under the aging and no-aging scenarios, we found that population aging can substantially change the structure of China's private consumption.

Next, we used the estimated age profiles of consumption categories to breakdown sectoral consumption data from Chapter 4 by age group. We found that older age groups had higher agricultural and industrial consumption shares but lower service consumption shares than younger age groups. Population aging can therefore impede structural change towards the service sector.

To study the driving forces behind the observed patterns of age-specific sectoral consumption, we wrote a three-sectors overlapping generations model with age-specific preferences. From the model, we derived age-specific sectoral consumption share functions. Using these functions, together with data on prices and on age-specific sectoral consumption, we estimated age-specific preferences for China. The results show that demands of all age groups are relative price inelastic. Furthermore, the elasticities fall with age. This means older age groups are less responsive to changes in relative prices and their nominal sectoral consumptions move more closely with sectoral relative prices. We found older age groups to have higher preference weights for agriculture and industry but lower preference weight for services compared to younger age groups. These imply that population aging can impede structural change towards services in the long term.

Finally, we investigated the roles played by relative price and income effects in determining age-specific sectoral consumption shares and how these effects differ across age groups. Like in the aggregate case, while income effect was the key driver behind the drops in agricultural consumption shares over time, both income effect and price effect played vital roles in lowering industrial consumption shares and raising service consumption shares. Since older age groups have lower price elasticities of demand than younger age groups, relative price effects on older age groups' nominal sectoral consumption shares were stronger in magnitude. Subsistence agricultural consumption's shares and endowment service consumption's shares in total consumption of older age groups were respectively higher and lower than those of younger age groups. Therefore, income effects played bigger roles in explaining the fall in agricultural consumption shares and smaller roles in explaining the rise in service consumption shares of older age groups than in those of younger age groups.

The elderlies' high subsistence consumption share prevented them from allocating consumption to the modern sectors and was therefore one factor behind the elderlies' under-transformed consumption structure. The main explanation for elderlies' high subsistence consumption share is not that they required more such consumption than others but that their per capita total consumption was much lower than those of younger age groups. To accelerate the structural change of elderly consumption, policymakers can raise elderly income and hence consumption by, for examples, extending the retirement ages and or redistributing income towards elderlies. Another explanation for the elderlies' high agricultural consumption share is associated with the rapid increases in agricultural relative price in China. Since elderlies are the least responsive to price changes, their agricultural consumption share increased the most with agricultural relative price. In the era of population aging, policymakers should pay close attention to inflation of agricultural necessities because it impedes structural change through elderlies' consumption and disproportionately harms the elderlies' welfare.

In this chapter, we studied the effects of population aging on the demand-side, taking variables such as prices and incomes as given. In reality, there are interactions between aging, demand, and supply side forces which in turn affect prices and incomes. We would therefore like to explore the effects of aging in a more complete model that accounts for these interactions. This will be one of our tasks in Chapter 6, where we calibrate and simulate an MSOLG model with both demand and supply sides. The data, modelling, and estimation of age-specific demand from this chapter will serve as the basis for the construction and calibration of our MSOLG model in Chapter 6.

Appendix 5.1: Cleaning and processing of household survey data

A5.1.1 CHIP

CHIP's sample sizes fluctuated slightly over time. On average, CHIP's rural survey covers 8,864 households with 38,963 individuals and CHIP's urban survey covers 6,944 households with 22,210 individuals between 1988 and 2007.

CHIP's team carried out preliminary data cleaning including consistency checks, standardization of missing values, and checks for undocumented codes before publishing the data. In this study, our processing and cleaning of CHIP's data focus on our variables of interest, namely individual age and household consumption.

In each CHIP wave, age data for a small number of individuals are missing. For these individuals, we try to estimate their age using the relations to household head variable. If an individual is the spouse of a household head whose age is reported, we replace the individual's missing age by his or her spouse's age. For the other individuals without age data, we drop their households from the data. There are a very small number of urban sample households with missing values on specific consumption categories. These households are dropped only when we run regressions for the categories for which they have missing data. On average, about 0.3% of households are dropped from CHIP datasets during our data cleaning process.

CHIP's consumption expenditure data generally follow the same classification system as NBS's household survey data, with items that constitute the 8 consumption categories. For CHIP's 1988 and 1995 rural datasets, we have to compile food consumption manually. We compile non-cash food consumption by adding up consumptions of self-produced food and food received in kind. We then compute food consumption as the sum of cash food consumption and non-cash food consumption. While CHIP1988 provides values of non-cash consumption items, CHIP1995 provides quantities and prices. We compute values of non-cash food consumption items by multiplying the quantities and prices. Some household did not report prices. In such cases, we replace their prices data by the average prices in their counties.

CHIP's 1988 rural dataset does not report housing consumption directly. We estimate rural housing consumption by adding up rent and expenditures on water, electricity, and fuel. For households who did not report rent data, we estimate the imputed rent of their houses following instructions in Griffin and Renwei (1991). Specifically, imputed rent of a house is computed as a share (8%) of the house's equity. A house's equity is computed as the price of the house net of housing loans. For each household who did not report house price, house price is estimated as house size in square meters times the county average per square meter house price.

Clothing and daily consumption data are not available from CHIP's 1988 rural dataset. We estimate 1988 rural clothing and daily age-consumption profiles by scaling 1995 rural clothing and daily age-consumption profiles downwards. The scaling ensured that the estimated profiles are consistent with NBS's 1988 rural clothing and daily consumption data.

In several cases, CHIP reports education consumption but not entertainment and cultural (EC) consumption of the EEC category. To estimate EEC profiles, we use the closest EC profile as replacement. In particular, we use the EC profile of the subsequent survey wave if it is available. If not, we use EC profile of the other area of the same year. The education profiles and their corresponding replacement profiles are first scaled to be consistent with NBS's household survey data and then added up to yield the estimated EEC profiles.

During data processing, we find some extremely large consumption values that are likely due to misreporting. To prevent our results from being skewed by extreme values, we trim the households that constitute the top one percentile of consumption when estimating age-consumption profiles. We do the same for datasets from all three projects described in this section.

A5.1.2 UHS

Out of a sample of 13,761 households, we drop 0.4% of them for missing household member age data and or for reporting zeros for all consumption categories. A further 1% of households that correspond to the top one percentile of consumption are dropped during estimation to alleviate the effects of extreme values. No households reported missing data for selective consumption categories.

A5.1.3 CFPS

Across the four survey waves, CFPS's datasets contain an average of 13825 unique households. CFPS conducted preliminary cleaning of data. For examples, CFPS corrected errors in the implementations process, ensured correspondence between individuals and households, and dropped or corrected illogical answers. Our cleaning of CFPS data focus on our variables of interest, namely individual age and household consumption.

In each wave of data, a small number of individuals reported missing age. If an individual's age data is missing, we try to estimate his age using other variables in the dataset such as relation to household head. If an individual's age cannot be estimated, he and his household are dropped from the sample.

Over time, people leave their original households for one reason or another. We drop people who were dead and people who left their households to serve the army, prison sentences, and to be monks.

In each survey after the 2010 baseline survey, location IDs for a small number of households are missing. The missing IDs lead to issues with weighting and data quality and forbid us from implementing an empirical strategy that accounts for the sampling design all together. We therefore drop households with missing location ID.

All in all, across the four waves, an average of 1.8% of households are dropped due to missing age, missing ID, and reporting zeros for all consumption categories. Like for CHIP and UHS, when estimating age-consumption profiles, we drop households that correspond to the top one percentile of consumption. Due to bunching of consumption values in CFPS datasets, the number of households dropped differ slightly across categories. In each CFPS wave, there are a very small number of households who reported missing values for selective categories. These households are dropped only when we run regressions for the categories for which the households have missing data.

Appendix 5.2 : Additional figures and tables

Figure 5.16: Consumer Price Index (CPI) by consumption category

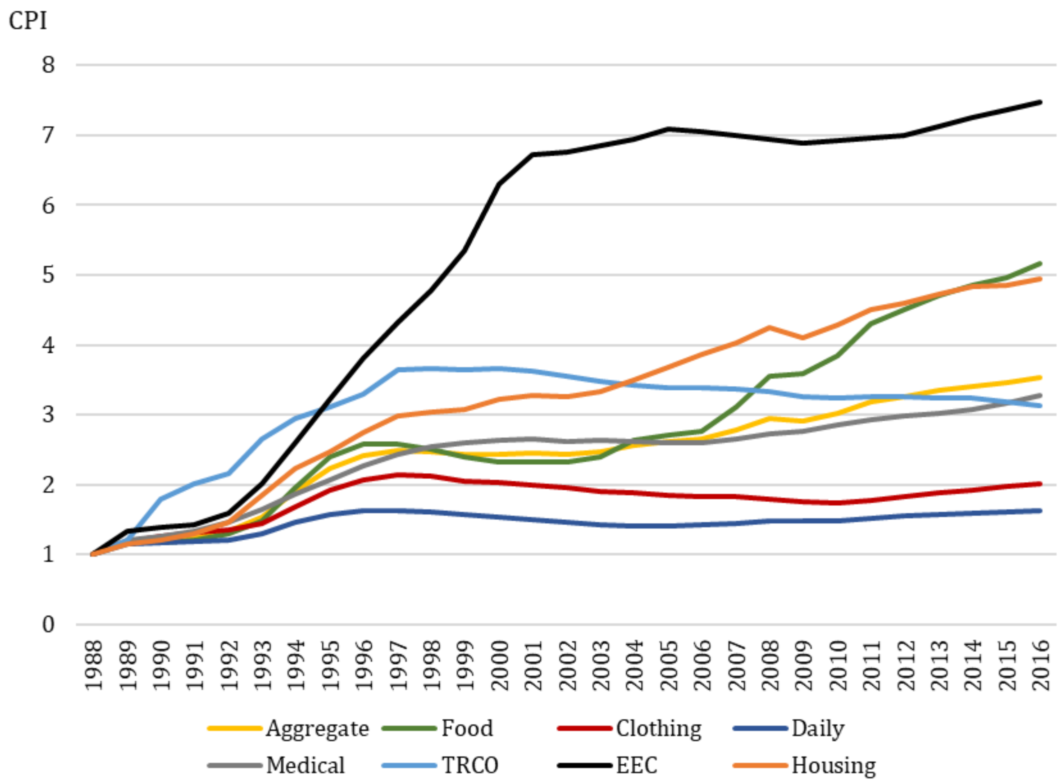


Table 5.2: Nominal age consumption profiles of the rural area in 1988

Age	Food	Medical	TRCO	EDU	Housing
0-15	74.47***	3.02***	0.42*	9.50***	-8.55
	(6.88)	(0.86)	(0.23)	(0.66)	(18.51)
16-20	123.43***	3.80***	1.93***	13.84***	94.27***
	(10.18)	(1.17)	(0.33)	(1.01)	(28.89)
21-25	158.84***	8.75***	2.23***	-1.37*	94.13***
	(10.07)	(1.16)	(0.35)	(0.82)	(28.14)
26-30	248.55***	19.58***	3.38***	-5.86***	146.19***
	(12.17)	(1.52)	(0.42)	(0.83)	(31.67)
31-35	318.80***	21.75***	3.12***	1.52*	238.24***
	(11.28)	(1.44)	(0.35)	(0.85)	(36.97)
36-40	332.32***	19.12***	3.45***	12.13***	222.44***
	(11.85)	(1.42)	(0.37)	(1.11)	(36.48)
41-45	356.27***	18.08***	3.79***	12.03***	197.72***
	(13.88)	(1.68)	(0.45)	(1.34)	(41.06)
46-50	327.16***	17.22***	4.78***	7.62***	122.83***
	(14.69)	(1.78)	(0.56)	(1.38)	(42.08)
51-55	330.20***	17.74***	4.02***	7.23***	80.61*
	(15.77)	(1.84)	(0.51)	(1.36)	(43.29)
56-60	280.46***	13.72***	2.79***	0.56	94.54**
	(16.03)	(1.99)	(0.53)	(1.08)	(43.48)
61-65	227.52***	16.39***	3.53***	1.26	17.08
	(17.95)	(2.24)	(0.60)	(1.22)	(44.09)
66-70	171.65***	18.05***	3.38***	-0.29	-25.24
	(21.53)	(2.95)	(0.79)	(1.53)	(53.67)
71+	185.79***	17.92***	0.64	5.03***	13.07
	(19.48)	(2.76)	(0.62)	(1.79)	(50.42)
Obs	10122	10123	10125	10123	10123

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EDU stands for Education. CHIP 1988 data are used in the estimations. The unit of measurement is Yuan.

Table 5.3: Nominal age consumption profiles of the urban area in 1988

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**-5.94**	**-12.53**	**-86.01**	**13.63**	**-2.68**	**-3.89**	**-3.63**
		**	***	***	***		***
	(10.92)	(4.98)	(8.57)	(1.14)	(0.67)	(7.72)	(2.54)
16-20	**47.35**	**48.46**	**-47.14**	**7.46**	**-0.92**	**1.78**	**7.63**
	***	***	***	***			**
	(12.92)	(5.92)	(10.24)	(1.21)	(0.81)	(9.03)	(3.26)
21-25	**356.03**	**138.60**	**123.10**	**6.64**	**4.03**	**61.06**	**37.37**
	***	***	***	***	***	***	***
	(14.98)	(6.96)	(11.83)	(1.28)	(0.93)	(11.37)	(3.73)
26-30	**759.97**	**223.80**	**247.91**	**18.10**	**11.10**	**136.36**	**72.25**
	***	***	***	***	***	***	***
	(11.69)	(5.39)	(10.48)	(1.16)	(0.73)	(9.21)	(2.64)
31-35	**892.98**	**249.95**	**321.31**	**15.84**	**14.37**	**182.98**	**91.19**
	***	***	***	***	***	***	***
	(10.02)	(4.42)	(9.83)	(0.98)	(0.66)	(8.51)	(2.52)
36-40	**974.81**	**269.92**	**334.51**	**13.62**	**16.82**	**177.57**	**102.66**
	***	***	***	***	***	***	***
	(10.85)	(5.03)	(10.82)	(1.12)	(0.72)	(8.97)	(2.74)
41-45	**1041.17**	**281.90**	**325.66**	**14.20**	**18.74**	**199.90**	**112.75**
	***	***	***	***	***	***	***
	(14.15)	(6.55)	(12.31)	(1.33)	(0.90)	(10.56)	(3.65)
46-50	**1025.19**	**284.39**	**282.65**	**14.95**	**20.88**	**183.33**	**108.11**
	***	***	***	***	***	***	***
	(14.76)	(7.02)	(12.28)	(1.29)	(0.98)	(11.50)	(3.85)
51-55	**1010.10**	**231.29**	**264.81**	**16.73**	**19.11**	**158.12**	**111.53**
	***	***	***	***	***	***	***
	(14.69)	(7.04)	(12.69)	(1.27)	(0.98)	(11.21)	(3.68)
56-60	**975.35**	**162.92**	**170.17**	**17.18**	**15.69**	**110.13**	**108.56**
	***	***	***	***	***	***	***
	(17.19)	(7.17)	(12.38)	(1.49)	(1.11)	(11.79)	(3.78)
61-65	**845.40**	**108.37**	**94.63**	**19.03**	**13.81**	**50.97**	**88.13**
	***	***	***	***	***	***	***
	(21.46)	(8.47)	(12.81)	(2.00)	(1.40)	(12.88)	(4.53)
66-70	**722.15**	**67.02**	**76.10**	**17.56**	**7.37**	**24.96**	**78.28**
	***	***	***	***	***	*	***
	(25.58)	(9.15)	(16.44)	(2.29)	(1.39)	(15.14)	(5.50)
71+	**369.24**	**7.74**	**-0.15**	**15.85**	**3.25**	**-9.02**	**42.06**
	***			***	**		***
	(25.35)	(9.49)	(16.30)	(2.23)	(1.35)	(14.44)	(5.63)
Obs	13568	13567	13568	13563	13568	13567	13568

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CHIP 1988 data are used in the estimations. The unit of measurement is Yuan.

Table 5.4: Nominal age consumption profiles of the rural area in 1995

Age	Food	Clothing	Daily	Medical	TRCO	EDU	Housing
0-15	**429.50** ***	**0.41**	**-10.31** **	**15.71** ***	**-4.20**	**92.14** ***	**10.79**
	(32.56)	(4.57)	(4.54)	(3.85)	(3.13)	(8.24)	(17.01)
16-20	**604.24** ***	**46.68** ***	**8.78**	**6.90**	**17.83** ***	**121.34** ***	**17.36**
	(44.53)	(6.72)	(6.38)	(5.55)	(4.10)	(12.48)	(24.04)
21-25	**888.77** ***	**53.38** ***	**46.60** ***	**20.73** ***	**20.63** ***	**-21.51** ***	**78.83** ***
	(42.90)	(6.07)	(6.17)	(5.49)	(3.79)	(7.85)	(21.07)
26-30	**1321.83** ***	**120.46** ***	**77.72** ***	**39.93** ***	**35.33** ***	**-19.95** **	**178.35** ***
	(43.58)	(6.20)	(6.26)	(5.18)	(4.50)	(7.73)	(24.37)
31-35	**1766.05** ***	**179.10** ***	**102.33** ***	**50.91** ***	**42.26** ***	**60.83** ***	**221.55** ***
	(47.10)	(7.45)	(6.68)	(5.36)	(5.13)	(10.01)	(28.69)
36-40	**1790.55** ***	**194.56** ***	**125.61** ***	**63.86** ***	**39.07** ***	**145.34** ***	**211.70** ***
	(47.83)	(7.60)	(7.64)	(6.03)	(4.52)	(12.01)	(25.59)
41-45	**1706.47** ***	**173.67** ***	**106.34** ***	**54.53** ***	**44.50** ***	**132.65** ***	**216.40** ***
	(48.24)	(7.40)	(6.75)	(5.55)	(4.78)	(12.29)	(23.55)
46-50	**1590.26** ***	**143.42** ***	**119.90** ***	**73.02** ***	**39.59** ***	**86.26** ***	**193.17** ***
	(50.45)	(7.29)	(7.57)	(6.37)	(4.79)	(12.44)	(25.07)
51-55	**1378.81** ***	**92.06** ***	**81.68** ***	**68.01** ***	**26.33** ***	**46.11** ***	**203.69** ***
	(51.84)	(7.39)	(8.65)	(8.00)	(4.84)	(9.87)	(30.04)
56-60	**1403.68** ***	**55.32** ***	**67.45** ***	**57.86** ***	**19.88** ***	**61.57** ***	**111.83** ***
	(59.54)	(8.93)	(8.64)	(9.00)	(4.86)	(13.37)	(28.42)
61-65	**1168.93** ***	**50.91** ***	**33.70** ***	**51.65** ***	**10.25** *	**9.94**	**43.17**
	(74.80)	(9.21)	(9.11)	(8.53)	(5.88)	(13.31)	(35.86)
66-70	**1083.21** ***	**12.05**	**36.99** ***	**34.85** ***	**10.02**	**-6.55**	**9.44**
	(96.04)	(12.38)	(13.23)	(10.36)	(7.57)	(14.95)	(37.38)
71+	**866.29** ***	**36.05** ***	**21.76** **	**35.29** ***	**12.43** *	**25.46**	**96.02** **
	(73.59)	(10.77)	(9.55)	(8.74)	(6.58)	(16.20)	(38.72)
Obs	7918	7918	7918	7918	7918	7918	7918

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EDU stands for Education. CHIP 1995 data are used in the estimations. The unit of measurement is Yuan.

Table 5.5: Nominal age consumption profiles of the urban area in 1995

Age	Food	Clothing	Daily	Medical	TRCO	EDU	Housing
0-15	**264.16**	**-0.81**	**-114.92**	**28.52**	**-36.13**	**219.12**	**9.53**
	***				***	***	
	(102.93)	(35.15)	(90.87)	(17.91)	(10.85)	(28.37)	(20.15)
16-20	**86.61**	**48.36**	**-180.14**	**-3.68**	**-27.64**	**436.18**	**31.83**
					**	***	
	(101.66)	(37.46)	(91.41)	(20.23)	(10.80)	(38.63)	(19.95)
21-25	**1083.35**	**443.66**	**425.60**	**84.25**	**66.54**	**11.08**	**100.46**
	***	***	***	***	***		***
	(98.45)	(40.96)	(96.01)	(18.86)	(11.04)	(24.62)	(19.02)
26-30	**2096.48**	**691.15**	**791.41**	**132.84**	**103.80**	**74.66**	**202.48**
	***	***	***	***	***	***	***
	(91.04)	(37.59)	(91.03)	(14.97)	(10.00)	(19.98)	(16.75)
31-35	**2671.60**	**803.51**	**930.53**	**132.70**	**130.56**	**197.68**	**238.49**
	***	***	***	***	***	***	***
	(78.44)	(28.59)	(76.37)	(13.32)	(8.49)	(21.26)	(14.92)
36-40	**3095.98**	**871.91**	**980.07**	**141.99**	**136.19**	**219.53**	**287.39**
	***	***	***	***	***	***	***
	(73.72)	(27.61)	(73.46)	(12.70)	(8.58)	(19.71)	(13.74)
41-45	**3225.64**	**827.44**	**1014.16**	**154.77**	**134.81**	**352.69**	**305.16**
	***	***	***	***	***	***	***
	(65.76)	(24.89)	(67.51)	(12.79)	(7.47)	(23.01)	(13.22)
46-50	**3346.02**	**758.82**	**1031.51**	**197.99**	**130.02**	**282.68**	**288.92**
	***	***	***	***	***	***	***
	(82.22)	(33.48)	(87.38)	(17.32)	(9.40)	(27.93)	(15.25)
51-55	**3167.24**	**616.64**	**935.89**	**155.58**	**125.30**	**167.34**	**304.56**
	***	***	***	***	***	***	***
	(91.47)	(38.20)	(94.64)	(17.87)	(10.45)	(25.11)	(17.53)
56-60	**3102.36**	**436.93**	**796.39**	**164.51**	**124.34**	**72.88**	**302.31**
	***	***	***	***	***	***	***
	(81.57)	(30.02)	(81.67)	(16.23)	(9.90)	(20.38)	(16.33)
61-65	**3056.12**	**291.44**	**583.07**	**137.75**	**93.90**	**33.69**	**301.28**
	***	***	***	***	***	**	***
	(87.42)	(32.45)	(82.88)	(16.79)	(9.73)	(15.86)	(17.37)
66-70	**2894.97**	**190.66**	**515.04**	**158.76**	**87.25**	**12.11**	**271.68**
	***	***	***	***	***		***
	(126.34)	(34.21)	(103.13)	(23.88)	(12.88)	(24.66)	(24.78)
71+	**1512.01**	**63.13**	**100.72**	**163.51**	**45.26**	**26.19**	**166.98**
	***	*		***	***		***
	(129.39)	(39.31)	(97.59)	(27.29)	(15.02)	(31.12)	(20.98)
Obs	6856	6856	6856	6856	6856	6856	6856

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EDU stands for Education. CHIP 1995 data are used in the estimations. The unit of measurement is Yuan.

Table 5.6: Nominal age consumption profiles of the rural area in 2002

Age	Food	Clothing	Daily	Medical	TRCO	EDU	Housing
0-15	**254.10*** **	**4.34**	**4.06**	**22.96*** **	**-24.03** **	**144.99*** **	**-26.71**
	(19.78)	(6.78)	(4.70)	(8.76)	(10.28)	(16.12)	(27.28)
16-20	**215.54*** **	**64.32*** **	**9.39**	**8.33**	**40.71*** **	**285.56*** **	**95.01** **
	(23.93)	(8.70)	(6.05)	(10.17)	(13.81)	(23.31)	(37.65)
21-25	**449.13*** **	**65.30*** **	**40.51*** **	**38.64*** **	**153.99*** **	**-25.52**	**227.22*** **
	(27.75)	(9.48)	(6.87)	(12.05)	(17.00)	(20.04)	(37.88)
26-30	**692.59*** **	**100.75*** **	**58.80*** **	**68.19*** **	**131.39*** **	**-69.70*** **	**214.87*** **
	(28.07)	(8.89)	(7.11)	(12.68)	(14.44)	(13.65)	(35.14)
31-35	**991.25*** **	**176.99*** **	**98.88*** **	**114.79*** **	**201.42*** **	**46.85*** **	**317.47*** **
	(25.86)	(9.24)	(6.52)	(11.66)	(14.08)	(14.62)	(32.84)
36-40	**1146.55*** **	**206.10*** **	**117.06*** **	**112.74*** **	**227.88*** **	**246.97*** **	**406.94*** **
	(23.45)	(8.50)	(6.44)	(10.19)	(13.69)	(21.72)	(36.86)
41-45	**1226.71*** **	**218.46*** **	**113.00*** **	**129.87*** **	**227.47*** **	**202.40*** **	**391.70*** **
	(28.96)	(11.37)	(6.71)	(11.86)	(17.20)	(27.47)	(41.55)
46-50	**1105.17*** **	**162.47*** **	**102.51*** **	**137.22*** **	**177.02*** **	**174.33*** **	**349.67*** **
	(24.61)	(9.52)	(7.01)	(11.68)	(15.62)	(22.82)	(33.56)
51-55	**1021.10*** **	**107.01*** **	**90.29*** **	**132.49*** **	**131.00*** **	**85.90*** **	**319.88*** **
	(26.03)	(8.17)	(7.55)	(11.69)	(13.19)	(17.01)	(35.21)
56-60	**879.69*** **	**61.55*** **	**61.19*** **	**160.98*** **	**89.29*** **	**17.29**	**193.01*** **
	(29.00)	(8.38)	(7.89)	(17.09)	(14.44)	(11.30)	(31.99)
61-65	**894.99*** **	**69.56*** **	**52.15*** **	**115.93*** **	**75.17*** **	**0.37**	**270.83*** **
	(35.03)	(12.91)	(9.45)	(17.64)	(19.30)	(15.17)	(51.41)
66-70	**626.19*** **	**37.95** **	**29.12*** **	**96.37*** **	**7.71**	**-57.44** **	**95.93** *
	(45.35)	(15.82)	(10.69)	(19.62)	(19.81)	(23.70)	(56.27)
71+	**506.50*** **	**22.81**	**29.88*** **	**124.96*** **	**63.62*** **	**50.80**	**59.11**
	(42.40)	(14.44)	(10.61)	(23.48)	(23.48)	(36.75)	(49.77)
Obs	9107	9106	9107	9107	9107	9106	9107

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EDU stands for Education. CHIP 2002 data are used in the estimations. The unit of measurement is Yuan.

Table 5.7: Nominal age consumption profiles of the urban area in 2002

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**898.14***	**54.18**	**36.43**	**49.38**	**0.57**	**560.93***	**316.32***
	(132.05)	(46.67)	(55.38)	(53.41)	(65.82)	(103.33)	(66.26)
16-20	**872.83***	**95.16***	**-68.80**	**9.07**	**41.24**	**1244.47***	**185.55***
	(138.82)	(50.33)	(55.92)	(53.52)	(69.88)	(127.20)	(58.61)
21-25	**1351.71***	**440.07***	**152.42**	**130.35**	**515.22***	**395.02***	**249.19***
	(136.32)	(52.66)	(62.67)	(60.24)	(77.11)	(118.62)	(58.52)
26-30	**1798.84***	**648.77***	**314.08***	**290.78***	**681.33***	**441.24***	**425.68***
	(120.71)	(47.06)	(55.51)	(51.93)	(61.38)	(84.83)	(59.06)
31-35	**2396.78***	**888.18***	**454.36***	**410.65***	**833.67***	**1023.63***	**460.17***
	(99.55)	(38.90)	(41.89)	(43.28)	(51.01)	(85.01)	(47.45)
36-40	**2708.54***	**934.98***	**480.15***	**301.88***	**804.72***	**1070.84***	**536.35***
	(90.31)	(35.03)	(39.96)	(35.83)	(43.60)	(76.46)	(40.52)
41-45	**3160.64***	**817.09***	**470.85***	**394.38***	**837.03***	**1151.88***	**618.55***
	(93.74)	(35.17)	(36.34)	(34.79)	(46.16)	(81.32)	(40.47)
46-50	**3003.91***	**700.99***	**523.60***	**400.50***	**857.34***	**1315.45***	**640.67***
	(70.08)	(27.76)	(34.65)	(28.34)	(37.89)	(69.66)	(30.23)
51-55	**3178.98***	**634.07***	**489.68***	**565.38***	**825.94***	**970.78***	**696.84***
	(79.85)	(32.67)	(35.49)	(37.05)	(43.01)	(71.77)	(37.17)
56-60	**3012.64***	**482.90***	**514.84***	**774.76***	**568.20***	**597.76***	**801.43***
	(106.07)	(41.75)	(48.63)	(61.91)	(55.19)	(78.95)	(68.27)
61-65	**2892.74***	**277.58***	**499.88***	**875.36***	**424.90***	**355.59***	**679.85***
	(125.68)	(38.08)	(55.24)	(67.31)	(54.00)	(75.73)	(57.05)
66-70	**2567.97***	**221.88***	**440.54***	**838.10***	**324.58***	**434.51***	**655.02***
	(127.84)	(38.57)	(60.78)	(83.87)	(49.38)	(99.96)	(60.08)
71+	**2075.40***	**114.59***	**285.49***	**733.30***	**208.19***	**283.05***	**418.55***
	(116.40)	(43.59)	(52.47)	(70.52)	(49.38)	(101.45)	(41.09)
Obs	6685	6684	6685	6685	6684	6685	6685

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CHIP 2002 data are used in the estimations. The unit of measurement is Yuan.

Table 5.8: Nominal age consumption profiles of the rural area in 2007

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**493.04** ***	**39.25** ***	**-8.58**	**93.26** ***	**28.50**	**-19.07**	**96.80** *
	(53.48)	(12.70)	(14.68)	(22.02)	(23.54)	(30.69)	(59.86)
16-20	**641.49** ***	**43.32** ***	**-8.73**	**37.15**	**132.95** ***	**316.70** ***	**168.83** **
	(58.24)	(15.00)	(17.91)	(25.40)	(30.85)	(45.06)	(75.42)
21-25	**883.34** ***	**106.29** ***	**107.00** ***	**124.63** ***	**266.84** ***	**17.71**	**414.41** ***
	(61.72)	(13.56)	(20.71)	(27.82)	(30.45)	(42.20)	(76.55)
26-30	**992.06** ***	**158.71** ***	**106.17** ***	**89.45** ***	**304.73** ***	**79.26** ***	**287.71** ***
	(67.39)	(16.04)	(19.48)	(29.32)	(29.45)	(29.70)	(69.81)
31-35	**1634.61** ***	**303.35** ***	**232.24** ***	**158.48** ***	**396.57** ***	**332.10** ***	**460.11** ***
	(70.00)	(18.00)	(21.02)	(27.27)	(29.65)	(36.92)	(71.24)
36-40	**2161.08** ***	**415.95** ***	**310.63** ***	**217.55** ***	**553.42** ***	**635.66** ***	**726.86** ***
	(59.80)	(15.26)	(18.15)	(24.79)	(27.53)	(39.11)	(76.49)
41-45	**2389.88** ***	**392.69** ***	**333.58** ***	**210.66** ***	**570.89** ***	**729.33** ***	**710.80** ***
	(54.40)	(15.51)	(18.20)	(22.22)	(28.89)	(45.26)	(67.41)
46-50	**2335.66** ***	**282.66** ***	**315.73** ***	**260.58** ***	**509.19** ***	**471.14** ***	**794.51** ***
	(62.52)	(14.77)	(23.92)	(27.04)	(33.39)	(44.64)	(93.31)
51-55	**2038.74** ***	**169.75** ***	**224.06** ***	**271.42** ***	**306.74** ***	**245.30** ***	**530.83** ***
	(47.77)	(11.39)	(16.50)	(22.83)	(22.91)	(26.76)	(52.58)
56-60	**1808.31** ***	**99.38** ***	**152.60** ***	**334.59** ***	**267.97** ***	**172.03** ***	**415.31** ***
	(53.11)	(12.37)	(14.78)	(28.30)	(24.93)	(26.76)	(63.20)
61-65	**1499.87** ***	**53.51** ***	**107.35** ***	**298.66** ***	**149.36** ***	**45.62** *	**291.05** ***
	(66.97)	(14.62)	(22.23)	(31.69)	(28.49)	(28.55)	(95.95)
66-70	**1402.66** ***	**53.39** **	**75.99** ***	**296.27** ***	**95.25** ***	**34.15**	**307.46** ***
	(91.29)	(21.78)	(24.19)	(44.84)	(33.89)	(46.27)	(112.12)
71+	**942.69** ***	**-8.44**	**50.34** **	**222.89** ***	**108.09** ***	**7.72**	**25.29**
	(93.13)	(19.04)	(24.07)	(43.86)	(40.13)	(57.66)	(90.50)
Obs	7914	7913	7913	7913	7914	7913	7913

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CHIP 2007 data are used in the estimations. The unit of measurement is Yuan.

Table 5.9: Nominal age consumption profiles of the urban area in 2007

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**2811.76*****	**192.63*****	**330.40*****	**621.01*****	**225.72***	**1329.02*****	**506.36*****
	(337.81)	(117.72)	(111.44)	(104.12)	(128.30)	(167.78)	(133.71)
16-20	**2835.82*****	**588.71*****	**297.57****	**339.02*****	**654.54*****	**2852.64*****	**500.18*****
	(421.92)	(156.77)	(121.86)	(127.66)	(150.32)	(273.49)	(154.68)
21-25	**4227.03*****	**1052.37*****	**708.07*****	**487.42*****	**1153.77*****	**675.70*****	**956.57*****
	(337.83)	(127.65)	(113.60)	(101.49)	(129.93)	(192.05)	(139.06)
26-30	**5603.24*****	**1756.30*****	**894.52*****	**648.26*****	**1543.33*****	**707.73*****	**1617.94*****
	(273.75)	(101.77)	(92.80)	(82.74)	(110.68)	(114.70)	(136.16)
31-35	**4840.12*****	**1631.28*****	**992.57*****	**555.97*****	**1326.41*****	**1072.09*****	**1205.71*****
	(275.32)	(97.80)	(98.52)	(82.64)	(109.61)	(127.89)	(115.70)
36-40	**4999.42*****	**1569.84*****	**776.66*****	**416.14*****	**1141.14*****	**1293.74*****	**1097.23*****
	(269.10)	(96.19)	(94.10)	(80.08)	(102.49)	(134.03)	(110.54)
41-45	**4911.78*****	**1286.58*****	**623.18*****	**540.70*****	**1035.35*****	**1604.87*****	**785.20*****
	(216.71)	(85.77)	(68.56)	(69.26)	(83.86)	(155.31)	(85.15)
46-50	**4792.55*****	**1091.97*****	**540.54*****	**624.27*****	**908.41*****	**1533.02*****	**790.79*****
	(220.89)	(85.34)	(67.86)	(73.65)	(83.57)	(144.41)	(89.87)
51-55	**4967.77*****	**1104.87*****	**517.98*****	**794.71*****	**832.81*****	**773.92*****	**658.42*****
	(206.68)	(80.99)	(66.22)	(73.29)	(78.47)	(100.47)	(82.61)
56-60	**4728.55*****	**730.35*****	**559.20*****	**902.58*****	**605.97*****	**762.91*****	**733.90*****
	(225.22)	(79.17)	(86.26)	(85.71)	(80.44)	(117.12)	(90.65)
61-65	**4705.53*****	**516.51*****	**430.82*****	**976.80*****	**389.33*****	**209.59****	**478.93*****
	(272.08)	(87.16)	(83.18)	(97.17)	(82.87)	(100.58)	(80.90)
66-70	**4677.37*****	**627.71*****	**521.02*****	**1441.84*****	**464.30*****	**278.02****	**809.64*****
	(300.67)	(98.65)	(94.50)	(139.15)	(94.75)	(126.54)	(111.48)
71+	**3879.02*****	**347.99*****	**542.79*****	**1662.84*****	**327.45*****	**278.57****	**623.01*****
	(243.82)	(70.20)	(81.56)	(117.90)	(72.04)	(120.86)	(79.42)
Obs	4949	4936	4941	4929	4942	4933	4947

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CHIP 2007 data are used in the estimations. The unit of measurement is Yuan.

Table 5.10: Nominal age consumption profiles in 2010

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**275.31**	**-102.26**	**-193.71**	**-85.71**	**-300.98**	**-509.96**	**-186.30**
	***	***	***		***	***	***
	(97.41)	(19.56)	(46.44)	(56.60)	(57.02)	(59.75)	(32.51)
16-20	**-4.84**	**64.01**	**-65.68**	**-141.40**	**187.68**	**1836.72**	**-98.27**
		**			**	***	**
	(127.67)	(26.05)	(64.34)	(88.14)	(84.97)	(132.66)	(50.33)
21-25	**404.96**	**220.19**	**520.05**	**148.00**	**589.70**	**455.61**	**144.48**
	***	***	***	*	***	***	***
	(117.22)	(26.96)	(70.18)	(77.01)	(68.93)	(89.70)	(45.44)
26-30	**1738.71**	**457.66**	**888.72**	**464.02**	**1196.97**	**381.22**	**497.23**
	***	***	***	***	***	***	***
	(140.21)	(30.75)	(74.75)	(81.68)	(80.53)	(77.16)	(56.27)
31-35	**2559.55**	**643.63**	**1219.02**	**826.23**	**1650.42**	**1193.55**	**559.46**
	***	***	***	***	***	***	***
	(147.64)	(32.24)	(74.50)	(87.42)	(95.14)	(74.66)	(46.00)
36-40	**3052.55**	**603.77**	**1139.65**	**689.27**	**1617.53**	**1592.39**	**693.55**
	***	***	***	***	***	***	***
	(125.30)	(26.93)	(64.29)	(73.86)	(86.81)	(89.50)	(45.45)
41-45	**3177.49**	**523.01**	**998.88**	**969.68**	**1348.18**	**1868.06**	**571.46**
	***	***	***	***	***	***	***
	(115.98)	(23.81)	(55.66)	(84.90)	(70.47)	(109.32)	(48.14)
46-50	**3119.97**	**421.90**	**989.94**	**1014.52**	**1216.20**	**1429.59**	**449.86**
	***	***	***	***	***	***	***
	(120.90)	(28.19)	(66.01)	(88.09)	(82.72)	(108.96)	(45.18)
51-55	**2957.07**	**258.52**	**637.44**	**960.43**	**745.69**	**816.60**	**397.45**
	***	***	***	***	***	***	***
	(131.77)	(25.42)	(57.39)	(75.03)	(73.94)	(89.86)	(44.16)
56-60	**2681.25**	**150.31**	**467.83**	**1173.86**	**529.58**	**308.86**	**303.86**
	***	***	***	***	***	***	***
	(119.32)	(21.99)	(52.02)	(90.66)	(63.43)	(60.14)	(38.56)
61-65	**2490.91**	**54.81**	**441.09**	**1107.27**	**249.63**	**175.47**	**241.95**
	***	**	***	***	***	***	***
	(134.64)	(22.15)	(67.04)	(104.75)	(74.63)	(66.17)	(41.56)
66-70	**1644.03**	**5.63**	**365.54**	**1358.11**	**10.24**	**-21.23**	**166.08**
	***		***	***			***
	(160.79)	(27.75)	(84.65)	(142.23)	(70.22)	(96.05)	(54.52)
71+	**1833.46**	**5.83**	**415.79**	**1517.28**	**120.25**	**72.28**	**264.26**
	***		***	***	**		***
	(123.80)	(18.05)	(63.48)	(104.47)	(58.18)	(73.98)	(44.58)
Obs	14496	14522	14582	14559	14579	14560	14582

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CFPS 2010 data are used in the estimations. The unit of measurement is Yuan.

Table 5.11: Nominal age consumption profiles in 2012

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**695.71**	**-64.00**	**-345.18**	**-24.60**	**-166.59**	**-290.43**	**-100.52**
	***	***	*		**	***	*
	(249.39)	(46.84)	(185.40)	(81.09)	(74.51)	(96.64)	(51.50)
16-20	**730.66**	**148.53**	**118.20**	**53.90**	**294.76**	**2082.79**	**-93.99**
	**	*			***	***	
	(342.11)	(77.56)	(299.82)	(134.86)	(112.48)	(253.77)	(75.84)
21-25	**1316.97**	**328.53**	**1142.15**	**429.34**	**516.30**	**196.59**	**206.58**
	***	***	***	***	***		***
	(265.12)	(49.34)	(250.48)	(93.84)	(74.32)	(129.99)	(48.11)
26-30	**3344.84**	**712.35**	**2239.71**	**310.49**	**1185.86**	**442.69**	**484.27**
	***	***	***	***	***	***	***
	(293.65)	(52.35)	(345.86)	(115.12)	(116.99)	(105.54)	(53.59)
31-35	**4481.42**	**851.36**	**2358.64**	**701.07**	**1509.84**	**1508.66**	**802.79**
	***	***	***	***	***	***	***
	(327.22)	(78.15)	(340.95)	(149.64)	(114.54)	(146.44)	(69.80)
36-40	**5104.92**	**986.68**	**2467.80**	**568.93**	**1550.98**	**1898.65**	**924.82**
	***	***	***	***	***	***	***
	(311.70)	(72.72)	(339.81)	(93.50)	(123.63)	(172.11)	(80.53)
41-45	**5618.30**	**845.41**	**2129.47**	**862.25**	**1316.89**	**2233.22**	**905.43**
	***	***	***	***	***	***	***
	(346.39)	(69.24)	(252.27)	(112.37)	(87.96)	(190.66)	(62.41)
46-50	**4974.23**	**720.32**	**1650.15**	**947.04**	**1278.01**	**1723.44**	**834.07**
	***	***	***	***	***	***	***
	(266.08)	(58.23)	(267.98)	(117.63)	(95.22)	(172.91)	(61.07)
51-55	**4532.47**	**432.94**	**764.00**	**1282.16**	**726.22**	**598.65**	**891.59**
	***	***	***	***	***	***	***
	(308.82)	(51.47)	(331.83)	(140.88)	(93.87)	(91.11)	(75.30)
56-60	**3981.68**	**360.95**	**531.36**	**1194.58**	**694.11**	**598.90**	**756.08**
	***	***	***	***	***	***	***
	(287.18)	(45.04)	(241.54)	(113.33)	(83.61)	(90.63)	(57.97)
61-65	**3548.51**	**168.64**	**218.22**	**1460.79**	**303.69**	**426.84**	**639.74**
	***	***		***	***	***	***
	(301.88)	(47.11)	(176.19)	(133.17)	(77.49)	(127.92)	(57.00)
66-70	**3146.72**	**36.18**	**-201.96**	**1556.61**	**197.22**	**33.80**	**553.10**
	***			***	***		***
	(289.36)	(47.00)	(208.00)	(175.40)	(69.99)	(122.48)	(63.97)
71+	**2661.75**	**37.92**	**-7.35**	**1564.21**	**141.19**	**-66.29**	**619.23**
	***			***	**		***
	(265.92)	(30.23)	(159.81)	(135.10)	(58.59)	(81.88)	(54.62)
Obs	12880	12898	12900	13017	13026	12900	12915

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CFPS 2012 data are used in the estimations. The unit of measurement is Yuan.

Table 5.12: Nominal age consumption profiles in 2014

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**-121.31**	**-58.97**	**-167.62**	**176.46**	**-53.68**	**48.70**	**101.55**
	(285.65)	(57.81)	(208.69)	(117.20)	(91.35)	(118.81)	(213.12)
16-20	**301.09**	**137.41**	**-369.95**	**90.59**	**358.78**	**2192.12**	**255.48**
		*	*		***	***	
	(448.51)	(81.88)	(227.24)	(166.48)	(135.56)	(239.83)	(371.77)
21-25	**2141.46**	**433.51**	**1392.22**	**508.33**	**858.76**	**577.05**	**1221.99**
	***	***	***	***	***	***	***
	(311.10)	(56.83)	(237.11)	(113.78)	(90.27)	(135.83)	(279.58)
26-30	**4528.63**	**891.41**	**2382.04**	**792.65**	**1416.63**	**301.31**	**1838.04**
	***	***	***	***	***	***	***
	(309.19)	(66.27)	(296.49)	(128.47)	(115.79)	(115.52)	(268.10)
31-35	**5916.45**	**1064.54**	**2332.37**	**1075.61**	**1743.89**	**1326.38**	**2166.58**
	***	***	***	***	***	***	***
	(481.29)	(91.17)	(284.75)	(183.84)	(146.36)	(183.31)	(349.15)
36-40	**6461.13**	**1066.26**	**1886.03**	**584.96**	**1707.82**	**1866.45**	**2439.85**
	***	***	***	***	***	***	***
	(489.11)	(79.36)	(238.56)	(139.12)	(123.37)	(173.72)	(270.64)
41-45	**6042.25**	**972.24**	**1939.90**	**822.70**	**1629.39**	**2118.43**	**2426.07**
	***	***	***	***	***	***	***
	(381.07)	(69.72)	(216.95)	(124.10)	(109.43)	(156.33)	(272.28)
46-50	**4945.15**	**761.32**	**1180.39**	**1060.46**	**1231.37**	**1639.83**	**2221.17**
	***	***	***	***	***	***	***
	(372.91)	(66.63)	(218.41)	(132.25)	(93.84)	(149.93)	(279.54)
51-55	**4955.90**	**602.76**	**847.39**	**1274.59**	**1196.42**	**767.45**	**1683.47**
	***	***	***	***	***	***	***
	(399.05)	(66.14)	(242.61)	(152.40)	(94.58)	(129.00)	(234.80)
56-60	**4119.14**	**335.63**	**632.08**	**1174.36**	**782.99**	**640.23**	**1671.70**
	***	***	***	***	***	***	***
	(374.48)	(61.11)	(234.66)	(136.50)	(105.77)	(114.76)	(298.69)
61-65	**3568.91**	**170.73**	**640.52**	**1786.94**	**455.02**	**462.18**	**892.84**
	***	***	***	***	***	***	***
	(330.33)	(45.39)	(177.04)	(152.31)	(85.77)	(110.41)	(213.80)
66-70	**3498.57**	**107.80**	**499.59**	**1605.70**	**144.76**	**69.50**	**550.43**
	***	*	***	***	*		***
	(400.19)	(57.10)	(184.74)	(187.77)	(80.94)	(131.26)	(207.88)
71+	**3452.68**	**111.72**	**163.24**	**2004.80**	**305.33**	**216.62**	**927.72**
	***	**		***	***	*	***
	(332.60)	(46.03)	(124.69)	(181.42)	(68.27)	(116.06)	(206.62)
Obs	13193	13176	13173	13176	13157	13185	13174

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CFPS 2014 data are used in the estimations. The unit of measurement is Yuan.

Table 5.13: Nominal age consumption profiles in 2016

Age	Food	Clothing	Daily	Medical	TRCO	EEC	Housing
0-15	**-196.87**	**-148.33** ***	**-510.29** *	**103.81**	**-205.04** ***	**85.64**	**-841.96** **
	(286.90)	(48.45)	(286.83)	(117.70)	(70.17)	(141.20)	(383.13)
16-20	**490.93**	**132.06** *	**-422.55**	**-43.79**	**510.30** ***	**2566.44** ***	**987.64**
	(442.27)	(76.98)	(419.62)	(195.07)	(129.54)	(286.05)	(1176.06)
21-25	**2105.69** ***	**545.51** ***	**2041.67** ***	**532.50** ***	**1195.36** ***	**963.36** ***	**3276.02** ***
	(382.22)	(78.02)	(441.13)	(154.81)	(101.63)	(211.02)	(692.42)
26-30	**5450.06** ***	**1096.95** ***	**3641.79** ***	**1098.08** ***	**2038.74** ***	**777.62** ***	**3900.58** ***
	(353.94)	(73.42)	(426.90)	(130.41)	(92.71)	(128.42)	(531.78)
31-35	**6557.90** ***	**1365.36** ***	**3792.32** ***	**1270.83** ***	**2426.61** ***	**2157.40** ***	**4316.14** ***
	(430.01)	(91.96)	(466.62)	(190.05)	(121.69)	(184.54)	(682.40)
36-40	**7321.05** ***	**1405.21** ***	**3987.89** ***	**1038.63** ***	**2420.17** ***	**2750.92** ***	**5459.16** ***
	(442.31)	(93.51)	(480.27)	(175.36)	(114.70)	(221.67)	(698.14)
41-45	**7150.81** ***	**1087.77** ***	**2822.26** ***	**1024.77** ***	**1868.27** ***	**2871.40** ***	**3776.02** ***
	(382.31)	(73.22)	(391.84)	(157.82)	(93.81)	(193.37)	(704.47)
46-50	**5289.16** ***	**818.16** ***	**2771.50** ***	**1334.79** ***	**1387.88** ***	**2075.92** ***	**2405.98** ***
	(355.73)	(62.35)	(407.64)	(148.03)	(81.99)	(178.88)	(524.28)
51-55	**5171.61** ***	**656.84** ***	**1981.68** ***	**1586.12** ***	**1229.95** ***	**921.84** ***	**2586.88** ***
	(368.93)	(75.74)	(338.92)	(134.15)	(99.63)	(149.39)	(625.95)
56-60	**4992.02** ***	**269.03** ***	**903.26** **	**1337.73** ***	**697.92** ***	**421.28** ***	**1147.18** ***
	(528.14)	(60.17)	(370.51)	(157.19)	(96.14)	(131.00)	(404.81)
61-65	**4707.35** ***	**315.28** ***	**573.25** *	**2148.15** ***	**584.02** ***	**617.64** ***	**2273.53** ***
	(401.51)	(51.82)	(336.04)	(164.29)	(82.78)	(141.85)	(472.84)
66-70	**4350.45** ***	**210.38** ***	**811.90** **	**2662.18** ***	**373.69** ***	**237.18**	**823.02** **
	(442.45)	(60.30)	(346.37)	(245.97)	(92.52)	(155.59)	(458.06)
71+	**3673.89** ***	**47.45**	**-99.46**	**2860.57** ***	**213.76** ***	**-12.30**	**1721.93** ***
	(384.85)	(41.04)	(235.91)	(183.91)	(62.62)	(117.28)	(478.74)
Obs	13108	13130	13066	13064	13138	13065	13195

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. TRCO stands for Transport and Communications. EEC stands for Education, Entertainment, and Culture. CFPS 2016 data are used in the estimations. The unit of measurement is Yuan.

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Chapter 6: Population Aging, Structural Change, and Economic Growth in China: A Perspective from a Multi-Sector Overlapping Generations Model

6.1 Introduction

Economic growth, structural change, and population aging are universal experiences along the path of development. Understanding population aging's effects on structural change and economic growth have profound implications for how societies adapt to them. However, there is not yet a consensus regarding the direction and magnitude of these effects. While existing studies have focused on developed countries where aging is at more advanced stages and where data are more readily available, less attention has been paid to developing countries which are aging just as fast.

China is an interesting case not only because of its sheer size, accounting for about 18% of the world's population and GDP in 2020 (World Bank Open Data, 2025), but also because of its impressive pace of development. Between 1981 and 2020, China's economy grew at an impressive average rate of 9% per year (National Data, 2025). Over the same period, the output shares of primary, secondary, and tertiary sectors changed respectively from 31%, 46%, and 23% to 8%, 38%, and 55% (National Data, 2025).

China's population began to age at a rapid and accelerating rate since the late 1970s due to a combination of demographic transition and population policies. The population share of elderlies aged 61 and above increased from 7% in 1990 to 17% in 2020 (United Nations, 2024). According to forecasts from the United Nations, China's elderly population share will reach 37% in 2050, making it older than the US and most Northern European countries (United Nations, 2024). In recent years, aging has accelerated dramatically and has become a priority issue for the Chinese government. From the abolition of the One-Child Policy to the clamp down on private tuition, the government attempted a range of policies to reverse population aging but to no avail. China's aging seems inevitable. As China's economic growth slows, the impact of population aging has become a hot topic.

In this study, we calibrate and simulate a Multi-Sector Overlapping Generations (MSOLG) model of China to investigate the impacts of population aging on structural change and economic growth via the channels of labour, savings, preferences, and government spending. In doing so, we use our work from the previous chapters as building blocks.

In Chapters 3 and 5, we investigated aging's effects via labour on the supply side and via preferences on the demand side of China's economy in isolation and under the ceteris paribus assumption. In reality, variables on both sides of the economy can change and interact with each other. There could be interactions among the aging effect channels. These interactions determine aging's effects. For example, sectoral relative productivity growths or aging-induced capital deepening can lead to changes in sectoral relative prices. The resulting effects on sectoral demand depends on the economy's preferences, which depends on the population's age structure and age-specific preferences. By accounting for these interactions in this chapter, we can obtain more realistic results about population aging's effects.

Our research is built on the foundation of existing structural change literature. The literature provides two broad types of explanations for structural change: demand side and supply side. On the demand side, studies such as Echevarria (1997), Kongsamut et al (2000), and Boppart (2014) emphasize the role of varying income elasticities of demand across sectors due to non-homothetic preferences. The supply side explanations, such as those in Baumol (1967), Ngai and Pissarides (2007), and Acemoglu and Guerrieri (2008), emphasize the roles of varying productivity growths and factor intensities across sectors.

A relatively small number of studies have investigated the sources of structural change in China, producing mixed results. Yan et al (2018), for example, found that China's structural change can be explained mainly by demand side mechanisms. Liao (2020), however, found that supply side mechanisms played the dominant role. Guo and Wang

(2020) put forth government infrastructure investment as a major driver of China's structural change. In our model, we incorporate both supply side and demand side mechanisms of structural change and investigate their interactions with population aging. Existing studies have recognized the importance of factor market frictions in the Chinese economy. In Chapter 3, we confirmed the presence of substantial factor price wedges between sectors in China. Therefore, we follow the common practice of incorporating these wedges into our model to better capture the supply-side realities of China's economy.

Population aging is a worldwide phenomenon. There is a vast literature on the effects of aging, including Auerbach and Kotlikoff (1987), Fougere and Merette (1999), Lee and Mason (2006), Bloom et al (2011), Gonzale-Eiras and Niepelt (2012), Jin et al (2023), Eggertsson et al (2016), and Acemoglu and Restrepo (2017). The literature has explored how aging affects the economy via savings, labour input, human capital, public expenditures, trade, and etc. However, there is limited consensus on these effects. This is partially because aging can affect each of these variables via multiple channels operating in different directions. For example, aging can reduce effective labour input by reducing working age population, but it can also raise effective labour input if older people are more experienced and productive. Although aging can reduce savings as older people save less than younger people, aging can also raise savings if people save more to finance for their longer expected retirement. The overall effect of aging is therefore an empirical matter that depends on each country's unique circumstances. Our study adds to the literature by investigating aging effects in the Chinese case.

As far as we know, studies that quantitatively analyse the links between population aging and structural change are few. Fougere et al (2007) and Fougere et al (2009) used computable MSOLGs to examine aging's effect on structural change in Canada via capital deepening, age-sensitive preferences, and public expenditures. Ishikawa et al (2012) used an MSOLG model with the additional channel of openness to study the case of Japan. Mao et al (2018) is the only study that used an MSOLG model to analyse how aging affects structural change in China. Specifically, they used an OLG model with two generations and two sectors to test their hypothesis that population aging can drive the movement of labour into the service sector via age specific labour intensity and preferences.

Our study is unique and contributes to the literature in a number of ways. We are the first to calibrate and simulate a three-sectors model with more than two overlapping generations to study aging's effect on China's structural change and growth. We explore a variety of aging effect channels, including novel ones. We analyse structural change not only in terms of labour but also in terms of output and capital.

The three sectors in our model refer to the primary, secondary, and tertiary sectors. This represents a major improvement over the previous study because much of China's structural change and growth involve the transition from agriculture to the modern sectors, and because agriculture is fundamentally different to the other sectors in terms of productivity and factor intensity in China. The extra generations in our model allow behaviours of age groups to be more realistically modelled and allow our calibration to be more rigorous.

Unlike past studies, preferences in our model vary across age not only in sectoral preference weights but also in price elasticities of demand and in non-homotheticity terms. The age-varying elasticities mean an older economy reacts differently to relative price changes compared to a younger economy, giving rise to a novel channel of effect.

While previous studies have focused only on aging effects due to falling fertility, we study the effects of both falling fertility and rising longevity. Considering China's life expectancy increased from 44 to 78 between 1950 and 2020 (United Nations, 2024), the effect channels associated with rising longevity in China should not be neglected.

Our model features both supply side and demand side drivers of structural change. In contrast, previous studies have featured constant income elasticities of demand across sectors, thereby allowing structural change to be driven only by supply side factors.

Chinese data have faced their fair shares of doubts and criticisms. Many of the concerns are reasonable because China is a rapidly evolving developing country that was founded only 75 years ago. As such, we take China's data issues seriously. In this chapter, we base our calibration on our works from previous chapters where we carefully compiled Chinese data and made adjustments whenever necessary. Rather than using data at one point in time to calibrate preferences and age efficiency profiles, we use time series data to estimate preferences and profiles. Our parameterisation is hence arguably more rigorous and accurate.

Our results in this chapter show that population aging raises per capita savings and reduces effective labour input in China. Population aging impedes China's structural change towards services through the preferences, savings, labour, and government consumption channels. Population aging raises per capita GDP growth as the positive aging effects through the savings and structural change channels outweigh the negative aging effect acting through the effective labour channel. At the aggregate level, population aging lowers China's real GDP growth due to its overwhelming negative effect acting through the effective labour input channel.

The rest of this chapter is organised as follows. Section 6.2 presents our MSOLG model of China. Section 6.3 uses a simplified version of the model with clear analytical results to demonstrate and analyse the aging effect channels. Section 6.4 describes the data and calibration procedure. Section 6.5 discusses our quantitative findings. Section 6.6 conducts a set of sensitivity analyses to test the robustness of our results. Section 6.7 concludes.

6.2 The model

In this section, we present our Multi-Sector Overlapping Generations (MSOLG) model. At any point in time, the model economy is populated by six generations of individuals. The six generations refer respectively to those aged 21 to 30, 31 to 40, 41 to 50, 51to 60, 61 to

70, and 71 and above. Given this setup, each model period corresponds to 10 years in reality. In each period, a new generation of youth enters the economy and the old generation dies.

The production side of the model economy consists of three sectors: primary, secondary, and tertiary. Like before, to avoid notational clashes and for brevity, we refer to the primary sector as agriculture, the secondary sector as industry, and the tertiary sector as services. For brevity, we sometimes refer to the secondary sector and the tertiary sector as the modern sectors and sometimes collectively as the modern sector.

The sectoral and age characteristics of variables in the model are distinguished via subscripts. Subscript g is the general indicator for generation or age group. g can take any integer value from 1 to 6 which correspond to the six age groups. i is the indicator for sector and can be a for agriculture, d for industry, and s for services. Subscript t refers to time. In the subscripts of variables with both age and time indicators, we put a comma before the time indicator t to clarify the distinction between the age and time indicators. As an example, $c_{gi,t}$ denotes age group g's consumption of sector i value added in period t.

6.2.1 Demographics

Demographics in the model are exogenous. Let N_t denote the population in t, $N_{g,t}$ denote the age g population in t, and n_t denote the youngest age group's growth between period $t-1$ and t. The evolution of the youngest group's population $N_{1,t}$ can thus be written as:

$$N_{1,t+1} = N_{1,t}n_{t+1}$$

Individuals face exogenous time and age specific mortality risks. Let the survival probability from age $g-1$ to age g in period t be denoted as $\pi_{g,t}$. Population of age group g thus follows:

$$N_{g,t} = N_{g-1,t-1}\pi_{g,t}$$

Since the last age group contains population aged 71 and above, an increase in the survival rate from 71-80 to 81-90 can make $\pi_{6,t}$ larger than one. $\pi_{6,t}$ should therefore not be interpreted as a survival rate. From this point on, we will refer to $\pi_{6,t}$ as the transition rate.

After normalisation, demographics in the model are solely captured by the exogenous demographic variables (n_t and $\pi_{g,t}$'s).

In the model, population aging can take place due to rising longevity and or falling fertility. The former is captured by an increase in $\pi_{g,t}$, and the latter by a decrease in n_t.

6.2.2 Consumers

A young individual entering the economy in t optimally chooses real consumption $c_{gi,t+g-1}$, savings $s_{g,t+g-1}$, and bequests b_{t+5} over his lifetime to maximise lifetime utility:

$$U_t = \sum_{g=1}^{g=6} \beta_g \left(\prod_{j=1}^{j=g} \pi_{j,t+j-1} \right) \frac{\left[\left(\sum_{i=a,d,s} \omega_{gi}^{\frac{1}{\sigma_g}} \left(c_{gi,t+g-1} - \frac{\bar{c}_{gi}}{E_{t+g-1}} \right)^{\frac{\sigma_g - 1}{\sigma_g}} \right)^{\frac{\sigma_g}{\sigma_g - 1}} \right]^{1-\rho}}{1-\rho} + \\ + \left(\prod_{j=1}^{j=6} \pi_{j,t+j-1} \right) v_6 \frac{b_{t+5}^{1-\rho}}{1-\rho}$$

The maximisation of lifetime utility is subject to budget constraints in the six stages of life:

$$w_t l_{1,t} + p_{kt}(1-\delta+r_t) f_t \frac{1}{h_{t-1}} b_{t-1} = \sum_i p_{it} c_{1i,t} + p_{kt} s_{1,t} + \sum_i p_{it} \tau_{1i,t} + \sum_i p_{it} x_{1i,t}$$

$$w_{t+1}l_{2,t+1} + p_{kt+1}(1-\delta+r_{t+1})\frac{1}{h_t}\left[s_{1,t} + \frac{1-\pi_{2,t+1}}{\pi_{2,t+1}}s'_{1,t} + f_{t+1}b_t\right] = \sum_i p_{it+1}c_{2i,t+1} +$$

$$+p_{kt+1}s_{2,t+1} + \sum_i p_{it+1}\tau_{2i,t+1} + \sum_i p_{it+1}x_{2i,t+1}$$

$$w_{t+2}l_{3,t+2} + p_{kt+2}(1-\delta+r_{t+2})\frac{1}{h_{t+1}}\left[s_{2,t+1} + \frac{1-\pi_{3,t+2}}{\pi_{3,t+2}}s'_{2,t+1} + f_{t+2}b_{t+1}\right] =$$
$$= \sum_i p_{it+2}c_{3i,t+2} + p_{kt+2}s_{3,t+2} + \sum_i p_{it+2}\tau_{3i,t+2} + \sum_i p_{it+2}x_{3i,t+2}$$

$$w_{t+3}l_{4,t+3} + p_{kt+3}(1-\delta+r_{t+3})\frac{1}{h_{t+2}}\left[s_{3,t+2} + \frac{1-\pi_{4,t+3}}{\pi_{4,t+3}}s'_{3,t+2} + f_{t+3}b_{t+2}\right] =$$
$$= \sum_i p_{it+3}c_{4i,t+3} + p_{kt+3}s_{4,t+3} + \sum_i p_{it+3}\tau_{4i,t+3} + \sum_i p_{it+3}x_{4i,t+3}$$

$$w_{t+4}l_{5,t+4} + p_{kt+4}(1-\delta+r_{t+4})\frac{1}{h_{t+3}}\left[s_{4,t+3} + \frac{1-\pi_{5,t+4}}{\pi_{5,t+4}}s'_{4,t+3} + f_{t+4}b_{t+3}\right] =$$
$$= \sum_i p_{it+4}c_{5i,t+4} + p_{kt+4}s_{5,t+4} + \sum_i p_{it+4}\tau_{5i,t+4} + \sum_i p_{it+4}x_{5i,t+4}$$

$$p_{kt+5}(1-\delta+r_{t+5})\frac{1}{h_{t+4}}\left[s_{5,t+4} + \frac{1-\pi_{6,t+5}}{\pi_{6,t+5}}s'_{5,t+4} + f_{t+5}b_{t+4}\right] = \sum_i p_{it+5}c_{6i,t+5} +$$

$$+p_{kt+5}b_{t+5} + \sum_i p_{it+5}\tau_{6i,t+5} + \sum_i p_{it+5}x_{6i,t+5}$$

In the utility function above, ρ denotes the inverse of intertemporal elasticity of substitution. β_g denotes the age g subjective discount factor which determines the consumption-savings decision. v_6 is a parameter that governs the incentives to leave bequests during old age.

In Chapter 5, we found substantial variations in the sectoral composition of consumption across age groups in China. We found that such variations can be explained by age-specific preferences. In this chapter, we incorporate such age-specific preferences into our model, thereby allowing population aging to affect the economy via preferences. As can be seen in the utility function above, there are several parameters that vary across age. σ_g is a parameter that governs age-specific price elasticities of demand. $\bar{c}_{gi}$ denotes age g's per capita subsistence consumption of sector i. When consumer income is low, sectoral composition of consumption is mainly driven by the need to satisfy subsistence consumption. As productivity E_t and hence income grows over time, subsistence consumption becomes negligible relative to income. Consequently, ω_{gi}'s become the key determinants of age g sectoral consumption shares in the long term. We refer to ω_{gi} as age group g's preference weight on sector i consumption value added.

While age specific preference weights have been used in the MSOLG literature, as far as we know, the incorporation of age specific subsistence consumption and price elasticities are novelties of our study.

From the budget constraints, we can see that the individual derives resources from labour, savings, and bequests. The resources are allocated across consumption, savings, bequests, taxation, and net exports.

The individual works in the first five stages of life and retires in the last. At working age g, the individual exogenously supplies $l_{g,t}$ units of effective labour. This effective labour input reflects age group g's labour participation rate, employment rate, and productive efficiency. The compilation of our effective labour input data using both national and household survey data was detailed in Chapter 3. For each unit of effective labour supplied, the individual receives composite wage w_t in return. The composite wage depends on the sectoral allocation of labour and on sectoral wages.

In each of the first five stages of life, the individual makes savings $s_{g,t+g-1}$ which are supplied to firms as capital input in the next period $(t + g)$, yielding a composite rent of r_{t+g} in return. The composite rent depends on the sectoral allocation of capital and on sectoral rent. A fraction δ of the savings depreciates during production, leaving the individual with $(1-\delta)s_{g,t+g-1}$ that can be used as resource in $t+g$.

In each period leading up to the final stage of life, a fraction $1-\pi_{g,t+g-1}$ of the individual's cohort dies. The savings of people who die are evenly distributed as accidental bequests to the remaining members of the same cohort in the next period. An individual therefore receives accidental bequest of $\frac{1-\pi_{g+1,t+g}}{\pi_{g+1,t+g}} s'_{g,t+g-1}$ in each stage of life except the first. The dash on the savings term emphasises that the term refers to savings of other people and is exogenous from the individual's perspective. When the individual chooses savings, he does not assume that other people would choose the same as he does, even though they turn out to do so in the equilibrium.

In old age, the individual sets aside bequest b_{t+5}. The aggregate bequest left by the elderlies in $t+5$ is evenly distributed across all age groups in $t+6$. $\frac{N_{6,t+5}b_{t+5}}{N_{t+6}}$ is therefore the amount of bequest allocated to each individual in period $t+6$. To simplify the equation, we introduce a variable $f_t = \frac{N_{6,t-1}}{N_t}$ which is a function of demographic variables (n_t and $\pi_{g,t}$'s). Bequests are left in the form of capital goods and are rented to firms in $t+6$, yielding interest income. Empirical evidences show that old people in China not only save but they also save more than other age groups. The elderly bequest element allows our model to capture the elderly saving observed in the Chinese economy.

p_{it} denotes the relative price of i which is defined as:

$$p_{it} = \frac{P_{it}}{P_t}$$

where P_{it} is the price of i and P_t is the price of the aggregate economy.

p_{kt} is the relative price of capital goods and hence savings:

$$p_{kt} = \frac{P_{kt}}{P_t}$$

The production of capital goods is spread across all three sectors. As such, p_{kt} depends on the sectoral allocation of investment production and sectoral prices.

The model is deflated by the aggregate productivity measure E_t. This gives rise to the term h_t which denotes productivity growth:

$$h_t = \frac{E_{t+1}}{E_t}$$

Rearranging the first order conditions of the consumer problem above, we obtain the following conditions which determine an age g consumer's sectoral consumption choice:

$$\frac{c_{gd,t+g-1} - \dfrac{\bar{c}_{gd}}{E_{t+g-1}}}{c_{gi,t+g-1} - \dfrac{\bar{c}_{gi}}{E_{t+g-1}}} = \frac{c_{gd,t+g-1} - \bar{c}_{gd,t+g-1}}{c_{gi,t+g-1} - \bar{c}_{gi,t+g-1}} = \left(\frac{p_{i,t+g-1}}{p_{d,t+g-1}}\right)^{\sigma_g} \frac{\omega_{gd}}{\omega_{gi}} \quad for\ \ i = a, s$$

where $\bar{c}_{gi,t+g-1}$ denotes an age g individual's sector i subsistence consumption deflated by productivity E_{t+g-1}.

The Euler equation that determines the consumer's consumption-savings choice in the first five stages of life ($g = 1, 2, \ldots, 5$) can be written as:

$$\frac{p_{kt+g}}{p_{dt+g}} \pi^{2-\rho}_{g+1,\,t+g} h^{-\rho}_{t+g-1} (1 - \delta + r_{t+g}) \beta_{g+1} \left[\sum_i \omega_{g+1i}^{\frac{1}{\sigma_{g+1}}} (c_{g+1i,t+g} - \bar{c}_{g+1i,t+g})^{\frac{\sigma_{g+1}-1}{\sigma_{g+1}}}\right]^{\frac{1-\rho\sigma_{g+1}}{\sigma_{g+1}-1}}$$

$$\cdot\, \omega_{g+1d}^{\frac{1}{\sigma_{g+1}}} (c_{g+1d,t+g} - \bar{c}_{g+1d,t+g})^{\frac{-1}{\sigma_{g+1}}} = \left[\sum_i \omega_{gi}^{\frac{1}{\sigma_g}} (c_{gi,t+g-1} - \bar{c}_{gi,t+g-1})^{\frac{\sigma_g-1}{\sigma_g}}\right]^{\frac{1-\rho\sigma_g}{\sigma_g-1}} \cdot$$

$$\cdot\, \omega_{gd}^{\frac{1}{\sigma_g}} (c_{gd,t+g-1} - \bar{c}_{gd,t+g-1})^{\frac{-1}{\sigma_g}} \frac{p_{kt+g-1}}{p_{dt+g-1}} \beta_g$$

Finally, the condition that pings down bequests left behind by the individual in the final stage of life is:

$$v_6 b^{-\rho}_{t+5} = \beta_6 \left[\sum_i \omega_{6i}^{\frac{1}{\sigma_6}} (c_{6i,t+5} - \bar{c}_{6i,t+5})^{\frac{\sigma_6-1}{\sigma_6}}\right]^{\frac{1-\rho\sigma_6}{\sigma_6-1}} \omega_{6d}^{\frac{1}{\sigma_6}} (c_{6d,t+5} - \bar{c}_{6d,t+5})^{\frac{-1}{\sigma_6}} \frac{p_{kt+5}}{p_{dt+5}}$$

6.2.3 Government and external sector

To finance for government spending on sector i in period t, the government collects taxes $p_{it}\tau_{gi,t}$ as an exogenous share $\tilde{T}_{it}$ of an age g individual's income:

$$p_{it}\tau_{\mathrm{g}i,t} = \tilde{T}_{it}\left\{w_t l_{\mathrm{g},t} + p_{kt}r_t\frac{1}{h_{t-1}}\left[s_{\mathrm{g}-1,t-1} + \frac{1-\pi_{\mathrm{g},t}}{\pi_{\mathrm{g},t}}s'_{\mathrm{g}-1,t-1} + f_t b_{t-1}\right]\right\}$$

Note that $l_{g,t}$ is zero for the sixth age group and that the tax rates in each period are the same for all age groups. The budget is balanced and government spending is non-productive.

Older people consume less education and more healthcare than other age groups. Therefore, population aging can bring about a contraction in education expenditure and an expansion in healthcare expenditure. The parts of these channels acting through private consumption have already been captured by the age-varying preferences. To capture the rest of these channels working through government spending, we allow government health and education spending to change with population aging structure. Given age spending profiles, government health and education spending and hence the required tax rates would change with population age structure. We will describe the calibration of tax rates in detail in the calibration section.

Net exports in our model are also exogenous. In particular, an age g individual's spending on net exports of sector i, denoted by $p_{it}x_{gi,t}$, is set to be an exogenous share $\tilde{X}_{it}$ of his/her income:

$$p_{it}x_{\mathrm{g}i,t} = \tilde{X}_{it}\left\{w_t l_{\mathrm{g},t} + p_{kt}r_t\frac{1}{h_{t-1}}\left[s_{\mathrm{g}-1,t-1} + \frac{1-\pi_{\mathrm{g},t}}{\pi_{\mathrm{g},t}}s'_{\mathrm{g}-1,t-1} + f_t b_{t-1}\right]\right\}$$

Through experiments we find that modelling net exports as lump sums makes little difference to our results. This is mainly because net exports constitute a very small share of GDP, averaging 2.2% over the 1981-2020 period.

6.2.4 Firms

In each of the three sectors, there is a representative firm producing output with Cobb-Douglas production technology. As discussed in Chapter 3, output is measured by value added in this thesis. In each period, the firm in sector i optimally chooses capital and labour input to maximise profit:

$$\max_{k_{it}, l_{it}} \; p_{it}\left(\frac{E_{it}}{E_t}\right)^{1-\alpha_i} k_{it}^{\alpha_i} l_{it}^{1-\alpha_i} - \theta_{kit} p_{kt} r_{at} k_{it} - \theta_{lit} w_{at} l_{it}$$

where k_{it} denotes capital per effective labour of sector i, l_{it} denotes sector i's share in aggregate effective labour, α_i denotes capital income share of i, E_{it} denotes productivity of i, r_{at} denotes real rent in agriculture, and w_{at} denotes real wage in agriculture. To simplify notations, we sometimes denote relative productivity $\frac{E_{it}}{E_t}$ by re_{it}.

In Chapter 3, we found substantial factor price wedges between sectors in China. This implies there are factor market frictions which impede the free movement of factor inputs across sectors. There is a lively literature on such frictions in China including: Brandt et al 2010, Cao and Birchenall (2013), and Cheremukhin et al (2015). Main explanations for the frictions include the household registration (Hukou) system which restricts movements of labour between rural and urban areas, and the financial sector's bias towards state owned enterprises.

Following the convention of Chinese structural change literature, we account for factor price wedges in our study. In particular, we introduce exogenous variables θ_{kit} and θ_{lit} which are calibrated respectively as the data ratios of rent and wage in sector i to those in agriculture.

The first order conditions of the firm's optimisation problem shows that factor inputs are paid their marginal revenue products:

$$\alpha_i p_{it}\left(\frac{E_{it}}{E_t}\right)^{1-\alpha_i} k_{it}^{\alpha_i-1} l_{it}^{1-\alpha_i} = \theta_{kit} p_{kt} r_{at}$$
$$(1-\alpha_i) p_{it}\left(\frac{E_{it}}{E_t}\right)^{1-\alpha_i} k_{it}^{\alpha_i} l_{it}^{-\alpha_i} = \theta_{lit} w_{at}$$

Since wage differs across sectors, the composite wage paid to individuals for supplying labour not only depends on the sectoral allocation of labour but also on sectoral wages:

$$w_t = w_{at} l_{at} + \theta_{ldt} w_{at} l_{dt} + \theta_{lst} w_{at} l_{st}$$

Similarly, the composite rent paid to individuals for supplying capital depends on the sectoral allocation of capital and on sectoral rent:

$$r_t = \frac{r_{at} k_{at}}{k_t} + \frac{\theta_{kdt} r_{at} k_{dt}}{k_t} + \frac{\theta_{kst} r_{at} k_{st}}{k_t}$$

6.2.5 Capital goods firm

Allocation of the production of capital goods across the three sectors is represented by an optimisation problem. There is a firm that turns sectoral investment value added i_{it} into investment value added i_t using a Cobb-Douglas production function. The investment value added is then sold to consumers at price p_{kt} for profit:

$$\max_{i_{at}, i_{dt}, i_{st}} p_{kt} i_t - \sum_i p_{it} i_{it}$$

$$s.t. \;\; i_t = A_{kt} \mu_a^{-\mu_a} \mu_d^{-\mu_d} \mu_s^{-\mu_s} i_{at}^{\mu_a} i_{dt}^{\mu_d} i_{st}^{\mu_s}$$

where A_{kt} is a measure of productivity. μ_i's are parameters that determine the sectoral allocation of capital goods production. Eventually, the investment is used to accumulate capital stocks in the three sectors.

Let relative capital price p_{kt} be defined as:

$$p_{kt} = A_{kt}^{-1} p_{at}^{\mu_a} p_{dt}^{\mu_d} p_{st}^{\mu_s}$$

The optimality conditions show that a share μ_i of total investment is produced in sector i:

$$p_{it} i_{it} = \mu_i p_{kt} i_t$$

Some studies in the structural change literature assume that investment expenditure is made up entirely of value added from the secondary sector. They then proceed to measure agricultural and service consumption value added as agricultural and service GDP and obtain industrial consumption value added as industrial GDP minus investment expenditure. In Appendix 6.1, we explain why this approach cannot be adopted in the case of China. In short, data show that industrial share in investment value added is far from one and that investment is so large that it exceeds industrial value added in China.

6.2.6 Market clearing conditions

In each period, supply is equal to demand in goods markets. One of the goods market clearing conditions is redundant and can be dropped. Here we drop the industrial goods market condition. The agricultural goods and service market clearing conditions are as follows:

$$p_{at}y_{at} = p_{at}\left(\frac{E_{at}}{E_t}\right)^{1-\alpha_a} k_{at}^{\alpha_a} l_{at}^{1-\alpha_a}$$
$$= p_{at}\sum_g \psi_{g,t}c_{ga,t} + p_{at}i_{at} + \sum_g p_{at}\psi_{g,t}\tau_{ga,t} + +p_{at}\sum_g \psi_{g,t}x_{ga,t}$$

$$p_{st}y_{st} = p_{st}\left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_{st}^{\alpha_s} l_{st}^{1-\alpha_s}$$
$$= p_{st}\sum_g \psi_{g,t}c_{gs,t} + p_{st}i_{st} + p_{st}\sum_g \psi_{g,t}\tau_{gs,t} + +p_{st}\sum_g \psi_{g,t}x_{gs,t}$$

where:

$$\psi_{g,t} = \frac{N_{g,t}}{L_t}$$

$\psi_{g,t}$ denotes the ratio of age g population $N_{g,t}$ to aggregate labour input L_t. $\psi_{g,t}$ boils down to a function of demographic variables and per capita effective labour which are exogenous. $\psi_{g,t}$ is introduced to simplify the equations.

The clearing conditions for factor markets are:

$$\sum_{g=1}^{g=5} \psi_{g,t}l_{g,t} = l_{at} + l_{mt} + l_{st}$$

$$\sum_{g=t}^{g=5} \psi_{g,t} s_{g,t} + \psi_{6,t} b_t = \epsilon_{t+1} h_t k_{t+1} = \epsilon_{t+1} h_t (k_{at+1} + k_{dt+1} + k_{st+1})$$

where ϵ_t is a variable measuring aggregate labour input growth:

$$\epsilon_{t+1} = \frac{L_{t+1}}{L_t}$$

Like $\psi_{g,t}$, ϵ_t is a function of exogenous demographic variables and per capita effective labour.

6.3 Model analysis

In this section, we use a simplified version of our model with tractable analytical results to demonstrate the channels through which population aging affects structural change and growth. All the key channels are covered with the exception of government spending channel, which is exogenous and straightforward. Unless specified otherwise, the simple model follows the same notations as the model in the previous section.

6.3.1 A simplified model

The simple model has two production sectors: a labour-intensive sector indicated by subscript a and a capital-intensive sector indicated by subscript s. The labour-intensive sector uses only labour ($\alpha_a = 0$) whereas the capital-intensive sector uses both labour and capital in production. For simplicity and clarity, capital goods are produced entirely in the capital-intensive sector. Factor markets are perfectively competitive so that factor payments are the same across sectors. Given the above, the firms' optimisation problems can be written as:

$$\max_{l_{at}} \; p_{at} \frac{E_{at}}{E_t} l_{at} - w_t l_{at}$$

$$\max_{k_{st}, l_{st}} \; p_{st} \left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_{st}^{\alpha_s} l_{st}^{1-\alpha_s} - p_{st} r_t k_{st} - w_t l_{st}$$

Firm’s first order conditions are:

$$p_{at}\frac{E_{at}}{E_t} = w_t$$

$$\alpha_s p_{st}\left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_{st}^{\alpha_s-1} l_{st}^{1-\alpha_s} = p_{st} r_t$$

$$(1-\alpha_s) p_{st}\left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_{st}^{\alpha_s} l_{st}^{-\alpha_s} = w_t$$

At any point in time, there are two generations of individuals alive: the young and the old, indicated by subscripts y and o, respectively. Since there are only two age groups and each is indicated by a letter, the distinction between age and time in subscripts is clear. We therefore supress the comma before t in the subscripts of age-specific variables for brevity. A young individual entering the economy in period t chooses savings (s_{yt}) and sectoral consumption in the two stages of life (c_{yit}’s and c_{oit+1}’s) to maximise lifetime utility:

$$U_t = ln\left[\left(\sum_{i=a,s} \omega_{yi}^{\frac{1}{\sigma_y}} c_{yit}^{\frac{\sigma_y-1}{\sigma_y}}\right)^{\frac{\sigma_y}{\sigma_y-1}}\right] + \pi_{t+1}\beta\ ln\left[\left(\sum_{i=a,s} \omega_{oi}^{\frac{1}{\sigma_o}} c_{oit+1}^{\frac{\sigma_o-1}{\sigma_o}}\right)^{\frac{\sigma_o}{\sigma_o-1}}\right]$$

The optimisation is subject to period-by-period budget constraints:

$$w_t l_{yt} = p_{at}c_{yat} + p_{st}c_{yst} + p_{st}s_{yt}$$

$$p_{st+1}\frac{(1-\delta+r_{t+1})}{h_t}\left[s_{yt} + \frac{(1-\pi_{t+1})}{\pi_{t+1}}s'_{yt}\right] = p_{at+1}c_{oat+1} + p_{st+1}c_{ost+1}$$

where π_t is the survival probability from youth to old age and β is the subjective discount factor. Like before, population aging can happen for two reasons. First, a rise in longevity which is captured by an increase in π_t. Second, a fall in fertility captured by a decrease in n_t.

As shown by the budget constraint, the individual enters the economy with no assets and relies on wages for consumption and savings. During old age, the individual does not work and consumes all his savings. In reality, especially in China, old people do make savings. We abstract from this reality in the simple model for analytical simplicity and clarity. We will, however, still describe the important implications of elderly savings.

6.3.2 Preferences and Consumption

Using consumer's first order conditions, we can derive the following sectoral choice equations which determine how total consumption at each phase of life is allocated across sectors.

$$\frac{c_{gst}}{c_{gat}} = \left(\frac{p_{at}}{p_{st}}\right)^{\sigma_g} \frac{\omega_{gs}}{\omega_{ga}}$$

Relative consumption of sector i is decreasing in its relative price and increasing in its preference weight ω_{gi}. If preference weight parameters vary across age, different age groups would demand sectoral consumption in different proportions. Resultantly, population aging can affect structural change by changing the sectoral composition of aggregate consumption.

σ_g determines the responsiveness of age g's sectoral demand to changes in relative prices. In Chapter 5, we found that older people have lower σ_g and hence lower price elasticities of demand in China. Population aging can therefore affect structural change by changing the economy's responsiveness to relative price changes originating from relative TFP changes and policies.

To explore the preference channels in more detail, note that the intertemporal budget constraint is:

$$\sum_{i=a,s} p_{it} c_{yit} + \frac{p_{st}}{p_{st+1}} \frac{h_t}{(1-\delta+r_{t+1})} \sum_{i=a,s} p_{it+1} c_{oit+1} = w_t l_{yt} + p_{st} \frac{(1-\pi_{t+1})}{\pi_{t+1}} s'_{yt}$$

The right-hand side of the equation shows that the individual's lifetime resource, which we shall denote by LR_t from now on for brevity, consists of wages during youth and accidental bequests received in old age.

Using the first order conditions, we can derive that the individual allocates a share $\frac{1}{1+\pi_{t+1}\beta}$ of lifetime resources to youth consumption and the rest to old-age consumption:

$$p_{at}c_{yat} + p_{st}c_{yst} = \frac{w_t l_{yt} + p_{st}\frac{(1-\pi_{t+1})}{\pi_{t+1}}s'_{yt}}{1+\pi_{t+1}\beta} = \frac{1}{1+\pi_{t+1}\beta}LR_t$$

$$\frac{p_{st}}{p_{st+1}}\frac{h_t}{R_{t+1}}\sum_{i=a,s} p_{it+1}c_{oit+1} = \frac{\pi_{t+1}\beta}{1+\pi_{t+1}\beta}\left[w_t l_{yt} + p_{st}\frac{(1-\pi_{t+1})}{\pi_{t+1}}s'_{yt}\right] = \frac{\pi_{t+1}\beta}{1+\pi_{t+1}\beta}LR_t$$

Higher survival probability makes it more likely for future consumption to be utilised. This induces the consumer to consume less and save more in young age.

Youth consumption of sector s value added is a share of total youth consumption:

$$p_{st}c_{yst} = \frac{\omega_{ys}p_{st}^{1-\sigma_y}}{\omega_{ya}p_{at}^{1-\sigma_y} + \omega_{ys}p_{st}^{1-\sigma_y}}\frac{LR_t}{1+\pi_{t+1}\beta} = \frac{1}{\frac{\omega_{ya}}{\omega_{ys}}\left(\frac{p_{at}}{p_{st}}\right)^{1-\sigma_y}+1}\ \frac{LR_t}{1+\pi_{t+1}\beta}$$

Similarly, old-age consumption of sector s value added is a share of total old-age consumption:

$$\begin{aligned}\frac{p_{st}}{p_{st+1}}\frac{h_t}{R_{t+1}}p_{st+1}c_{ost+1} &= \frac{\omega_{os}p_{st+1}^{1-\sigma_o}}{\omega_{oa}p_{at+1}^{1-\sigma_o} + \omega_{os}p_{st+1}^{1-\sigma_o}}\frac{\pi_{t+1}\beta LR_t}{1+\pi_{t+1}\beta} \\ &= \frac{1}{\frac{\omega_{oa}}{\omega_{os}}\left(\frac{p_{at+1}}{p_{st+1}}\right)^{1-\sigma_o}+1}\frac{\pi_{t+1}\beta LR_t}{1+\pi_{t+1}\beta}\end{aligned}$$

In addition to confirming the importance of ω_{gi} in determining age g's sectoral allocation of consumption, the equations above clarify the roles played by σ_g. When σ_g is less than one, as is the case in China, the consumer's price elasticity of demand is low. An increase in sector i relative price p_{it} leads to a less than proportionate decrease in sector i real consumption c_{git}, resulting in an increase sector i's share in nominal consumption. Since σ_g falls with age in China, population aging can affect structural change at the real and nominal levels by changing the economy's responsiveness to price changes.

6.3.3 Savings

Youth savings in t, which is the source of the economy's capital stock in $t+1$, can be written as:

$$s_{yt} = n_{t+1} l_{yt+1} h_t k_{t+1} = \frac{\pi_{t+1}^2 \beta}{1 + \pi_{t+1}^2 \beta} \frac{1}{p_{st}} w_t l_{yt}$$

where k_{t+1} is capital per productive labour in $t+1$.

From the savings equation above we can see that an increase in survival probability π_t raises individual savings. The term $\frac{\pi_t^2 \beta}{1+\pi_t^2 \beta}$ captures two channels of effect. Firstly, as people expect to live longer, they save more to finance for consumption during retirement. Secondly, a higher survival probability reduces accidental bequests received in old age, forcing people to save more to finance for their retirement.

Diminishing fertility, captured by a decrease in n_t, leads to an increase in capital per productive labour. Intuitively, lower youth population growth leads to a shrinking effective labour supply and hence less workers sharing the capital stock. In a model with more working generations, the fall in effective labour supply is exacerbated by the fact that older workers tend to be less effective.

The aforementioned savings channels operate at the individual level. At the aggregate level, there is an additional channel of effect. If old people save differently to young people, an increase in the elderly share of population can change the aggregate saving rate. Since elderlies do not save at all in this simple model, an increase in the elderly population share reduces the aggregate saving rate. While elderlies are dis-savers relative to younger people in many developed countries, the same is not true in China. Empirical studies show that elderlies in China not only save but also save more than people from other age groups. This means population aging can potentially increase rather than decrease savings via the aggregate savings channel. In our main model, we capture elderly savings via bequests.

Using firm's condition, we can substitute prices away and rewrite the savings recursively as:

$$s_{yt} = n_{t+1} l_{yt+1} h_t k_{t+1} = \frac{\pi_{t+1}^2 \beta}{1 + \pi_{t+1}^2 \beta} (1 - \alpha_s) \left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_t^{\alpha_s} l_{st}^{-\alpha_s} l_{yt}$$

This equation suggests that capital depends on demographic developments in the past. Capital per productive labour in t increases due to past population aging, which raises the savings in t and hence capital in $t+1$ by raising income.

Savings are used as capital input in production. If population aging raises savings, it can facilitate economic growth by raising capital input. Aging can also facilitate structural change towards the capital-intensive sector because said sector uses capital more intensely and is where capital is produced. This still holds in our main setting where capital is produced in all sectors because according to data, the vast majority of capital is produced in industry, the most capital-intensive sector. The change in savings due to aging also interacts with other variables, leading to some additional aging effects which will be described later in Section 6.3.5.

6.3.4 Labour input

Population aging diminishes the working age population, thereby reducing effective labour input in the economy. In Chapter 3, we found that older age groups have lower per capita effective labour supplies because they have lower labour participation rates, employment rates, and effectiveness in production compared to young age groups. Resultantly, aging of the working age population can reduce aggregate effective labour input by reducing per capita effective labour input. In the simple model, this effect is captured by a reduction in l_{yt}, the exogenous per capita effective labour of working age people. In our main model, there are five working age groups with different per capita effective labour ($l_{g,t}$'s). Older age groups have lower per capita effective labour than young age groups. Therefore, increases in the population shares of older age groups and decreases in the shares of young age groups reduce per capita effective labour of the population.

6.3.5 Capital deepening and relative prices

The equation below shows that relative price between sectors is a function of capital labour ratio k_t:

$$\frac{p_{at}}{p_{st}} = (1-\alpha_s)\left(\frac{E_{st}}{E_{at}}\right)\left(\frac{k_t}{l_{st}}\right)^{\alpha_s} = (1-\alpha_s)\left(\frac{E_{st}}{E_{at}}\right)\left(\frac{K_t}{L_{st}}\right)^{\alpha_s}$$

where K_t denotes real aggregate capital input and L_{st} denotes the capital-intensive sector's labour input.

The positive aging effects on per capita savings and negative aging effects on labour cause the capital labour ratio to increase. This phenomenon is referred to as capital deepening. As capital becomes more abundant relative to labour, capital becomes cheaper relative to labour. This lowers the cost of production in the capital-intensive sector relative to the labour-intensive sector. Consequently, price of the capital-intensive sector falls relative to that of the labour-intensive sector.

In response to the price changes, real consumption of sector s rises and real consumption of sector a falls. The reaction of nominal consumption depends on the economy's price elasticity of demand. If the economy's demand is price inelastic, like that in China, then sectoral real consumption would change less than proportionately in response to the price changes. Resultantly, sector s nominal consumption would fall relative to sector a nominal consumption.

In Chapter 5, we found that older age groups have lower price elasticities of demand than younger age groups. Population aging can therefore lead to reductions in the economy's price elasticity of demand. This effect interacts with the aforementioned capital deepening effects. In the event of capital deepening, the reductions in elasticity would cause real consumption of sector s to rise less relative to that of sector a, and nominal consumption of sector s to fall more sharply relative to that of sector a.

6.3.6 Sectoral labour allocation

The reallocation of labour across sectors is a key indicator of structural change. This subsection describes how population aging affects sectoral labour allocation via the aforementioned channels.

We start with the goods market clearing conditions:

$$\frac{E_{at}}{E_t} l_{at} = \psi_{yt} c_{yat} + \psi_{mt} c_{mat}$$

$$\left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_{st}^{\alpha_s} l_{st}^{1-\alpha_s} = \psi_{yt} c_{yst} + \psi_{yt} s_{yt} + \psi_{mt} c_{mst} - (1-\delta) * \frac{1}{n_t l_{yt} h_{t-1}} s_{yt-1}$$

As shown in the equations, sector a output is used purely for consumption while sector s output is used for both consumption and investment. Looking at the sector s condition above, the second term on the Right-Hand-Side (RHS) corresponds to savings of youth while the last term on the RHS corresponds to dissaving of the elderly.

For brevity, let η_{git} denote sector i's share in age g consumption. η_{git} is a function of preference parameters and relative prices:

$$\eta_{gst} = \frac{\omega_{gs} p_{st}^{1-\sigma_g}}{\omega_{ga} p_{at}^{1-\sigma_g} + \omega_{gs} p_{st}^{1-\sigma_g}} = 1 - \eta_{gat}$$

After some algebra, we can derive sectoral labour share of s as:

$$l_{st} = \eta_{yst} \frac{1-\alpha_s}{1+\pi_{t+1}^2 \beta} + \eta_{ost}(1-\delta)\left(\frac{E_t}{E_{st}}\right)^{1-\alpha_s} k_t^{1-\alpha_s} l_{st}^{\alpha_s} + \eta_{ost}\alpha_s l_{st} + \frac{\pi_{t+1}^2 \beta}{1+\pi_{t+1}^2 \beta}(1-\alpha_s)$$
$$-(1-\delta)\left(\frac{E_t}{E_{st}}\right)^{1-\alpha_s} k_t^{1-\alpha_s} l_{st}^{\alpha_s}$$

The first term on the RHS originates from youth consumption of s. In expectation of rising longevity, young people save more and consume less in t. The second and third terms reflect elderly consumption using income from rent and from selling capital. Suppose population aging raises capital per productive worker and hence these capital incomes. The combination of lower youth consumption and higher elderly consumption means that the elderlies' weight in the economy's preferences is greater. As long as preferences differ across age, population would induce structural change by changing the economy's preferences.

The fourth term corresponds to youth savings. As discussed earlier, higher survival probability raises youth savings. Since capital goods are produced in sector s, this raises sector s's labour share.

In this simple model, old people consume all their savings. Population aging can therefore impede capital accumulation and hence structural change. This channel is captured by the fifth term. In reality, however, elderlies do save. The introduction of elderly savings would introduce a positive term in the labour share equation that mitigates this channel. In the Chinese case, elderlies save more than other age groups. This means that elderly savings via, for example, bequests, can potentially reverse the negative savings channel.

Rearranging age g sectoral consumption share η_{gst} as a function of relative price, we obtain:

$$\eta_{gst} = \frac{1}{\frac{\omega_{ga}}{\omega_{gs}}\left(\frac{p_{at}}{p_{st}}\right)^{1-\sigma_g} + 1} = \frac{1}{\frac{\omega_{ga}}{\omega_{gs}}\left((1-\alpha_s)\left(\frac{E_{st}}{E_{at}}\right)\left(\frac{k_t}{l_{st}}\right)^{\alpha_s}\right)^{1-\sigma_g} + 1}$$

The relative price of the capital-intensive sector can fall if population aging leads to capital deepening and or if the relative productivity of the capital-intensive sector increases. As can be seen in the equation above, the impact of sector s's relative price drop depends on elasticity parameter σ_g. If σ_g is less than one, real sector s consumption rises less than proportionately in response to the fall in sector s relative price, leading to a reduction in nominal consumption share and hence labour share of sector s. If σ_g decreases with age, population aging would dampen the rise in real sector s consumption and magnify the fall in nominal sector s consumption.

6.3.7 Sectoral output

From the perspective of demand, we can think of aging affecting sectoral output shares through sectoral consumption and investment. Alternatively, we can think of aging affecting sectoral output via sectoral capital and labour from the perspective of supply. Sector i nominal output per productive worker can be written as:

$$p_{at}y_{at} = p_{at}\frac{E_{at}}{E_t}l_{at}$$

$$p_{st}y_{st} = p_{st}\left(\frac{E_{st}}{E_t}\right)^{1-\alpha_s} k_t^{\alpha_s} l_{st}^{1-\alpha_s}$$

where y_{it} denotes sector i's real output per productive worker.

To the extent that aging affects sectoral capital and labour shares, and to the extent that aging affects how the economy responds to price changes, aging can affect sectoral output shares in both real and nominal terms. As discussed earlier, aging affects capital and labour via a number of channels. The overall direction and magnitude of such effects are empirical matters that depend on the data and parameter values specific to the Chinese case.

6.3.8 Aggregate and per capita output

At the aggregate and per capita levels, population aging hinders economic growth by reducing effective labour supply. However, this negative effect can be alleviated if population aging facilitates capital accumulation and structural change towards more productive sectors. The overall effect of aging is again an empirical matter which will be studied in the next two sections.

6.4 Calibration

6.4.1 Calibration of steady state model

We calibrate the steady state model to match Chinese data in the initial period of 1981-1990. When the deflated model economy is in a steady state, the level economy is on a balanced growth path along which variables grow at the same constant rate. This rate of growth is driven by the constant growth rates of population and productivity.

In Chapters 2 and 3, we compiled supply-side data on sectoral value added, investment, capital, effective labour, total factor productivity, capital income share, and depreciation for China. In this chapter, a number of constant parameters are computed directly using said data. Table 6.1 below provides a list of calibrated parameter values. The ten-year depreciation rate δ is set to be 0.52, corresponding to an annual rate of 7.16%. The capital income shares (α_i) of the primary, secondary, and tertiary sectors are 0.09, 0.52, and 0.50, respectively.

In Chapter 3, we compiled sectoral consumption expenditure data on the demand side. We then broke them down into sectoral consumption value-added components using Input-Output Tables (IOTs). We follow the same procedure to compile sectoral investment value added and net exports value added data. These give rise to demand side data that can be used in our value-added MSOLG model. In this chapter, sectoral consumption, sectoral investment, and sectoral net exports refer to sectoral consumption value added, sectoral investment value added, and sectoral net exports value added, respectively.

Using the supply-side data, we compute the initial period factor payments r_{at} and w_{at} in agriculture using the firm First Order Conditions (FOCs). We then compute factor payments in the modern sectors. Not surprisingly, modern sectors' factor payments are different to those in agriculture. We set factor price wedges (θ_{kit} *and* θ_{lit}) so that modern sectoral factor payments $\theta_{kit} r_{at}$ and $\theta_{lit}\mathrm{w}_{\mathrm{at}}$ are consistent with data. In other words, the factor price wedges allow firm FOCs to hold given data on prices, capital, labour, and productivity (α_i, p_{it}, p_{kt}, E_t, k_{it}, E_{it}, and l_{it}).

For the capital goods firm, we calibrate μ_i's to be the long-term averages of sectoral investment value added shares. As can be seen in Table 6.1, capital goods are produced mostly in the secondary sector. The $\mu_i's$, together with data of p_{it} and p_{kt}, allow us to compute the initial period capital productivity A_{kt}.

Given the aforementioned data and factor payments, we can compute individuals' composite factor income w_t and r_t in the initial steady state. We use compiled data values for the exogenous shares of taxation ($\tilde{T}_{it}$'s) and shares of net exports ($\tilde{X}_{it}$'s) in national income.

Using Chapter 5's data and method, we estimate age-consumption profiles for the six age groups. Given the known values of prices, age-consumption profiles, exogenous variables, and parameters, we can compute consumer savings $s_{g,t}$ and bequests b_t that allow budget constraints to hold. We set β_g and v_6 so that the Euler equations and the bequest condition can hold with these values of $s_{g,t}$ and b_t. In other words, we set β_g and v_6 to target $s_{g,t}$ and b_t values which in turn ping down age specific total consumptions at data values.

Using age consumption profiles of the six age groups, we estimate age specific preferences following the same method as that in Chapter 5. The results are presented in Appendix 6.2 of this chapter. For use in the current model, subsistence consumptions are deflated into per productive person terms. The estimated preferences show familiar variations across age. Compared to younger people, older people have greater estimated preference weights for agriculture, lower preference weights for services, and lower price elasticities.

Given age-specific preference parameters, age-specific total consumption, and prices, the sectoral consumption choice conditions give rise to age-specific sectoral consumption solutions that are consistent with data.

The only equations that are yet to be mentioned are the market clearing conditions which automatically hold because we have used data values of output and inputs in the calibration. This concludes the steady state calibration as we have set constant parameter values and exogenous variable values such that the model solution matches data in the initial period.

Table 6.1: Calibrated parameter values

Parameter	Value	Parameter	Value	Parameter	Value
δ	0.52	ρ	1.00	ω_{5a}	0.03
α_a	0.09	ω_{1a}	0.02	ω_{5d}	0.59
α_d	0.52	ω_{1d}	0.50	ω_{5s}	0.38
α_s	0.50	ω_{1s}	0.48	ω_{6a}	0.05
μ_a	0.13	ω_{2a}	0.001	ω_{6d}	0.57
μ_d	0.62	ω_{2d}	0.53	ω_{6s}	0.38
μ_s	0.25	ω_{2s}	0.47	σ_1	0.58
β_2	1.51	ω_{3a}	0.02	σ_2	0.52
β_3	1.34	ω_{3d}	0.45	σ_3	0.71
β_4	0.74	ω_{3s}	0.53	σ_4	0.37
β_5	0.52	ω_{4a}	0.001	σ_5	0.31
β_6	0.37	ω_{4d}	0.59	σ_6	0.31
v_6	2.01	ω_{4s}	0.41		

6.4.2 Paths of exogenous variables

The simulations involve solving for the paths of endogenous variables given the paths of exogenous variables. For our baseline simulation, we set the exogenous variables using data and forecasts for the first ten model periods which correspond to the 1981-2080 period in reality. After period ten, we let the exogenous variables to gradually become constant, allowing the model economy to transition to a terminal steady state.

The exogenous variables in the model are productivity growth rate h_t, sectoral relative productivity re_{it}, factor price wedges θ_{kit} and θ_{lit}, effective labour supply per age g person $l_{g,t}$, capital productivity A_{kt}, tax rate $\tilde{T}_{it}$, net exports' share in GDP $\tilde{X}_{it}$, survival probabilities and transition rate $\pi_{g,t}$'s, and youth population growth rate n_t.

The first four simulation periods correspond to the past periods of 1981-1990, 1991-2000, 2001-2010, and 2011-2020. For these periods, the exogenous variables are set using data. The demographic variables are computed using data from United Nations' World Population Prospects (UNWPP) 2022 (United Nations, 2024). The tax and net export rates are computed as shares of government spending and net exports in GDP, respectively. To calibrate factor price wedges, we start by inserting data into firm first order conditions to estimate sectoral factor prices. Like what we did for the steady state calibration, we then compute factor price wedges as ratios of modern sectors' factor payments to those of agriculture. Capital productivity is computed using the calibrated μ_i's and data values of capital prices. The rest of the exogenous variables are computed using our data and results from Chapter 3 where we conducted sectoral growth accounting using data from national accounts and household surveys.

As China's population aging is expected to accelerate, we would like to account for the future effects of aging in our study. To this end, we set demographic variables using forecasts from the UNWPP up to the 2070-2080 period, which corresponds to period ten in the model. After period ten, we assume demographic variables stay constant for five periods. From that point on, we assume youth population growth rate converge gradually to 1.1046 over five periods and survival probabilities and transition rate stay constant. The gross ten-year growth rate of 1.1046 corresponds to an annual rate of 1.01.

We project aggregate and sectoral productivity growth rates after period 3 to be weighted averages of two scenarios. In the first scenario, projected productivity growth rates stay constant. In the second scenario, projected aggregate productivity growth rate (h_t) stays constant for three periods and then gradually transitions to 1.1046 over four periods. In the second scenario, sectoral productivity growth rates are equal to the aggregate productivity growth rate. The weights start off as 0.5 for both scenarios. Over five periods, the weights of the two scenarios transition gradually to 0 and 1, respectively. Given the data values of productivities in period 4 and the projected productivity growth rates, we compute the projected productivities and relative productivities (re_{it}'s). In this setup, productivity growth rates and hence relative productivities stay constant after period ten.

Age specific effective labour per capita, net exports rate, and factor price wedges are assumed to stay constant after period four.

In theory, capital used by all firms have the same sectoral origin. Therefore, the price of capital p_{kt} should not deviate much from the weighted average of sectoral capital prices. This is consistent with the observation that the capital productivity A_{kt} fluctuates closely around one in the first four periods. After period four, we assume that A_{kt} stays constant.

Healthcare and education expenditures are important channels through which aging affects the economy. These channels have been partially accounted for by the age-varying preferences over private consumption. We seek to also capture the aging effects on healthcare and education components of government consumption. We obtain data on government healthcare and education consumptions from China's Input-Output Tables (NBS, 1991-2022). We assume that government education consumption is entirely given to the 0-22 age group. Although the very young (0-20) age groups are not economically active in our model economy, they are nevertheless present in the background. We breakdown government health consumption by age using the age-consumption profiles of private healthcare consumption. Beyond model period four (2010-2020), we assume the age profiles of government healthcare and education consumptions follow the same patterns as those in period four. We assume that the age profiles grow at the same rate as GDP after period four. In this way, the expenditures would not disappear as shares of GDP as the economy grows over time. Population aging raises government healthcare consumption and reduces government education consumption. These channels can now manifest in our model as changes in government spending and hence changes in tax rates required to finance such spending.

6.5 Results

In this section, we discuss our simulation results. According to UNWPP's forecast, China's population will age till the early 2080s, after which it will reverse. We therefore focus on the 1981-2080 period in this section. Our baseline simulation is conducted following the calibration discussed in Section 6.4. We first test the validity of our model by comparing the simulated paths of variables in the baseline with data. After showing that our model captures reality well, we conduct counterfactual simulations to analyse the effects of population aging.

6.5.1 Baseline simulation

6.5.1.1 Demographics

As described in Section 4, baseline demographics for the 1981-2080 period follow UNWPP data. Figure 6.1 and 6.2 below show the baseline evolutions of demographic variables which determine the population and its age structure in China.

As can be seen in Figure 6.1, youth population aged from 20 to 31 grew at a ten-year gross rate of 1.278 in period 1 (1981-1990). This corresponds to an annual gross growth rate of 1.025. Over time, youth population growth follows a downward trend. By period 10 (2071-2080), gross youth population growth rate is expected to reach 0.890, or 0.988 in annual terms. The plummeting fertility not only causes youth population to shrink relative to older population but also causes population growth rate to decline.

Figure 6.2 shows that survival rates, especially for older age groups, rise rapidly over time. Over the 1981-2080 period, survival probabilities of those aged 41 to 50 and of those aged 51 to 60 increase from 0.918 to 0.985 and from 0.812 to 0.967, respectively. Figure 6.3 shows the transition rate of the 61-70 age group. This rate should not be interpreted as the survival rate because the last age group contains population aged above 70 and an increase in survival rate from 71-80 to 81-90 can make the transition rate larger than one. As can be seen in the figure, the transition rate increases rapidly from 0.726 to 1.984 over the 1981-2080 period.

Figure 6.1: Youth population growth rate n

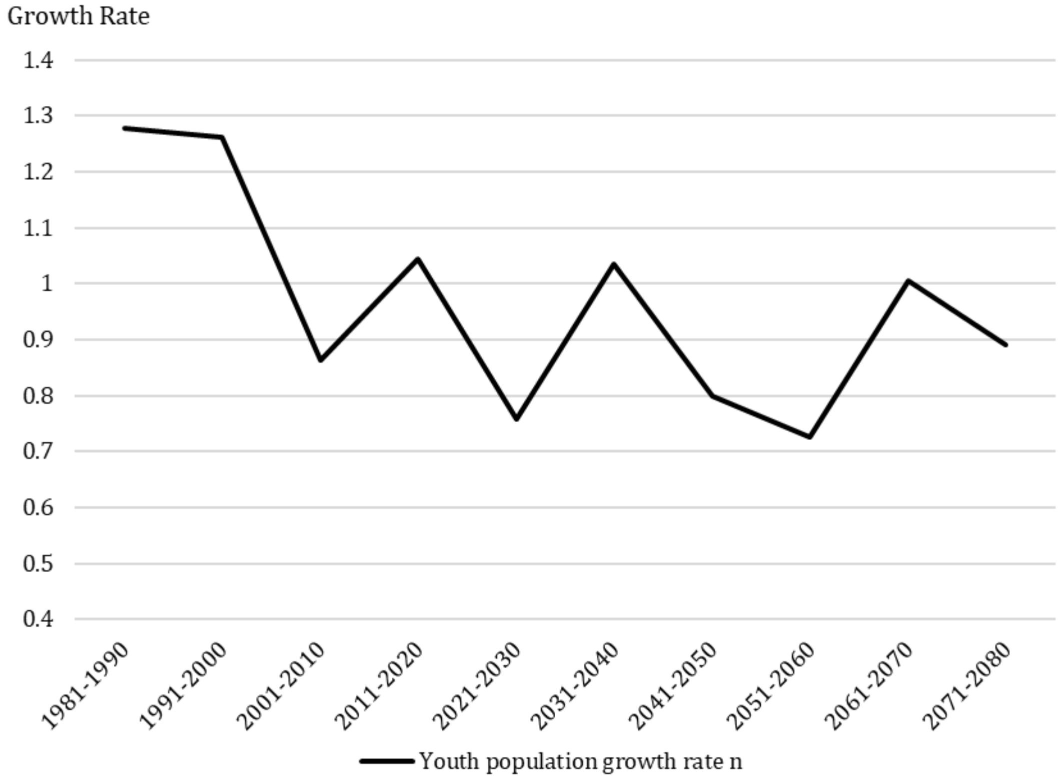


Figure 6.2: Survival rate by age group

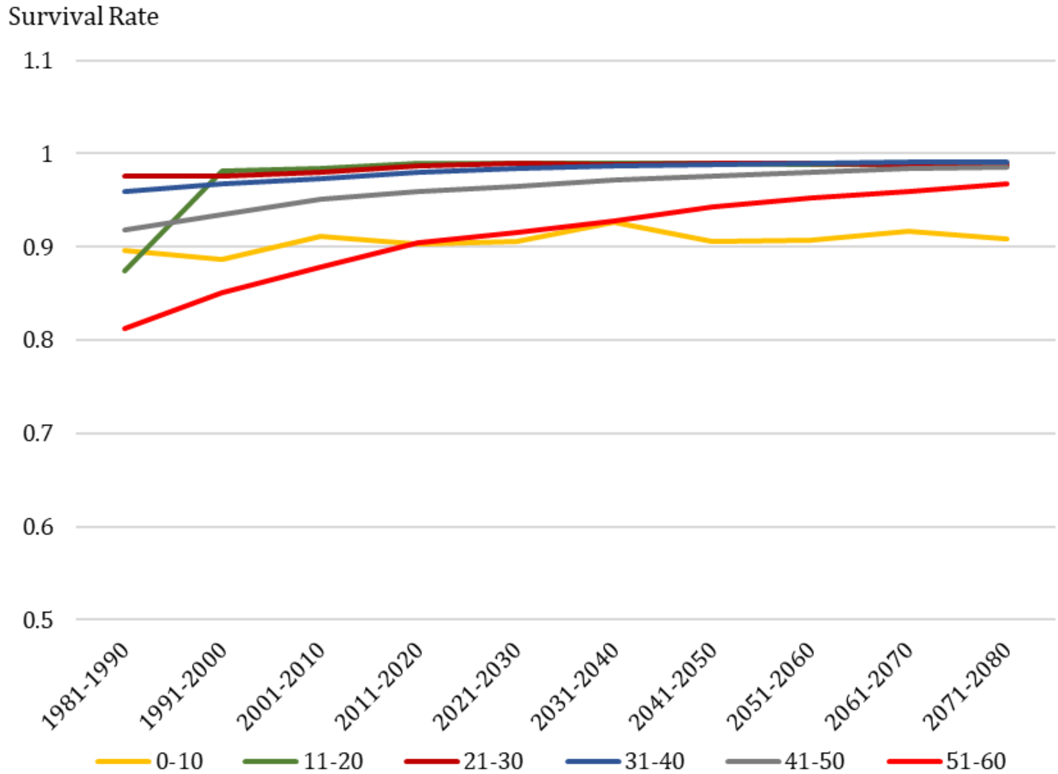


Figure 6.3: Transition rate of the 61-70 age group

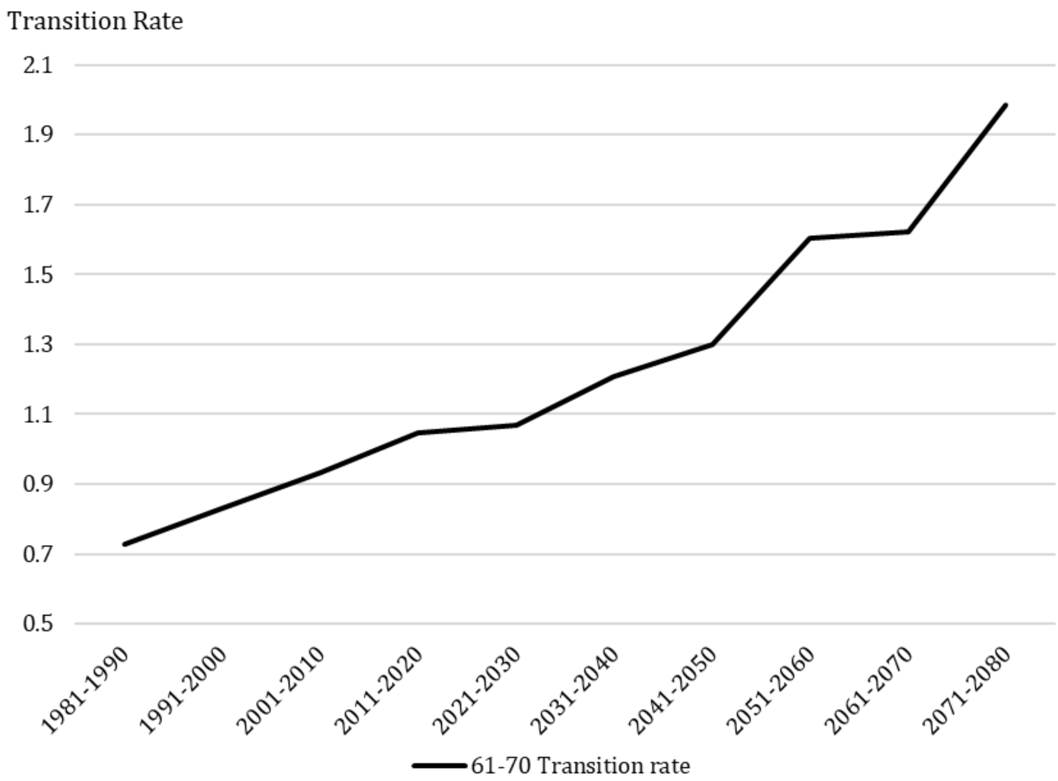
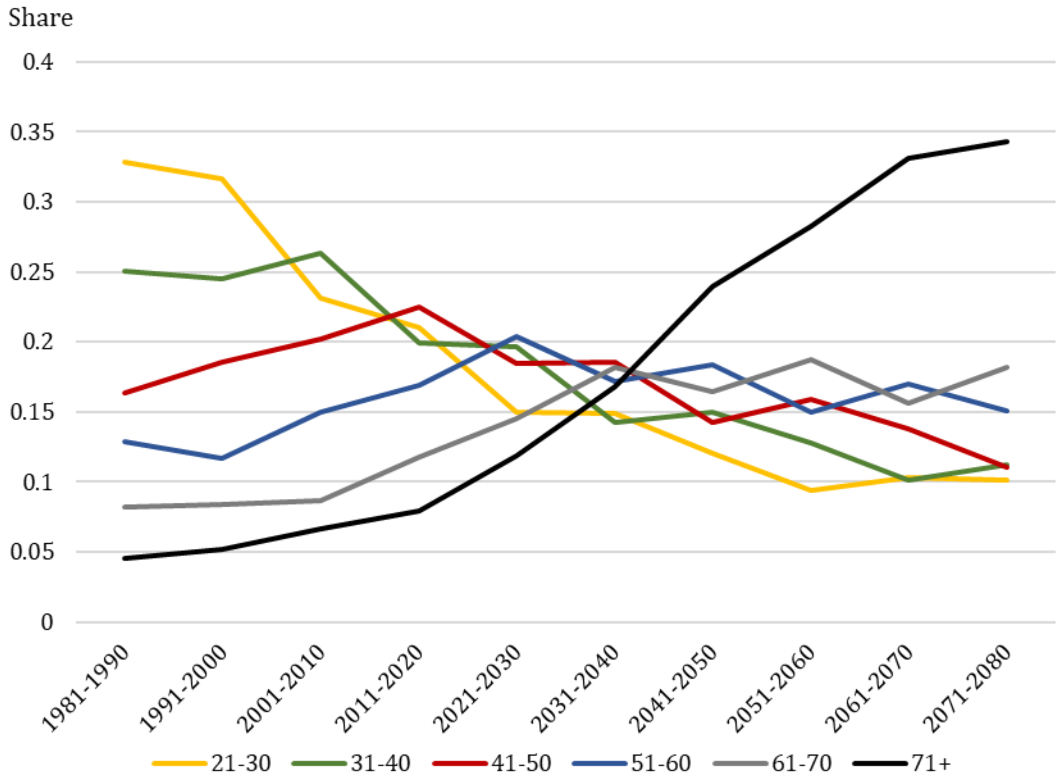


Figure 6.4: Age population shares



The aforementioned increases in survival and transition rates are behind the predicted increase in mean life expectancy of China from 64.8 years in 1981 to 78.0 years in 2020 and eventually to 87.5 years in 2080. Rising longevity is a key driver of population aging in China and can have profound impacts on the economy. Past studies tend to focus on the impacts of population aging due to falling fertility. In this study, we investigate the effects of both falling fertility and rising longevity.

Figure 6.4 plots the shares of age groups in population aged 21 and above. As old people live longer and as the number of young people falls, China's population ages rapidly. Initially, aging in China involved falling shares of youth population aged 21 to 40 and rising shares of those aged 40 and above. From period 4 (2011-2020), the 41-60 mid age population share also starts to fall. The share of elderlies aged 61 and above rises continually over the period shown. Between period 1 (1981-1990) and 10 (2071-2080), elderly population share rises from 12.8% to 52.5% and youth population share falls from 57.9% to 21.4%. Mid-age population share starts off at 29.3%, rises to 39.3% in period 4 (2011-2020), and then falls to 21.6% in period 10 (2071-2080).

6.5.1.2 Effective labour input

Population aging affects the economy's labour input directly by changing the size of the working age population. Figure 6.5 shows that working age (21-60) population increased initially between 1981 and 2020. This is due to the positive youth population growth and rising working age survival rates. As the survival rates reached bottlenecks and as the young and mid-age population started to fall, the working age population started to fall in the 2011-2020 period.

As people get older, their labour participation rates, employment rates, and effectiveness in production fall. As such, older age groups have lower per capita effective labour supplies ($l_{g,t}'s$). Aging of the working age population therefore lowers its per capita effective labour, thereby diminishing aggregate effective labour input.

Figure 6.5: Working age (21-60) population

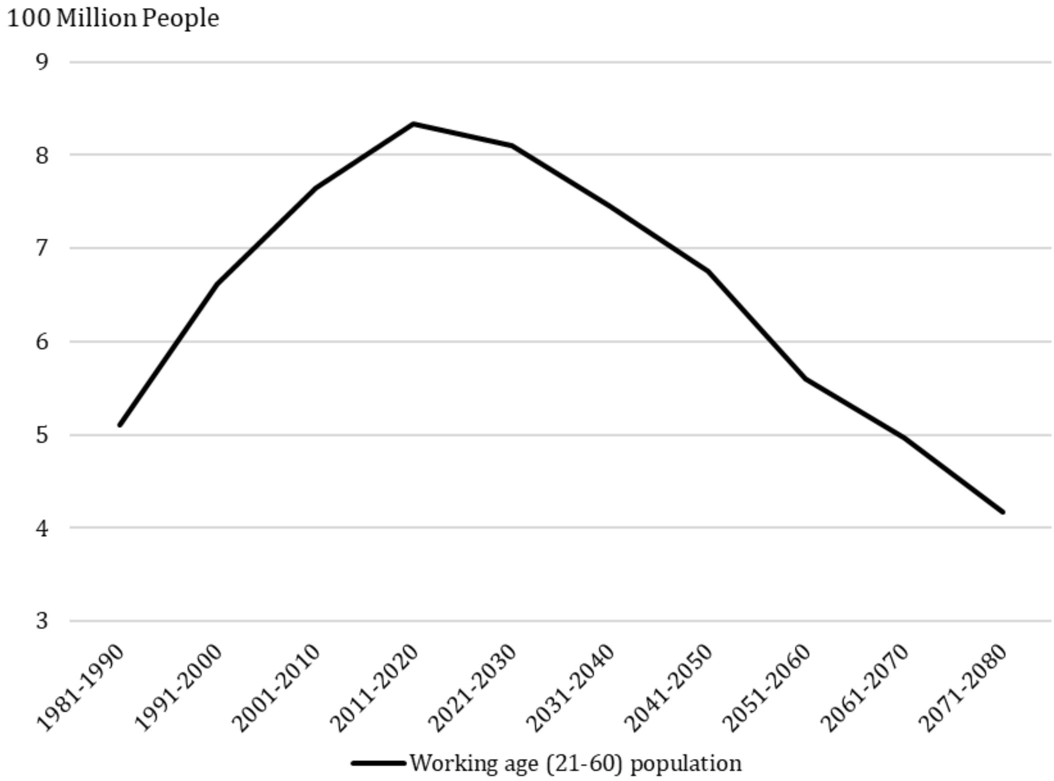
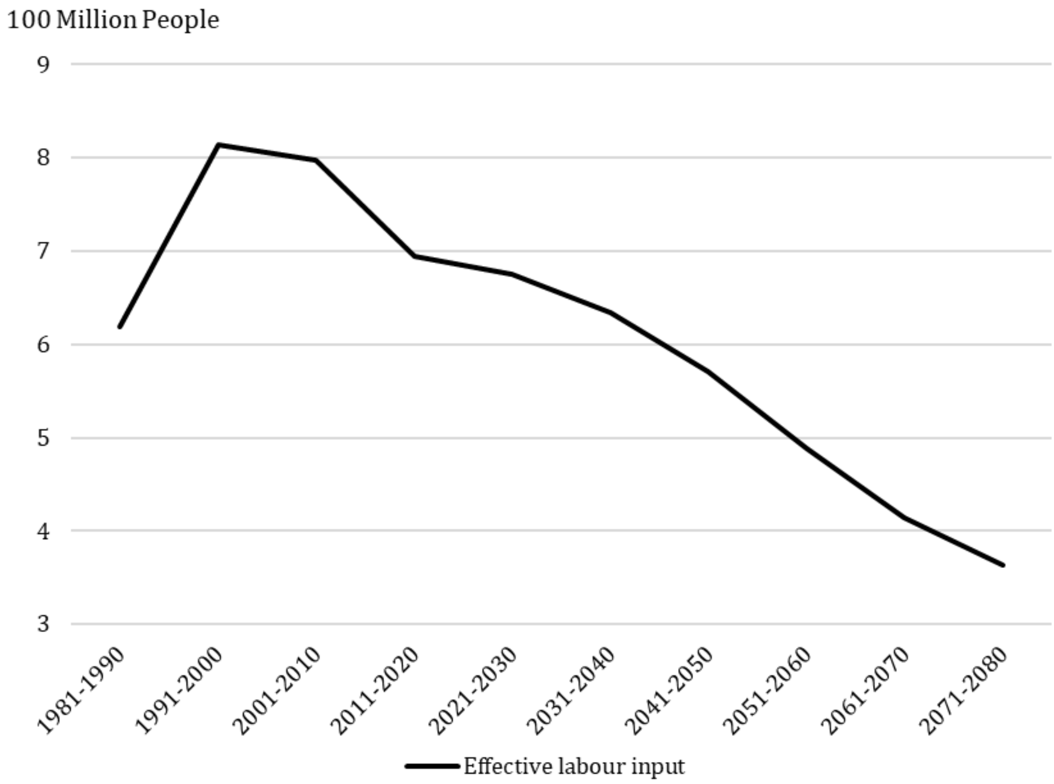


Figure 6.6: Effective labour input



As can be seen in Figure 6.6, effective labour input starts to fall 20 years earlier and falls more sharply than working age population. Between 1991 and 2080, effective labour input in the aging economy falls at an average annual rate of 1.0%. By 2080, China's effective labour is 58.7% of its size in 1981.

6.5.1.3 Baseline simulation results versus data

Figures 6.7-6.17 below show the simulated paths of endogenous variables and their data counterparts. As can be seen in the figures, our baseline simulation results match the observed patterns of variables well.

Our model replicates well the impressive economic growth of China over the sample period. A key driver behind this growth is the soaring savings in China in the past few decades. Our model replicates the observed rise in per capita investment, thereby providing explanations for the Great Savings Puzzle of China. Our model captures the observed structural changes from agriculture to the modern sectors in terms of output and factor inputs.

Although subjective discount factors are assumed to be constant, the simulated age-specific total consumption coincide with data. As the model predicted prices and age specific consumption match with data, the preference parameters ensure that simulated age-specific sectoral consumption are consistent with data.

Figure 6.7: Data versus simulated sectoral relative prices p_{it} and capital goods relative price p_{kt}

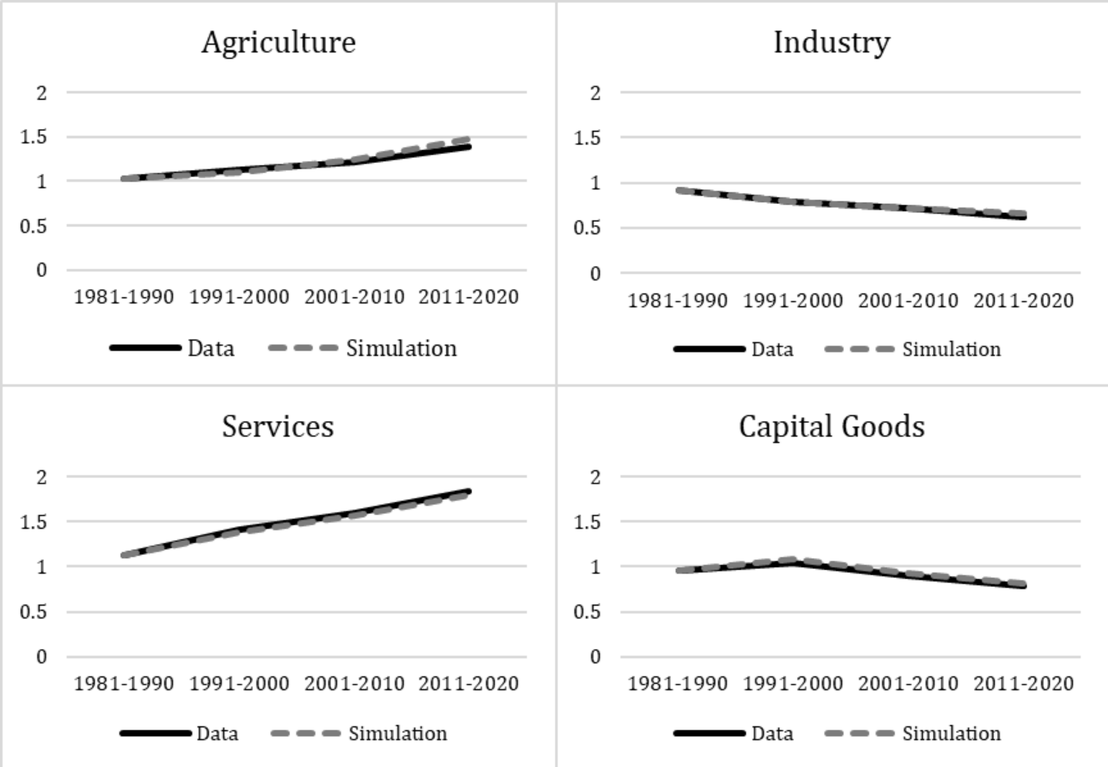


Figure 6.8: Data versus simulated sectoral labour shares l_{it}

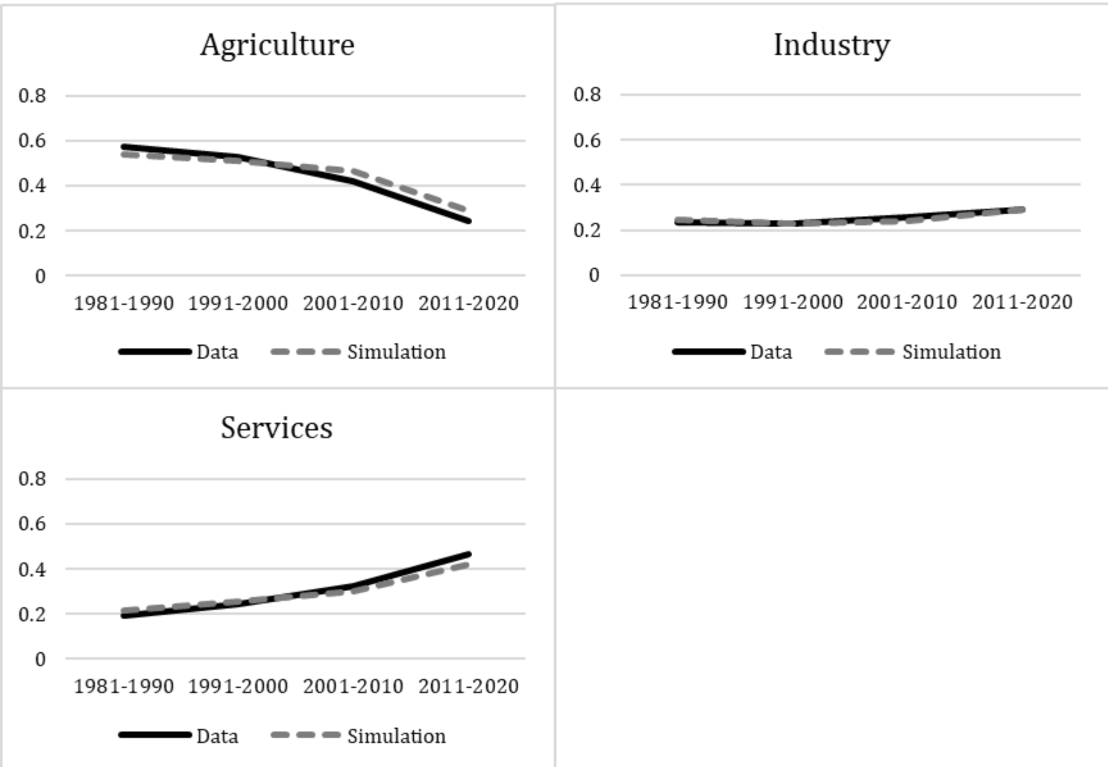


Figure 6.9: Data versus simulated aggregate and sectoral real capital per productive labour k_t and k_{it} (unit=10000 Yuan)

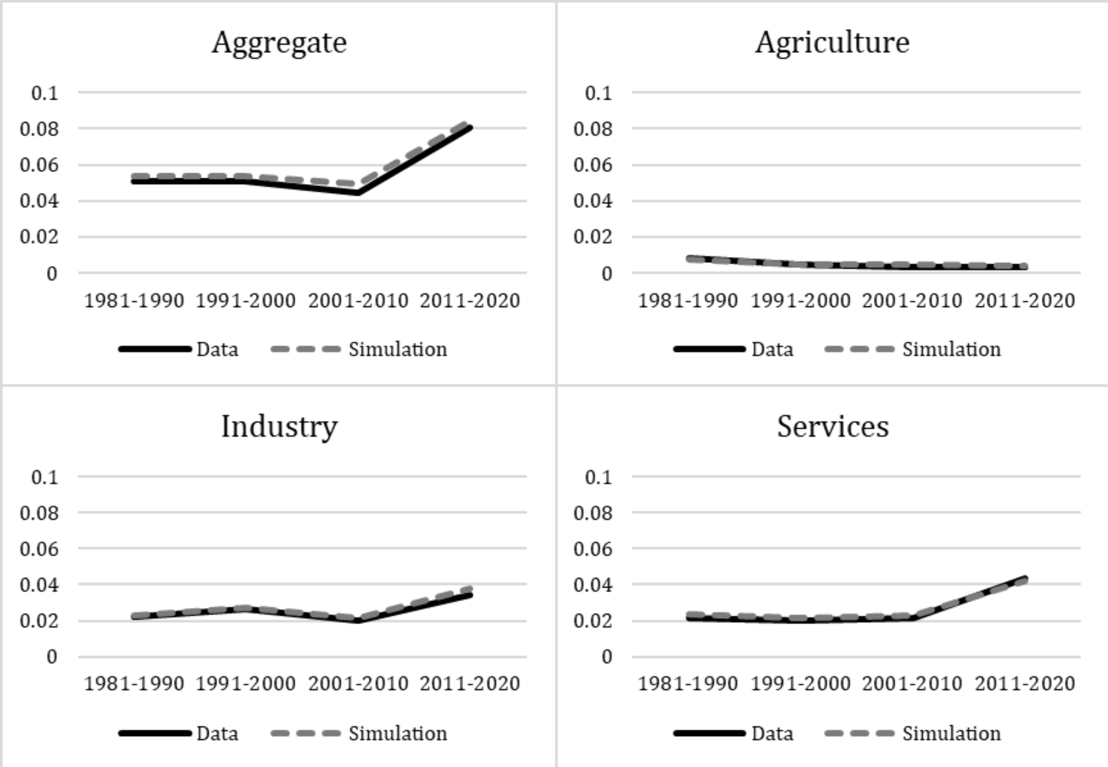


Figure 6.10: Data versus simulated aggregate and sectoral real output per productive labour y_t and y_{it} (unit=10000 Yuan)

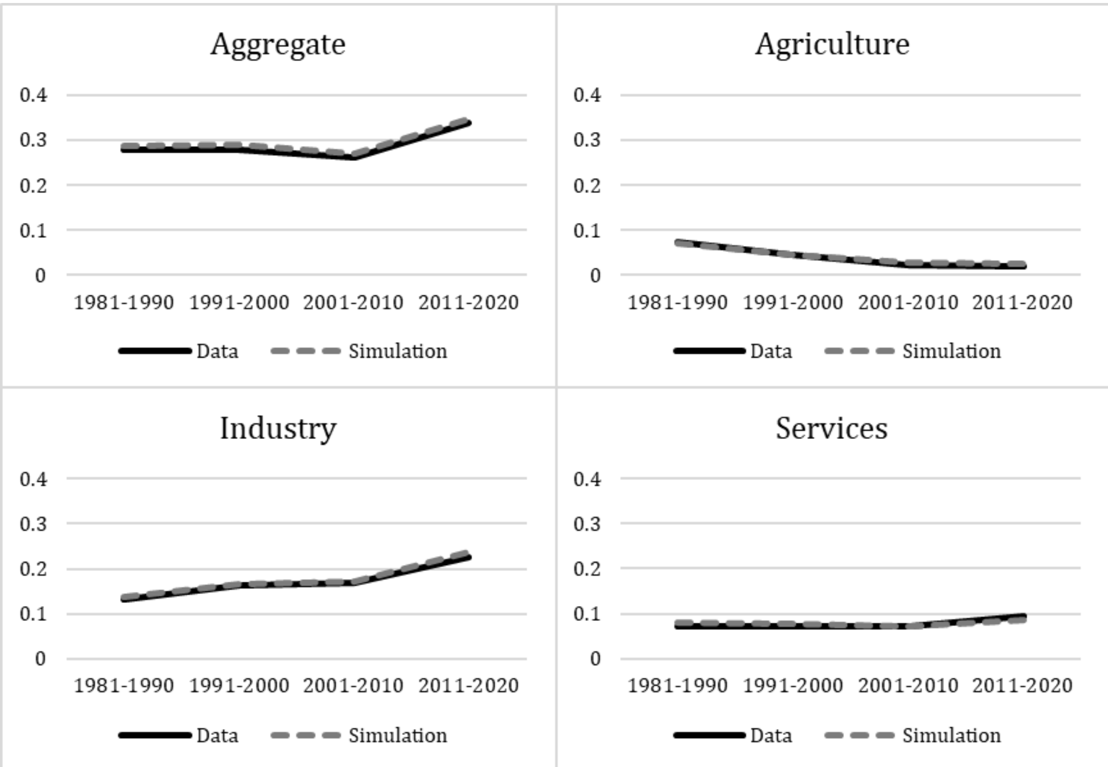


Figure 6.11: Data versus simulated real consumption and investment per productive labour (unit=10000 Yuan)

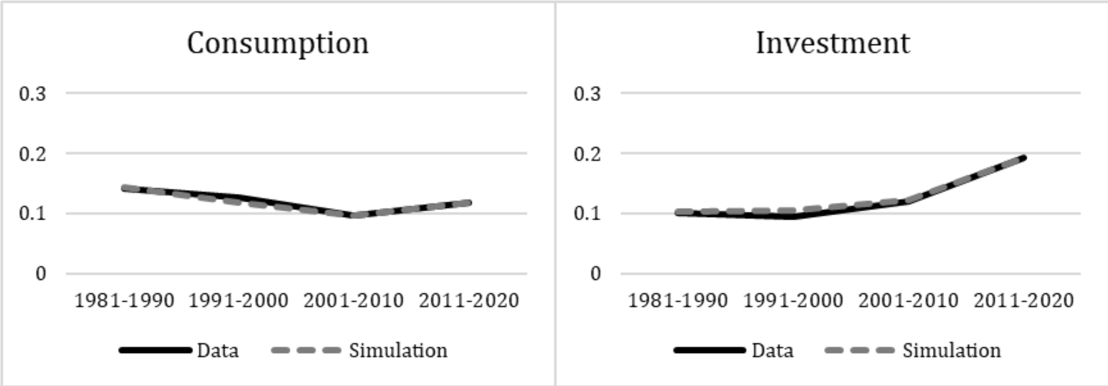


Figure 6.12: Data versus simulated real total and sectoral consumption per productive person of the 21-30 age group ($c_{1,t}$ and $c_{1i,t}$) in 10000 Yuan

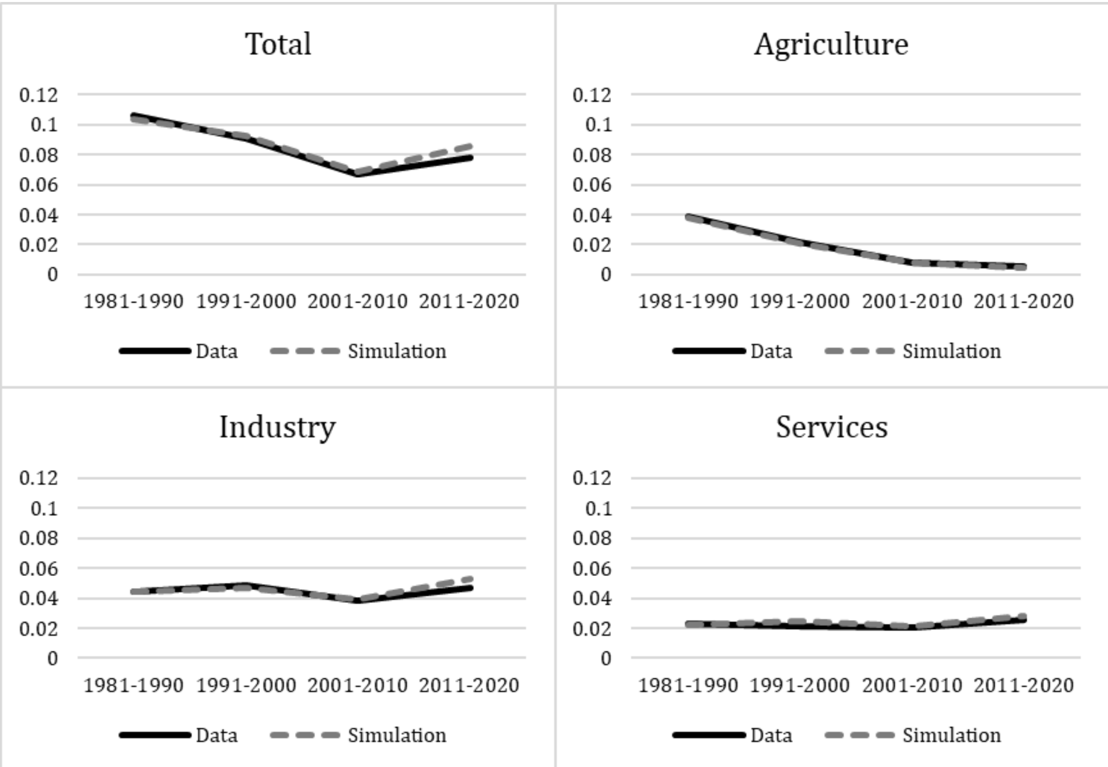


Figure 6.13: Data versus simulated real total and sectoral consumption per productive person of the 31-40 age group ($c_{2,t}$ and $c_{2i,t}$) in 10000 Yuan

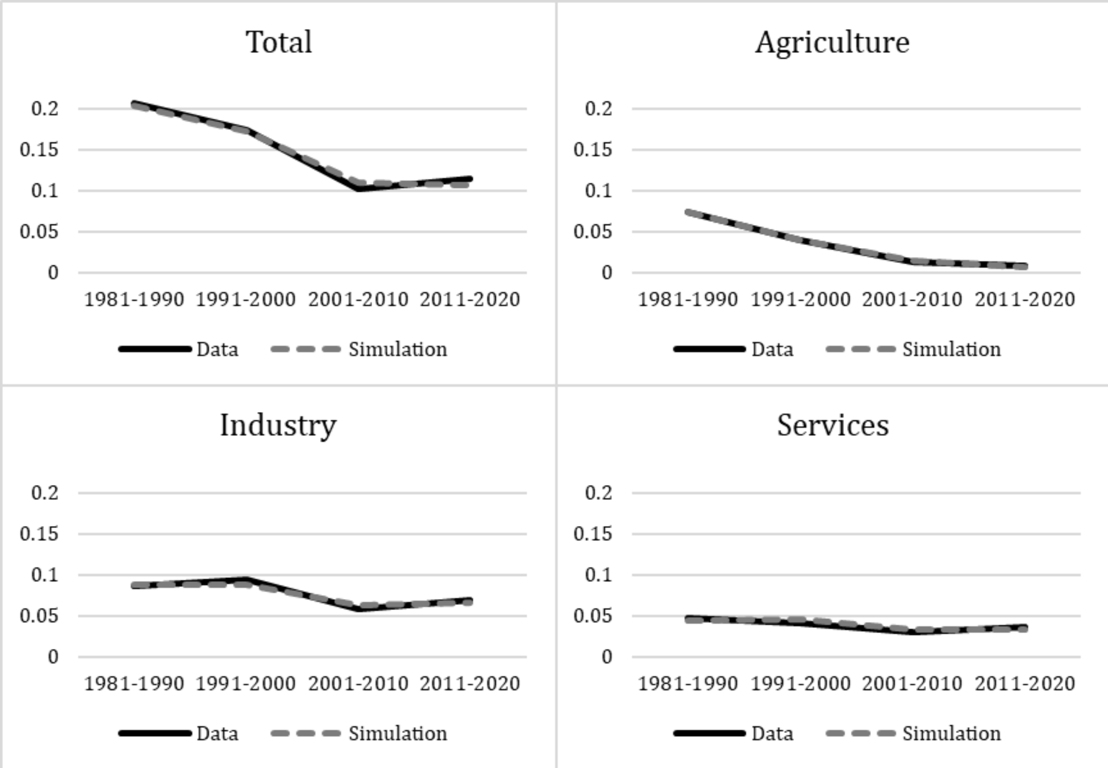


Figure 6.14: Data versus simulated real total and sectoral consumption per productive person of the 41-50 age group ($c_{3,t}$ and $c_{3i,t}$) in 10000 Yuan

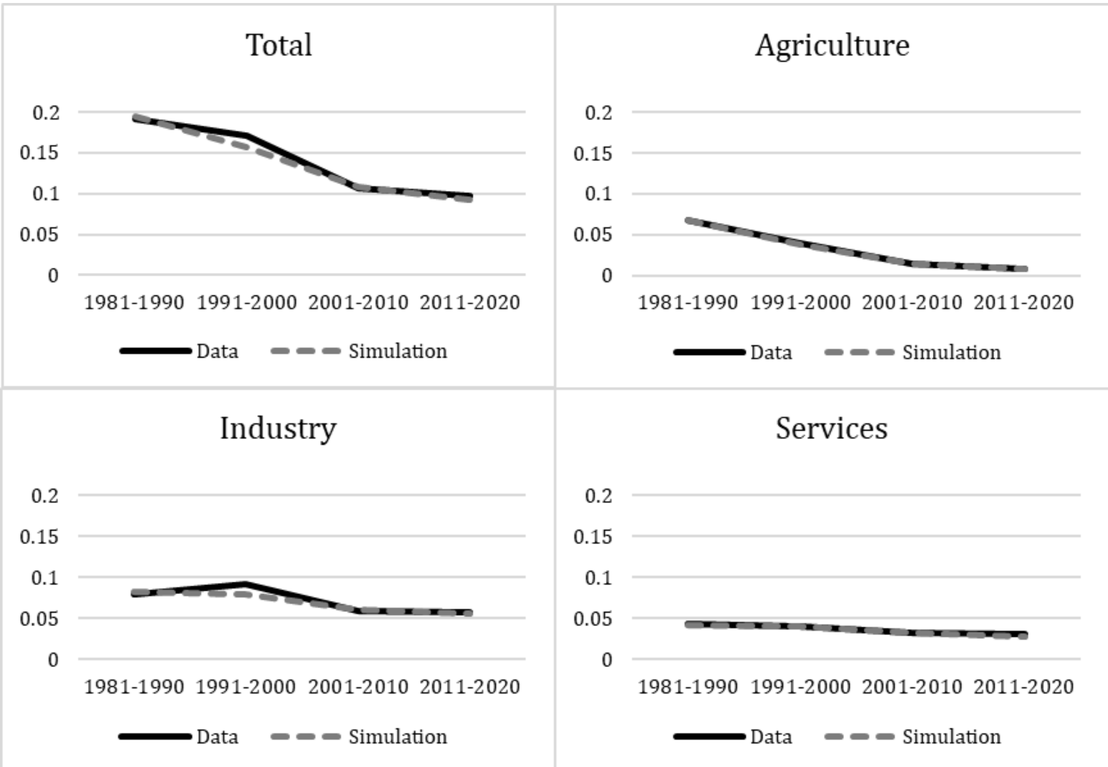


Figure 6.15: Data versus simulated real total and sectoral consumption per productive person of the 51-60 age group ($c_{4,t}$ and $c_{4i,t}$) in 10000 Yuan

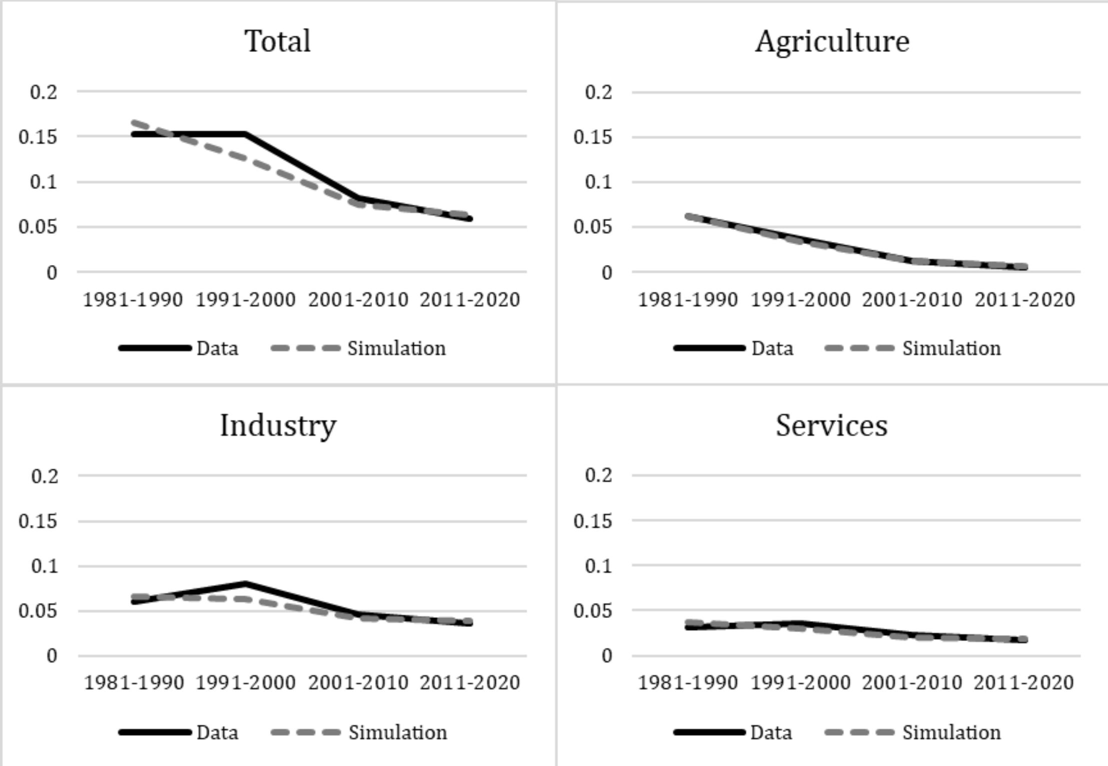


Figure 6.16: Data versus simulated real total and sectoral consumption per productive person of the 61-70 age group ($c_{5,t}$ and $c_{5i,t}$) in 10000 Yuan

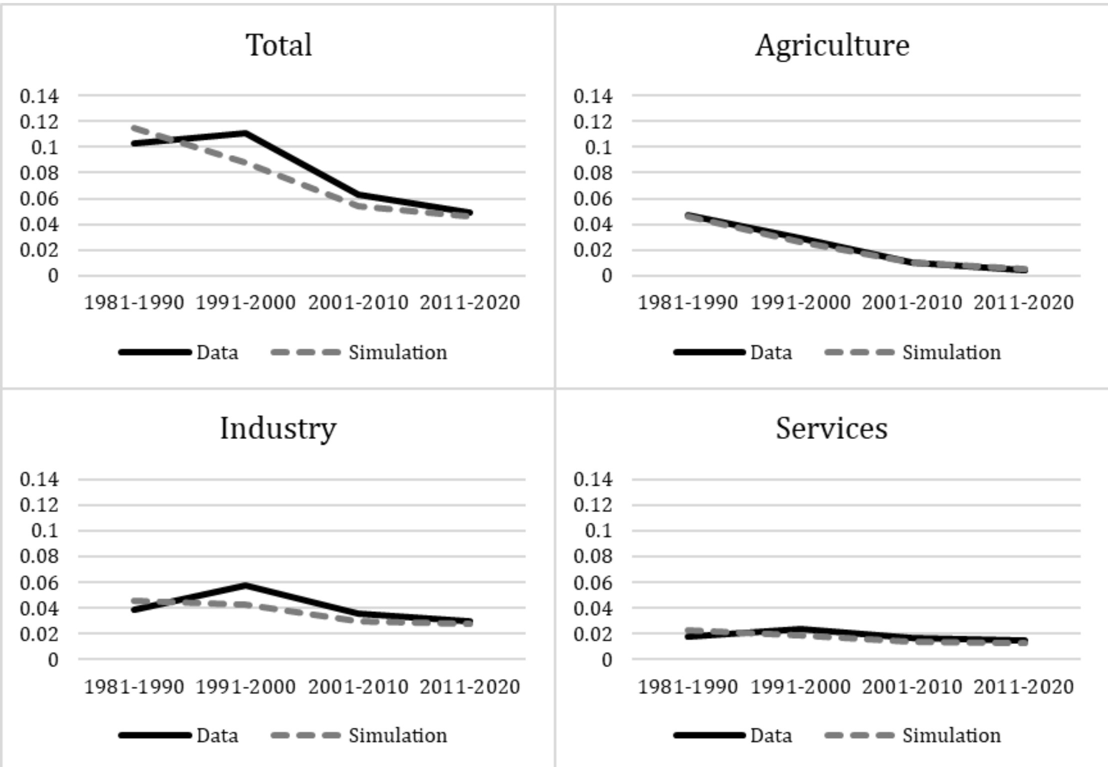
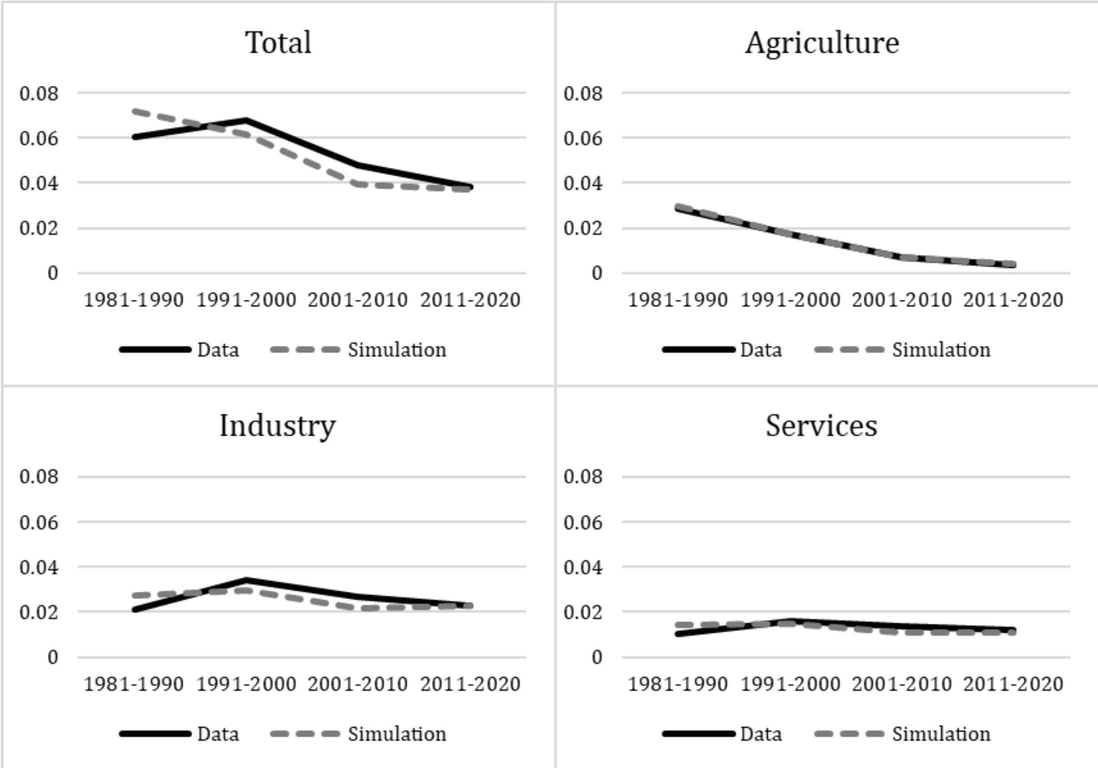


Figure 6.17: Data versus simulated real total and sectoral consumption per productive person of the 71+ age group ($c_{6,t}$ and $c_{6i,t}$) in 10000 Yuan



6.5.1.4 Out of sample predictions

Figures 6.18-6.23 show the within sample and out of sample predictions of the model. As subsistence consumptions dwindle away and relative productivities change, structural change is predicted to continue in terms of output and factor inputs. The model predicts that with an aging population, investment and hence capital per productive labour increase over time. The structural change and rise in capital per productive labour in turn cause output per productive labour to increase. In Section 6.5.2, we will comparatively analyse baseline and counterfactual simulation results. In the process, we will analyse the baseline out of sample predictions in more detail.

Figure 6.18: Baseline simulation of sectoral relative prices p_{it} and capital goods relative price p_{kt}

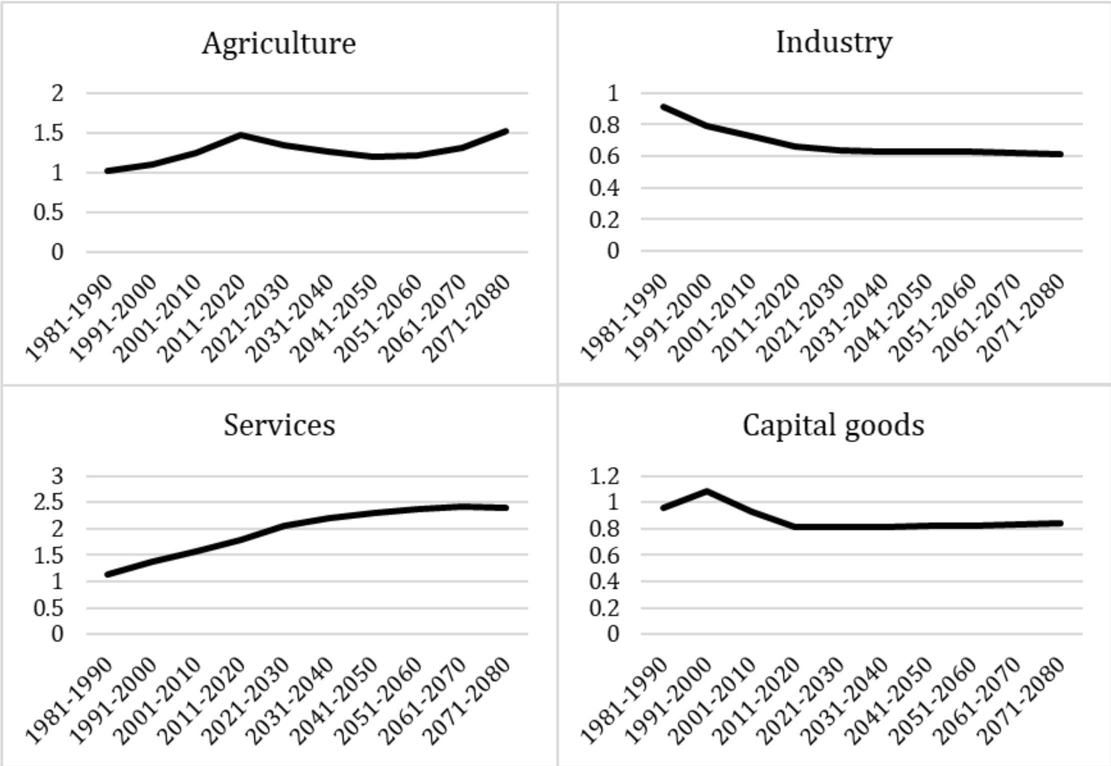


Figure 6.19: Baseline simulation of sectoral labour shares l_{it}

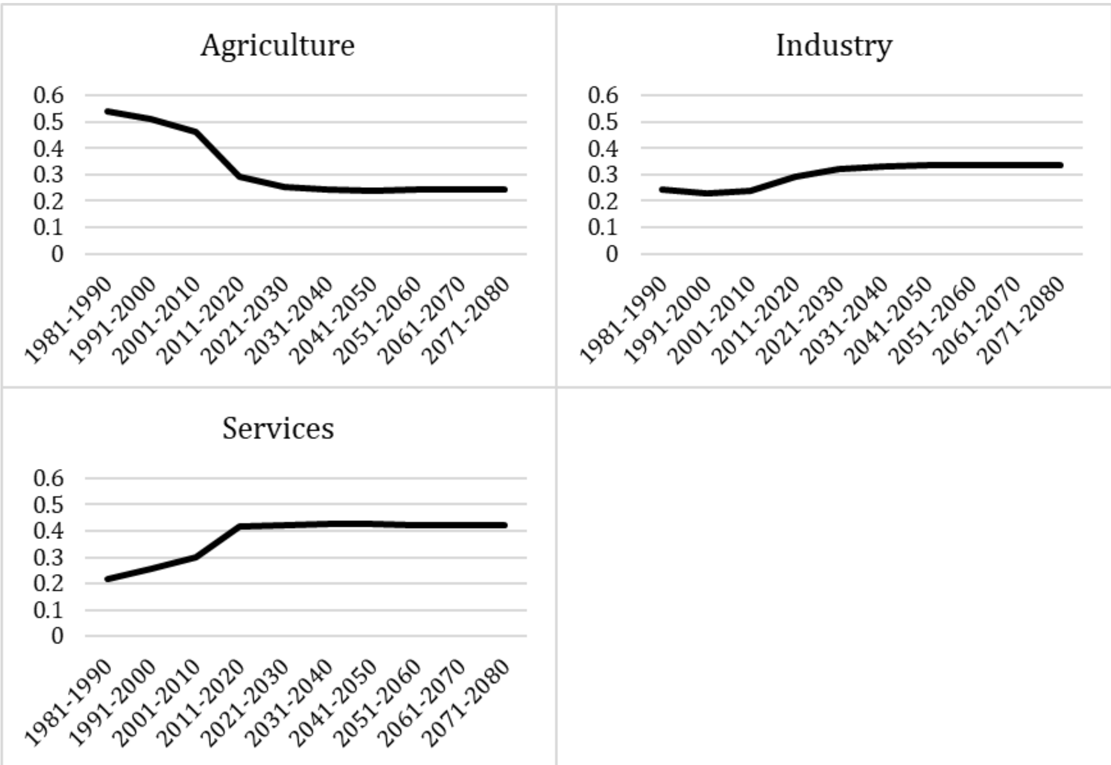


Figure 6.20: Baseline simulation of real aggregate and sectoral capital per productive labour k_t and k_{it} (unit=10000 Yuan)

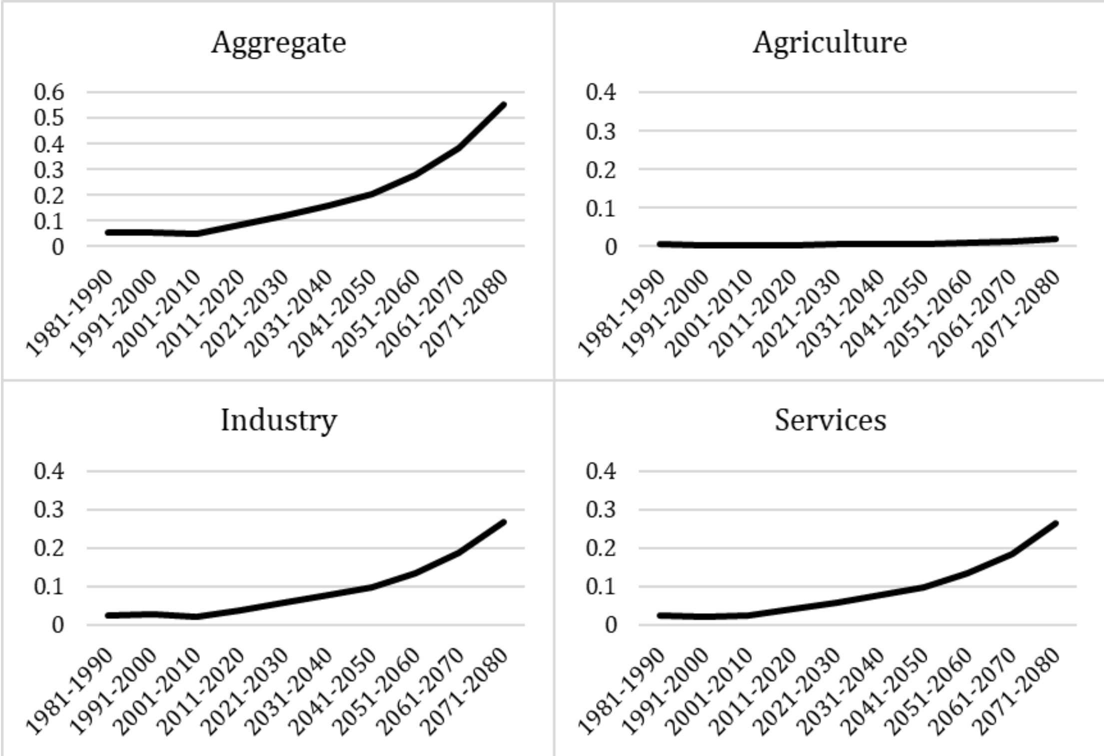


Figure 6.21: Baseline simulation of real aggregate and sectoral output per productive labour y_t and y_{it} (unit=10000 Yuan)

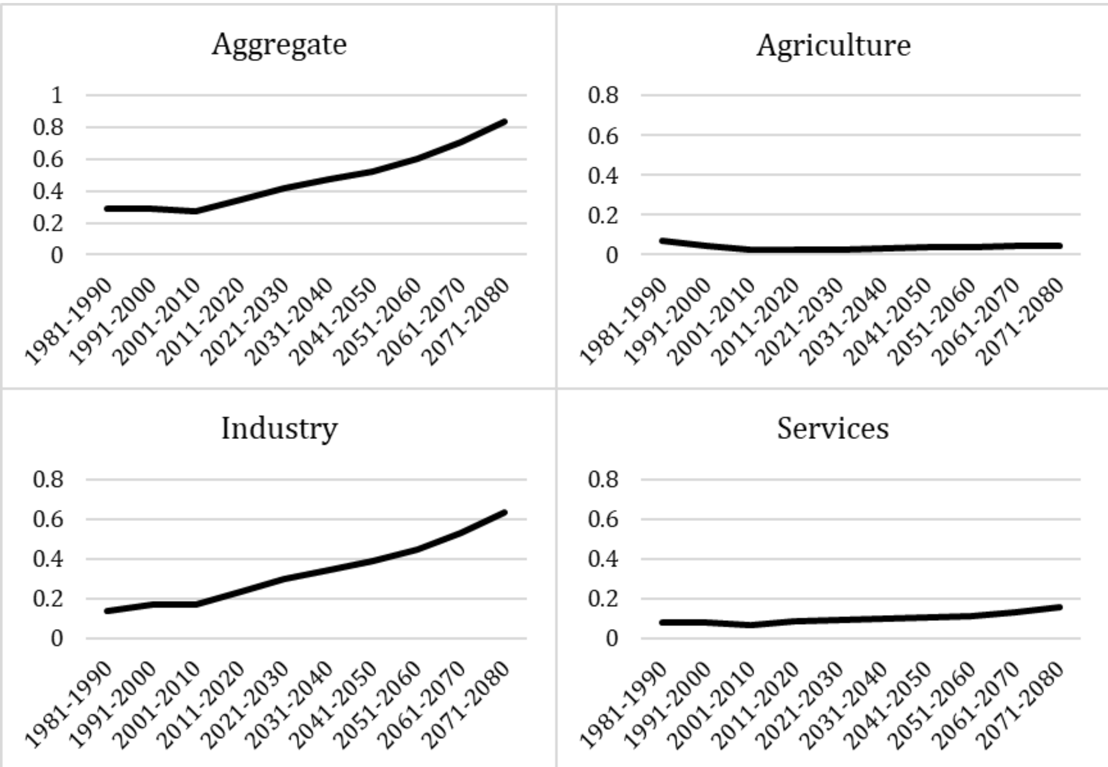


Figure 6.22: Baseline simulation of nominal sectoral output per productive labour $p_{it}y_{it}$ (unit=10000 Yuan)

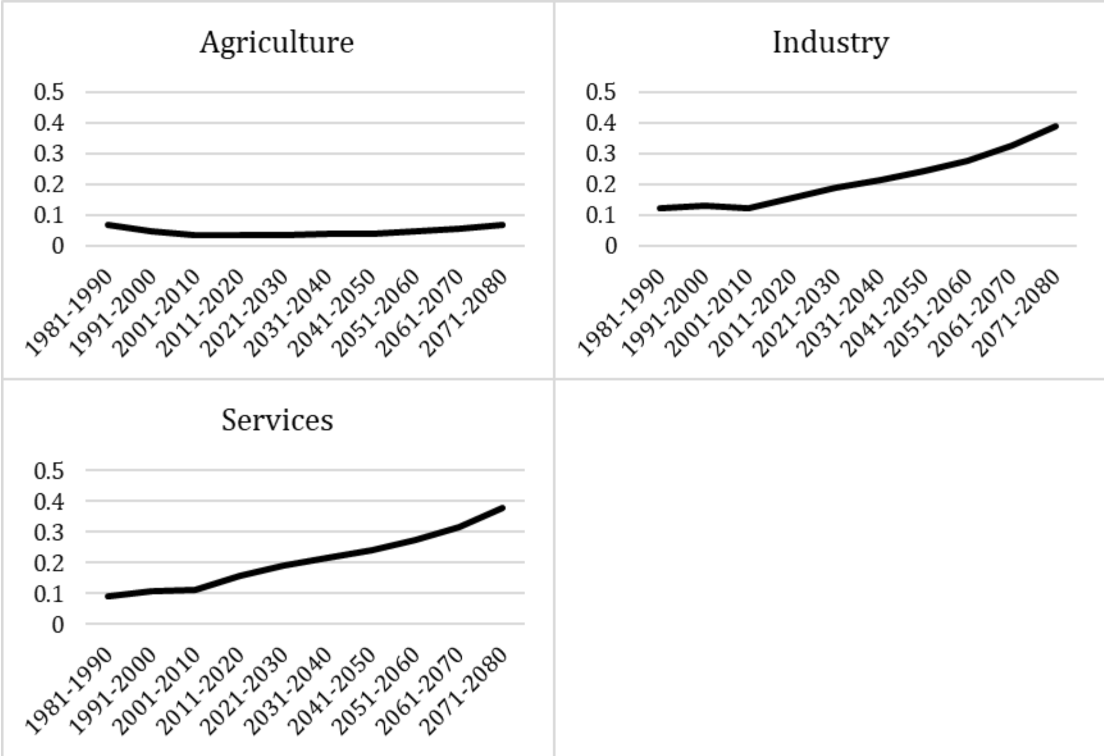
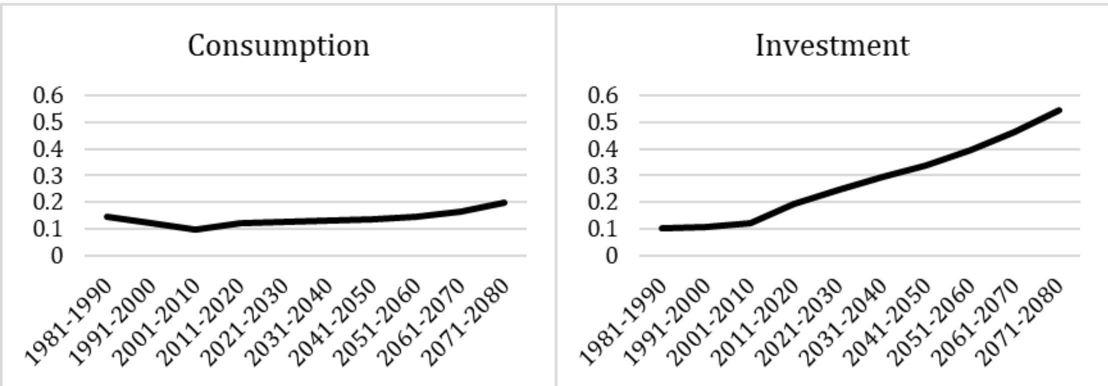


Figure 6.23: Baseline simulation of real consumption and investment per productive labour (unit=10000 Yuan)



6.5.2 Counterfactual simulation

Population aging is determined by the demographic variables for fertility and mortality. To investigate the effects of population aging in China, we conduct a counterfactual simulation in which demographic variables are held constant at initial levels. The effects of aging can then be revealed by comparing the counterfactual simulation with the baseline simulation.

6.5.2.1 Savings and capital

As can be seen in Figure 6.24 and Figure 6.25, per capita real investment and capital in the aging economy grow faster than those in the counterfactual. In accordance with the pace of aging, the aging effects start off strong and then weaken over time. On average, baseline annual real investment and capital per person growth rates are respectively 1.0 and 1.5 percentage points higher than their counterfactual counterparts.

Note that the differences between scenarios in growth rates of per capita variables are the same as differences in growth rates of per productive capita variables. This is because baseline and counterfactual scenarios are deflated by the same productivity measure.

Figure 6.24: Counterfactual and baseline average annual growth rate of real investment per capita

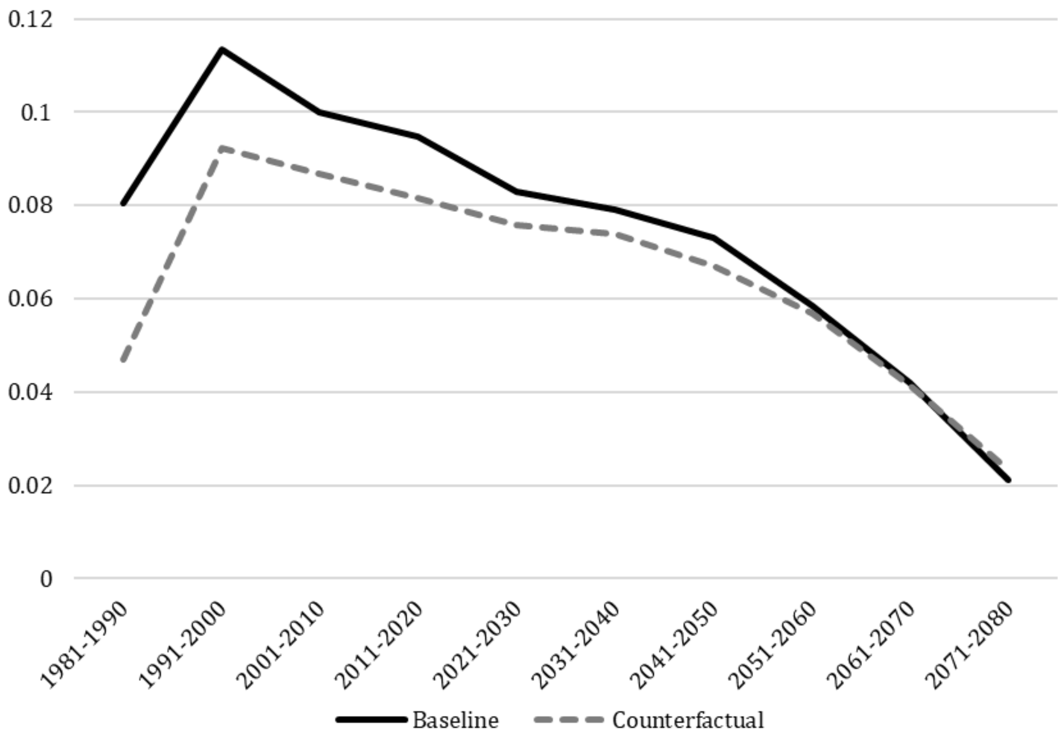
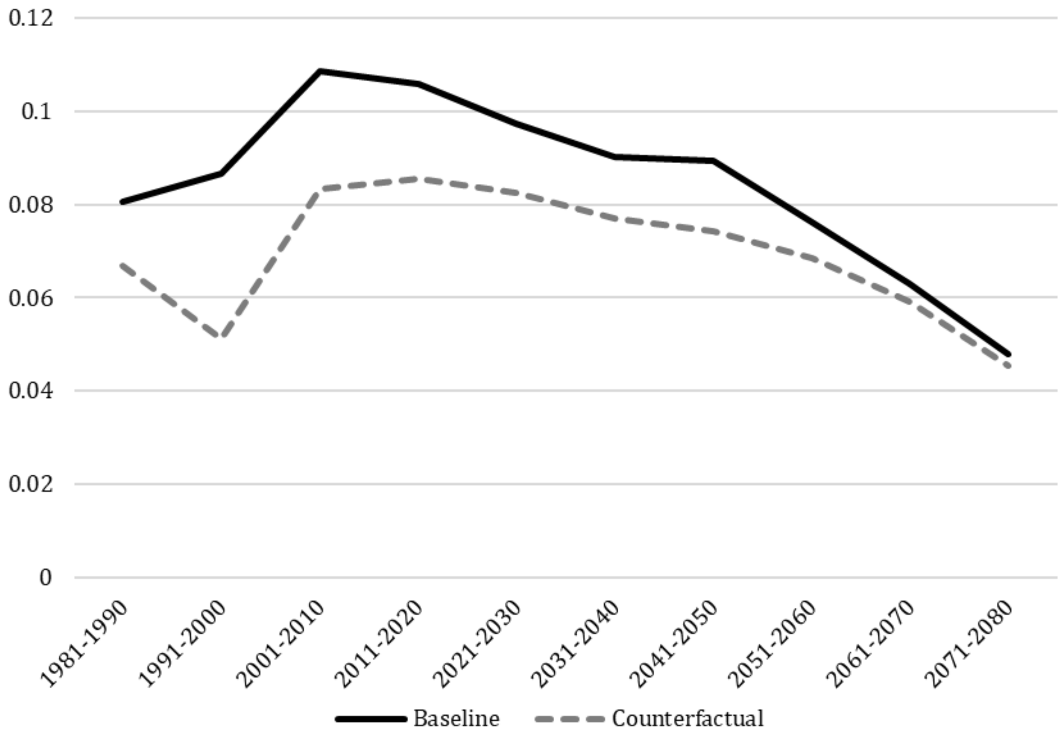


Figure 6.25: Counterfactual and baseline average annual growth rate of real capital per capita



As survival rates increase in the aging economy, people expect to live longer. Consequently, people save more to finance for their retirement. Since savings are the source of capital, aging causes baseline capital per capita to rise faster than the counterfactual.

As fertility plummets in the aging economy, there are less and less people sharing the capital stock. This further contributes to the relative increase in capital per capita in the aging economy.

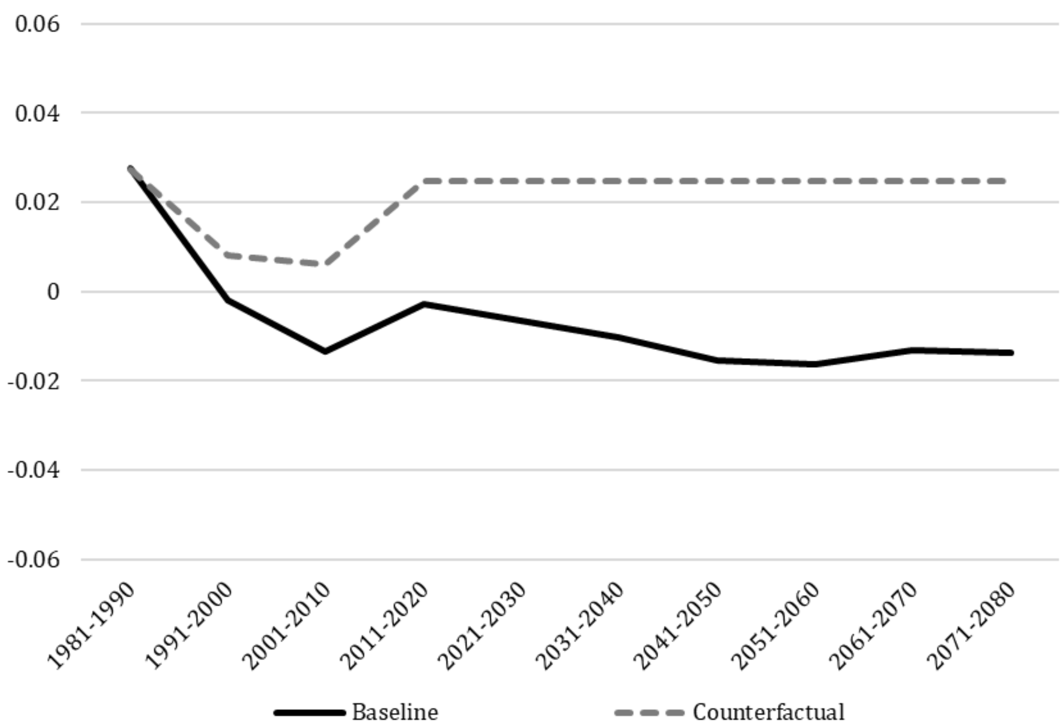
Aging raises the share of elderlies in the population. If elderlies have lower saving rates than younger people, then aging could lower the national saving rate. This is a main mechanism behind the adverse effects of aging in many developed countries. In China, however, elderlies save more than other age groups. Resultantly, population aging does not diminish national saving rate via the aggregate savings channel in China.

The surge in China's saving rates in recent decades have caught a lot of attention. Our results show that the strong positive savings channels and the lack of an adverse savings channel mean that population aging can help explaining the Great Savings Puzzle of China.

6.5.2.2 Labour

In the baseline scenario, population aging causes working age population to shrink, reducing effective labour input directly. Since older people have lower labour participation rates, employment rates, and effectiveness in production, aging of the working age population further diminishes aggregate effective labour by lowering per capita effective labour. The counterfactual economy, on the other hand, features constant population growth and population age structure. Figure 6.26 plots the annualised effective labour growth rates of the two scenarios. As can be seen in the figure, baseline effective labour growth rate falls behind from period 2 onwards. On average, annual effective labour input growth in the aging economy is 2.8 percentage points lower than that in the counterfactual.

Figure 6.26: Counterfactual and baseline average annual growth rate of effective labour



6.5.2.3 Structural change

Private consumption

The preference weight parameters are key determinants of sectoral consumption shares. As captured by the age-varying preference weights in Appendix 6.2, in the long term, elderlies spend greater shares of their incomes on agricultural and industrial consumption, and smaller shares of their incomes on service consumption compared to younger people. Population aging therefore impedes structural change from agriculture to the modern sectors. Within the modern sector, population aging facilitates structural change away from services and towards industry.

Older people have lower price elasticities of demand as captured by their lower σ_g's. Resultantly, the aging economy reacts differently to relative price changes compared to the counterfactual economy. The implications of this will be discussed later.

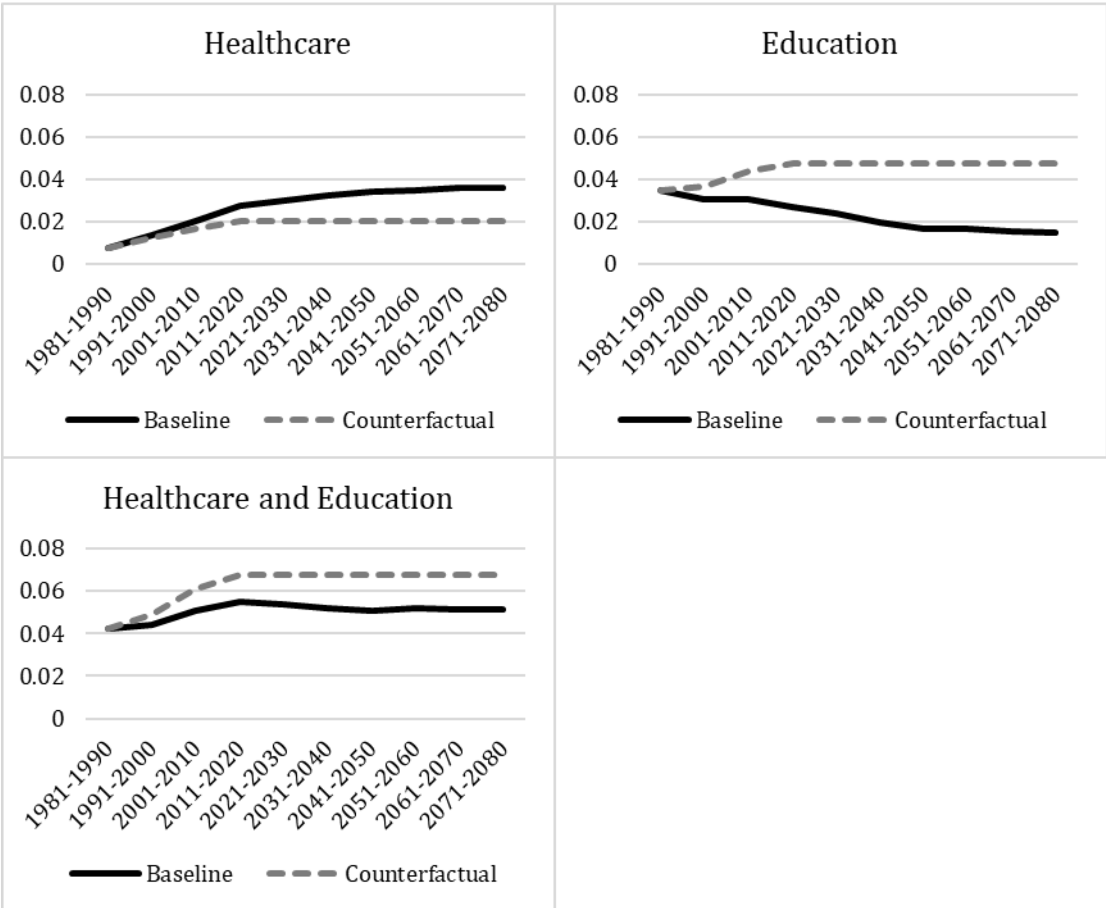
Income effect associated with subsistence and endowment consumptions is a key driver of structural change in the first three periods. However, after 2020, income effect ceases to have much impact as subsistence and endowment consumptions become very small relative to income.

Public consumption

Compared to younger people, older people require more public healthcare and less education. Government consumption can therefore depend on the economy's age structure. Following the procedure described in Section 6.4, we estimate government health and education spending in the two scenarios. Figure 6.27 shows that baseline government healthcare spending's share in GDP rises relative to the counterfactual, opening up a gap that expands to 1.6% of GDP by the 2071-2080 period. Meanwhile, government education expenditure's share in the aging economy falls relative to that in the counterfactual. By the 2071-2080 period, the aging economy devotes 3.2% less of its

GDP to public education than the counterfactual economy. Overall, government healthcare and education consumption's share in GDP in the baseline is predicted to be 1.6 percentage points smaller than that in the counterfactual by the 2071-2080 period. This means population aging's net effect on government spending as a share of GDP is negative. Since government consumption is overwhelmingly on services, population aging impedes structural change towards the service sector via the government consumption channel.

Figure 6.27: Counterfactual and baseline government spending on healthcare and education as shares of GDP



To explain the result, we turn to the data behind it. In the baseline scenario, the increase in elderly (61+) population share between 1981 and 2080 is large, from 13% to 53%. However, the decrease in population share of very young people aged from 0 to 22 is also large, from 49% to 17%. While elderlies occupy a large share of public healthcare consumption, the very young are the sole users of public education consumption. The impact of aging on public education is therefore more direct and stronger than that on public healthcare. The overall effect of aging is amplified by the fact that the Chinese government spends relatively more on education than on health.

Capital deepening

As mentioned earlier, population aging raises per capita capital accumulation and reduces per capita labour input. These cause capital per labour in the aging economy to increase relative to that in the counterfactual. Such relative capital deepening affects the structure of the economy in a number of ways.

Since the vast majority of capital goods are produced in industry, capital deepening in the aging economy leads to structural change towards the industrial sector.

As labour becomes scarcer and capital becomes more abundant, factor price of labour rises relative to that of capital. This raises the relative costs of production and hence relative price of the more labour-intensive sectors. In China, labour intensity is the highest in agriculture, followed by services, and then by industry. Therefore, aging induces agricultural price to rise relative to service price, and service price to rise relative to industrial price (Figure 6.28). The positive aging effect on agricultural price is strong enough to eventually outweigh the negative effects resulting from relative productivity growths. The positive effect is strong because agriculture in China is overwhelmingly labour intensive and is thus more sensitive to the aforementioned factor cost changes.

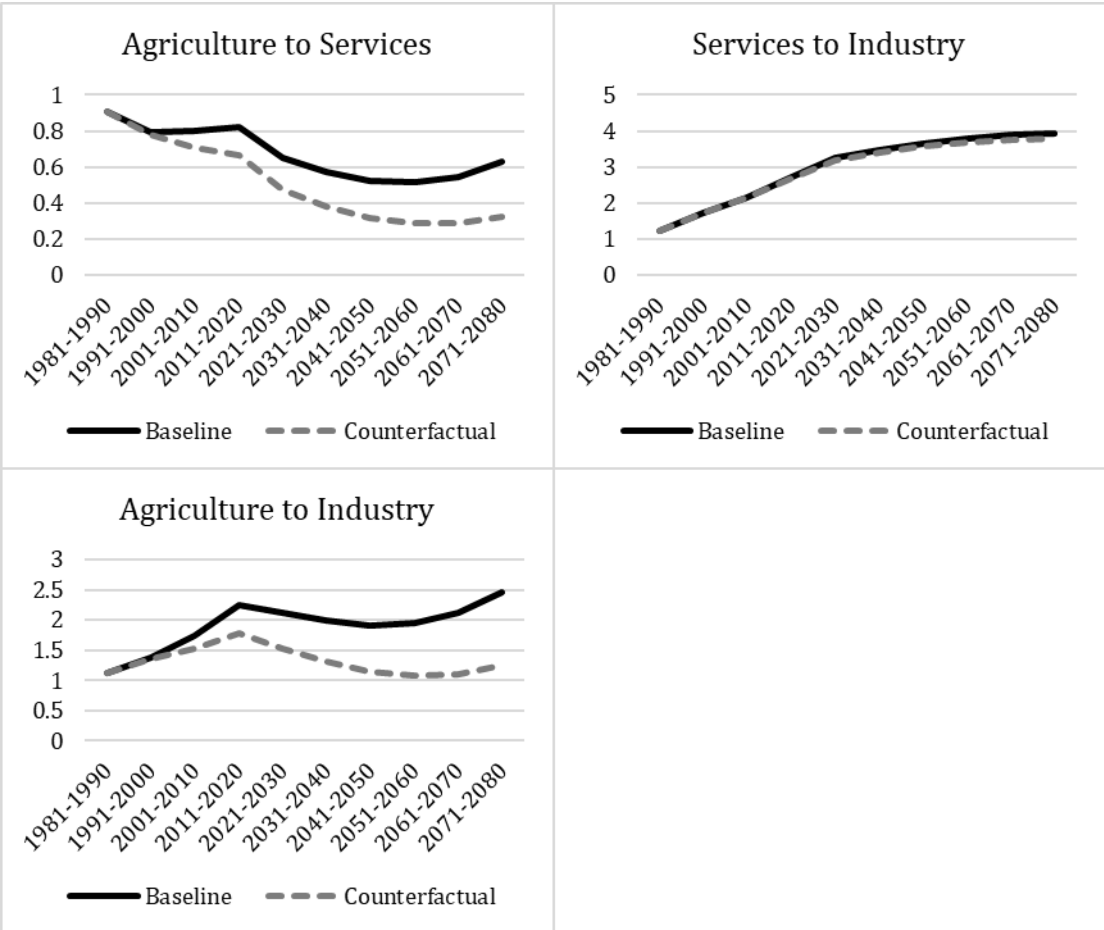
In response to the relative price changes caused by aging, consumers reduce real agricultural consumption and increase real modern sector consumption. Within the modern sector, real consumption is induced to shift from services to industry.

The implications for nominal consumptions are different. Since σ_g's of all age groups are less than one, the economy's demand is price inelastic. When prices change, real consumption respond less than proportionately. The aforementioned relative price changes therefore cause agricultural nominal consumption to rise relative to modern sector nominal consumption.

The aforementioned effects of capital deepening interact with aging's effect on preferences. As mentioned earlier, population aging lowers the economy's price elasticity of demand. This makes capital deepening's effects on real consumption smaller and those on nominal consumption bigger.

In summary, aging-induced capital deepening facilitates structural change in real terms but impedes structural change in nominal terms. Aging-induced reductions in the economy's price elasticity of demand hinder capital deepening's facilitation of real structural change and intensify capital deepening's impediment to nominal structural change.

Figure 6.28: Counterfactual and baseline relative prices between sectors



Relative productivity and price changes

Over the 1981-2080 period, service productivity experienced the least growth. This induces service relative price to rise (Figure 6.28 and Figure 6.18). Agricultural productivity growth starts off as the slowest of the three but it surges between 1981 and 2020. These partially explain why agricultural relative price rises and then falls. The fall in agricultural relative price reverts eventually due to the convergence of sectoral productivity growth rates and capital deepening. Overall, agricultural price falls relative to service price and rises relative to industrial price between 1981 and 2080.

The aforementioned price changes induce real service consumption to fall relative to real agricultural consumption, and real agricultural consumption to fall relative to real industrial consumption. In nominal terms, the price changes induce service consumption to rise relative to agricultural consumption, and agricultural consumption to rise relative to industrial consumption. In the aging economy, price elasticity of demand is smaller. As a result, the aforementioned real changes in sectoral consumptions are smaller and the nominal changes are bigger in the aging economy than in the no-aging economy.

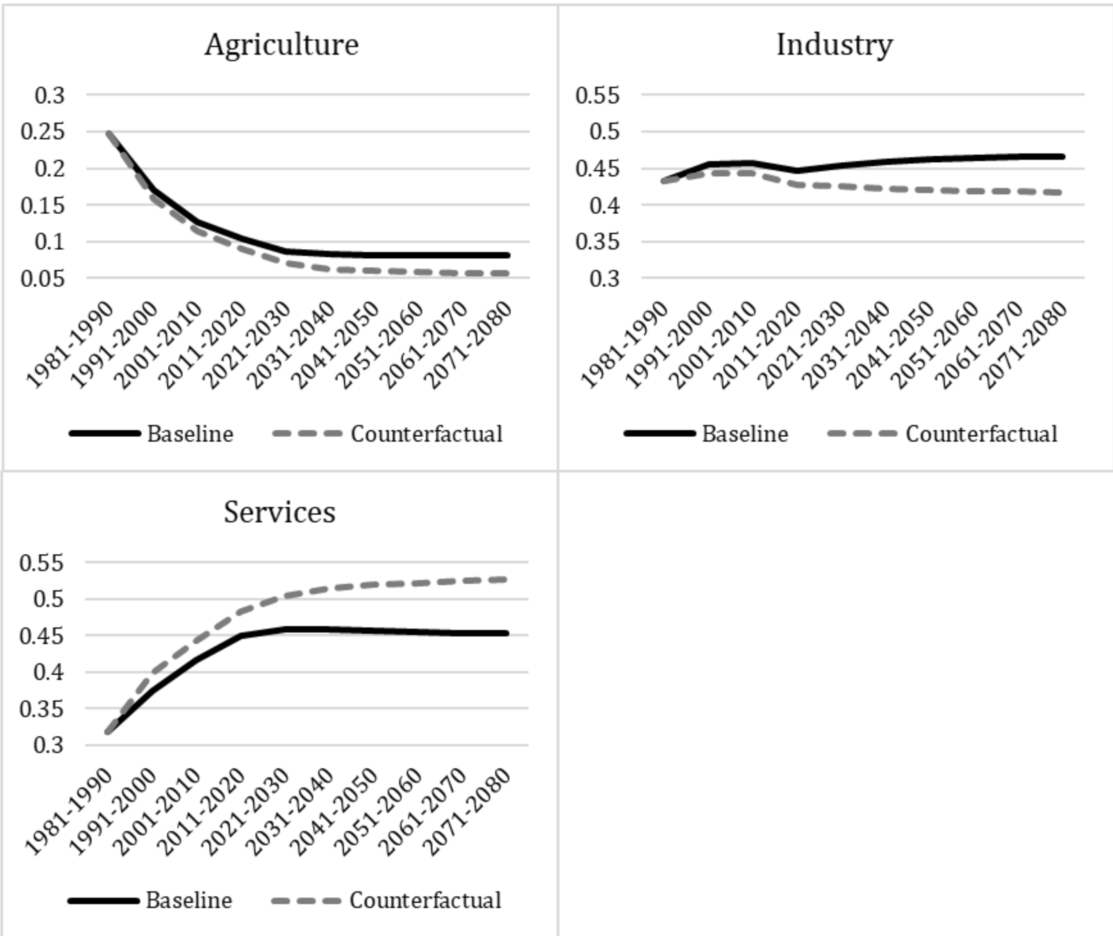
Sectoral nominal output

Figures 6.29 plots sectoral nominal output shares. As can be seen in the figure, population aging facilitates structural change towards industry but impedes structural change towards services. Compared to the counterfactual, baseline service share grows slower and industrial share grows faster. By period 10 (2071-2080), baseline service share is 7.3 percentage points lower and industrial share is 4.9 percentage points higher than their counterfactual counterparts.

Figure 6.29 shows that agricultural share in the aging scenario falls slower compared to that in the counterfactual. By period 10 (2071-2080), the gap between baseline and counterfactual shares reaches 2.5 percentage points. This means population aging impedes structural change in China overall. The aging effect on agricultural share is not small considering that agriculture constitutes a small share of GDP of about 10% as early as the 2011-2020 period, and that the total change in agricultural share between the 2011-2020 and 2071-2080 periods is about 3 percentage points in both scenarios.

The results in Figure 6.29 are not surprising as age effects through the channels of preferences, government consumption, and savings serve to impede China's structural change from agriculture to the modern sectors and or from industry to services. Although some opposite effects are generated as the relative price changes originating from productivity changes interact with aging's effect on elasticities, such effects turn out to be relatively small.

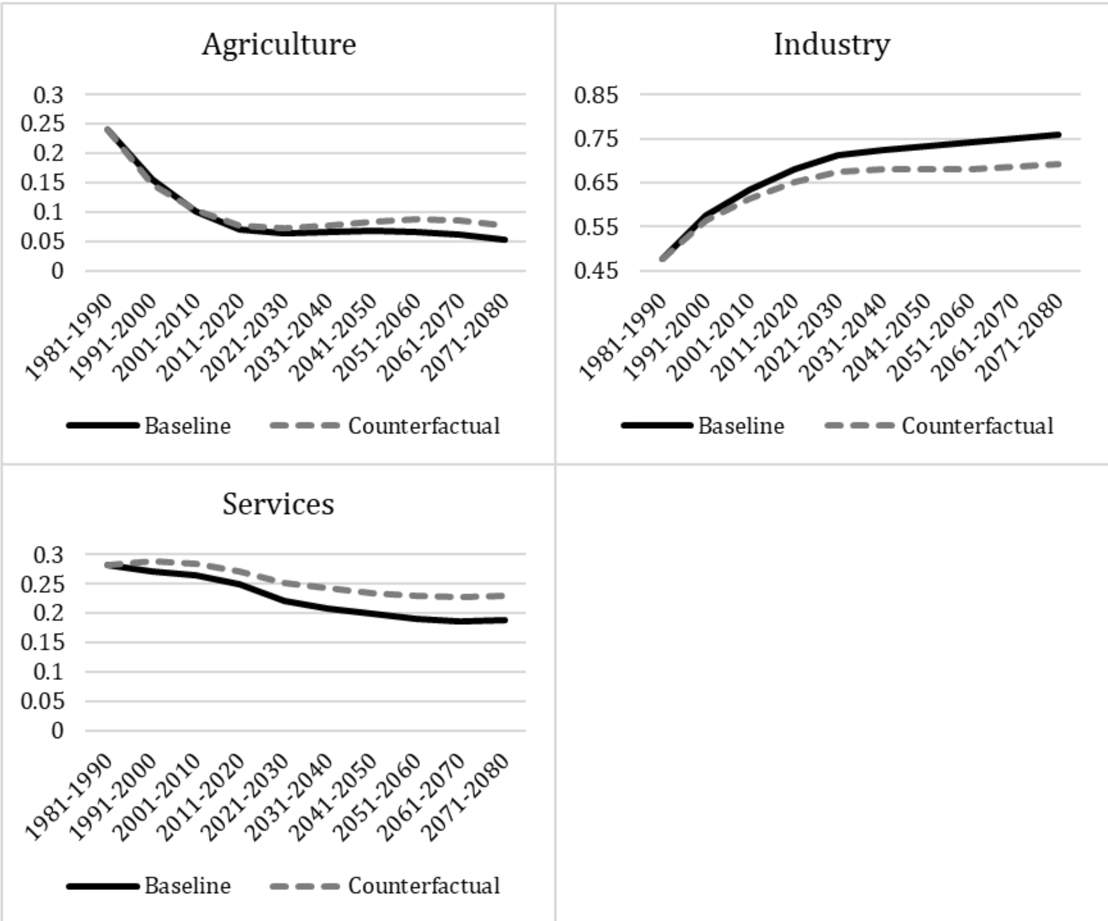
Figure 6.29: Counterfactual and baseline sectoral shares in nominal GDP



Sectoral real output

Simulation results for real sectoral output shares can be found in Figure 6.30. Through the channels of savings, preferences, and government consumption, aging facilitates structural change towards industry but impedes structural change towards services. By the 2071-2080 period, baseline service share is 4.3 percentage points lower and industrial share is 6.5 percentage points higher than their counterfactual counterparts.

Figure 6.30: Counterfactual and baseline sectoral shares in real GDP

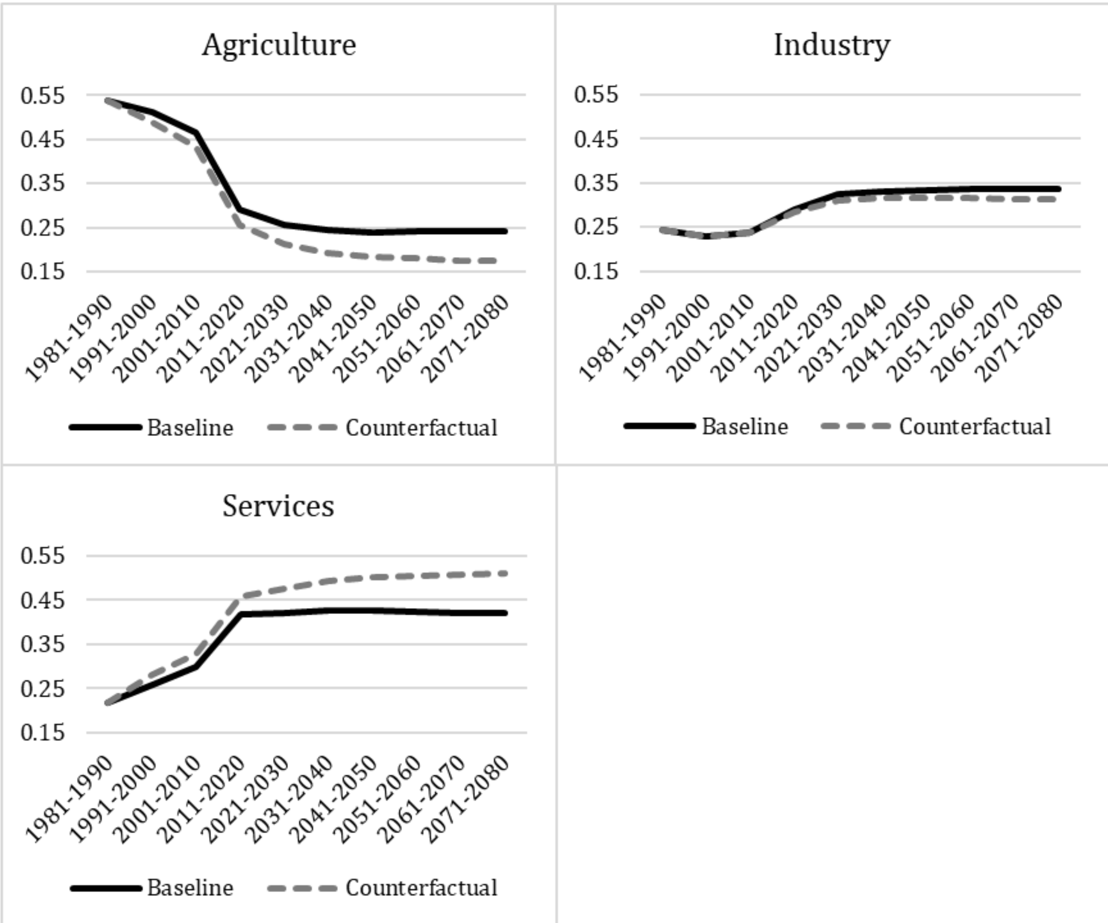


Contrary to the positive aging effect on nominal agricultural share, the aging effect on real agricultural share is negative. By period 10 (2071-2080), baseline agriculture share is 2.2 percentage points lower than the counterfactual. The negative aging effect on real agricultural share can be explained by the aging-induced capital deepening. For a start, capital deepening shifts economic activity from agriculture to industry where capital is produced. More importantly, capital deepening raises the relative price of agriculture. The increase in agricultural price is strong due to the overwhelming labour intensity of Chinese agriculture. In response, real demand and hence output for agriculture falls, explaining the observations in Figure 6.30.

<u>Sectoral factor input</u>

The higher agricultural and industrial output shares in the aging economy are achieved by drawing factor resources from services. Figure 6.31 shows the evolutions of sectoral labour shares.

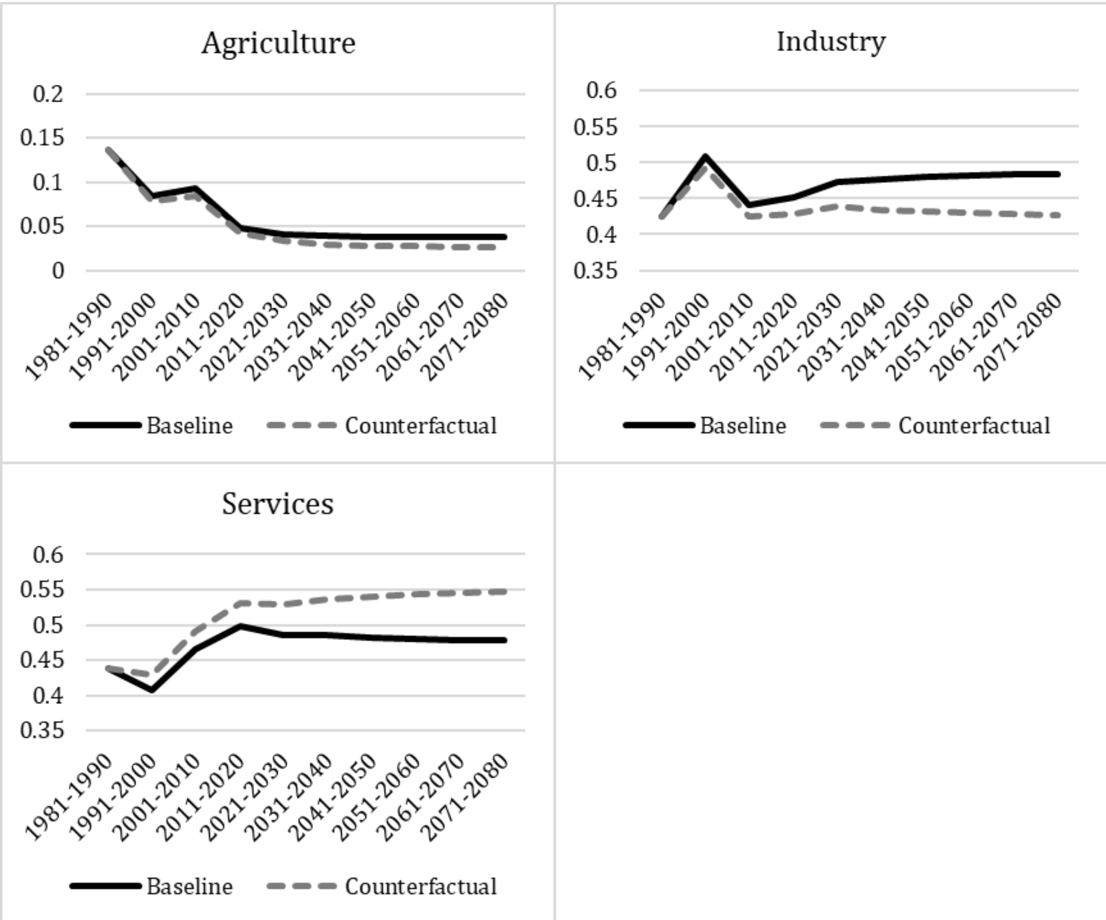
Figure 6.31: Counterfactual and baseline sectoral shares in effective labour



As can be seen in Figure 6.31, by the 2071-2080 period, the aging economy's agricultural labour share is 6.6 percentage points higher, industrial labour share is 2.3 percentage points higher, and service labour share is 8.9 percentage points lower than their counterfactual counterparts. The increase in agricultural labour share due to aging is large considering the relatively small increase in nominal agricultural output share. This is due to the fact that agriculture is much less productive and much more labour intensive than industry.

Sectoral capital shares also shift from service to agriculture and industry as a result of aging. As shown in Figure 6.32, by the 2071-2080 period, baseline agricultural share is 1.2 percentage points higher, industrial share is 5.7 percentage points higher, and service share is 6.9 percentage points lower than their counterfactual counterparts.

Figure 6.32: Counterfactual and baseline sectoral shares in capital



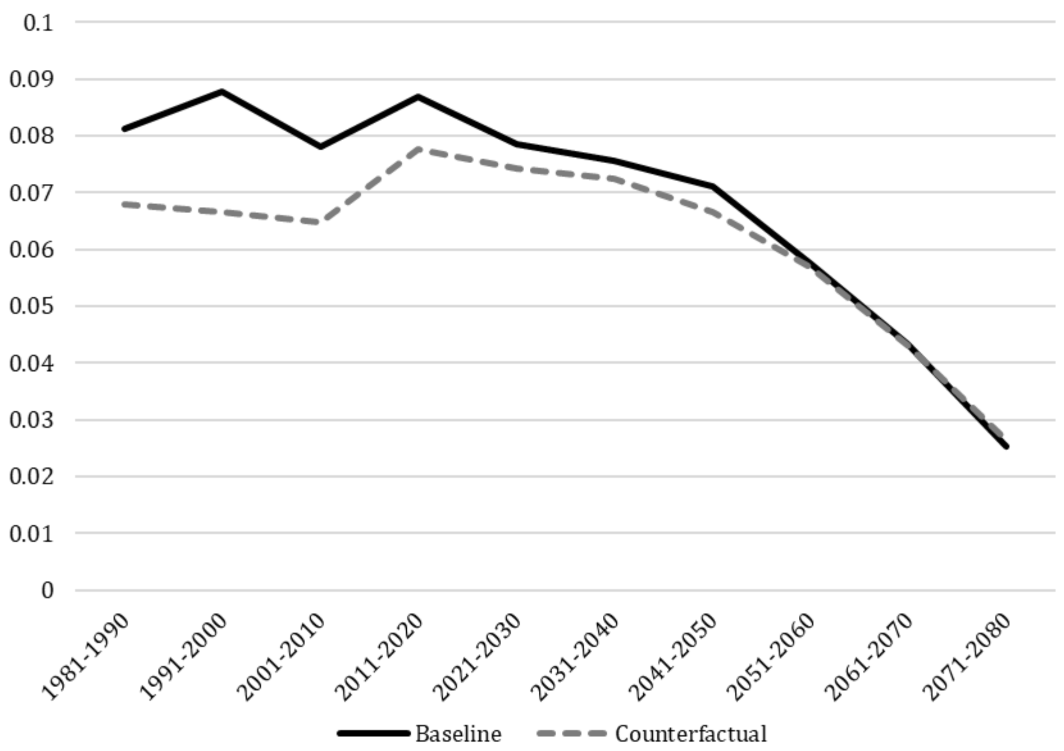
6.5.2.4 Output

Per capita output

Figure 6.33 shows that population aging leads to faster real per capita GDP growth. Consistent with the pace of aging, the effect is relatively stronger in the first three periods, after which it diminishes. On average, population aging raises annual real per capita GDP growth by 0.7 percentage points over the 1981-2080 period.

Aging raises per capita GDP mainly by raising per capita savings and hence capital input. Aging also raises per capita GDP growth through structural change. As mentioned earlier, aging impedes structural change towards services and facilitates structural change towards industry. Since productivity is the highest in industry, these aging effects raise aggregate productivity growth. Although aging causes structural change towards agriculture, the change is relatively small. Overall, population aging raises aggregate productivity and hence per capita GDP growth through structural change.

Figure 6.33: Counterfactual and baseline average annual growth rate of real GDP per capita



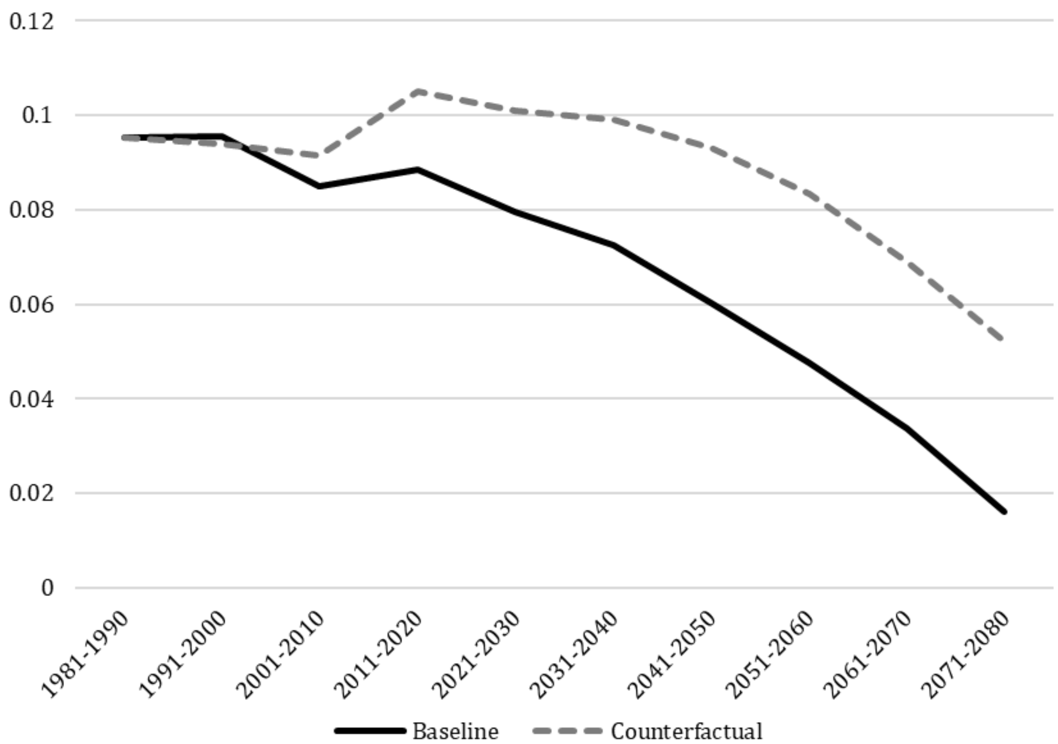
Population aging shrinks the working age population relative to the population. In addition, older people have lower labour participation rates, employment rates, and labour effectiveness. These mean that population aging lowers per capita effective labour input, thereby negatively affecting per capita output.

Overall, the results in Figure 6.33 show that aging's effect on per capita income growth is positive as the positive aging effects acting through capital and structural change outweigh the negative effects acting through effective labour.

Aggregate output

As can be seen in Figure 6.34, aggregate real GDP growth in the aging economy falls below that in the counterfactual in the third period (2001-2010) and increasingly so over time. On average, real GDP in the aging economy grows by 2.1 percentage points slower each year than that in the counterfactual.

Figure 6.34: Counterfactual and baseline average annual growth rate of real GDP



All the aging mechanisms discussed above that affect per capita GDP growth also influence aggregate GDP growth. The key explanation for the aging economy's relative decline lies in its plummeting effective labour supply. As mentioned earlier, while effective labour drops sharply in the aging economy due to the shrinkage and aging of working age population, effective labour in the counterfactual grows at a constant rate. In the first two periods, baseline annualised real GDP growth is higher than the counterfactual because the shortfall of baseline effective labour growth is small, allowing the positive aging effects to dominate. After the second period (1991-2000), the difference in effective labour growth between the two scenarios expands rapidly, causing baseline real GDP growth to fall below its counterfactual counterpart.

6.6 Sensitivity analysis

In this section, we examine how alternative assumptions about parameters and exogenous variables affect our results. Tables 6.2 and 6.3 summarise the results under alternative scenarios. The scenario discussed in the previous section is referred to as the main scenario and is listed first in the tables.

In general, our results are robust to changes parameters and exogenous variables. Although the aging effect sizes might change, the age effect directions stay the same under a large variety of alternative scenarios that we experimented with.

6.6.1 No government spending channel

In our main simulation analysis, we estimated and incorporated the changes in government healthcare and education spending due to population aging. We assumed that age profiles of government healthcare consumption can be approximated by those of private healthcare consumption. This assumption could lead to inaccuracies. In addition, the assumption that age consumption profiles stay constant in the future is questionable.

A number of studies have put forth that education and health spending may increase in an aging environment. They have argued that, for example, as capital deepening takes place, wages increase relative to rents, which causes human capital investment to become more attractive relative to physical capital investment. Rising longevity also expands the horizon over which the return to human capital investment can be realised, thereby encouraging human capital investment. If age profiles of public education and healthcare spending shift upwards due to aging, then aging may not reduce government spending.

Table 6.2: Sensitivity test results: Percentage difference between baseline and counterfactual scenarios by the 2071-2080 period

	Sectoral nominal GDP shares			Sectoral real GDP shares			Sectoral labour shares			Sectoral capital shares		
	a	d	s	a	d	s	a	d	s	a	d	s
Main scenario	2.5	4.9	-7.3	-2.2	6.5	-4.3	6.6	2.3	-8.9	1.2	5.7	-6.9
No Government spending channel	2.4	4.3	-6.7	-2.1	6.0	-3.8	6.4	1.9	-8.3	1.2	5.1	-6.3
$\delta = 0.401$	2.5	4.9	-7.4	-2.2	6.6	-4.4	6.8	2.3	-9.1	1.2	5.8	-7.0
$\rho = 1.2$	2.3	4.4	-6.7	-2.3	6.2	-3.9	6.2	2.0	-8.3	1.1	5.1	-6.3
$\rho = 0.8$	2.7	5.5	-8.2	-2.2	6.9	-4.7	7.1	2.6	-9.7	1.3	6.5	-7.8
Alternative capital productivity path	2.4	4.8	-7.3	-1.7	6.1	-4.4	6.5	2.2	-8.8	1.2	5.7	-6.9
Alternative data for capital price and investment	2.5	4.9	-7.3	-2.3	6.5	-4.2	6.6	2.3	-8.9	1.2	5.7	-6.9

For reasons mentioned in the previous paragraph, we conduct a simulation in which the government spending channel is shut down. In this simulation, government spending's share of GDP is non-responsive to aging and stays constant after the 2011-2020 period. As can be seen in Tables 6.2 and 6.3, shutting down the government spending channel does not change our qualitative results. The aging effects on structural change are slightly smaller, by about 8% on average. In other words, the government spending channel in our main simulation accounted for about 8% of the effects of aging on structural change. The impact of shutting down the government spending channel on the growth rate results in Table 6.3 are very small.

Table 6.3: Sensitivity test results: Percentage differences between baseline and counterfactual average annual growth rates over the 1981-2080 period

	Real investment per person	Real capital per person	Real GDP per person	Real GDP
Main scenario	1.00	1.52	0.69	-2.09
No Government spending channel	0.96	1.48	0.66	-2.12
$\delta = 0.401$	1.05	1.61	0.73	-2.05
$\rho = 1.2$	0.98	1.51	0.67	-2.11
$\rho = 0.8$	1.03	1.54	0.71	-2.08
Alternative capital productivity path	0.97	1.48	0.67	-2.13
Alternative data for capital price and investment	1.00	1.51	0.68	-2.11

6.6.2 Alternative depreciation rate

In Chapter 2, we obtained a long-term average depreciation rate of 7.2% for China. The annual depreciation rate used in the Chinese literature typically ranges from 5% to 10%. We test the robustness of our results to changes in the depreciation rate by setting annual depreciation rate to 5%. Since each period in our model corresponds to 10 years, this amounts to reducing periodic depreciation rate in our model from 0.52 to 0.40. As can be seen in Tables 6.2 and 6.3, The change in depreciation rate has little impact on our results.

6.6.3 Alternative intertemporal elasticity of substitution

The intertemporal elasticity parameter ρ is the only parameter that we did not estimate. We simply took a commonly used value of 1 which implies log utility and thus better analytical tractability. The empirical literature has shown that ρ could be higher or lower than one. We therefore conduct two sensitivity tests, with the value of ρ set to 1.2 and 0.8, respectively. As can be seen in Tables 6.2 and 6.3, alternative values of ρ lead to little changes in results.

6.6.4 Alternative future path of capital productivity

In our main scenario, we assumed that capital productivity A_{kt} stays constant after period four because A_{kt} is close to one and fluctuates around one in the within sample period. To test the robustness of our results, we experiment with a scenario in which A_{kt} continues to grow in the future at the same growth rate as that between period three and four. Since p_{kt} cannot deviate much from $p_{at}^{\mu_a} p_{dt}^{\mu_d} p_{st}^{\mu_s}$ in theory, we do not expect A_{kt} to explode. We therefore assume A_{kt} would stop growing in period twelve and stays constant afterwards. As can be seen in Tables 6.2 and 6.3, changing the future path of A_{kt} has little effect on our results.

6.6.5 Alternative capital price and real investment series

In the main scenario, we used data for capital price index p_{kt} and obtained real investment by deflating nominal investment. An alternative approach would be to compute aggregate real investment data by adding up sectoral real investment and estimate p_{kt} as the ratio of nominal to real aggregate investment. A_{kt} and μ_i can then be calibrated like before. The results using alternative p_{kt} and i_t series can be seen in Tables 6.2 and 6.3. Once again, the results are almost the same as those from the main scenario.

6.7 Conclusion

In this chapter, we calibrated and simulated an overlapping generations model of China with six generations and three sectors. We investigated how population aging affects structural change and economic growth in China via the channels of preferences, savings, effective labour, and government expenditures.

The preference channel stems from differences in preferences across age. In China, older people have greater preferences for agricultural and industrial consumption and less preference for services compared to younger people. Therefore, population aging impedes China's structural change towards services. Elderlies in China have lower price elasticities of demand than others. This means aging lowers the economy's responsiveness to changes in prices. To alleviate aging's negative effects on services, policymakers can consider encouraging elderly service consumption by, for example, facilitating the development of service industries that meet the elderlies' wants and needs.

As people expect to live longer, they save more to finance for their retirement. As fertility plummets, there are less and less people sharing the capital stock. Furthermore, old people in China tend to save more than others. These mean population aging raises savings and hence capital per capita in China. The positive aging effect on savings can hinder China's efforts to transition towards a more consumption-oriented economy. Reforming the pension system and improving elderlies' access to consumption can help raise elderlies' consumption vis a vis savings.

Population aging shrinks the working age population, thereby shrinking the economy's effective labour input. Since older people have lower labour participation rates, employment rates, and effectiveness in production, aging further diminishes aggregate effective labour by lowering per capita effective labour. To tackle these adverse effects, policymakers can consider extending the retirement age and improving working conditions for old workers.

The higher savings and lower effective labour supply per capita caused by aging lead to capital deepening. This facilitates structural change towards industry where capital goods are produced. In addition, capital deepening lowers the relative cost of capital to labour, causing the relative price of more capital-intensive sectors to fall. This interacts with aging's negative effect on price elasticities to impede China's structural change in nominal terms. Improving elderlies' access to markets by, for example, promoting their usage of modern technologies to shop online, can increase elderlies' elasticities of demand.

Although older people use more public healthcare, they use much less public education than younger people. Therefore, population aging reduces government spending on healthcare and education as a whole in China. Government education consumption need not decrease, however, if the education system reacts to population aging by spending more on the quality of education and or by providing more education and training to adults.

Through the aforementioned effect channels, population aging impedes the structural changes of nominal output, labour, and capital from agriculture to the modern sectors and from industry to services in China. Aging's effects on the structural change of real output are similar except that aging induces agricultural real output share to fall. This can be explained by the age-induced capital deepening. Due to the fact that agriculture in China is overwhelmingly labour intensive, capital deepening causes agricultural relative price to rise. This in turn causes real agricultural consumption and hence real agricultural output to fall.

The negative aging effects on services can be mitigated through each channel as mentioned earlier. However, if industry continues to have the highest productivity in China, such mitigation may not be necessary. By impeding structural change from industry to services, population aging can actually improve China's aggregate productivity.

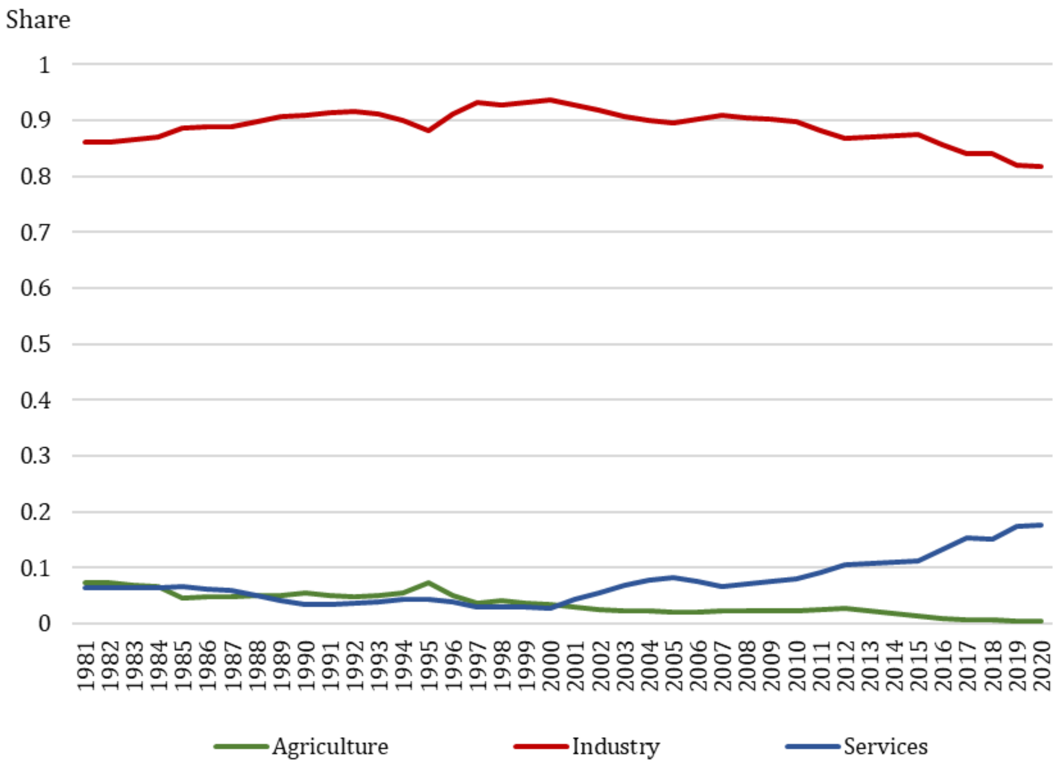
Our results show that aging raises per capita GDP growth in China. This is because the positive aging effects through savings and structural change outweigh the negative effect through effective labour. At the aggregate level, however, population aging lowers real GDP growth in China due to the negative and dominant aging effect on effective labour. Out of the channels of aging effects investigated in this chapter, the effective labour channel is therefore the most pressing concern for policymakers.

This study has some limitations. Firstly, our model features only six generations which constrains the realism in the modelling of individual behavior. Secondly, we assume that public health and education consumption profiles stay constant in our forecasts. A number of studies have pointed out that per capita human capital investment can react to population aging. Thirdly, our model assumes that China is a closed economy. In reality, China is a major participant and beneficiary of international trade. Trade can interact with population aging, structural change, and economic growth in a number of ways. The aging of labour and the aging-induced fall in labour can erode China's comparative advantage in manufacturing but bring about comparative advantages in 'age-appreciating' industries. The aging-induced capital-deepening can reduce the returns to capital, leading to shrinking investment and capital outflows. If aging raises savings relative to investment, it can facilitate an expansion of China's current account surplus. If the aging-induced changes in sectoral demand were met by international producers, aging's effects on China's structural change via the preferences channel would be diminished. The aging-induced increases in healthcare and pension costs can force the government to raise debts in the international market, exposing China to exchange rate risk, interest rate risk, and refinancing risk. These limitations of our study point to potential areas for our future research.

Appendix 6.1 The production of investment

In reality and in our model, capital goods are produced using value added from the three sectors. Some studies assume that investment is instead made up entirely of value added from the secondary sector. They then proceed to measure agricultural and service consumption value added as agricultural and service GDP and obtain industrial consumption value added as industrial GDP minus investment expenditure.

Figure 6.35: Sectoral shares in investment expenditure



Unfortunately, this approach is refuted by Chinese data. In Figures 6.35 and 6.36, we plot sectoral investment expenditure shares and sectoral investment value added shares, respectively. We compile such sectoral investment data following the same methods that we used for sectoral consumption data in Chapter 4. Specifically, we obtain sectoral investment expenditure shares using IOT data, and then apply the extraction matrices to obtain sectoral investment value added shares.

As can be seen in Figure 6.35, industrial investment expenditure share fluctuated around 90% and then followed a downward trend, reaching 82% in 2020. Between 1981 and 2020, the agricultural share decreased from 7% to 0% while the service share increased from 7% to 18%. China's IOTs show that the rise in service investment expenditure share was largely due to the surge in investment expenditure on software services and research and development. As China's economy rely more on technological progress for growth and as software become more involved in economic activities, the 'servicification' of investment is likely to continue in the future.

Figure 6.36: Sectoral shares in investment value added

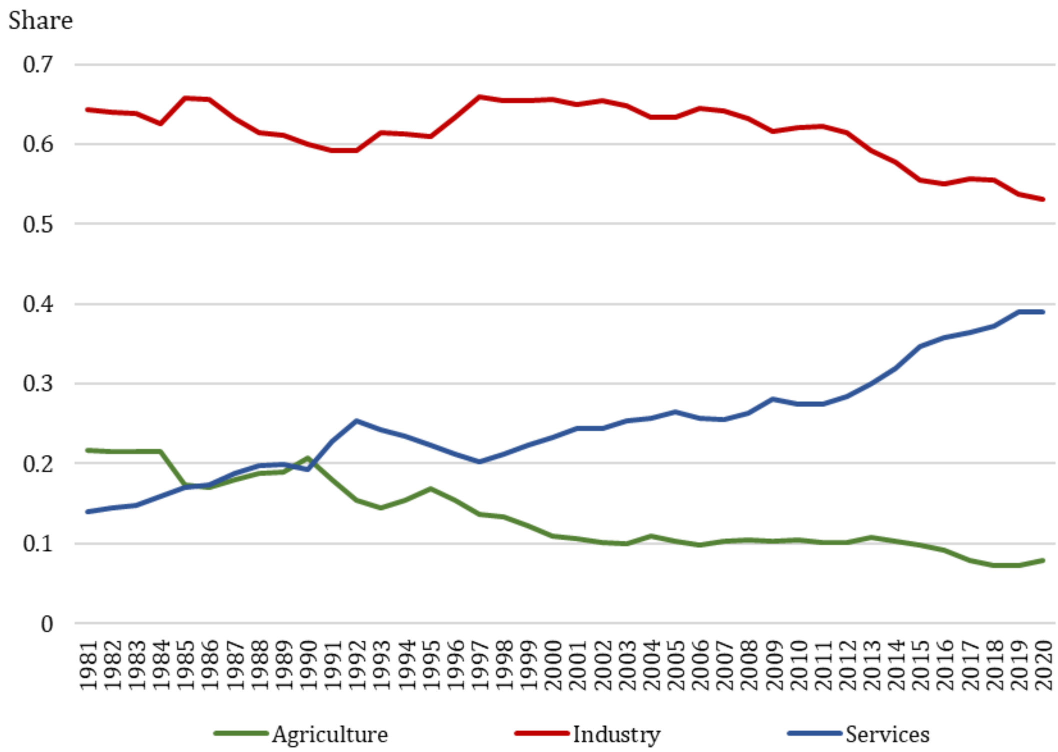


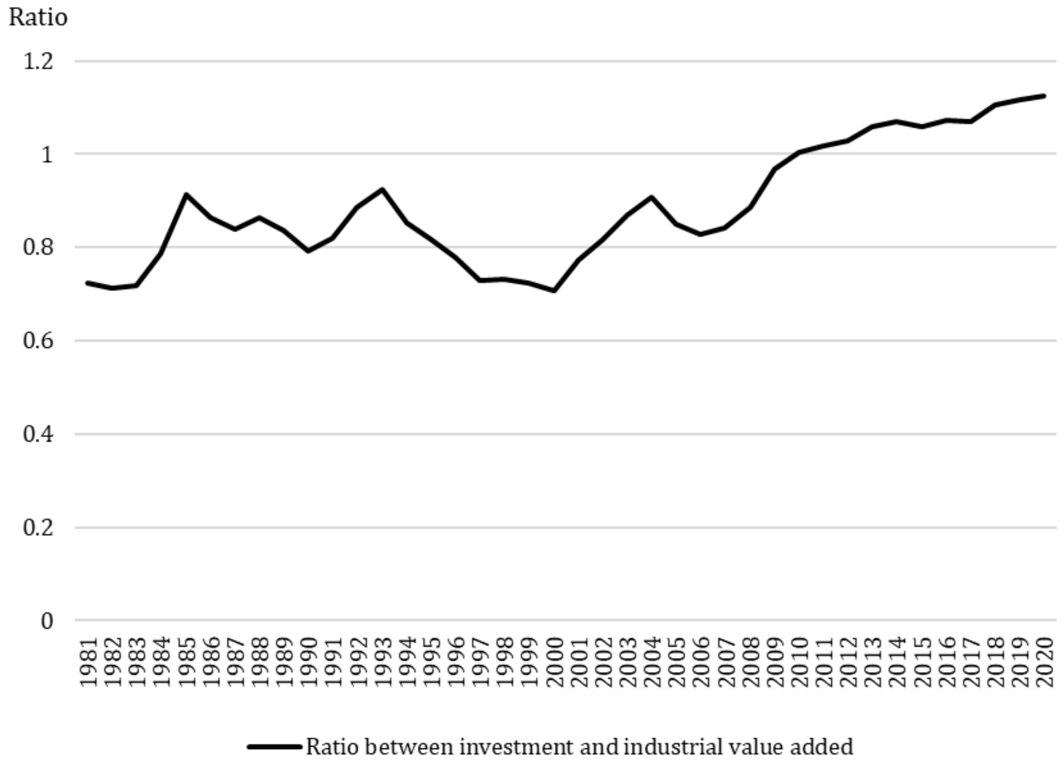
Figure 6.36 shows that industrial investment value added share fluctuated at about 65% between 1981 and 2000. After 2000, the industrial share fell steadily, reaching 53% in 2020. In 1981, the agricultural and service shares were respectively 22% and 14%. Over time, the agricultural share fell while the service share rose, reaching 8% and 39% in

2020, respectively.

Figures 6.35 and 6.36 show that large parts of investment were made of agricultural and service value added. Furthermore, there were rapid structural changes of investment value added from agriculture and industry towards services. Therefore, the assumption that investment is made up entirely of secondary sector value added cannot be justified in the Chinese case.

More importantly, investment in China has been higher than secondary sector value added since 2011 and that the gap has widened continuously (Figure 6.37). If we were to assume that investment is produced only in industry, we would obtain negative industrial consumption values for the post-2010 period, which are unrealistic.

Figure 6.37: Ratio between investment and secondary sector value-added



In summary, we need to account for the sectoral composition of investment value-added in order to analyse structural change in China. As such, we incorporate the capital goods firm that determines the sectoral production of investment into our model.

Appendix 6.2 Preference estimation results for the six age groups

We estimate sectoral demand share functions and hence the preference parameters following the same steps as those in Chapter 5. For the purposes of Chapter 6, we estimate the functions for the six age groups rather than the three age groups. The estimation results are shown in Table 6.4 below.

Table 6.4: Age-specific preference estimation results

	Age Group					
	21-30	31-40	41-50	51-60	61-70	71+
σ_g	0.58***	0.52**	0.71***	0.37**	0.31***	0.31***
	(0.17)	(0.21)	(0.19)	(0.15)	(0.12)	(0.11)
ω_{ga}	0.023***		0.020***		0.031***	0.050***
	(0.0070)		(0.0063)		(0.0097)	(0.0067)
ω_{gd}	0.50***	0.53***	0.45***	0.59***	0.59***	0.57***
	(0.049)	(0.066)	(0.058)	(0.040)	(0.028)	(0.025)
ω_{gs}	0.48***	0.47***	0.53***	0.41***	0.38***	0.38***
	(0.048)	(0.066)	(0.057)	(0.040)	(0.028)	(0.024)
$\bar{c}_{ga}$	166.37***	336.94***	300.44***	287.76***	198.83***	125.05***
	(4.53)	(3.65)	(7.69)	(3.63)	(5.75)	(2.42)
$\bar{c}_{gs}$	-77.62***	-128.12*	-193.15**	-46.79*	-26.97**	-15.99**
	(29.64)	(76.28)	(75.54)	(28.03)	(11.45)	(6.19)
R^2_{ga}	0.994	0.974	0.996	0.964	0.990	0.995
R^2_{gs}	0.994	0.995	0.996	0.995	0.993	0.994
$RMSE_{ga}$	0.021	0.017	0.018	0.022	0.033	0.024
$RMSE_{gd}$	0.020	0.021	0.021	0.016	0.017	0.013
$RMSE_{gs}$	0.028	0.028	0.023	0.025	0.029	0.028

Note: Standard errors in parentheses. *Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level. R^2_{ga} is for the s_{ga} regression and R^2_{gs} is for the s_{gs} regression. $RMSE_{gi}$ refers to Root Mean Squared Errors for the s_{gi} regression.

For the 31-40 and 51-60 age groups, the estimates for ω_{ga} turned out to be statistically indistinguishable from zeroes in our preliminary estimations. We therefore estimate sectoral demand share functions for 31-40 and 51-60 age groups with ω_{ga}'s restricted to be zeroes and show the results in Table 6.4. The differences between results estimated with the restriction and without are tiny and have negligible impacts on this Chapter's simulation results.

When simulating the model in this chapter, we set ω_{ga} for 31-40 and 51-60 age groups to be 0.001 to speed up the simulations. Setting the ω_{ga}'s to be zeroes have negligible impact on our results.

As can be seen in Table 6.4, all age groups prefer modern sector consumption value added to agricultural consumption value added. Older age groups have greater preference weights for agriculture and industry but smaller preference weights for services compared to younger age groups. Demand of all age groups are relative price inelastic. Older age groups tend to have smaller σ_g and hence lower price elasticities of demand compared to young age groups. Subsistence agricultural consumption occupies greater shares and endowment service consumption occupies smaller shares in total consumption of older age groups. These results are consistent with those in Chapter 5.

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Chapter 7: Conclusion

In this thesis, we investigated population aging, structural change, and economic growth in China. Each of the five essay chapters has its own conclusion section. In this final chapter, we briefly summarise the main results and implications of the five essays.

In Chapter 2, we compiled, analysed, and compared two measures of China's sectoral capital input and their returns: sectoral capital stock and sectoral capital services. Our results show that unlike those in labour and output, agriculture's share in capital was already low in 1981 and structural change in capital between 1981 and 2020 was mostly from industry to services. Capital therefore has less potential for further structural change compared to labour and output. The return to capital in China rose steadily till 2008, after which it fell. The fall was mainly driven by diminishing returns in the secondary sector. These imply that capital accumulation, especially those in construction and industry, were running out of steam as drivers of economic growth in China. The returns to capital differed substantially across sectors. After an initial period of convergence, the returns between agriculture and the other sectors diverged after 1995. This points to the presence of frictions in China's capital markets. There are significant differences between the capital stock and capital service measures of sectoral capital input and returns. Compared to the capital stock measures, the capital services measures show higher industrial capital share, slower structural change, and smaller gaps in returns between sectors. The gaps between sectoral capital services returns were smaller because the composition of capital goods used in industry was more productive than that in services, which was more productive than that in agriculture.

In Chapter 3, we conducted sectoral growth accounting for China. In the process, we investigated supply-side forces, including that of population aging, that were behind China's structural change and growth. Some studies in the literature found China's growth to be driven overwhelmingly by capital accumulation. In contrast, our results show that factor accumulation and TFP growth were both important drivers of China's growth between 1981 and 2020. This implies that despite diminishing returns to factor inputs, China can sustain a reasonably high growth rate if it can maintain rapid TFP growth. Structural change will likely be an important source of China's growth in the future as we found that a large share of past TFP growth in China originated from structural change. At the sectoral level, growth in agriculture was driven almost entirely by TFP growth while growth in services was driven almost entirely by factor accumulation. At the observed rates, agricultural TFP will overtake service TFP and the vast majority of China's workers will be in services. These raise doubts about the sustainability and benefits of China's ongoing structural change towards services. In particular, China's rapid structural change towards services could be a symptom of Baumol's cost disease (Baumol, 1967). Compared to young workers, older workers were more likely to be employed in agriculture. Despite initially having higher labour productivities than young workers, older workers became less and less productive over time, and eventually became less productive than young workers in the early 2010s. These mean population aging impeded China's structural change and economic growth. Such adverse aging effects are expected to intensify as China's population aging accelerates in the future. To alleviate such effects, policymakers can attempt to boost elderlies' labour participation rate, employment rate, and productivity, especially in the modern sectors. These can be achieved by, for examples, raising the retirement age and providing transferable skills training to elderlies. Our results show that there were substantial factor price wedges in China. The wedges were higher in industry than in services and were higher for labour than for capital. Once we accounted for the productivity effects of changes in the composition of capital and the composition of labour within each sector, the wedges became smaller. This implies that some of the structural change in China were achieved through changes in the composition of factor inputs at the sectoral level.

In Chapter 4, we turned our focus to the demand side. We compiled and analysed sectoral consumption expenditure and sectoral consumption value added data for China. We estimated sectoral demand functions and used them to study the demand side drivers of structural change in China. Our results show that a utility function with non-homotheticity terms and a substitution elasticity parameter is the most suitable for explaining China's sectoral consumption patterns. We found the relative price elasticities of demand in China to be low. This means a change in sectoral relative price would induce sectoral consumption to move in the same direction. The presence of subsistence agricultural consumption and endowment service consumption in China mean that in the early years of development, agricultural consumption share was high and service consumption was low. As income grew, individuals substituted away from agricultural consumption and towards the industrial and service consumptions that they prefer. While the relative price effect can explain the observed fall in industrial consumption share and rise in service consumption share with their corresponding relative prices, only the income effect can explain the fall in agriculture consumption share following increases in agricultural relative price. Today, income effect is no longer a key driver of structural change because the shares of subsistence and endowment consumption in total consumption have become very small. Therefore, China will have to rely on other drivers for future structural change. Our estimates for preference weights show that people in China prefer service consumption to industrial consumption, and strongly prefer industrial consumption to agricultural consumption. Transitioning towards a more consumption-oriented economy can therefore lead to structural change towards services in China.

In Chapter 5, we investigated aging's effects on structural change through private consumption. More specifically, we estimated and analysed individual age profiles of consumption by type and by sector. We estimated age-specific sectoral demand functions that are derived from a three-sectors overlapping generations model. We analysed the variations in preferences across age and their implications. Our results show that individual age-profiles of total consumption are hump-shaped rather than smooth. Population aging can therefore reduce consumption in China and undermine China's transition towards a more consumption-oriented economy. The estimated age-profiles of consumption categories show large variations in consumption across age, category, and time. It is therefore unrealistic to assume that such profiles are constant across time. Compared to younger age groups, older age groups spend larger shares of consumption on food and healthcare but similar or smaller shares on other categories. By comparing predicted consumption under the aging and no-aging scenarios, we find that aging can substantially change the composition of China's private consumption. The estimated age-profiles of sectoral consumption and age-specific preferences show that compared to younger age groups, older age groups have greater preferences for agricultural and industrial consumption but less preferences for service consumption. These imply that in the long term, population aging impedes structural change towards services. Such impediment may not be detrimental to the economy if service TFP continues to grow slower than the others. The estimated preferences also show that older age groups have lower price elasticities of demand, higher subsistence consumption share, and lower endowment consumption share. These explain why the magnitudes of relative price effect and income effect on consumption intensify over age. Due to the elderlies' low total consumption and price elasticities of demand, they have been particularly vulnerable to the rapid increases in agricultural relative price in the past few decades. This partially explains the elderlies' under-transformed consumption structure and hence the adverse effects of aging on structural change. Potential remedies to these effects include controls on agricultural prices and extensions of the retirement ages.

In Chapter 6, building on our work from the previous chapters, we calibrated and simulated a three-sectors model of China with six overlapping generations. Through counterfactual analyses, we investigated aging's effects on China's structural change and economic growth through the channels of preferences, savings, labour, and government consumption. Our results show that population aging raises savings and capital per capita, and hence partially explains the Great Savings Puzzle of China in several ways. First, as people expect to live longer, they save more to finance for their retirement. Second, as the birth rate falls, the population sharing capital stock shrinks. Third, elderlies in China save more than others. Although elderlies consume more public healthcare than younger people, they consume little to no public education. Therefore, population aging reduces government spending on healthcare and education as a whole. The labour and preference channels are conceptually the same as those in Chapter 3 and 5, respectively. Overall, we found that population aging impedes China's structural change from agriculture to the modern sectors through the preferences, savings, and labour channels. With regard to the modern sectors, aging impedes China's structural change from industry to services via the preferences, savings, and government consumption channels. Policymakers can mitigate aging's negative effects on services by targeting the channels. For examples, policymakers can attempt to stimulate elderlies' service consumption, reform the social security system, and spend more on education quality. However, such mitigation may not be necessary. Since TFP in services is lower than that in industry, aging can increase aggregate TFP by impeding structural change from industry to services. Our results show that population aging raises per capita output growth by boosting per capita capital growth and aggregate TFP growth. However, aging's effect on aggregate output growth is negative due to the large and dominant negative aging effect on effective labour input. According to our findings, the effective labour channel poses the biggest challenge for policymakers. As remedies, policymakers can attempt to extend the retirement ages, subsidize elderly employment, and promote elderly-friendly working conditions.

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