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Xilu Chen
Guangyu Pei
Zheng Michael Song
Fabrizio Zilibotti

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ABSTRACT

We document a process of rapid tertiarization of the Chinese economy since 2005. The employment and value-added shares of the service sector have increased significantly. Moreover, total factor productivity growth has increased faster in the service sector than in the manufacturing sector. Measures of dynamism at the firm level confirm the growing importance of tertiarization. The boom is not limited to services that are used as inputs to industrial production. Consumer services have also grown significantly in terms of both value-added share and productivity. The results are robust to different growth accounting methodologies, including the recent method proposed by Fan, Peters, and Zilibotti (2022) that gets around potentially problematic official price indexes.

Xilu Chen
135 Xingang West Rd, Haizhu District
Room 205, Wu S.T. Library
Sun Yat-sen University
Guangzhou, Guangdong 510275
China
chenxlu23@mail.sysu.edu.cn

Guangyu Pei
Department of Economics
The Chinese University of Hong Kong
Shatin, Hong Kong,
China
guangyu.pei@cuhk.edu.hk

Zheng Michael Song
Department of Economics
Chinese University of Hong Kong
Shatin, N.T., Hong Kong
zheng.michael.song@gmail.com

Fabrizio Zilibotti
Department of Economics
Yale University
28 Hillhouse Avenue
New Haven, CT 06520
and NBER
fabrizio.zilibotti@yale.edu

1 Introduction

Since the onset of economic reforms in the 1980s, the economic development of China has been intertwined with its process of rapid industrialization. The path followed by China shares many features with that of earlier industrializers in East Asia, such as Japan, South Korea, and more recently, Vietnam. Export of manufacturing goods has been a key driver of the process. Initially, the economy specialized in low value-added industries like textiles, apparel, leather, and toys that could benefit from low labor costs. Since 2000, China has progressively moved up the technology ladder and become a dominant exporter of electronics, machinery, and transport equipment.

Consistent with this trend, over the last ten years China has consistently been the largest exporting nation (and, since 2014, even the largest trading nation) worldwide. The value of its exported goods in 2020 exceeded that of the United States by more than a third. However, while growing in absolute terms, the share of China's exports has not kept pace with its overall economic growth. As a result, exports as percent of GDP have halved, falling from 37% in 2005 to 18% in 2020.

Part of the reason for this reversal is the decline of the manufacturing sector, which is the most export-oriented sector, as a share of GDP. In 2011, the value-added of the manufacturing sector accounted for 32% of China's GDP, while in 2020, that share was down to 26%. Likewise, the employment share of the industrial sector has consistently declined since 2012. This decline is especially remarkable in light of the relentless urbanization process: the share of employment in agriculture has fallen from 35% in 2011 to 24% in 2020, according to the *China Statistical Yearbook* (CSY).

China is currently undergoing a rapid tertiarization process. Namely, service industries are growing as a share of GDP at the expense of both agriculture and manufacturing. Yet, the salience of such a transformation of China's economic development is still underappreciated. For instance, it is not reflected in the existing economics research, whose main focus is the manufacturing sector and its dynamics (see, e.g., Hsieh and Klenow, 2009; Song et al., 2011, 2014; Storesletten and Zilibotti, 2014; and König et al., 2022). Part of the reason is data availability. China has a detailed census of manufacturing firms as well as a National Business Survey that covers all manufacturing plants above a threshold size. There is no comparable survey for service firms. Moreover, measuring productivity in the service sector is notoriously difficult.

In this article, we provide an anatomy of the growing service sector in China. We start with a comparative analysis of China relative to other developing and emerging economies. We argue that the experience of China is overall exceptional in terms of the prominence of its industrial sector in the development process. However, China's exceptionalism is rapidly vanishing, and the structure of the Chinese economy is becoming more similar to that of other economies at a comparable stage of development. Next, we consider the nature of the tertiarization process of

China and contrast the data with different hypotheses that could explain the rapid tertiarization. The first hypothesis is that the decline of the employment share of manufacturing is explained by the boom in construction and the building of infrastructure. While the importance of these activities has grown significantly in the last two decades, we document that the growth of the service sector is a robust feature of the data and is not limited to activities associated with the construction activity. A second hypothesis is that tertiarization is mainly driven by services used as inputs for the production of goods. This would be consistent with the view that the growth of the Chinese service sector is ancillary to industrial production, which would remain the main focal point of the economic activity. In other words, the reason for a shift in the demand for production inputs toward services would be strictly technological. There are some indications that are consistent with this view. In particular, we document a rapid growth of service industries providing inputs to the industrial sector, which we label *producer services*. However, producer services are by no means the sole driver of tertiarization. We also observe a boom of service industries that improve consumers' access to goods (e.g., retailers or restaurants) or provide services that are directly consumed by households (e.g., recreation, health, community services). Finally, one might conjecture that tertiarization results from a growing role of the government in the Chinese economy. Contrary to this hypothesis, we do not find government-provided services play an important role in the tertiarization process. Public services are, in fact, the only nongrowing service industry as a share of GDP.

A focal point of our analysis is productivity growth in the service sector. A common view stretching back to Baumol (1967) is that productivity is inherently stagnant in the service sector. If so, tertiarization could be a threat to the continuation of rapid economic growth. However, our findings suggest that in the last decade, productivity growth has been faster in the service sector than in the industrial sector. While consumer services is the most dynamic sector (namely, the one with the fastest total factor productivity (TFP) growth), TFP has also grown quickly in the producer services sector. An important concern toward reaching conclusions in this regard is that standard estimates of sectoral TFP growth hinge on sectoral price indexes that are notoriously difficult to measure in the service sector. The problem is even more severe if people have general nonhomothetic preferences, which makes the same definition of price indexes ambiguous. To tackle this issue, we estimate productivity growth using a novel methodology recently proposed by Fan et al. (2022)—henceforth, FPZ. Their approach is based on a structural model in which both demand and supply forces are drivers of the structural transformation. Importantly, the methodology of FPZ circumvents problems associated with the published price index for services. Their structural model specifies a class of nonhomothetic preferences and estimates its parameters, which include an income elasticity whose value one can infer from microdata. The procedure allows one to estimate productivity growth in services without relying on any published price index. The results confirm a high productivity growth in the service sector, especially, consumer services. In all scenarios considered, we find that productivity in consumer service industries significantly outpaced productivity in manufacturing during the period

2005–2015, for which we have data.

In the final section of the paper, we corroborate these findings by constructing a variety of measures of sectoral dynamism at the firm level. First, we observe that both producer and consumer services have undergone a faster process of skill upgrading (as measured by the educational attainment of the workforce) than any other sector in the economy. This is not a mere consequence of some convergence process: we document that the tertiary sector is more skill-intensive both in level and in growth terms. Second, we consider firm-level data from the registration records of China's State Administration for Market Regulation (SAMR), which covers all registered firms in China, including service firms. We find that standard measures of turnover are higher for service firms than for manufacturing firms. What's more, the gap across sectors has increased over time in the last two decades. The entry rate in the tertiary sector increased from 15% in 1996 to 20% in 2019 while it remained constant around 12% in the industrial sector. We document similar findings for the exit rate, although this measure is subject to large low-frequency fluctuations. All these facts align well with the view that tertiarization is not a mere corollary of the development process. Rather, it is an increasingly important part of the Chinese economy and a driver of economic growth.

2 Related Literature

Our article contributes to a growing literature on the structural transformation of China. Most existing studies focus on the decline of agriculture. Brandt et al. (2008) emphasize the importance of TFP growth in agriculture for structural change as well as that of TFP growth in the nonstate, nonagricultural sector in explaining the aggregate productivity growth during the period 1978–2004.[1] Dekle and Vandenbroucke (2012) and Cao and Birchenall (2013) echo their conclusions. Cheremukhin et al. (2017) study the structural transformation of China since the foundation of the People's Republic of China and discuss the role of intra- and intertemporal wedges and how these were affected by different policies. Storesletten et al. (2019) study the effect of modernization and capital accumulation in agriculture on the structural transformation out of agriculture. Hao et al. (2020) use a spatial model of trade and migration to highlight the importance of China's migration policy changes on the structural transformation out of agriculture and the reduction of provincial labor income inequality.

There is a smaller body of literature focusing, as we do, on the tertiary sector of China. Contrary to ours, most existing papers draw no explicit distinction between producer and consumer services, which is central in our analysis (see, e.g., Naughton, 2007; Naughton, 2018; Nabar et al., 2013). Guo et al. (2021) investigate the importance of tertiarization in the investment sector of China. Ge et al. (2019) provide a variable market approach that explains why the ser-

[1] See also Brandt and Zhu (2010) and Zhu (2012) for related extensions and updates for the results in Brandt et al. (2008).

vice sector of China was unusually small prior to 2008. Lu et al. (2022) argue that the Hukou system, by hindering China's urbanization, is responsible for the low share of the service sector relative to countries at a comparable stage of development. Their quantitative exercise shows that the reduction in migration costs between 2000–2010 explains more than half of the increase in the service employment share. Among the few papers that do not treat the service sector as a homogenous sector, Liao (2020) studies the role of personal and distributional services. He documents an important role of TFP growth in personal services during the period of 1978–2007. Using an alternative classification, Fang and Herrendorf (2021) split the sector into high- and low-skill services and argue that large wedges in high-skill services have hindered China's tertiarization and income growth.[2]

3 International Evidence

In this section, we compare the process of structural change in China with that of other economies. Figures 1 and 2 show the pattern of structural transformation for a set of industrialized (OECD) and large developing and emerging (non-OECD) economies. The data are from the Groningen Growth and Development Centre (GGDC) dataset, complemented with historical data for developed economies provided by Mitchell (2007) and Schön and Krantz (2012).[3] More details on the data construction are provided in Appendix A. Figure 1 plots the sectoral employment shares against the GDP per worker in 2017 USD. The upper and lower panels refer to the set of OECD and non-OECD economies, respectively. In all graphs, we highlight the path of two large economies, China and India. Because of our special interest in these two economies, we extend the GGDC data using local data sources. In particular:

1. For China, we only display the data since 1978 even though the GGDC data go back to 1952. The reason is twofold. First, the quality of earlier data is lower. Second, China's planned economy under Mao Zedong was very different, and the focus of this article is on contemporary China. We use the 2002 guidelines of China's National Bureau of Statistics (NBS) to ensure consistency with the GGDC data.

[2] According to Fang and Herrendorf (2021), productivity in the goods sector outgrew that in the service sector between 2005 and 2009. An important difference in our study is that we postulate a production function with both capital and labor, whereas labor is the only input factor in their analysis. If we abstract from capital, our data indeed confirm their findings even for later years because the secondary sector experienced a faster capital accumulation and a higher capital output elasticity than the tertiary sector, as we document below.

[3] Because there are different data sources for countries, we adopt the following rule to chain the data sources and construct the time series. First, we take the most recent observation as the benchmark. Second, we assume the annual changes of the concerned variable from the historical dataset to be reliable and extend the benchmark series back. For example, the most recent observation about the Indian sectoral employment share is from the World Bank 2019 World Development Indicators (WDI). Therefore, we adopt the employment share from WDI from 2011 to 2019. For the years earlier than 2011, we assume the annual changes of sectoral employment shares from the GGDC dataset to be reliable, and so we extend the WDI series from 2010 back to 1960. The same rule applies to the OECD countries when we construct their historical data.

2. The most recent GGDC observation for China is 2012. We extend the time series until 2021 using the China Statistical Yearbook (CSY) 2021. We checked that the time series from these two sources are identical in the overlapping years.

3. For India, the GGDC data end in 2010. We extend the time series to 2019 by chaining the GGDC series for the sectoral employment shares calculated from the WDI. See footnote 3 for details.

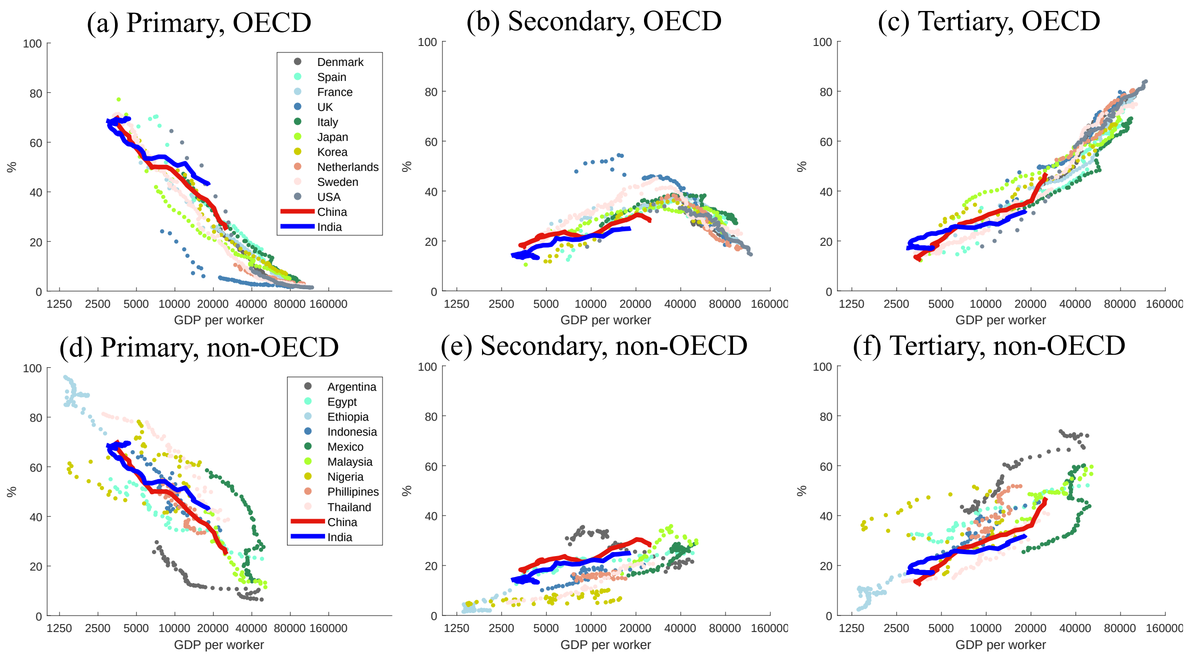

Figure 1: Sectoral Employment Share, All Broad Sectors

Note: GDP per worker is measured in 2017 USD. The data sources are discussed in the text. The selected OECD countries include Denmark, France, Italy, Japan, the Netherlands, South Korea, Spain, Sweden, the United Kingdom, and the United States; the selected non-OECD countries include Argentina, Egypt, Ethiopia, Indonesia, Malaysia, Mexico, Nigeria, the Philippines, and Thailand.

The figure highlights that economic growth goes hand in hand with tertiarization. As countries' GDP per worker grows, so does the employment share of the tertiary sector. In contrast, the primary sector declines over the process of development. The employment share of the secondary sector is hump-shaped: among OECD countries, it increases until about 40,000 USD and decreases thereafter. The corresponding plot for the non-OECD countries shows a monotonically increasing pattern for most countries, arguably because these economies have not yet reached the 40,000 USD peak. There is, however, a remarkable difference between OECD and non-OECD economies: conditional on GDP per worker, the employment share of the secondary sector is significantly lower for today's developing countries than for earlier industrializers. We also note that the spread of variation in the size of the tertiary sector is significantly larger across non-OECD countries than across OECD countries.

Next, we zoom in on India and China. In the earlier stages of the development process, the trajectory of China is characterized by an exceptionally large industrial employment share and a correspondingly small tertiary share. However, over the last decade, China has entered a fast process of tertiarization while the share of industrial activity has stagnated and even slightly declined. In part, this shift reflects a global economic trend: the share of employment in the industry increased from 20% to 23% between 2000 and 2012 but stagnated—even marginally declined—thereafter. When compared with other non-OECD countries, China is an outlier: the industrial employment share is significantly higher than in the standard non-OECD country. In contrast, the development pattern of India is more similar to that of the typical non-OECD economy. Relative to the OECD countries, instead, India experiences a slower decline in agriculture and less industrialization.

Figure 2 shows the same data from a different angle: it focuses on the split of the nonprimary sector between the secondary and tertiary sectors. For each country, the data in the two panels sum up to 100% horizontally. This cut of the data highlights the sharp difference between China and India. When its GDP per worker was below 5,000 USD, China was far more specialized in industrial production. Thereafter, China embarked on a tertiarization process that made the country more similar to the typical pattern of development.

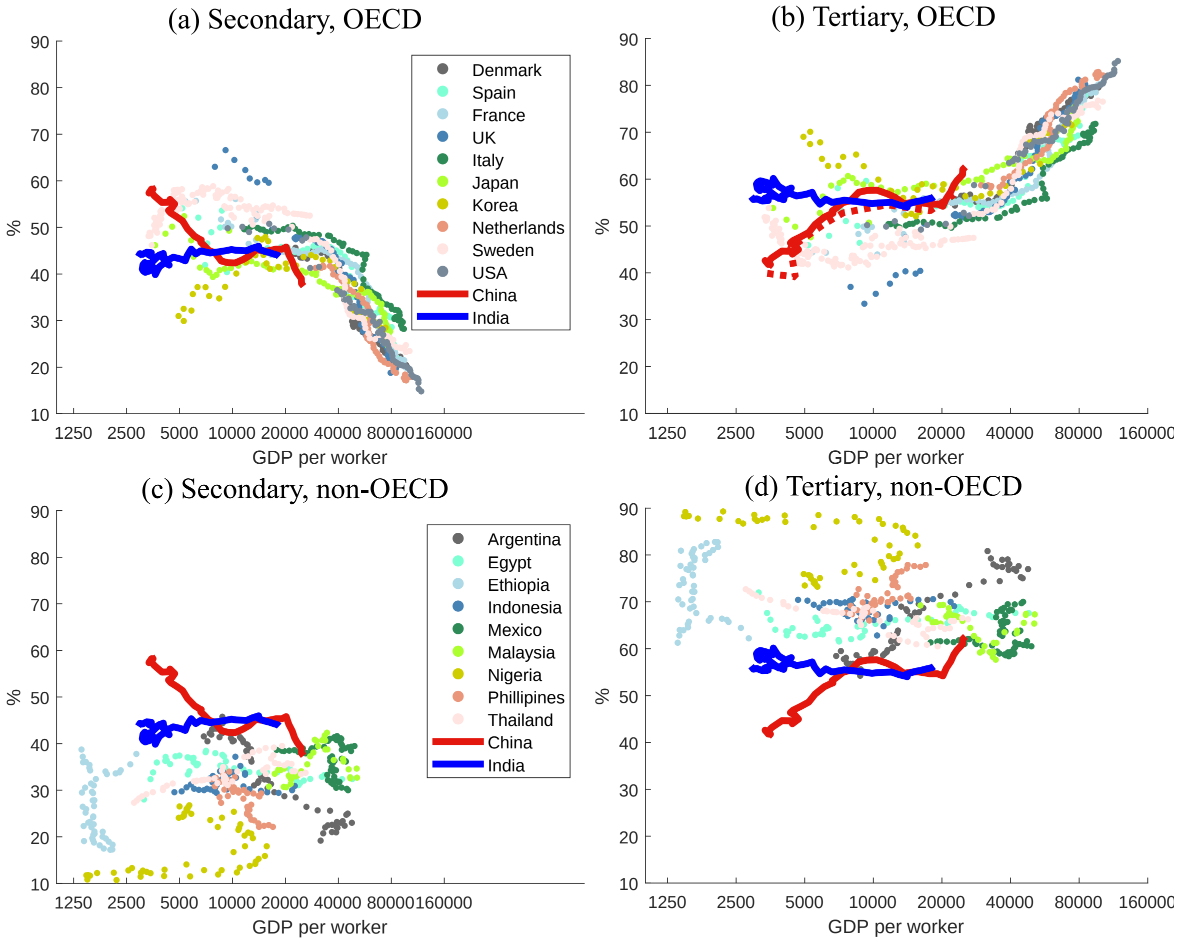

Figure 2: Sectoral Employment Shares, Broad Sectors Excluding Primary Sector

The comparison at the macro level could hide important differences in the composition of the service sector. For instance, FPZ show that in India, traditional service industries (retail, hotel, personal services) account for a very large share of employment in the tertiary sector. We will document that in China, producer services play a more prominent role than in India.

To summarize, at an early stage of its pro-market reforms, China's service sector was exceptionally small. However, over time, employment in the tertiary sector caught up, thereby reducing the extent of China's exceptionalism. In the rest of this paper, we document the anatomy of the tertiarization process in China. The existing literature has documented several facts about the structural transformation of China—see Brandt et al. (2008) and Naughton (2018). Our analysis builds on those studies, updating and extending their findings.

4 An Anatomy of China's Tertiarization

To gain insight into China's tertiarization process, we will use both aggregate and firm-level data. This section focuses on aggregate sector-level data.

We start by presenting our classification of industries. We first split the economy into three broad sectors in line with the NBS.[4] According to this classification, the primary sector includes agriculture, forestry, animal husbandry, and fishery industries; the secondary sector includes mining, manufacturing, public utilities, and construction; the tertiary sector includes all service industries. Then, we break down the tertiary sector into three subsectors: producer services, consumer services, and public services. The motivation is that these subsectors perform very different roles in the economy: producer services provide inputs to the production of goods, whereas consumer services support consumers' access to final goods (e.g., restaurant and retail sector). We also split the secondary sector into industry and construction. We further treat public services as a separate category. These services are mostly government-provided and cannot be easily classified as either consumer or producer services. We include in this category: public administration; education; and the management of water conservancy, the environment, and public facilities. This classification echoes the earlier work of Stigler (1956) and Greenfield (1966), and has more recently been revived and updated by FPZ.[5]

In some cases, there is a natural correspondence between the NBS service industries and our three-group classification. For instance, entertainment services are consumer services, while business services are mostly producer services. In other cases, the mapping is more ambiguous. This issue is especially salient for two large service industries: financial intermediation and real estate services. For these industries, we rely on supplementary information. For the financial intermediation industry, we use the Summary of Sources and Uses of Credit Funds of Financial

[4] The NBS has revised the classifications of broad sectors in 2011 and 2017. However, it made no corresponding changes in the employment data. We resolve this consistency issue between the value-added and employment data by following the 2002 classification. The discrepancy is minor. See Appendix B.1 for more details.

[5] The decomposition is also discussed in Browning and Singelmann (1975), Hubbard and Nutter (1982), Daniels (1985), Grubel and Walker (1989), and Sassen (2001).

Institutions from the People's Bank of China. This summary reports the sources of deposits and the destination of loans, which allows us to track the share of deposits and loans coming from (or going to) households, firms, or government agencies. Then, we determine the share of the value of loans and deposits associated with each of the three categories and use it as a proxy for the extent to which financial firms provide services to consumers, producers, and the government. Figure 13 in Appendix B.3 shows the results. On average, this approach attributes 51%, 33%, and 16% of the activity of financial firms to producer, consumer, and public services, respectively. Concerning the real estate service industry, we split its value-added into consumer and producer services according to the information on the floor space of commercialized buildings sold. Appendix B.4 provides further details. Figure 16 in Appendix B.4 shows that between 91% and 95.5% of the value-added of real estate services is classified as part of the consumer service sector.

For the other service industries, we classify the following as producer services: transport, storage, and post; IT, computer services, and software; leasing and business services; scientific research, technical services, and geologic prospecting. We classify the remaining service industries as consumer services.[6] Table 1 summarizes the breakdown of industries.[7]

Table 1: Industry Classification

Broad Sector	Subsectors	Industry Description
Primary	Primary	Agriculture, Forestry, Animal Husbandry, and Fishery
Secondary	Industrial	Mining
		Manufacturing
		Production and Supply of Electricity, Gas, and Water
	Construction	Construction
Tertiary	Consumer Services	Wholesale and Retail Trades
		Hotels and Catering Services
		Financial Intermediation (partial)
		Real Estate (partial)
		Services to Households and Other Services
		Culture, Sports, and Entertainment
		Health, Social Security, and Social Welfare
	Producer Services	Transport, Storage, and Post
		Information Transmission, Computer Services, and Software
		Financial Intermediation (partial)
		Real Estate (partial)
		Leasing and Business Services
		Scientific Research, Technical Services, and Geologic Prospecting
	Public Services	Financial Intermediation (partial)
		Management of Water Conservancy, the Environment, and Public Facilities
		Education
		Public Management and Social Organizations

[6] The NBS provides an independent classification of consumer and producer services. Our classification is broadly consistent with the NBS classification from 2019 with a few exceptions.

[7] The labels of one-digit industries in Table 1 follow the classification in 2002. The classification changed twice in 2011 and 2017, respectively, but the coverage of each one-digit industry does not vary much. Therefore, we simply map the one-digit industries in 2011 and 2017 to 2002 by their names.

4.1 Trends in Value Added, Employment, and Human Capital

In this section, we document trends in sectoral value-added shares, relative prices, employment shares, and human capital.

4.1.1 Sectoral Value-Added Shares and Relative Prices

We construct time series for the sectoral nominal value-added and for the price indexes at the industry level using the national account statistics provided by the NBS. We use the most recent available update after the fourth economic census of 2018.

The left panel of Figure 3 plots the trends of nominal value-added broken down for primary, secondary, and tertiary sectors. We also separately show the industrial sector that we recall is part of the secondary sector. The primary sector's nominal value-added share has steadily declined since the mid-1980s. The share of the secondary sector (dotted line) is approximately constant until 2012 and sharply declines thereafter. This decline is driven by a falling share of the industrial sector, while the share of the construction sector has been increasing. Finally, the nominal value-added share of the tertiary sector (solid line) has systematically increased over the last four decades, with three accelerating waves: 1984–1992, 1997–2002, and 2012 until the present. The first two waves reflect accelerations of the urbanization process. In contrast, the ongoing post-2012 tertiarization wave is associated with a decline in the industrial sector. The tertiary sector's nominal value-added share increased from 45% in 2012 to 54% in 2020, while the corresponding secondary sector's share fell from 46% to 38%. There is no change in the declining trend of the primary sector during this recent period.

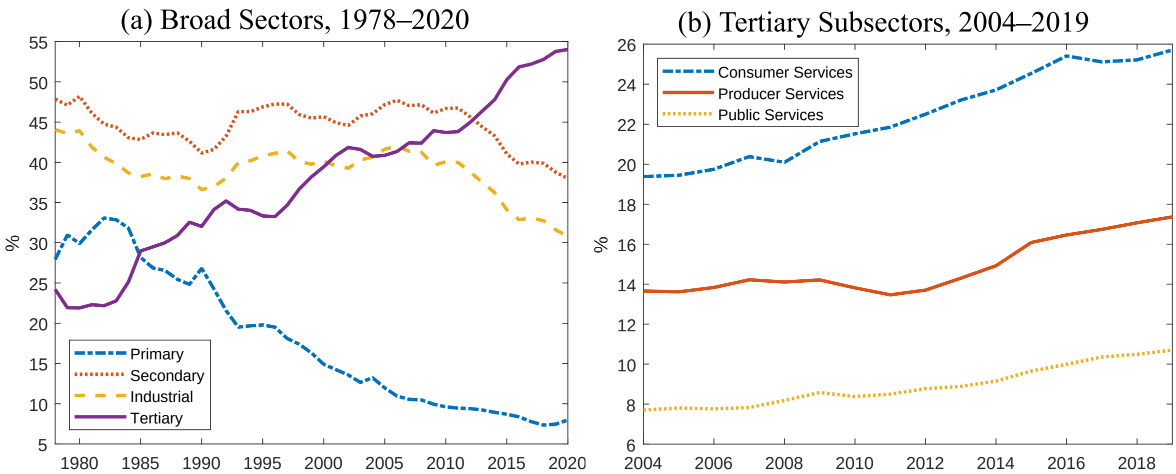

Figure 3: Sectoral Nominal Value-Added Shares in China (All Sectors)

The right panel of Figure 3 decomposes the tertiary sector's nominal value-added into consumer services, producer services, and public services since 2004.[8] As the graph shows, consumer

[8] We focus on the post-2004 period because for the earlier period, it is not possible to break down the service industries in a comparable way.

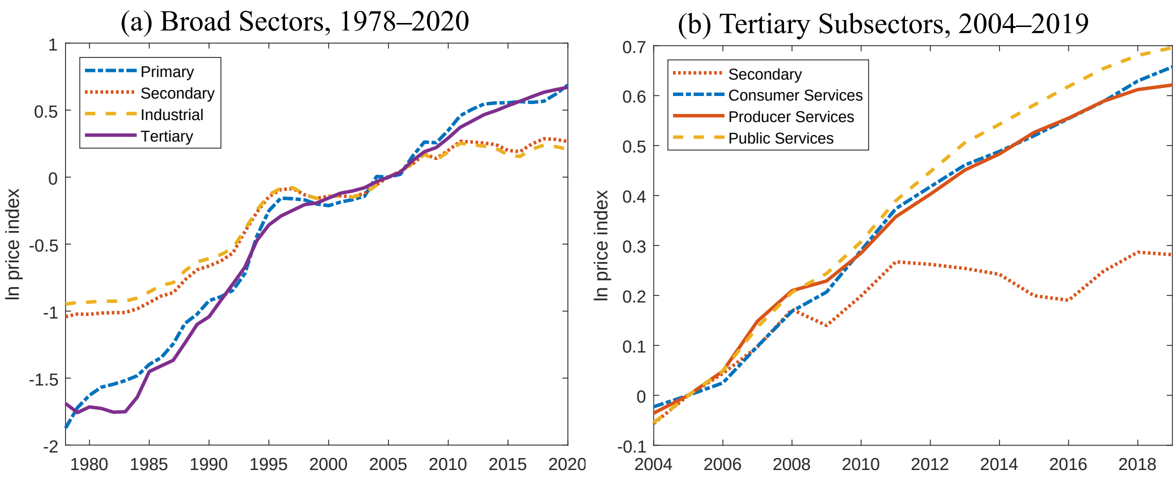

Figure 4: Sectoral Value-Added Deflators in China (All Sectors)

services is the largest component, followed by producer services. The shares of the three components of the tertiary sector all grew steadily. The gap between the shares of consumer and producer services grew over time, from 5.7 percentage points in 2004 to 8.3 percentage points in 2019.

The heterogeneity could in part reflect changes in relative prices across sectors. To uncover the role of price changes, Figure 4 plots the time series of sectoral price indexes on a logarithmic scale, with all indexes normalized to unity in 2005. The left panel shows a secular decline in industrial prices relative to the price indexes of both the primary and tertiary sectors. The decline is particularly accentuated between 1978 and 1995 and after 2008, while relative prices are more stable in the interim period. Within the tertiary sector, the relative price of consumer and producer services is approximately constant.

Combining data for nominal value-added with the price indexes, we can compute deflated (or *real*) value-added shares—see Figure 5.The deflated value-added data are evaluated at 2005 prices. Namely, the real and the nominal value-added shares are by construction the same in 2005. The deflated data paint a partially different picture from those in nominal terms. In the earlier period, the secondary sector was the fastest-growing sector with an increase from 30% in 1978 to 50% in 2012. The deflated data keep showing some evidence of mild deindustrialization in the most recent decade when the deflated value-added share of the secondary sector decreased from 50% in 2012 to 48% in 2020, while the corresponding share of the tertiary sector went up from 42% to 45%. Within the secondary sector, the share of construction increased, as shown by the growing gap between the dotted and the dashed line in the left panel of Figure 5. Within the tertiary sector, producer services have outgrown consumer services since 2012.

Our findings are consistent with those of recent studies based on firm-level data. For example, Bai et al. (2021) find similar patterns of tertiarization from the Annual Firm Survey conducted by China's Administration of Taxation.

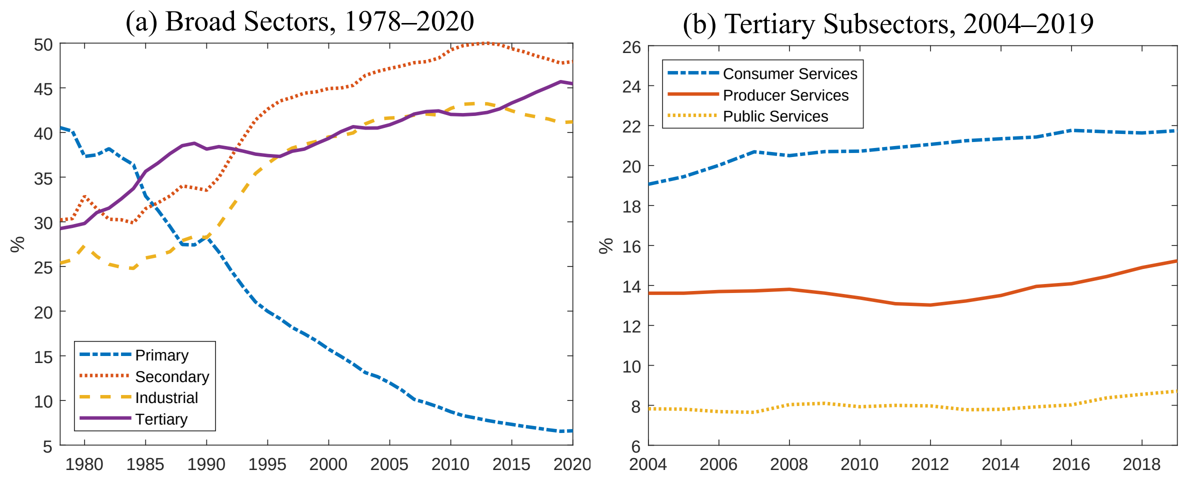

Figure 5: Sectoral Deflated Value-Added Shares in China (All Sectors) at 2005 Prices

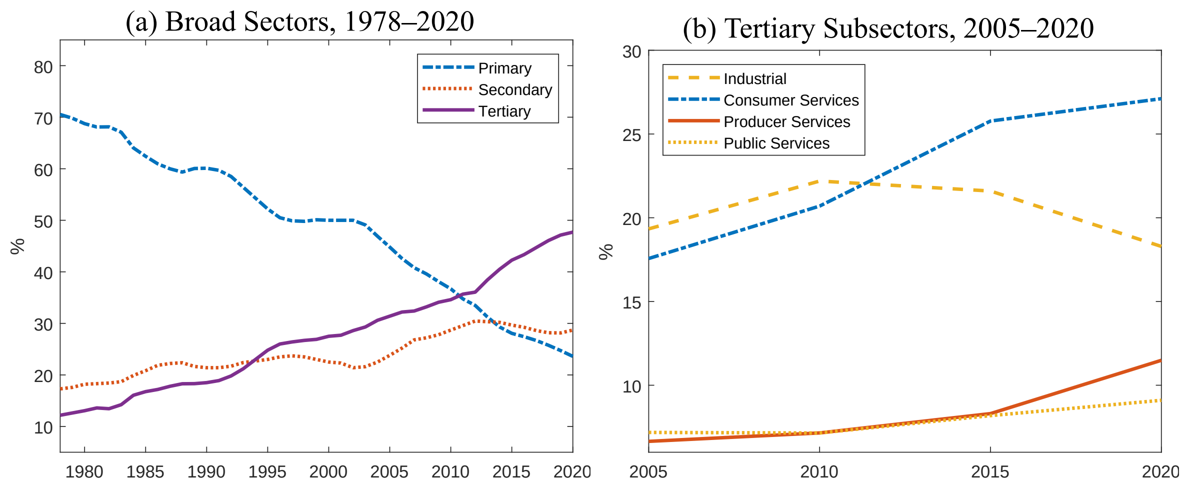

Figure 6: Sectoral Employment Shares in China (All Sectors)

4.1.2 Sectoral Employment Shares and Human Capital

The left panel in Figure 6 displays the sectoral employment shares based on the CSY data compiled by the Department of Population and Employment Statistics.[9] At the outset of the process of economic reforms, over 70% of Chinese workers were employed in the primary sector, while 17% and 12% of them worked in the secondary and tertiary sectors, respectively. The tertiary employment share grew steadily thereafter with an acceleration in the last decade, which raised it up to almost half of the Chinese workforce. The employment share of the secondary sector grew more slowly and has declined since 2012.

The right panel of Figure 6 shows the decomposition of the tertiary sector. In this case, we cannot use the data from the CSY because it does not report the breakdown of employment across service industries. We rely instead on the information from either the Population Census or 1%

[9] Annual employment series in CSY uses information from Reporting Form System on Labour and Wage Statistics and the National Monthly Labour Force Survey.

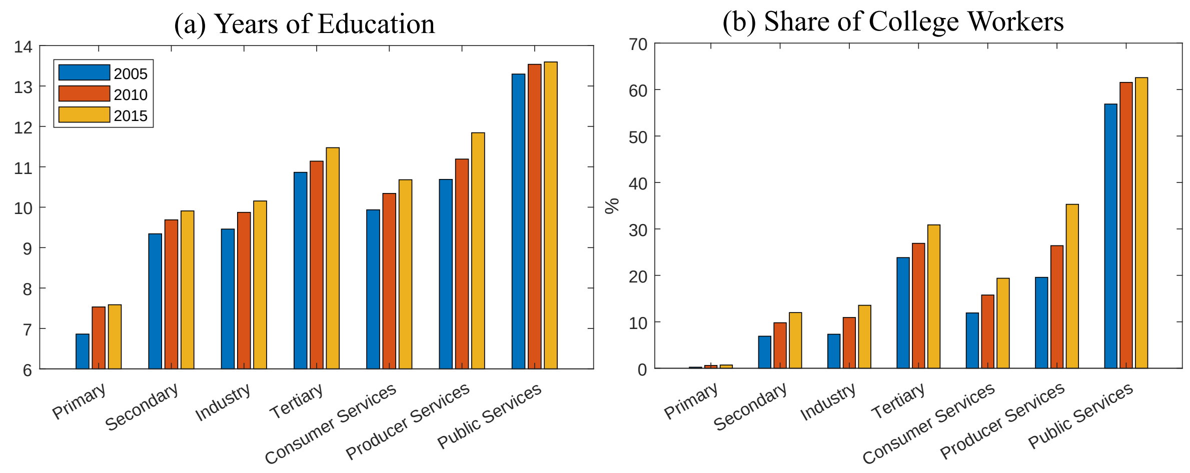

Figure 7: Educational Attainments by Sector

Population Surveys.[10] We observe a marked trend difference between producer and consumer services. The employment share of consumer services increased from 17.6% in 2005 to 27.1% in 2020, while the employment share of producer services only increased from 6.6% to 11.5% in the same period.

The educational attainment of the Chinese workforce has increased remarkably over the years. Back in 1990, only 36% of the Chinese population aged 25 and older had attained some secondary education. That percentage increased to about 60% by 2005 and to over 80% today. This change tracks major progress in enrollment rates. For instance, the gross enrollment rate in tertiary education was a mere 3% in 1990. By 2005, it climbed to 19%. Today, it is close to 60%, higher than the average enrollment for OECD countries. It is interesting to study which industries attracted this growing number of educated workers. Toward this aim, we use the Population Census and 1% Population Survey to construct two standard measures of educational attainment at the sectoral level: (1) average years of education (left panel of Figure 7); (2) the share of college-educated workers (right panel of Figure 7).[11]

As Figure 7 shows, the service sector is the most human capital-intensive sector by both measures. Within the tertiary sector, public services attract the largest share of educated workers, followed by producer and consumer services. At the time in which we write this article, the NBS has not yet released sectoral educational attainment data from the 2020 Census. In the 2015 Population Survey, tertiary sector workers have, on average, 11.5 years of education, which compares with 7.6 and 9.9 years in the primary and secondary sectors, respectively. Over 30% of service workers have some college education, substantially more than the 0.7% and 12% in

[10] The Population Censuses are available in 1982, 1990, 2000, 2010, and 2020. The 1% Population Surveys are available in 1987, 1995, 2005, and 2015. Because of a change in the industry classification, pre- and post-2004 data are not comparable. For this reason, we focus on post-2004 data.

[11] In the Population Census and Survey, the average years of education are overstated because the NBS does not take note of partial school attainment.

the primary and secondary sectors. Within the tertiary sector, producer service workers have 11.9 years of education on average, 1.2 years more than consumer service workers and 1.7 years fewer than public service workers.

Over time, producer services exhibit the fastest growth in educational attainment: the average number of years of education increased from 10.7 years in 2005 to 11.9 years in 2015. The educational attainment of this sector outgrew those of both consumer services and the industrial sector, as shown by columns 4–6 of Table 2.[12] The heterogeneous human capital growth across sectors with a strikingly fast skill upgrade in producer services is a salient feature of the tertiarization process in China.

Table 2: Sectoral Labor Productivity Growth, 2005–2015

Sector	Annual Growth			Average Edu. Years			Annual Growth
	$\frac{P_j Y_j}{L_j}$	P_j	$\frac{K_j}{L_j}$	2005	2010	2015	H_j (05–15)
Primary	15.3%	5.7%	16.0%	6.86	7.53	7.59	0.73%
Secondary	9.6%	2.0%	12.1%	9.34	9.69	9.91	0.57%
Industrial	10.2%	1.7%	13.5%	9.46	9.87	10.15	0.69%
Tertiary	12.6%	5.5%	9.9%	10.86	11.14	11.47	0.61%
CS	12.0%	5.3%	10.1%	9.94	10.34	10.68	0.75%
PS	13.0%	5.4%	9.6%	10.69	11.19	11.84	1.16%
Pub.S	14.6%	6.0%	10.6%	13.29	13.54	13.59	0.30%

4.2 Growth Accounting and Sectoral TFP Growth

In this section, we decompose the nominal growth rates of sectoral labor productivity across different sources. Our main goal is to estimate real productivity growth in services. Toward this aim, we combine the NBS data on sectoral value-added and employment to calculate growth rates of value-added per worker in the period 2005–2015.[13] Table 2 shows the sectoral trends.

The primary sector features the highest growth rate of nominal labor productivity (15.3% annually)—a finding that is arguably related to the dramatic decrease in rural employment. The tertiary sector has the second-highest growth in nominal labor productivity (12.6%). Within the tertiary sector, productivity grows slightly faster in public services (14.6%) and producer services (13%) than in consumer services (12%). The secondary sector has the lowest labor productivity growth in nominal terms (9.6%). This result is robust to separating construction from manufacturing.

[12] Overall, human capital growth in the tertiary sector is slightly lower than in the industrial sector because public services, the most human capital-intensive subsector, has a very low increase in human capital over the period of 2005–2015.

[13] Sectoral value-added data are available at annual frequency since 2004, whereas sectoral employment data are only available for 2005, 2010, and 2015, which correspond to the three years of the Population Census or 1% Population Survey.

Apart from reflecting changes in relative prices (as discussed above) these differences in nominal labor productivity growth across sectors could reflect differences in investment rates. To examine the role of physical capital, we calculate sectoral capital $K_{j,t}$ using the perpetual inventory method.[14] As shown in column 3 in Table 2, capital deepening was significantly faster in the secondary (and industrial) sector than in the service sector.

Next, we calculate the growth rate of sectoral human capital:

$$g_{j,t}^{H} = \xi \times \text{Annual Change in Average Education Years}_{j},$$

where ξ is estimated using Mincerian regressions. For China, we find a return to schooling of about 10%, which is rather stable across time and sectors. Therefore, we set $\xi = 0.1$. We report the sectoral growth rates of human capital in column 7 of Table 2. Finally, we estimate sectoral labor output elasticities for each two-digit industry by using firm-level SAT data (see Appendix C.4 for more information). Because of insufficient firm-level data in the SAT data, we exclude public services. The average sectoral labor output elasticity, weighted by the industry value-added, is 0.58 for the industrial sector, 0.84 and 0.67 for consumer and producer services, respectively. Human capital growth is higher in the tertiary than in the secondary sector, albeit lower than in the industrial sector. As noted above, this result hinges on the fact that public services, which is the most human capital-intensive sector, experienced the lowest growth in educational attainment. If we zoom in on private services, human capital actually grows faster than in the industrial sector. We also note that the labor share is significantly higher in the service sector.

In summary: relative to the secondary sector, the tertiary sector exhibits higher growth in value-added per worker, an increase in the relative price, and lower physical capital accumulation. Private services also exhibit a significantly higher human capital growth.

Total Factor Productivity To calculate total factor productivity, we postulate Cobb-Douglas sectoral production functions:

$$Y_{j,t} = A_{j,t} K_{j,t}^{\alpha_j} \left(H_{j,t} L_{j,t}\right)^{1-\alpha_j},$$

where j denotes the sector and A, K, L, and H denote TFP, capital, labor, and human capital input, respectively. We denote by g^X the growth rate of variable X. We use the following accounting equation:

$$g_{j,t}^{PY/L} = g_{j,t}^{P} + g_{j,t}^{A} + \alpha_j g_{j,t}^{K/L} + \left(1 - \alpha_j\right) g_{j,t}^{H}.$$

[14] In the NBS data, there is no information regarding the one-digit industry composition of Fixed Capital Formation, which is equivalent to the Investment in Chinese official statistics. However, the NBS does provide one-digit industry composition of Fixed Asset Investment, which can be used to infer the one-digit industry composition of investment. See Appendix C.3 for more details.

In words, the growth rate of nominal labor productivity can be decomposed into the growth rates of the sectoral price level, sectoral TFP, and factor inputs—a weighted average of the growth rates of the capital-labor ratio and human capital. As usual, TFP is not directly measured and is calculated as a residual.

Table 3 reports the results expressed as differences between producer and consumer services, on the one hand, and secondary and industrial sectors, on the other hand. As documented in the previous section, the nominal value-added grows more in the service sector than in the secondary sector. An important part of the nominal differences is explained by changes in relative prices. However, this is not the whole story. Service industries also experience less capital deepening, which is partially offset by higher growth in the human capital input. Ultimately—perhaps surprising—TFP growth is larger in both producer and consumer services than in the secondary sector. The gap is larger in the case of consumer services (+2.0% annually) than in producer services (+1.3% annually). Excluding the construction activity and restricting the comparison to the manufacturing sector yields quantitatively smaller differences without altering the overall picture.

Table 3: The Decomposition of Sectoral Labor Productivity Growth, 2005–2015

Sector i	Sector j	Relative Annual Growth $\Delta g_{i,j}^{X}$				
		PY/L	P	$(K/L)^{\alpha}$	$H^{1-\alpha}$	A
PS	Secondary	3.38%	3.39%	-1.77%	0.44%	1.32%
CS	Secondary	2.32%	3.32%	-3.32%	0.29%	2.02%
PS	Industrial	2.83%	3.73%	-2.48%	0.37%	1.21%
CS	Industrial	1.77%	3.66%	-4.02%	0.22%	1.91%

In summary, tertiarization in China during the period of 2005–2015 is associated with a change in relative prices that likely reflects demand forces. The joint observation of a higher sectoral TFP growth in service industries and an increase over time in the relative price of services suggests an important role of nonhomothetic demand. Namely, services appear to be *luxuries*.

However, we also document an important role of supply factors. Even though services (especially producer services) already had the highest human capital intensity back in 2005, they also experienced high growth in this input. This suggests that service industries were the main destination for an increasingly educated labor force. Moreover, fast human capital accumulation might have been an engine of tertiarization in China.[15] Last but not least, TFP growth has been high in services—even higher than in the industrial sector. This finding runs against the traditional view that the ultimate driver of the development process is the productivity growth in manufacturing, while tertiarization is a corollary of development merely resulting from income

[15] See Buera and Kaboski (2012) for a theoretical model in which human capital development facilitates tertiarization as well as an empirical analysis for the United States since the 1960s.

effects. It is instead in line with the findings of FPZ for India. Human capital and TFP growth jointly account for a differential annual growth in value-added per worker of +1.8% for producer services and +2.3% for consumer services. These gaps partially offset the lower physical investments in service industries.

5 A Model-Based Accounting Approach

Table 3 shows a large productivity growth in both producer and consumer services. A caveat is that the growth accounting method used hinges on price indexes whose accuracy is dubious.[16] The price indexes for services are especially problematic because of the notorious difficulties in measuring the quality of services. In the Chinese case, there are additional issues, especially salient in the service sector (see, e.g., Han, 2014; Nakamura et al., 2016; and Lai and Zhu, 2022).

To address these concerns, in this section we infer productivity growth by an alternative approach that does not rely on published price indexes for services. We estimate prices and productivity growth from a general equilibrium (GE) model, following the methodology recently proposed by FPZ. This approach requires specifying a demand system to the production side of the economy. The crux of the procedure is the estimation of an income elasticity that we obtain from household-level data.

5.1 Model

We start by presenting the model. We deviate from FPZ in two respects. First, we only consider aggregate productivity, while FPZ construct a spatial equilibrium model and carry out the analysis at the Indian district level. Second, we embed investment goods into our analysis, while FPZ abstract from savings and investments.

Preferences There is a continuum of heterogeneous households indexed by $i \in [0, 1]$, each of them comprising a large number N_t of identical members. N_t grows at the exogenous rate n. Each member of household i is endowed with $l_i = 1$ units of raw labor and $q_{i,t} \in [\underline{q}_t, \infty)$ efficiency units of labor, where $\underline{q}_t > 0$. For all households, $q_{i,t}$ grows at a constant rate n_q. We denote $L_t \equiv N_t \int_0^1 l_i di$ and $Q_t \equiv N_t \int_0^1 q_{i,t} di$ the aggregate supply of raw labor and efficiency units of labor, respectively.

In addition, each member of the household is endowed with $a_{i,0} \in \mathbb{R}^+$ units of wealth. Following

[16] The nominal sectoral value-added data are instead generally regarded as reliable. For instance, Bai et al. (2021) document that the recent trends in sectoral value-added implied by China's official statistics are consistent with those found in firm-level data.

Boppart (2014), we assume that the relative factor endowment is the same across all households:

$$\frac{a_{i,0}}{q_{i,0}} = \frac{K_0}{Q_0}, \quad \forall i.$$

This assumption ensures tractability avoiding that the joint distribution of $\{q_{i,0}, a_{i,0}\}$ is a state variable that affects the equilibrium allocation.

Household i's lifetime utility is given by

$$U_i = \sum_{t=0}^{\infty} \beta^t N_t \left[V \left(P_{F,t}, P_{G,t}, P_{CS,t}, E_{i,t} \right) \right],$$

where $P_{F,t}$, $P_{G,t}$, and $P_{CS,t}$ denote the price of food, industrial goods, and consumer services, respectively. Let $\boldsymbol{S} \equiv \{F, G, CS\}$. We denote by $E_{i,t} = \sum_{s \in \boldsymbol{S}} P_{s,t} c^i_{s,t}$ household i's consumption expenditure. Following Alder et al. (2022) and FPZ, we assume households are endowed with nonhomothetic preferences in the class of Price Independent General Linear (PIGL), parameterized by the following indirect utility function:

$$V \left(P_{F,t}, P_{G,t}, P_{CS,t}, E_{i,t} \right) = \frac{1}{\mu} \left(\frac{E_{i,t}}{\prod_{\tilde{s} \in \boldsymbol{S}} \left(P_{\tilde{s},t} \right)^{\omega_{\tilde{s}}}} \right)^{\mu} - \sum_{\tilde{s} \in \boldsymbol{S}} \nu_{\tilde{s}} \ln P_{\tilde{s},t}.$$

The associated expenditure shares, which can be derived from Roy's Lemma, are given by $\vartheta_{i,s,t} = \omega_s + \nu_s \left(\frac{E_{i,t}}{\prod_{\tilde{s} \in \boldsymbol{S}} \left(P_{\tilde{s},t} \right)^{\omega_{\tilde{s}}}} \right)^{-\mu}$, for $s \in \boldsymbol{S}$. Here, ω_s stands for the asymptotic expenditure share of sector s satisfying $\sum_{\tilde{s} \in \boldsymbol{S}} \omega_{\tilde{s}} = 1$; the sign of ν_s determines whether a good is a luxury ($\nu_s < 0$) or a necessity ($\nu_s > 0$), with the constraint that $\sum_{\tilde{s} \in \boldsymbol{S}} \nu_{\tilde{s}} = 0$; finally, μ is an elasticity that regulates the income effects.

Households earn labor income by supplying efficiency units of labor and earn capital income returns on the assets they hold. The budget constraint for household i is:

$$E_{i,t} = (1 + r_t) \, a_{i,t} + W_t q_{i,t} + T_t - (1 + n) \, a_{i,t+1},$$

where W_t and r_t stands for the wage rate and the return on assets in period t, and T_t is a lump-sum transfer received from the government.

Production The production side of the model is as in the previous section. Sector $j \in \boldsymbol{J} \equiv \{F, M, CS, PS\}$ employs labor $N_{j,t}$ and capital $K_{j,t}$ to produce sectoral output by the following Cobb-Douglas production function:

$$Y_{j,t} = A_{j,t} \left(K_{j,t} \right)^{\alpha_j} \left(e_{j,t} N_{j,t} \right)^{1-\alpha_j},$$

where $A_{j,t}$ is the sectoral TFP, $\alpha_{j,t}$ and $1-\alpha_{j,t}$ are the sectoral capital and labor output elasticities, and $e_{j,t}$ is a measure of human capital. Firms' profits in sector j are given by

$$\Pi_{j,t} = P_{j,t}Y_{j,t} - \left(1+\tau_{j,t}^{N}\right) W_t e_{j,t} N_{j,t} - \left(1+\tau_{j,t}^{K}\right) R_t K_t,$$

where $\tau_{j,t}^{N}$ and $\tau_{j,t}^{K}$ stand for the sectoral labor and capital wedges in the form of distortionary taxes.

The industrial good is produced using manufacturing goods and producer services as inputs according to the CES production function:

$$Y_{G,t} = \left[(\psi_M)^{\frac{1}{\rho}} \left(X_{M,t}\right)^{\frac{\rho-1}{\rho}} + (1-\psi_M)^{\frac{1}{\rho}} \left(X_{PS,t}\right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where ρ is the elasticity of substitution between manufacturing inputs and producer services.

The investment goods are produced using sectoral outputs and capital:

$$Y_{I,t} = A_t F\left(X_{F,t}^{I}, X_{G,t}^{I}, X_{CS,t}^{I}, K_t^{I}\right),$$

where A_t denotes the productivity of producing investment goods and $F(\cdot)$ is a linearly homogeneous function, which is increasing and concave in each of its arguments. This specification nests several existing models as particular cases. For instance, Ngai and Pissarides (2007) assume that $Y_{I,t} = A_t X_{G,t}^{I}$ and $\psi_M = 1$; Acemoglu and Guerrieri (2008) and Herrendorf et al. (2020) assume that $Y_{I,t} = A_t X_{G,t}^{I}$ and $\psi_M \in (0,1)$;[17] and Boppart (2014) assumes that $Y_{I,t} = A_t K_t^{I}$. Our results do not hinge on any particular parameterization of the production function $F(\cdot)$. The only important restriction is that $X_{G,t}$ enters the production function for investment goods, where $X_{G,t}$ is a CES aggregate of manufacturing goods and producer services as postulated above. We normalize the price of the investment good to unity.[18]

Next, we assume a standard law of motion for capital: $K_{t+1} = (1-\delta) K_t + I_t$. Finally, we assume that the government runs a balanced budget:

$$N_t T_t = \sum_{j \in \boldsymbol{J}} \left(\tau_{j,t}^{N} W_t e_{j,t} N_{j,t} + \tau_{j,t}^{K} R_t K_{j,t}\right).$$

Market Clearing To solve for the equilibrium allocation, we specify a set of market-clearing conditions. We have six goods equilibrium conditions:

[17] Acemoglu and Guerrieri (2008) additionally postulate the same technology for final consumption goods.

[18] This normalization implies that when we take the model to the data, we express all nominal variables, including sectoral value-added $VA_{s,t}$ and sectoral prices $P_{s,t}$ in terms of the price index of fixed asset investment, which is the price of new capital or investment published by NBS in official statistics of China.

- for agricultural goods, industrial goods, and consumer services:

$$Y_{s,t} = X^{I}_{s,t} + N_t \int_i c^{i}_{s,t} di, \quad \forall s \in \{F, G, CS\};$$

- for manufacturing goods and producer services $\quad Y_{s,t} = X_{s,t}, \quad \forall s \in \{M, PS\}$;

- for investment and industrial goods: $\quad I_t = Y^{I}_t$.

Finally, we have factor market-clearing conditions for raw labor, efficiency units of labor, and capital:

$$N_t = \sum_{j \in \boldsymbol{J}} N_{j,t}, \quad Q_t = \sum_{j \in \boldsymbol{J}} e_{j,t} N_{j,t}, \ \text{ and } \ N_t \int_i a_{i,t} di = K_t = \sum_{j \in \boldsymbol{J}} K_{j,t}.$$

5.2 Equilibrium Accounting Framework

The competitive equilibrium is a set of sectoral prices $\{P_{k,t}\}_{k \in \boldsymbol{S} \cup \boldsymbol{J}}$ and labor allocations $\{N_{j,t}\}_{j \in \boldsymbol{J}}$ and capital $\{K_{j,t}\}_{j \in \boldsymbol{J}}$ such that consumers maximize utility, firms maximize profits, and all markets clear. Denote by $\boldsymbol{\Theta}$ the set of parameters of the model:

$$\boldsymbol{\Theta} \equiv \left\{ \{\alpha_j\}_{j \in \boldsymbol{J}}, \psi_M, \rho, \mu, \{\omega_s, \nu_s\}_{s \in \boldsymbol{S}} \right\}.$$

Conditional on $\boldsymbol{\Theta}$, the equilibrium allocation and prices are determined by the sectoral TFPs $\mathbf{A}_t \equiv \{A_{j,t}\}_{j \in \boldsymbol{J}}$ and sectoral wedges $\boldsymbol{\tau}_t \equiv \{\tau^{N}_{j,t}, \tau^{K}_{j,t}\}_{j \in \boldsymbol{J}}$:

$$\left(\{N_{j,t}\}_{j \in \boldsymbol{J}}, \{K_{j,t}\}_{j \in \boldsymbol{J}}, \{P_{k,t}\}_{k \in \boldsymbol{S} \cup \boldsymbol{J}} \right) = \boldsymbol{M} \left(\mathbf{A}_t, \boldsymbol{\tau}_t; \boldsymbol{\Theta} \right),$$

where the mapping $\boldsymbol{M}$ is determined by equilibrium conditions of the model consisting of a supply block and a demand block. Conditional on a vector of parameters $\boldsymbol{\Theta}$ and wedges $\boldsymbol{\tau}_t$, one can invert the mapping $\boldsymbol{M}$ and infer the productivities from data on prices and value-added. If preferences are homothetic, the set of First Order Conditions for competitive firms in each sector is sufficient to infer sectoral TFPs. This is the standard procedure we followed in the growth accounting approach of Section 4.2.

In this section, we postulate instead a demand system consistent with nonhomothetic PIGL preferences and use it to infer the equilibrium price of consumer services. The crux of the identification strategy is the income elasticity μ. We now proceed to calibrate the technology and preference parameters.

Calibration We calibrate three sets of parameters. The first set is the sectoral labor output elasticities, α_j. We set the agriculture labor output elasticity α_F to 0.5 following Brandt and

Zhu (2010). Then, we infer α_M, α_{PS}, and α_{CS} from the firm-level data as in Section 4.2.

The second set of parameters (ψ_M and ρ) governs the CES production function of industrial firms. To calibrate ρ, we use the optimality condition for industrial firms:

$$\frac{VA_{PS}}{VA_M} = \frac{1-\psi_M}{\psi_M}\left(\frac{P_M}{P_{PS}}\right)^{\rho-1}.$$

We have data observation for both the relative price P_M/P_{PS} and relative value added VA_{PS}/VA_M. Using the observations for 2005 and 2015, we infer the elasticity $\rho-1$. This yields $\rho = 0.0642$. We note that this value of ρ is larger than that obtained by Herrendorf et al. (2020), who find the elasticity of substitution between manufacturing and service in the investment goods to be 0.01. For this reason, as a robustness check, we set $\rho = 0.0321$, which is half as large as in our preferred calibration. We should in principle also calibrate ψ_M. However, ψ_M only affects the estimates of productivity levels, not their growth. Since we are not interested in those levels, we don't need to take stand on the value of ψ_M.

The third set of parameters comes from the PIGL preferences and includes μ and $\{\omega_s, \nu_s\}_{s\in\boldsymbol{S}}$. We follow the calibration strategy in FPZ. ω_F pins down the asymptotic agricultural expenditure share as the household income goes to infinity. We set $\omega_F = 0.01$ to match the agricultural share in the United States. Because a higher ω_F yields a higher estimated TFP growth in the consumer service sector, we view setting $\omega_F = 0.01$ as a conservative calibration strategy. Next, we set $\nu_{CS} = -1$, a normalization of no importance.[19]

Next, we turn to μ, the key income elasticity. We estimate μ using household data on consumption expenditures following the methodology of FPZ. As anticipated above, the First Order Conditions of the consumer problem imply the following expenditure shares:

$$\vartheta_{i,s} = \omega_s + \nu_s\left(\frac{E_i}{\prod_{\tilde{s}\in\boldsymbol{S}}(P_{\tilde{s}})^{\omega_{\tilde{s}}}}\right)^{-\mu}, \quad \forall s\in\boldsymbol{S}, \tag{1}$$

where, recall, $\vartheta_{i,s}$ denotes household i's consumption expenditure share on food (s=F), industrial goods (s=G), or consumer services (s=CS), respectively. Aggregating up Equation 1 over all households and combining it with the set of market-clearing conditions yields:

$$\frac{VA_s^C}{\sum_{\tilde{s}\in\boldsymbol{S}} VA_{\tilde{s}}^C} = \omega_s + \phi\nu_s\left(\frac{\sum_{\tilde{s}\in\boldsymbol{S}} VA_{\tilde{s}}^C/N}{\prod_{\tilde{s}\in\boldsymbol{S}}(P_{\tilde{s}})^{\omega_{\tilde{s}}}}\right)^{-\mu}, \quad \forall s\in\boldsymbol{S}, \tag{2}$$

where VA_s^C is the value-added of sector s that enters into final goods consumption and $N \equiv \sum_{j\in\boldsymbol{J}} N_j$ is the size of labor force.[20] The term ϕ depends, among other things, on the extent of

[19] As discussed by FPZ, the structural parameter ν_{CS} is not separately identified from the average productivity *level* in the consumer service sector. However, such a level has no interpretation in our analysis—we are only interested in the productivity growth of sectoral TFPs.

[20] We follow Herrendorf et al. (2013, 2020) to estimate $VA_{s,t}^C$ by sectoral value-added and IO tables. See

income inequality. As long as ϕ is constant over time—which is guaranteed by the households' Euler equation (see Appendix D.3)—its value has no effect on the estimates of productivity growth.

The PIGL preferences we postulate entail two important restrictions. First, the same elasticity μ regulates the behavior of the expenditure share for all goods. Second, this elasticity is constant. In principle, one could estimate μ from Equation 1 for any of the three sectors. In practice, it is easier to use Equation 1 for food (s=F) since individual data for household consumption expenditure on food items are both readily available and better measured than other expenditure. Moreover, because ω_F is a small number, one can estimate a log-linear regression.[21]

To estimate μ, we exploit the variation in food expenditure shares across households with different income levels. We use data from the Chinese Household Income Project (CHIP), a repeated cross-sectional survey that is closely related to the household surveys conducted by the NBS. We obtain an estimate of $\mu = 0.375$. A concern is that the measurement of expenditure shares becomes less accurate as one considers households with a large share of home production as is common in rural areas. Reassuringly, restricting the regression to the urban sample yields a very similar estimate of $\mu = 0.371$. As a robustness check, we use China Family Panel Studies (CFPS), a PSID-like annual longitudinal survey conducted by Peking University. The estimated income elasticity falls significantly to 0.272 and 0.292 for the whole and urban samples, respectively. We have no good explanation for this puzzling difference. The details are provided in Appendix D.1. Given this discrepancy, we report results under different estimates of μ.

Finally, following again FPZ, we estimate $\phi\nu_F$ and ω_{CS} by combining Equation 2 for s=F and s=CS:

$$\frac{VA^C_{F,t}}{\sum_{\tilde{s}\in \boldsymbol{S}} VA^C_{\tilde{s},t}} = \omega_F + \phi\nu_F \cdot \frac{\frac{VA^C_{CS,t}}{\sum_{\tilde{s}\in \boldsymbol{S}} VA^C_{\tilde{s},t}} - \omega_{CS}}{\phi\nu_{CS}} \tag{3}$$

We set the values of $\phi\nu_F$ and ω_{CS} so that Equation 3 holds for $VA^C_{F,t}/\sum_{\tilde{s}\in \boldsymbol{S}} VA^C_{\tilde{s},t}$ and $VA^C_{CS,t}/\sum_{\tilde{s}\in \boldsymbol{S}} VA^C_{\tilde{s},t}$ in the data for 2005 and 2015. The remaining PIGL parameters, ω_G and $\phi\nu_G$, are obtained from the normalizations $\sum_{\tilde{s}\in \boldsymbol{S}} \omega_{\tilde{s}} = 1$ and $\sum_{\tilde{s}\in \boldsymbol{S}} \nu_{\tilde{s}} = 0$. We summarize the calibrated parameters in Table 4.

Table 4: Baseline Calibration

	Cobb-Douglas				CES	PIGL Preference						
Parameters	α_F	α_M	α_{CS}	α_{PS}	ρ	μ	ω_F	ω_G	ω_{CS}	$\phi\nu_F$	$\phi\nu_G$	$\phi\nu_{CS}$
Values	0.50	0.41	0.16	0.33	0.0642	0.375	0.01	0.37	0.62	0.48	0.52	-1

Appendix D.2 for the detailed construction of $VA^C_{s,t}$.

[21] Ignoring the small ω_F, we can rewrite the food expenditure of household i as $\ln \frac{P_{F,t}c^i_{F,t}}{E_{i,t}} \approx b_t - \mu \ln E_{i,t}$, where b_t is constant across households. FPZ follows the same approach using Indian data.

Results We start from the baseline calibration in Table 5. The estimated annual difference in the growth rate of P_{CS} relative to P_M is 3.73 percentage points. The TFP growth of consumer services exceeds that in the manufacturing sector by 1.55 percentage points. This finding is qualitatively consistent with the growth accounting results in Section 4.2. However, the estimated relative price increase of consumer services is now 0.40 percentage points higher than in the official data. This implies that the estimated annual productivity growth is 0.47 percentage points lower than is implied by the official statistics. Using the estimated elasticity from urban households in the CHIP data yields similar results.

Table 5: Baseline Results

	Growth Accounting	CHIP (All)	CHIP (Urban)	CFPS (All)	CFPS (Urban)
		$\mu = 0.375$	$\mu = 0.371$	$\mu = 0.272$	$\mu = 0.292$
$\Delta g^P_{CS,M}$	3.32%	3.732%	3.595%	-1.00%	0.159%
$\Delta g^A_{CS,M}$	2.02%	1.550%	1.688%	6.284%	5.124%

Note: The table reports the annual growth of consumer services prices relative to that of manufacturing (row 1) and the annual growth of consumer services TFP relative to that of the manufacturing sector (row 2). Column 1 reports relevant relative growth calculated by growth accounting using official statistics. Columns 2–5 report the estimates of our GE approach. Columns 2 and 3 report the estimates when income elasticity μ is estimated using all (column 2, $\mu = 0.375$) and urban households (column 3, $\mu = 0.371$) consumption data in CHIP, respectively. Columns 4 and 5 report the estimates when income elasticity μ is estimated using all (column 4, $\mu = 0.272$) and urban households (column 5, $\mu = 0.292$) consumption data in CFPS, respectively.

We find instead a quantitatively sizable difference if we use the estimates of μ from the CFPS data. The CFPS yields a significantly lower income elasticity, as we noted. Therefore, the estimated productivity growth in consumer services is bound to be larger. Indeed, the model-inferred relative price of consumer services falls over time relative to manufacturing goods in this low-μ scenario. This implies very high productivity growth in consumer services equal to about 6.28% per annum in excess of productivity growth in manufacturing.

As an additional robustness check, we consider a stronger complementarity between manufacturing and producer services by letting $\rho = 0.0321$. This elasticity is inconsistent with the official price index for producer services. Rather, the model now generates a producer services price index that we can compare with the official price index. The model predictions are reported in Table 6. Reassuringly, the results are not sensitive to ρ. Assuming a stronger complementarity implies a slightly lower relative price increase in producer services (the third row) and a slightly higher relative TFP growth. The differences are less than 0.2 percentage points.

Taking Stock The main take-home message of this section is that with all the methodologies and datasets considered, we consistently find that productivity in the consumer service sector outgrew productivity in manufacturing during the period of 2005–2015. The only unsettling finding is that two highly reputed datasets yield significantly different estimates for the income elasticity of consumer expenditure on food items, which in turn affects the quantitative predictions of the theory for TFP growth. In spite of this discrepancy, the conclusion that growth in

Table 6: Results under Different ρ

	Growth Accounting	Baseline	Stronger Complementarity
		$\rho = 0.0642$	$\rho = 0.0321$
$\Delta g^{P}_{CS,M}$	3.32%	3.732%	3.749%
$\Delta g^{A}_{CS,M}$	2.02%	1.550%	1.533%
$\Delta g^{P}_{PS,M}$	3.39%	3.39%	3.28%
$\Delta g^{A}_{PS,M}$	1.32%	1.07%	1.18%

Note: The table reports the annual growth of consumer services prices relative to that of manufacturing (row 1), annual growth of consumer services TFP relative to that of manufacturing or secondary sector (row 2), the annual growth of producer services prices relative to that of manufacturing (row 3) and finally the annual growth of producer services TFP relative to that of manufacturing (row 4). Column 1 reports relevant relative growth calculated by growth accounting using official statistics. Columns 2 and 3 report the estimates of our GE approach: in the baseline estimation (column 1), the elasticity of substitution between producer services and manufacturing goods is estimated to be 0.0642; in the robustness check, ρ is chosen to be one-half of the baseline estimates. In both columns, income elasticity is set equal to 0.375, which is our baseline parameterization estimated using all households in the CHIP data.

China is turning service-led is robust.

6 Firm-Level Evidence

Thus far, we have studied aggregate data. In this section, we present some complementary evidence of the process of tertiarization based on firm-level data. For this purpose, we use the dataset on registration records from SAMR, which covers all registered firms in China, including financial institutions. The information this data set provides is more limited than that in the existing surveys of manufacturing firms but has the advantage of covering service industries. Specifically, we have access to the 2019 data covering over 37 million active firms reporting at the end of 2019. The information includes location, industry, registered capital, starting year, and ending year for firms exiting on or before 2019.

Active Firms Figure 8 plots the sectoral share of all active firms excluding those in the primary sector for which there is no information in the SAMR data. The left panel shows that the share of active firms in the tertiary sector increased from 61% in 1995 to 79% in 2019. As a mirror image, the share of the secondary (industrial) sector has declined over time from about 39% (35%) in 1995 to 21% (13%) in 2019. The right panel of Figure 8 further decomposes the tertiary sector into producer, consumers, and public services,[22] showing that since 2005 it has been the rise of producer services that has accounted for almost the entire growth of the tertiary share of the number of active firms.[23]

[22] The number of active firms in financial intermediation and real estate is attributed to consumer, producer, and public services in the same way as employment. See Appendix B.3 and B.4 for details.

[23] Figure 8 displays sectoral shares of the total number of firms without weighting firms by size for which we have no information. We return to this issue below.

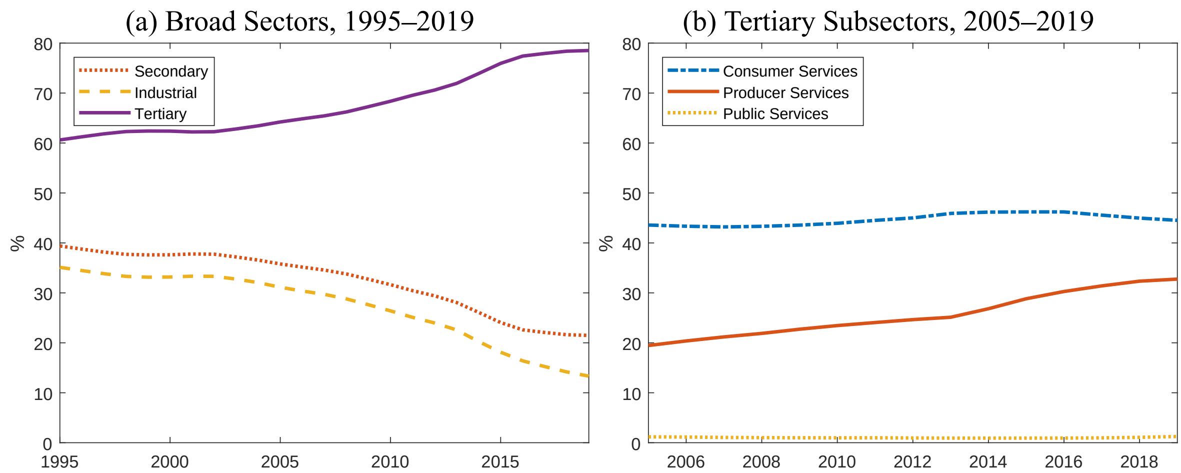

Figure 8: Share of Active Firms by Sector (Excluding Primary Sector)

Entry and Exit The registration data allow us to measure the extent to which changes in the share of active firms relate to entry and exit. Figure 9 plots the sectoral entry rate of firms from 1995 to 2019. As the left panel shows, the entry rate is higher in the tertiary than in the secondary sector for the entire period. Over time, entry rates increased in both the secondary and tertiary sectors, but the growth was faster in the latter. Moreover, since 2012, firms in the construction industry account for most of the positive trend in the secondary sector, while the industrial entry rate kept hovering around 12%.[24] When we disaggregate the tertiary sector (right panel), we see that for most years, the entry rate is higher in producer than in consumer services.

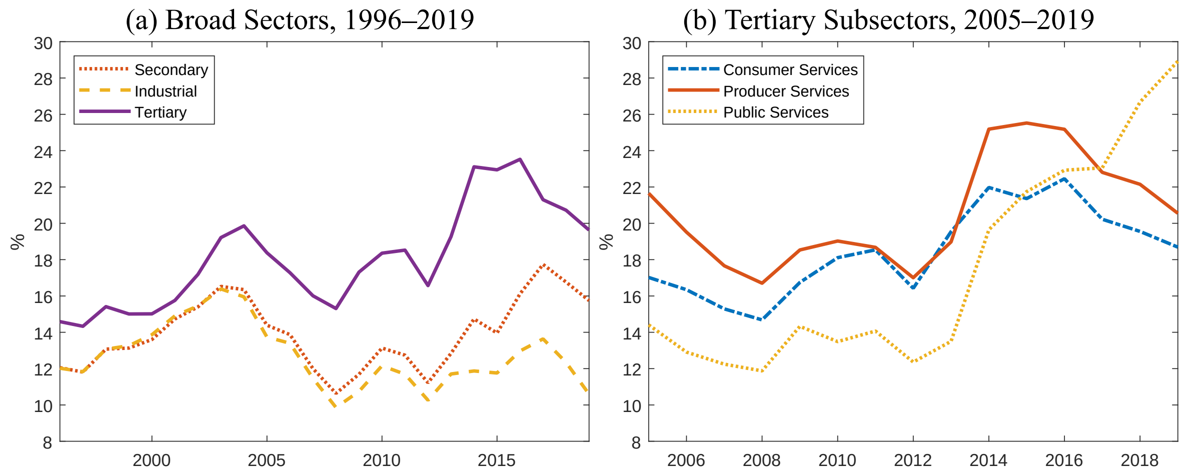

Figure 9: Firm Entry Rates by Sector

Figure 10 plots exit rates. The left panel shows a sharp increase in exit rates during the late 1990s, followed by a prolonged decline lasting until 2014. Thereafter, the exit rate again increased, especially in the tertiary sector.

Overall, we see more churning in the service sector than in the industrial sector—both entry and exit rates are higher among service firms. While this pattern is consistent throughout the entire

[24] Registration reforms contribute to the high entry rates around 2015 (Barwick et al., 2022).

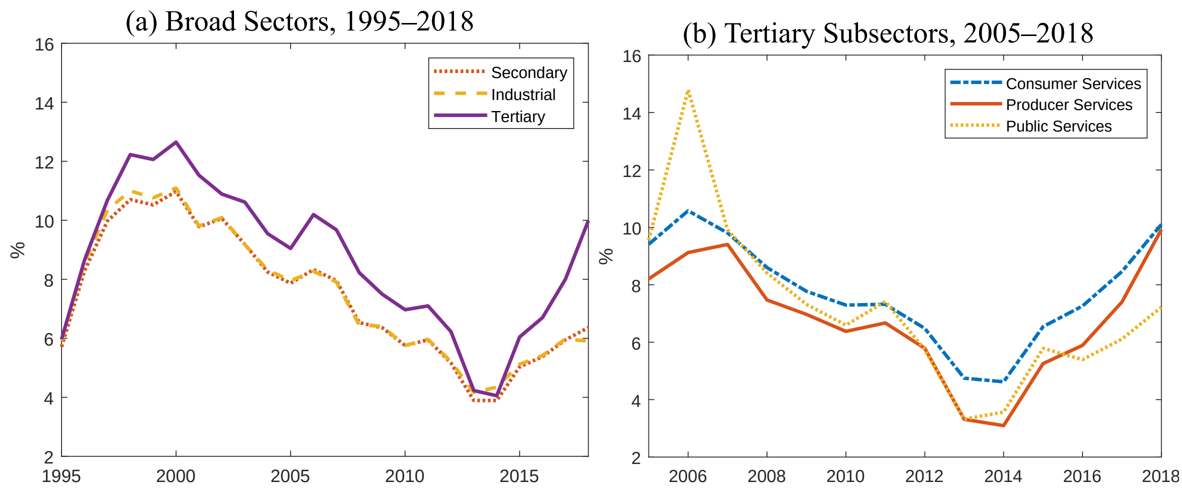

Figure 10: Firm Exit Rates by Sector

period for which we have data, the gap has increased over time. In 1996, the entry rate in the tertiary sector was two percentage points higher than in the secondary sector, while the exit rates were approximately the same across sectors. In 2019, both the entry and exit rates were four percentage points higher in the tertiary sector than in the secondary sector. In 2019, the gaps were even larger if one excludes construction activities.

Controlling for Firm Size The evidence discussed above refers to the number of active firms without weighting them by size. We now study whether the patterns in Figure 8 are robust to controlling for a proxy measure for firm size. Toward this aim, we use the information on registered capital. SAMR provides information about the registered capital of firms, although this is only available in the year of registration.[25] While these data do not allow us to construct time series for the sectoral stock of capital, we can compare two snapshots of firms that registered in 2013 and 2019—see Figure 11. The share of registered capital in the tertiary sector appears to increase from 67% in 2013 to 75% in 2019, while that of the secondary sector declined accordingly. Within the secondary sector, the decline of the industrial sector is especially sharp; from 27% in 2013 to 15% in 2019. Within the tertiary sector, producer services are the main driver of growth, consistent with the evidence provided above on the number of active firms.

Taking Stock To summarize, the firm-level data confirm the view that the service sector has become a centerpoint of China's economic activity during the last decade. The service sector exhibits both more net entry and more churning than the industrial sector in the period of 2013–2019. Within the tertiary sector, producer services have a higher entry rate and a lower exit rate. Both observations imply a growing share of producer service firms during the recent tertiarization wave. The evidence is robust to controlling for firm size as proxied by the firms' registered capital.

[25] Registered capital is highly correlated with total assets across industrial firms (Bai et al.,2022).

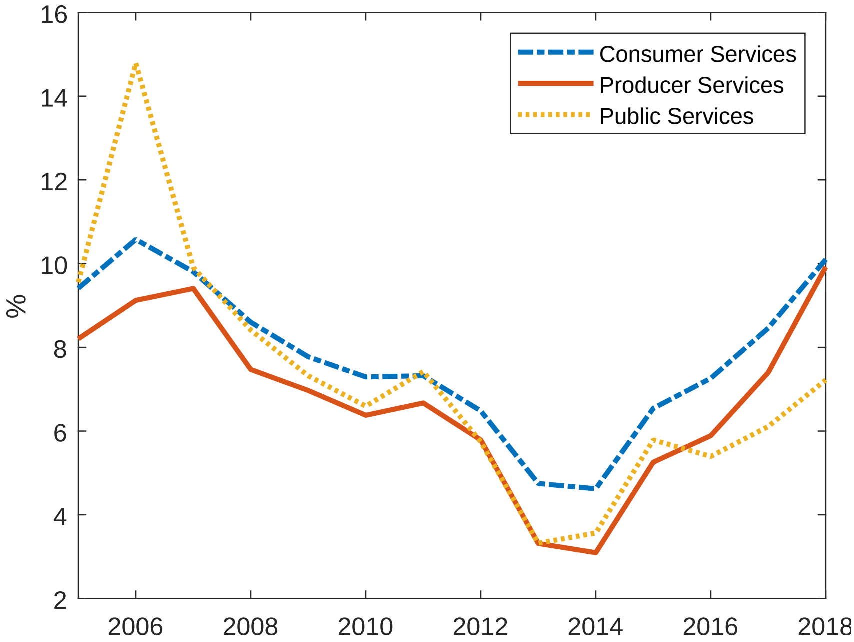

Figure 11: Registered Capital Share by Sector, 2013 and 2019 (Excluding Primary Sector)

7 Conclusion

We have documented the following recent trends in China's economy:

1. The tertiary sector is expanding relative to the secondary and industrial sectors in terms of both value-added and employment shares.

2. The three subsectors of the tertiary sector we constructed— producer services, consumer services, and public services—feature relatively balanced growth in terms of value-added. However, the employment shares of consumer services grew faster than that of producer and public services.

3. The relative prices of all services grew over time.

4. Skill upgrading has been stronger in the service sector (especially for producer services but also for consumer services) than in the industrial sector and the construction sector.

5. In the last decade, productivity has grown faster in both consumer and producer service sectors than in the industrial sector. The results are robust to different methodologies to calculate productivity growth, including the recent procedure proposed by FPZ that gets around measurement issues for the price index of services.

6. At the firm level, we observe a higher turnover (as measured by entry and exit rates) in the service sector than in the industrial sector. The gap across sectors has increased over time.

7. According to registration firm-level data, the share of active firms and the share of registered capital in the service sector has increased relative to the industrial sector.

8. Within the tertiary sector, producer services have a higher entry rate but a lower exit rate, resulting in higher growth in the share of active firms for producer services. Producer services also exhibit higher growth in the share of registered capital.

This set of findings suggests that China's development process might have entered a new stage in which services play an increasingly important role. We could well be at the beginning of a major tertiarization process. The disruption of international trade caused by recent tensions in international relations could speed up the process of structural transformation by shifting the focus of further economic development to the internal market. The consolidation of an urban middle class after decades of fast growth is likely to sustain growing demand for services in the coming years. As emphasized by FPZ in the Indian context, tertiarization could exacerbate regional inequality. The supply of consumer services is concentrated in urban areas, and many such services are local in nature. To the extent demand forces are an important driver of the direction of technical change—as pointed out in the Chinese context by a recent study of Beerli et al. (2020)—the growing focus on services could skew the benefits of growth even further in favor of large city dwellers. On a more optimistic note, services cause less environmental damage than industrial production. Thus, tertiarization could alleviate the future environmental impact of economic growth. Finally, the process of tertiarization will likely interact with another dimension of structural transformation, that is, the transition from imitation and adoption to innovation (see Acemoglu et al., 2006; Zilibotti, 2017; and König et al., 2022). China is already a leader in some manufacturing industries, while, with some notable exceptions, its relative position in the service sector is still less advanced. The COVID shock has been the source of new demand for health and other local services. Part of this demand is likely to persist after the pandemic. The trend of an aging population will continue to raise the demand for health services, for instance. Meanwhile, the introduction of automation and artificial intelligence will contribute to reducing the demand for labor services in the manufacturing sector, while growing wages will continue to erode China's comparative advantage in labor-intensive industries.

In summary, we expect China to gradually reposition itself in the global supply chain. Its role in technology-intensive industries will increase while a growing share of its labor force will be employed in the production of nontraded services. To the extent the supply of local services will make cities more attractive, the structural transformation will foster further migratory pressure from rural to urban areas (see Song et al., 2015). The share of the urban population in China, which today is already approaching two-thirds—a level similar to that of the US in the mid-1960s—will likely keep growing in the coming decade.

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Supplementary Online Appendix

A Sources for Cross-Country Data

In Table 7, we summarize the sources of the cross-country data that are used in Section 3.

Table 7: Sources for Cross-Country Data

Comparable GDP per worker for countries

Sources:

- Penn World Table (PWT) 10.0
  - Variables: Output-side real GDP at chained PPPs (in 2017 USD); Number of persons engaged (in millions)
- Maddison Project Database (MPD) 2020
  - Variables: Real GDP per capita in 2011 USD; Population, mid-year (thousands)

Calculation Method:

- 1950–2019: directly calculate from PWT
- Years before 1949: infer from the 1950 value in PWT and the growth rate of GDP per capita from MPD

Employment (for countries except China)

Sources:

- *Denmark*:
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *Spain*:
  - 1860–1940: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release

(Table 7 Continued on the next page)

(Table 7 Continued)

- *France*:
  - 1856–1946: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *United Kingdom*:
  - 1841–1931: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *India*:
  - 1960–2010: GGDC 10-Sector Database, 2014 release
  - 1991–2019: WDI
- *Italy*:
  - 1951–2011: GGDC 10-Sector Database, 2014 release
- *Japan*:
  - 1953–2012: GGDC 10-Sector Database, 2014 release
  - 1890–1950: Mitchell (2007)
- *South Korea*:
  - 1963–2010: GGDC 10-Sector Database, 2014 release
- *Netherlands*:
  - 1959–2011: GGDC 10-Sector Database, 2014 release
- *Sweden*:
  - 1800–1949: Schön and Krantz (2012)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *United States*:
  - 1850–1940: Mitchell (2007)
  - 1950–2010: GGDC 10-Sector Database, 2014 release

(Table 7 Continued on the next page)

(Table 7 Continued)

- *Argentina*:
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *Egypt*:
  - 1960–2012: GGDC 10-Sector Database, 2014 release
- *Ethiopia*:
  - 1961–2011: GGDC 10-Sector Database, 2014 release
- *Indonesia*:
  - 1971–2012: GGDC 10-Sector Database, 2014 release
- *Mexico*:
  - 1950–2012: GGDC 10-Sector Database, 2014 release
- *Malaysia*:
  - 1975–2011: GGDC 10-Sector Database, 2014 release
- *Nigeria*:
  - 1960–2011: GGDC 10-Sector Database, 2014 release
- *Phillipines*:
  - 1971–2012: GGDC 10-Sector Database, 2014 release
- *Thailand*:
  - 1960–2011: GGDC 10-Sector Database, 2014 release

B Classification of Industries

The sectoral composition of variables is the focus of our analysis. We first identify three broad sectors: primary, secondary, and tertiary, following the instructions of NBS. Then, we will decompose the tertiary sector into three subsectors, including consumer, producer, and public services.

B.1 Broad Sectors

NBS published four rounds of instructions on the classification of broad sectors, one each in 1985, 2002, 2011, and 2017. In the 1985 version, the classification is rather simple, only declaring that: (1) the primary sector includes agriculture, forestry, animal husbandry, and fishery, (2) the secondary sector includes mining, manufacturing, production and supply of electricity, gas, and water, and construction, and (3) the tertiary sector includes other industries without any guidance on how to allocate one- and two-digit industries into broad sectors. The 2002 classification filled in the gap by providing detailed guidance on how to match the one- and two-digit industries to the three broad sectors. NBS revised the classification of broad sectors after new industry classifications were published in 2011 and 2017. In these two new versions, NBS moved: (1) the support activities for agriculture, forestry, animal husbandry, and fishery from the primary sector to the tertiary sector, and (2) the support activities for mining and repair service of metal products, machinery, and equipment from the secondary sector to the tertiary sector. Even though these adjustments better fit the essence of the broad sectors, NBS neither correspondingly adjusts the employment series in CSY nor publishes the comparable series from the population censuses. Meanwhile, the differences in sectoral value-added between the 2002 version of classification and the new ones are smaller than 0.5% of economy-wide GDP (Figure 12). As a result, we adopt the classification of broad sectors published by NBS in 2002 to ensure consistency of the sectoral value-added and employment data.

B.2 Tertiary Sectors

We further decompose the tertiary sector into consumer services, producer services, and public services.[26] By definition, consumer services are services for the final use of consumption, while producer services are supportive activities for firms to facilitate their operations. Public services are mostly provided by the government, which cannot be classified into consumer or producer services directly.

[26] This way of breaking down of tertiary sector into subsectors originates from Stigler (1956) and Greenfield (1966), which is further discussed in the literature such as Browning and Singelmann (1975), Hubbard and Nutter (1982), Daniels (1985), Grubel and Walker (1989), and Sassen (2001).

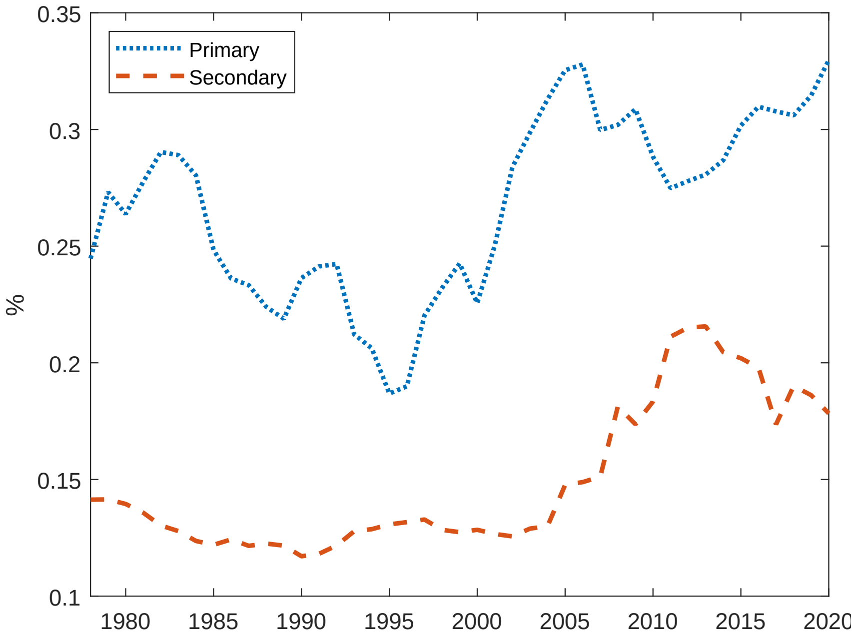

Figure 12: Nominal Value-Added Share: Old Versus New Classification, 1978–2020

Despite the definitions being clear, mapping them to the current industry classification is not apparent. Our classification originates from instructions from both the literature and NBS. On the one hand, without knowing the share of value-added of services to different destinations, most studies classify the tertiary industries as consumer and producer services according to the name of the industries.[27] Within the studies focusing on China, Yeh and Yang (2013) provide a list of one-digit industries included in producer services under the industry classification provided by NBS in 2002. Their categorization may distort the image since most one-digit industries simultaneously serve consumers and producers.

On the other hand, NBS initially decomposed the tertiary sector into four subsectors back in the 1980s to include (1) distributive services, (2) services for consumers and producers, (3) services for developing technology, culture, and human capital, and (4) services for public administration. China's 11th Five-Year Plan and 12th Five-Year Plan explicitly introduced consumer and producer services and elaborated on their coverage. In 2015 and 2019, NBS published two versions of classifications, explaining in detail how to classify the four-digit industries into consumer and producer services. The scope of consumer and producer services in the latest classification is shown in Table 8. Although NBS provided a detailed list of four-digit industries, it is hard to be implemented in our context when we are interested in sectoral value-added and employment shares for the following two reasons. First, value-added or employment data at the four-digit industry level are not available. Second, a certain fraction of industries provide services to both consumers and producers, and we do not know the exact shares of them that went to consumers or producers.

[27] One exception is FPZ, which identify the share of consumer services in tertiary industries with the Indian firm-level data reporting the identity of firms' primary purchasers.

Table 8: Coverage of Consumer and Producer Services in 2019 NBS classification

Consumer Services	**Producer Services**
Residential and household services	R&D, design and other technical services for production
Health care	Cargo transportation
Elderly care	General aviatic production, warehousing, and postal express services
Tourism and entertainment services	Information services
Sports	Financial services
Cultural services	Energy conservation and environmental protection
Residential retail and online sales	Leasing services for production
Residential traveling services	Business services
Accommodation and catering	Human resource management and vocational training services
Education and training	Wholesale and trade brokerage agency services
Residential housing services	Supporting activities for production
Other consumer services	

We enhance the classification strategy of the literature with the following sequel. We first determine the public services according to FPZ, which classifies public administration and education as public services. We also add management of water conservancy, the environment, and public facilities to public services. Then, we follow Yeh and Yang (2013) to identify producer services. As industries, such as financial intermediation and real estate, serve both consumers and producers, we divide the value-added and employment of these two industries into consumer and producer services with supplementary information (Appendix B.3 and B.4).[28] The remaining one-digit industries are assigned to consumer services. Table 1 summarizes our classification.

B.3 Distributing Value-Added and Employment in Financial Intermediation to Consumer, Producer, and Public Services

To attribute the value-added and employment in financial intermediation to tertiary subsectors, we rely on the information contained in the Summary of Sources and Uses of Credit Funds of Financial Institutions (in RMB) provided by the People's Bank of China. The summary reports the sources of deposits and the destinations of loans. See Table 9 for details. It allows us to track the share of deposits and loans coming from (or going to) households, firms, or government agencies. Then, we calculate the share of the value of loans and deposits associated with each of the three categories and use it as a proxy for the extent to which financial firms provide service to consumers, producers, and the government. For example, we calculate *the value-added of financial intermediation related to consumer services* by multiplying *total value-added of financial intermediation* by *the ratio between value of loans and deposits associated with consumer services and total value of loans and deposits*. Value-added related to producer and public services can be calculated in a similar manner. Figure 13 reports these shares.

[28] Other producer service industries may suffer from the same criticism, but we currently cannot separate them with appropriate indicators. Therefore, our analysis may overstate producer services, and consumer services may be understated.

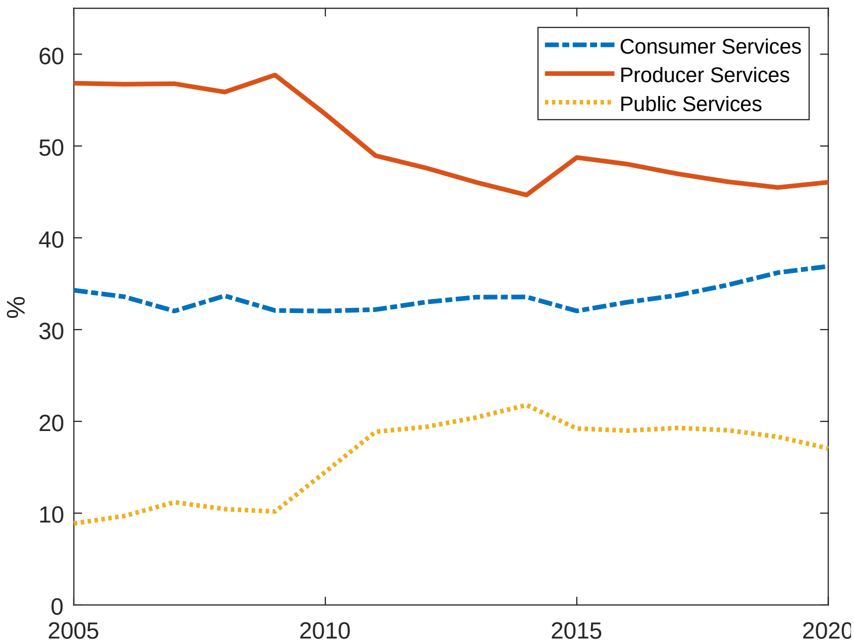

Figure 13: Share of the Tertiary Subsectors in Financial Intermediation, 2005–2020

Notes: The People's Bank of China does not report the categorical data in 2004. We decompose the value-added in financial intermediation in 2004 using the shares in 2005.

B.4 Distributing Value-Added and Employment in Real Estate to Consumer and Producer Services

Value-Added Real estate value-added consists of virtual depreciation values of owner-occupied housing and value-added from real estate firms. We classify all virtual depreciation as consumer services and divide the value-added from real estate firms using the information on the floor space of commercialized buildings sold.

To calculate the virtual depreciation values of owner-occupied housing, we follow the instructions of NBS (2008). Specifically, NBS calculates the virtual depreciation by the following formula:

$$\begin{aligned}\text{Virtual depreciation} = {} & \text{Housing area per person } (m^2/\text{person}) \\ & \times \text{Average population during the year (persons)} \\ & \times \text{Housing owner-occupancy rate} \\ & \times \text{Construction cost of housing (yuan}/m^2) \\ & \times \text{Depreciation rate.}\end{aligned}$$

To account for the difference in urban and rural housing, NBS develops different calculation methods for each of the components in the above equation for urban and rural housing separately. Table 10 summarizes these methods in detail and provides information about the sources of the data. As demonstrated by Figure 14, the share of virtual depreciation in real estate value-added

Table 9: Distribution of Deposits and Loans

Description of Deposits and Loans	Apportionment
Deposits	
Deposits of households	Consumer
Deposits of nonfinancial enterprises	Producer
Deposits of government departments and organizations	Public
Fiscal deposits	Public
Deposits of nonbanking financial institutions	Producer
Overseas deposits	Producer
Loans	
Loans to households for consumption	Consumer
Loans to households for business concerns	Producer
Loans to nonbanking firms and government & overseas loans	Producer/Public

Note: The People's Bank of China does not separately report the loans to government departments and organizations. We use public services' share in deposits to infer their share in the last category of loans.

dropped gradually from 56% in 2004 to 39% in 2020.

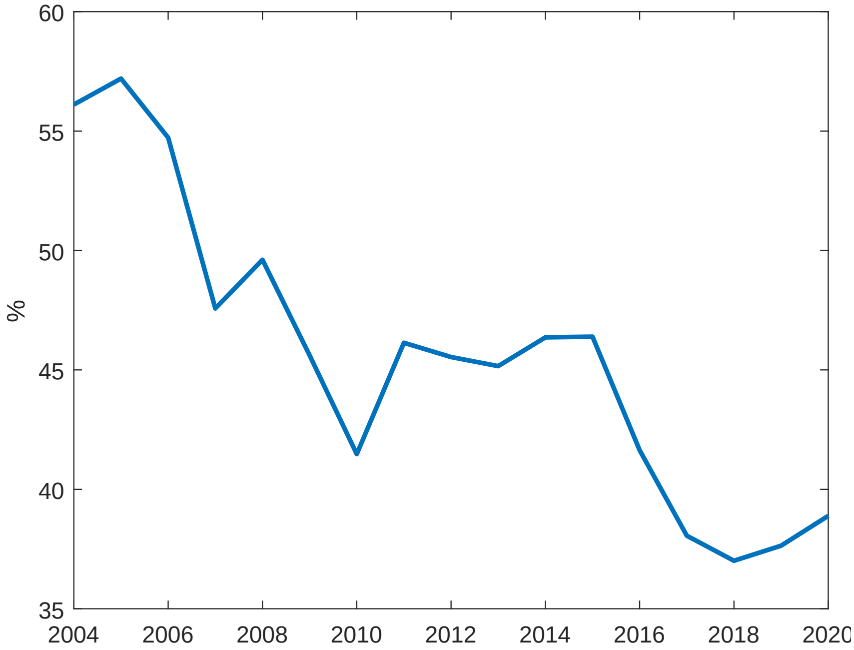

Figure 14: Share of Virtual Depreciation in Real Estate, 2004–2020

Table 10: Data Sources and Calculation Methods of Virtual Depreciation

Housing area per person: urban and rural

Data Sources:

2004–2012: China Statistical Abstract 2015

2013–2015: by linear interpolation

2016: http://house.people.com.cn/n1/2017/0706/c164220-29387856.html

2017: http://www.stats.gov.cn/ztjc/ztfx/ggkf40n/201809/t20180907_1621436.html

2018: http://www.stats.gov.cn/tjsj/zxfb/201907/t20190731_1683002.html

2019: http://www.stats.gov.cn/tjsj/sjjd/202007/t20200727_1778643.html

2020: use 2019 data and the annual growth rate of 2016–2019 to predict

Average population during the year: urban and rural

Calculation Method:

$$\frac{1}{2}\,(\text{Population at the beginning of the year} + \text{Population at the end of the year})$$

Data Sources: NBS website

Housing owner-occupancy rate: urban

Sources:

2002 and 2006: http://www.stats.gov.cn/ztjc/ztfx/shfzhgxlbg/200710/t20071010_60543.html

2008: http://www.stats.gov.cn/ztjc/ztfx/qzxzgcl60zn/200909/t20090910_68636.html

2010: http://www.stats.gov.cn/ztjc/ztfx/sywcj/201103/t20110307_71321.html

2003, 2004, 2005, 2007, and 2009: by linear interpolation

2011–2020: use the number in 2010

Note: *There are no officially published national urban housing owner-occupancy rates after 2010. To proceed, we assume that the rate kept constant between 2010 and 2019 based on two conjectures. First, the rate is not likely to decline because it kept increasing from 2002 to 2010 and because several other surveys estimate that recently it has been higher than 90%. Second, since the rate was as high as 89.3% in 2010, its growth would be limited afterward.*

Housing owner-occupancy rate: rural

Always equals 1 following NBS (2008).

Construction cost of housing: urban

Calculation Method:

$$\text{2004–2014:}\quad \frac{\text{Total value of residential buildings completed in urban area}}{\text{Total floor space of residential buildings completed in urban area}}$$

2015–2020: inferred by the cost of 2014 and the growth of the following ratio:

$$\frac{\text{Total value of buildings completed by real estate development firms}}{\text{Total floor space of buildings completed by real estate development firms}}$$

(Table 10 Continued on the next page)

(Table 10 Continued)

Sources: NBS website
Construction cost of housing: rural
Sources: 2004–2012: Value of houses of rural households per m^2, from NBS website 2013–2020: Construction cost of buildings completed by rural households in rural area this year, from China Yearbook of Household Survey, 2021
Depreciation Rate
Following NBS (2008), the depreciation rate for urban is 2%, while that for rural is 3%.

Next, we divide value-added of real estate firms into that of consumer and producer services. To proceed, we utilize information about sold space of commercialized buildings, which is a time series published by NBS. Specifically, NBS keeps track of four types of sold space of commercialized buildings, including residential buildings, office buildings, buildings for business use, and other commercialized buildings. We compute the share of sold space of residential buildings (Figure 15) and assume this share reflects the share of value-added by real estate firms that belongs to consumer services.

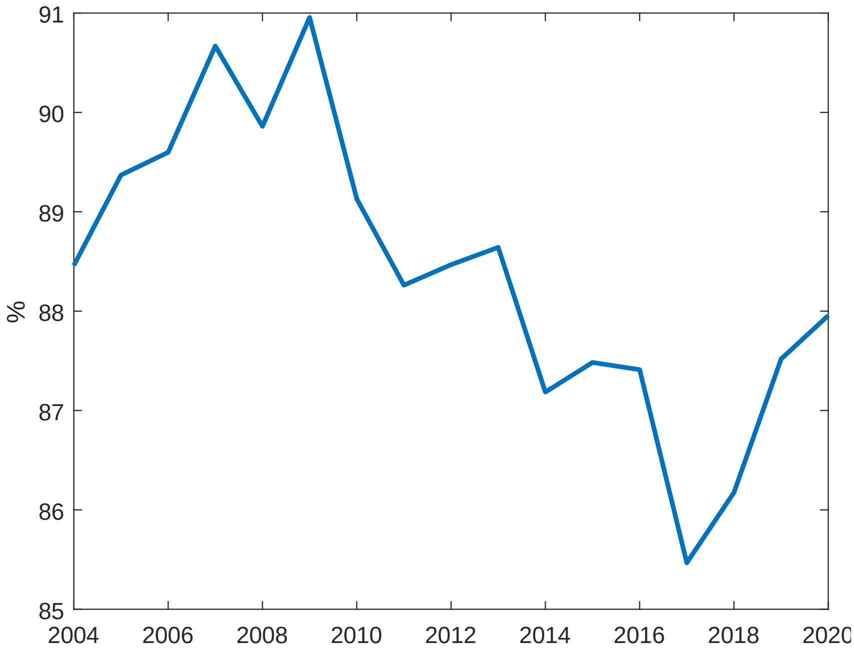

Figure 15: Share of Residential Building in Total Sold Commercialized Building, 2004–2020

By summing the virtual depreciation values of owner-occupied housing and value-added of real estate firms that belong to consumer service, we can obtain the total value-added of the real estate industry that belongs to consumer services. Figure 16 reports the share of real estate value-added that belongs to consumer services, which was around 95% in the late 2000s but dropped gradually to 91% from 2009 to 2017, presumably a consequence of the declining share of virtual depreciation and residential buildings. Finally, value-added of the real estate industry that belongs to producer services then equals total value-added of the real estate industry minus the part of value-added that belongs to consumer services.

Employment Since virtual depreciation has nothing to do with labor input, when calculating employment of the real estate industry that belongs to consumer services, we focus on the shares of space sold of residential buildings only. We then calculate employment of the real estate industry that belongs to consumer services equals total employment of the real estate industry times the share of space sold of residential buildings.[29] Employment of the real estate industry

[29] There is a potential caveat such that adopting the share space sold of residential buildings can be undermined by the fact that the employment share of real estate development firms, those who are primarily responsible for

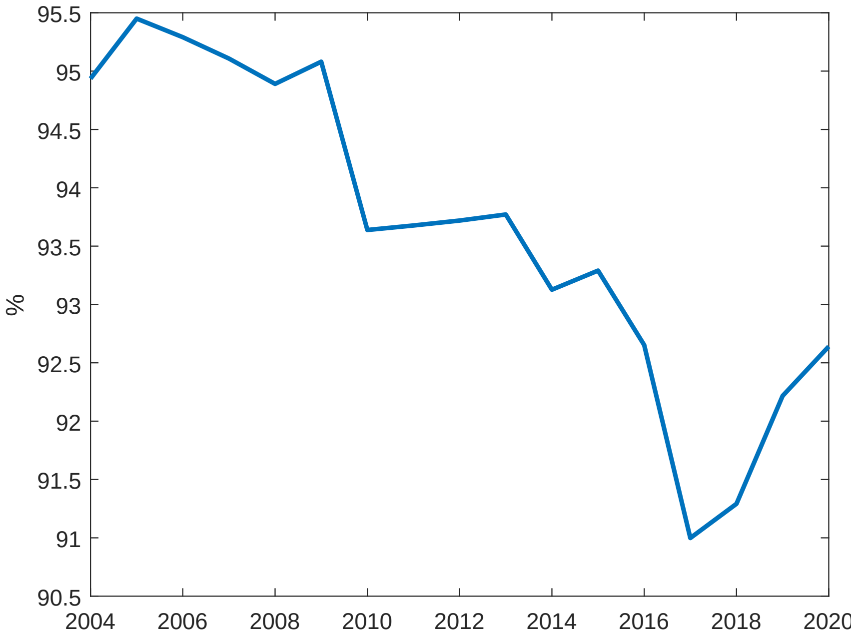

Figure 16: Share of Consumer Services in Real Estate Value-Added, 2004–2020

that belongs to producer services then equals total employment of the real estate industry minus the part of employment that belongs to consumer services.

C Data Construction

In this section, we discuss the construction of our datasets. Specifically, we use time series for GDP in current and constant prices (nominal and real GDP, respectively), employment (number of workers), and educational attainment of workers. Finally, we also describe how to estimate sectoral capital stock and capital output elasticities.

C.1 Nominal and Real GDP

Data on nominal GDP are available from the China Statistics Yearbook (CSY) and the NBS website. Occasionally, NBS revises historical value-added data and publishes them on their websites. The most recent round of revisions happened in 2018, according to the economic census.

However, NBS does not publish revised annual value-added for all one-digit tertiary industries. Instead, they only report the sum of value-added for nine industries, including: (1) information

newly constructed buildings, is only 60 to 70%. Nevertheless, the impact is limited because the percentage of residential buildings in total sold buildings is stable over time, which implies a similar share of residential buildings in the entire housing stock. Therefore, the consumer service share in other real estate industries serving the economy-wide housing would also be close to the percentage of space sold of residential buildings in total sold space of all types of buildings.

transmission, computer services, and software, (2) leasing and business services, (3) scientific research, technical services, and geologic prospecting, (4) services to households and other services, (5) management of water conservancy, the environment, and public facilities, (6) education, (7) health, social security, and social welfare, (8) culture, sports, and entertainment, and (9) public management and social organizations. We then proportionally adjust the value-added in these nine industries reported in CSY by the ratio of the sum disclosed on the NBS website to that in the yearbook. Finally, we apply our industry classification to calculate the value-added in the tertiary subsectors. Note that because the one-digit industry classification for nominal GDP in CSY is different before and after 2004, to avoid the complexity, we focus on the tertiary subsectors from 2004 onward only.

Real GDP can be calculated by nominal GDP and GDP indexes published by NBS. For consistency with nominal GDP data, we use the GDP indexes from the NBS website. We then set 2005 as the base year and calculate the real GDP from 2004 to 2019. NBS also combines the nine tertiary industries mentioned above and publishes the GDP index for their sum only. We separate the real value-added of the nine tertiary industries following the same procedure as in the case of nominal GDP.

C.2 Employment and Educational Attainments

We get sectoral employment data for all broad sectors from CSY. However, there are no employment data for one-digit industries in CSY. To measure employment for tertiary subsectors, we turn to the Population Census and 1% Population Surveys for additional information.

Specifically, the Population Censuses are available for 1982, 1990, 2000, 2010, and 2020. The 1% Population Surveys are available for 1987, 1995, 2005, and 2015. Because of a change in the industry classification, pre- and post-2004 data are not comparable. For this reason, we focus on post-2004 data. For the years 2005, 2010, 2015, and 2020, we calculate the employment shares of each tertiary subsectors and then multiply the shares by the total employment of the tertiary sector from CSY to obtain the size of employment for each tertiary subsectors. Once we get employment data for broad sectors and tertiary subsectors, we compute and report the sectoral employment shares in Figure 6.

The Population Census and 1% Population Survey also report the educational attainment of employees. There are seven levels of education with different levels of years of schooling in the questionnaire as listed in Table 11. Using information about the educational composition and the number of workers for all the one-digit industries, we calculate the average years of schooling and share of workers with some higher education for the broad sectors and tertiary subsectors. Note that there is a potential caveat such that when NBS published the aggregate educational attainment data, it did not separate partial and complete fulfillment within the educational level. Therefore, our calculation may overestimate the average years of schooling. Nevertheless, we can use the household-level census data to check the possible measurement error. The micro-level data in 2005 show that over 93% of the workers fulfilled the graduation requirements, implying that the overstatement of average years of schooling is only modest.

Table 11: Classification of Educational Attainment

Educational Level	Educational Years
No formal schooling	0
Primary school	6
Lower middle school	9
Upper middle school	12
Vocational middle school	12
Three-year college	15
Four-year university	16
Postgraduate education	18

C.3 On the Estimation of Capital Stock

We use the perpetual inventory method to calculate capital stock. Assume a standard capital accumulation equation:

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

where K_t stands for the capital stock at the beginning of year t, δ denotes the capital depreciation rate, and I_t is the investment in year t. To compile a time series of capital stock, we need information about the time series of investment, the initial level of capital stock, and the depreciation rate.

Broad sectors Due to the limitation of sectoral data, we set the initial year to $t = 1978$. The nominal investment spending on physical assets in China is officially called the gross fixed capital formation (FCF). Being part of expenditure-side GDP, the national FCF is published on the NBS website. We directly adopt the series on the NBS website.[30]

The FCF data for the three broad sectors from 1978 to 2002 can be found in Hsueh and Li (1999) and NBS (2004). From 2003 onward, NBS did not publish the FCF disaggregated by sector. To disaggregate total FCF into sectoral FCF, we use sectoral shares of investment in fixed assets (FAI), another investment-related time series published by NBS. Specifically, we assume that the sectoral shares of FCF equal to those of FAI. Upon calculating sectoral shares of FAI, we may back out the implied sectoral FCF using the shares and total FCF. Note that sectoral FAI

[30] The National FCF was retrospectively revised downward after the economic census in 2018. Nevertheless, the adjustment is quite equal and lower than 3% for all years except 2015.

data are directly available from CSY until 2017. In addition, NBS isssued the growth rate of sectoral FAI in 2018 and 2019, which can be used to infer sectoral FAI in both 2018 and 2019.

We then deflate the sectoral FCF series. From 1978 to 1989, we directly use the implicit FCF deflator implied by the FCF index from Hsueh and Li (1999). For the years after 1990, we use the price indexes for fixed-asset investment provided by NBS.

Using the sectoral real investment, we initialize the sectoral capital stock at the end of 1977 (i.e., K_{1978}). Specfically, we assume that all annual growth rates of real investment prior 1978 are equal to the average annual growth in 1978–1983.[31] Then, the capital stock at the end of 1977 can be calculated as the ratio of investment in 1978 to the sum of the average annual sectoral investment growth rate during 1978–1983 and the depreciation rate. We set the depreciation rate to 9%, following Brandt, Van Biesebroeck, and Zhang (2012).

Tertiary subsectors For the tertiary subsectors, we calculate their capital stock from 2005 onward. NBS published FAI from 2003 to 2017 for one-digit industries. We use the FAI share of tertiary subsectors to divide FCF in tertiary sector into FCF in tertiary subsectors including consumer, producer, and public services. To determine the initial capital stock of the tertiary subsectors at the end of 2004, we assume that the sectoral composition of capital within the tertiary sector was identical at the end of 2004 and 2005.[32] Finally, we follow the same procedures for broad sectors when dealing with price indexes and depreciation rates.

C.4 Labor Output Elasticity Estimation

We aggregate the elasticities of two-digit industries in Bai et al. (2021) to obtain the sectoral elasticities, weighted by the average value-added share of the two-digit industries in 2007 and 2012. Nevertheless, two remarks about these weights are worth noting here. First, Bai et al. (2021) did not report the elasticities for all the tertiary two-digit industries. Most of the industries with missing elasticities are in public services. It is implicitly assumed that the sectoral elasticities will not be affected if we exclude the elasticities in the industries without elasticity estimation. Second, to be consistent with one-digit industry value-added data, which are subject to NBS revision in 2018, we manually adjust the value-added shares of two-digit industries in the I-O tables of 2007 and 2012 when calculating the weights. Finally, to address the concern that SOEs might not aim for profit maximization[33], we also run the estimation with private firms only. It turns out that the estimated sectoral labor output elasticities using private firms only are

[31] Although critics may cast doubt on this assumption, different assumptions on K_{1978} will not essentially alter the quantitative results in the 2000s. We adopt this conventional assumption in Bai, Hsieh, and Qian (2006) without loss of generality.

[32] Our results are robust to this assumption because the sectoral composition within the tertiary sector did not change radically since 2005.

[33] Note that to estimate labor output elasticity, it is implicitly assumed that all firms are maximizing profits.

very close to those used in our paper.

D Appendix for the Model-Based Accounting Approach

In this section, we explain in detail how we estimate the income elasticity. We then move on to discuss how we estimate sectoral value-added that belongs to consumption for final use using information provided in I-O table. Finally, we provide the mathematical derivations for equation (2), which are the key equations governing the accounting of our alternative approach.

D.1 On the Estimation of Income Elasticity

We follow the method in FPZ in estimating the income elasticity μ in Section 5.2. Specifically, we use the household-level data from the Chinese Household Income Project (CHIP), which is a subsample of NBS-led annual surveys collecting the socio-economic status for urban, rural, and migrant households.[34] As in FPZ, μ can be approximately estimated from regressing food expenditure share $\ln \frac{P_{F,t} c^i_{F,t}}{E_{i,t}}$ on households income $E_{i,t}$:

$$\ln \frac{P_{F,t} c^i_{F,t}}{E_{i,t}} = D_t - \mu \ln E_{i,t} + \boldsymbol{Z}'_{i,t} \boldsymbol{\varphi} + u_{i,t},$$

where D_t is a time fixed effect, and $\boldsymbol{Z}_{i,t}$ are a set of variables on household features that presumably affect the food expenditure share and the consumption expenditure simultaneously.[35]

To control for the regional time-invariant unobservables, we include a full set of dummies for the pair of provinces and years. As in FPZ, we also controlled for the number of members in the households. The last control variable in the regression is the dummy for urban households, which is constructed according to the categorization of NBS in the survey year. All control variables are plainly provided in the dataset. The regression results are shown in columns 1 and 3 in Table 12.

We also estimate the income elasticity using China Family Panel Studies (CFPS), which is conducted by the Institute of Social Science Survey (ISSS) of Peking University and documents a set of thorough details covering household expenditures.[36] The regression results are shown in columns 2 and 4 in Table 12.

[34] Since we focus on the period before 2015 in this paper, we use 2007 and 2013 CHIP.

[35] If $\omega_F = 0$, then the estimated coefficient from the regression coincides with μ. If $\omega_F > 0$, then we can obtain a consistent estimate of μ by indirect inference. Although we set $\omega_F = 0.01$, the μ from indirect inference is almost identical to the regression coefficient. As a result, we directly adopt the estimates from the regressions.

[36] Since we focus on the period before 2015 in this paper, we use the first three waves of CFPS data: 2010, 2012, and 2014. However, the published dataset also includes information for a minority of households collected in 2011, 2013, and 2015. We drop the households that were not surveyed in 2010, 2012, and 2014 in our baseline regression, but the estimation is more or less the same if we include these households.

Table 12: Estimation of Income Elasticity

	Dependent variable: log food expenditure share			
	All Households		Urban Households	
	(1) CHIP	(2) CFPS	(3) CHIP	(4) CFPS
log consumption expenditure	-0.375***	-0.272***	-0.371***	-0.292***
	(0.004)	(0.004)	(0.006)	(0.006)
Dummies for province $\times$ year	Y	Y	Y	Y
Dummy for rural households	Y	Y	-	-
Dummy for migrant households	-	Y	-	-
Dummies for number of family members	Y	Y	Y	Y
N	34773	35520	11242	16818
R^2	0.168	0.360	0.152	0.365

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

Table 13: Estimation of Income Elasticity with 2013 CHIP Data

	Dependent variable: log food expenditure share			
	All Households		Urban Households	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
log consumption expenditure	-0.398***	-0.419***	-0.383***	-0.434***
	(0.005)	(0.025)	(0.008)	(0.028)
F statistic	-	99.64	-	22.37
Dummies for province	Y	Y	Y	Y
Dummy for rural households	Y	Y	-	-
Dummy for migrant households	Y	Y	-	-
Dummies for number of family members	Y	Y	Y	Y
N	13460	13460	4905	4905
R^2	0.378	0.377	0.348	0.343

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

Finally, as a robustness test, we also use a full set of occupation fixed effects as instrumental variables of the total expenditures following FPZ. The results are shown in Table 13.

D.2 On the Estimation $VA^C_{s,t}$ by I-O Tables

This section describes our estimation procedure of sectoral value-added that belongs to final consumption $VA^C_{s,t}$ by I-O tables based on the methods in Herrendorf et al. (2013, 2020). We make two assumptions in our estimation. First, we consider imported goods as if they were produced domestically with the same technology that China uses to produce them. Given this assumption, we do not have to take a stand on whether the intermediate inputs are produced domestically or imported. Second, we allocate all of inventory change and net exports to consumption, which has the benefit that the concepts of investment and capital in the model match the domestic investment and capital from the I-O tables. Because inventory change and net exports are not large in the data, the impacts from different ways to allocate them are quite limited.

We closely follow the estimation procedure described in the Online Appendix B.2 in Herrendorf et al. (2013). Since the Chinese I-O tables assume that industries and commodities satisfy a one-to-one mapping, we calculate the total requirement matrix with the same method that Herrendorf et al. (2013) applied to the US data before 1972.

Note that the NBS might revise the historical value-added data without updating the I-O tables. Therefore, we assume that the ratio of $VA^C_{s,t}/VA_{s,t}$ inferred from the I-O tables is reliable. Then, we use this ratio with the revised value-added in each one-digit industry to calculate $VA^C_{s,t}$.

D.3 Derivations of Equation (2)

Using Roy's identity, households' optimal consumption is such that

$$P_{s,t}c^i_{s,t} = E_{i,t}\left[\omega_s + \nu_s\left(\frac{E_{i,t}}{\prod_{\tilde{s}\in \boldsymbol{S}}\left(P_{\tilde{s},t}\right)^{\omega_{\tilde{s}}}}\right)^{-\mu}\right], \quad \forall s \in \boldsymbol{S}. \tag{4}$$

Furthermore, the inter-temporal optimality condition for asset holding is such that

$$\beta\left(1+r_{t+1}\right) = \left(\frac{E_{i,t+1}}{E_{i,t}}\right)^{1-\mu}\left(\frac{\prod_{\tilde{s}\in \boldsymbol{S}}\left(P_{\tilde{s},t+1}\right)^{\omega_{\tilde{s}}}}{\prod_{\tilde{s}\in \boldsymbol{S}}\left(P_{\tilde{s},t}\right)^{\omega_{\tilde{s}}}}\right)^{\mu}, \quad \forall i \in [0,1]. \tag{5}$$

Aggregating Equation (4) over all households and divide both sides of the equation by $\int_i E_{i,t}di$ leads to

$$\frac{\int_i P_{s,t}c^i_{s,t}di}{\int_i E_{i,t}di} = \omega_s + \nu_s\left(\prod_{\tilde{s}\in \boldsymbol{S}}\left(P_{\tilde{s},t}\right)^{\omega_{\tilde{s}}}\right)^{\mu}\frac{\int_i E^{1-\mu}_{i,t}di}{\int_i E_{i,t}di}, \quad \forall s \in \boldsymbol{S}. \tag{6}$$

Using the market-clearing conditions, we can then derive the following expressions:

$$\int_i P_{s,t}c^i_{s,t}di = \frac{1}{N_t}VA^C_{s,t} \qquad\qquad \int_i E_{i,t}di = \frac{1}{N_t}\sum_{\tilde{s}\in \boldsymbol{S}} VA^C_{\tilde{s},t}$$

Next, define $\phi_t \equiv \int_i \frac{E^{1-\mu}_{i,t}}{\bar{E}^{1-\mu}_t}di$ where $\bar{E}_t \equiv \int_i E_{i,t}di$. Using Equation (5), we can establish that

$$\frac{E_{i,t+1}}{E_{i,t}} = \frac{E_{j,t+1}}{E_{j,t}} \quad \forall i,j \in [0,1].$$

Then,

$$\phi_t = \int_i \frac{E_{i,t}^{1-\mu}}{\bar{E}_t^{1-\mu}} di = \int_i \frac{E_{i,t+1}^{1-\mu}}{\bar{E}_{t+1}^{1-\mu}} di = \phi_{t+1}, \quad \forall t \geq 0.$$

Therefore, $\phi_t = \phi$ is time-invariant. We then conclude that

$$\frac{VA_{s,t}^C}{\sum_{\tilde{s}\in \boldsymbol{S}} VA_{\tilde{s},t}^C} = \omega_s + \nu_s \phi \left(\frac{\sum_{\tilde{s}\in \boldsymbol{S}} VA_{\tilde{s},t}^C / N_t}{\prod_{\tilde{s}\in \boldsymbol{S}} \left(P_{\tilde{s},t}\right)^{\omega_{\tilde{s}}}} \right)^{-\mu}, \quad \forall s \in \boldsymbol{S}.$$

which is the key equation for our accounting procedure.

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