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ABSTRACT

This article documents a rapid shift toward services (tertiarization) of the Chinese economy since 2005, as evidenced by the significant increase in both employment and value-added shares of the service sector. Notably, our analysis reveals that a variety of measures of productivity growth have been greater in the service sector than in the manufacturing sector. Firm-level measures of dynamism corroborate this ongoing tertiarization trend, which is not limited to services used as inputs to industrial production but also extends to consumer services. These findings are robust across different growth accounting methodologies, including a recently proposed method by Fan et al. (2023) that addresses challenges associated with the measurement of quality improvements in service industries.

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1 Introduction

China's economic development since the 1980s has been closely tied to its rapid industrialization. In many ways, China's path mirrors that of earlier East Asian industrializers, such as Japan, South Korea, and more recently, Vietnam. The export of manufacturing goods has been a key driver of this process, initially focusing on low value-added industries like textiles, apparel, leather, and toys that benefited from low labor costs. However, since 2000, China has progressively moved up the technology ladder, emerging as a dominant exporter of high-tech products such as electronics, machinery, and transport equipment.

In line 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.

One of the reasons for the decline in China's exports as a share of GDP is the shrinking role of the manufacturing sector, which is the most export-oriented sector. In 2011, manufacturing accounted for 32% of China's GDP, but by 2020, that share had fallen to 26%. The decline is also evident in the employment share of the industrial sector, which has consistently decreased since 2012. This trend is particularly noteworthy given the ongoing process of urbanization, which has led to a significant decline in the employment share of agriculture, from 35% in 2011 to 24% in 2020, according to the *China Statistical Yearbook* (CSY).[1]

China is currently experiencing a rapid tertiarization process, with the service industries expanding their share of GDP at the expense of both agriculture and manufacturing. However, the significance of this structural transformation is still underappreciated in economics research, which tends to focus on 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). This is partly due to data availability issues, as China has a detailed census of manufacturing firms and a National Business Survey covering all manufacturing plants above a certain size, but lacks a comparable survey for service firms. Additionally, measuring productivity in the service sector is notoriously challenging.

In this article, we provide a detailed account of the growing role of services in the Chinese economy. We start with a comparative analysis of China relative to other developing and emerging economies. We argue that, among late industrializers, the experience of China is 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

[1] `http://www.stats.gov.cn/sj/ndsj/2022/indexeh.htm`.

similar to that of other economies at a comparable stage of development.

We study the nature of the process of structural change in China and contrast the data with different hypotheses that could explain the rapid tertiarization. The first hypothesis is that the decline in the employment share of manufacturing is explained by the boom in construction and infrastructure building. Despite the importance of construction-related services, our data shows that the growth of the service sector in China is not limited to these activities. A second hypothesis is that the main driver of tertiarization is services used as inputs for the production of goods. This would suggest that the growth of the Chinese service sector is ancillary to industrial production, which would remain the main focal point of 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 observe a rapid growth of service industries providing inputs to the industrial sector, which we label producer services. However, other service industries also contribute significantly to tertiarization. We 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 stems from a growing role of the government in the Chinese economy. Contrary to this hypothesis, we do not find that government-provided services play an important role in the tertiarization process. Public services are, in fact, the only non-growing service industry as a share of GDP.

We center our analysis on productivity growth in the service sector, which has long been viewed as inherently stagnant; see, e.g., Baumol (1967). This view suggests that the sustained economic growth of China could be threatened by tertiarization. However, contrary to this view, our findings indicate that productivity has grown faster in the service sector than in the industrial sector over the last decade. This holds true for both consumer and producer services. Yet, studying productivity growth in the service sector poses a significant challenge, given that standard estimates of sectoral total factor productivity (TFP) rely on sectoral price indexes, which are difficult to measure accurately due to the challenges of accounting for quality improvements in service industries. This issue is further complicated by non-homothetic preferences, making it difficult to consistently define price indexes across sectors.

To tackle this issue, we generalize the methodology recently proposed by Fan et al. (2023) to estimate productivity growth circumventing problems associated with the published price index for services. Their methodology is based on a structural model that accounts for both demand and supply factors that drive structural transformation. Specifically, they specify a class of nonhomothetic preferences and estimates their parameters, which include an income elasticity that can be derived from microdata. We extend their model by incorporating savings and investment into a standard growth model with capital accumulation. This approach enables us to estimate productivity growth in services without relying on published price indexes. Our results confirm that the service sector has experienced high productivity growth, particularly in consumer services. In all scenarios considered, we find that productivity growth in consumer service industries significantly outpaced productivity growth in manufacturing during the period 2005–2015.

In the second part of the article, we provide additional evidence supporting our findings on productivity growth in the service sector. Firstly, we show that both producer and consumer services have undergone a faster process of skill upgrading compared to other sectors in the economy, as measured by the educational attainment of the workforce. This is not due to a convergence process, as we find that the tertiary sector is more skill-intensive in both level and growth terms.

Secondly, we use firm-level data from China's State Administration for Market Regulation (SAMR) to compare turnover rates between service and manufacturing firms. Our results show that service firms have higher turnover rates than manufacturing firms, and that this gap has widened over the last two decades. Specifically, the entry rate in the service sector has increased from 15% in 1996 to 20% in 2019, while it has remained constant around 12% in the industrial sector. We also observe similar trends for the exit rate, although this measure is subject to significant low-frequency fluctuations.

Taken together, these findings support the argument that tertiarization is not simply a byproduct of the development process, but rather an increasingly important driver of economic growth in China.

2 Related Literature

Our article is part of a growing literature on the structural transformation of China. Prior studies have predominantly focused on the decline of agriculture, such as Brandt et al. (2008), who highlight the importance of TFP growth in agriculture for explaining the aggregate productivity growth during the period 1978–2004, and Hao et al. (2020), who use a spatial model of trade and migration to analyze China's migration policy changes on the structural transformation out of agriculture and the reduction of provincial labor income inequality. See also Brandt and Zhu (2010), Dekle and Vandenbroucke (2012), Zhu (2012), and Cao and Birchenall (2013). Other studies have explored the effect of modernization and capital accumulation in agriculture on the structural transformation, such as Storesletten et al. (2019). Cheremukhin et al. (2017) studied the structural transformation of China since the foundation of the People's Republic of China and discussed the role of intra- and intertemporal wedges and how these were affected by different policies. Our article contributes to this literature by examining the role of the service sector in China's structural transformation and productivity growth.

Our study is related to a smaller body of literature focusing on the tertiary sector of China. Most existing papers do not explicitly distinguish between producer and consumer services, unlike our study (see, e.g., Naughton, 2007, Nabar et al., 2013, and Naughton, 2018). Some papers, such as Guo et al. (2021), investigate the importance of tertiarization in specific sectors, while Ge et al. (2019) provide a variable markup approach to explain the small size of China's service sector 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 distinguish between different types of services, Liao (2020) focuses on the role of personal and distributional services finding an important role of TFP growth in personal services during the period of 1978–2007. Finally, 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 China's process of structural change with that of other economies at similar stages of development. 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); see Appendix A for more details.[3] Figure 1 displays the sectoral employment shares against the GDP per worker in 2017 USD. Panels *a–c* and panels *d–f* refer to the set of OECD and non-OECD economies, respectively.

In all graphs, we emphasize the path of China. Due to our particular interest in the Chinese economy, we extend the GGDC time series, which ends in 2012, by using the CSY 2020.[4] We checked that the GGDC and CSY are identical in the overlapping years. We use the 2002 guidelines of China's National Bureau of Statistics (NBS) to ensure consistency between the different data sources.[5]

[2] An important difference between our study and that of Fang and Herrendorf (2021) is that their model considers labor as the only input, while we postulate a production function that includes both capital and labor. They find that productivity in the goods sector outgrew that in the service sector between 2005 and 2009. However, if we abstracted from capital, we would confirm their findings even for later years because the industrial sector experienced a faster capital accumulation (and has a higher capital-output elasticity) than the tertiary sector.

[3] When the data come from different sources, we follow a standard chain rule to construct the time series. First, we use the most recent observation as the benchmark. Second, we extend the benchmark series backward using the annual changes from the earlier source. For instance, the latest observation on the Indian sectoral employment share is from the World Bank 2019 World Development Indicators (WDI). Hence, we use the WDI data from 2011 to 2019. For earlier years, we rely on the annual changes of sectoral employment shares from the GGDC to extend the time series back to 1960. We apply the same procedure to the historical data for OECD countries.

[4] For comparison with another large fast-growing economy, we also extend the GGDC data for India to 2019 by chaining the GGDC data for the sectoral employment shares calculated from the WDI.

[5] Although the GGDC data for China go back to 1952, we only display the data from 1978 onward. The reason

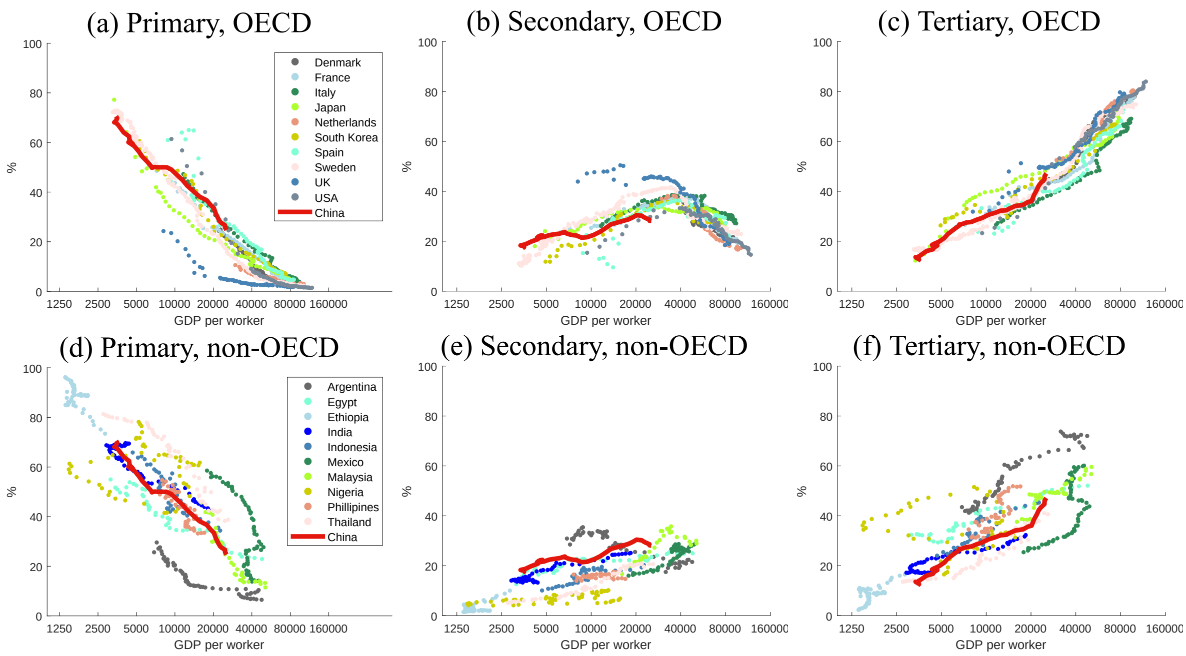

Figure 1: Sectoral Employment Share, All Broad Sectors

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, India, Indonesia, Malaysia, Mexico, Nigeria, the Philippines, and Thailand.

The figure highlights the link between economic development and structural change.[6] As countries' GDP per worker grows, so does the employment share of the tertiary sector, while the employment share of the primary sector declines during the development process. For the secondary sector, the employment share exhibits a hump-shaped pattern: among OECD countries, it increases until about 40,000 USD and then decreases. The corresponding plot for non-OECD countries shows a generally increasing trend for most nations. Although these economies have not yet reached the peak of 40,000 USD, there is a notable difference: given the same GDP per worker, the employment share of the secondary sector is significantly lower for developing (non-OECD) countries today than for earlier industrializers. Moreover, the spread of variation in the size of the tertiary sector is greater across non-OECD countries than across OECD countries.

In the earlier stages of development, China's industrial employment share was exceptionally high. However, over the last decade, China has undergone a process of tertiarization, with the share of industrial activity first stagnating and then starting to decline. This trend is consistent with the global pattern, where the share of employment in the industry increased from 19% to 22% between 2000 and 2010 but then leveled off or slightly declined. China's development

for not showing the earlier data is twofold. First, the quality of earlier data is dubious. Second, China's planned economy under Mao Zedong was very different, and the focus of this article is on contemporary China.

[6]We use GDP per worker as a measure of development. One could alternatively used GDP per capita. The broad picture would be similar. In some cases, GDP per capita and GDP per worker differ significantly due to demographics and participation rates. For instance, the gap between China and India in terms of GDP per capita is significantly larger than that in terms GDP per worker.

trajectory is more akin to earlier OECD countries than to that of other non-OECD economies. If we compare China with India, we note that India's development pattern is marked by a lower industrialization, which is in line with the typical non-OECD country experience.

Figure 2 presents the same data from a distinct perspective: it partitions the non-primary sector into the secondary and tertiary sectors, so that the two panels sum up to 100% horizontally for each country. This view accentuates the contrast between China and other developing economies. When GDP per worker was below 5,000 USD, China exhibited an exceptionally high industrial employment share compared to economies at the same stage of development. Subsequently, the growth of China's service sector brought its structure closer to the norm of development.

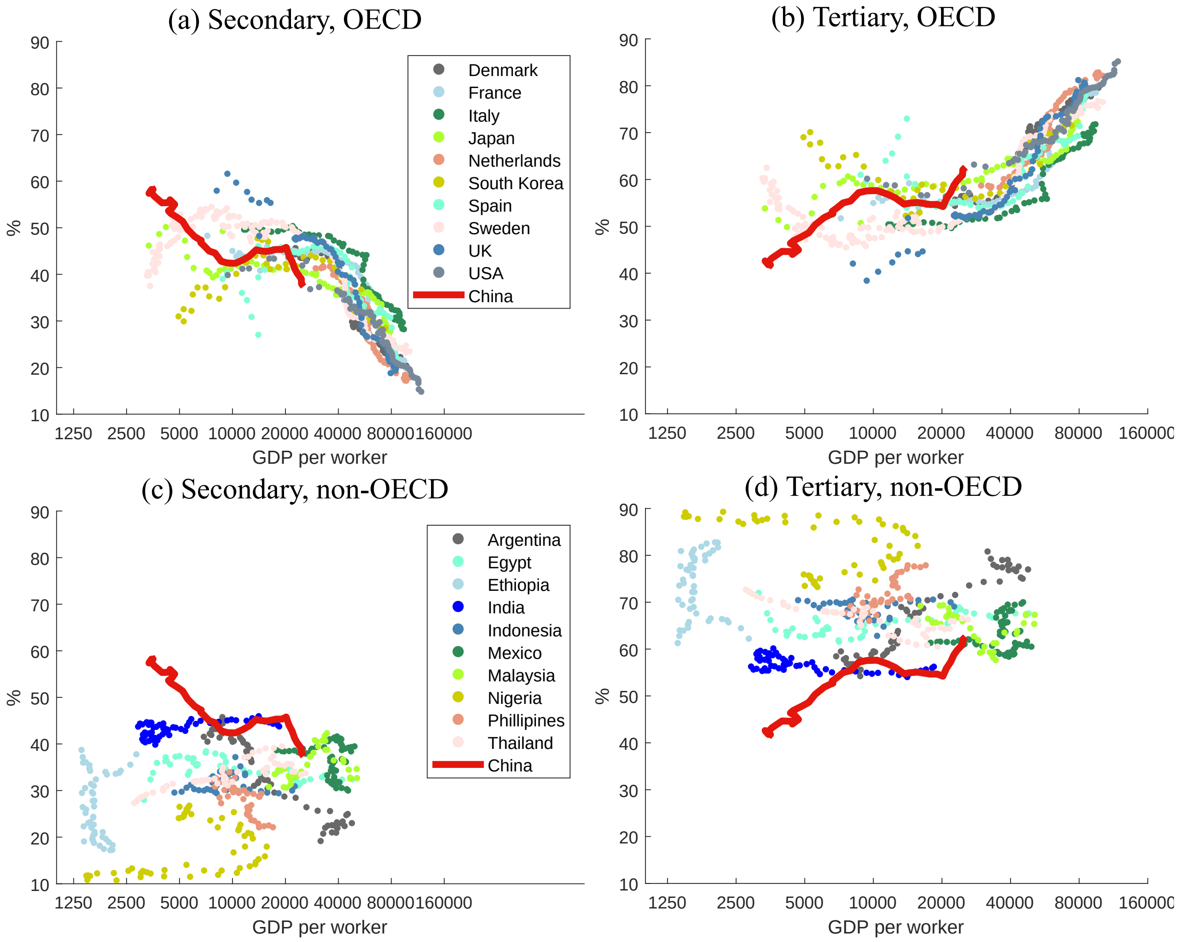

Figure 2: Sectoral Employment Shares, Broad Sectors Excluding Primary Sector

However, a macro-level comparison may obscure significant variations in the composition of the service sector across countries. For instance, Fan et al. (2023) document that in India traditional service industries, such as retail, hotels, and personal services, represent a substantial fraction of employment in the tertiary sector. In contrast, our analysis indicates that producer services play a more significant role in China.

In light of the discussion on China's structural transformation, we now turn to the drivers of the tertiarization process in China. The existing literature has documented several facts about the process of structural transformation of the Chinese economies; see, for instance, Brandt et al. (2008) and Naughton (2018). In this paper, we update and extend their findings with the aid of both aggregate and firm-level data and present new evidence about the growth of the service sector.

4 An Anatomy of China's Tertiarization

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 classification. The primary sector comprises agriculture, forestry, animal husbandry, and fishing. The secondary sector includes mining, manufacturing, and construction. The tertiary sector consists of services such as wholesale and retail, transport and storage, finance, and other services.[7] Then, we break down the tertiary sector into three sub-sectors: producer services, consumer services, and public services. The motivation is that these sub-sectors 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., the 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 the more recent work by Fan et al. (2023).[8]

In some cases, there is a natural correspondence between the NBS service industries and our three-group classification. For example, entertainment services are consumer services, while business services are mainly producer services. However, for other service industries, the classification is less clear-cut, particularly for financial intermediation and real estate services, which are large industries. To address this, we use supplementary information.

For financial intermediation, we use the Summary of Sources and Uses of Credit Funds of Financial Institutions from the People's Bank of China. This summary provides information on the sources of deposits and the destination of loans, allowing us to track the share of deposits and loans coming from households, firms, or government agencies. We then use this information to estimate 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, pro-

[7] 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 by following the 2002 classification. Appendix B.1 shows that this entails only minor discrepancies.

[8] Related decompositions can be found in Browning and Singelmann (1975), Hubbard and Nutter (1982), Daniels (1985), Grubel and Walker (1989), and Sassen (2001).

ducers, and the government. Figure 13 in Appendix B.3 shows the results, with an average of 51%, 33%, and 16% attributed to producer, consumer, and public services, respectively.

For the real estate service industry, we split its value-added into consumer and producer services based on the information on the floor space of commercialized buildings sold. Appendix B.4 provides more 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 consumer services.

For the other service industries, we classify the following as producer services: transport, storage, and post; information technology, computer services, and software; leasing and business services; scientific research, technical services, and geologic prospecting. We classify the remaining service industries as consumer services.[9] Table 1 summarizes the breakdown of industries.[10]

Table 1: Industry Classification

Broad Sector	Subsectors	One-Digit 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

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.

[9] The NBS provides an independent classification of consumer and producer services. Our classification is highly correlated with the NBS classification from 2019.

[10] Following the NBS industry classification in 2002, we list all the one-digit industries in Table 1 except for "international organizations", for which value-added is not available. The classification changed twice in 2011 and 2017, respectively, but the coverage of each one-digit industry did not vary much. Therefore, we simply map the one-digit industries in 2011 and 2017 to 2002 using their names.

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 from the NBS. We use the most recent update after the 2018 economic census.

Figure 3*a* plots the trends of nominal value-added broken down for primary, secondary, and tertiary sectors. We also separately show the industrial sector (of which manufacturing is the largest component) that 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 red line) is approximately constant until 2012 and sharply declines thereafter. The driver of this decline is a falling share of the industrial sector (mostly, the manufacturing sector) while the share of the construction sector has been increasing. Finally, the nominal value-added share of the tertiary sector (solid purple line) has consistently grown 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 trend break in the decline of the primary sector during this recent period.

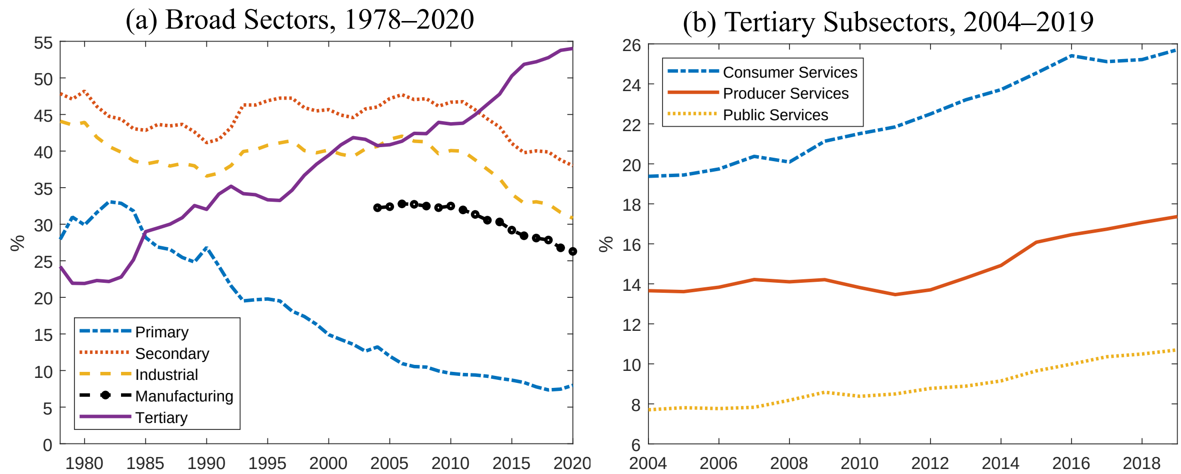

Figure 3: Sectoral Nominal Value-Added Shares in China (All Sectors)

Figure 3*b* decomposes the tertiary sector's nominal value-added into consumer services, producer services, and public services since 2004.[11] As the graph shows, consumer 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

[11] For the years prior to 2004, it is not possible to break down the service industries in a consistent way.

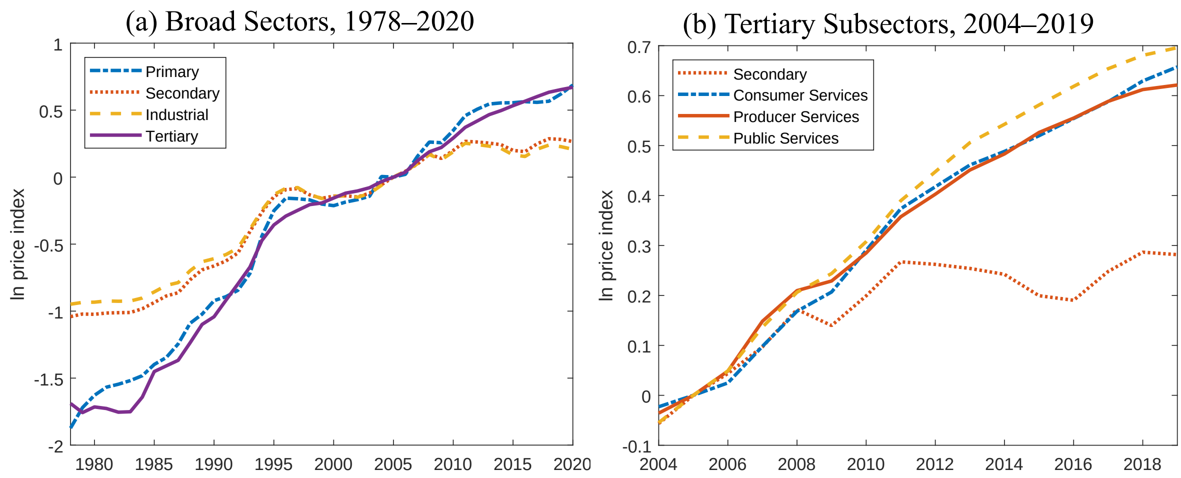

Figure 4: Sectoral Value-Added Deflators in China (All Sectors)

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. Figure 4*a* 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 the data for nominal value-added with the price indexes, we can compute deflated (or real) value-added shares, as shown in Figure 5. The deflated value-added data are evaluated at 2005 prices. Namely, the real and 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 continue to show some evidence of mild deindustrialization in the most recent decade, as 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 increased from 42% to 45%. Within the secondary sector, the share of construction increased, as shown by the growing gap between the orange dotted and the yellow dashed line in Figure 5*a*. Within the tertiary sector, producer services have outgrown consumer services since 2012, as illustrated in Figure 5*b*.

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.

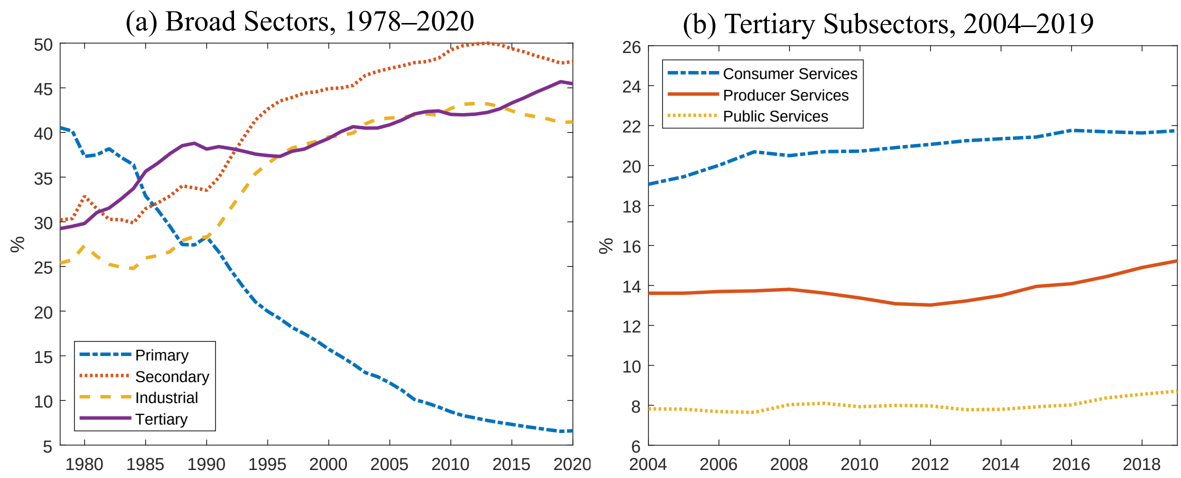

Figure 5: Sectoral Deflated Value-Added Shares in China (All Sectors) at 2005 Prices

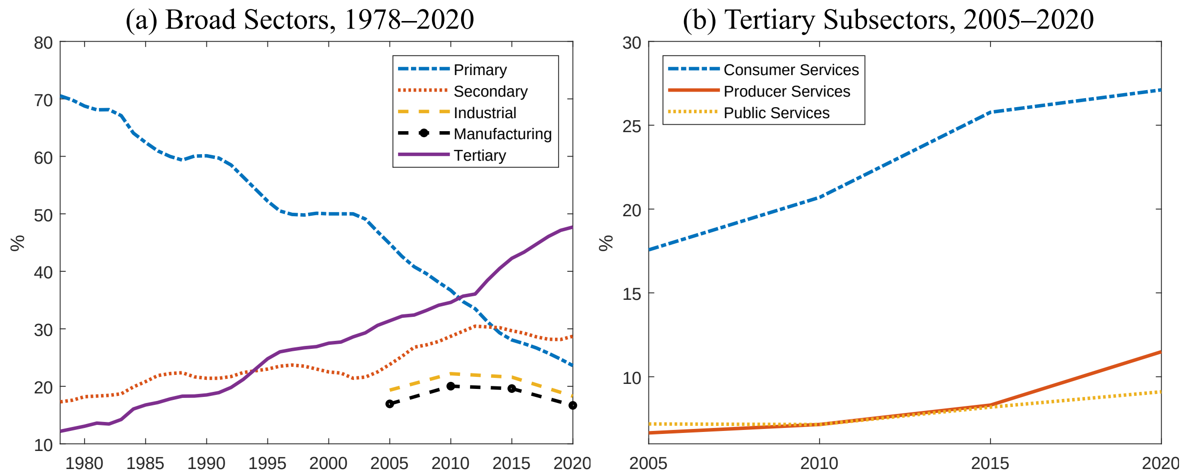

Figure 6: Sectoral Employment Shares in China (All Sectors)

4.1.2 Sectoral Employment Shares and Human Capital

Figure 6*a* displays the sectoral employment shares based on the CSY data compiled by the Department of Population and Employment Statistics.[12] 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 to almost half of the Chinese workforce. The employment share of the secondary sector grew more slowly and has declined since 2012. The employment shares of the industrial and manufacturing sector closely track this decline.

Figure 6*b* 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% Population

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

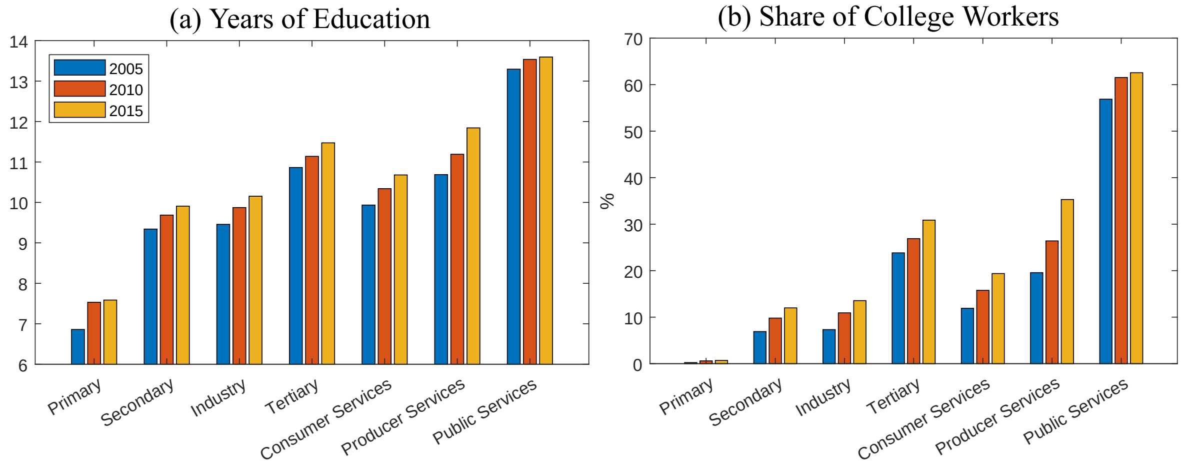

Figure 7: Educational Attainments by Sector

Surveys.[13] We observe some differences 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 increased from 6.6% to 11.5% over the same period.

The Chinese workforce has undergone significant educational upgrading over the years. In 1990, only 36% of the Chinese population aged 25 and older had attained some secondary education. This figure increased to about 60% by 2005 and to over 80% today. This progress can be attributed to major improvements in enrollment rates, with the gross enrollment rate in tertiary education increasing from a mere 3% in 1990 to 19% by 2005 and close to 60% today, which is higher than the average enrollment for OECD countries. To explore which industries attracted this growing number of educated workers, 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 (Figure 7*a*); (2) the share of college-educated workers (Figure 7*b*). However, it is important to note that the average years of education may be overstated in the Population Census and Survey due to the NBS not taking note of partial school attainment.

As shown in Figure 7, both measures indicate that the service sector is the most human capital-intensive sector. Within the tertiary sector, public services attract the largest share of educated workers, followed by producer and consumer services. As of the time of writing, the NBS has not yet released sectoral educational attainment data from the 2020 Census. However, based on the 1% Population Survey in 2015, workers in the tertiary sector have, on average, 11.5 years of education, which is higher than the 7.6 and 9.9 years observed in the primary and secondary sectors, respectively. More than 30% of service workers have some college education, which is significantly higher than the 0.7% and 12% observed in the primary and secondary sectors, respectively. Within the tertiary sector, producer service workers have, on average, 11.9 years

[13] 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.

of education, which is 1.2 years more than consumer service workers and 1.8 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 5–7 of Table 2.[14] 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 Education Years		
	$\frac{P_jY_j}{L_j}$	P_j	$\frac{K_j}{L_j}$	H_j	2005	2010	2015
Primary	15.3%	5.7%	16.0%	0.73%	6.86	7.53	7.59
Secondary	9.6%	2.0%	12.1%	0.57%	9.34	9.69	9.91
Industrial	10.2%	1.7%	13.5%	0.69%	9.46	9.87	10.15
Tertiary	12.6%	5.5%	9.9%	0.61%	10.86	11.14	11.47
CS	12.0%	5.3%	10.1%	0.75%	9.94	10.34	10.68
PS	13.0%	5.4%	9.6%	1.16%	10.69	11.19	11.84
Pub.S	14.6%	6.0%	10.6%	0.30%	13.29	13.54	13.59

Note: In this table, $\frac{P_jY_j}{L_j}$ refers to the sectoral nominal labor productivity, P_j is the sectoral price level, $\frac{K_j}{L_j}$ is the sectoral capital–labor ratio, and H_j is the sectoral human capital. Abbreviations: CS, consumer services; PS, producer services; Pub.S, public services.

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.[15] 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 partly related to the dramatic decrease in rural employment, given decreasing returns to land. The tertiary sector has the second-highest growth in nominal labor productivity (12.6%), with limited differences across subsectors (14.6% in public services, 13% in producer services, and 12% in consumer services). The secondary sector features the lowest labor pro-

[14]The reason why human capital grew slightly less in the tertiary sector than in the industrial sector is that public services, the most human capital-intensive subsector, featured a very low increase in human capital over the period of 2005–2015.

[15]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.

ductivity growth in nominal terms (9.6%). This result is robust to separating construction from manufacturing.[16]

Apart from changes in relative prices, 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.[17] 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 4 of Table 2. Finally, we estimate labor output elasticities for each two-digit industry by using the annual firm survey conducted by China's State Administration of Taxation (SAT) and aggregate them to obtain the sectoral labor output elasticities; see Appendix C.4 for more details.[18] 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 secondary sector (0.57 for the industrial sector), and 0.84 and 0.75 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 reflects 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 industrial sector, the service 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.

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

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

[16] The fast productivity growth in public services is noteworthy. This could possibly reflect some rationalization that echoes the fast labor productivity growth of state-owned enterprises documented in manufacturing by Hsieh and Song (2015). However, it could also reflect some measurement issue, as it is notoriously difficult to measure real output and productivity in public services.

[17] In the NBS data, there is no information regarding the one-digit industry composition of fixed capital formation. 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.

[18] There are 95 two-digit industries by the 2002 NBS industry classification.

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:

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

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 faster in the service sector than in the secondary sector. An important part of the nominal differences is driven by changes in relative prices. However, this is not the whole story. Service industries also experienced less capital deepening, which is partially offset by higher growth in the human capital input. Ultimately, TFP grew faster in both producer and consumer services than in the secondary sector. The gap is similar in the case of consumer services and producer services (+2.1% 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
Producer Services	Secondary	3.38%	3.39%	-2.69%	0.54%	2.14%
Consumer Services	Secondary	2.32%	3.32%	-3.44%	0.30%	2.14%
Producer Services	Industrial	2.83%	3.73%	-3.49%	0.48%	2.11%
Consumer Services	Industrial	1.77%	3.66%	-4.24%	0.23%	2.11%

Note: In this table, $\Delta g_{i,j}^X$ denotes the relative annual growth of variable X between sector i and sector j, with X representing the variables listed below. PY/L refers to the nominal labor productivity, P is the price level, K/L is the capital–labor ratio, H is the human capital, A is the total factor productivity, and α is the capital output elasticity.

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 find 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.[19] 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 productivity growth in manufacturing is the ultimate driver of economic development, while tertiarization is a mere corollary resulting from income effects and technological complementarities with the industrial sector. It is instead in line with the findings of Fan et al. (2023) for India. Human capital and TFP growth jointly account for a differential annual growth in value-added per worker of +2.7% for producer services and +2.4% for consumer services. These gaps partially offset the lower physical investments in service industries.

5 A Model-Based Accounting Approach

The estimates of Table 3 hinge on official price indexes whose accuracy is dubious. 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).[20]

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 Fan et al. (2023). 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: Fan et al.'s (2023) Model with Capital Accumulation

We generalize Fan et al.'s (2023) model by introducing investment goods and capital accumulation into their theory—they abstract from savings and investments. We view embedding their approach into a standard growth model as a contribution of independent interest on which future research can build. In another respect, our analysis is more restrictive: we only consider aggregate productivity, while they carry out the analysis at the more granular district level.

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

[19]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.

[20]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.

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

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

This assumption ensures tractability by preventing the joint distribution of $\{q_{i,0}, a_{i,0}\}$ from being 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), 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.[21]

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:

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

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.

[21] We define the indirect utility function and the associated expenditure shares on value-added aggregates. Fan et al. (2023) show that this indirect utility has an explicit microfoundation in terms of a demand system defined on a set of heterogeneous final goods under appropriate assumptions on the input-output matrix.

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, R_t is the rental rate of capital (where, in equilibrium, $R_t = 1+r_t$), $\alpha_{j,t}$ 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 $\tau_{j,t}^K$ denote sectoral labor and capital wedges whose role is discussed in Footnote 24 below.

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

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

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 $\psi_M \in (0,1)$;[22] 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.[23]

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

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

[23] 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.

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:

1. For agricultural goods, industrial goods, and consumer services:

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

2. For manufacturing goods and producer services: $Y_{s,t} = X_{s,t}, \quad \forall s \in \{M, PS\}$;
3. For investment and industrial goods: $I_t = Y_t^I$;
4. For raw labor: $N_t = \sum_{j \in \boldsymbol{J}} N_{j,t}$;
5. For efficiency units of labor: $Q_t = \sum_{j \in \boldsymbol{J}} e_{j,t} N_{j,t}$;
6. For capital: $N_t \int_i a_{i,t} di = K_t = \sum_{j \in \boldsymbol{J}} K_{j,t}$.

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 efficiency labor $\{e_{j,t} N_{j,t}\}_{j \in \boldsymbol{J}}$ and capital $\{K_{j,t}\}_{j \in \boldsymbol{J}}$ allocations 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 $\boldsymbol{\tau}_t \equiv \{\tau_{j,t}^N, \tau_{j,t}^K\}_{j \in \boldsymbol{J}}$:[24]

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

[24] The wedges $\boldsymbol{\tau}_t \equiv \{\tau_{j,t}^N, \tau_{j,t}^K\}_{j \in \boldsymbol{J}}$ capture sector-specific frictions in the product and factor markets and guarantee that the profit maximization conditions are consistent with the observed data on nominal capital and labor productivities at the sector level. They are pinned down by the following conditions:

$$\left(1 + \tau_{j,t}^N\right) W_t = (1 - \alpha_j) \frac{VA_{j,t}}{e_{j,t} N_{j,t}}, \qquad \left(1 + \tau_{j,t}^K\right) R_t = \alpha_j \frac{VA_{j,t}}{K_{j,t}},$$

where VA_j denotes sectoral nominal value-added. Our estimation of sectoral TFPs is orthogonal to the estimation of the sectoral wedges.

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 $\boldsymbol{\Theta}$, one can invert a subset of equations in the mapping $\boldsymbol{M}$ and infer the productivities from data. The exact subset of equations used in the accounting process depends crucially on the availability of the data and the model structures. For example, if there are data on sectoral value-added, prices, efficient labor and capital, the set of Cobb-Douglas sectoral production functions 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 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 Fan et al. (2023). ω_F pins down the asymptotic agricultural expenditure share as the household income goes to infinity. First, 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 return to formulas for the individual expenditure shares derived above:

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

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.[25] The term ϕ depends, among other things, on the extent of 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. Following Fan et al. (2023), we set $\phi\nu_{CS} = -1$, a normalization of no importance.[26]

To estimate μ, we make use of two restrictions imposed by the PIGL preferences. 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.[27]

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 $\mu = 0.375$, which is very similar to the elasticity Fan et al. (2023) estimate for India (0.395). 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 difference. The details are provided in Appendix D.1. Given this discrepancy, we report results under different calibrations of μ.

Finally, following again Fan et al. (2023), we estimate $\phi\nu_F$ and ω_{CS} by combining Equation 2

[25] We follow Herrendorf et al. (2013, 2020) to estimate $VA_{s,t}^C$ by sectoral value-added and input–output tables. See Appendix D.2 for the detailed construction of $VA_{s,t}^C$.

[26] The term $\phi\nu_{CS}$ is not separately identified from the average TFP in the consumer service sector. However, such TFP level has no economic interpretation in our analysis—we are only interested in the productivity growth of sectoral TFPs.

[27] Ignoring the small ω_F, we can rewrite the food expenditure of household i as $\ln \frac{P_{F,t}c_{F,t}^i}{E_{i,t}} \approx b_t - \mu \ln E_{i,t}$, where b_t is constant across households.

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	0.42	0.16	0.25	0.0642	0.375	0.01	0.37	0.62	0.48	0.52	-1

Note: In this table, α_j is the capital output elasticity of sector $j \in \boldsymbol{J}$, ρ is the elasticity of substitution between manufacturing inputs and producer services, μ is an elasticity that regulates the income effects, ω_s is the aymptotic expenditure share of sector $s \in \boldsymbol{S}$, ϕ is a constant indicating the income inequality across households, and υ_s is a parameter that governs whether the consumption of sector $s \in \boldsymbol{S}$ is a luxury or a necessity. Abbreviations: CES, constant elasticity of substitution; PIGL, Price Independent General Linear.

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 1.67 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%	3.73%	3.59%	-1.00%	0.16%
$\Delta g^A_{CS,M}$	2.14%	1.67%	1.81%	6.40%	5.24%

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 general equilibrium 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. Abbreviations: CFPS, China Family Panel Studies; CHIP, Chinese Household Income Project.

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 6.40% 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 fourth row). The differences are only about 0.11 percentage points.

Table 6: Results under Different ρ

	Growth Accounting	Baseline	Stronger Complementarity
		$\rho = 0.0642$	$\rho = 0.0321$
$\Delta g^P_{CS,M}$	3.32%	3.73%	3.75%
$\Delta g^A_{CS,M}$	2.14%	1.67%	1.65%
$\Delta g^P_{PS,M}$	3.39%	3.31%	3.19%
$\Delta g^A_{PS,M}$	2.14%	2.14%	2.25%

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 2), the elasticity of substitution between producer services and manufacturing goods is estimated to be 0.0642; in the robustness check (column 3), 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 Chinese Household Income Project data.

Caveat. The estimation of sectoral productivity in this section is based on a closed-economy model. In reality, an important share of the Chinese economy is associated with import and export activities. Fan et al. (2023) extend their analysis of India to international trade and find that introducing an external sector has only marginal effects on the quantitative results of the accounting exercise. While we conjecture this might also be true for China, we leave it to future research to explicitly address this concern. We note that import-export and foreign direct investment likely played an important role in sustaining productivity growth in industrial activity, including producer services. However, an analysis of the determinants of productivity growth is beyond the scope of our analysis.

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 quantitative discrepancy, the conclusion that growth in 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. Figure 8*a* 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. Figure 8*b* further decomposes the tertiary sector into producer, consumers, and public services, 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.[28]

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 Figure 9*a* 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%.[29] When we disaggregate the tertiary sector (Figure 9*b*), we see

[28]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 Appendixes B.3 and B.4 for details.

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

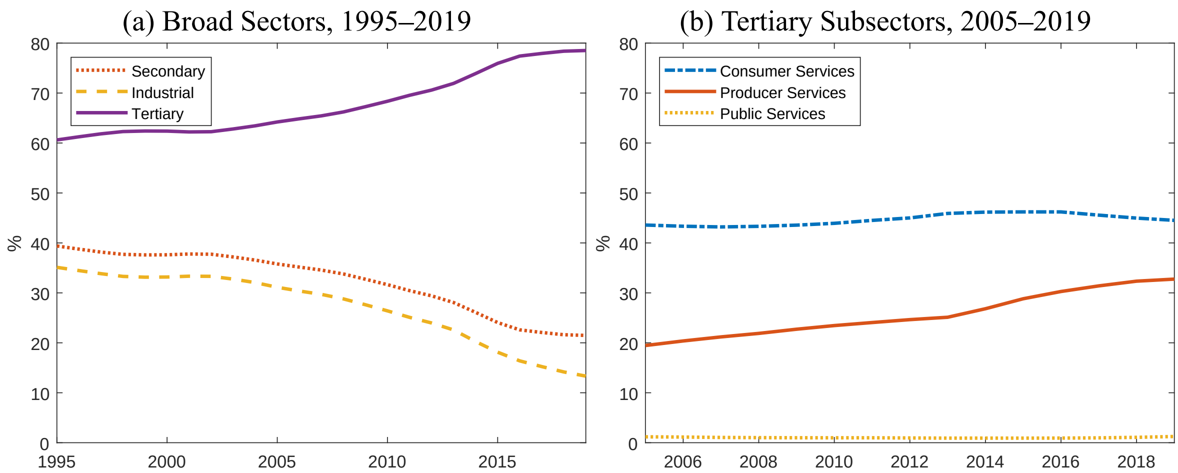

Figure 8: Share of Active Firms by Sector (Excluding Primary Sector)

that for most years, the entry rate is higher in producer than in consumer services.

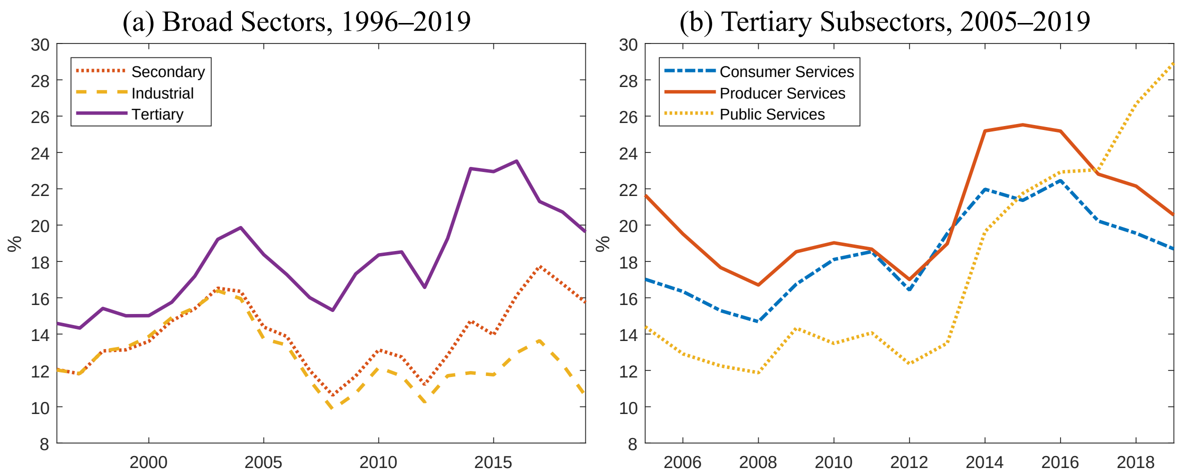

Figure 9: Firm Entry Rates by Sector

Figure 10 plots exit rates. Figure 10*a* 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. The decline in entry and increase in exit since 2015 likely reflect to the slowdown of economic growth.

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 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.

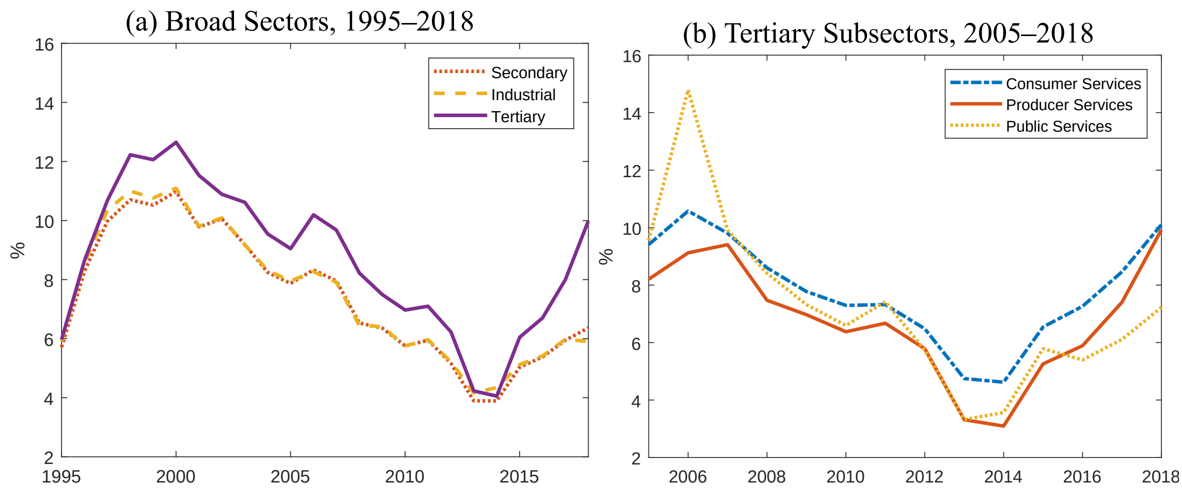

Figure 10: Firm Exit Rates by Sector

Controlling for Firm Size. The evidence discussed above refers to the number of active firms without weighting them by size for which we have no direct information. 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.[30] 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 increases 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 The firm-level registration data confirm the view that the service sector has become a centerpoint of China's economic activity during the last decade. The service sector is the most dynamic part of the Chinese economy in the period of 2013–2019, meaning that it exhibits both more net entry and more churning than the industrial sector. 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.

7 Conclusion

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

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

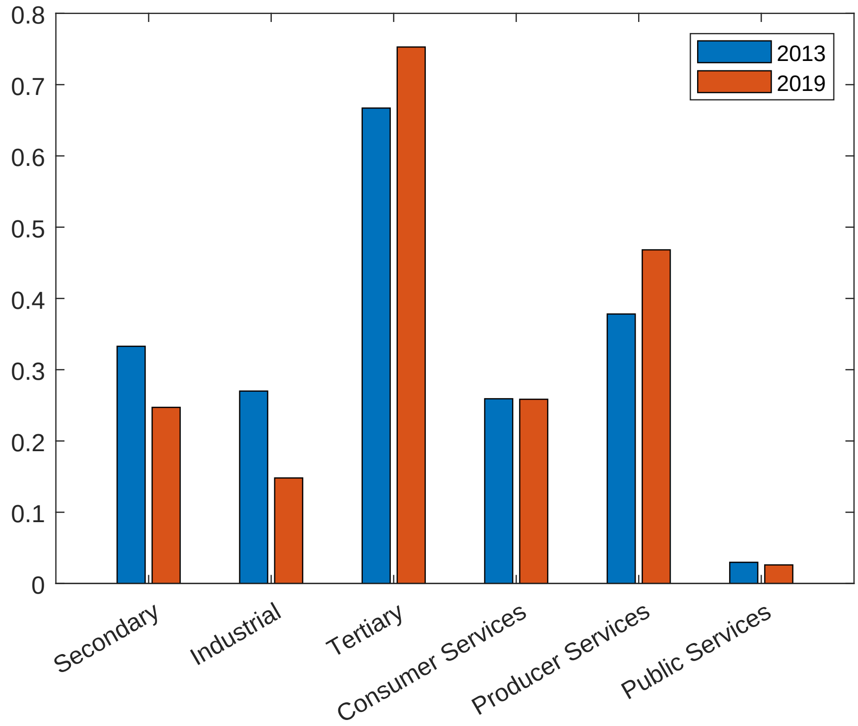

Figure 11: Registered Capital Share by Sector, 2013 and 2019 (Excluding Primary Sector)

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

2. All three subsectors of the tertiary sector we constructed— producer services, consumer services, and public services—grew steadily in nominal value-added. However, the employment share of consumer services grew faster than that of producer and public services.

3. The published 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 Fan et al. (2023) 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 have increased relative to their counterparts in the industrial sector.

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

These findings provide suggestive evidence that China's development process has entered a new stage in which services play an increasingly important role. This could be the start of a significant shift towards a service-based economy. The disruption of international trade, caused by recent tensions in international relations, will likely accelerate the process of structural change by steering further economic development toward the internal market. The consolidation of an urban middle class, after decades of rapid growth, is expected to sustain growing demand for services in the coming years.

The shift toward a service economy could exacerbate welfare inequality across Chinese regions. The supply of consumer services is concentrated in urban areas, and many such services are local in nature. If market size and demand are key drivers of the direction of technical change—as pointed out in the Chinese context by a recent study of Beerli et al. (2020)—the increasing weight of services could skew the benefits of growth even further in favor of large city dwellers. At the same time, services cause less environmental damage than industrial production. Thus, the shift towards services may help to reduce the environmental impact of economic growth. Finally, the process of tertiarization will likely interact with another dimension of the ongoing structural transformation, that is, the transition from imitation and adoption to innovation. Recent papers by Zilibotti, 2017 and König et al., 2022 (building on the insights of Acemoglu et al., 2006) discuss this transition. As of today, China is already a leader in some manufacturing industries such as electrical machinery, computers, plastics, and furniture while, with some notable exceptions, its relative position in service industries is still less advanced. The COVID shock has been the source of new demand for many local services, especially, retail and health. As China's population ages, the demand for health services is expected to continue growing after the pandemic. At the same time, 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.

To sum up, we expect China to gradually reposition itself in the global supply chain. On the one hand, it will further specialize in technology-intensive manufacturing industries; on the other hand, a growing share of its labor force will be employed in the production of non-traded services. This evolution of the Chinese economy will affect other countries and the global economy as a whole. For instance, it could speed up industrialization in African and South Asian developing economies where wages are lower. These economies can progressively replace China in labor-intensive tradable industries.

Because the availability of local services makes cities more attractive, the structural transformation will increase people's desire to move from rural to urban areas (see Song et al. (2015)).

If currently, almost two-thirds of China's population live in urban areas—a level similar to that of the US in the mid-1960s—the urban share of population will likely continue to grow 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
- *France*:
  - 1856–1946: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release

(Table 7 Continued on the next page)

- *Italy*:
  - 1951–2011: GGDC 10-Sector Database, 2014 release
- *Japan*:
  - 1890–1950: Mitchell (2007)
  - 1953–2012: GGDC 10-Sector Database, 2014 release
- *South Korea*:
  - 1963–2010: GGDC 10-Sector Database, 2014 release
- *Netherlands*:
  - 1959–2011: GGDC 10-Sector Database, 2014 release
- *Spain*:
  - 1860–1940: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *Sweden*:
  - 1800–1949: Schön and Krantz (2012)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *United Kingdom*:
  - 1841–1931: Mitchell (2007)
  - 1950–2011: GGDC 10-Sector Database, 2014 release
- *United States*:
  - 1850–1940: Mitchell (2007)
  - 1950–2010: GGDC 10-Sector Database, 2014 release
- *Argentina*:
  - 1950–2011: GGDC 10-Sector Database, 2014 release

(Table 7 Continued on the next page)

(Table 7 Continued)

- *Egypt*:
  - 1960–2012: GGDC 10-Sector Database, 2014 release
- *Ethiopia*:
  - 1961–2011: GGDC 10-Sector Database, 2014 release
- *India*:
  - 1960–2010: GGDC 10-Sector Database, 2014 release
  - 2011–2019: World Development Indicator (WDI)
- *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.

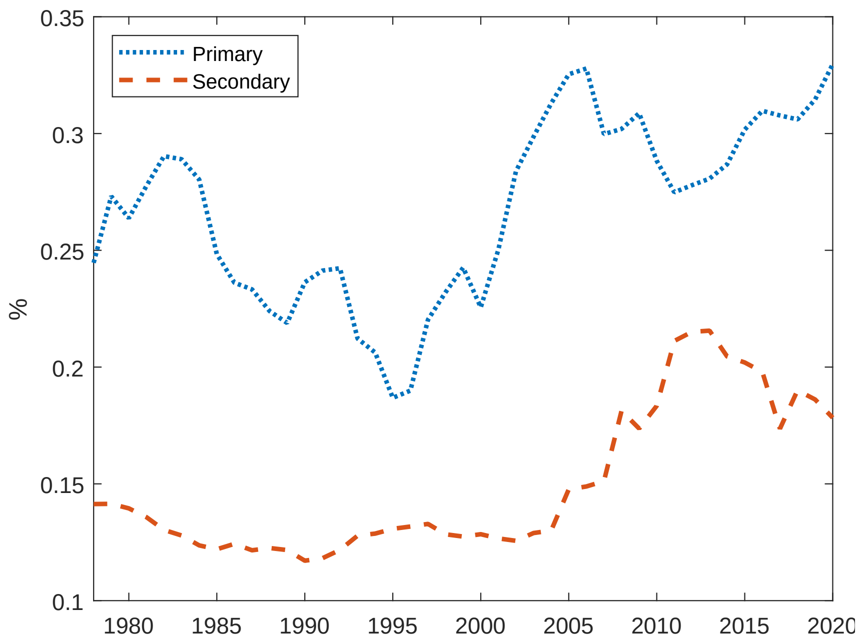

Figure 12: Nominal Value-Added Share: Old Versus New Classification, 1978–2020

B.2 Tertiary Sectors

We further decompose the tertiary sector into consumer services, producer services, and public services.[31] 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.

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.[32] 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.

We enhance the classification strategy of the literature with the following sequel. We first determine the public services according to Fan et al. (2023), 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

[31] 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).

[32] One exception is Fan et al. (2023), 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	

into consumer and producer services with supplementary information (Appendix B.3 and B.4).[33] 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

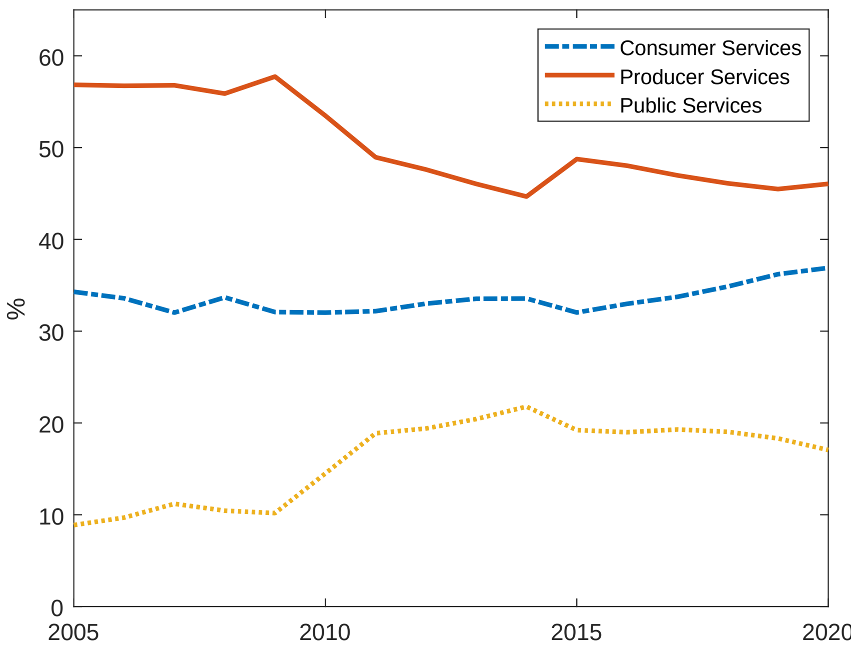

Figure 13: Share of the Tertiary Subsectors in Financial Intermediation, 2005–2020

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.

[33]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.

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.

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.

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

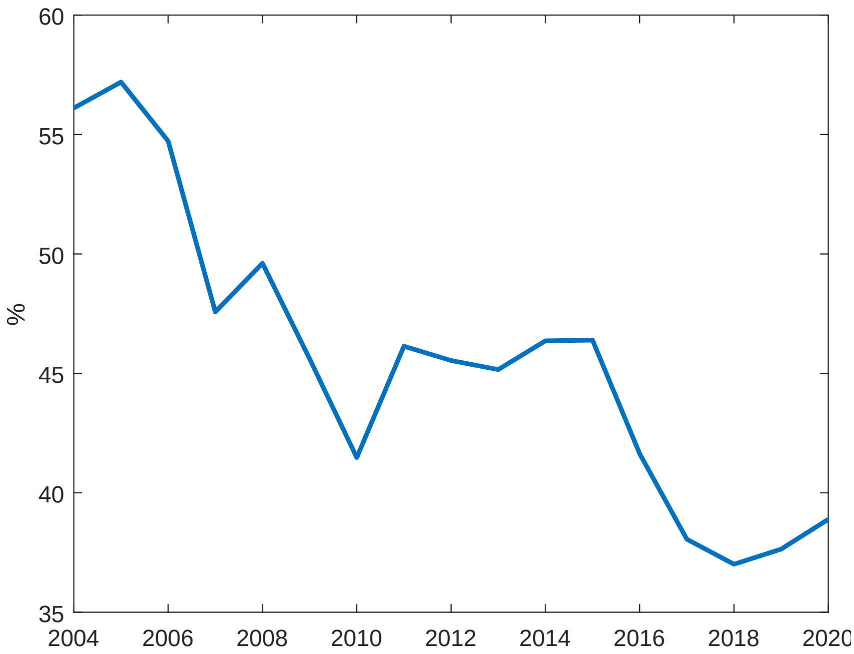

Figure 14: Share of Virtual Depreciation in Real Estate, 2004–2020

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:
$\frac{1}{2}$ (Population at the beginning of the year + 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:
2004–2014: $\dfrac{\text{Total value of residential buildings completed in urban area}}{\text{Total floor space of residential buildings completed in urban area}}$
2015–2020: inferred by the cost of 2014 and the growth of the following ratio: $\dfrac{\text{Total value of buildings completed by real estate development firms}}{\text{Total floor space of buildings completed by real estate development firms}}$

(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.

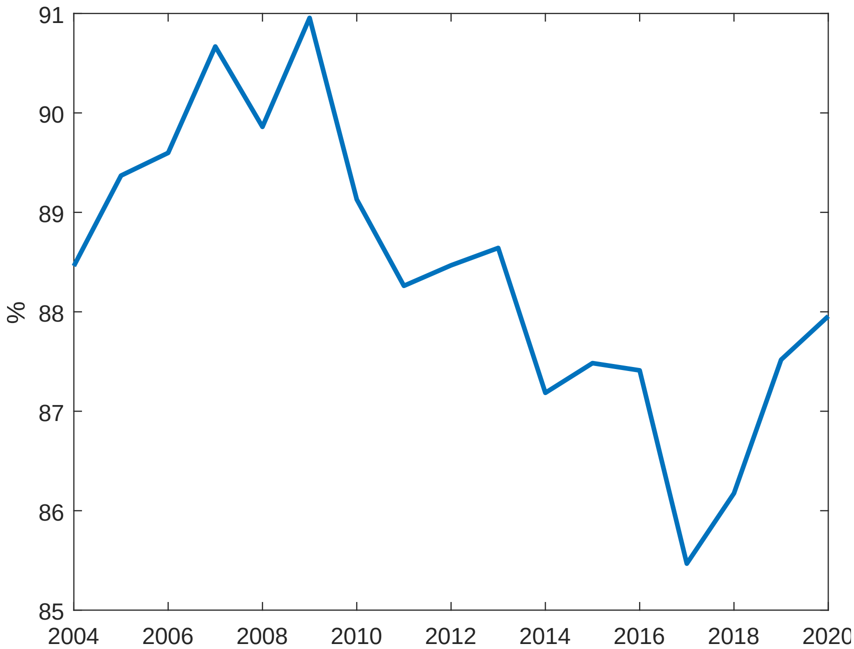

Figure 15: Share of Residential Building in Total Sold Commercialized Building, 2004–2020

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.

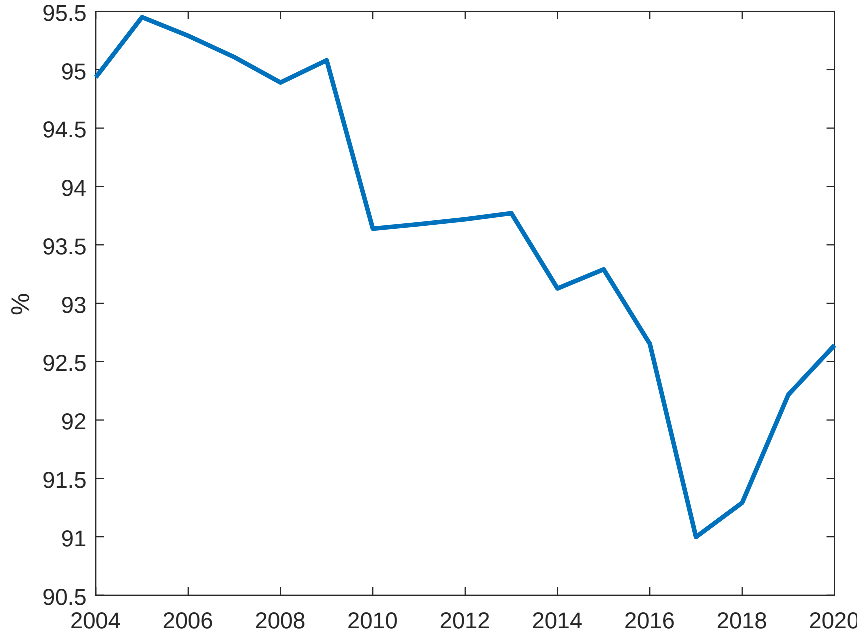

Figure 16: Share of Consumer Services in Real Estate Value-Added, 2004–2020

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.[34] Employment of the real estate industry 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.

[34]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 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.

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 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.[35]

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 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}). Specifically, we assume that all annual growth rates of real investment prior 1978 are equal to the average annual growth in 1978–1983.[36] 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 the 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.[37] Finally, we follow the same procedures for broad sectors when dealing with price indexes and depreciation rates.

C.4 Labor Output Elasticity Estimation

We estimate the output elasticities of labor and capital using the SAT data, which covers about 500,000 firms each year in all non-agricultural industries from 2007 to 2015. The data set provides firm-level information on sales, the number of employees, the book value of fixed as-

[35]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.

[36]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.

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

sets, and the county and industry in which a firm operates. Only a part of firms report their value-added. Following König et al. (2022), we impute firm value-added from observed firm sales using the industry-specific average value-added to sales ratio between 2007 and 2015. Although the industry classification changed in 2011, we establish a consistent classification from the correspondence table published by NBS.

We assume a Cobb-Douglas production function for each two-digit industry, which applies to all firms in the same industry. We then adopt the same implementation as in Bai et al. (2021), which is based on Ackerberg et al. (2015) and Brandt et al. (2017), to estimate the output elasticities of labor and capital in each two-digit industry. Finally, to obtain the sectoral labor output elasticities, we aggregate the elasticities of two-digit industries weighted by the average value-added share of each two-digit industry in 2007 and 2012, which are reported in China's input-output tables (input–output tables).

Two remarks are in order. First, we do not estimate the labor output elasticities for all the two-digit industries in the tertiary sector because in some industries—most notably in public services—the number of observations is too small. According to the input–output tables, the missing industries accounts for about 13% of the value-added of non-public services. 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 input–output tables of 2007 and 2012 when calculating the weights for the aggregation.

D Appendix for the Model-Based Accounting Approach

In this section, we first explain how we estimate the income elasticity. Then, we move on to discuss how we estimate sectoral value-added that belongs to consumption for final use using information provided in input–output table. Finally, we provide the mathematical derivations for equation 2.

D.1 On the Estimation of Income Elasticity

We follow the method in Fan et al. (2023) 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.[38] As in Fan et al. (2023), μ can be approximately

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

estimated from regressing food expenditure share $\ln \frac{P_{F,t} c^i_{F,t}}{E_{i,t}}$ on households income $\ln E_{i,t}$:

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

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.[39]

To control for the regional time-invariant unobservables, we include a full set of dummies for the pair of provinces and years. As in Fan et al. (2023), 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.

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

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

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.[40] The regression results are shown in columns 2 and 4 in Table 12.

Finally, as a robustness test, we also use a full set of occupation fixed effects as instrumental variables of the total expenditures following Fan et al. (2023). The results are shown in Table 13.

[39] 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.

[40] 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 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

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

D.2 On the Estimation $VA^C_{s,t}$ by input–output Tables

This section describes our estimation procedure of sectoral value-added that belongs to final consumption $VA^C_{s,t}$ by input–output tables based on the methods in Herrendorf et al. (2013, 2020). We make two assumptions in our estimation, both of which closely follow Herrendorf et al. (2013, 2020). First of all, imported goods are assumed to be produced with the same production technology that China uses to produce them. Such an assumption follows Herrendorf et al. (2013) and has the advantage that no stance on where intermediate inputs are produced, domestically or imported, is required. Second, we allocate all inventory change and net exports to consumption following Herrendorf et al. (2020). Such an assumption helps us consolidate the concepts of investment and capital in the model with their empirical counterparts in the input–output tables.

We closely follow the estimation procedure described in the Online Appendix B.2 in Herrendorf et al. (2013). Since the Chinese input–output 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.

Finally, note that the NBS might revise the historical value-added data without updating the input–output tables. Therefore, we assume that the ratio of $VA^C_{s,t}/VA_{s,t}$ inferred from the input–output 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,

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

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

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

which is the key equation for our accounting procedure.

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