Consumer Service Productivity Growth and Structural Transformation: A Provincial-Level Analysis in China (work in process)

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Highlights

- I adopt the strategy in Fan, Peters, and Zilibotti (2023) to recover consumer service (CS) price indexes from changes in consumption shares and then estimate productivity growth by comparing the input and output price indexes for 28 provinces in China over 2002-2017.
- Following Chen et al. (2023), I derive the value-added consumption shares of CS from Input-Output tables, and try to improve their method by accommodating the non-tradable nature of CS.
- My provincial-level estimates of CS price indexes are more dispersed, and higher than the service GDP deflator growth in over half of the provinces. The simple average of the estimated growth across the 28 provinces is 6.76%, about 2.7% higher than the official numbers.
- The annual growth rate of CS productivity averaged across provinces is 0.66% for the period. 15 out of the 28 provinces experienced positive growth. These are mainly in the northeast and southeast regions.
- CS productivity growth accounts for 23% of the structural transformation in provinces with positive productivity change during 2002-2017. For provinces experiencing negative growth, the contribution is -36%, hindering the process.

1 Introduction

Measuring productivity has long been important to economic research. In contrast to the extensive effort devoted to the agricultural and manufacturing sectors (see Brandt et al., 2017; Brandt, Van Biesebroeck, and Zhang, 2012; Adamopoulos et al., 2022, as examples conducted for China), the service sector, characterized by product diversity and subjective quality assessment, has received much less attention mostly due to challenges in quantifying its price index.

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Two recent studies stand out in this context. Fan, Peters, and Zilibotti (2023) (hereafter FPZ) develop a model to estimate the price growth of consumer services (CS) [1] for Indian cities. Building upon this methodology breakthrough, Chen et al. (2023) (Chen, Pei, Song, and Zilibotti, CPSZ hereinafter) identify an annual productivity growth rate of approximately 1.67% for China's CS sector relative to the manufacturing sector from 2005 to 2015.

In FPZ, productivity is measured by labor productivity. To calculate total factor productivity (TFP), CPSZ include capital as a production factor. However, their country-level study of China abstracts from the regional heterogeneity of FPZ's model. In this paper, I apply FPZ's strategy to estimate TFP growth in the CS sector of 28 Chinese provinces during 2002-2017 [2]. My framework accounts for both spatial variations and capital factors. Given that most CS are not tradeable [3], and that China has a very high investment rate, these two adjustments are not trivial.

An integral step of FPZ's strategy involves distinguishing between CS and producer services (PS). CPSZ classify several tertiary industries as CS and the remainder as PS or government services based on industry names [4]. In this work, I try to recover the value-added (VA) consumption shares of CS from Input-Output (I-O) tables with a different method under an alternative set of assumptions. Here, CS is defined as services exclusively used outside of food and goods production. This definition ensures that CS is not traded as part of VA in tradeable products, an important assumption in FPZ's framework.

While the estimated CS price growth isn't perfectly comparable with published service price indexes due to differences in scope arising from PS, a positive correlation between them exists. The simple average of the estimated growth across the 28 provinces is 6.76%, about 2.7% higher than the official numbers. However, the distribution of estimates is more dispersed. While 8 provinces experienced CS price growth of over 10% each year, 3 showed negative growth. Considering that my estimates are adjusted for quality change, these numbers should not be deemed abnormal. Then, I calculate productivity changes by comparing input prices and estimated output prices of CS. From 2002 to 2017, CS productivity in the 28 provinces increased at an average annual rate of 0.66%. Among them, 15 experienced positive growth, primarily in the northeast and southeast regions, with Beijing and Guangdong leading the trend. Section 5 delves into the reliability of the applied strategy and the robustness of the results.

Using the estimated CS price indexes and productivity growth, I can examine key aspects of

[1] FPZ decompose the service sector to CS and producer services (PS). CS are services directly consumed by individuals (such as catering, healthcare, and entertainment), while PS refers to services catering to goods producers (like consulting services, legal services, and ICT). I follow this decomposition and propose a slight advancement by classifying services catering service providers into CS and PS, which will be discussed in Section 4.

[2] I exclude Xizang, Taiwan, Hong Kong, and Macao for insufficient data access. Xinjiang is also excluded as the share of its CS declined substantially during 2002-2017, which the model can hardly explain. Finally, Qinghai is excluded due to some obvious measurement error in its Input-Output tables.

[3] Apart from existing empirical evidence cited by FPZ, it's also intuitive to understand the assumption that CS are not tradeable. Because consumers usually buy just a small amount of services, it does not pay to ship the services as the cost of shipment probably exceeds the benefits of enjoying the services. However, if a service targets (or is related to) producers, the scale of transactions can be huge, and the transportation cost might seem minute compared to the benefits (or profits) of the transaction. As a result, PS are tradeable. For example, a barber may not travel any distance to provide services for individual consumers, but he/she is likely to provide services for TV drama producers even though the cast is very far away from his/her shop.

[4] CPSZ calculate the consumed (instead of invested) VA of tertiary industries from the final consumption vector in China's Input-Output table using the method developed by Herrendorf, Rogerson, and Valentinyi (2013). A detailed discussion on the difference between VA and final consumption can also be found in Herrendorf, Rogerson, and Valentinyi (2013).

structural change. A great body of studies focuses on forces driving the process (to name a few, Buera and Kaboski, 2012; Herrendorf, Herrington, and Valentinyi, 2015; Foellmi and Zweimüller, 2008; Kongsamut, Rebelo, and Xie, 2001; Eckert and Peters, 2022; Matsuyama, 2019). Two forces merit particular attention: the income effect, whereby sectors with higher demand elasticity of income grow faster with income growth, and the relative price effect (substitution effect), whereby sectors with lower price growth grow (shrink) in share if sectors are gross substitutes (gross complements). Empirical studies probing the relative importance of these forces are numerous but inconclusive [5]. Results vary across time, region, and preference specifications.

In analyses of China, Yan, Guo, and Hang (2018) and Guo, Hang, and Yan (2017) find that both forces played a role and the income effect is more important than the relative price effect. The generalized Stone-Geary preference in their model is not able to account for persistent income effect (Alder, Boppart, and Müller, 2022; Comin, Lashkari, and Mestieri, 2021). Based on the price-independent generalized linear (PIGL) preference, I find a stronger role of the income effect, accounting for 124% of structural change in provinces with positive CS productivity growth and 268% in provinces with negative growth. Thus, consistent with previous findings, the relative price effect (-24% and -168%) is less important than the income effect in both groups. However, the negative contributions suggest that the relative price change of the three sectors hindered structural change during 2002-2017. This is because the estimated CS price growth is higher than food and goods sectors, causing people to consume less CS when the sectors are gross substitutes. CPSZ also document that the service sector's price growth outpaced the secondary sector's from 1978 to 2015 and closely matched that of the primary sector.

A key determinant in relative price change is the relative productivity growth. Duarte and Restuccia (2010) find a very small impact of productivity growth in the service sector on change in employment shares of sectors in their cross-country analysis. However, FPZ's investigation reveals the opposite for the Indian economy, which is unsurprising given India's service-led growth trajectory. In this study, I find that CS productivity growth accounts for 23% of the structural change in provinces with positive CS productivity change during 2002-2017. In contrast, for provinces experiencing negative growth, the contribution is -36%, hindering structural change.

The rest of this paper unfolds as follows. Section 2 presents provincial-level features of structural transformation in China. Section 3 describes the model. Section 4 outlines the calibration strategies and presents the estimated CS price and productivity growth. Section 5 discusses the reliability of my results. Section 6 conducts counterfactual analyses. Section 7 concludes.

2 Stylized Facts

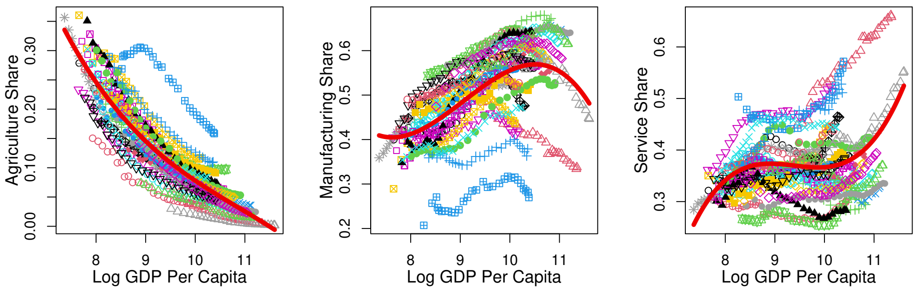
International data deliver three prevalent features of structural change (see, for example, Herrendorf, Rogerson, and Valentinyi, 2014; Alder, Boppart, and Müller, 2022; Comin, Lashkari, and Mestieri, 2021): (1) a persistent decline in the agricultural sector's share, (2) a hump-shaped trajectory for the manufacturing sector's share, and (3) an accelerating increase in the service sector's share. Although similar patterns have been observed for China at the national level (Liao, 2020; Guo, Hang, and Yan, 2021; Chen et al., 2023), evidence from the provincial level

[5] For the postwar United States, Boppart (2014) finds that the two forces play almost the same roles with the price-independent generalized linear (PIGL) preference being specified. In contrast, Comin, Lashkari, and Mestieri (2021) find that income effects account for the bulk of sectoral reallocation in their sample of 39 countries with an average number of observations of 42 years per country using the non-homothetic CES preference.

remains relatively underexplored. In this section, I present patterns of China's provincial-level structural transformation from both production and consumption perspectives.

From the production standpoint, the real and nominal VA shares of the three sectors between 1992 and 2020 exhibit similar patterns, as depicted in Figures 1 and 2. The aforementioned three features are present in China's provincial-level data. The VA share of the agricultural sector consistently declines as per capita GDP increases. The manufacturing share initiated its decline when log per capita GDP reached around 9 to 10 (2000 CNY) for most provinces. This evidence roughly coincides with the turning point found in Herrendorf, Rogerson, and Valentinyi (2014) after adjusting for the exchange rate. Notably, provinces with higher manufacturing shares tend to start declining later. Concurrent with the peaking point of the manufacturing sector, the increase in service VA share accelerates.

Two distinctive features of China's structural change pattern warrant mention. Firstly, the growth of nominal VA shares of the secondary sector during the first half of the sample period is slower than the real VA shares. The discrepancy arises from the decrease in the price of manufacturing goods relative to the other sectors during the period [6]. Secondly, the VA shares of the service sector in most provinces experienced growth when the log per capita GDP was less than 8.5, both in real and nominal terms, followed by stagnation or decline in some provinces when the log per capita GDP went from 9 to 10. This can be attributed to the swift expansion of China's secondary sector post its accession to the WTO in 2001, coupled with increased exports of manufactured goods. Furthermore, the 4 trillion yuan fiscal stimulus launched by the Chinese government in 2008 further propelled the rapid growth of VA shares of the secondary sector until around 2013 [7].



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

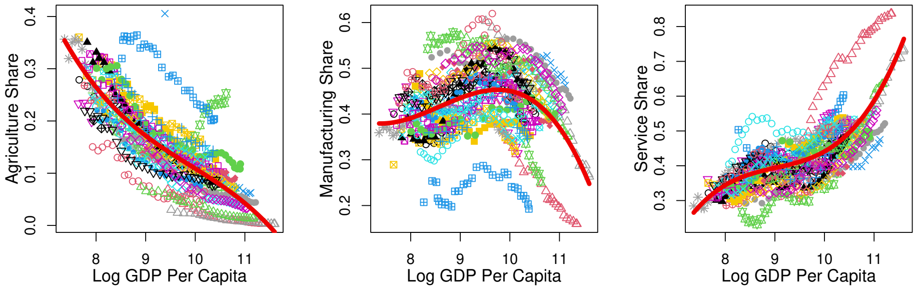
Figure 1: Real Production VA Shares. The figures plot the real production VA shares of the primary, secondary, and tertiary sectors against log per capita real GDP (in 2000 CNY) from 1992 to 2020. The data come from the NBS. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. The red cubic curves are fitted by OLS. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.

On the consumption side, I compute the sectoral nominal final consumption (FC) and VA consumption shares using provincial I-O tables in 2002, 2007, 2012, and 2017 and plot them against the log per capita consumption in 2000 CNY, accompanied by fitted quadratic lines [8].

[6] Chen et al. (2023) show that the price index of the agricultural sector relative to the manufacturing sector kept increasing during 1978-2015.

[7] For the plots of sectoral shares against years, see Appendix B.

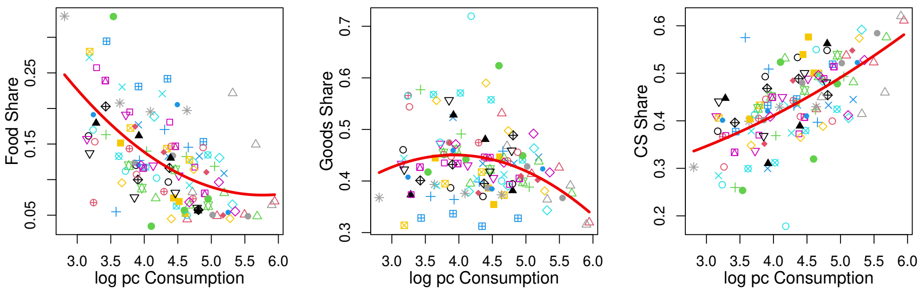
[8] The VA consumption shares are derived employing the method proposed by Herrendorf, Rogerson, and Valentinyi (2013).



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

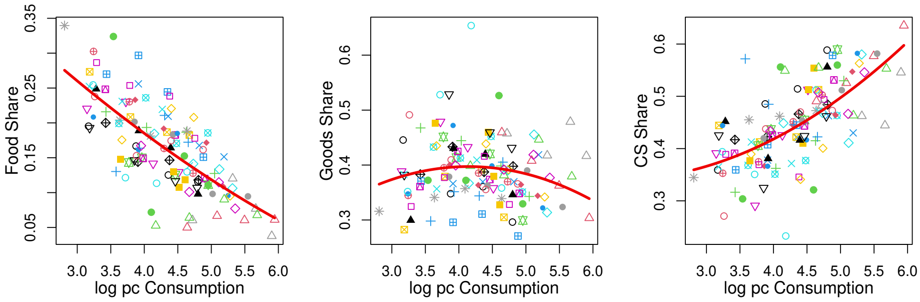
Figure 2: Nominal Production VA Shares. The figures plot the nominal production VA shares of the primary, secondary, and tertiary sectors against log per capita real GDP (in 2000 CNY) from 1992 to 2020. The data come from the NBS. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. The red cubic curves are fitted by OLS. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.

The patterns of structural changes observed in both the FC shares and VA shares are very similar, showing a consistent decline in the agricultural sector and an increasing trend in the service sector. However, the hump-shaped curve in the manufacturing sector appears less prominent. Correspondingly, the accelerating trend in the increase in the consumption share of services is not observed, and the relationship between service share and log per capita total consumption appears more linear. It's noteworthy that the stagnation of service shares during the middle of the sample period evident in the production-based data is much less obvious in the consumption-based data. This observation supports the hypothesis that the surge in manufacturing VA during the period was mainly driven by exogenous export demand and infrastructure construction initiatives.



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 3: Final Consumption Shares. The figures plot the shares of consumption on final (gross) goods/services from the primary, secondary, and tertiary sectors against log per capita consumption level (in 2000 CNY) in 2002, 2007, 2012, and 2017. The FC shares are calculated based on China's provincial I-O tables. The x-axis is deflated by CPI published by the NBS. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. The red quadratic curves are fitted by OLS. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 4: VA Consumption Shares. The figures plot the shares of consumption on VA from the primary, secondary, and tertiary sectors against log per capita consumption level (in 2000 CNY) in 2002, 2007, 2012, and 2017. The consumption VA shares are calculated based on China's provincial I-O tables. The x-axis is deflated by CPI published by the NBS. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. The red quadratic curves are fitted by OLS. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.

3 Model

My model closely follows FPZ's framework, with the addition of a capital production factor. However, it remains static, abstracting the production and accumulation of capital for simplicity. This section introduces the production technology in subsection 3.1, presents the PIGL preference in subsection 3.2, and outlines the market clearing conditions in subsection 3.3.

3.1 Production

The economy is structured mainly around three sectors: food (F), goods (G), and consumer service (CS) with F, G measured as gross output (GO), and CS measured as value-added (VA) [9]. In region r and time t, VA in CS y_{CSrt} are produced using both human capital H_{CSrt} and physical capital K_{CSrt} via a Cobb-Douglas production function with a sector-specific capital share α_{CS}:

$$y_{CSrt} = A_{CSrt} \left(K_{CSrt}\right)^{\alpha_{CS}} \left(H_{CSrt}\right)^{1-\alpha_{CS}} \tag{1}$$

Within region r, CS enterprises strive to minimize cost $w_{rt}H_{CSrt} + q_{rt}K_{CSrt}$ with w_{rt} and q_{rt} denoting the wage rate and the user cost of capital. The first-order condition establishes the relationship between A_{CSrt} and the price of CS VA, P_{CSrt}. A productivity increase induces a price decrease holding w_{rt} and q_{rt} constant. This relationship is exploited in the calibration of productivity growth for CS:

$$A_{CSrt} = \left(P_{CSrt} \left(\frac{\alpha_{CS}}{q_{rt}}\right)^{\alpha_{CS}} \left(\frac{1-\alpha_{CS}}{w_{rt}}\right)^{1-\alpha_{CS}}\right)^{-1} \tag{2}$$

The production function for final good $n \in [0,1]$ in region r at time t is:

[9] Processed food is classified in G. Food provided by a restaurant is decomposed into gross food output and VA in CS.

$$Y_{nrt} = \tilde{\lambda}_n \cdot y_{Frt}^{\lambda_{nF}} \cdot y_{Grt}^{\lambda_{nG}} \cdot y_{CSrt}^{\lambda_{nCS}} \tag{3}$$

To illustrate this, each region produces a continuum of differentiated final products using food y_{Frt}, goods y_{Grt}, and CS VA y_{CSrt}. For example, a restaurant meal is a combination of unprocessed food (F), processed ingredients (G), services provided by local cooks (human capital in CS), and kitchen equipment (physical capital in CS). Here, y_{Frt} and y_{Grt} are produced using human capital $H_{\tilde{s}rt}$, physical capital $K_{\tilde{s}rt}$, and tradeable intermediate inputs from sectors F, G, and PS in all regions, represented by X_{Ft}, X_{Gt}, and X_{PSt}:

$$y_{\tilde{s}rt} = F\left(H_{\tilde{s}rt}, K_{\tilde{s}rt}, X_{Ft}, X_{Gt}, X_{PSt}\right), \quad \tilde{s} \in \{F, G\} \tag{4}$$

3.2 Preference

My model focuses on the intra-temporal household decisions on allocating budgets to different final goods, which can be mapped to the three fundamental sectors — F, G, and CS [10]. Following the price-independent generalized linear (PIGL) preference parametrized by FPZ, the optimal share of total consumption c_{irt} that household i allocates to *final good* n is described by:

$$\vartheta_{inrt}^{FC}\left(c_{irt}, \mathbf{P_{rt}}\right) = \beta_n + \kappa_n \left(\frac{c_{irt}}{exp\left(\beta_n \ln p_{nrt}\right)}\right)^{-\varepsilon} \tag{5}$$

Here, β_n represents the asymptotic consumption share on final good n, κ_n determines whether the final good is a luxury or a necessity. Constraints $\sum_n \kappa_n = 0$ and $\sum_n \beta_n = 1$ ensure that household i's consumption shares of all final goods sum to 1. The parameter ε governs the slope of the Engel curve and determines the speed of the consumption shares converging to the asymptotic shares. p_{nrt} denotes the price of final good n.

The PIGL class preference facilitates a direct mapping from FC to food, goods, and CS VA while maintaining the key parameter ε unchanged. In region r at time t, household i's consumption shares on y_{Art}, y_{Mrt}, and y_{CSrt} are determined by [11]:

$$\vartheta_{isrt}\left(c_{irt}, \mathbf{P_{rt}}\right) = \omega_s + \nu_s \left(\frac{c_{irt}}{P_{Frt}^{\omega_F} P_{Grt}^{\omega_G} P_{CSrt}^{\omega_{CS}}}\right)^{-\varepsilon}, \quad s \in \{F, G, CS\} \tag{6}$$

In this equation, ω_s represent the asymptotic sectoral consumption shares [12]. The parameter ν_s determines whether the sector is a luxury or a necessity [13]. Similarly, $\sum_s \nu_s = 0$ and $\sum_s \omega_s = 1$ ensure a valid share function. P_{CSrt} denotes the VA price of CS, while P_{Frt} and P_{Grt} represent the producer's prices of food and goods GO.

According to Muellbauer (1975), the PIGL preference enables a "representative" consumer in the sense that the consumption shares of y_F, y_G, and y_{CS} in region r at time t are expressed as:

[10] Typically, in a model with capital accumulation, household decisions consist of two parts: intra-temporal (sectoral consumption) decisions and inter-temporal (saving) decisions. This work focuses exclusively on the first one. The rationale for this split has been well-established in the structural change literature (Herrendorf, Rogerson, and Valentinyi, 2014; Eckert and Peters, 2022; Chen et al., 2023).

[11] A proof is present in Appendix C.

[12] $\omega_s \equiv \int_n \lambda_{ns} \beta_n dn$.

[13] $\nu_s \equiv \int_n \lambda_{ns} \kappa_n dn$.

$$\vartheta_{srt}\left(\bar{c}_r, \mathbf{P_{rt}}\right) = \omega_s + \nu_s \phi_r \left(\frac{\bar{c}_{rt}}{P_{Frt}^{\omega_F} P_{Grt}^{\omega_G} P_{CSrt}^{\omega_{CS}}}\right)^{-\varepsilon} \tag{7}$$

Here, $\bar{c}_{rt} = \mathbf{E}(c_{irt})$ denotes the average level of households' total consumption in region r at time t. ϕ_r is an inequality adjustor of region r, assumed to be constant over time.

3.3 Equilibrium

Local market clearing for food, goods and CS VA:

$$y_{srt} = \left(\omega_s + \nu_s \phi_r \left(\frac{\bar{c}_{rt}}{P_{Frt}^{\omega_F} P_{Grt}^{\omega_G} P_{CSrt}^{\omega_{CS}}}\right)^{-\varepsilon}\right) C_{rt} \tag{8}$$

where $C_{rt} = \sum_i c_{irt}$ represents total consumption.

Local human capital and national physical capital market clearing:

$$\sum_s H_{srt} = H_{rt}; \quad \sum_r \sum_s K_{srt} = K_t \tag{9}$$

4 Data & Calibration

In this section, I first outline my method of calculating food GO, goods GO, and CS VA used in the calibration [14]. Then I detail the calibration strategies and present the estimated CS productivity growth.

4.1 Computation of Food GO, Goods GO, and CS VA

I leverage provincial I-O tables to calculate VA of CS and GO of food and goods. It's important to note that the calculated GO is GO consumed by local residents instead of GO produced by local factories. These are different as food and goods are tradeable. Additionally, clear differentiation between consumption and investment is crucial. While the model only specifies the consumption part, in reality, the output of each sector can be consumed or invested. Therefore, it's necessary to subtract investment from total output when applying the data to the model to ensure that all computations are based on consumption.

VA of sector CS, y_{CSrt}: In this work, CS VA are defined as VA of services that never serve food and goods producers. Otherwise, CS VA will enter these tradeable products and finally become tradeable, violating the key assumption of the model. In practice, CS VA must be consumed either directly by consumers (eg. the VA generated by cooks in a restaurant) or indirectly by catering CS providers (eg. the VA generated by drivers delivering ingredients to a restaurant) [15]. It is computed by

$$y_{CS} = \mathbf{C}_S{}'\mathbf{Q}\mathbf{V}_S. \tag{10}$$

[14] I state the construction of other variables in Appendix F.

[15] Put differently, any services catering to food and goods producers, either directly or indirectly (by serving service providers of food and goods producers), are classified as PS, and the rest are CS.

Here, $\mathbf{V}_S$ is a $p \times 1$ vector, where p is the number of service industries in the I-O tables. Each entry in this vector, $v_s = VA_s/TI_s$, represents the share of value-added (VA_s) in the total input (TI_s) of a service industry s. $\mathbf{C}_S$ is a $p \times 1$ vector representing the final consumption of tertiary industries. $\mathbf{Q} = (\mathbf{I} - \mathbf{A}'_S)^{-1}$ denotes the 'quasi' total requirement matrix ($p \times p$) for service industries, where $\mathbf{A}_S$ is the direct consumption coefficient matrix ($p \times p$) for service industries. By applying the FC vector of services to the inverse I-O matrix, I can trace all intermediate service inputs used in the production of consumed gross services. The inverse I-O matrix is restricted to the service sector as services used in agricultural and manufacturing production are PS and should be excluded here. Finally, the vector of VA shares $\mathbf{V}_S$ translates the CS inputs into VA terms. I just give formulas and intuitions in the section, Appendix E characterizes the derivation in detail.

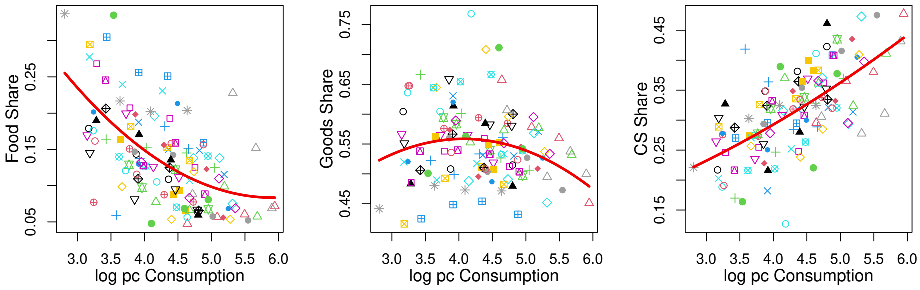
GO of sector F, y_{Frt}: As processed food is classified as goods, food defined here is either directly bought by consumers or used as intermediate inputs of CS. In practice, all the consumed agricultural GO that never goes into manufacturing factories is food here. It is defined and computed by

$$y_F = \mathbf{C}_S{}'\mathbf{Q}\mathbf{W}_A^S + \mathbf{M}'\mathbf{C}_A. \tag{11}$$

Here, $\mathbf{W}_A^S$ is a $q \times 1$ vector, where q is the number of agricultural industries in the I-O tables. Each entry in this vector, $w_A^s = II_A/TI_s$, represents the share of agricultural intermediate input (II_A) in the total input (TI_s) of a tertiary industry s. $\mathbf{C}_A$ is the FC vector ($q \times 1$) of the agricultural sector. $\mathbf{M}$ is a $q \times 1$ vector with 1's in all entries. The first term in Equation 11 recovers food from FC on services. The idea is similar to Equation 10, changing $\mathbf{V}_S$ to $\mathbf{W}_A^S$ to recover different parts from the input variety. For example, vegetables used in restaurant meals can be recovered from people's consumption of catering services. The second term simply adds consumers' direct consumption of food. As China's I-O tables are measured in producer's prices, the value of (within-province) distribution services (should be CS) is not included in this term.

GO of sector G, y_{Grt}: After getting data analogs for y_{CSrt} and y_{Frt}, y_{Grt} can be calculated as a residual by subtracting y_{Frt} and y_{CSrt} from total consumption. Although CS are measured as VA and F and G are measured by GO, it's reasonable to have their sum equal to the total consumption given that CS VA never enters any GO of F and G (thus there is no worry of double counting or misallocation).

I present provincial shares of food GO, goods GO, and CS VA in Figure 5. I also bring my method to I-O tables of 42 countries during 2002-2014 provided by WIOD and show international evidence in Figure 6. Comparing the right panel of Figure 5 with the right panel of Figure 4, I observe a discrepancy of approximately 10%-20% between the shares of CS VA and VA consumption on services, which is attributed to PS. This phenomenon, also noted in India by FPZ, underscores the smaller share of PS relative to CS. Despite quantitative differences, the positive linear correlation between CS share and log per capita total consumption remains evident. This positive relationship is further supported by international evidence (Figure 6). Among the 42 countries, the US boasts the highest share of consumption on consumer service VA, nearing 0.7. Moreover, the hump-shaped manufacturing goods shares and the accelerating increase in CS VA shares are present.



(a) Food Shares (b) Goods Shares (c) CS VA Shares

Figure 5: Provincial Consumption Shares on Food, Goods, and CS VA. The figures plot food, goods, and CS VA consumption shares against log per capita consumption level (in 2000 CNY) in 2002, 2007, 2012, and 2017. The consumption shares are calculated based on China's provincial I-O tables. The x-axis is deflated by CPI published by the NBS. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. The red quadratic curves are fitted by OLS. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.

4.2 Calibration Strategies

Following the strategies of FPZ and CPSZ, I estimate ε by Equation 5 restricting n to food items. Assuming the asymptotic share of aggregate final goods that can be classified as food (denoted as $\mathcal{F}$) to be 0, and taking log of both sides of the share function aggregated for $\mathcal{F}$, I obtain the following empirical counterpart:

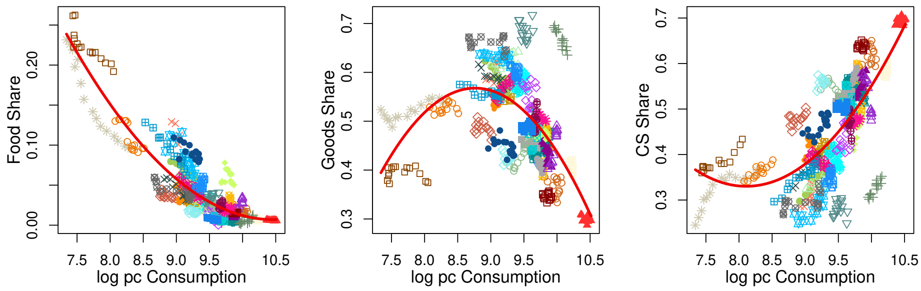
$$\ln \vartheta_{i\mathcal{F}rt} = \delta_{rt} + \varepsilon \times \ln c_{irt} + x'_{irt}\psi + u_{irt} \tag{12}$$

Here, i denotes household, δ_{rt} represents a province-year fixed effect to accommodate different regional price vectors in different years, and x_h denotes a set of household characteristics that could induce a correlation between total spending $\ln c_{irt}$ and food shares, including the household's location (rural or urban), number of workers in the household, and household size. To deal with potential measurement error and unobserved income shock, I follow FPZ to instrument household consumption by the occupation of the household's principal. I utilize CHIP data from 2002, 2007, 2013, and 2018 (pooled cross-sectional data) to estimate ε. My result is very close to FPZ's (0.395) and CPSZ's (0.375), at approximately 0.417. As the expenditure data in 2002 only covered rural residents, and 2018 falls outside my analysis period, I re-run the regression using data from each year and found consistent results across different years. Detailed information with more robustness checks can be found in Appendix D.

I set the asymptotic shares by letting $\omega_F = 0.01$ and $\omega_{CS} = 0.65$ to match the average food/CS VA shares of the five nations exhibiting the lowest food shares/the highest CS VA shares, found in Figure 6. Then the asymptotic share of goods ω_G is simply $1 - \omega_F - \omega_{CS} = 0.34$. While this may appear arbitrary at first glance, I delve into the rationale and robustness of these values in Section 5.

I determine the growth rate of P_{CSrt} utilizing the following relationship:

$$d\ln(\vartheta_{CSrt} - \omega_{CS}) = -\varepsilon \times d\ln \bar{c}_{rt} + \sum_{s} (\varepsilon \cdot \omega_s \times d\ln P_{srt}) \tag{13}$$



(a) Food Shares (b) Goods Shares (c) CS VA Shares

Figure 6: Consumption Shares on Food, Goods, and CS VA in 42 Countries. The figures plot food, goods, and CS VA consumption shares against log per capita real consumption (in 2017 international dollar) in 42 countries from 2000 to 2014. The consumption shares are calculated based on I-O tables from the WIOD database (Nov. 2016 released version). The x-axis is deflated by GDP deflators and adjusted by PPP from the World Bank database. Each style of point denotes a country according to the legend presented in Figure 14 in Appendix A. The red quadratic curves are fitted by OLS.

where I use GDP deflators of the primary and secondary sectors as data analogs for P_{Frt} and P_{Grt}, the prices of food and goods GO. Although GDP is measured in VA, their deflators are GO prices calculated from farm-gate and factory-gate prices. As ν_s and ϕ_r do not enter this equation, they are not calibrated in this paper.

The idea of Equation 13 can also be graphed. In Figure 7, the horizontal axis is consumption (income) level normalized by 2002 prices, namely $c_t/\left(P_{F2002}^{\omega_F} P_{G2002}^{\omega_G} P_{CS2002}^{\omega_{CS}}\right)$ (the region subscript is suppressed). The purple curve is the estimated Engel curve. As the prices of CS are calibrated from the model, all the blue dots representing provincial CS shares in 2002 lie exactly on the curve [16]. The distances between the Engel curve and the green triangles representing CS shares in 2017, which the income effect can not explain, give the estimated CS price growth (after subtracting food and goods price changes).

On the production side, $1-\alpha_{CS}$ is set to 0.45 matching the average labor share in the service sector observed in China's I-O tables published for 2002, 2005, 2007, 2010, 2012, 2015, and 2017. One may argue that the labor share of CS is not equal to the one of the whole service sector due to the existence of PS. However, this parameter is trivial to the regional ranking of CS productivity growth as it's common to all provinces. Now, the productivity growth of CS can be calculated based on Equation 2.

4.3 Results

In this subsection, I present the estimated CS VA price indexes and CS productivity growth. Except for Beijing, Guangdong, and Liaoning, all provinces showed positive CS price growth during 2002-2017. Figure 8 displays the estimated growth rates of CS VA prices alongside the service GDP deflator growth. While not directly comparable in definition (as the PS part of the service sector is not included in the estimated prices), a positive correlation between the two is evident. The simple average of the estimated growth across the 28 provinces is 6.76%,

[16] I set $\nu_{CS} = -1$ and $\nu_F = 0.7$ to calculate P_{CS2002} and make the figure. Recall that these parameters do not enter Equation 13 and would not affect the estimated price growth.

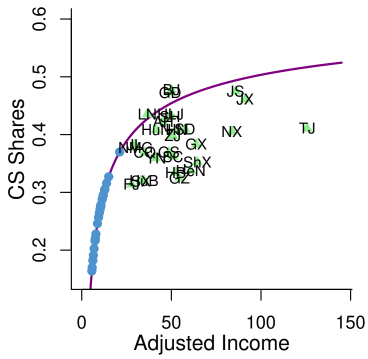


Figure 7: The Engel Curve & Data Points. The blue dots (green triangles) represent CS shares in 2002 (2017). The purple curve is the estimated Engel curve. The x-axis is income adjusted by the price vector in 2002 so that all the blue dots lie in the estimated Engel curve. In this case, any horizontal distance between green triangles and the curve is attributed to relative price change.

about 2.7% higher than the official numbers. However, the estimates are more dispersed, with 8 provinces achieving annual growth rates higher than 10%. Considering that my estimates are adjusted for quality change, these numbers are not unlikely. Notably, the estimated CS price growths are higher than the growths of published service prices in more than half of provinces, which can result from a low (even negative) price growth of PS or an overall underreporting of service price growth in data. As the hypothesis of negative price growth in the PS sector does not match the real-world observations, it seems that service price indexes in these provinces were downward mismeasured in data.

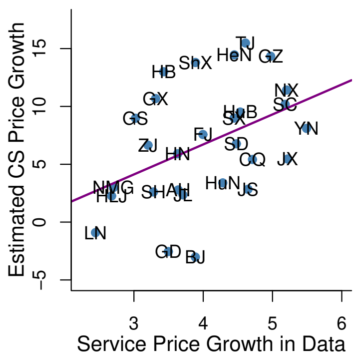


Figure 8: Estimated CS Price Growth v.s. Data. This figure plots the estimated CS price growth against the growth rates of provincial GDP deflators of the tertiary sector (2002-2017, annualized, in percentage points) with each point denoting a province. The correlation between the two series is 0.43. The purple line is fitted by OLS. Data on provincial service GDP deflators are obtained from the NBS.

Figure 9 illustrates the provincial distribution of CS productivity growth in China spanning from 2002 to 2017. The annual CS growth rate averaged across the 28 provinces is 0.66%. Notably, 15 out of 28 provinces experienced positive growth, with Beijing and Guangdong as the highest. Most provinces in the southeast area (like Zhejiang and Jiangsu), which have high urbanization rates, open economies, and high per capita income, exhibited positive CS productivity growth. However, it's a little bit surprising to see the strong CS productivity growth in provinces in the northeast area (like Heilongjiang and Liaoning). These provinces experienced slower economic growth than other provinces since China's reform and opening up and had relatively weak manufacturing foundations. Their performance in CS productivity may suggest that they have shifted their focus from the manufacturing sector to the service sector for development, resembling the practice in India. Finally, it's also interesting to have an informal discussion on the relationship between the CS sector and the manufacturing sector. While the strong productivity growth in the CS sector of provinces like Guangdong and Chongqing may serve as a hint of the productivity spillover effect from the manufacturing sector to the service sector, the negative CS productivity growth in provinces like Hebei also suggests that a large manufacturing sector can hinder the development of the tertiary sector.

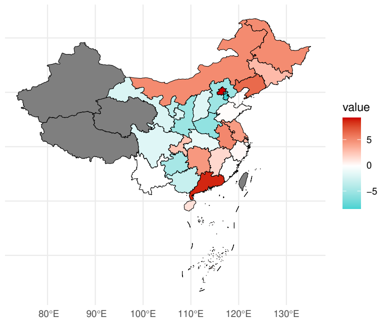


Figure 9: Provincial CS Productivity Growth. This figure shows the productivity growth of CS in 28 Chinese provinces. The legend denotes the growth rates (in percentage points) with the red shadow denoting positive productivity growth and the blue shadow denoting negative productivity growth. The grey parts in the map are provinces without estimates.

5 Discussions

In this section, I delve into the reliability of the estimates of CS price and productivity growth. Given the substantial reliance on the functional form of the utility function, I begin by discussing the rationale behind selecting the PIGL preference and its fit to the data. Subsequently, I explore an alternative calibration strategy for some preference parameters and discuss the robustness of my results. Before introducing details, Figure 20 in Appendix B showcases the model's fair performance in predicting food shares in 2017 (not targeted in the baseline calibration) with estimated CS price indexes.

5.1 Functional-Form

The estimation of CS price growth heavily hinges on the functional form of the preference. There are at least three compelling reasons for choosing the PIGL preference: (1) It accommodates both income and relative price effects; (2) It facilitates a seamless transition between consumption defined over VA and final goods; (3) It enables a representative consumer (although not in the traditional sense). The first feature of PIGL guarantees a good fit to data while the following two enable the necessary tactability of the model in estimating CS prices. To the best of my knowledge, among the prevalent preference forms employed in the structural change literature — such as the generalized Stone-Geary preference, non-homothetic CES, and intertemporal aggregable (IA) preference introduced in Alder, Boppart, and Müller (2022) — PIGL uniquely satisfies all three requirements mentioned above [17].

Equation 13 delineates that the change in CS VA share can be decomposed into two components: the income effect and the relative price effect. If the income effect can be adequately captured by the first term in Equation 13 and ω_{CS}, the residual price effect gives the CS price indexes (also under the assumption that only these two forces are driving structural change). Thus, I can check the linear relationship between $\ln c$ and $\ln(\omega_s - \vartheta_s)$ holding prices constant to examine fit of the model to data. As derived above, the linear relationship between $\ln c$ and $\ln(\omega_s - \vartheta_s)$ is equivalent to the linearity between $\ln c$ and $\ln\left(\beta_n - \vartheta_n^{FE}\right)$ (as long as the production side is specified as in Equation 3). Using the same waves of CHIP data in the estimation of ε, I find clear evidence supporting the linear relationship for food items (Figure 10).

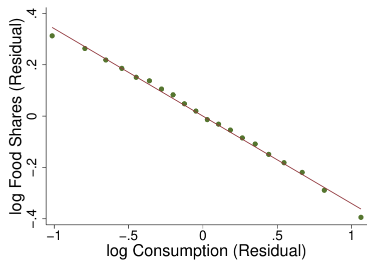


Figure 10: Residual Log Food Consumption Shares v.s. Residual Log Total Consumption. The figure shows a binscatter plot of the residuals of a regression of the log consumption share on food in province r at time t on province-year fixed effects against the residuals of a regression of the log total consumption on the same set of fixed effects.

In Alder, Boppart, and Müller (2022), the authors suggested that the income effect delivered by PIGL lacks the flexibility to capture the accelerated increase in the service share. They propose the IA preference as a more versatile alternative. However, PIGL seems sufficient in my study. Firstly, after classifying services into CS and PS, Figure 5 indicates no clear accelerated increase in CS shares of the provinces during 2002-2017. Moreover, a parameterized form of IA preference proposed by Alder, Boppart, and Müller (2022) nest PIGL when some parameters are set to be 0. I estimate this form (by the iterated feasible generalized nonlinear least square method) utilizing China's provincial data and find that all parameters distinguishing IA from PIGL are very close to 0. Moreover, with additional moments given by provincial food shares, I can estimate CS prices and preference parameters for the IA preference concurrently. While the estimated CS prices vary with initial guesses, the estimated parameters consistently suggest the PIGL form [18]. Appendix G presents more details.

[17] Although not exploited in this work, several properties of PIGL are also preferred in the growth dynamics context as documented in Boppart (2014) and CPSZ.

[18] I do not use the estimated CS price vector to do this exercise as they come from the PIGL preference and should give parameters that are consistent with the PIGL preference.

5.2 Alternative Calibration

In the baseline model, I set the asymptotic share of the CS sector to match the average share of CS VA in the five countries highest in this value. In fact, ω_{CS} and ω_F can also be estimated from the moments of F and CS shares. To illustrate, the market-clearing condition for F given in Equation 8 implies that

$$\left(\frac{\bar{c}_{rt}}{P_{Frt}^{\omega_F} P_{Grt}^{\omega_G} P_{CSrt}^{\omega_{CS}}}\right)^{-\varepsilon} = \left(\frac{y_{Frt}}{C_{rt}} - \omega_F\right) (\nu_F \phi_r)^{-1}, \tag{14}$$

which can be plugged into the market-clearing condition of CS to get

$$\vartheta_{CSrt} = \omega_{CS} + \frac{\nu_{CS}}{\nu_F} (\vartheta_{Frt} - \omega_F), \tag{15}$$

where I use the definition of ϑ_{srt}. With data on ϑ_{CSrt} and ϑ_{Frt} in 2002 and 2017 calculated in Section 4, I can estimate ω_{CS}, ω_F, and ν_{CS}/ν_F through a NLS process. The results suggest that $\omega_{CS} = 0.62$ and $\omega_F = 0$, which is very close to the assigned parameters in the baseline calibration. Moreover, as these two parameters are common to all provinces, they only affect the levels of CS productivity growth. Put differently, the key result of this study, the regional distribution of CS productivity growth is robust to these parameters.

5.3 Housing Prices

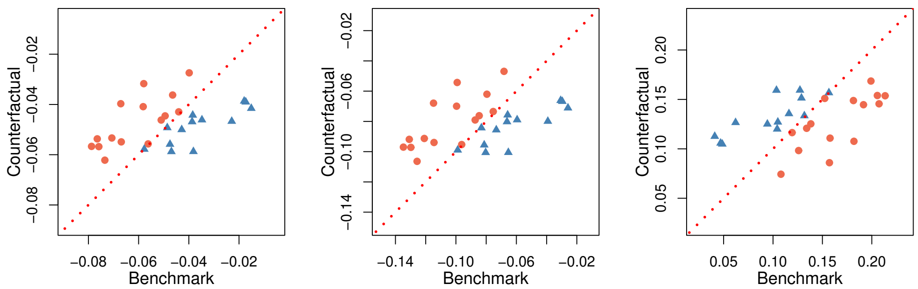
In China, a notable difference across provinces lies in the housing price and its growth rates during the last decade. For example, if the rents for CS providers in some (perhaps more developed) provinces increased more drastically from 2002 to 2017, then the price of CS would increase faster and lead to lower estimates of productivity growth. However, it's unlikely to be the case in that the prices estimated in this work are for CS VA, where the cost of intermediate housing service inputs has already been stripped out. In practice, this is achieved when my method extracts CS VA from FC on services by removing the value of food, goods, and PS intermediate inputs. In this process, the value of housing services (rents) that do not belong to CS is excluded from the calculated CS VA. More importantly, there is no negative correlation between estimated CS productivity growth and housing price growth, which can be seen from Figure 21 in Appendix B.

6 Counterfactual Analysis

To elucidate the roles of CS productivity growth and the income effect in driving structural change, I conducted a series of counterfactual analyses. My analyses are different from existing ones for China in three aspects: (1) It does not rely on published service price data; (2) It's conducted at the provincial level; (3) It employs the PIGL preference, allowing for a persistent income effect. In contrast, the income effect delivered by the (generalized) Stone-Geary preference popular in existing works fades quickly as income grows.

Before conducting the counterfactual analyses, two predictions are immediate from the comparative statics of the model: (1) When there is no productivity growth in the CS sector, provinces with positive (negative) CS productivity growth will have lower (higher) CS VA shares and higher (lower) food and goods shares in 2017; (2) If there is no real consumption (income) growth, the structural change process will become slower. The counterfactual results presented in Figure 11, Figure 12, Figure 13, and Table 1 add quantitative insights to the qualitative predictions.

In Figure 11, I plot the change in shares of food, goods, and CS VA when CS productivity growth is set to 0 against the actual changes. The figure verifies the first prediction mentioned above. It also shows that the impact of CS productivity growth on the CS share (own price elasticity) is larger and more diverse compared to food and goods shares (cross-price elasticities). In Table 1, I show that if there is no CS productivity change, the changes in sectoral shares will be 23% lower on average in 2017 for provinces with positive CS productivity growth, and this number is -36% for provinces with negative growth.



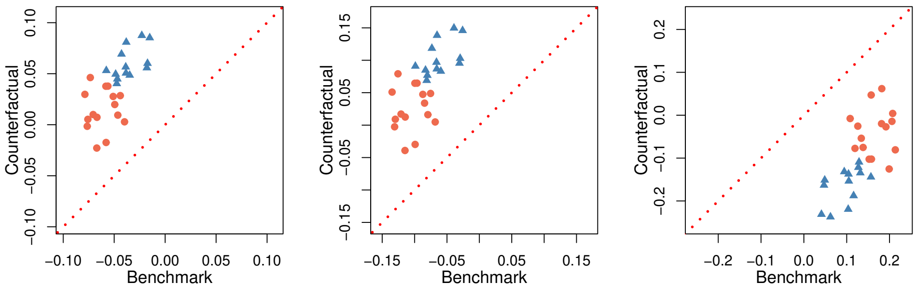
(a) Food Shares (b) Goods Shares (c) CS VA Shares

Figure 11: Counterfactual — No CS Productivity Growth. The figures plot changes in food, goods, and CS VA shares (in percentage points) under the counterfactual scenario when the productivity growths of CS is set to 0 against the actual changes in data. Orange dots (blue triangles) are provinces with positive (negative) CS productivity growth. The red dashed line represents the case when the counterfactual does not affect the shares.

In Figure 12, I plot the changes in sectoral shares when real consumption (income) growth is set to 0 (with the price of the goods sector as the numeraire) against actual changes. The figure verifies the second prediction mentioned above. Moreover, it highlights that provinces with positive CS productivity growth generally suffer less from the nullified income effect. Table 1 shows that the income effect accounts for 173% of structural change in the 28 provinces on average. It also verifies that the contribution of the income effect in provinces with increased CS productivity (124%) is considerably smaller than in the others (268%). These provinces' CS shares are higher and closer to the asymptotic share, where the income effect is minimal and the substitution effect dominates.

Finally, I nest the two counterfactuals together and present their combined impacts in Figure 13. The figures indicate that the income effect dominates the impact of CS productivity growth in all 28 provinces, as the diverse patterns in different province groups shown in Figure 11 are absent here. Table 1 confirms this conclusion, demonstrating that the contribution of the income effect to structural change surpasses that of CS productivity growth in both provinces with positive and negative changes in CS productivity. Additionally, the combined contribution of the two forces does not equal the sum of their respective contributions, suggesting the presence of interacted effects.

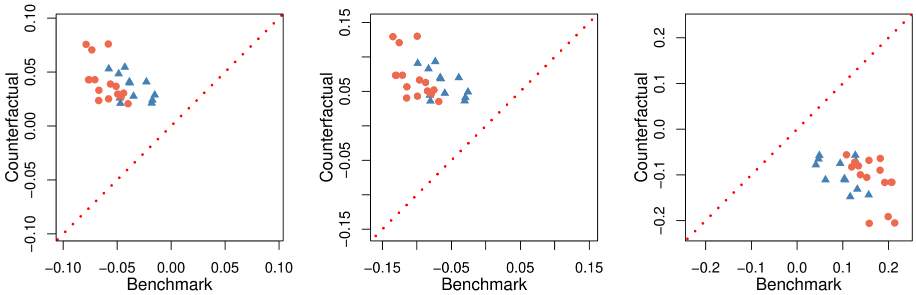
A caveat when interpreting these results is that the consumption levels are exogenously given



(a) Food Shares (b) Goods Shares (c) *CS* VA Shares

Figure 12: Counterfactual — No Real Consumption Growth. The figures plot changes in food, goods, and *CS* VA shares (in percentage points) under the counterfactual scenario when the real consumption (income) growth (with the price of goods being the numeraire) is set to 0 against actual changes in data. Orange dots (blue triangles) are provinces with positive (negative) *CS* productivity growth. The red dashed line represents the case when the counterfactual does not affect the shares.

in the model. In reality, it is unreasonable to assume *CS* productivity increases while holding real consumption (income) unchanged. Thus, the impact of productivity growth in the *CS* sector would be intertwined with the income effect, becoming more prominent in reality.



(a) Food Shares (b) Goods Shares (c) *CS* VA Shares

Figure 13: Counterfactual — No *CS* Productivity Growth & No Real Consumption Growth. The figures plot changes in food, goods, and *CS* VA shares (in percentage points) under the counterfactual scenario when both *CS* productivity growth and the real consumption (income) growth (with the price of goods being the numeraire) are set to 0 against actual changes in data. Orange dots (blue triangles) are provinces with positive (negative) *CS* productivity growth. The red dashed line represents the case when the counterfactual does not affect the shares.

7 Conclusion

As structural change moves forward, the share of the service sector increases in China and many other countries. As a result, productivity growth in this sector is becoming more and more essential for development. However, Baumol (1967) raised an early concern that there is no productivity growth in producing services. This famous hypothesis invokes a great body of research. However, studying service productivity growth is challenging, given that standard

Table 1: Summary of Counterfactual Results.

		Benchmark	$\Delta A_{CS} = 0$	$\Delta \bar{c} = 0$	Both
All Provinces	Changes in:				
	(1) Food shares	-4.93	-4.77	3.58	3.87
	(2) Goods shares	-8.43	-8.17	6.13	6.62
	(3) CS VA shares	13.36	12.94	-9.72	-10.48
	Contribution	—	3%	173%	178%
Provinces with $A_{CS} > 0$	Changes in:				
	(1) Food shares	-6.08	-4.69	1.47	4.11
	(2) Goods shares	-10.41	-8.02	2.52	7.03
	(3) CS VA shares	16.49	12.7	-3.99	-11.13
	Contribution	—	23%	124%	168%
Provinces with $A_{CS} < 0$	Changes in:				
	(1) Food shares	-3.59	-4.87	6.02	3.59
	(2) Goods shares	-6.15	-8.34	10.3	6.14
	(3) CS VA shares	9.74	13.21	-16.32	-9.73
	Contribution	—	-36%	268%	200%

Notes. The table provides the average change in consumption shares (in percentage points) for each sector between 2002 and 2017 across all provinces, those with positive CS productivity growth, and those with negative growth, under different scenarios. I calculate the contributions of CS productivity growth, income effect, and both of them to structural change by (benchmark change − counterfactual change) ÷ benchmark change. The PIGL specification makes the contributions of each force to the three sectors the same.

methods of measuring TFP rely on price indexes, which are difficult to measure accurately due to characteristics such as diverse products and subjective quality assessment of services.

For China, Bai et al. (2021) calculate provincial service productivity growth from 2007 to 2015 using firm-level data. They find firm TFP growth in services to be much faster than that in manufacturing. Without relying on price data, CPSZ found that productivity growth in China's CS sector exceeded that of the manufacturing sector. In this work, I show that more than half of the 28 provinces studied exhibit positive CS productivity growth, with some exceeding an annual rate of 5%. Taken together, these findings support the potential for productivity growth in the tertiary sector.

Beyond that, my provincial-level analysis provides insights into the relationship between the service and manufacturing sectors. In the literature, it is traditionally believed that regions with stronger manufacturing sectors and better economic performance gain advantages in developing the tertiary sector due to its luxury properties (Matsuyama, 2019). What's more, Liu et al. (2020) suggest that a developed service sector enables a country's manufacturing sector to gain comparative advantages in international trade. However, the service-led growth patterns observed in India and some African countries suggest a more intriguing relationship between the service and manufacturing sectors. Three related hypotheses are proposed in this work, inspired by the regional distribution of CS productivity growth estimated from the model: (1) Rich regions (eg. the coastal provinces) gain advantages in developing the CS sector; (2) A strong manufacturing sector can have either a spillover effect (eg. Guangdong) or a hindrance effect (eg. Hebei) on CS productivity growth. (3) Provinces with weaker industrial foundations may shift their focus of development to the service sector, supported by the strong CS productivity growth observed in the northeast area of China. Of course, further empirical evidence is required to evaluate these hypotheses.

Although the reliability of my estimates is discussed in Section 5, there are three major concerns regarding the estimation strategy. First, a main advantage of the framework is addressing challenges associated with the measurement of quality changes in CS. However, quality changes in manufacturing goods are also huge but not recognized. As a result, the estimated CS price growth not only adjusts for quality change in CS but also in goods and PS, which can not be disentangled from each other. Second, the demand side of the model is deterministic. Although it greatly simplifies the analysis, it may misallocate exogenous demand shocks into CS productivity change. Finally, the underlying assumption in the strategy — that CS are not traded — is increasingly questionable with the proliferation of online services like e-commerce and the diminishing costs of transportation relative to high-income individuals' willingness to pay for high-quality services. Given these, more efforts are needed to develop better techniques for measuring service price indexes and understanding service productivity dynamics.

Appendices

Due to the page limit, the appendix is not printed out. Please visit https://github.com/Czysyq/appendix to download the electronic version, or contact the author by email: *ChiZiyi5718@tom.com*.

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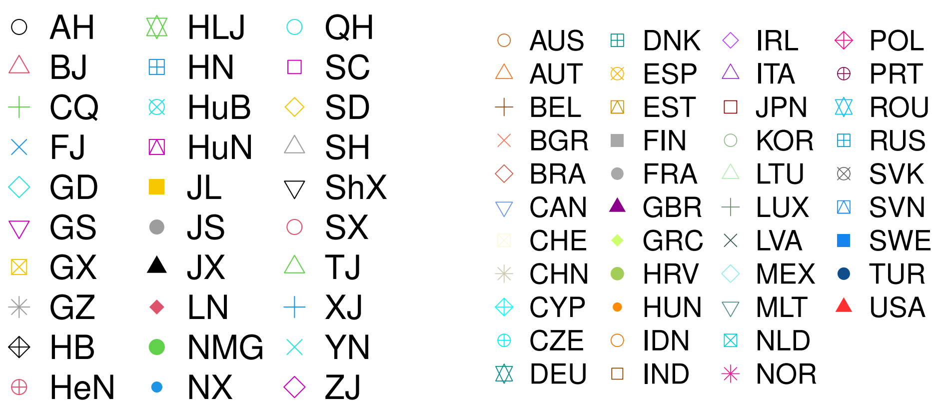
Appendices

A Abbreviations & Legends

Province	Abbreviation	Province	Abbreviation
Beijing	BJ	Henan	HeN
Tianjin	TJ	Hubei	HuB
Hebei	HB	Hunan	HuN
Shanxi	SX	Guangdong	GD
InnerMongolia	NMG	Guangxi	GX
Liaoning	LN	Hainan	HN
Jilin	JL	Chongqing	CQ
Heilongjiang	HLJ	Sichuan	SC
Shanghai	SH	Guizhou	GZ
Jiangsu	JS	Yunnan	YN
Zhejiang	ZJ	Shaanxi	ShX
Anhui	AH	Gansu	GS
Fujian	FJ	Qinghai	QH
Jiangxi	JX	Ningxia	NX
Shandong	SD	Xinjiang	XJ

Table 2: Abbreviations of Province Names. This table shows the abbreviations of province names used in this work.

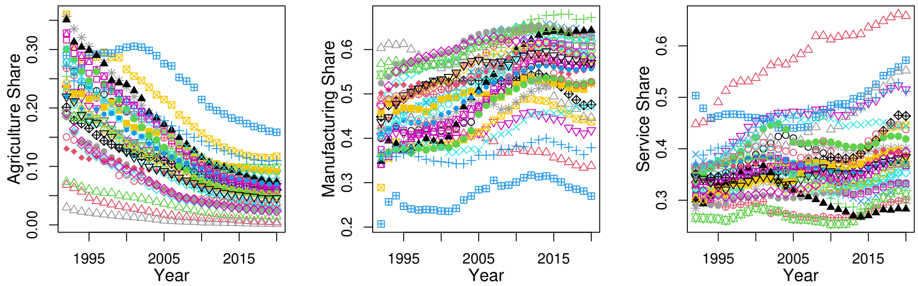


(a) Legend for China Provinces

(b) Legend for Countries

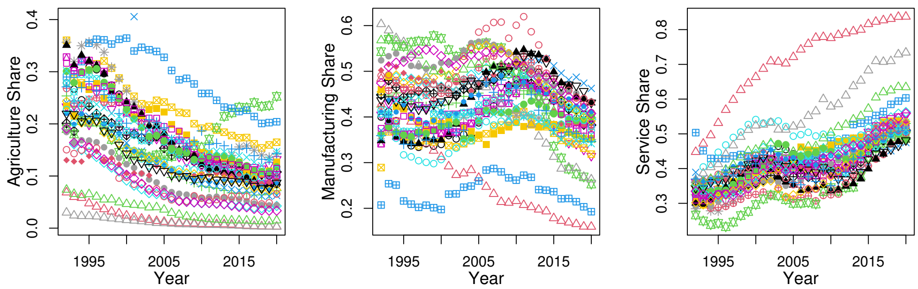
Figure 14: Legends. These figures show the legends used in this work. The left panel shows the legend for selected China provinces. The right panel shows the legend for selected countries.

B More Figures and Tables



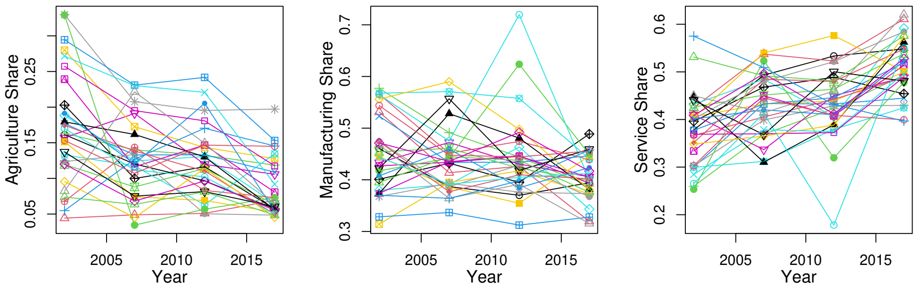
(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 15: Real VA Shares. This figure plots the real production VA shares of the primary, secondary, and tertiary sectors in the years from 1992 to 2020. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data. The data come from the NBS website.



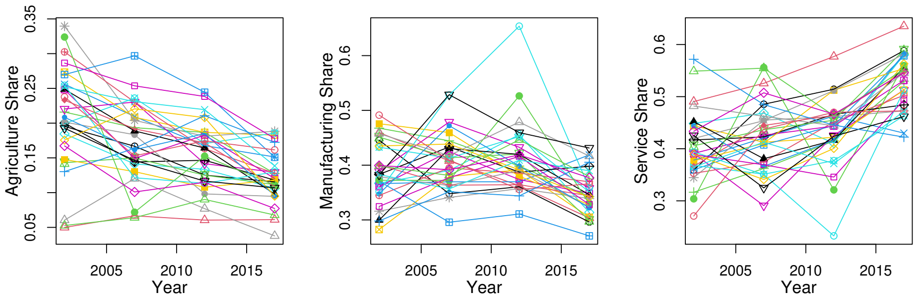
(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 16: Nominal VA Shares: This figure plots the nominal production VA shares of the primary, secondary, and tertiary sectors in the years from 1992 to 2020. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data. The data come from the NBS website.



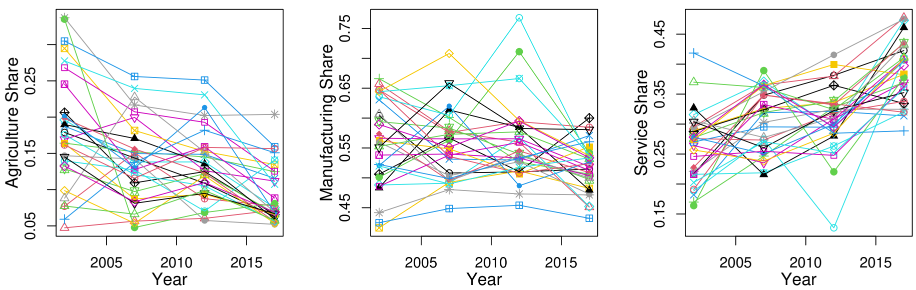
(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 17: Final Consumption Shares: This figure plots the shares of consumption on final goods/services from the primary, secondary, and tertiary sectors in 2002, 2007, 2012, and 2017. The FC shares are calculated based on China's provincial I-O tables. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 18: Consumption VA Shares: This figure plots the shares of consumption on VA from the primary, secondary, and tertiary sectors in 2002, 2007, 2012, and 2017. The consumption VA shares are calculated based on China's provincial I-O tables. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.



(a) Agricultural Shares (b) Manufacturing Shares (c) Service Shares

Figure 19: Provincial Consumption Shares on Food, Goods, and *CS* VA: This figure plots the shares of consumption on farm-gate products (food), factory-gate (goods), and *CS* VA in the years 2002, 2007, 2012, and 2017. The consumption shares are calculated based on China's provincial I-O tables. Each style of point denotes a province according to the legend presented in Figure 14 in Appendix A. Xizang, Taiwan, Hong Kong, and Macao are absent in the figure lacking data.

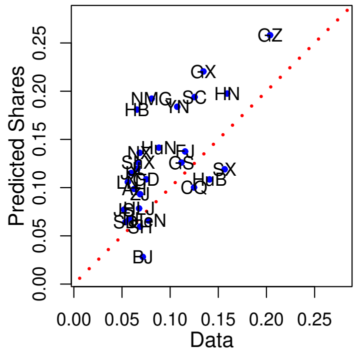


Figure 20: Predicted Food Shares in 2017. This figure illustrates the predictive capacity of my model for consumption shares of foods. Predicted food consumption shares in 2017 are compared against the shares in data. First, I compute $d\ln(\vartheta_A - \omega_A)$ as $-\varepsilon \times d\ln e + \sum_s(\varepsilon \cdot \omega_s \times d\ln P_s)$, then combine it with food consumption share data in 2002 to predict the shares in 2017.

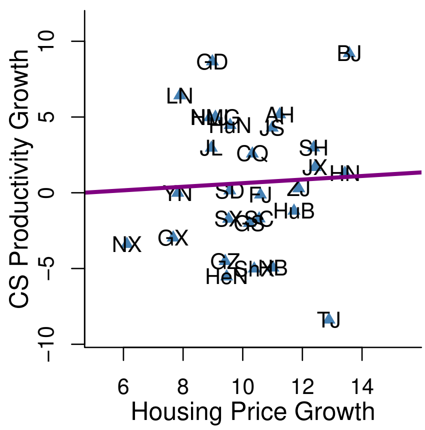


Figure 21: *CS* Productivity Growth v.s. Housing Price Growth. This figure plots the growth rates (in percentage points) of *CS* productivity growth against housing prices in the 28 Chinese provinces during 2002-2017 with a line fitted by OLS. Data on housing price growth are obtained from the NBS.

C Derivation of Equation 6

For this derivation, I suppress the individual, region, and time subscripts i, r, and t. From Equation 3 we know that λ_{sj} is the share of VA/PFG of sector j used in sector s's FG production, which is also the income share of sector s when the firms maximize profits. Thus we have the following relationships between p_n's and P_s's:

$$p_n = P_F^{\lambda_{nF}} P_G^{\lambda_{nG}} P_{CS}^{\lambda_{nCS}} \tag{16}$$

Recall that ω_s's and β_s's are the asymptotic shares of F, G, and CS, thus we also have:

$$\omega_s = \int_n \lambda_{ns} \beta_n dn \tag{17}$$

Similarly, we have symmetric relationships between the current shares of VA/PFG and the FG consumption:

$$\vartheta_s = \int_n \lambda_{ns} \vartheta_n^{FE} dn \tag{18}$$

Finally, we can define ν_s's in the following way as combinations as κ_s's:

$$\nu_s = \int_n \lambda_{ns} \kappa_n dn \tag{19}$$

Now we are ready to transform the consumption share of FG into the consumption share of VA/PFG consumption. Combining Equation 16 and Equation 17, we get:

$$\int_n p_{nrt}^{\beta_n} = P_{Art}^{\omega_A} P_{Mrt}^{\omega_M} P_{Srt}^{\omega_{CS}} \tag{20}$$

Then we plug Equation 17, 19, and 20 into Equation 18 and substitute ϑ_s^{FE} by Equation 5 to get Equation 6.

D Estimation of ε

I estimate ε based on the regression of Equation 12 using household survey data from CHIP. Table 3 summarizes the results [19]. In column (1), I simply regress food consumption share on log consumption and province-year fixed effect. In column (2), additional controls of household size, number of workers, and household location (rural or urban) are included, which causes the estimated elasticity to increase from 0.341 to 0.412. In column (3) to column (8), I report the results of IV estimations, where the first-stage F statics are all significant. Besides column (4), the household principal's occupation serves as the instrument and column (4) reports the results when an overidentification is done with the first three household members' (following the order in the survey data) occupations are instrumented. Columns (5) to column (8) report the results using CHIP 2002, CHIP 2007, CHIP 2013, and CHIP 2018, respectively. The estimated ε varies within a very small range with a length of 0.07 from 0.378 to 0.439. I thus choose 0.41 as the value for ε used in the calibration.

[19] In all the columns I trim the top and bottom 5% consumption levels to avoid bias caused by potential misreporting.

	Food Consumption share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln c$	-0.341	-0.412	-0.417	-0.392	-0.423	-0.441	-0.439	-0.378
	(0.032)	(0.033)	(0.020)	(0.020)	(0.042)	(0.065)	(0.059)	(0.029)
Year	ALL	ALL	ALL	ALL	2002	2007	2013	2018
IV	N	N	Y	Y (3)	Y	Y	Y	Y
Addtl. Controls	N	Y	Y	Y	Y	Y	Y	Y
N	52970	52967	52967	52967	8280	11709	14569	18406
R^2	0.411	0.445	0.254	0.254	0.412	0.244	0.242	0.205
First-Stage F	-	-	420.458	371.386	102.174	45.754	55.871	174.400

Table 3: Estimates of ε. This table

E Measurement of CS Share

E.1 Deduction

To illustrate the precise method, first consider an economy with only three sectors: non-service (NS), service 1 (S1), and service 2 (S2), which produce final products with each other as intermediate inputs. For example, one unit of final expenditure on S1 could be decomposed to VA in NS, in S2, and in itself. However, this process is not straightforward, as we can only observe how many final products of NS, S1, and S2 are used in the production of S1, and these inputs are, again, a combination of VA of the three sectors. This nesting relationship can be traced to infinity (See Figure 22).

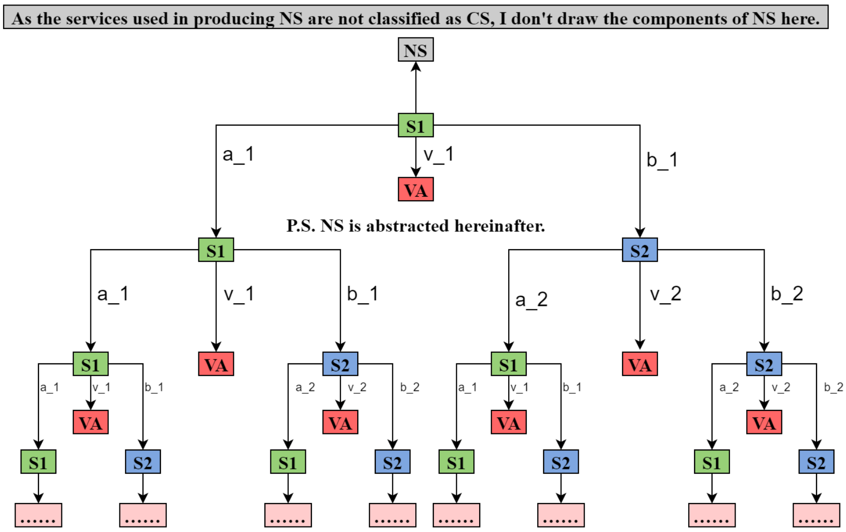


Figure 22: Decomposition of final expenditure on S1

According to my definition of CS, I should add all the VA (in red) in the figure to obtain the CS VA recovered from the final consumption of S1. To do this, assume that 1 unit of S1 final consumption contains x_1 units of CS VA (which is what I am interested in), and to produce 1 unit of S1 final product, a_1 units of S1 final product and b_1 units of S2 final product are used as intermediate inputs, v_1 units of VA is added when making use of the intermediate inputs ($a_1 + b_1 + v_1 \leq 1$ as I abstract NS from the figure for simplicity). Similarly, x_2, a_2, b_2, and v_2 are notations for S2 with equivalent meanings.

Then Figure 22 can be simplified to Figure 23.

Or, I can express this figure in a linear system:

$$\begin{cases} x_1 = v_1 + a_1 x_1 + b_1 x_2 \\ x_2 = v_2 + a_2 x_1 + b_2 x_2 \end{cases} \tag{21}$$

Solving the system to obtain:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 - a_1 & -b_1 \\ -a_2 & 1 - b_2 \end{bmatrix}^{-1} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \tag{22}$$

As all the parameters on the right-hand side of the above equation are observable from the IO tables, I can apply this method to the data. In the more generalized case, the CS VA shares can be expressed in the following way:

$$VA_{CS} = \mathbf{v}_S \cdot \mathbf{Q} \cdot \mathbf{c}_S \tag{23}$$

Similar ideas extend to the calculation of the agricultural PFG shares with slight modifications mentioned in the main text.

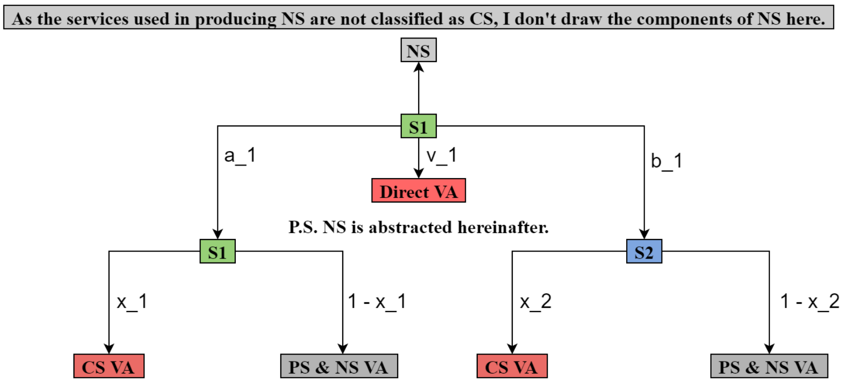


Figure 23: Decomposition of final expenditure on S1 (Simplified)

E.2 Discussions

In this section, I discuss the implicit assumptions of the method used to calculate the *CS* VA shares. When the assumptions are satisfied, the *CS* shares calculated align exactly with the definition of *CS* in the model. I exploit two sets of I-O tables (single-region and multi-region) to discuss the extent to which the assumption can be satisfied when possible and the potential results of them being violated. Three assumptions are needed to unbiasedly calculate the *CS* VA shares:

Assumption 1 A tertiary industry's input structure (consisting of shares of intermediate inputs and own VA) is the same no matter whether it's produced for goods producers or consumers. If this assumption is violated, the calculated *CS* share is biased either upward or downward depending on whether *CS* contains more VA or uses more intermediate inputs than PS. In my opinion, this assumption is reasonable in many tertiary industries. For example, a chief's VA share in each dish is almost the same no matter whether he works for a firm or a restaurant. A more obvious example is that a software firm sells the same products (thus the same share of VA contained) to both consumers and producers. However, it's hard to statistically examine this assumption given the data I have at hand. Reassuringly, even though the production of *CS* and *PS* have different input structures, if this difference is uniform in all provinces, the results of productivity growth in terms of provincial rankings are not affected too much.

Assumption 2 Direct service inputs for the production of *CS* (thus also CS) are produced locally. If this assumption is violated, local consumers may indirectly consume *CS* VA from other provinces and my method will classify some inflowed *CS* VA as locally produced. If *CS* VA is produced more efficiently in other provinces, I may overestimate the local *CS* productivity. To see the severity of this problem, I look at the multi-regional I-O table published in 2012. On average, to produce one unit of final service product (either *PS* or CS), 0.2 units of service (final product) are input, in which 87% is from local and only 13% is inflowed. However, if the 13% unit is only used in the production of *PS* (and *PS* and *CS* still share the same input structure), this would not cause any problems. Intuitively, the production of *CS* is usually small in scale and is not able to pay for inflowed services due to high trade costs.

Assumption 3 The final consumption vector should not contain inflowed and imported services. Similar to the last one, if this assumption is violated, local consumers may directly consume *CS* VA from other provinces and my method will classify some inflowed *CS* VA as locally produced. If *CS* VA is produced more efficiently in other provinces, we may finally overestimate the local *CS* productivity. However, this assumption can be easily violated considering industries like online shopping, transportation, etc. To see the severity of this issue, I again look at the multi-regional IO table in 2012. If I exclude Beijing and Tianjin and exclude retail & wholesale and transportation, most of the services produced by one province are consumed by this province's residents. The local consumed shares averaged higher than 90%, and almost all of them are above 80%. However, the issue is still severe if a province has a high share of retail & wholesale or transportation. Reassuringly, for some *CS* noted as inflowed, it's actually that local residents consume services in other localities when they're traveling, in which case the "trade" of services would not affect the non-tradability of CS and its implications [20]. The only assumption we need for these kind of "inflowed" services is that they are produced by the same technology in and out of the consumers' residential location.

F Measurement of Other Variables

This section introduces the data and methods I use to calculate several key variables in the estimation process, which are provincial household consumption levels, provincial wage levels, provincial capital rates, and price indexes for tradeable PFGs. The statistic summary of these variables is provided in Table 4.

F.1 Household Consumption Level

Provincial total consumption is first computed using I-O tables, ensuring consistency with consumption on CS VA and agricultural PFG. Total consumption is then divided by average population obtained from the *China Population & Employment Statistics Yearbook* to derive consumption per capita. As ε is estimated as the elasticity between household consumption and consumption share, consumption per capita is multiplied by the average number of household members to obtain consumption per household. Provincial data on the average number of household members is sourced from the NBS website, based on the ratio of total population to the number of households in the annual sample survey of household population.

F.2 Wage and Capital Rate

Assuming uniform wage levels across sectors within a region, wages are computed as total labor compensation divided by total human capital. Total human capital is calculated as:

$$H_{rt} = \text{population} \times e^{0.1 \times \text{average education year}} \tag{24}$$

The return to education (0.1) is estimated by CPSZ using CHIP. Education level shares of the population are obtained from the *China Statistical Yearbook* and multiplied by corresponding education years to calculate the average education year. Provincial capital rates are derived directly from the fixed asset investment price index published by NBS.

F.3 Price Indexes for PFGs

Price indexes for primary and secondary sectors' PFGs are derived from the difference between real and nominal value-added published on the NBS website (sectoral GDP deflators). Real VA is deflated using various producer price indices, rendering the prices consistent with PFG prices. Despite calculations being based on local factory information, imported PFG_M should be priced similarly to local manufacturing PFGs post inter-provincial transportation to satisfy equilibrium conditions.

G Alternative Functional Form: IA

In Alder, Boppart, and Müller (2022), the authors propose the inter-temporal aggregatable (IA) preference. They argue that this preference is more flexible than PIGL in that it can explain the hump-shaped trend in manufacturing shares, allowing a sector to be a luxury and a necessity at different income levels. One form of IA preference given as indirect utility is [21]:

$$\mathcal{V}(c_i, \mathbf{P}) = \frac{1-\epsilon}{\epsilon} \left(\frac{c_i}{\mathbf{B}(\mathbf{P})} - \mathbf{A}(\mathbf{P}) \right)^{\epsilon} - \mathbf{D}(\mathbf{P}) \tag{25}$$

where $\mathbf{A}(\mathbf{P})$ and $\mathbf{D}(\mathbf{P})$ are functions homogeneous of degree zero in prices, and $\mathbf{B}(\mathbf{P})$ is a linearly homogeneous function of prices. I impose the following parametrization:

[20] For example, assume that you live in Fujian and take a trip to Beijing. During the trip, you find that the catering services in Beijing charge much higher prices than in Fujian. But you probably will accept the high prices as you cannot quit eating in Beijing and compensate yourself after you are back. As a result, the CS price in a locality still can not affect the CS price in another locality.

[21] I suppress the time and region subscripts in this part.

Table 4: Annual Growth Rates of Variables

region	C_{rt}	P_{rFt}	P_{rGt}	w_{rt}	q_{rt}
BJ	10.662	4.639	1.709	10.191	1.740
TJ	12.488	1.102	-0.381	9.638	2.160
HB	11.030	3.541	3.134	12.516	2.374
SX	12.820	5.225	3.443	11.526	2.807
NMG	11.577	4.908	-0.748	13.720	2.532
LN	10.564	3.917	-0.605	8.889	2.238
JL	7.217	2.144	1.844	9.097	1.939
HLJ	9.512	5.816	-3.525	12.254	2.493
SH	9.743	5.510	0.884	9.475	2.082
JS	14.753	5.452	1.538	11.806	2.788
ZJ	10.870	4.229	1.835	11.644	2.356
AH	13.638	3.842	1.984	13.499	2.711
FJ	11.021	4.097	1.142	12.875	2.064
JX	13.402	3.020	1.557	11.600	2.967
SD	13.252	4.384	0.904	11.505	2.487
HeN	12.981	3.376	1.467	13.475	2.782
HuB	11.803	5.174	2.398	13.447	3.044
HuN	12.933	3.740	1.889	12.641	3.470
GD	9.335	4.104	1.209	9.696	2.365
GX	13.141	5.194	2.572	12.790	2.052
HN	12.123	2.624	1.329	11.783	2.945
CQ	12.642	3.827	-0.371	13.745	2.516
SC	12.623	4.536	0.370	13.677	3.020
GZ	15.390	7.052	3.350	15.842	2.450
YN	13.119	4.674	0.982	13.506	2.710
ShX	13.038	6.150	4.119	13.352	2.932
GS	11.435	2.981	0.394	11.273	2.475
QH	12.223	5.712	2.005	12.125	2.872
NX	16.282	5.083	3.947	12.707	2.609

$$\mathbf{B}\left(\mathbf{P}\right)=\prod_{s}\left(P_{s}\right)^{\omega_{s}}; \quad \mathbf{A}\left(\mathbf{P}\right)=\mathbf{B}\left(\mathbf{P}\right)^{-1}\sum_{s\in S}P_{s}\bar{c}_{s}; \quad \mathbf{D}\left(\mathbf{P}\right)=\sum_{s}\nu_{s}\ln P_{s} \tag{26}$$

where $\omega_s \geq 0$, $\sum_{s\in S}\omega_s = 1$, and $\sum_{s\in S}\nu_s = 0$. After applying Roy's Identity, it gives the following consumption share function:

$$\vartheta_s\left(c_i,\mathbf{P}\right)=\omega_s+\frac{P_s\bar{c}_s}{c_i}-\omega_s\cdot\frac{\sum_{j\in S}P_j\bar{c}_j}{c_i}+\nu_s\left(\frac{c_i-\sum_{j\in S}P_j\bar{c}_j}{\prod_j\left(P_j\right)^{\omega_j}}\right)^{1-\varepsilon}\times\frac{\prod_j\left(P_j\right)^{\omega_j}}{c_i} \tag{27}$$

In this case, if $\bar{c}_s = 0$, $\forall s$, then the IA preference here is the same as the PIGL preference parametrized above. I estimate parameters in Equation 27 using the iterated feasible generalized nonlinear least square (IFGNLS) estimation with pooled data of consumption shares on agricultural PFG and CS VA of the 28 Chinese provinces. Since the expenditure shares sum to one, I can drop the demand for manufacturing goods during estimation. More details about the IFGNLS estimation can be found in Herrendorf, Rogerson, and Valentinyi (2013), Alder, Boppart, and Müller (2022), and the Stata document for the *nlsur* command.

Table 5: IA Estimates

	ω_A	ω_M	o_{CS}	ε	ν_A	ν_{CS}	$\bar{c}_A$	$\bar{c}_M$	$\bar{c}_{CS}$
Coefficient	0.068	0.437	0.496	0.816	0.061	-0.708	0.017	-0.698	0.401
Std. err.	0.014	0.044	0.048	0.083	0.027	0.209	0.017	0.281	0.171
P-value	0.000	0.000	0.000	0.000	0.023	0.001	0.317	0.013	0.019

We can see that in all the specifications reported in Table 5, the $\bar{c}$'s are not significant either statistically or economically or both, which supports that the PIGL preference suffice for the aim of this work.