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Chong-En Bai, Xilu Chen, Zheng (Michael) Song and Xin Wang

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Chong-En Bai
Tsinghua University

Xilu Chen
Chinese University of Hong Kong

Zheng (Michael) Song
Chinese University of Hong Kong

Xin Wang
Chinese University of Hong Kong

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Abstract

China's service sector has experienced a rapid expansion since the late 2000s. Ac-cording to the official statistics, the service GDP share increased from 43% in 2007 to 55% in 2020. In this paper, we first present evidence from additional datasets showing that the recent rise of the service sector is a robust phenomenon. We then use the firm-level survey data from China's State Administration of Taxation between 2007 and 2015 to estimate firm TFP, capital and labour wedges, and to aggregate them into sectoral TFP and misallocation. We find firm TFP growth in services to be much faster than that in manufacturing. However, misallocation in service deteriorated much more than in industry, such that the aggregate TFP in the industrial sector outgrew that in the service sector by 1 percentage points per year. The lower service TFP growth suggests that demand-side forces play a more important role in the recent expansion of China's services.

* Email: Bai: baichn@sem.tsinghua.edu.cn, Chen: chenxilu@link.cuhk.edu.hk, Song: zheng.michael.song@gmail.com and Wang: wangx2.04@gmail.com

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1 Introduction

China, as the world factory, has a large industrial sector. Despite its decade-long decline, industry still accounted for more than 30% of China's GDP by 2020. The mirror image is the relatively small service sector. According to the World Bank, China's service GDP share was ranked at 186th among 225 economies in 2007. Nevertheless, China's service sector has experienced a rapid expansion since the late 2000s. Based on the country's official statistics, the service GDP share increased from 43% in 2007 to 55% in 2020, while the industry GDP share declined from 41% to 31%. Consequently, China's service GDP share ranking advanced to 105th among 202 economies in 2019. The official data also show that the rising service sector and declining industrial sector occurred in every province of China.

The first question we ask in this study is whether the structural transformation is real or simply an outcome of mismeasurement. We find service contribution to GDP growth to be highly counter-cyclical. One may wonder whether service output, which is arguably more difficult to measure than industry output, is overstated in economic downturns to smooth out volatility. We address the issue by using two firm-level datasets from Chinese government branches outside the National Bureau of Statistics (NBS). The first is the registration records from China's State Administration for Market Regulation (SAMR). The administrative data provides basic information for all firms registered in China (over 37 million active firms in 2019). The second is the firm survey data from China's State Administration of Taxation (SAT), which covers about half a million firms. Unlike the widely used Annual Survey of Industrial Firms conducted by NBS that only covers the industrial sector, the SAT survey covers all sectors and has a reasonably good sectoral composition. The aggregate and regional statistics from the two datasets are in line with those from NBS, confirming that China has undergone a fast structural transformation in recent years.

We next use the two datasets separately for different purposes. First, using the registration records, we show that the fast growth of the service sector by firm number and registered capital was essentially driven by the high entry rate of service firms. Specifically, the total number of active firms increased by 22 million in the service sector from 2007 to 2019, while the corresponding number in the industrial sector is only 2.5 million. Moreover, the registration data provides complete information on firm equity structure. Following Bai et al. (2020), we trace equity shareholding throughout the whole firm ownership network and back out state equity shares. Although the state share has stabilized around 20% in the manufacturing sector from 2013 to 2019, it declined dramatically in the service sector from 38% to 29%. Since most new firms are privately owned, the high entry rate is also the key to the rapidly falling state share in the service sector.

For the firms in the SAT survey, we know their output, capital, and employment, all of which are not included in the registration records. These variables allow us to estimate TFP at various disaggregate levels. Following Ackerberg et al. (2015), we first estimate production function at the industry level. We then adopt the monopolistic competition model with heterogeneous firms in Hsieh and Klenow (2009) to estimate firm TFP and misallocation at different levels. We find that service firm TFP grew at an annual rate of 16.5%, double the TFP growth of 7.6% for industrial firms. However, misallocation in service deteriorates much more than that in industry, such that the aggregate TFP in the industrial sector actually outgrew that in the service sector by 1 percentage points per year. The sectoral TFP growth is 5.3% and 6.3% for service and industry, respectively.

We discuss the aggregate statistics and other basic facts in Section 2. Section 3 presents the model-based accounting framework and estimates sectoral TFP growth. Section 4 decomposes sectoral TFP growth into firm TFP growth and misallocation at different levels. We present the results for capital returns and markups in Section 5. Section 6 concludes.

2 Basic Facts

2.1 Aggregate Statistics

We first use the official data released by NBS to document the evolution of the service sector in terms of its value added and employment shares. Our starting point is 1992, the year when Deng Xiaoping's southern tour reactivated China's transition to a market economy. The solid line in panel A in Figure 1 plots service value added as a percentage of GDP. To control for the effect of the fast-shrinking agriculture sector, we also plot the service share in GDP excluding agriculture value added (the dotted line). In addition to output shares, service shares are presented in non-agricultural employment in panel B. The employment shares are calculated from two sources: *China Statistical Yearbook* (the solid line) and census data (the dotted line with circles). The service share increased steadily between the late 1990s and early 2000s. It stabilized in the mid-2000s but picked up again in the late 2000s. In 2019, the service sector accounted for 54% of China's nominal GDP and 47% of its total employment (58% and 63% if agriculture is excluded).

Using official sectoral deflators, we find that most of the increase in the service GDP share is explained by price effects. Panel A of Figure 2 plots the price index for the tertiary sector (service) relative to the price index for the secondary sector (industry and construction), with the initial-year relative price normalized to one. Consequently, Panel B of Figure 2 shows that the service GDP share in real terms increased by only five percentage points after 1992, accounting for approximately a quarter of the increase in nominal terms. Excluding agriculture, we find that the service share in real terms

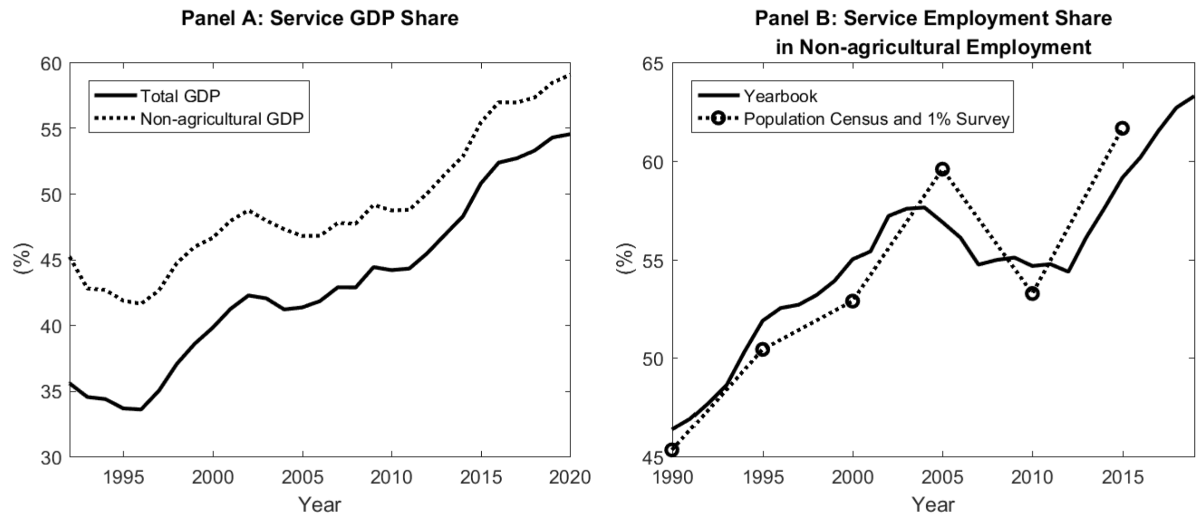

Figure 1: Service Shares

declined by two percentage points.

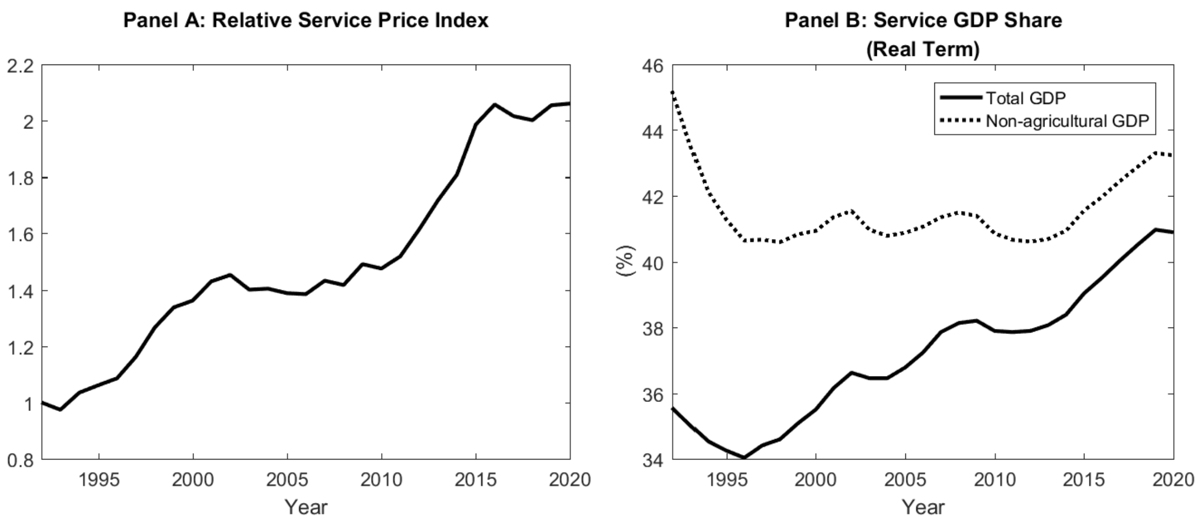

Figure 2: Relative Price

We are aware of the potential problems in the official deflators. NBS uses various methods to construct price indices across sectors. For instance, output price indices are used to deflate manufacturing output, while some service industries such as Transport, Storage, and Post adopt the quantity-based "extrapolation" (Xu, 2004). Even among the sectors applying the same method, sectoral deflators are not entirely reliable as price indices themselves are likely to be smoothed.[1]

A perhaps bigger concern is whether the official data on sectoral nominal output are reliable. Figure 3 compares service contribution to nominal GDP growth with real GDP growth. A remarkable counter-cyclicality of service contribution to GDP growth in

[1] See, for instance, Nakamura et al. (2016) for over-smoothness in CPI.

nominal terms occurred from 1992 to 2020 with a correlation coefficient of -0.73. Such counter-cyclicality is not observed in developed economies such as the United States and Japan and seems considerably weaker in developing economies like India (see Appendix A for details).[2] As service output is more difficult to measure than industrial output, one hypothesis is that NBS deliberately overstates service output in economic downturns to smooth out GDP volatility.

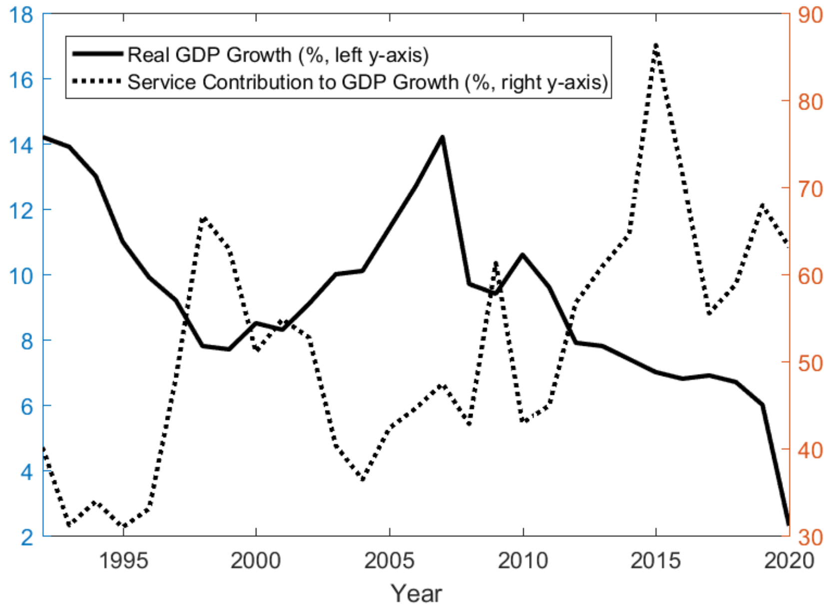

Figure 3: Counter-cyclicality of Service Contribution to GDP Growth

Chen et al. (2019) compare value added growth with corporate income tax revenue growth in different industries. The difference between the two growth rates is actually smaller in the service sector. The finding does not support the hypothesis that service output is more likely to be manipulated than industrial output. Moreover, corporate income tax revenue in the service sector outgrew that in the manufacturing sector in most years after 2005. This is consistent with the increasing service output share in GDP.

We use two firm-level datasets to check the validity of the rapid expansion of the service sector declared by the official aggregate statistics. The first is the registration records that covers all registered firms in China (including financial institutions). We have access to the 2019 data that covers over 37 million active firms. Figure 4 plots the number of surviving service firms relative to the number of all surviving non-agricultural firms. The share of service firms increased by approximately 12 percentage points from 1995 to 2019. Moreover, the service shares in terms of registered capital are 67% and 75% for 2013 and 2019, respectively. These numbers are quantitatively comparable to

[2] The service contribution to GDP growth in real term is also counter-cyclical (although much less volatile), with a correlation coefficient of -0.56.

their counterparts in the national account.

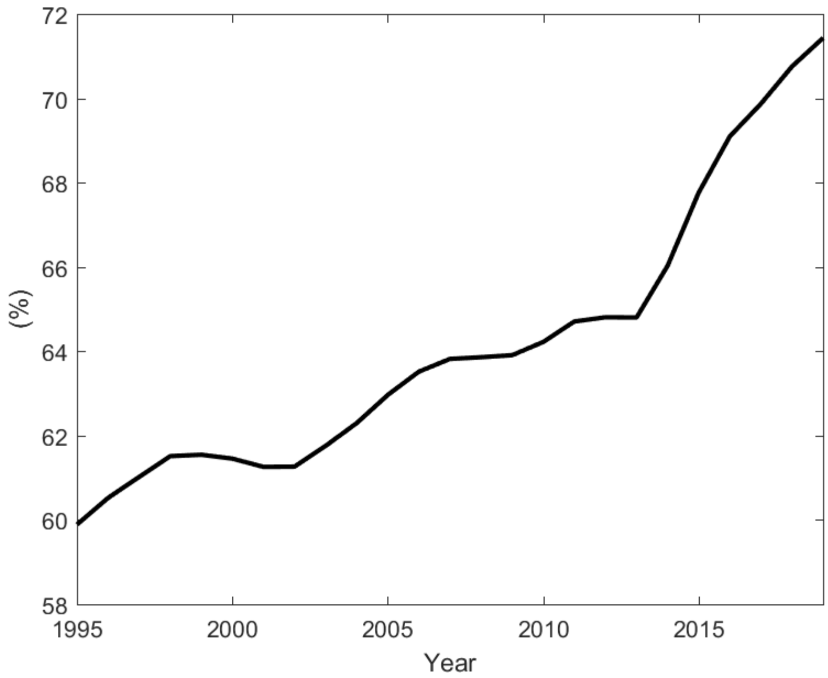

Figure 4: Service Firm Number Share in SAMR Data

Figure 5 plots the number of entrants (panel A) and exiters (panel B), the entry rate (panel C), and the exit rate (panel D). The solid and dotted lines represent industry and services, respectively. There is a growing trend of entrants in both sectors, though less obvious in industry. As a result, the gap of firm entry rate in the two sectors has widened since the late 2000s. The number of exiters was fairly stable in the 2000s and increased sharply afterwards. Nevertheless, unlike the entry rates, the exit rates of the two sectors were almost parallel. This explains the increase in the service share by firm number increased since the late 2000s.[3]

The second dataset is from the annual firm survey conducted by China's SAT. The survey covers about half a million firms each year. Table 1 reports the number of firms in the survey by year and industry. In 2007, 49% of the firms included in the SAT survey are in industry and 48% of them are in service. The number of industrial firms is rather stable between 2007 and 2013, when the number of service firms increases by one quarter. The number of construction firms, although relatively small, increases by more than half. The survey consists of two samples: (i) the random sample selected by the SAT following stratified random sampling method; (ii) the key sample chosen by local bureaus of SAT according to some criteria set by the central SAT. The SAT sampling scheme changed dramatically in 2014. The SAT raised the proportion of the random sample from 19%

[3] By registered capital, the share of entrants is 7% and 10% in 2013 and 2019, respectively, while the share of exiters is 1% and 4%.

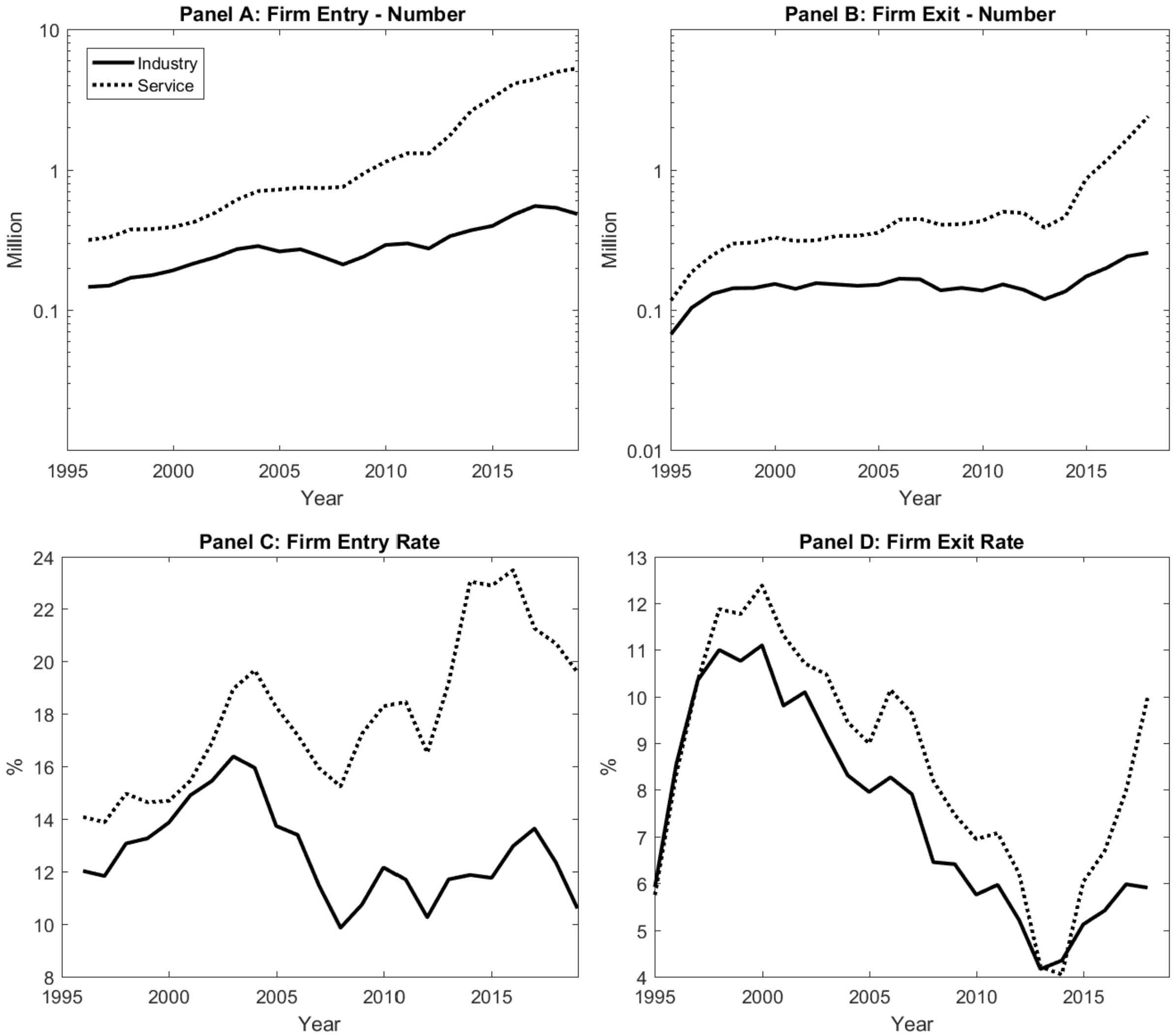

Figure 5: Firm Entry and Exit

Note: The definition of entry rate and exit rate follows Brandt et al. (2012).

in 2013 to 74% in 2014. It also took back the authority of choosing the key sample from local bureaus.[4] The number of industrial firms drops by a third from 2013 to 2014, while the number of service firms increases by 22%.

In the following analysis, we will work on three samples from the SAT data: (1) the full sample in 2007–13; (2) the 2007–13 balanced panel and (3) the 2013–15 balanced panel. The balanced panels will be used to estimate firm TFP growth. As will be shown below, only one-sixth of industrial firms and one-tenth of service firms in the full sample are in the 2007-13 balanced panel. The high turnover rate is a consequence of the high entry rate and the significant proportion of random sampling in the SAT survey (for year 2014 and 2015).

Table 1 also reports sectoral value added in the SAT survey as a percentage of that in

[4] See Chen et al. (2018) and Liu and Mao (2019) for a brief description of the SAT survey and the random sample, respectively.

Table 1: SAT Firm Survey

Year	Firm Number			SAT Value Added / Sectoral Value Added in National Account		
	Industry	Construction	Service	Industry	Construction	Service
All Observations						
2007	293,106	22,307	288,924	50.45%	20.03%	32.45%
2008	333,569	24,889	353,998	53.96%	23.58%	38.72%
2009	333,155	26,828	358,561	61.64%	27.37%	41.08%
2010	342,890	29,926	356,653	60.76%	31.01%	44.73%
2011	310,295	29,231	317,177	63.12%	29.84%	47.01%
2012	295,214	32,619	333,560	57.24%	31.62%	50.17%
2013	285,058	36,453	362,465	55.23%	31.62%	48.00%
2014	209,392	29,182	435,069	49.41%	22.22%	42.42%
2015	210,676	23,499	434,191	45.37%	22.85%	43.83%
Balanced Panel 2007–2013						
2007	37,800	1,035	16,800	17.36%	1.87%	5.01%
2008	37,800	1,035	16,800	16.43%	1.79%	5.12%
2009	37,800	1,035	16,800	16.02%	1.59%	4.40%
2010	37,800	1,035	16,800	15.88%	1.60%	4.22%
2011	37,800	1,035	16,800	14.50%	1.38%	3.89%
2012	37,800	1,035	16,800	13.75%	1.32%	3.66%
2013	37,800	1,035	16,800	13.51%	1.32%	3.48%
Balanced Panel 2013–2015						
2013	50,179	1,764	47,625	17.76%	3.49%	6.96%
2014	50,179	1,764	47,625	17.47%	3.31%	6.29%
2015	50,179	1,764	47,625	17.03%	3.34%	5.29%

the national account. Many service firms do not report value added in the SAT survey. We convert firm sales to firm value added by the ratio of total value added to total sales, averaged over time, from the firms in the industry that report value added.[5] Although the SAT survey only covers a small proportion of active firms in China, it accounts for more than half of industrial value added and more than 40% of service value added in the national account. The output shares also imply that SAT survey over-represents large firms and under-represent small firms. Figure 6 compares firm size distribution in the SAT survey with that in the 2008 economic census data. Panel A shows industrial firms

[5] Take wholesale and retail, the largest sector in service, as an example. From 2007 to 2013, there are, on average, 48,000 wholesale and retail firms each year that report both sales and value added in the survey. The annual value added sales ratio varies from 0.068 to 0.088 for wholesale firms and from 0.095 to 0.138 for retail firms. The average value added sales ratio is 0.072 and 0.115 for wholesale and retail firms, respectively. We use the ratios to estimate wholesale and retail firm value added in the SAT survey. The same procedure was adopted by Chen et al. (2019).

and Panel B indicates service firms. The solid, dotted, and dashed lines are for the 2008 economic census, 2007 and 2013 SAT survey, respectively. The over-representation of large firms in the SAT survey is obvious. As an important robustness check, we resample the firms in the SAT data to match the firm size distribution of the 2008 economic census data. The main results are robust and reported in Appendix C.

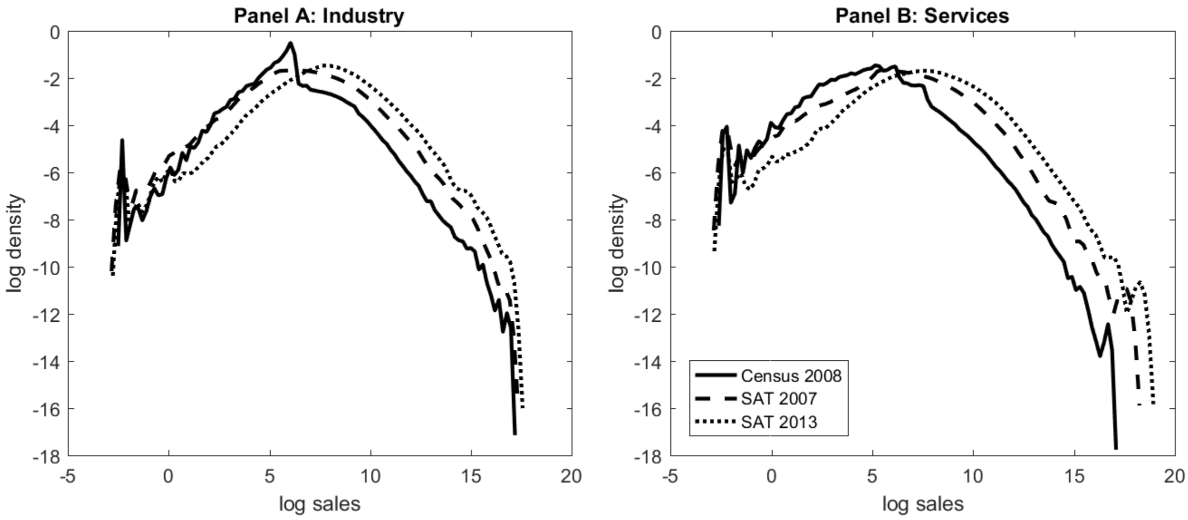

Figure 6: Firm Size Distribution in the SAT Survey and 2008 Economic Census

Figure 7 plots the service value added as a percentage of total value added in the full sample of SAT survey. The basic trends are identical to what we have found in Figure 1: The service share increased steadily. Quantitatively, the service value added share rose by 10 percentage points in the full sample between 2007 and 2013. The changes are comparable to their counterparts in the national account during the period.

2.2 Sectoral Composition in Services

Tables 2 report sectoral composition in service. We select the nine largest service sectors by their 2007 value added in the national account. In addition to the output shares by value added in the national account, we also report the shares by value added in the SAT survey and by registered capital in the registration records.

According to the national account, wholesale and retail is by far the most important service sector, which alone accounts for one-fifth of service value added. Transport, storage, and post, financial intermediation, and real estate are the other large service industries that account for more than 10% of service value added. Wholesale and retail is also the largest service industry in the SAT survey. However, its value-added share is about 10 percentage points higher than that in the national account. The SAT survey also over-represents the financial and information technology sectors. The misalignment of service sectoral composition is an important caveat of using the SAT survey data.

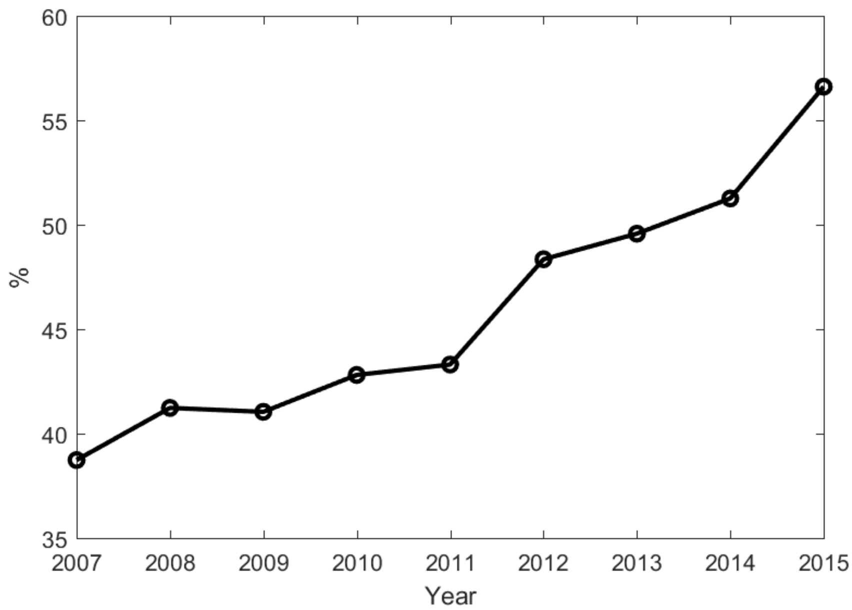

Figure 7: Service Value Added Share in the SAT Data

The sectoral distribution of registered capital is more similar to that of value added in the national account, reinforcing the reliability of the official aggregate statistics. There are two exceptions. The very high registered capital share of the industry of leasing and business services may be caused by high capital intensity of the industry. The much higher value added share of the education industry, as opposed to the essentially zero registered capital share, is because most of education value added is contributed by publicly funded schools that are not in the firm registration data.

Table 2: Sectoral Composition in Service

	National Accounts (by Value Added)			SAT (by Value Added)		SAMR (by Registered Capital)	
	2007	2013	2018	2007	2013	2013	2019
Wholesale & Retail	18.16%	20.62%	18.33%	27.74%	26.00%	17.88%	18.09%
Transport, Storage & Post	14.25%	9.54%	8.31%	7.38%	7.90%	8.89%	5.82%
Hotels & Catering	5.34%	3.75%	3.41%	1.49%	0.97%	1.08%	0.76%
Information Technology	5.78%	4.96%	5.92%	13.56%	8.71%	3.69%	4.87%
Financial Intermediation	12.83%	15.09%	14.55%	32.55%	34.81%	13.84%	10.77%
Real Estate	11.82%	13.18%	13.32%	11.63%	14.71%	14.83%	8.65%
Leasing & Business Services	3.63%	4.87%	6.07%	1.41%	2.60%	29.45%	34.20%
Services to Households	3.85%	3.16%	3.05%	1.94%	1.33%	1.09%	1.62%
Education	7.01%	6.75%	7.01%	0.07%	0.15%	0.08%	0.20%

Service sectoral composition changes over time. According to the official data, the service GDP share increased by 11 percentage points from 2004 to 2018 (Figure 1). The financial sector and real estate accounted for more than half of the increase in the service GDP share. Wholesale and retail, leasing and business services, and scientific research and technical services account for the other half of the increase (see Figure 8). The other nine service sectors, which remained sizeable and accounted for 44% of service value added in 2018, played essentially no role in the recent rise of China's service sector.

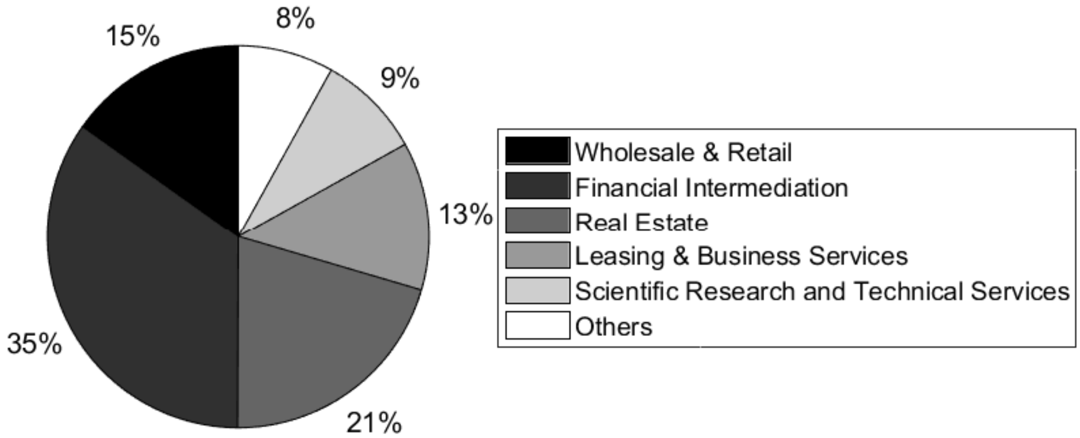

Figure 8: Sectoral Contributions to Increase in the Service GDP Share

2.3 Regional Disparity

The x axis and y axis in Figure 9 show the provincial service GDP share in 2007 and 2019. To control for regional heterogeneity in agriculture, we exclude the agricultural sector. The size of the service sector is highly unequal across provinces. Not surprisingly, services concentrated in rich cities. Beijing had the highest service share of 74% and 84% in 2007 and 2019, respectively, which is about 30 percentage points higher than the national level.

To check the reliability of provincial official statistics, we calculate the service registered capital shares at the provincial level in 2013 and 2019. Figure 10 shows a positive correlation between the provincial service GDP share and service registered capital share. The correlation coefficient is 0.62 and 0.65 for 2013 and 2019, respectively.

We also calculate the provincial service value added share in the SAT data. Figure 11, again, shows a strong positive correlation between the provincial service GDP share and service value added share in 2007 (panel A) and 2013 (panel B). The correlation coefficient is 0.87 and 0.81 for panels A and B, respectively. The SAT survey data has a reasonably good regional composition.

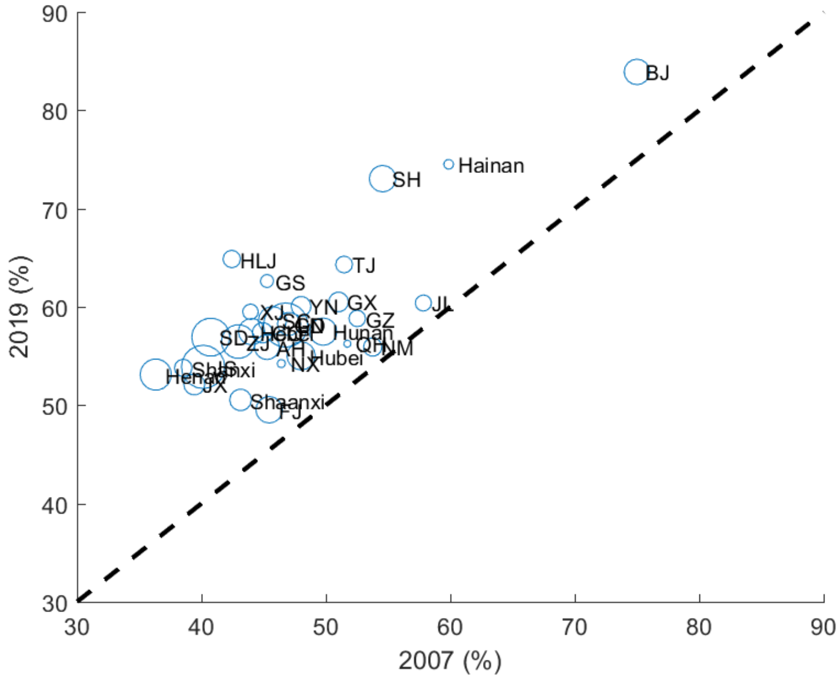

Figure 9: Provincial Service GDP Share, 2007 and 2019

2.4 State Shares

Although the registration data provide rich information on firm ownership, identifying state-owned or state-controlled firms is far from trivial. The difficulty comes from two aspects. The first is lack of a complete list of state shareholders. The Ministry of Finance is clearly a state shareholder. The problem is how to recognise many other central and local government subsidiaries as state shareholders. The second is to identify state shares in a universe where firms are connected through shareholding. To overcome the two issues, we adopt the method in Bai et al. (2020). Specifically, they developed a set of conditions to identify state shareholders in the registration data. For instance, they identified about 60,000 state owners which are central or local governments or firms directly and wholly owned by central or local government in 2019. Then, they use the following algorithm to back out state equity share.

Let S_i denote the state equity share in firm i: $S_i = S_i^D + S_i^I$, where S_i^D and S_i^I represent the equity share directly owned by state owners and indirectly owned through other firms, respectively. The complexity of the firm ownership network does not allow us to compute S_i^I directly from the data. Rather, S_i has to be a fixed point of the following linear equation system:

$$S_i = S_i^D + S_i^I = S_i^D + \sum_j \pi_{ij} S_j,$$

where π_{ij} denotes the equity share of firm j in firm i. As the registration data cover 37

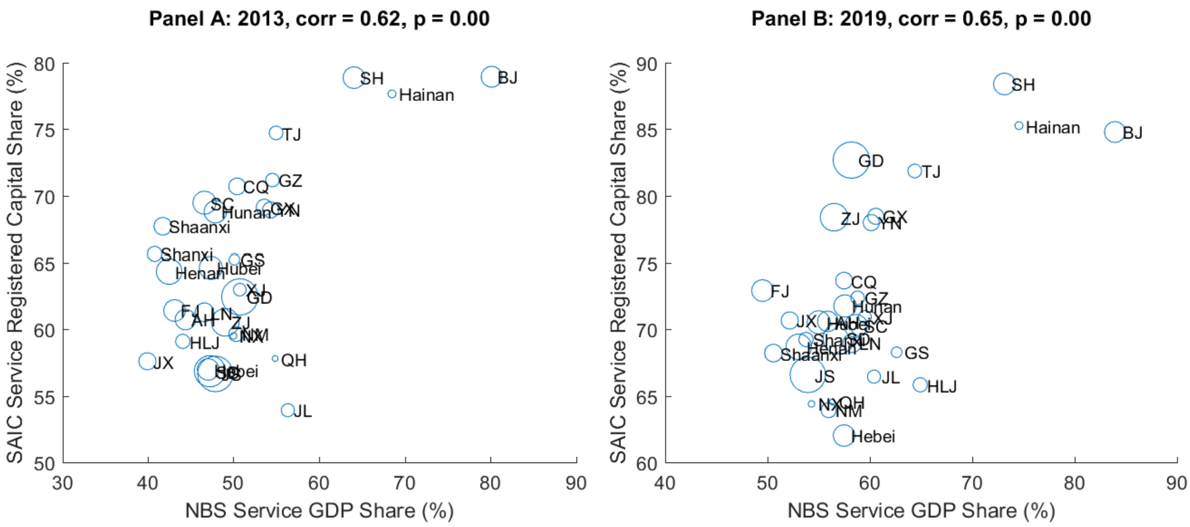

Figure 10: Provincial Service Registered Capital Share

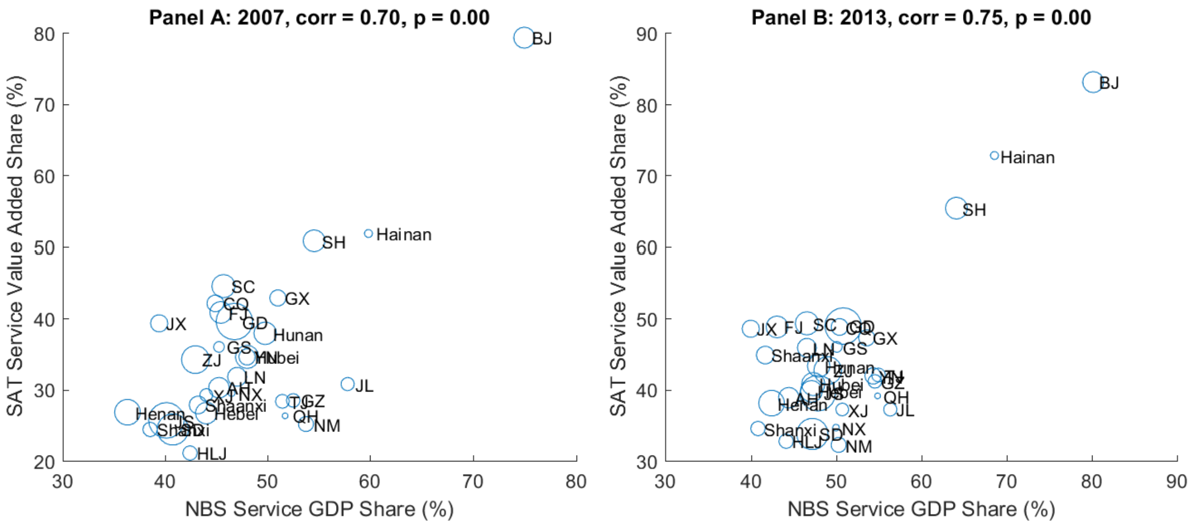

Figure 11: Provincial Service Value Added Share

million firms, the matrix of π_{ij} consists of 37 million rows and columns. We solve S_i by iteration. A firm is defined as state-owned or state-controlled if its $S_i \geq 50\%$ or $S_i \geq 25\%$. Bai et al. (2020) shows that distinguishing state-controlled from state-owned firms does not make significant differences. So, we only present results for state-controlled firms. All the findings are very robust with state-owned firms.

We calculate the state share as the ratio of total registered capital of state-controlled firms to total registered capital of all firms. The state share in the service sector dropped from 38% to 29% from 2013 to 2019, while the share in manufacturing stabilized around 20%.[6] Hsieh and Song (2015) document the rapid decline of the state share in industry between 1998 and 2007. Our registration records show that the state share continued

[6] We choose manufacturing instead of industry here because the state shares in mining and public utilities sector are extraordinarily high (see industry B and D in Figure 12).

to fall afterwards, albeit more slowly. The state share was much higher in services and declined dramatically between 2013 and 2019. This is driven by the high firm entry rate in service as shown in Figure 5.

Figure 12 plots the state registered capital share by industry. As expected, public utilities and mining are the two industries associated with the highest state share (65% and 57% in 2019). By contrast, the state share is much lower in manufacturing (20% in 2019). Many service industries have state share higher than that in manufacturing. The three service industries with the highest state share in 2019 are transport, storage, and post (57%), financial intermediation (53%), and the management of water conservancy, environment, and public facilities (43%).

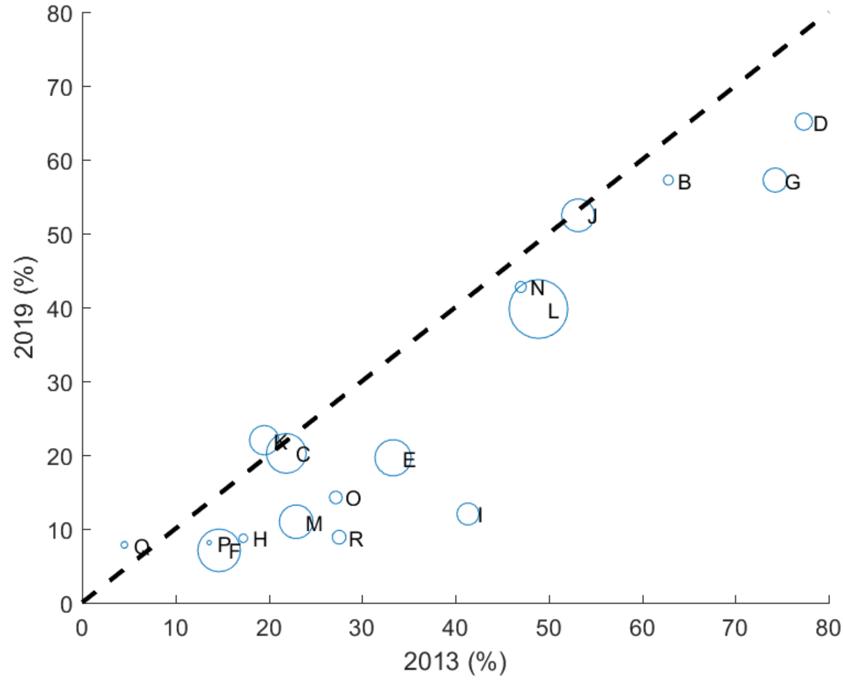

Figure 12: State Shares by One-digit Industry

Note: This figure plots the state shares for one-digit sectors. Each notation in the figure corresponds to an one-digit sector: B for mining, C for manufacturing, D for public utilities, E for construction, F for wholesale and retail, G for transport, storage, and post, H for hotels and catering, I for information technology, J for financial intermediation, K for real estate, L for leasing and business services, M for scientific research and technical services, N for services to households, O for education, P for health and social services, Q for culture, sports, and entertainment.

While we have used data from different sources, they all point to a pronounced structural transformation that China has been undergoing since the late 2000s. The structural change can be summarised by the following facts.

- There is a rapid increase in the nominal output and employment share of service.

- The real output share of service also increases, albeit less pronounced.
- The state share of service is higher than that of industry.

3 Productivity Growth

3.1 Labour Productivity Growth

Can the rise of China's service sector be explained by sectoral productivity growth? We first use the NBS aggregate data to calculate labour productivity in service relative to that in industry. The solid line in panel A of Figure 13 plots the relative labour productivity in nominal term. The dotted line repeats the service GDP share in Figure 1. The increase in the service share in both phases seems associated with higher labour productivity in service. The correlation coefficient is 0.54. The solid line in panel B of Figure 13 plots the relative labour productivity in real terms, with industrial and service prices normalized to one in the initial year. The dramatic relative price change in Figure 2 turns the recent growing labour productivity to a declining trend.

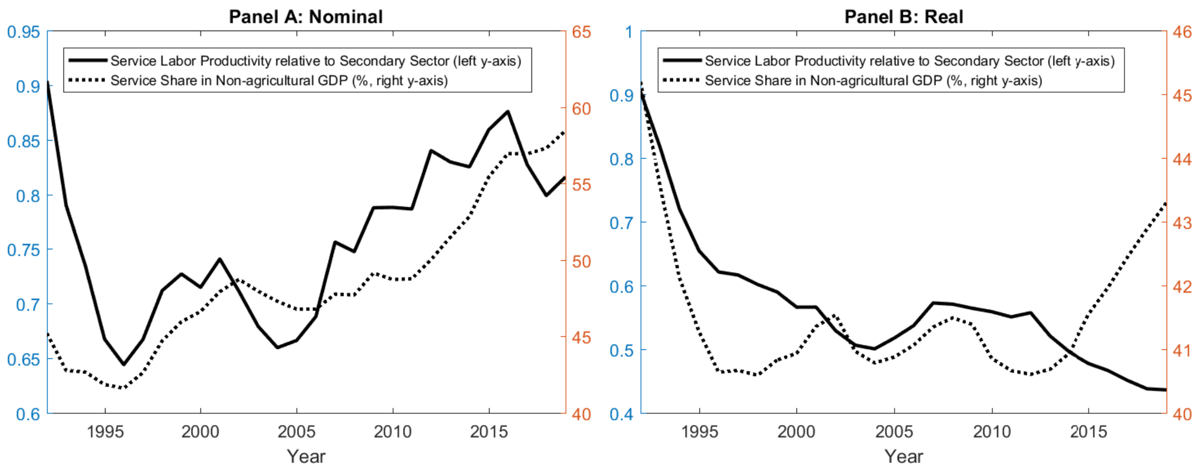

Figure 13: Relative Labour Productivity

Labour productivity is certainly a coarse measure of productivity. Using official statistics to estimate sectoral TFP does not alleviate much of the concern. Chen et al. (2019) found that investment has been severely over-reported by local governments since the mid-2000s. The official sectoral employment statistics are also challenged in the literature (see, e.g., Brandt and Zhu, 2010). Given these challenging issues, we decide not to estimate sectoral TFP growth by the NBS data. Instead, we use firm-level survey data to estimate TFP growth at the firm and more aggregate levels.

3.2 TFP Growth

We adopt the model in Hsieh and Klenow (2009). Industry output Y_s is aggregated from the differentiated goods Y_{si} produced by each of the M_s firms in industry s: $Y_s = \left(\sum_{i=1}^{M_s} (Y_{si})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, where $\sigma > 1$ is the elasticity of substitution. Cost minimization of the industry output producer implies $P_s (Y_s)^{1/\sigma} = P_{si} (Y_{si})^{1/\sigma}$, where P_{si} is the price of Y_{si} and $P_s = \left(\sum_{i=1}^{M_s} (P_{si})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the price of Y_s.

The production function of Y_{si} is also Cobb-Douglas: $Y_{si} = A_{si} K_{si}^{\beta_{ks}} L_{si}^{\beta_{\ell s}}$, where $\beta_{ks} + \beta_{\ell s} = 1$. Then, for firm i in industry s, we can obtain the following firm-level TFPR and TFPQ:

$$TFPR_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\beta_{ks}} L_{si}^{\beta_{\ell s}}}, \tag{1}$$

$$TFPQ_{si} = A_{si} = \kappa_s \cdot \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\beta_{ks}} L_{si}^{\beta_{\ell s}}}, \tag{2}$$

where $\kappa_s \equiv \frac{(P_s Y_s)^{\frac{1}{1-\sigma}}}{P_s}$. We can aggregate firm-level TFP to sectoral TFP:

$$TFPQ_s = \frac{Y_s}{K_s^{\beta_{ks}} L_s^{\beta_{\ell s}}} = \frac{TFPR_s}{P_s} = \left[\sum_{i=1}^{M_s} \left(A_{si} \cdot \frac{TFPR_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{3}$$

where

$$TFPR_s = \frac{P_s Y_s}{K_s^{\beta_{ks}} L_s^{\beta_{\ell s}}} = \frac{\sum_{i=1}^{M_s} P_{si} Y_{si}}{\left(\sum_{i=1}^{M_s} K_{si}\right)^{\beta_{ks}} \left(\sum_{i=1}^{M_s} L_{si}\right)^{\beta_{\ell s}}}. \tag{4}$$

The model has a variety effect. Equation (3) shows that holding other things equal, sectoral TFPQ increases in firm number. The effect is particularly relevant for the SAT sample where the coverage in an industry may vary over time. To control for the variety effect, we use the following formula for sectoral TFPQ:

$$\overline{TFPQ}_s = (M_s)^{-\frac{1}{\sigma-1}} \left[\sum_{i=1}^{M_s} \left(A_{si} \cdot \frac{TFPR_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}. \tag{5}$$

For notional convenience, sectoral TFP in what follows refers to $\overline{TFPQ}_s$ in sector s. We keep TFPR alive to indicate its distinction from TFP.

It is worth mentioning the determination of $P_s Y_s$. In Hsieh and Klenow (2009), final goods production technology is Cobb-Douglas: $Y = \prod_{s=1}^{S} (Y_s)^{\theta_s}$, where $\sum_{s=1}^{S} \theta_s = 1$. Cost minimization of the final goods producer implies $P_s Y_s = \theta_s P Y$, where $P \equiv \prod_{s=1}^{S} (P_s/\theta_s)^{\theta_s}$ is the price of final goods. This implies constant sectoral shares θ_s in

GDP, which does not fit our analysis. There are two ways to make the model more flexible. The first is to allow time-varying θ_s and to assume it to follow what we observe in the data. The second is to be agnostic about the demand side by assuming exogenous P_s, which is assumed to follow the official sectoral deflators. Both ways are observationally equivalent.

We apply the method in Ackerberg et al. (2015) (ACF) to estimate β_{ks} and $\beta_{\ell s}$ for each two-digit industry s. Firms with missing capital or labour are dropped.[7] ACF is briefly summarised in Appendix B, where the estimated output elasticities are also reported.

We set $\sigma = 5$. We use the estimated industry-specific β_{ks} and $\beta_{\ell s}$ and equation (2) to back out firm-specific TFP, A_{si}. Then, sectoral TFPQ and TFPR can be obtained by equations (4) and (5), respectively. To aggregate two-digit industry TFPQ or TFPR growth to one-digit industry, we use average industry value added share in the beginning and ending of the year as weight:

$$g_{s,t}^{TFPQ} = \frac{TFPQ_{s,t} - TFPQ_{s,t-1}}{TFPQ_{s,t-1}}, \tag{6}$$

$$g_{c,t}^{TFPQ} = \sum_s \left(\frac{\omega_{s,t-1} + \omega_{s,t}}{2} \right) g_{s,t}^{TFPQ}, \tag{7}$$

where $\omega_{s,t}$ denotes the share of two-digit industry s' value added in total value added of one-digit industry c, to which the two-digit industry belongs, in period t. The growth of $\overline{TFPQ}_c$ is calculated in the same manner.

Table 3 reports TFP growth for all the one-digit industries with firm number above 5,000 in 2007. The industry TFP grew at an annual rate of 6.3% in the sample period, roughly 1 percentage point higher than the service TFP growth rate of 5.3%. All service industries experienced TFP growth in 2007–2010. However, the TFP growth slowed down in all service industries in 2010–2013. Between 2007 and 2013, wholesale and retail exhibited the fastest TFP growth of 9.5%, but the TFP growth in information technology and real estate is negative.

Table 4 reports the sectoral TFP growth in the balanced panels. Service TFP grew at an annual rate of 5.6%, 0.7 percentage point higher than the growth rate of industrial TFP. The difference is mainly driven by the low TFP growth of the incumbent industrial firms in 2010–13. The last two columns in Table 4 report the results from the 2013–15 balanced panel. TFP growth rates in all non-agricultural industries are lower in this period than the previous one, and all service industries except hotel and catering have negative TFP growth rates. The magnitude of the decline in service TFP growth is about three times as large as that in industry TFP growth. Although the change of SAT sampling schemes may obscure the true TFP growth after 2013, the lower TFP growth of service relative to industry between the two balanced panels is consistent with its falling

[7] The variables that we use in the following analysis are elaborated in Appendix B.2.

Table 3: Sectoral TFPQ Growth (SAT Full Sample)

	Firm Number		TFP Growth		
	2007	2013	2007–2013	2007–2010	2010–2013
Industry	266,345	271,317	6.32%	5.36%	7.29%
Construction	18,108	30,297	3.34%	9.88%	-2.82%
Services	208,862	302,758	5.29%	8.30%	2.35%
Wholesale & Retail	133,051	153,592	9.51%	14.35%	4.87%
Transport, Storage & Post	11,056	23,121	5.52%	8.72%	2.42%
Hotel & Catering	8,239	12,458	1.63%	4.64%	-1.30%
Information Technology	5,850	16,011	-1.23%	1.34%	-3.74%
Financial Intermediation	10,699	18,887	6.32%	6.72%	5.92%
Real Estate	16,281	39,910	-2.36%	2.97%	-7.42%
Leasing & Business Services	8,644	15,929	5.68%	6.03%	5.34%
Service to Households	9,131	11,641	-0.40%	3.88%	-4.50%

labour productivity growth in Figure 13.

Figure 14 plots provincial industrial TFP growth (x axis) and service TFP growth (y axis) from different SAT samples. Panel A shows the provincial sectoral TFP growth in 2007–2013 from the full sample. Most provinces have positive service TFP growth, and Beijing (BJ) and Qinghai (QH) are the two provinces with highest TFP growth in the service sector. Compared to industrial TFP growth, service TFP growth is higher in one-third of provinces. The basic patterns of TFP growth in 2007–2013 do not essentially change if we use balanced panel (panel B): the non-agricultural TFP grew in the incumbents in all provinces.

Panel C of Figure 14 reveals the sectoral TFP growth rates in 2013–2015. Service TFP growth is lower than the industrial TFP growth in 22 out of 30 provinces. Moreover, the service TFP growth is negative in 20 provinces.

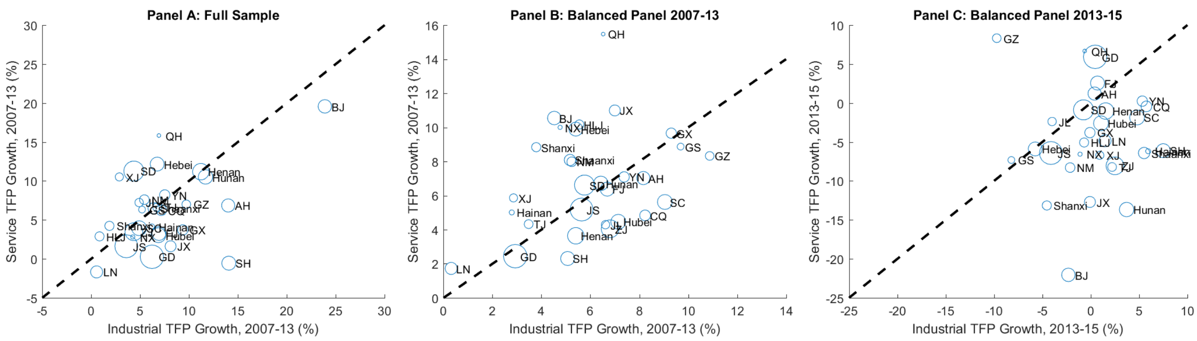

Figure 14: Provincial Industrial and Service TFP Growth

Table 4: Sectoral TFPQ Growth (SAT Balanced Panels)

	Balanced Panel, 2007–2013				Balanced Panel, 2013–2015	
	Firm Number	TFP Growth			Firm Number	TFP Growth
		2007–2013	2007–2010	2010–2013		2013–2015
Industry	37,800	4.88%	6.92%	2.87%	50,179	-1.65%
Construction	1,035	9.69%	14.01%	5.53%	1,764	5.01%
Services	16,800	5.64%	6.66%	4.63%	47,625	-10.33%
Wholesale & Retail	10,521	4.72%	7.73%	1.80%	22,041	-15.79%
Transport, Storage & Post	1,338	1.32%	3.64%	-0.94%	9,305	-10.31%
Hotel & Catering	871	1.03%	3.66%	-1.54%	836	1.88%
Information Technology	519	0.82%	1.96%	-0.31%	3,516	-6.72%
Financial Intermediation	1,483	8.92%	7.28%	10.59%	2,597	-4.02%
Real Estate	1,169	-1.80%	-1.38%	-2.21%	3,759	-13.59%
Leasing & Business Services	214	3.22%	4.39%	2.06%	2,362	-8.94%
Service to Households	143	5.32%	7.50%	3.18%	658	-14.89%

We conduct three robustness checks in Appendix C. First, we re-estimate production function for each three-digit industry in construction and service. Second, we relax the constant-return-to-scale production function. Third, we calculate TFP growth in a resampled balanced panel that matches the firm size distribution in the 2008 economic census data. Our main findings are robust.

4 Misallocation

In this section, we take a closer look at aggregate TFP growth by decomposing aggregate TFP into efficient TFP and misallocation.

4.1 Misallocation and Efficient TFP Growth

The industry-level TFP growth is co-determined by firm TFP growth and resource misallocation in the industry. Hsieh and Klenow (2009) and many other subsequent studies have shown severe resource misallocation in developing economies including China. The basic idea is that if the markets are efficient, then $TFPR_{si}$ in equation (1) should be equalised across firms. Let $\overline{TFPQ}_s^*$ denote the efficient sectoral TFP. With equalised firm TFPR, equation (5) can be rewritten as

$$\overline{TFPQ}_s^* = (M_s)^{-\frac{1}{\sigma-1}} \left[\sum_{i=1}^{M_s} (A_{si})^{\sigma-1} \right]^{\frac{1}{\sigma-1}} . \tag{8}$$

The difference between sectoral TFPQ growth and its efficient TFPQ growth can tell us the extent to which misallocation erodes productivity growth at the industry level. The magnitude of welfare losses caused by misallocation can be easily quantified by the following formula:

$$\frac{Y_s}{Y_s^*} = \left[\sum_{i=1}^{M_s} \left(\frac{TFPQ_{si}}{TFPQ_s} \cdot \frac{TFPR_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}, \tag{9}$$

where Y_s^* denotes the efficient output level of industry s. When $TFPR_{si}$ follows log normal distribution, Hsieh and Klenow (2009) show that the variance of firm TFPR becomes a summary statistic of welfare losses.

To aggregate two-digit industry welfare losses to one-digit industry, we use the current year industry value added share as weight:

$$\frac{Y_c}{Y_c^*} = \prod_s \left(\frac{Y_s}{Y_s^*} \right)^{\omega_s}, \tag{10}$$

where ω_s denotes the share of two-digit industry s' value added in total value added of one-digit industry c, to which the two-digit industry belongs.

The first column in Table 5 repeats the estimated TFP growth in Table 3. The second column reports the efficient TFP growth, that is, how much TFP growth can be generated by the observed firm TFP growth under the efficient allocation of labour and capital across SAT firms in the industry. The efficient TFP growth is close to the estimated TFP growth for the industrial sector and, yet much higher than the estimated TFP growth for most service industries. One possibility is a worsening of misallocation in service industries. This can be seen from the last two columns, which report the magnitude of misallocation in 2007 and 2013, respectively. The estimated misallocation for industry is quantitatively similar to those in Hsieh and Klenow (2009) and Hsieh and Song (2015). Misallocation was indeed a lot more severe in many service industries. The gap between efficient and actual output was nearly or more than doubled in 6 out of the 8 major service industries.

We now turn to balanced panels, where the efficient TFPQ growth is an aggregation of TFP growth of incumbent firms. The left panel of Table 6 reports the results for the 2007-13 balanced panel. Compared with the full sample, efficient TFP growth is lower in the balanced panel, suggesting lower TFP growth of the incumbent firms. The 2% of efficient TFP growth rate in the industrial sector is consistent with negligible industrial firm TFP growth in 2011–2013 reported by Brandt et al. (2017). The gap between the efficient and actual output is also smaller in the balanced panels, suggesting less severe misallocation across the incumbent firms. In the more recent 2013–15 balanced panel, the efficient TFP growth is negative in most service industries, while misallocation remains

Table 5: Sectoral TFP Growth and Misallocation (SAT Full Sample)

	TFP Growth	Efficient TFP Growth	Efficient Output / Actual Output	
	2007–2013	2007–2013	2007	2013
Industry	6.32%	7.64%	4.07	4.38
Construction	3.34%	21.45%	9.27	24.44
Services	5.29%	16.47%	5.88	10.77
Wholesale & Retail	9.51%	23.70%	10.18	21.16
Transport, Storage & Post	5.52%	22.97%	10.03	25.11
Hotel & Catering	1.63%	8.46%	2.05	3.03
Information Technology	-1.23%	17.68%	3.40	9.72
Financial Intermediation	6.32%	10.51%	3.06	3.86
Real Estate	-2.36%	1.59%	11.21	14.23
Leasing & Business Services	5.68%	21.67%	9.61	22.38
Service to Households	-0.40%	9.64%	14.11	25.10

stable.

Figure 15 shows the changes of allocation efficiency across provinces between 2007 and 2013. Misallocation in the industrial sector worsened in about half of the provinces (Panel A), especially in northwestern provinces including Xinjiang (XJ) and Shaanxi. Allocation efficiency in the service sector deteriorated in almost all provinces (Panel C). Consistent with what we found above, allocation efficiency among incumbent firms remained more stable (Panel B and D).

4.2 Decomposition

Misallocation can be further decomposed into capital and labour misallocation. Rewrite equation (1) as

$$TFPR_{si} = \left(\frac{P_{si}Y_{si}}{K_{si}}\right)^{\beta_k} \left(\frac{P_{si}Y_{si}}{L_{si}}\right)^{\beta_\ell}, \tag{11}$$

where $P_{si}Y_{si}/K_{si}$ and $P_{si}Y_{si}/L_{si}$ are capital and labour productivity, respectively. Under the assumptions of Cobb-Douglas production and CES preferences, capital and labour productivity, or average revenue product of capital and labour, are proportional to marginal revenue product of capital and labour. Thus, efficient allocation implies equalised capital productivity and equalised labour productivity across firms within an industry. The dispersion of capital and labour productivity can measure capital and labour misal-

Table 6: Sectoral TFP Growth and Misallocation (SAT Balanced Panels)

	SAT Balanced Panel 2007–2013				SAT Balanced Panel 2013–2015			
	TFP Growth	Efficient TFP Growth	Efficient Output / Actual Output		TFP Growth	Efficient TFP Growth	Efficient Output / Actual Output	
	2007–2013	2007–2013	2007	2013	2013–2015	2013–2015	2013	2015
Industry	4.88%	2.19%	3.70	3.17	-1.65%	0.44%	3.53	4.00
Construction	9.69%	3.28%	4.92	3.43	5.01%	0.66%	8.45	6.56
Services	5.64%	4.77%	4.67	4.45	-10.33%	-10.69%	10.24	9.99
Wholesale & Retail	4.72%	6.44%	9.18	10.12	-15.79%	-13.96%	18.21	20.72
Transport, Storage & Post	1.32%	-1.01%	4.59	3.99	-10.31%	-14.34%	25.29	19.20
Hotel & Catering	1.03%	-0.87%	1.85	1.65	1.88%	2.72%	2.26	2.37
Information Technology	0.82%	-0.99%	2.49	2.24	-6.72%	-3.66%	4.17	5.06
Financial Intermediation	8.92%	7.02%	2.77	2.49	-4.02%	-1.16%	3.68	4.39
Real Estate	-1.80%	2.48%	5.46	7.06	-13.59%	-13.62%	10.05	10.03
Leasing Business & Services	3.22%	1.10%	5.41	4.78	-8.94%	-9.72%	12.00	11.39
Service to Households	5.32%	8.97%	6.87	8.43	-14.89%	-15.59%	11.16	10.62

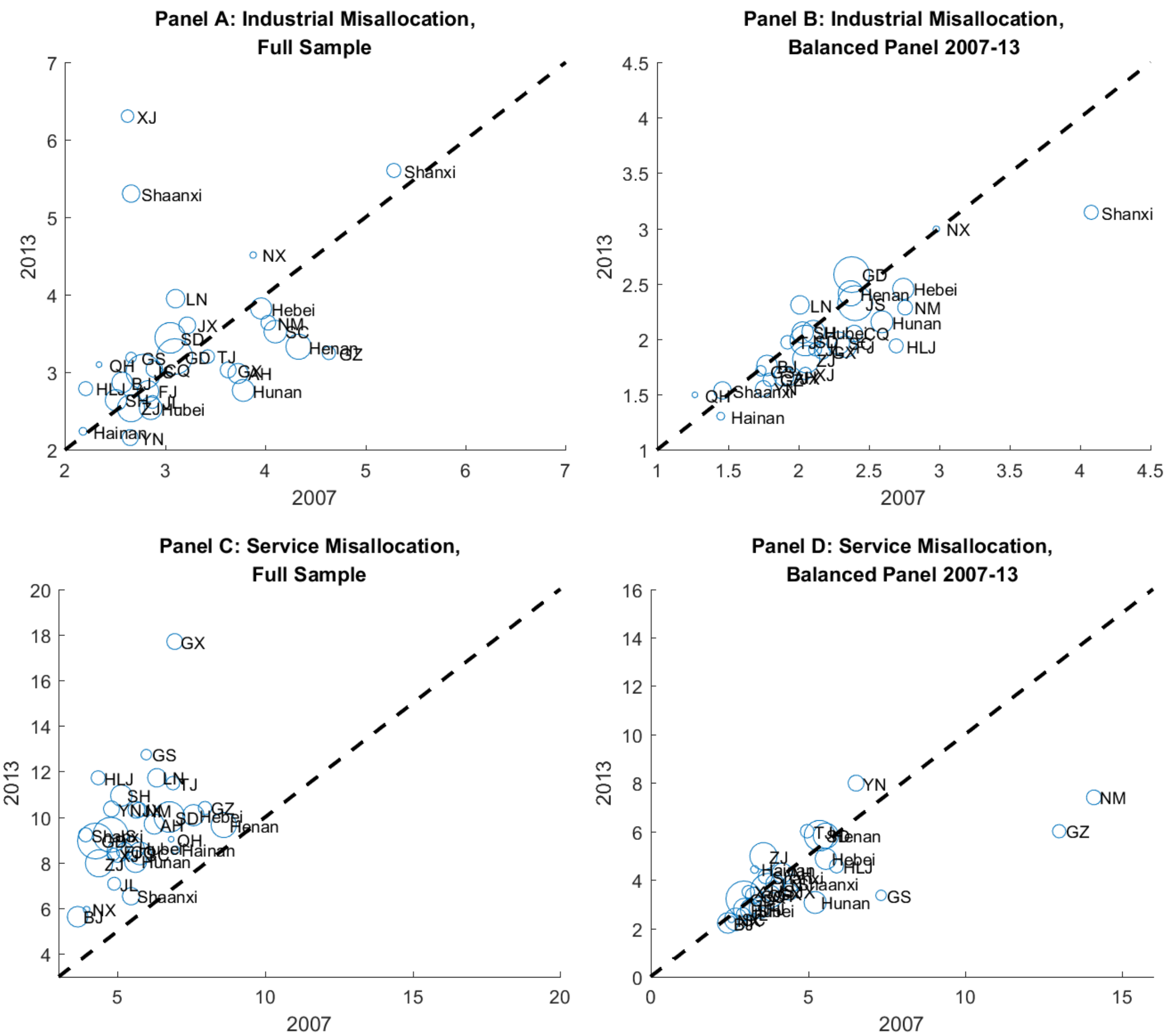

Figure 15: Provincial Misallocation

location.

Tables 7 and 8 report the results. Consistent with Hsieh and Song (2015), capital misallocation is more severe than labour misallocation in the industrial sector. The new finding is that capital misallocation is much more severe than labour misallocation in all the major service industries. The welfare gain of removing capital misallocation in the service industries in 2013 is at least 50% more than the gain of removing labour misallocation.

Table 7: Sectoral Capital and Labour Misallocation (SAT Full Sample)

	Variance of Log Capital Productivity		Variance of Log Labour Productivity	
	2007	2013	2007	2013
Industry	1.47	1.41	1.15	1.08
Construction	1.66	1.80	1.51	1.55
Services	2.04	2.17	1.51	1.55
Wholesale & Retail	2.11	2.19	1.52	1.60
Transport, Storage & Post	1.64	1.93	1.41	1.35
Hotel & Catering	1.64	1.76	0.80	0.72
Information Technology	1.77	1.81	1.45	1.23
Financial Intermediation	1.37	1.65	1.16	1.09
Real Estate	2.43	2.68	1.95	1.99
Leasing & Business Services	2.12	2.39	1.56	1.49
Service to Households	1.97	2.10	1.46	1.37

The evolution of capital misallocation in services is also different from that of labour misallocation. From the full sample (Table 7), capital misallocation worsened over time from 2007 to 2013. By contrast, the labour misallocation remained stable, and the efficiency even improved in most of the service industries. Capital and labour misallocation among incumbent firms were improved in almost all sectors in 2007–2015 (Table 8).

Panel A of Figures 16 and 17 plots the magnitude of capital misallocation in industry in different provinces. Panel B plots the same figures for labour misallocation in industry. Panels C and D repeat the upper panels for service. Industrial capital misallocation turns out to be persistent in the full sample (Panel A in Figure 16), while service capital misallocation is more time-varying (Panel C in Figure 16). The worsening of capital misallocation in service is more severe and widespread. The only outliers are Beijing (BJ), Anhui (AH) and Guangxi (GX), where service capital misallocation improved slightly. Although industrial labour misallocation improved in most provinces, service labour misallocation remained stable.

Table 8: Sectoral Capital and Labour Misallocation (SAT Balanced Panels)

	SAT Balanced Panel 2007–2013				SAT Balanced Panel 2013–2015			
	Variance of Log Capital Productivity		Variance of Log Labour Productivity		Variance of Log Capital Productivity		Variance of Log Labour Productivity	
	2007	2013	2007	2013	2013	2015	2013	2015
Industry	1.06	1.01	0.97	0.94	1.15	1.15	0.97	0.97
Construction	1.24	1.14	1.33	1.30	1.35	1.38	1.32	1.29
Services	1.59	1.49	1.23	1.24	1.83	1.81	1.31	1.31
Wholesale & Retail	1.70	1.57	1.34	1.36	1.91	1.91	1.46	1.46
Transport, Storage & Post	1.24	1.21	1.09	1.03	1.74	1.63	1.20	1.18
Hotel & Catering	1.29	1.15	0.57	0.53	1.46	1.40	0.57	0.64
Information Technology	1.11	1.04	0.93	0.84	1.50	1.50	0.99	1.01
Financial Intermediation	1.06	1.04	0.91	0.78	1.31	1.33	0.93	0.93
Real Estate	1.83	1.91	1.28	1.41	2.40	2.46	1.42	1.47
Leasing & Business Services	2.04	1.80	1.35	1.26	1.92	1.82	1.28	1.27
Service to Households	1.45	1.44	1.18	1.11	1.76	1.72	1.18	1.18

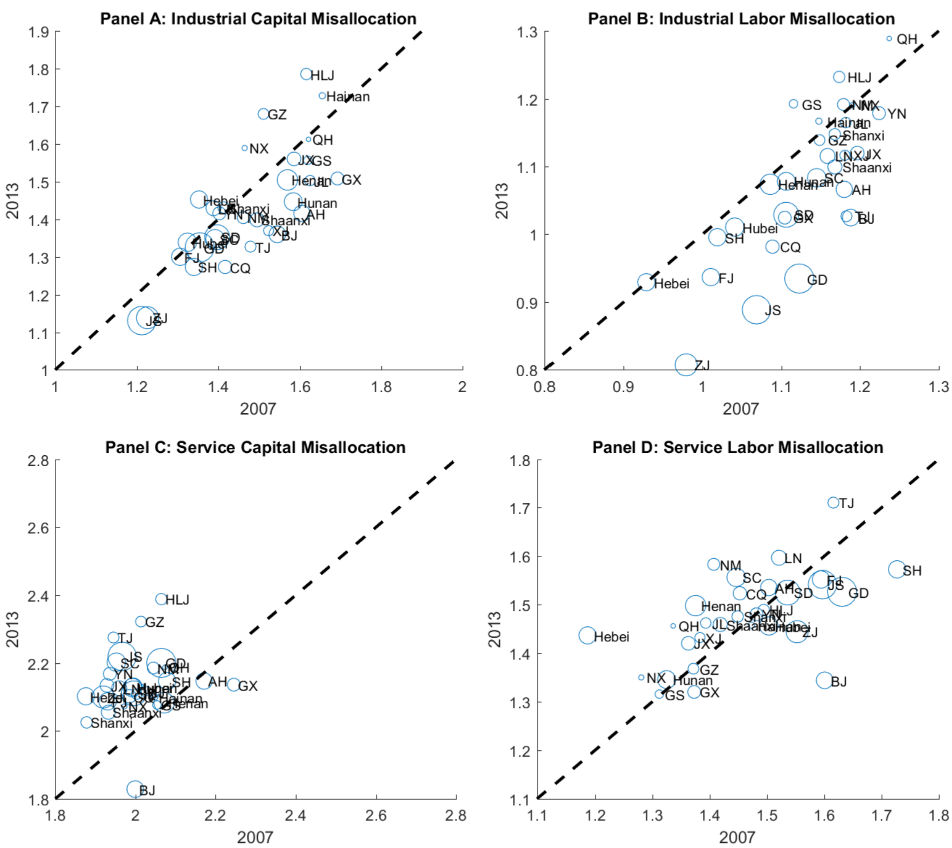

Figure 16: Provincial Capital and Labour Misallocation, SAT Full Sample

Again, capital and labour misallocation are more persistent in the balanced panel (Figure 17). Both labour and capital misallocation across incumbent firms are less severe than those in the full sample. Capital misallocation in both industry and services improved over time in most of the provinces in 2007–13 (panels A and C), while the labour misallocation was relatively stable (panels B and D).

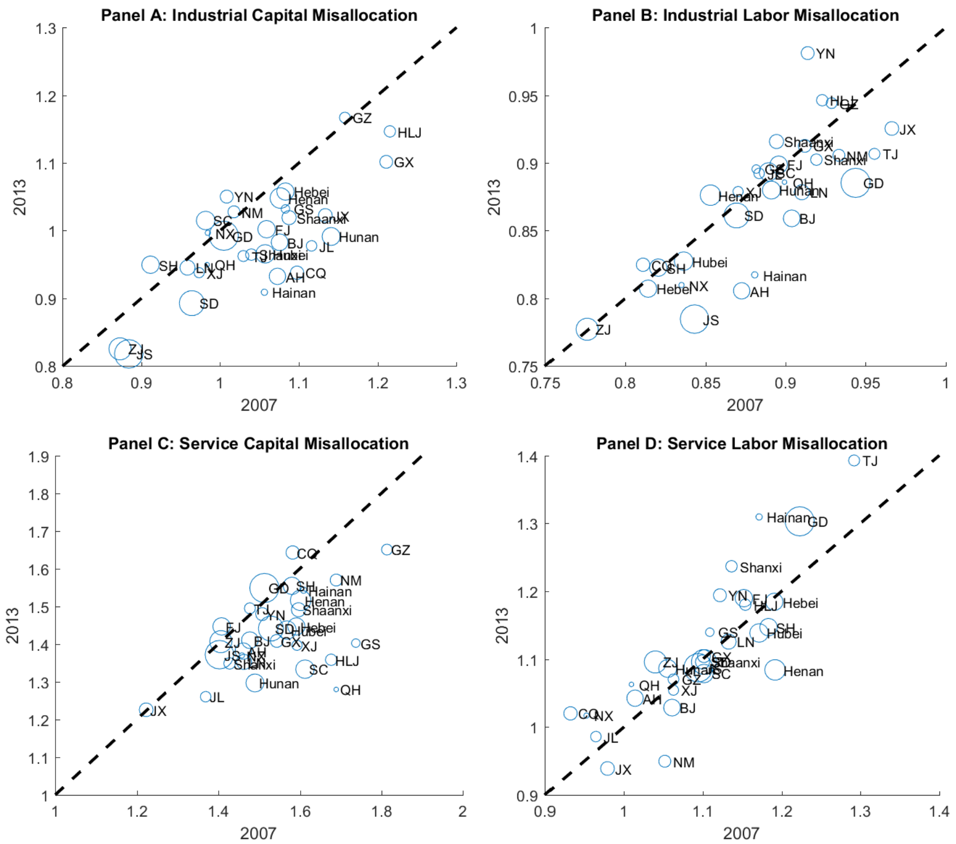

Figure 17: Provincial Capital and Labour Misallocation, SAT Balanced Panel 2007–2013

5 Conclusion

We find that the rise of China's service sector is associated with three phenomena on the supply side: (i) very high TFP growth for service firms (doubling that for industrial firms), (ii) worsening of misallocation in service industries (much more than that in industry), (iii) modest sectoral TFP growth for service (approximately two percentage points lower than that for industry). Consistent with the Balassa-Samuelson hypothesis, the lower service TFP growth may be a driving force behind the rise of service relative price.

Can the supply-side force alone explain China's recent structural transformation? The answer is perhaps no, as the fact that service goods are becoming more expensive than industrial goods seems more in line with a relative increase in demand of services (see, for example, Kongsamut et al., 2001). A model that incorporates both demand- and supply-side forces would be needed to identify the underlying mechanisms for the rise of the service sector in China. We will leave it for our future research.

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Appendices

A International Evidence on Countercyclicality of Service Contribution to GDP Growth

This section provides some international evidence on the counter-cyclicality of service contribution to GDP growth. We collect data from the World Bank. The service contribution to GDP is defined as follows:

$$\text{Service Contribution} = \frac{\text{GDP}_t^{service} - \text{GDP}_{t-1}^{service}}{\text{GDP}_t^{total} - \text{GDP}_{t-1}^{total}}.$$

Table 9 reports the correlation coefficient between service contribution and GDP growth in China, US, Japan, and India. The cyclical patterns of service contribution can also be seen in Figure 18.

Table 9: Correlation Coefficient between Service Contribution and GDP Growth

	China, 1992-2019	US, 1998-2018	Japan, 1995-2018	India, 1992-2019
Nominal	-0.752	0.399	0.094	-0.473
Real	-0.689	0.347	0.046	-0.651

B Technical Summary of Elasticity Estimation

B.1 Model Specification

We suppress the industry subscript s here. For each industry, the value added production function in the model is

$$P_{i,t}Y_{i,t} \propto (A_{i,t})^{\frac{\sigma-1}{\sigma}} (K_{i,t})^{\beta_k \frac{\sigma-1}{\sigma}} (L_{i,t})^{(1-\beta_k)\frac{\sigma-1}{\sigma}}. \tag{12}$$

Our goal is to estimate β_k, the output elasticity of capital in the value added production function. Specifically, we estimate $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ in the following equation for each industry:

$$q_{i,t} = \widetilde{\beta}_k k_{i,t} + \widetilde{\beta}_\ell \ell_{i,t} + \omega_{i,t} + \epsilon_{i,t}, \tag{13}$$

where $q_{i,t} \equiv \log(P_{i,t}Y_{i,t})$ is log value added, $k_{i,t} \equiv \log(K_{i,t})$, $\ell_{i,t} \equiv \log(L_{i,t})$, $\omega_{i,t} \equiv \frac{\sigma-1}{\sigma}\log(A_{i,t})$, and $\epsilon_{i,t}$ is an i.i.d. shock to value added or simply measurement errors. Note that $\widetilde{\beta}_k = \beta_k \frac{\sigma-1}{\sigma}$ and $\widetilde{\beta}_\ell = (1-\beta_k)\frac{\sigma-1}{\sigma}$. There is no guarantee that the estimated $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ would be consistent with the constant-return-to-scale technology – i.e., $\widetilde{\beta}_k + \widetilde{\beta}_\ell = \frac{\sigma-1}{\sigma}$ for all industries. So, we will infer β_k from

$$\beta_k = \frac{\widetilde{\beta}_k}{\widetilde{\beta}_k + \widetilde{\beta}_\ell}. \tag{14}$$

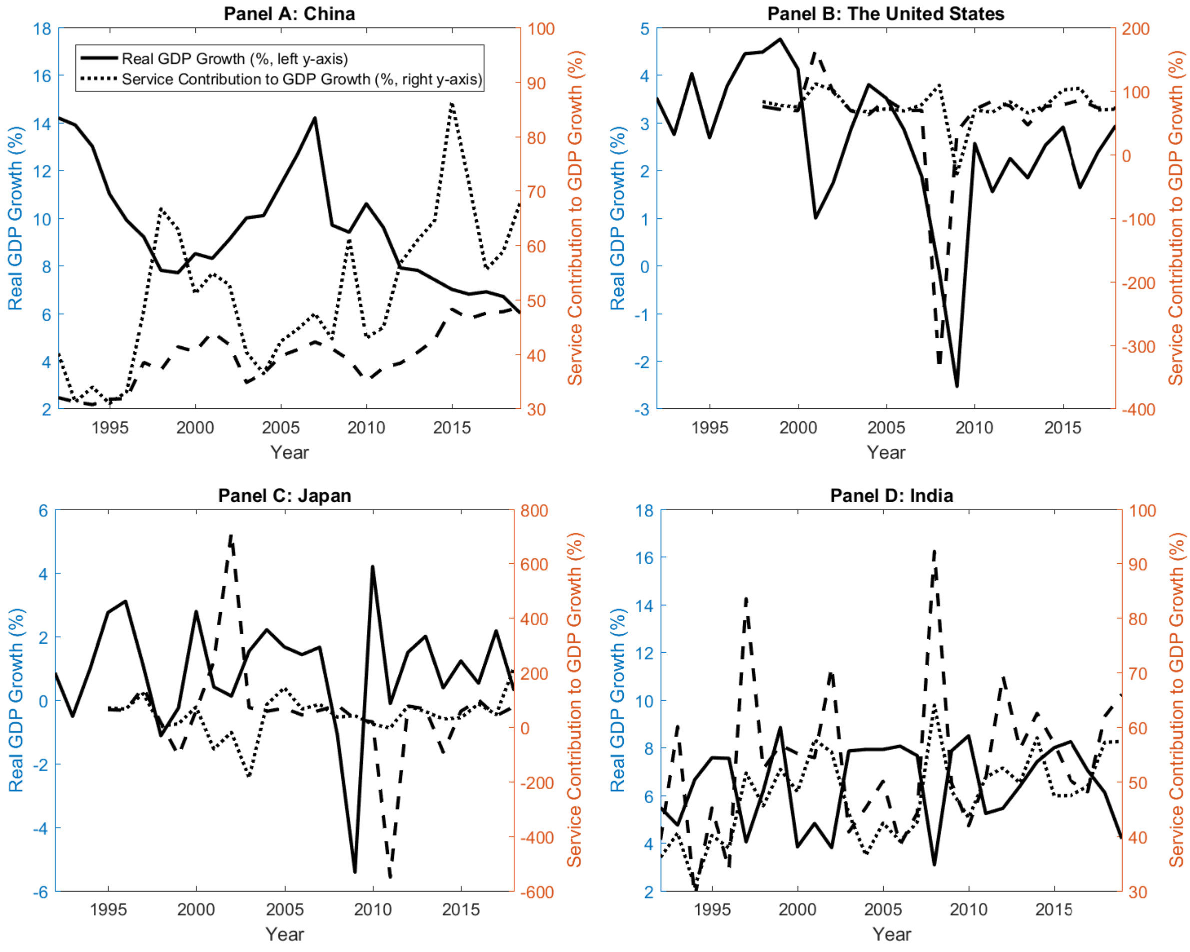

Figure 18: Cyclicality of Service Contribution to GDP Growth

Before presenting our estimation procedure, we refer to a seminal paper, Brandt et al. (2017), that estimates the following gross output (NOT value added) production function for each manufacturing industry in China, using methods built on De Loecker and Warzynski (2012) and Ackerberg et al. (2015) (ACF henceforth):

$$q^G_{i,t} = \widetilde{\gamma}_k k_{i,t} + \widetilde{\gamma}_\ell \ell_{i,t} + \widetilde{\gamma}_m m_{i,t} + \omega_{i,t} + \epsilon_{i,t}, \tag{15}$$

where $q^G_{i,t}$ is log gross output and $m_{i,t}$ is intermediate input. The simplest way is to use their estimates by converting them to β_k in our model. Since $1-\widetilde{\gamma}_m$ represents the value added share in the gross output, we have $\widetilde{\gamma}_k = \beta_k \frac{\sigma-1}{\sigma}(1-\widetilde{\gamma}_m)$ and $\widetilde{\gamma}_\ell = (1-\beta_k)\frac{\sigma-1}{\sigma}(1-\widetilde{\gamma}_m)$. We then infer β_k from

$$\beta_k = \frac{\widetilde{\gamma}_k}{\widetilde{\gamma}_k + \widetilde{\gamma}_\ell}. \tag{16}$$

We refer to β_k converted from the estimates in Brandt et al. (2017) as BVWZ estimates.

There are three issues when we use BVWZ estimates. First, $\widetilde{\gamma}_k$ and $\widetilde{\gamma}_\ell$ are not directly estimated from value added production function. Second, two important industries (smelting and pressing of ferrous metals and non-ferrous metals) are found to have negative $\widetilde{\gamma}_k$ in Brandt et al. (2017). Moreover, BVWZ estimates do not cover industries other than manufacturing. So, we directly estimate $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ in the value added production function. Our estimation procedure is based on Brandt et al. (2017). In particular, we include tariffs as additional controls to identify productivity shocks, which Brandt et al. (2017) find vital for obtaining reasonable estimates. We also take tax rate into account, which is crucial for service industries where tariff data are not available.

The only major deviation from Brandt et al. (2017) is that instead of using intermediate inputs, we use firms' investment, $i_{i,t}$, as a proxy for their TFP. As in Olley and Pakes (1996),

$$i_{i,t} = \begin{cases} i_t(\omega_{i,t}, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^I_{i,t-1}, \tau^O_{i,t-1}, \tau^A_{i,t-1}), & \text{for industries with tariff data,} \\ i_t(\omega_{i,t}, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^A_{i,t-1}), & \text{otherwise,} \end{cases} \tag{17}$$

where $i_{i,t}$ is real investment of firm i at period t. Here, we include log wage $w_{i,t}$ since we need to control for the serially correlated firm-specific shocks to the price of labour, which may affect the firm's optimal labour input and, in turn, investment choice.[8] The time-variant function, $i_t(\cdot)$, will capture some fixed effects in the first-stage estimation below. Following Brandt et al. (2017), we also include firm's export status ($e_{i,t}$). For industries where tariff data are available (all but one industries in the industrial sector), we include input tariffs ($\tau^I_{i,t-1}$) and output tariffs ($\tau^O_{i,t-1}$), assuming that firms make production decision based on tariffs at time $t-1$.[9] Finally, we include firm's tax sales ratio ($\tau^A_{i,t-1}$). Like tariffs, we assume that firms make production decisions based on tax sales ratio in the previous period.

Under the assumptions that $\omega_{i,t}$ is the only unobserved firm-specific factor and that there exists a conditionally monotonic relationship between $\omega_{i,t}$ and $i_{i,t}$, we can rewrite the above equation as

$$\omega_{i,t} = \begin{cases} h_t(i_{i,t}, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^I_{i,t-1}, \tau^O_{i,t-1}, \tau^A_{i,t-1}), & \text{for industries with tariff data,} \\ h_t(i_{i,t}, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^A_{i,t-1}), & \text{otherwise.} \end{cases}$$

We further assume that the law of motion of firm TFP hinges on the lagged TFP, output and input tariffs, tax rates, and firms' current export status:

$$\omega_{i,t} = \begin{cases} g(\omega_{i,t-1}, e_{i,t}, \tau^I_{i,t-1}, \tau^O_{i,t-1}, \tau^A_{i,t-1}) + \xi_{i,t}, & \text{for industries producing exportable goods,} \\ g(\omega_{i,t-1}, e_{i,t}, \tau^A_{i,t-1}) + \xi_{i,t}, & \text{otherwise,} \end{cases} \tag{18}$$

where $\xi_{i,t}$ is the innovation to firm TFP.

We can now write the procedure of estimating $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ in two steps. In the first stage, we estimate

$$q_{i,t} = \begin{cases} \phi_t(i_t, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^I_{i,t-1}, \tau^O_{i,t-1}, \tau^A_{i,t-1}, \boldsymbol{Z}_{i,t}) + \epsilon_{i,t}, & \text{for industries with tariff data,} \\ \phi_t(i_t, \ell_{i,t}, k_{i,t}, w_{i,t}, e_{i,t}, \tau^A_{i,t-1}, \boldsymbol{Z}_{i,t}) + \epsilon_{i,t}, & \text{otherwise.} \end{cases} \tag{19}$$

[8] The existence of the serially correlated firm-specific shocks also ensures that lagged labour is a valid instrument in the orthogonality condition below.

[9] Tariffs are vital for obtaining reasonable estimates (Brandt et al. (2017)).

Analogous to Brandt et al. (2017), we proxy $\phi(\cdot)$ by a third-order polynomial of capital, labour, and investment, and include the interactions of the polynomial terms with lagged industry-level input and output tariffs, firm-level wage and export status dummy. We also control for year, industry, and province fixed effects, which are all in the vector $\boldsymbol{Z}_{i,t}$. The predicted value of equation (19) is the expected output, denoted by $\widehat{\phi}_{i,t}$. Given any $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$, an estimate of firm TFP $\omega_{i,t}$ can be obtained by $\widehat{\omega}_{i,t}(\widetilde{\beta}_k, \widetilde{\beta}_\ell) = \widehat{\phi}_{i,t} - (\widetilde{\beta}_k k_{i,t} + \widetilde{\beta}_\ell \ell_{i,t})$.

In the second stage, we assume that the law of motion of firm TFP (18) is linear:

$$\omega_{i,t} = \begin{cases} \alpha_0 + \alpha_1 \omega_{i,t-1} + \alpha_e e_{i,t} + \alpha_O \tau^O_{i,t-1} + \alpha_I \tau^I_{i,t-1} + \alpha_A \tau^A_{i,t-1} + \xi_{i,t}, & \text{for industries with tariff data,} \\ \alpha_0 + \alpha_1 \omega_{i,t-1} + \alpha_e e_{i,t} + \alpha_A \tau^A_{i,t-1} + \xi_{i,t}, & \text{otherwise.} \end{cases}$$

We regress the above equation by using $\widehat{\omega}_{i,t}(\widetilde{\beta}_k, \widetilde{\beta}_\ell)$. The residual is $\widehat{\xi}_{i,t}(\widetilde{\beta}_k, \widetilde{\beta}_\ell)$. We then use the following orthogonality condition

$$E\left(\xi_{i,t}(\widetilde{\beta}_k, \widetilde{\beta}_\ell)\begin{pmatrix}\ell_{i,t-1} \\ k_{i,t}\end{pmatrix}\right) = 0 \tag{20}$$

to estimate $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$, following the method in De Loecker and Warzynski (2012) and Brandt et al. (2017).

B.2 Data

We use the SAT data to estimate output elasticities. As a robustness check, we also use the Annual Survey of Industrial Firms conducted by the National Bureau of Statistics (NBS data). Tariff data will also be used in our estimation.

B.2.1 SAT Data

We establish firm ID by the unique taxpayer identification number. To estimate firm-level productivity, we use the following key variables: total sales (output), total employment (labour), wage bills, and book value of capital stock at original price. Other firm characteristics used in the analysis are location (province), year of establishment, and export status. Due to changes in industry classification in 2011, we adjust the industry code to make it consistent before and after 2011.[10]

The SAT data does not report materials. We convert firm sales to firm value added by the ratio of total value added to total sales, averaged over time, from the firms in the industry that report value added. We deflate firm value added by industry-specific output deflator. We construct the output deflator using a two-digit (39 industries) ex-factory price index provided by NBS.

We calculate the real capital stock $K_{i,t}$ of firm i at time t from the book value of capital stock at original price. Define $K_{i,t}$ as

$$K_{i,t} = (1-\delta)K_{i,t-1} + \frac{BK_{i,t} - BK_{i,t-1}}{P^K_t}, \tag{21}$$

where BK is the book value of capital and P^K is the price of capital. The price of capital in 1978–2006 is from Brandt et al. (2008). The price of capital in 2007–2015 and the price

[10] The concordance code is available upon request.

index of fixed assets are from NBS. We assume a depreciation rate of 9% as in Brandt et al. (2012).

For the firms established after 2007, the initial book value of capital stock is the initial book value reported by the firms. For the firms established before 2007, we assume that the book value in its birth year t_0 is given by

$$K_{i,t_0} = \frac{BK_{i,2007}}{(1+g_i)^{2007-t_0}},$$

where g_i is the average growth rate of capital stock in the industry and province, to which the firm i belongs, in the period of 2007–2015. We also use g_i to infer the missing book value of capital stock for years in between.

We calculate firms' nominal investment as the difference of book value of capital stock at original price between two subsequent years, as implied by (21). We deflate nominal investment by the price index of fixed assets.

The tax rate is proxied by the ratio of tax payable to sales. Tax payable includes all kinds of taxes reported in the SAT data, including corporate income tax, value added tax, consumption tax, business tax, real estate tax, urban land use tax, vehicle and vessel use tax, land value increment tax, resource tax, urban maintenance and construction tax, and tobacco tax.

B.2.2 NBS Data

We follow Brandt et al. (2012) to establish firm ID in the NBS data. Investment, output deflators, and investment deflators are obtained in the same way as above. We also follow the same formula to derive the real capital stock.

One important difference between two datasets is that the NBS data report material inputs. Therefore, we can calculate firms' real value added. The input price deflator for each industry is constructed as an average of the output deflators of all manufacturing industries, weighted by the input shares in the 2002 National Input-Output (I-O) table.

B.2.3 Tariff Data

We follow Brandt et al. (2017) to construct tariffs after 2007. We obtained applied import tariff rates for most favoured nations at the 8-digit level of the Harmonized System (HS) product classification from the WTO-IDB dataset. We use the correspondence table from Brandt et al. (2017) to map them into China's Industrial Classification (CIC) system at the 4-digit level to obtain output tariffs that we use at the firm and industry levels.[11] To avoid bias in the industry average due to low trade volumes in heavily protected product lines, we use unweighted average as in Brandt et al. (2017). Input tariffs are an average of output tariffs, weighted by the industry input shares from the 2012 I-O table. Figure 19 compares the output tariff rates in 2007 from Brandt et al. (2017) and ours. The correlation coefficient is 0.98.

[11] We find that tariffs in 2010 are abnormal in most industries. We use the average of 2009 and 2011 tariffs to proxy tariffs in 2010.

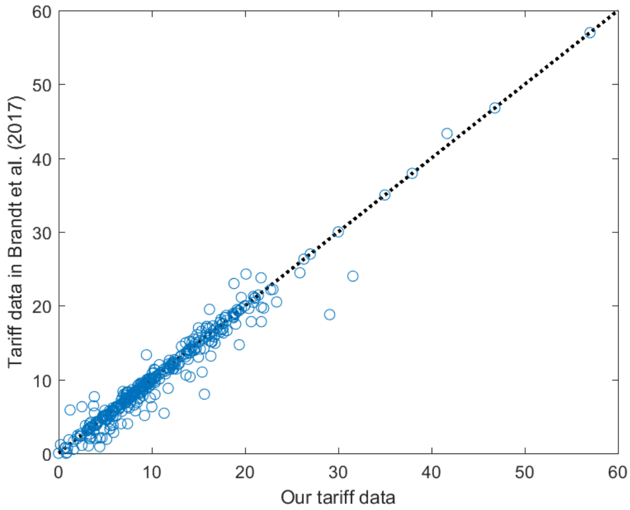

Figure 19: Tariff Rates at 4-digit Manufacturing Industries, 2007

B.3 Results for Industries with Tariff Data

The estimates in Brandt et al. (2017) serve as an external validity check for our estimates. To begin with, we follow the procedure above to estimate $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ with the NBS data and derive the estimations of β_k.[12] The values of $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ are displayed in Table 10. The left panel of Figure 20 plots β_k for two-digit manufacturing industries inferred from our estimates (x-axis) and from Brandt et al. (2017) (y-axis). The dashed line is a 45-degree line. The correlation coefficient is 0.45, statistically significant at the 5% level.

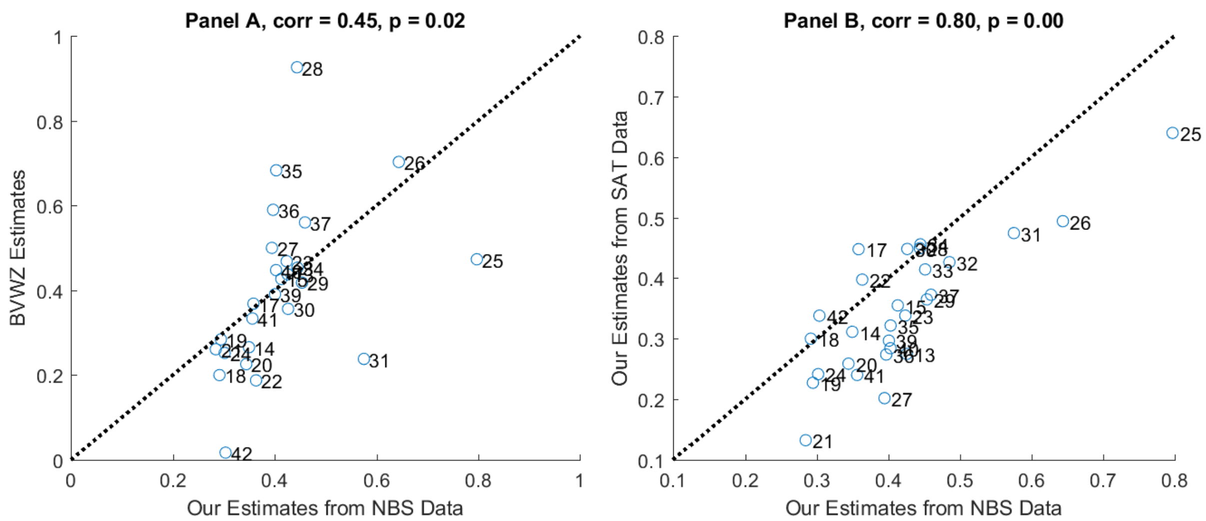

Figure 20: Output Elasticity of Capital in Value Added Production Function

Notes: The industry classification follows GB/T 4754–2002. We exclude industry 16 (manufacturing of tobacco) in the figure. We also drop 32 (smelting and processing of ferrous metals) and 33 (smelting and processing of non-ferrous metals) in Panel A.

We then estimate the elasticities in the value added production function for industries

[12] As tax rates are not available in the NBS data, we exclude the tax rates in our estimation with NBS data.

with tariffs using SAT data. Tariff data are available for all industries in the industrial sector except production and supply of water, whose industry code is 46. The results are shown in Table 10. We compare $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ from the two datasets in Figure 21. We plot the estimates using the NBS data on the x-axis and the estimates using the SAT data on the y-axis. From panels A and B, both labour and capital coefficients are highly correlated. Accordingly, we can find a significantly positive correlation of β_k with a correlation coefficient around 0.8 (Panel B in Figure 20).

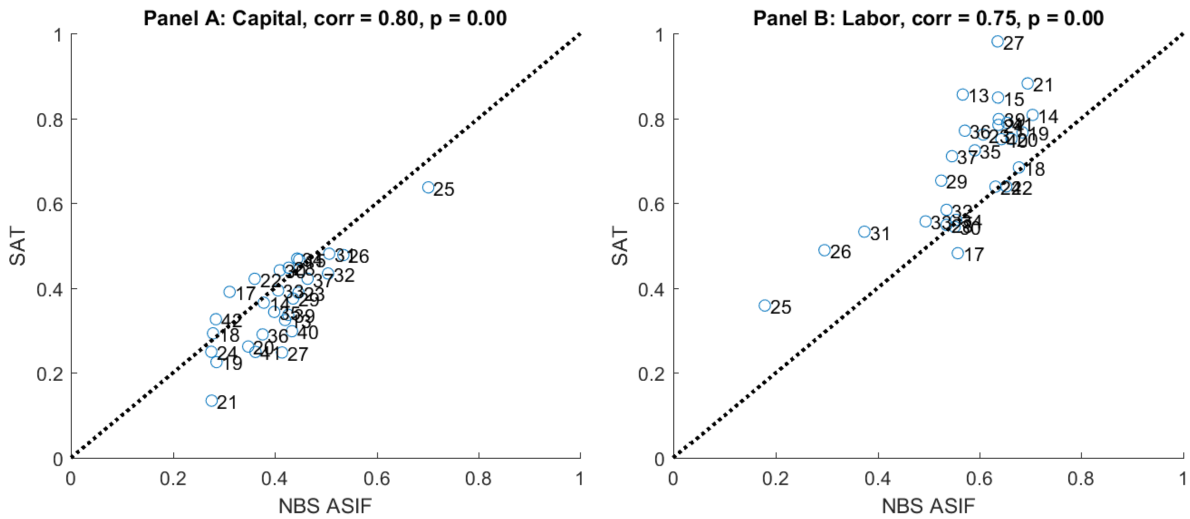

Figure 21: Estimated $\widetilde{\beta}_k$ and $\widetilde{\beta}_\ell$ in Value Added Production Function

Notes: The industry classification follows GB/T 4754–2002. We exclude industry 16 (manufacturing of tobacco) in the figure.

B.4 Results for Industries without Tariff Data

Tariff data is not available for all service industries. In the SAT data, there are a limited numbers of firms in some service industries. We only estimate the service industries with more than 500 observations. There are a few abnormal estimates. The estimated labour elasticity is negative for industry 47 (Building and civil engineer work industry), and the estimated capital elasticity is negative for industry 55 (air transport) and 67 (catering services), respectively. To calculate TFP growth in these industries, we use the bootstrapped mean of the estimated elasticity, which is positive for industry 47 and 55. For industry 67, we assume that firms' value added is proportional to their labour input.[13] The estimation results are reported in Table 11.

C Robustness Checks for Estimating Output Elasticities

In this appendix, we do three robustness checks to the sectoral and provincial TFP growth. First, we estimate production function for each three-digit industry in construc-

[13] The ratio of total capital to total value added in industry 67 is lower than 0.001 in 2007–2013. Therefore, it is appropriate for us to assume the linear production technology in labour.

Table 10: Estimates of Value Added Production Function Coefficients

Industry Code (2002 classification)	$\widetilde{\beta}_\ell$ NBS	$\widetilde{\beta}_\ell$ SAT	$\widetilde{\beta}_k$ NBS	$\widetilde{\beta}_k$ SAT
6		0.351		0.580
7		0.594		0.396
8		0.577		0.400
9		0.455		0.524
10		0.285		0.532
11		0.398		0.484
13	0.567	0.856	0.420	0.325
14	0.704	0.808	0.379	0.365
15	0.636	0.849	0.448	0.467
16	0.869	0.330	0.732	1.048
17	0.557	0.482	0.311	0.391
18	0.677	0.684	0.279	0.293
19	0.684	0.767	0.286	0.226
20	0.663	0.751	0.348	0.262
21	0.694	0.882	0.276	0.135
22	0.631	0.639	0.361	0.422
23	0.607	0.761	0.446	0.389
24	0.637	0.784	0.276	0.250
25	0.179	0.359	0.702	0.637
26	0.296	0.489	0.535	0.478
27	0.636	0.981	0.414	0.248
28	0.535	0.549	0.427	0.448
29	0.525	0.653	0.436	0.375
30	0.551	0.544	0.410	0.442
31	0.374	0.533	0.507	0.481
32	0.535	0.584	0.505	0.434
33	0.494	0.557	0.407	0.394
34	0.554	0.560	0.444	0.469
35	0.591	0.724	0.399	0.344
36	0.571	0.771	0.376	0.291
37	0.546	0.711	0.464	0.422
39	0.638	0.798	0.427	0.337
40	0.643	0.751	0.434	0.298
41	0.654	0.789	0.362	0.250
42	0.652	0.639	0.285	0.327
43		0.730		0.325
44		0.423		0.665
45		0.359		0.544

Note: The industry classification in the first column follows GB/T 4754–2002.

Table 11: Estimates of Value Added Production Function Coefficients

Industry Code	Coefficients		Bootstrapped Means		Bootstrapped Standard Errors		Obs.
	$\widetilde{\beta}_\ell$	$\widetilde{\beta}_k$	$\widetilde{\beta}_\ell$	$\widetilde{\beta}_k$	$\widetilde{\beta}_\ell$	$\widetilde{\beta}_k$	
46	0.397	0.567	0.403	0.563	0.034	0.022	6,730
47	-0.037	0.699	0.130	0.647	0.422	0.199	8,408
48	0.581	0.370	0.592	0.366	0.039	0.025	9,485
49	0.900	0.364	0.833	0.406	0.343	0.191	1,871
50	0.677	0.364	0.697	0.348	0.219	0.098	1,637
51	0.324	0.588	0.292	0.650	0.098	0.098	556
52	0.560	0.309	0.560	0.311	0.023	0.021	18,261
53	0.567	0.369	0.535	0.407	0.156	0.116	2,092
54	0.207	0.474	0.175	0.515	0.164	0.074	1,639
55	1.529	-0.023	1.495	0.013	0.428	0.217	699
57	0.647	0.308	0.668	0.297	0.092	0.037	3,679
58	0.299	0.404	0.300	0.432	0.106	0.049	1,488
59	0.310	0.387	0.365	0.334	0.251	0.152	1,041
60	0.578	0.387	0.566	0.390	0.173	0.090	4,002
61	0.726	0.342	0.751	0.337	0.068	0.037	3,141
62	0.909	0.241	0.914	0.237	0.030	0.021	8,916
63	0.780	0.296	0.782	0.296	0.012	0.007	122,881
65	0.808	0.214	0.810	0.212	0.013	0.008	53,072
66	1.053	0.115	1.025	0.127	0.071	0.036	9,973
67	1.075	-0.015	1.077	-0.016	0.035	0.022	5,774
68	1.053	0.061	1.049	0.064	0.086	0.054	17,107
69	0.665	0.351	0.684	0.327	0.073	0.061	2,820
70	0.814	0.147	0.819	0.145	0.039	0.032	5,439
71	0.958	0.168	0.985	0.156	0.103	0.058	2,715
72	0.914	0.081	0.915	0.080	0.031	0.009	48,315
73	0.687	0.284	0.685	0.308	0.329	0.174	691
74	0.996	0.196	1.005	0.197	0.079	0.042	8,146
75	1.062	0.105	0.361	0.384	0.679	0.278	937
76	0.919	0.278	0.923	0.288	0.055	0.033	5,088
83	0.617	0.326	0.646	0.318	0.053	0.030	6,328
84	1.354	0.377	1.048	0.303	3.547	0.891	1,037
85	0.757	0.242	0.882	0.238	0.409	0.253	785
88	0.836	0.190	0.841	0.186	0.104	0.055	3,010
89	0.789	0.282	0.899	0.245	0.443	0.153	1,802

Note: The industry classification in the first column follows GB/T 4754–2002.

tion and service with more than 500 observations. The corresponding TFP growth is reported in Table 12, 13 and Figure 22. The service TFP growth in 2007–13 rose to 6.5% due to high wholesale and retail TFP growth in 2010–13. Nevertheless, the similar TFP growth in industry and services still cannot deny the importance of demand-side factors in service expansion.

Second, we use the estimated $\widetilde{\beta}_{ks}$ and $\widetilde{\beta}_{\ell s}$ to calculate TFP growth. That is, the production function is not necessarily constant-return-to-scale. The results are reported in Table 14, 15, Figure 23 and 24. The main findings are robust.

Third, we calculate TFP growth in a resampled 2007–2013 balanced panel, which match the firm size distribution in the 2008 economic census data. We assign a specific weight to each firm in the balanced panel such that the weighted sales distribution of the balanced panel in each two-digit industry matches the corresponding distribution in the 2008 economic census data.[14] The results in Table 16 indicate that TFP growth rates in the resampled balanced panel are higher than those from the original balanced panel in Table 4. This is not surprising since small firms that are under-represented in the SAT survey tend to have higher TFP growth.

Table 12: Sectoral TFPQ Growth (SAT Full Sample)

	Firm Number		TFP Growth		
	2007	2013	2007–2013	2007–2010	2010–2013
Construction	17,851	30,108	6.10%	11.68%	0.79%
Services	199,510	286,772	6.51%	8.96%	4.12%
Wholesale & Retail	130,859	151,734	12.97%	15.51%	10.48%
Transport, Storage & Post	9,328	20,513	3.30%	10.97%	-3.83%
Hotel & Catering	7,678	11,131	1.27%	3.44%	-0.86%
Information Technology	5,478	15,120	-2.85%	-1.63%	-4.05%
Financial Intermediation	9,843	16,987	6.28%	6.02%	6.55%
Real Estate	15,528	38,451	-0.98%	7.34%	-8.65%
Leasing & Business Services	7,059	13,311	6.57%	11.24%	2.10%
Service to Households	8,859	11,084	-1.06%	1.01%	-3.08%

Note: We first estimate the production function in each three-digit industry with more than 500 observations. Then we report the aggregated sectoral TFP growth here.

[14] The SAT survey does not cover many small firms. As a result, we only keep the firms with sales over 2 million yuan in the two datasets.

Table 13: Sectoral TFPQ Growth (SAT Balanced Panels)

	Balanced Panel, 2007–2013				Balanced Panel, 2013–2015	
	Firm Number	TFP Growth			Firm Number	TFP Growth
		2007–2013	2007–2010	2010–2013		2013–2015
Construction	979	11.49%	17.82%	5.50%	1,692	5.07%
Services	12,312	5.99%	7.04%	4.95%	39,903	-7.42%
Wholesale & Retail	7,060	5.55%	8.35%	2.81%	17,735	-11.39%
Transport, Storage & Post	1,045	3.17%	5.92%	0.49%	8,198	-3.57%
Hotel & Catering	599	0.64%	2.36%	-1.05%	673	3.17%
Information Technology	514	0.49%	1.72%	-0.72%	3,263	-6.17%
Financial Intermediation	1,335	8.36%	6.43%	10.33%	2,332	-2.96%
Real Estate	1,068	1.03%	7.48%	-5.04%	3,585	-11.52%
Leasing & Business Services	158	10.44%	17.70%	3.63%	1,715	-6.26%
Service to Households	142	6.83%	7.61%	6.05%	628	-14.01%

Note: We first estimate the production function in each three-digit industry with more than 500 observations. Then we report the aggregated sectoral TFP growth in this table.

Table 14: Sectoral TFPQ Growth (SAT Full Sample)

	Firm Number		TFP Growth		
	2007	2013	2007–2013	2007–2010	2010–2013
Industry	266,351	271,310	4.03%	3.51%	4.55%
Construction	18,108	30,291	3.08%	8.81%	-2.34%
Services	208,785	302,688	1.56%	3.94%	-0.77%
Wholesale & Retail	132,999	153,544	8.75%	10.99%	6.55%
Transport, Storage & Post	11,056	23,119	4.27%	5.73%	2.84%
Hotel & Catering	8,241	12,452	-0.62%	0.51%	-1.74%
Information Technology	5,842	16,007	-4.13%	-2.35%	-5.88%
Financial Intermediation	10,710	18,892	-2.19%	0.72%	-5.02%
Real Estate	16,278	39,905	-4.74%	-0.89%	-8.45%
Leasing & Business Services	8,631	15,927	0.38%	2.56%	-1.75%
Service to Households	9,120	11,644	-4.14%	-3.73%	-4.56%

Note: We do not force the technology in two-digit industries to be constant returns to scale when we calculate the sectoral TFPQ growth in this table.

Table 15: Sectoral TFPQ Growth (SAT Balanced Panels)

	Balanced Panel, 2007–2013				Balanced Panel, 2013–2015	
	Firm Number	TFP Growth			Firm Number	TFP Growth
		2007–2013	2007–2010	2010–2013		2013–2015
Industry	37,559	4.70%	6.46%	2.97%	50,027	0.43%
Construction	1,038	9.71%	13.84%	5.73%	1,762	5.08%
Services	16,747	3.45%	5.70%	1.25%	47,480	-12.86%
Wholesale & Retail	10,485	4.44%	7.33%	1.63%	21,943	-20.67%
Transport, Storage & Post	1,330	-0.11%	2.53%	-2.69%	9,282	-9.86%
Hotel & Catering	869	1.71%	4.45%	-0.95%	834	3.94%
Information Technology	514	-0.93%	0.45%	-2.29%	3,502	-9.56%
Financial Intermediation	1,477	4.41%	4.77%	4.04%	2,592	-5.16%
Real Estate	1,173	-0.52%	6.03%	-6.66%	3,764	-14.15%
Leasing & Business Services	217	3.77%	6.49%	1.13%	2,354	-13.65%
Service to Households	143	4.88%	7.48%	2.33%	660	-14.79%

Note: We do not force the technology in two-digit industries to be constant returns to scale when we calculate the sectoral TFPQ growth in this table.

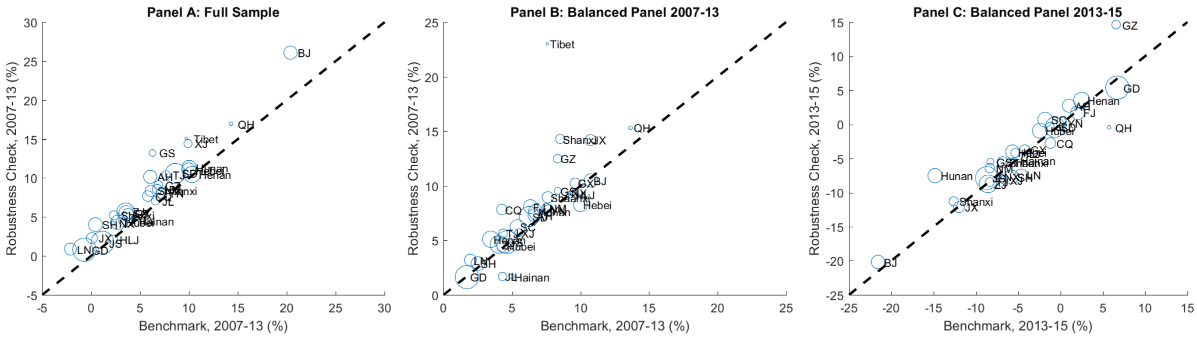

Figure 22: Provincial Service TFP Growth

Notes: We first estimate the production function in each three-digit industry with more than 500 observations. Then we report the aggregated sectoral TFP growth on y axis. The TFP growth on x axis is from our benchmark results.

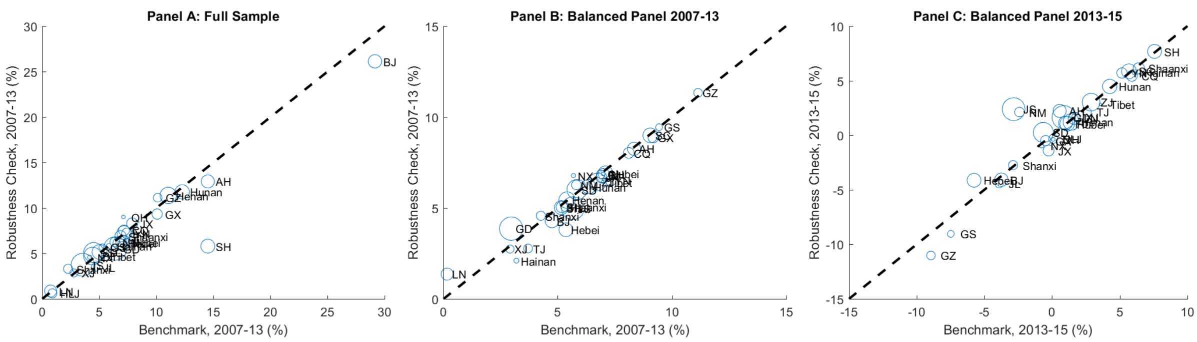

Figure 23: Provincial Industrial TFP Growth

Notes: For the TFP growth on y axis, we do not force the technology to be constant returns to scale. The TFP growth on x axis is from our benchmark results.

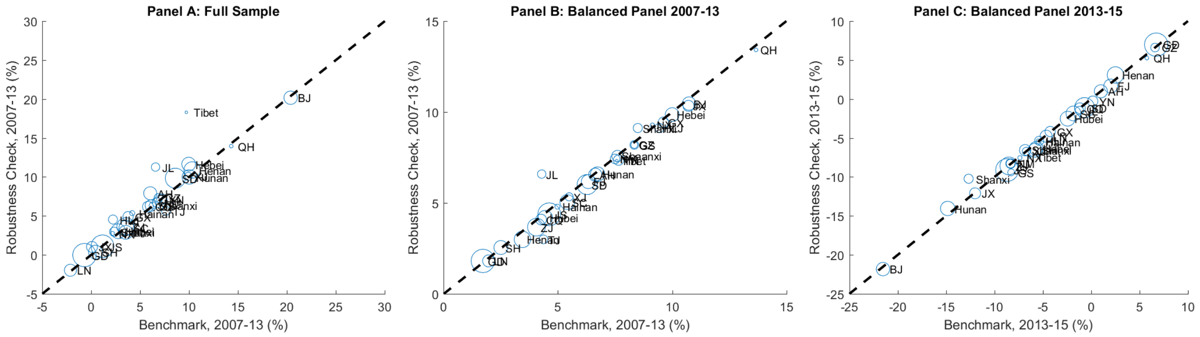

Figure 24: Provincial Service TFP Growth

Notes: For the TFP growth on y axis, we do not force the technology to be constant returns to scale. The TFP growth on x axis is from our benchmark results.

Table 16: Sectoral TFPQ Growth (Resampled SAT Balanced Panel, 2007–2013)

	Resampled Balanced Panel, 2007–2013		
	TFP Growth		
	2007–2013	2007–2010	2010–2013
Industry	5.91%	7.61%	4.24%
Construction	11.19%	15.38%	7.15%
Services	5.23%	7.13%	3.36%
Wholesale & Retail	5.33%	8.12%	2.61%
Transport, Storage & Post	1.11%	3.05%	-0.80%
Hotel & Catering	3.75%	5.89%	1.65%
Information Technology	0.70%	0.81%	0.59%
Financial Intermediation	6.68%	7.64%	5.72%
Real Estate	0.01%	7.56%	-7.00%
Leasing & Business Services	5.57%	9.92%	1.40%
Service to Households	4.44%	8.81%	0.25%

Note: We resample the firms in 2008 of the balanced panel in 2007–2013 to match the firm size distribution of the 2008 economic census data and report the TFP growth of the resampled balanced panel in this table.