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High-Skilled Services and Development in China

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Abstract: We document that the employment share of high-skill-intensive services is much lower in China than in countries with similar gross domestic product (GDP) per capita. We build a model of structural change with goods and low- and high-skill-intensive services to account for this observation. We find that large distortions limit the size of high-skill-intensive services in China. If they were removed, both high-skill-intensive services and GDP per capita would increase considerably. We document a strong presence of state-owned enterprises in high-skill-intensive services and suggest that this leads to important distortions.

JEL classification: 041, 047, 051

Key words: China, high-skill intensive services, state-owned enterprises, structural change

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1 Introduction

Since the economic reforms of 1978, Chinese GDP per capita has grown by around 7% per year. The impressive growth performance involved a large reallocation of workers from agriculture to higher-productivity employment outside of agriculture, in particular in manufacturing.[1] Although many Chinese still work in agriculture, and could also leave agriculture and thereby prolong the first phase of structural change, an important question is what the future will hold for those who already left agriculture. The historical experiences of structural change teach us that the first phase of structural change is followed by a second phase that involves moving workers into the services sector; see for example the evidence presented in Herrendorf et al. (2014).

This paper is about the second phase of structural change in China. The potential of moving workers into the services sector is particularly large in China because its services sector is underdeveloped in comparison to that of other countries at a similar stage of development. We establish this fact by comparing China with a group of countries with similar ppp-adjusted GDP per capita. We find that while the comparison countries have about half of their employment in services, in China it is only about one third. Interestingly, the difference is not evenly distributed between high- and low-skill-intensive services. Instead, China has a similar employment share of low-skill-intensive services as the comparison countries have on average but has a much lower employment share of high-skill-intensive services (7% in China versus 17% in the comparison countries). In other words, the high-skill-intensive services sector is severely underdeveloped for China's stage of development.[2]

We ask why the high-skill-intensive services sector is underdeveloped in China and what it would take for it to develop. Possible reasons for its underdevelopment include large distortions in high-skill-intensive services, relatively low productivity of high-skill-intensive services, and an overall scarcity of high-skilled labor. There is a lively policy debate about which of these reasons is most important. For example, Nabar and Yan (2013) suggested that China's main development challenges are its large distortions and low productivity in services. In contrast, Khor et al. (2016) emphasized that the Chinese workforce is "undereducated", which would particularly affect the development of the high-skill-intensive services sector. We will keep an open mind and entertain all three possibilities and let our analysis determine their relative importance.

We approach the question why the high-skill-intensive services sector is underdeveloped

[1] Brandt et al. (2008), Dekle and Vandenbroucke (2012), and Cao and Birchenall (2013) offer detailed analyses of this first phase of structural change in China.

[2] High-skill-intensive services industries make intensive use of skilled workers, which we define as having at least some college education. Low-skill-intensive services industries make intensive use of workers with less than some college. Given that it normally takes 12 years to complete high school in China or the U.S., the cutoff "at least some college" corresponds to at least 13 years of schooling.

in China by building a model of structural change among goods, low-skill-intensive services, and high-skill-intensive services. Our utility function allows for time varying, long-run income effects, which have been found to be important for the development of the services sector in other countries; see for example Boppart (2014) and Alder et al. (2020). Our production function features skilled and unskilled workers in all sectors, and allows the skill intensities to differ across sectors and to change over time; see for example Buera et al. (2018). To capture that the nominal labor productivities differ across sectors in China even after controlling for sectoral differences in the skill intensity, we introduce output wedges. The wedges stand in for factors that affect the allocation of labor among sectors, including monopoly power in the product or labor markets.

We calibrate our model to match salient features of the Chinese economy during 1988–2009, including the behavior of the sectoral labor, real value added, relative nominal productivity, and relative prices, as well as of the economy-wide skill premium. Since the Chinese data show large gaps between the nominal sectoral labor productivities in the high-skill-intensive services sector and the other sectors, the calibration results in large output wedges in high-skill-intensive services sector that generate a high output price. To put this finding into perspective, we also conduct the analysis for the U.S. during 1950–2010 and find that the wedge in high-skill-intensive services is an order of magnitude smaller than in China.

We find that removing the output wedges would imply sizeable increases in the employment share of high-skill-intensive services that would close most of the gap to the average employment share in the comparison countries. In contrast, increasing the labor productivity in high-skill-intensive services or the share of skilled workers affects the employment share of high-skill-intensive services much less. Lastly, we find that removing the wedges would imply sizeable increases in GDP per capita. In sum, our results suggest that distortions are the main reason for the small size of the high-skill-intensive services sector in China, and that removing them would lead to sizeable GDP per capita gains.

Our results raise the question, What causes the large wedges in high-skill-intensive services? Going beyond our formal analysis of identifying the wedges, we document that in China in 2009, state-owned enterprises ("SOEs") played a prominent role in high-skill-intensive services. Interestingly, they did not only dominate Government Services, which naturally have a large public component, but they also employed one in three workers in Business Services, which are mostly private elsewhere. We document that in both parts of high-skill-intensive services, there are large price distortions. This is consistent with the view that the Chinese public sector provides excessively expensive services and that SOEs have strong monopoly power that leads to high markups and prices.

Our work is related to several recent papers on the growth performance of the Chinese economy. In particular, Zhu (2012) conducted a growth accounting exercise for China and concluded that TFP growth has been the main driver of GDP growth since the reform in 1978. In contrast to us, he disaggregated the economy into agriculture and non-agriculture and focused on the first phase of structural change. Several studies found severe misallocation of production factors in China and sizeable gains in productivity from eliminating the underlying distortions. Examples include Hsieh and Klenow (2009) for manufacturing, Adamopoulos et al. (2017) for agriculture, and Brandt et al. (2017) for regions. In contrast to them, our focus here is on services, which are likely to be more important than manufacturing in the second phase of structural change. Song et al. (2011) highlighted that the private sector had higher productivity than the state sector, and that the reallocation of labor from state-owned to privately-owned enterprises led to large aggregate productivity growth. Our results are consistent with the view that state-owned enterprises ("SOEs") hold back Chinese development, but we find that during the second phase of structural change this is mostly a problem in high-skill-intensive services.

Our work is also related to several recent papers that observed that the usual three–sector split into agriculture, manufacturing, and services becomes less meaningful during the second phase of structural change when most of production is already in the service sector. Since productivity growth is heterogenous within the service sector, with some industries showing strong productivity growth while others showing no productivity growth, the effects of reallocation within the service sector are crucial when one seeks to understand the aggregate implications of the second phase of structural change [Jorgenson and Timmer (2011)]. There are several recent examples that take up this point. Buera and Kaboski (2012) built a model in which after a GDP threshold is passed structural change leads to employment reallocation into high-skill-intensive services. Buera et al. (2018) built on the previous work and studied the quantitative implications of reallocation into high-skill-intensive services for the skill premium. Duarte and Restuccia (2019) studied the role of market versus non-market services in the context of cross-country differences in productivity. Duernecker et al. (2017) distinguish between services with high versus low productivity growth in the context of Baumol's cost disease. Our paper contributes to this literature by identifying distortions as the main cause for the underdevelopment of high-skill-intensive services in China.

The remainder of the paper is organized as follows. The next section presents stylized facts about the second phase of structural change. Section 3 presents the model and Section 4 connects it to the Chinese economy. Section 5 contains our results and Section 6 discusses possible explanations for the wedges, mis-measurement, and possible extensions of our analysis. Section 7 concludes. An Appendix contains additional tables, the details of the solution of our model, and the results from several robustness exercises.

Table 1: Share of High-skilled Workers in U.S. Industry Employment (in %)

Sector	**1950**	**1960**	**1970**	**1980**	**1990**	**2000**	**2010**
	High skilled at least some college						
Low-skill-intensive Services							
Transport & Telecommunication	9	12	18	31	49	45	49
Wholesale & Retail	15	16	19	29	43	38	45
Personal Services	10	9	14	28	46	42	48
Utilities	17	17	21	33	54	46	59
High-skill-intensive Services							
Business & Repair	20	24	31	43	59	58	61
Public Administration	22	26	32	45	65	62	69
Finance, Insurance & Real Estate	27	32	37	49	68	65	72
Professional Services	57	56	56	62	72	70	75
	High skilled at least 2 years of college						
Low-skill-intensive Services							
Transport & Telecommunication	6	8	12	22	22	26	29
Wholesale & Retail	11	11	13	21	19	20	24
Personal Services	7	6	9	20	22	24	28
Utilities	13	12	15	25	28	29	40
High-skill-intensive Services							
Business & Repair	17	19	24	35	36	42	45
Public Administration	16	20	24	35	35	41	47
Finance, Insurance, Real Estate	21	24	29	39	39	45	53
Professional Services	52	51	50	55	53	55	59
	High skilled at least 4 years of college						
Low-skill-intensive Services							
Transport & Telecommunication	3	3	4	10	14	18	20
Wholesale & Retail	5	5	6	10	13	14	17
Personal Services	3	2	4	10	15	18	21
Utilities	7	7	8	13	19	20	29
High-skill-intensive Services							
Business & Repair	9	11	14	22	28	35	37
Public Administration	9	11	14	21	26	31	36
Finance, Insurance & Real Estate	11	13	16	23	31	37	44
Professional Services	38	38	38	41	44	46	49

Data for 1950–2000 constructed from Censuses reported by IPUMS.
Data for 2010 constructed from American Community Survey reported by IPUMS.

2 Facts about the Second Phase of Structural Change

2.1 Constructing Low- and High-skill-intensive Services

Since our paper is about the second phase of structural change in China, we group Agriculture, Construction, Manufacturing, and Mining together as the goods sector, which we do not disaggregate further. Instead, we disaggregate the services sector into high- and low-skill-intensive services. High-skill-intensive services are the services industries that have a higher share of high-skilled workers than the median services industry.

We define high- and low-skilled worker in the usual way by choosing a minimum number of years of schooling required to become high skilled, that is, high-skilled workers have at least as many years of schooling as the chosen cutoff whereas low-skilled workers have fewer years of schooling. The literature has worked with different cutoffs: at least some college, at least an associate's degree, or at least a college degree. In the U.S. the usual years of schooling are 12 for a high-school degree, 14 for an associate's degree (two additional years of higher education), and 16 for a college degree (four additional years of higher education). Choosing a cutoff is complicated by the fact that not all countries have a degree between a high-school degree and a U.S. college degree, and if they do it, then it may have a different meaning or different years of requirement. For example, in China it usually takes three years to obtain the first degree after high school. Although this degree is called a college degree, it has a different meaning from a college degree in the U.S. which takes four years to complete. In China it usually takes four years to complete a university degree, which corresponds to a U.S. college degree.

Table 1 shows the classification that results for the U.S. from using the three common cutoff years for being high skilled. The data are from the Censuses as reported by IPUMS.[3] High-skilled services are: Business and Repair; Public Administration; Finance, Insurance, and Real Estate; Professional Services. Low-skill-intensive services industries are the remaining ones: Transport and Telecommunication; Wholesale and Retail; Personal Services; Utilities. We note that the classification is the same for the three main cutoffs for being high skilled, namely, some college, 2 years of college, and 4 years of college. The classification is also robust over time. While the shares of high-skilled workers went up in all services industries and some industries switched rank, the switches happened within one of the two services sectors so that the assignments of industries to services sectors remain unaffected.

We have started with the U.S. classification of services industries because the U.S. has higher-quality data than China and is a natural benchmark in the group of comparison countries against which we contrast our results for China. This raises the question as to whether the classification would be the same if we used Chinese data on workers' sector and education.

[3]For the period 1990–2010, the U.S. Census does not have information about the years of college attendance but reports whether college was attended and what degree was obtained.

Table 2: Share of High-skilled Workers in Chinese Industry Employment (in %)

Sector	**1990**	**2000**	**2005**	**2010**
Low-skilled				
Transport & Telecommunication	2	7	7	11
Wholesale & Retail	2	5	8	12
Personal Services	2	9	7	9
Utilities	–	16	26	34
High-skilled				
Business and Repair	30	–	35	40
Public Administration	17	39	50	54
Finance, Insurance, Real Estate	11	37	46	48
Professional Services	22	40	56	64

Data constructed from the Chinese Census.

The Chinese Census has the required information for 2010, 2005, 2000, and 1990 but there is an issue with how to define being high skilled in China. The related literature on China uses cutoffs below a university degree; see for example Meng (2012), Ding and He (2018), and Bai et al. (2020). The reason for this is that only very few Chinese have a university degree early on in our period of investigation. To ensure that we have sufficiently many observations, we start with the lowest cutoff "at least some college". We note that the numbers of workers with at least some college are practically identical to those with at least a Chinese college, reflecting that almost everyone who starts college in China also finishes it. Table 2 establishes that the broad classification of industries into low-skill and high-skill intensive services is the same in the Chinese Census as it is in Table 1.[4]

In sum, this subsection has established a classification of services industries into low-skill-intensive and high-skill-intensive services. The classification is the same in the U.S. for the most commonly used definitions of high-skilled. The classification is also the same in China for high skilled defined as at least some college or at least Chinese college.

2.2 Underdevelopment of Chinese High-skill-intensive Services

We now turn to establishing that the Chinese high-skill-intensive services sector is underdeveloped compared to other countries at a similar stage of development. Table 3 compares the Chinese sectoral composition with that of country-year pairs for which the country has a ppp-adjusted GDP per capita within plus/minus $500 of China's GDP per capita in 2009. The table is based on the 10-Sector Database and a crosswalk between the sector classifications in the

[4]Utility was not part of the Chinese industry classification in 1990 and Business Services were not part of the Chinese industry classification in 2000. The lack of observations for Utilities in 1990 and Business Services in 2000 is unlikely to matter because they were small industries.

U.S. Census and the 10-Sector data base is in Table A.1.1 in Appendix A.1.[5]

Table 3 shows that the Chinese share of the services sector in total employment (second column) is lower than the share in any comparison country and is 12 percentage points lower than the average share over all comparison countries. Interestingly, the difference is not evenly distributed over low- and high-skill-intensive services. Instead, the third and fourth columns show that China has a similar employment share of low-skill-intensive services as the average over the comparison countries (0.28 versus 0.30), but a dramatically lower employment share of high-skill-intensive services (0.07 versus 0.17). Thus, what is abnormal in China is the composition of services employment, with only 1/5 of total services employment in high-skill-intensive services compared to an average of more than 1/3 in the comparison countries. We emphasize that the abnormality is about the *composition* of the services sector, instead of its *overall size* relative to the goods sector. Put differently, irrespective of how large the goods sector and how small the services sector are in China, the composition of services is completely off in comparison to the other countries.

Several remarks about the stylized fact follow. We define being at the same stage of development as having a similar GDP per capita as China, which is the most commonly used and widely available measure of development. Of course, countries could differ in many other dimensions, but they should wash out since we compare China with the averages over 17 countries. We use data for China in the year 2009, instead of a more recent year, because our sample for the rest of the analysis stops in 2009. We have verified that the employment share of high-skill-intensive services has not increased much after 2009. In 2016, for example, it was just 9%.

The employment share of Chinese high-skill-intensive services relative to the comparison countries is not the result of business cycle fluctuations around the Great Recession.[6] Instead, it was low also before the year 2009. To establish this, Figure 1 plots the employment share of high-skill-intensive services against the log of GDP per capita for all countries in the 10-Sector Database. The observations for China are from our period of investigation 1988–2009. The figure clearly shows that, compared to the other countries with similar GDP per capita, the Chinese high-skilled-services sector was not at all developed during our entire period of investigation.

The low relative employment share of Chinese high-skill-intensive services is not the result of business cycle fluctuations in the comparison countries. To establish this, Table A.1.3 in the Appendix A.1 reports the shares if we average sectoral employment shares over a five-year interval with its middle point being the year in which the country has comparable GDP per

[5]The 10-Sector Data is published by the GGDC of the University of Groningen. The website states: "GDP and employment data by broad sectors (agriculture, industry, and services) match those from the Chinese Statistical Yearbook 2012 for the period from 1978 onwards."

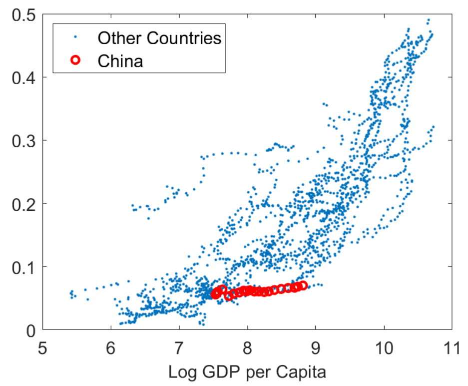
[6]Tan et al. (2017) and Yao and Zhu (2020) are recent analyses of the interaction between structural change and business cycles in China.

Table 3: Sectoral Employment Shares at similar GDP per capita as China in 2009

Country, Year	Services / Total	LSS / Total	HSS / Total	HSS / Services
Argentina, 1994	0.67	0.39	0.28	0.42
Brazil, 2005	0.60	0.38	0.21	0.36
China, 2009	**0.35**	**0.28**	**0.07**	**0.20**
Costa Rica, 2004	0.63	0.40	0.23	0.37
Denmark, 1951	0.42	0.30	0.13	0.30
France, 1957	0.42	0.21	0.21	0.51
Germany, 1959	0.41	0.26	0.15	0.37
Italy 1966	0.39	0.23	0.16	0.41
Japan, 1966	0.46	0.28	0.18	0.39
Malaysia, 1991	0.50	0.30	0.20	0.40
Mauritius, 1988	0.42	0.28	0.14	0.33
Mexico, 1973	0.37	0.23	0.13	0.36
South Africa, 2002	0.58	0.34	0.23	0.41
Spain, 1967	0.41	0.30	0.11	0.26
Taiwan, 1977	0.39	0.27	0.11	0.30
Thailand, 2004	0.37	0.27	0.10	0.27
United Kingdom, 1950	0.51	0.33	0.18	0.36
United States, 1940	0.50	0.33	0.17	0.34
Average	**0.47**	**0.30**	**0.17**	**0.35**

LSS and HSS stand for low- and high-skill-intensive services, respectively.
GDP per capita is in international dollar and is computed from Penn World Tables 8.1.
Employment shares other than in the U.S. are constructed from GGDC 10-sector Database.
Employment share in the U.S. are constructed from U.S. Census accessed through IPUMS.

Figure 1: Employment Share of High-skill-intensive Services around the World



Employment shares are constructed from the GGDC 10-Sector Database. GDP per capita is in international dollar and is computed from Penn World Tables 8.1.

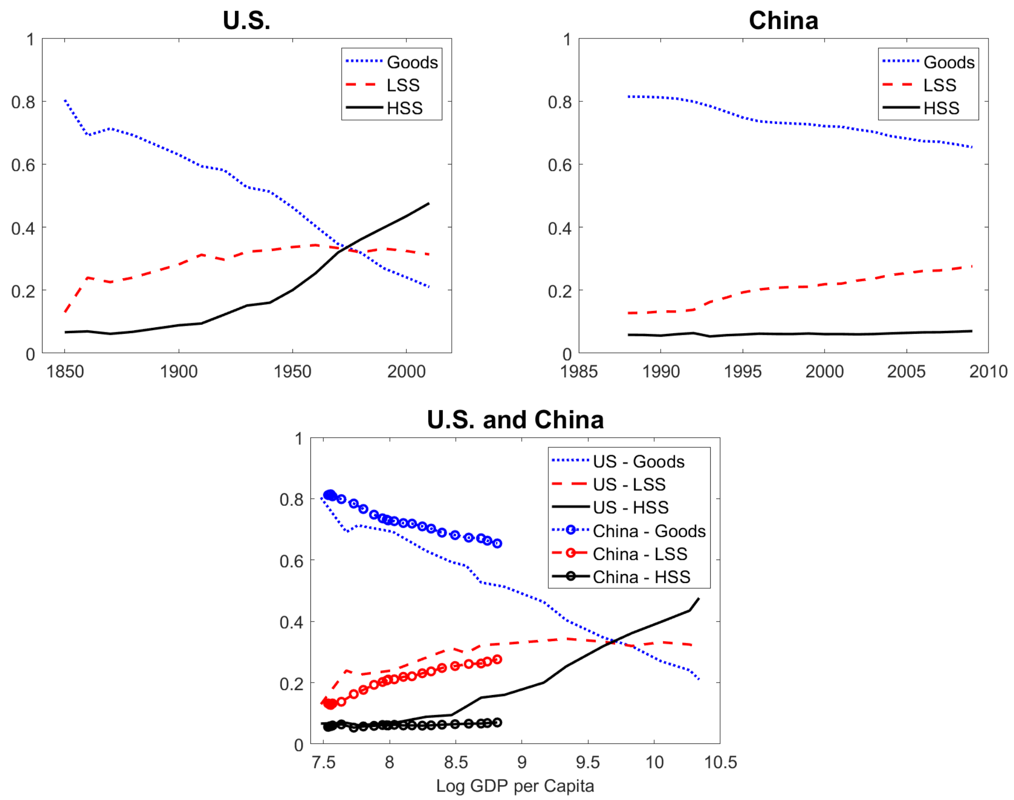
capita with China in 2009. The results are nearly the same as in the benchmark table, although the number of comparison countries drops because going back for two additional years means that the 10-Sector Database no longer has information for all countries of Table 3.

The stylized fact is not driven by the public sector. The 10-Sector Database includes Public Administration in the broader category Government Services. Table A.1.4 in Appendix A.1 reports the stylized fact without Government Services. The main message remains unchanged, but in all countries the high-skill-intensive services share drops considerably compared to the benchmark case. This reflects that Government Services is a large sector that also contains the industries Education and Health Care, which are partly private.

Lastly, the stylized fact is not driven by misclassification of agricultural employment. Yao and Zhu (2020) argued that the official Chinese data overstate agricultural employment, part of which should be reclassified as employment in manufacturing and low-skill-intensive services. If the same issue applied to the 10-Sector Database, then an appropriate reclassification would strengthen our stylized fact, because it would increase the share of low-skill-intensive services, which would decrease the ratio of high-skill-intensive to low-skill-intensive services.

Given how underdeveloped high-skill-intensive services are in China, it is useful to get an idea about the possible scope of future development of high-skill-intensive services during the second phase of structural transformation. Figure 1 suggested that the scope is large. To make the same point with a concrete example, the upper left panel of Figure 2 plots the U.S. employment shares of goods, low-skill-intensive services, and high-skill-intensive services during 1850–2010. The figure shows the well-known fact that the employment share in the goods sectors has steadily declined (which is the net effect of the decline in agriculture and the hump shape in manufacturing). In contrast, the employment share of low-skill-intensive services has been mostly flat and the high-skill-intensive services sector took off after World War II and has

Figure 2: Sectoral Labor Shares in the U.S. and China



LSS and HSS stand for low- and high-skill-intensive services, respectively. U.S. employment shares are constructed from Censuses for 1850–2000 and from the American Community Survey for 2010 reported by IPUMS. Chinese employment shares are constructed from GGDC 10-Sector Database. GDP per capita is taken from the Maddison data and is in 1990 international dollars.

become the largest sector and the only sector that is still growing in relative size.[7] For comparison, the upper right panel of Figure 2 plots the Chinese employment shares of goods, low-skill-intensive services, and high-skill-intensive services during our sample period of 1988–2009. The figure shows that the Chinese share of high-skill-intensive services is at the same level as it was in the U.S. in the 19th century. The lower panel of the figure brings the two countries together by plotting their employment shares against the log of GDP per capita in international dollars. In 1988, China was as poor as the U.S. was around in 1850 and the two countries had similar sectoral compositions. Since then, the high-skill-intensive services sector developed strongly in the U.S. but not in China.

If the experience of the U.S. is anything to go by, then there is huge scope for the development of Chinese high-skill-intensive services. The rest of our paper is about why that has not yet happened and what it would take to make it happen. To provide answers to the questions, we focus on the three most common explanations of the underdevelopment of high-skill-intensive services: large distortions; relatively low productivity; a scarcity of high-skilled labor. To assess how important each of them is, we need a model in which we can isolate their effects by conducting counterfactual exercises. We turn to developing a natural yet simple model now.

3 Model

3.1 Environment

There are three sectors producing goods, low-skill-intensive services, and high-skill-intensive services. We index them by $\{g, l, h\}$, respectively. There are two types of workers: low-skilled and high-skilled workers. Workers can move freely across sectors. Production in each sector uses both types of workers, but the intensity of the types differs across sectors.

The production function in sector $i \in \{g, l, h\}$ combine low-skilled and high-skilled workers according to:

$$y_{it} = Z_{it} L_{it}, \qquad i \in \{g, l, h\}, \tag{1}$$

where L_{it} is an aggregator of high- and low-skilled labor in the sector:

$$L_{it} \equiv \left(\alpha_{it} h_{it}^{\frac{\rho-1}{\rho}} + (1-\alpha_{it}) \ell_{it}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}. \tag{2}$$

y_{it}, h_{it}, and ℓ_{it} are sector $i's$ output, high-skilled labor, and low-skilled labor; Z_{it} is the total factor productivity ("TFP") of sector i; $\alpha_{it} \in (0, 1)$ captures differences in the intensity of high-skilled labor across sectors and time; $\rho \in [0, \infty)$ is the elasticity of substitution between the

[7] Buera and Kaboski (2012) made similar observations.

two labor inputs. To justify calling h high skill intensive and l low skill intensive, we impose that $\alpha_{ht} > \alpha_{lt}$. Note that ρ is assumed to be constant and equal across sectors, which will be an important identifying assumption in our calibration below.

Our production function is as in Buera et al. (2018), and so labor is the only input and we do not model capital accumulation. To capture the effects of capital accumulation, we will calibrate sectoral TFP from the model, Z_{it}, such that we match labor productivity in the data, y_{it}/n_{it} where $n_{it} \equiv h_{it} + l_{it}$ is total sectoral labor. Changes in Z_{it} in the model therefore reflect changes in both sectoral TFP and capital in the data. Looking ahead, we will find that low sectoral productivity is not the main reason for the underdevelopment of high-skill-intensive services. Therefore, distinguishing between changes in TFP and capital would not affect the core of our results. We will come back to the possible role of capital in Subsection 4.2 where we will establish that decreasing returns to labor with different sectoral labor-income shares would not affect the core of our results either.

A key feature of the Chinese data is that nominal labor productivity differs across sectors. In our context, it is essential to capture the differences because they will affect the sectoral allocation of labor, and thus the size of high-skill-intensive service sector. Differences in the sectoral compositions of labor imply differences in value added per average worker, but it turns out that these differences are not sufficient to capture what is in the data. We therefore follow Hsieh and Klenow (2009) and introduce an output distortion, that is, firms must pay an amount τ_{it} per unit of revenue they sell. The payments are lump-sum rebated back to the households.[8] We think of the distortion more broadly than actual taxes as capturing everything that causes differences among nominal labor productivities across sectors. A prominent example is the effect from monopoly power in the product market.[9]

There is representative household with a measure one of members. In period t, a fraction $\Omega_t^h \in [0, 1]$ of the household members is high skilled and a fraction $\Omega_t^l = 1 - \Omega_t^h$ is low skilled. Each household member is endowed with one unit of time in each period, which it supplies inelastically to the labor market. Therefore, the total number of workers equals the population in our model, and GDP per worker and per capita will be the same.

We use the indirect utility function proposed by Alder et al. (2020) because it permits *persistent* income effects. In contrast, the income effects implied by the more commonly used Stone-Geary utility are not *persistent* and vanish when GDP per capita increases considerable as is the case in a fast growing economy like China. To be concrete, during our sample period

[8] Note that if instead we assumed that the revenues from the distortion were thrown away, then the output gains from removing the distortions would increase.

[9] Other authors introduced a labor distortion that increases the wage firms pay; see for example Restuccia et al. (2008) and Herrendorf and Schoellman (2018). Labor distortions are a natural way to capture the effect from monopoly power in the labor market. It is straightforward to show that output and labor distortions have the same main effects in our context: they increase the relative price and decrease the employment share of the sector which they affect.

1988–2009, Chinese GDP per capita went up by a factor of 5. As a result, expressed relative to total income, the income effect resulting from a constant non-homotheticity term shrinks to 20% of its initial size. In contrast, we will find below the income effect on high-skill-intensive services falls by much less in China. This observation is closely related to the result of Alder, Mueller, and Boppart that a non-homothetic CES is not able to match the evolution of the services share in the U.S. during the entire last century. In particular, if it matches the first half of the century, then it cannot match the takeoff of services which started in the late 1940s. Chinese GDP per capita in 2009 was getting close to that in the U.S. during the 1940s. Hence, the result of Alder et al. (2020) implies that even if a non-homothetic CES could match the past growth miracle of China, it would not be able to speak to the future growth of Chinese high-skilled intensive services. Since we want to investigate what would lead to a takeoff of the high-skill-intensive services at the end of our sample, it is crucial to use a utility specification that achieves this in the U.S. when it had similar GDP per capita as China. The utility specification of Alder et al. (2020) is designed to deliver that.

As usual, the indirect utility function depends on prices and consumption expenditure. Let $\vec{P}_t \equiv (p_{gt}, p_{lt}, p_{ht})$ denote the price vector and E_t denote the consumption expenditure of the representative household. The indirect utility function is given by:

$$v(E_t, \vec{P}_t) = \frac{1}{\varepsilon}\left(\frac{E_t}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{\varepsilon} - \frac{1}{\varepsilon} + D(\vec{P}_t). \tag{3}$$

$A(\vec{P}_t)$ and $D(\vec{P}_t)$ are homogeneous functions of degree 0 in the price vector and $B(\vec{P}_t)$ is a linear homogeneous function. These restrictions imply that the indirect utility function does not change when expenditures and all prices are scaled by the same positive factor, which is a minimal requirement for a well specified household problem. Moreover, the Slutsky matrix is negative semi-definite and the indirect utility function decreases in each price. These are the requirements for a valid indirect utility function.

We want a functional form that is flexible enough to capture income effects that are persistent yet may change over time. Alder et al. (2020) proposed the following functional form:

$$A(\vec{P}_t) = \bar{A} \prod_{i \in \{g,l,h\}} p_{it}^{\mu_i - \phi_i}, \tag{4a}$$

$$B(\vec{P}_t) = \prod_{i \in \{g,l,h\}} p_{it}^{\phi_i}, \tag{4b}$$

$$D(\vec{P}_t) = \bar{D} \sum_{i \in \{l,h\}} \nu_i \frac{1}{\psi_i} \left(\frac{p_{it}}{p_{gt}}\right)^{\psi_i}. \tag{4c}$$

The parameters satisfy the following restrictions:

- $0 \le \phi_i \le 1$, $\epsilon \neq 0$, $\psi_i \neq 0$
- $\sum_{i=g,l,h} \phi_i = \sum_{i=g,l,h} \mu_i = \sum_{i=l,h} \nu_i = 1$.

3.2 Equilibrium

We use the following notation: $s_{it}(\vec{P}_t, E_t)$ is the aggregate consumption expenditure share of sector $i \in \{g, l, h\}$; w_t^h and w_t^l are the wages for high-skilled and low-skilled workers; T_t is the aggregate transfer; $Y_t \equiv \sum p_{it} y_{it}$ is GDP.

Equilibrium Definition

- Given $(\vec{P}_t, w_t^h, w_t^l)$, $(y_{it}, h_{it}, \ell_{it})$ solves the problem of the representative firm in sector $i \in \{g, l, h\}$ and period t.
- Given $(\vec{P}_t, w_t^h, w_t^l, E_t)$, $s_{it}(\vec{P}_t, E_t)$ are the expenditure shares of categories $i \in \{g, l, h\}$ that result from the solutions of the household problem.
- Labor markets clear:

$$\sum_{i \in \{g,l,h\}} h_{it} = \Omega_t^h, \tag{5}$$

$$\sum_{i \in \{g,l,h\}} \ell_{it} = \Omega_t^l. \tag{6}$$

- Consistency:

$$\frac{p_{it} y_{it}}{Y_t} = s_{it}(\vec{P}_t, E_t), \tag{7}$$

$$Y_t = E_t, \tag{8}$$

$$T_t = \sum_{i \in \{g,l,h\}} \tau_{it} p_{it} y_{it}. \tag{9}$$

Next, we turn to characterizing the equilibrium. In the main text, we describe the solutions to the household's problem and the firms' problems given expenditure and the skill premium, $\hat{w}_t \equiv w_t^h / w_t^l$. In the appendix, we describe the remaining steps of solving for the equilibrium allocation of the model.

We start with the household's problem. Since each member has the same weight in the household's utility, they consume the same in equilibrium. Roy's identity says that the consumption of good i is given by:

$$c_{it} = -\frac{\partial v(E_t, \vec{P}_t)/\partial p_{it}}{\partial v(E_t, \vec{P}_t)/\partial E_t}, \quad i \in \{g, l, h\}. \tag{10}$$

Let A_{pit}, B_{pit}, and D_{pit} denote the partial derivatives of A_t, B_t, and D_t with respect to p_{it}. Applying Roy's identity to (3), the expenditure shares are:

$$s_{it}(\vec{P}_t, E_t) \equiv \frac{p_{it}c_{it}}{E_t} = \frac{B_t}{E_t} p_{it}A_{pit} + \frac{1}{B_t} p_{it}B_{pit} - \frac{B_t}{E_t}\left(\frac{E_t}{B_t} - A_t\right)^{1-\varepsilon} p_{it}D_{pit}, \quad i \in \{g, l, h\}. \tag{11}$$

We can see that the expenditure shares depend on prices and expenditure in a non-linear way. This will allow the model to capture persistent yet changing non-homotheticities.

Turning to the problems of the firms, given perfect competition in the product and labor markets, the firm in sector $i \in \{g, l, h\}$ solves:

$$\max_{y_{it}, h_{it}, \ell_{it}} (1 - \tau_{it})p_{it}y_{it} - (w_t^h h_{it} + w_t^l \ell_{it}) \quad \text{s.t.} \quad (1).$$

We choose goods in each period as the numeraire, $p_{gt} = 1$. Since relative distortions are what matters for the equilibrium outcome, we also choose $\tau_{gt} = 0$ and call $1/(1 - \tau_i)$ the (output) wedge between sector i and g.

The first-order conditions for $i \in \{g, l, h\}$ are:

$$(1 - \tau_{it})p_{it}Z_{it}\alpha_{it}\left(\frac{L_{it}}{h_{it}}\right)^{\frac{1}{\rho}} = w_t^h, \tag{12}$$

$$(1 - \tau_{it})p_{it}Z_{it}(1 - \alpha_{it})\left(\frac{L_{it}}{\ell_{it}}\right)^{\frac{1}{\rho}} = w_t^l. \tag{13}$$

Dividing equations (12) and (13) by each other gives:

$$\frac{h_{it}}{\ell_{it}} = a_{it}^{\rho}\hat{w}_t^{-\rho}, \quad i \in \{g, l, h\}, \tag{14}$$

where $a_{it} \equiv \alpha_{it}/(1-\alpha_{it})$. Thus, the skill premium pins down the high-to-low-skilled employment ratios in the sectors.

Using equation (14), the production function can be written as:

$$y_{it} = Z_{it}\varphi_{it}(\hat{w}_t)\ell_{it}, \tag{15}$$

where

$$\varphi_{it}(\hat{w}_t) \equiv (1 - \alpha_{it})^{\frac{\rho}{\rho-1}} \left(a_{it}^{\rho}\hat{w}_t^{1-\rho} + 1\right)^{\frac{\rho}{\rho-1}}, \quad i \in \{g, l, h\}.$$

Plugging equation (15) into the first-order condition (13) gives relative prices as functions of the skill premium:

$$\frac{p_{it}}{p_{gt}} = \frac{1}{1-\tau_{it}} \left(\frac{1-\alpha_{gt}}{1-\alpha_{it}}\right) \frac{Z_{gt}}{Z_{it}} \left(\frac{\varphi_{gt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1}{\rho}}, \quad i \in \{l, h\}. \tag{16}$$

Using the expenditure shares from equation (11) together with the previous equation, we obtain an expression for the ratio of low-skilled labor in sectors i and g:

$$\frac{\ell_{it}}{\ell_{gt}} = (1-\tau_{it}) \left(\frac{1-\alpha_{it}}{1-\alpha_{gt}}\right) \frac{s_i(\vec{P}_t, E_t)}{s_g(\vec{P}_t, E_t)} \left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}, \quad i \in \{l, h\}. \tag{17}$$

The labor allocation has six unknowns: $\{\ell_{it}, h_{it}\}_{i \in \{g,l,h\}}$. Given $\hat{w}_t$ and E_t, they are pinned down by the following six equations: equation (5), the three equations in (14), and the two equations in (17). Equation (6) holds by Walras law.

In the Appendix A.2, we show that there is a unique $(\hat{w}_t, E_t)$ for which the solutions of the household's and the firm's problems are consistent with each other.

4 Connecting the Model to the Data

We calibrate the model to match salient features of the Chinese Economy during 1988–2009. We first lay out the calibration strategy and then explain how we construct the data targets.

4.1 Calibration Strategy

The calibration of the preference parameters is standard and effectively follows the procedure that Herrendorf et al. (2013) used when estimating a CES aggregator for consumption with agriculture, non-agricultural goods, and services. Specifically, the expenditure shares $s_{it}(\vec{P}_t, E_t)$ are functions of aggregate expenditures, E_t, and of the prices, $\vec{P}_t$. We calibrate the parameter values of the utility function (4) such that the $s_{it}(\vec{P}_t, E_t)$ implied by the model provide the best fit to the expenditure shares in the data, $p_{it}y_{it}/Y_t$. We use annual data on GDP per capita, sectoral prices, and sectoral expenditure shares and choose the preference parameters to minimize the sum of squared deviations between the implied relative expenditure shares and the relative expenditure shares in the data. Since the expenditure shares add up to one, there are only two independent targets.

The calibration of the production parameters combines the strategies in Buera et al. (2018) and Duernecker et al. (2017). Following Katz and Murphy (1992), we set the elasticity of substitution between high and low-skilled labor $\rho = 1.42$. This amounts to assuming that the U.S. value of the elasticity of substitution also applies to China. There are three reasons for doing this. First, the elasticity of substitution has been re-estimated extensively for the U.S. and it comes out within a reasonable range of the value of Katz and Murphy; see Buera et al. (2018) for more discussion. Second, we do not have data for China to discipline the value of the elasticity of substitution. Third, our results are robust to reasonable changes in the value of the elasticity of substitution. We have established this by varying the elasticity of substitution in the range between 1 and 2 and found that the results hardly change. See Appendix A.3 for the details.

Given the normalization $\{\tau_{gt}\}_{t=0,1,2,...}$ to zero, we are left with nine parameters for each period:[10]

$$\left\{\Omega_t^h, Z_{gt}, Z_{lt}, Z_{ht}, \alpha_{gt}, \alpha_{lt}, \alpha_{ht}, \tau_{lt}, \tau_{ht}\right\}_{t=0,1,2,...}.$$

We jointly target the following nine statistics: GDP in units of goods, Y_t; the three ratios between high-skilled and low-skilled workers by sector, $\{h_{it}/\ell_{it}\}_{i\in\{g,l,h\}}$; the two relative nominal sectoral productivities, $\{(p_{it}y_{it}/n_{it})/(p_{gt}y_{gt}/n_{gt})\}_{i\in\{l,h\}}$; the economy-wide skill premium $\hat{w}_t$; the two relative sectoral prices, $\{p_{it}/p_{gt}\}_{i\in\{l,h\}}$.

It is helpful to give some sense for how the different production parameters are identified. The obvious ones are Z_{gt}, which directly affect the observed Y_t; $\{\alpha_{it}\}_{i\in\{g,l,h\}}$, which directly affect the observed $\{h_{it}/\ell_{it}\}_{i=g,l,h\}}$ as indicated by equation (14); Ω_t^h, which directly affects the observed $\hat{w}_t$. Note that we could have directly targeted Ω_t^h, but targeting $\hat{w}_t$ instead is more convenient when solving the model.

This leaves the identification of $\{\tau_{it}, Z_{it}\}_{i\in\{l,h\}}$ and the particular question of how to identify the wedges separately from the sectoral TFPs. The usual intuition is that the wedges are crucial for matching the observed gaps in *nominal* labor productivities in the data whereas the sectoral TFPs are crucial for matching the gaps in *real* labor productivities. To see this formally in the context of our model, combine (15) and (16) to find:

$$\frac{p_{it}y_{it}/\ell_{it}}{p_{gt}y_{gt}/\ell_{gt}} = \frac{1}{1-\tau_{it}}\left(\frac{1-\alpha_{gt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{gt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}, \quad i \in \{l,h\}. \tag{18}$$

Using that $n_{it} \equiv h_{it} + \ell_{it}$ together with equations (14), (16), and (18) implies that the nominal and real labor productivity gaps are:

$$\frac{p_{it}y_{it}/n_{it}}{p_{gt}y_{gt}/n_{gt}} = \frac{1}{1-\tau_{it}}\left(\frac{1-\alpha_{gt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{gt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}{1+a_{it}^{\rho}\hat{w}_t^{-\rho}}\right), \tag{19}$$

$$\frac{y_{it}/n_{it}}{y_{gt}/n_{gt}} = \frac{Z_{it}}{Z_{gt}}\left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)\left(\frac{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}{1+a_{it}^{\rho}\hat{w}_t^{-\rho}}\right), \quad i \in \{l,h\}. \tag{20}$$

In words, given the calibrated values of $a_{it} \equiv \alpha_{it}/(1-\alpha_{it})$ and ρ and the observed $\hat{w}_t$, wedges

[10]Note that since $\Omega^l + \Omega^h = 1$, the economy-wide share of high-skilled workers is Ω^h.

lead to *nominal* labor productivity gaps whereas sectoral TFP differences lead to *real* labor productivity gaps. Note that sectoral TFP differences leave nominal labor productivity gaps unaffected because they are offset by relative price changes.

In sum, targeting both nominal and real productivity gaps allows us to distinguish between wedges and sectoral TFP gaps. In order to avoid confusion, we should mention that although we do not directly target real labor productivity gaps, they are implied by the nominal labor productivity gaps and the relative prices, which we both target.

Table 4: Sectoral Labor Shares in the U.S. (averages over 1987–2017)

Sector	Labor Share
Goods	0.59
High-skilled services	0.61
Low-skilled services	0.58

4.2 Differences in the Sectoral Labor Shares

A more general production function than our specification (1) would allow for decreasing returns to labor and differences in the sectoral labor-share parameters. Such differences would lead to differences in nominal sectoral labor productivity even in the absence of wedges [Herrendorf and Schoellman (2015)]. This could be modelled either with decreasing returns and labor as the only input or with constant returns and an additional input like capital or land. To see how differences in the sectoral labor-share parameters would affect our calibration strategy, consider the former case and modify the production function to:

$$y_{it} = L_{it}^{\theta_i}, \quad \theta_i \in (0,1), \quad i \in \{g, l, h\}, \tag{21}$$

where L_{it} is as before. Going through the same derivations as in the previous subsection then gives:

$$\frac{p_{it}y_{it}/n_{it}}{p_{gt}y_{gt}/n_{gt}} = \frac{\theta_g}{\theta_i(1-\tau_{it})}\left(\frac{1-\alpha_{gt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{gt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}{1+a_{it}^{\rho}\hat{w}_t^{-\rho}}\right), \quad i \in \{l, h\}. \tag{22}$$

The equation shows that differences in the labor-share parameters lead to nominal productivities gaps too. While this presents a potential challenge to our calibration strategy of using the observed nominal productivity gaps to calibrate the wedges, it is a quantitative question to what extent the differences in the labor-share parameters actually affect our calibration results. If θ_g and θ_i are close to each other, then the effect is small and we can abstract from it.

To see whether differences in the labor-share parameters matter in our context, we calculate the average sectoral labor-share parameters for the U.S. during 1987–2017. While it would be preferable to calculate them for China, we unfortunately do not have the required information.[11] Table 4 shows that the sectoral labor-share parameters for the U.S. are close to each other, and the ratios are actually both slightly *smaller* than one: $\theta_g/\theta_h = 0.97$ and $\theta_g/\theta_l = 0.95$. We conclude from these numbers that modelling differences in the sectoral labor-share parameters is not of first-order importance in our context. Taking the differences in the sectoral labor-share parameters into account would lead to only small *increases* in the implied wedges $1/(1-\tau_{it})$. Since we will find that the wedges are larger – and often much larger – than one anyways, this would reinforce our conclusion that there are large wedges in China.

4.3 Data Targets

We use the numbers from Meng (2012) to construct the Chinese skill premium during 1988–2009. He runs a Mincer regression with the dependent variable log-real annual earnings. The independent variables are three education categories (college and above, senior high school, and junior high school, with primary school being the omitted category); nine categories of work experience; control variables (employment in the state sector; occupational dummies; female dummy; province dummy). The premium of a Chinese college degree compared to primary school is the exponential of the coefficient on college. The premium of less than a Chinese college degree compared to primary school is the employment weighted average of the exponentials of the coefficient on senior high school and on junior high school. The skill premium is the ratio of the two coefficients.

There is a slight inconsistency between Meng's skill premium and our definition of having high skills. Meng defines high skilled as having at least a Chinese college degree whereas we define high skilled as having at least some college. Luckily, the difference does not matter for China because almost all students who start college also finish it. As a result, in China, the numbers for "at least some college" are almost the same as for "at least a college degree".

We use the data from the GGDC 10-Sector Database to construct the sector-level variables for China from 1988–2009.[12] We aggregate industry-level variables to construct sector-level employment, output, prices, nominal and real labor productivities. Since the GGDC 10-Sector Database is built around Törnqvist indexes, which are not additive, aggregating industry-level variables cannot be done by just adding them up. Duernecker et al. (2017) describe in detail how to proceed instead.

Since the 10-Sector Database does not contain data on education by industry, we need an

[11]To be sure, WORLDKLEMS provides sectoral labor share parameters for China. However, they are calculated by assigning all proprietors' income to labor income, instead of following the best practice of splitting it between labor and capital income; see Valentinyi and Herrendorf (2008) for an example of a best-practice calculation of the sectoral labor share parameters.

[12]The industry classification in the 10-Sector data is similar to the classification in the Census Data. Table A.1.2 in Appendix A.1 provides the cross walk between the two classifications.

additional data source to construct high- and low-skilled sectoral labor. There are two possibilities: the Census has the education-industry information for the four years 1990, 2000, 2005, and 2010; the Chinese Household Income Project ("CHIP") has the education-industry information for the five years 1988, 1995, 2002, 2007, and 2013.[13] The Census has the advantage that it is based on many more observations than CHIP. The CHIP has the advantage that it has more years, particularly at the beginning of our sample when the Chinese economy grew very strongly. Our main analysis therefore constructs high- and low-skilled sectoral labor from the CHIP. A subsequent robustness analysis redoes the entire analysis with Census data. We will establish below that our main message holds for both ways of proceeding.[14]

We restrict the CHIP sample to individuals who are older than 15 and are employed. The first step is to construct in CHIP the ratio between high- and low-skilled workers by sector in the separate rural, urban, and migrant surveys. Since CHIP does not contain survey weights, we weight the sectoral ratios by the national shares of urban, rural, and migrant workers.[15] This gives us the ratios between high-skilled and low-skilled workers by sector for all workers in the years 1988, 1995, 2002, 2007, and 2013. We linearly interpolate between theses years to obtain the ratios also for the other years. We calculate the levels of employment of high-skilled and low-skilled workers by sector by multiplying the previous ratios with the total sectoral employment from the GGDC 10-Sector Database.

Table 5: Calibrated Preference Parameters

$\phi_g = 0.00$	$\phi_l = 0.08$	$\phi_h = 0.92$	$\mu_g = 0.92$	$\mu_l = -0.02$	$\mu_h = 0.10$
$\psi_l = 0.81$	$\psi_h = -0.05$	$\nu_l = -0.30$	$\nu_h = 1.30$	$\epsilon = 0.05$	$\bar{D} = 0.98$
		$\bar{A} = 728$			

4.4 Calibrated Parameter Values

Table 5 reports the calibrated parameters from the household side. The individual parameters do not have much of an economic interpretation, except that they must imply that the Slutsky matrix is negative semi-definite and the indirect utility function decreases in each price. We have verified that this is the case. What matters is their implications for the demand system. This is best illustrated by reporting the implied elasticities. Figure 3 depicts the income elasticities. The key implication of the calibration is that high-skill-intensive services are strong

[13]CHIP separately surveyed rural and urban households before 2002 and also separately surveyed migrant households from 2002 onwards. We cannot use the CHIP data from 1999 and 2008 because the 1999 wave only surveyed urban households and the 2008 wave missed education information for many rural households.

[14]Note that if we use CHIP, the classification of industries into low- and high-skilled is the same as with the Census.

[15]The numbers of urban and rural workers come from the Labor Statistical Year Book and the number of migrant workers comes from the Migrant Worker Survey.

Figure 3: Calibrated Income Elasticities

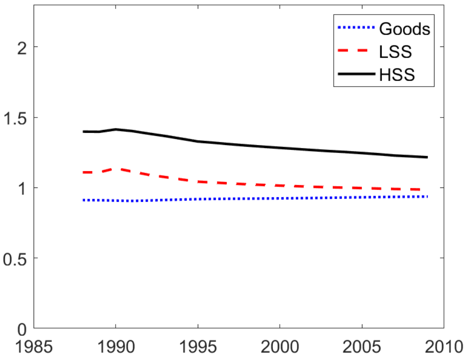
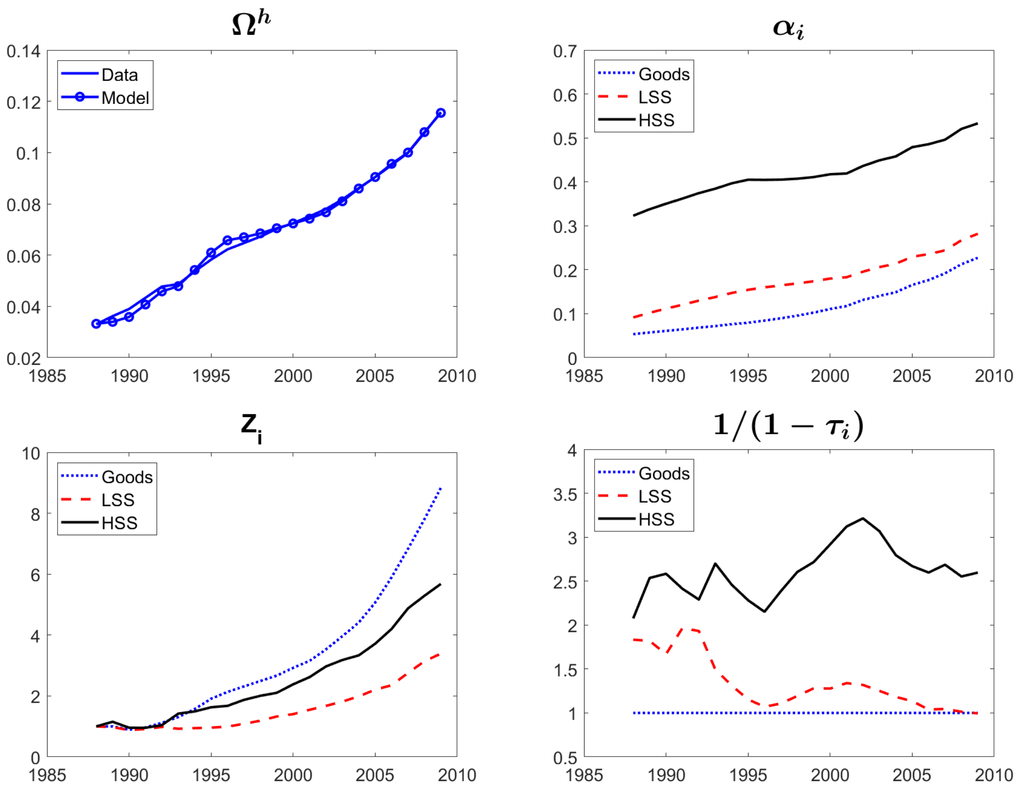


Figure 4: Calibrated Parameters – Production Side



luxuries (i.e. have an income elasticity clearly above one), whereas low-skill-intensive services are luxuries and goods are necessities (i.e., have income elasticities below one). Moreover, the income elasticity of high-skill-intensive services does not decline much over time. We could not capture this with a variant of the Stone-Geary utility specification, because it would introduce the non-homotheticity through time-invariant terms whose quantitative importance would decline as income grows. A second important implication of the calibration is that the elasticities of substitution among the three categories come out close to one. In particular, the average elasticity of substitution between high-skill-intensive services and goods is 0.95, that is, the two are complements. Moreover, the average elasticity of substitution between high and low-skill-intensive services is one, that is, the two are neither complements nor substitutes.

The calibrated parameters from the production side are reported in Figure 4. The share of high-skilled workers, Ω_t^h, increased from 3% to 11%. Although Ω_t^h was not directly targeted, the calibrated Ω_t^h (circles) are very close to the data (solid line). The skill intensities, α_{it}, are highest in high-skilled intensive services and lowest in goods and they increased in each sector. The sectoral labor productivities, Z_{it}, increased in all sectors, and the increase was largest in goods and smallest in low-skill-intensive services. The wedge in low-skill-intensive services, $(1-\tau_{lt})^{-1}$, declined to around one whereas the wedge in high-skill-intensive services, $(1-\tau_{ht})^{-1}$, fluctuated around the large mean of 2.5 without showing a clear trend.

The calibrated model matches the Chinese targets well. In fact, as shown in Figure 5, it exactly matches GDP per capita, the skill premium, relative prices, relative nominal labor productivity, and the high-to-low-skilled employment ratios by sector. The calibrated model also matches the expenditure shares well. Lastly, as shown in Figure 6, the calibration gets very close to the real labor productivities and sectoral employment shares, which are not directly targeted. Note that although real labor productivities are not directly targeted, they are effectively targeted because nominal labor productivities and relative prices are.

One notable feature of the graphs is that in the initial years the skill premium is almost zero. While one might find this hard to believe, it is in fact consistent with the evidence from a variety of studies. In particular, Meng (2012) points out that before the reform, all Chinese workers essentially worked under the same wage system, which offered sizeable returns to years of experience and hardly any returns to schooling. Consistent with that observation, Zhang et al. (2005) found that in 1988 the skill premium was just 4% in urban China. Moreover, Appleton et al. (2005) found that most of the observed wage differences in 1988 were due to experience differences. The roles of experience and schooling were reversed in the 1990s, with a considerable decrease in the experience premium and a considerable increase in the schooling premium.[16]

[16]To avoid confusion, note that while we use the term skill premium instead of schooling premium, the two mean the same thing.

Figure 5: Targeted Variables – Model and Data

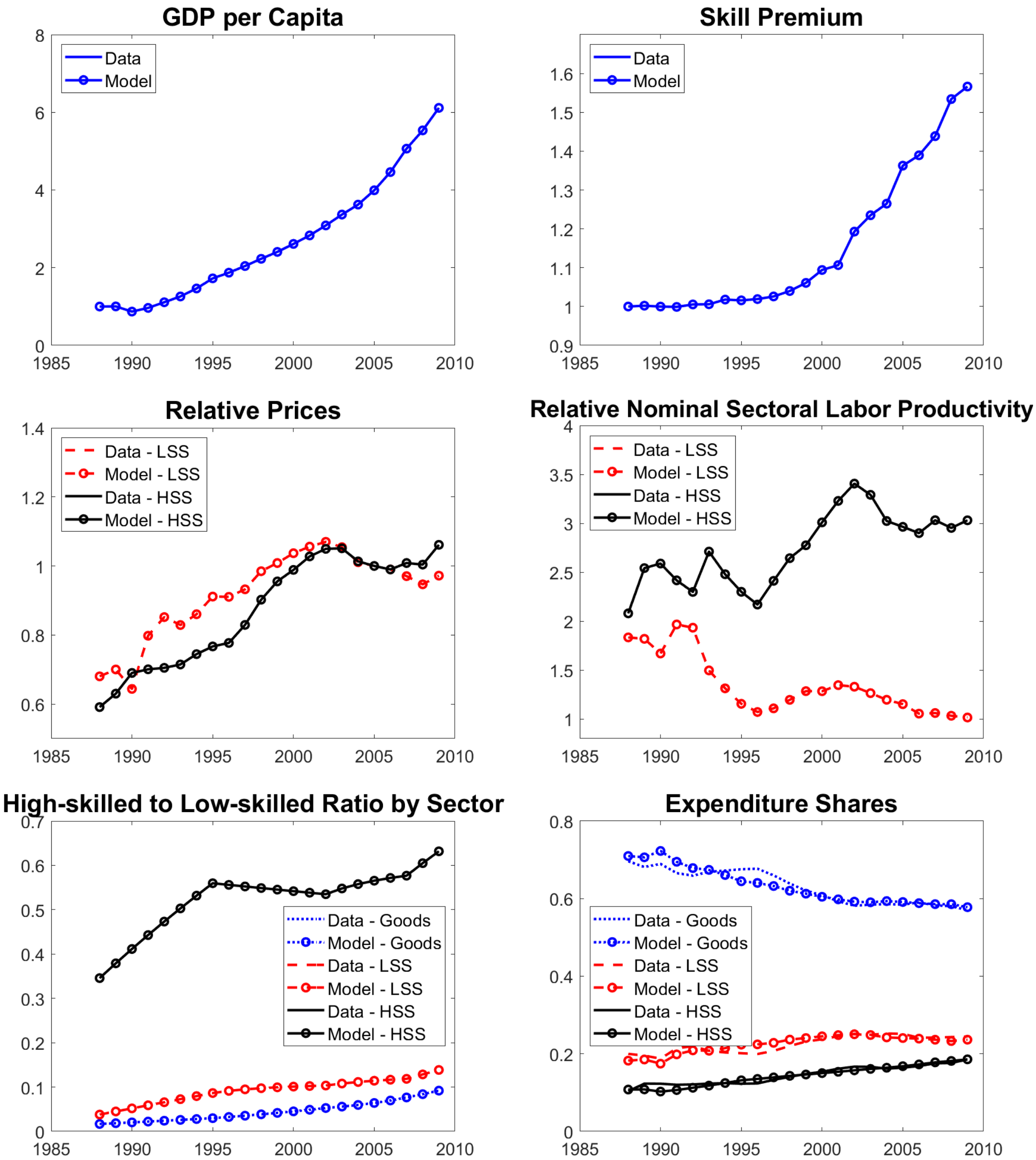
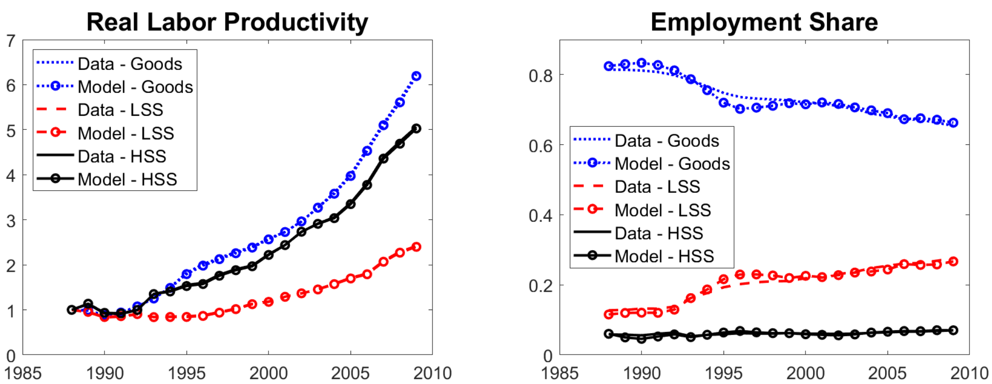


Figure 6: Non-targeted Variables – Model and Data



5 Results

This section studies the effects of labor productivity, wedges, and skill composition on the development of China. We first use our model to identify their contributions to the Chinese growth miracle. We then identify which factor led to the underdevelopment of the high-skill-intensive services sector in China. Lastly, we analyze how much Chinese GDP per capita would increase if the high-skill-intensive services sector developed.

5.1 What Drove Chinese Growth during 1988–2009?

This subsection uses the calibrated model to identify the contributions of changes in the different exogenous variables to Chinese GDP growth during 1988–2009. To achieve this, we keep one of the exogenous variables constant at its 1988 value and let the other variables change as dictated by the calibration.

Before we delve into the results, it is necessary to spend a moment on how to measure counterfactual changes in GDP per capita. We have so far just expressed GDP per capita in units of goods. While that is convenient from the point of view of solving the model, this is not the way in which GDP per capita is calculated in the 10-Sector Database. Instead of using the numeraire goods in each period, it is built around Törnqvist indexes. To be able to compare our counterfactual results with past GDP per capita growth, we will therefore measure changes in GDP per capita with the Törnqvist index. The growth rate between periods t and $t+1$ of GDP per capita is defined as:[17]

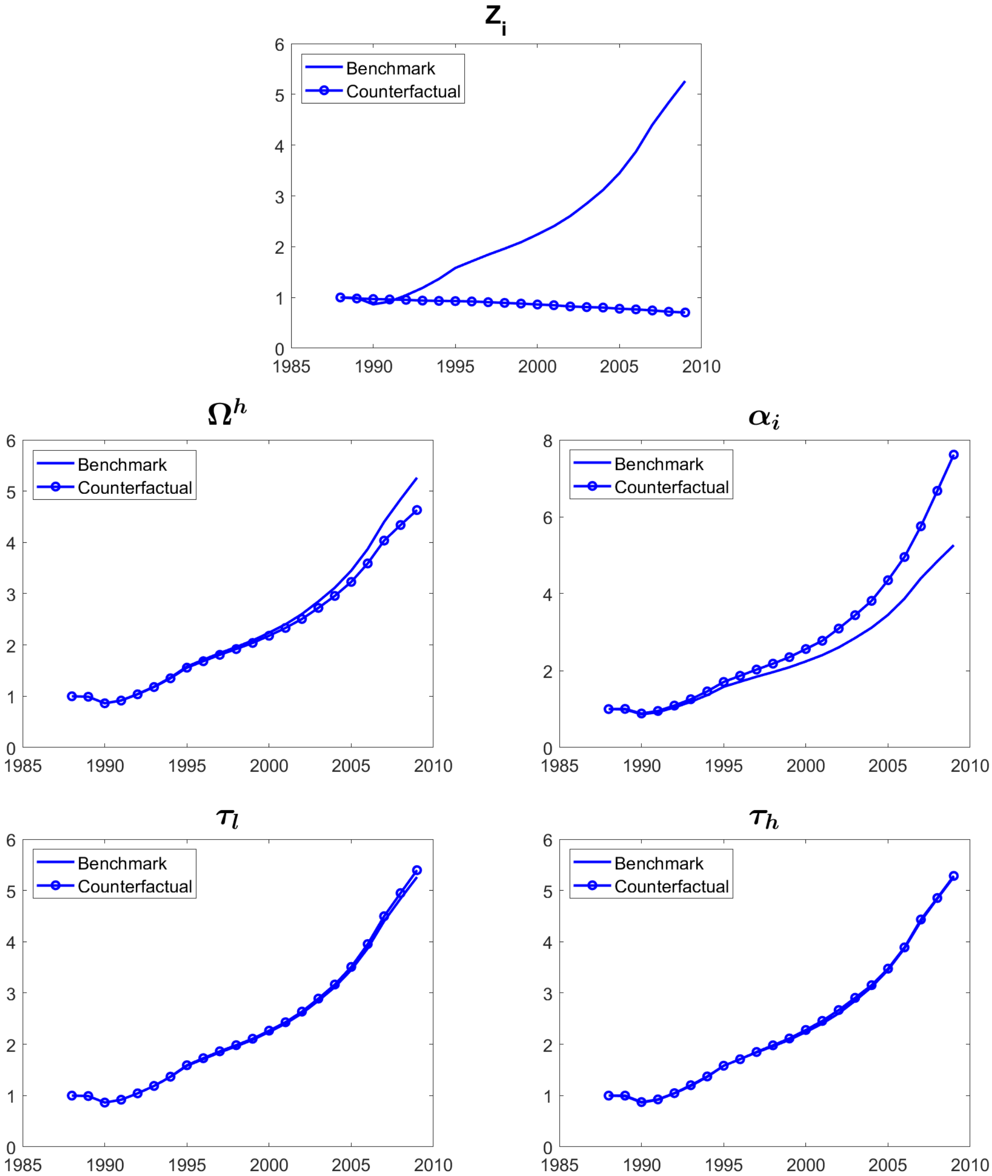
$$\Delta \log Y_t = \sum_{i=g,l,h} \frac{s_{it} + s_{i,t+1}}{2} (\log y_{i,t+1} - \log y_{it}). \tag{23}$$

As above, y_{it} denotes output in sector i and s_{it} denotes the share of nominal value added of sector i in the economy-wide total. The Törnqvist indexes uses the average share over the adjacent periods between which the growth rates are calculated.

Figure 7 reports the results. As a point of reference, the figure also reports what happens when all variables change as dictated by the calibration (solid lines), so the difference between the two lines is the contribution of a particular variable to Chinese economic growth between 1988 and 2009. Clearly, the growth of labor productivity is the main driver of the Chinese growth miracle since 1980s. Without labor productivity growth, real GDP per capita would actually have declined. The increase in the fraction of high-skilled labor also contributes to the growth in real GDP per capita, but the contribution is small in comparison to that of labor productivity. In sharp contrast to the results on labor productivity and education, the effect of increases in the skill intensity, α_{it}, is *negative* and *decreases* real GDP per capita. While this

[17] Note that the total number of workers is normalized to one.

Figure 7: Counterfactual GDP per capita Keeping one Parameter Constant



result may seem surprising at first sight, upon closer inspection one realizes that during the period of investigation high-skilled labor remained rather scarce, increasing from 3% at the beginning to 11% at the end of the period. The relative scarcity of high-skilled labor implies that real GDP per capita would actually have been larger if the relative weights of high-skilled labor had not increased. Lastly, there are hardly any effects from changes in the wedges τ_{lt} and τ_{ht} on GDP per capita. In both cases, the benchmark and the counterfactual lie almost on top of each other. This comes about because the wedge in high-skill-intensive services is very large throughout and does not have a strong trend. Keeping the wedge in low-skill-intensive services at its high 1988 value would therefore have had two effects: it would have minimized the distortion between low-skill-intensive and high-skill-intensive services; it would have maximized the distortion between low-skill-intensive services and goods. It turns out that the net effect is a wash.

It is reassuring that our results about the relative importance of labor productivity and education for Chinese growth are consistent with those of Zhu (2012). Doing a growth-accounting exercise, he found that TFP growth was the main driver of China's rapid growth after 1978 whereas the contribution of human capital was positive yet modest. Although the basic conclusions are the same, it is important to keep in mind that our labor productivity growth includes the effects of capital accumulation whereas Zhu's TFP growth did not.

5.2 Why is the Chinese High-skill-intensive Services Sector Underdeveloped?

We now assess the three possible reasons for the underdevelopment of high-skill-intensive services sector that are being discussed in the literature: a large distortion in high-skill-intensive services as measured by our wedge (i.e., high τ_{ht}); a low labor productivity in high-skill-intensive services (i.e., low Z_{ht}); a shortage of high-skilled workers (i.e., low Ω_t^h).

We start with noting that, despite claims to the opposite, it is far from obvious that China suffers from a shortage of high-skilled workers. For example, looking at the skill composition for the subset of comparison countries from Table 3 for which we have data, Table 6 shows that in China 11% of the employed workers have some college, which exceeds the country averages of 10%. Judging by this comparison, workers in China are not at all "undereducated" given China's stage of development. Our formal analysis will confirm this first impression.

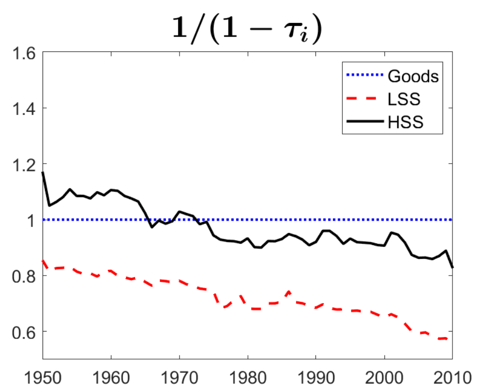
We approach the question why the high-skill-intensive services sector is underdeveloped in China by asking how the sectoral composition is affected by the wedge in high-skill-intensive services, the sectoral labor productivities and the skill composition. To understand what lower bound is reasonable for the wedges, we compare the wedges in China with those in the U.S. In particular, we recalibrate our model to the U.S. during 1950–2010 and calculate the wedges in the same way as for China. To ensure comparability with the analysis for China, we again define

Table 6: Share of High-Skilled Workers in Total Employment at similar GDP per capita (in %, high skilled defined as at least some college)

Country, Year	Education Year	Share of High-skilled
Argentina, 1994	1991	9
Brazil, 2005	2000	11
China, 2009	**2009**	**11**
Costa Rica, 2004	2000	21
Malaysia, 1991	1991	6
Mexico, 1973	1970	3
South Africa, 2002	2007	8
Thailand, 2004	2000	10
United States, 1940	1940	12
Average		**10**

Education shares are computed from IPUMS International where available. Education years are within plus or minus five years of the years reported for the same country in Table 3.

Figure 8: Output Wedges in the U.S.



high skilled as having at least some college. Figure 8 shows that in the U.S. the wedges are much smaller than in China. In fact, over the entire period 1950–2010, the average U.S. wedge in high-skill-intensive services equals 0.97. Moreover, the U.S. wedges in the two services sectors fall over time and end up way below the normalized goods sector wedge of one. This is likely to capture that goods are getting more distorted compared to services, for example because of subsidies for agriculture, steel production, etc. We think that it is not desirable to impose increasing distortions in the U.S. goods sector on our counterfactuals, and so we use zero wedges in the counterfactual experiments for China.

Table 7: Results about Sectoral Shares and Nominal Labor Productivity Gaps

Parameter Values	n_h	n_l	n_g	s_h	s_l	s_g	$\frac{p_h y_h/n_h}{p_g y_g/n_g}$	$\frac{p_l y_l/n_l}{p_g y_g/n_g}$
Benchmark	0.07	0.27	0.66	0.19	0.24	0.58	3.03	1.02
$\tau_h = 0$	**0.15**	**0.24**	**0.61**	**0.18**	**0.23**	**0.59**	**1.22**	**1.02**
$Z_h = 1.5Z_{h,09}$	0.07	0.26	0.67	0.18	0.23	0.58	3.03	1.02
$Z_h = 1.5Z_{h,09}, \tau_h = 0$	0.15	0.23	0.62	0.18	0.23	0.60	1.22	1.02
$Z_h = 2Z_{h,09}$	0.07	0.26	0.67	0.18	0.23	0.59	3.03	1.02
$Z_h = 2Z_{h,09}, \tau_h = 0$	0.15	0.23	0.62	0.17	0.23	0.60	1.21	1.02
$\Omega^h = 1.5\Omega^h_{09}$	0.08	0.26	0.66	0.19	0.23	0.58	2.71	1.00
$\Omega^h = 1.5\Omega^h_{09}, \tau_h = 0$	0.16	0.23	0.61	0.18	0.23	0.59	1.10	1.01
$\Omega^h = 2\Omega^h_{09}$	0.09	0.26	0.65	0.18	0.23	0.59	2.41	0.99
$\Omega^h = 2\Omega^h_{09}, \tau_h = 0$	0.18	0.23	0.60	0.18	0.23	0.60	1.00	1

"09" is for 2009 calibration. n_h, n_l and n_g are the employment shares and s_h, s_l and s_g are the value-added shares of high-skill-intensive services, low-skill-intensive services, and goods. $(p_i y_i/n_i)/(p_g y_g/n_g)$ and $(y_i/n_i)/(y_g/n_g)$ are nominal and real labor productivity for HSS and LSS relative to goods

Table 7 reports the sectoral shares of employment and value added for three counterfactual exercises: we reduce the wedge in high-skill-intensive services to zero; increase the labor productivity of high-skill-intensive services by 50 and 100%; increase the economy-wide ratio of high- to low-skilled workers by 50% and 100%. The main takeaway of Table 7 is that the wedge in high-skill-intensive services is the primary reason for why employment in high-skill-intensive services is so low. In particular, if we eliminate the wedge in high-skill-intensive services (second row), then employment in high-skill-intensive services increases to 15%. This is close to the 17% average share over the comparable countries listed in Table 3. The rise in the employment in high-skill-intensive services results in a decline of 3 percentage points in employment for the low-skill-intensive services sector and a decline of 5 percentage points for the goods sector. It is remarkable that just removing the wedge in high-skill-intensive services sector brings us most of the way to the average over the comparable countries. Moreover, if we eliminate the wedge of high-skill-intensive services together with changes in Z_h or Ω^h, then we get even larger effects on the employment in high-skill-intensive services. But they are essentially the combination of the separate effects, implying that possible interaction terms remain small.

In contrast, if we increase the productivity of high-skill-intensive services or the share of high-skilled workers in isolation, then the effects on the employment share of high-skill-intensive service remain modest. We also find that the expenditure shares hardly change in any experiment and eliminating the wedge in high-skill-intensive services is the only change that considerably reduces the nominal productivity gaps of high-skill-intensive services (second last column). The last finding is useful to keep in mind for later when we will use nominal productivity gaps as proxies for wedges in case we cannot measure the wedges.

To build intuition for our findings, it is helpful to rewrite equation (19) from above as:

$$\frac{n_{it}}{n_{gt}} = (1-\tau_{it})\frac{p_{it}y_{it}}{p_{gt}y_{gt}}\underbrace{\left(\frac{1-\alpha_{it}}{1-\alpha_{gt}}\right)\left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{1+a_{it}^{\rho}\hat{w}_t^{-\rho}}{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}\right)}_{\text{does not move much}}, \quad i \in \{l,h\}. \tag{24}$$

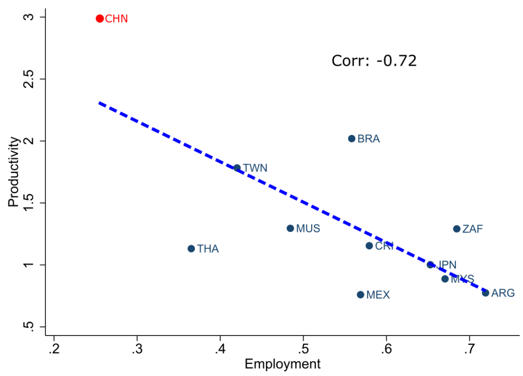
The last three terms of the right-hand side do not move much for the counterfactual experiments, so we can ignore them for the purpose of building intuition. That leaves the wedge and the expenditure ratio. The findings of Table 7 are a combination of two effects: the wedge of high-skill-intensive services strongly moves the employment ratio of high-skill-intensive services;[18] nothing moves the expenditure ratio much. The first finding is clearly illustrated by equation (24). To understand the second finding, note that three different channels affect the expenditure ratio. First, the substitution within services will not affect the expenditure ratios much because the elasticity of substitution between the two services is almost one. Second, the relative price of high-skill-intensive services falls when we remove the wedge of high-skill-intensive services, increase the TFP of high-skilled services, or make high-skilled workers become more abundant. Since the elasticity of substitution between high-skilled services and goods is 0.95, the fall in the relative price leads to a decline in the expenditure shares for both services and a rise for goods. However the quantitative effect through this channel is small since the elasticity of substitution is close to one.

Third, in 2009, the income elasticities are 25% in high-skill-intensive services and close to 0 in low-skill-intensive services and goods.[19] Decreasing the wedge of high-skill-intensive services or increasing their TFP does not increase income by much because they are only 7% of total employment. Doubling the share of high-skilled workers does not increase income by much either because, at the end of the sample, high-skilled worker are around 10% of all workers while the skill premium is about 60%. Combining the income elasticity of 25% with modest income changes implies that income effects on the expenditure share of high-skill-intensive ser-

[18] The direct effect is proportional to the change in the wedge and is large. The indirect effect depends on the implied change in the skill premium and is small.

[19] Figure 3 plots the income elasticities. The income elasticity of the expenditure share is the income elasticity of expenditure minus one.

Figure 9: Ratios of Nominal Productivity and of Employment in HSS versus LSS
(when country has similar GDP pc as China in 2009)



Sectoral nominal productivities and employment are from GGDC 10-Sector Database.

vices remain modest. Taken the substitution and income effects together, it becomes clear that the experiments hardly affect the expenditure shares. TFP in high-skill-intensive services and skill composition affect employment shares mainly through the income effects. Since changes of them have limited income effects, they also have limited effects on the employment share of high-skill-intensive services.

We end this subsection by pointing out that our analysis has an interesting cross-country implication. If the wedges vary across countries, then our model implies a negative correlation between nominal productivity gaps and employment ratios in high- relative to low-skill-intensive services. The reason is that equation (19) implies that a larger wedge leads to a higher nominal-labor-productivity ratio while the quantitative results of this section imply that a larger wedge leads to a lower employment ratio. Figure 9 shows that the negative correlation is strongly present in the subset of our comparison countries for which the 10-Sector Database has nominal sectoral value added data. We interpret this as evidence for the validity of our model.

5.3 What are the Output Gains from Removing the Distortions?

Having established that wedges are the primary reason for the underdevelopment of high-skill-intensive services in China, this subsection studies the quantitative effects on GDP per capita of removing them. As before, the benchmark is the calibrated 2009 Chinese economy and GDP per capita is calculated with the Törnqvist index.

Table 8 reports the effects of wedges in high-skill-intensive services on nominal and real sectoral labor productivities relative to goods and on GDP per capita. The table shows that removing the wedge in high-skill-intensive services leads to an increase in GDP per capita by 5%. This is a large gain! As we saw above, the increase involves a strong reallocation of labor to high-skill-intensive services, implying that the employment share in high-skill-intensive services increases from 7% to 15%. The table also shows that increases in Z_h and Ω^h increase GDP per capita as well, although they have only small effects on the sectoral allocation of labor. Not surprisingly, only increases in Z_h increase the relative real productivity in high-skill-intensive services considerably. Lastly, the interaction effects are again modest, that is, if we change Z_h or Ω^h together with τ_h, the percentage increase of the combined effect equals about the sum of the separate percentage increases.

Table 8: Results about Relative Productivities and GDP per capita

Parameter Values	$\frac{y_h/n_h}{y_g/n_g}$	$\frac{y_l/n_l}{y_g/n_g}$	Y
Benchmark	2.86	1.04	1
$\tau_h = 0$	**2.80**	**1.04**	**1.05**
$Z_h = 1.5Z_{h,09}$	4.29	1.05	1.08
$Z_h = 1.5Z_{h,09}$, $\tau_h = 0$	4.21	1.04	1.13
$Z_h = 2Z_{h,09}$	5.72	1.05	1.13
$Z_h = 2Z_{h,09}$, $\tau_h = 0$	5.61	1.04	1.19
$\Omega^h = 1.5\Omega^h_{09}$	2.89	1.05	1.03
$\Omega^h = 1.5\Omega^h_{09}$, $\tau_h = 0$	2.90	1.05	1.08
$\Omega^h = 2\Omega^h_{09}$	2.91	1.05	1.04
$\Omega^h = 2\Omega^h_{09}$, $\tau_h = 0$	2.92	1.05	1.09

"09" is for 2009 calibration. $(y_i/n_i)/(y_g/n_g)$ are real labor productivity for HSS and LSS relative to goods. Y is output.

As we mentioned earlier, an alternative to using CHIP for the education-industry information is to use Census data. Appendix A.4 reports the results when we redo our analysis with Census instead of CHIP data. While the exact numbers change somewhat, the main messages prevail: labor productivity growth was the main driver of the growth in Chinese GDP per capita in the past decades; large wedges in high-skill-intensive services are the main cause of the under-development of high-skill-intensive services in China; removing the wedges in high-skill-intensive services leads to sizeable gains in Chinese GDP per capita. We now turn to discussing these results further.

6 Discussion

6.1 State-owned Enterprises

Our formal analysis stops with identifying where the wedges are located at the level of our three broad sectors. In this subsection, we go a step beyond our formal analysis and ask, What may cause the large wedges in high-skill-intensive services? We document that in China in 2009 state-owned enterprises ("SOEs") played a prominent role in high-skill-intensive services and we suggest that they led to important distortions.

Table 9 lists the employment shares of SOEs (including the public sector) in China in 2009 along with the industries' employment shares and nominal productivity gaps and the sectoral wedges for China and also the U.S. The industry classification of the table is based on the 10-Sector Database. The U.S. wedges are from the calibration of our model to the U.S. described above. Table 9 shows that in 2009 SOEs (including the public sector) employed more than two thirds of the workers in the high-skill-intensive services sector, but fewer than one in ten of the workers in the low-skill-intensive services sector and fewer than one in 30 of the workers in the goods sector. Within high-skill-intensive services, SOEs dominated Government Services, which contain Public Administration, Education, and Health Care. While Public Administration is state run by definition, Education and Health Care are partly private in the U.S. SOEs also had a strong presence in Business Services where they employ one in three workers. Business Services contain Business and Repair, Banking, Insurance, and Real Estate, and Professional Services, all of which are mostly private in the U.S.[20]

To provide further evidence, we compare the Chinese wedges with those in the U.S. The Maddison Data imply that, in 1990 international dollars, Chinese GDP per capita in 2009 is comparable to U.S. GDP per capita between 1939 and 1940. The first year for which we have reliable data to calculate U.S. wedges is 1950, for which U.S. GDP per capita is not far away from Chinese GDP per capita in 2009. Table 9 shows that in China the wedge in high-skill-intensive services is more than twice as large as in the U.S., implying that high-skill-intensive services are much more distorted in China. It would also be helpful to know the values of the wedges at the level of the two subsectors of high-skill-intensive services. Unfortunately, it is not possible to calculate them without fundamentally complicating the model by introducing additional sectors. However, we can calculate the nominal-labor-productivity gaps for the two subsectors directly from the data. This is still informative, because, as equation (19) shows, the wedges are mainly determined by the nominal productivity gaps since other terms do not change much. Table 9 shows that in both parts of high-skill-intensive services, the nominal productivity gaps relative to goods are more than twice as large in China in 2009 than in the U.S. in 1950. This implies that the relative prices of both high-skill-intensive services are excessively high in China. This is consistent with the view that the Chinese public sector provides excessively expensive services and that SOEs in high-skill-intensive services have strong monopoly power that leads them to charge high markups and prices.

There is ample independent evidence that Chinese SOEs indeed have strong monopoly power. To begin with, they have strong monopoly power in the product markets. Zhu (2012) (in the second paragraph of the last page) sets the scene: *"Protected by barriers to entry of*

[20]We can disaggregate the two high-skilled services industries further because Census data distinguishes Business and Repair; Public Administration; Finance, Insurance, Real Estate; Professional Services. Table A.1.5 in the Appendix shows that the share in total employment of each of these industries' employment was at least twice as high in the U.S. in 1950 than it was in China in 2010.

Table 9: Employment, Wedges, and Productivity Gaps in China and the U.S.

	Ind. Emp. (% in tot.)	SOE Emp. (% in ind.)	Nom. Prod. Gap (rel. to goods)	Wedge
China in 2009				
Goods	0.65	0.03	1	1
Low-skill-intensive Services	0.28	0.09	1.02	1
Transport & Telecommunication	0.04	0.36	2.20	–
Trade Services	0.10	0.03	1.33	–
Personal Services	0.13	0.13	0.22	–
Utilities	0.01	0.65	6.46	–
High-skill-intensive Services	0.07	0.71	3.03	2.60
Business Services	0.01	0.27	8.27	–
Government Services	0.06	0.96	1.83	–
U.S. in 1950				
Goods	0.45	–	1	1
Low–skill-intensive Services	0.34	–	0.87	0.86
Transport & Telecommunication	0.06	–	1.25	–
Trade Services	0.20	–	0.78	–
Personal Services	0.07	–	0.59	–
Utilities	0.01	–	2.74	–
High–skill-intensive Services	0.21	–	1.23	1.17
Business Services	0.05	–	2.81	–
Government Services	0.16	–	0.79	–

Chinese industry SOE shares are computed from the Chinese Labor Statistical Yearbook. Chinese industry employment shares and nominal productivity gaps are from the 10-Sector Database. Wedges for China are from our model. U.S. wedges are from our model calibrated to the U.S. using Data from World KLEMS. Table A.1.1 and A.1.2 in Appendix A.1 offer the crosswalks between the industry classifications of the U.S. Census and of the 10-Sector Database and the Chinese Labor Statistical Yearbook, respectively. The cross walk between the 10-Sector Database and KLEMS is at https://www.rug.nl/ggdc/productivity/10-sector/?lang=en.

private and foreign firms, state controlled firms continue to enjoy substantial monopoly rights and profits in industries ranging from energy, transportation, and telecommunication to banking, entertainment, education, and health care." On a more detailed level, Bai et al. (2006) and Firth et al. (2009) document that Chinese SOEs have preferential access to loans from banks, which constitutes a barrier to entry that leads to monopoly power. Berkowitz et al. (2017) establish that even after the reforms of the late 1990s, SOEs were under fierce political pressure to hire excess labor, which is feasible only if they can charge monopoly mark ups above true marginal cost. Turning to barriers to entry into specific high-skilled services industries, there are severe entry barriers in the banking and insurance industry and the health industry. The banking sector in China has a strong presence of SOEs and it is accessible to foreign investors only through joint venture structures with Chinese companies. Hence, large Western banks are largely absent in China. The health sector in China is also dominated by SOEs and only recently were foreign investors allowed to enter the Chinese market. Specifically, at the end of 2011, investors from Hong Kong, Macau, and Taiwan were allowed to establish entirely foreign-owned hospitals in designated cities and provinces. While that was extended to the whole country in 2014, there are still only few private and foreign hospitals in China.[21] Yue et al. (2011) and Qi and Liang (2016) document that there is also monopoly power in the labor markets. Worker in the industries that are dominated by SOEs earn considerably more than workers in private companies, but only about half of the earnings gaps can be attributed to workers' characteristics. Thus, the employees in the SOE dominated industries must have monopoly power. For our purposes, monopoly power of workers has the same effect as monopoly power of firms: both increase the price of final output above the one that would prevail under perfect competition in product and labor markets.

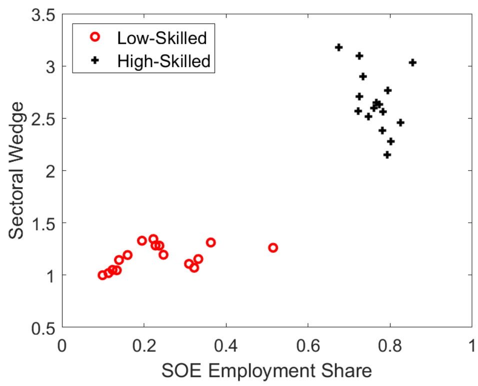
The previous discussion suggests that SOEs lead to important distortions. Our model picks up the distortions through wedges. If SOEs are responsible for the distortion that drive the wedges, then we expect a positive relationship between the observed employment shares of SOEs and the measured wedges in the two services sectors. Figure 10 plots the two against each other for all years for which we have observations. The relationship between them is clearly positive, suggesting that a larger SOE presence is associated with larger distortions.

6.2 Alternative Explanations

There are several alternative explanations for why the high-skill-intensive services sector is underdeveloped in China. The first one is migration barriers, in particular, the hukou system. Lu et al. (2020) argue that migration barriers from the country side to the city explain part of the low employment share of services in China. In the analysis of Lu et al. (2020) migration

[21] Brandt et al. (2017) establish more generally that entry barriers had notable effects on private Chinese firms, because convergence among them happened only where the local entry barriers were removed.

Figure 10: Sectoral Wedges versus Sectoral SOE Employment Shares



SOE employment share constructed from the Chinese Labor Statistical Year Book 1994–2009.

barriers affect all services, implying that they cannot explain why only the employment of high-skill-intensive services is unusually low. For that, one would have to establish that migration barriers affect only high-skill-intensive services.

One possibility is that high-skill-intensive services are available only in the cities whereas low-skill-intensive services are available everywhere. We note though that rural residents are poorer than urban residents, and so they would not demand as many high-skill-intensive services even if they were available in the rural areas. Moreover, rural residents who live reasonably close to a city can get most high-skill-intensive services by going there. So it seems that migration barriers mostly prevent rural residents from getting high-skill-intensive services that require a city hukou. We leave exploring this issue in more depth to future research.

International trade is a second alternative explanation for why the high-skill-intensive services sector is underdeveloped in China. Since high-skilled labor is relatively scarce in China, the textbook Heckscher-Ohlin trade theory suggests that China should import high-skill-intensive services. This would suppress the employment in high-skill-intensive services. Perhaps surprisingly, this explanation does not apply to China because its international trade in high-skill-intensive services is balanced. Nonetheless, the trade surplus in goods may still suppress the employment of high-skill-intensive services. The reason for this is that if trade was balanced, then the actual trade surplus in goods would be allocated among goods, low-skill-intensive services, and high-skill-intensive services. Since high-skill-intensive services are luxuries, its expenditure share would increase more strongly than that of low-skill-intensive services.

To assess by how much trade surplus in goods contributes to the low employment in high-skill-intensive services in China, we need to incorporate unbalanced trade in our model. Following Yao and Zhu (2020), we take the net exports in each of the three sectors from the data and subtract them from the total expenditure on sectoral output. We also subtract the total trade surplus from the total domestic expenditure, thereby changing what the household allocates among the three sectors. This procedure of introducing unbalanced trade leaves the production side unchanged but splits the expenditure shares into an exogenous foreign part and an endogenous domestic part, which is governed by household decisions. The model still has no trouble matching the targets. Table 10 reports the employment share in high-skill-intensive services. The row “Benchmark Model” contains the calibration from before and the row “Model with Net Exports from Data” contains the new calibration. We do not report the results from the counterfactual experiments in Section 5 because they also turn out to be very close to what they were before.

Having modelled international trade in this tractable way, we can now assess what happens when we shut down the trade surplus. To do that in the calibrated model with unbalanced trade, we assume that the exogenous foreign components are zero in all sectors and that the household decides how to allocate the overall trade surplus among the three sectors. Table 10 shows that the share of high-skill-intensive services increases as conjectured above; compare the row “Model with Zero Net Exports” with the other rows. However, quantitatively the difference is tiny, suggesting that the trade surplus is not of first-order importance for understanding the underdevelopment of Chinese high-skill-intensive services.

Table 10: Benchmark Model versus Modified Model with Net Exports

	n_h	Y
Benchmark Model	0.070	1.001
Model with Net Exports	0.069	1
Model with Zero Net Exports	0.071	1.003

6.3 Measurement Error

A valid concern is that the large wedges in high-skill-intensive services reflect mostly measurement error. While we agree that it is a potentially important issue, in particular in China, we would like to offer three arguments for why we think that measurement error is not likely to be the main driver of our results.

To make the first one, it is helpful to go back to equation (24), which we can rewrite as:

$$\frac{1}{1-\tau_{ht}} = \frac{p_{ht}y_{ht}}{p_{gt}y_{gt}} \frac{n_{gt}}{n_{ht}} \left(\frac{1-\alpha_{ht}}{1-\alpha_{gt}}\right) \left(\frac{\varphi_{ht}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}} \left(\frac{1+a_{ht}^{\rho}\hat{w}_t^{-\rho}}{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}\right). \tag{25}$$

The rewritten equation highlights that the wedge in high-skill-intensive services depends on the ratio of nominal sectoral value added between high-skill-intensive services and goods, the employment ratio between high-skill-intensive services and goods, and three additional terms. The employment ratio is fairly straightforward to measure. The three additional terms are related to the skill premium and the skill intensity of the sectors, and they do not differ by much from one. That leaves the ratio of the nominal sectoral value added as the main source of measurement error.

We note that to measure *nominal* sectoral value added, one only needs information on revenues and intermediate inputs in current prices but does not need information on prices themselves. If sectoral revenue and intermediate inputs are traded in the market, then one observes the corresponding expenditures on gross output and intermediate goods in current prices and the corresponding payments to capital and labor. Hence, one can calculate sectoral value added in current prices. This logic suggests that the measurement problem is likely to be in the government-dominated part of high-skill-intensive services, a sizeable part of which are not traded in the market, implying that the value of production is imputed. But if we break the high-skill-intensive services into a mostly private part (Business Services and Finance, Insurance, and Real Estate) and a mostly public part (Public Admin, Education and Health Care), Table 9 reports that in 2009 the nominal productivity gap relative to goods is 8.27 for the mostly private part and 1.83 for the mostly public part in China. Hence the nominal productivity gap is more than four times higher in the mostly private part where mis-measurement should be less of an issue. That suggests that measurement error is not likely to be the main reason for the gaps in the relative nominal productivity and for the resulting high wedges in the high-skill-intensive services sector.

Second, from the discussion of the equation (25), the implied wedge will be close to one if the nominal-value-added shares are close to the employment shares. In 2009, the nominal-value-added share of high-skill-intensive services was 19% while the employment share was 7%. It is hard to believe that mis-measurement of nominal value added in high-skill-intensive services is large enough to cause a discrepancy of almost a factor of three (19/7). Put differently, even if there was mis-measurement in high-skill-intensive services, a sizeable part of the large discrepancy between the nominal-value-added share and the employment share in the high-skilled services would likely remain. Thus, a sizeable nominal productivity gap between high-skill-intensive services and goods would remain and our model would still imply a large wedge in high-skill-intensive services.

Third, if for the sake of the argument we assumed for a moment that the nominal-labor-productivity gap was mostly measurement error, then wedges in high-skill-intensive services would all but disappear. While in this case we could still calibrate the model to the revised Chinese economy, we would be let to conclude that the employment share of high-skill-intensive services is so low in China because the Chinese people like high-skill-intensive services much less than the people of other countries at similar stages of development. The reason for drawing the conclusion is that none of the other obvious explanations moves the employment share of high-skill-intensive services by much. So if there are no wedges to hold it down, then preferences must be the residual claimant. Usually we shun away from explaining cross-country differences in variables of interest by preference differences, because there is a maintained hypothesis that people around the world want reasonably similar things, at least at the aggregate level.

For these reasons, we think that measurement error is not likely to be the main reason for the wedges we identify.

6.4 Extensions

While our static model is a natural first step to address our question, distortions in our model exclusively lead to a static misallocation of labor among sectors. Our results are a lower bound on the effects of distortions on GDP per capita, because removing the distortions in high-skill-intensive services may lead to several additional dynamic output gains. First, physical capital accumulation may propagate the distortions and make their effects larger. Herrendorf and Teixeira (2011) developed an environment with monopoly power and rent extraction in which physical capital accumulation importantly amplifies the effects of removing barriers to entry on aggregate output. In addition, since SOEs enjoy preferential financing of investment, capital accumulation would be distorted which would make the output gains from removing the distortion even larger [Song et al. (2011)]. Second, human capital accumulation may amplify the output gains of removing distortions in eduction. On the intensive margin, a distorted education sector means that each year of schooling leads to less human capital. On the extensive margin, the incentive to obtain higher education increases when the quality of education increases. Lastly, removing distortions may additionally affect output also through the entry of new and more productive firms. Peng (2019) demonstrated that the effect is sizeable for China. Studying the recent experience of Ireland, Klein and Ventura (2018) showed that if the entering firms are multinationals that have higher average productivity than domestic firms, then entry can further increase aggregate output.

The effects of distortions on GDP per capita may also be propagated through input-output linkages. The high-skill-intensive services category includes industries that generate not only a direct impact on GDP, but also an indirect impact through their effect on other sectors that they interact with. For example, distortions in banking and finance matter also for the goods sector because it uses banking-and-finance services. Abstracting from possible inter-sectoral linkages can therefore under-estimate the effects of distortions on aggregate output. To assess how important that may be in our context, Table 11 reports the Chinese input-output linkages among our three sector in 2009. High-skill-intensive services play a relatively minor role as intermediate inputs, implying that the propagation effects of distortions in high-skill-intensive service through input-output linkages are currently modest.

Table 11: Chinese Input–Output Table for Three-sector Split in 2009
(an entry represents the share of gross output from *row* sector in gross output of *column* sector)

	Goods	LSS	HSS
Goods	0.57	0.06	0.04
LSS	0.11	0.06	0.03
HSS	0.05	0.03	0.03

Data source: Chinese Input-output Tables from World KLEMS.

7 Conclusion

We have documented that the employment share of high-skill-intensive services is much lower in China than in countries with similar GDP per capita, although the employment share of low-skill-intensive services is in the same ballpark. We have built a model of structural change between goods, low-skill-intensive services, and high-skill-intensive services to account for this observation. We have found that large distortions limit the size of high-skill-intensive services in China. If they were removed, both high-skill-intensive services and GDP per capita would increase considerably. We have documented a strong presence of state-owned enterprises in high-skill-intensive services and have suggested that this leads to important distortions. Additional research into their behavior is required to establish our suggestion conclusively.

Our analysis is related to the commonly heard claim that the Chinese economy needs "re-balancing". Although the claim is sometimes left vague, we understand it to mean that consumption is too low and investment is too high in China compared to "some undistorted benchmark".[22] Since we do not have savings in our model, we cannot speak to this view of re-balancing. But we note that our results do imply that re-balancing *within* the Chinese services sector is called for.

An important goal for future work is to conduct a cross-country analysis of the development of high-skill-intensive services, in particular, and of the second phase of structural change, in general. While we have touched on some aspects, conducting it goes beyond the scope of the current paper. We hope that our work on China will constitute a useful first step towards a broader cross-country analysis.

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A Appendix

A.1 Robustness of the Facts

Table A.1.1: Industry Classifications in U.S. Census and in 10-Sector Database

U.S. Census	10-Sector Database
Low-skill-intensive Services	
Transport & Telecommunication	Transport & Telecommunication
Wholesale & Retail plus Hotels & Restaurants	Trade services
Personal Services minus Hotels & Restaurants	Personal Service
Utilities	Utilities
High-skill-intensive Services	
Business & Repair Finance, Insurance & Real Estate Professional Services minus Education and Health Care & Social work	Business Service
Public Administration plus Education and Health Care & Social Work	Government Services

U.S. Census accessed through IPUMS.

Table A.1.2: Industry Classifications in U.S. Census and in Chinese Labor Statistical Yearbook

U.S. Census	**Chinese Labor Statistical Yearbook**
Low-skill-intensive Services	
Transport & Telecommunication	Transportation, Storage & Post
Wholesale & Retail	Wholesale & Retail
Personal Services	Resident, Repair & Other Services Accommodation & Catering Trade Culture, Sport & Recreation
Utilities	Electricity, Gas & Water Production & Supply
High-skill-intensive Services	
Business & Repair	Leasing & Commercial Service
Public Administration	Public Management & Social Organization Water Conservancy, Environment & Public Utility Management
Finance, Insurance & Real Estate	Financial Intermediation Real Estate Management
Professional Services	Education Health Care, Social Security & Social Welfare Information Transmission, Software & Information Technology Service Scientific Research & Polytechnic Service

U.S. Census accessed through IPUMS.

Table A.1.3: Sectoral Employment Shares at similar GDP per capita as China in 2009 – Five-year Averages around Year when Country has Similar GDP pc as China in 2009

Country, Year	Services / Total	LSS / Total	HSS / Total	HSS / Services
Argentina, 1994	0.67	0.39	0.28	0.42
Brazil, 2005	0.61	0.39	0.22	0.36
China, 2009	**0.35**	**0.28**	**0.07**	**0.20**
Costa Rica, 2004	0.63	0.40	0.23	0.37
France, 1957	0.42	0.21	0.21	0.51
Germany, 1959	0.41	0.26	0.15	0.37
Italy 1966	0.39	0.23	0.16	0.40
Japan, 1966	0.46	0.28	0.18	0.39
Malaysia, 1991	0.50	0.30	0.20	0.40
Mauritius, 1988	0.41	0.27	0.14	0.34
Mexico, 1973	0.37	0.24	0.14	0.36
South Africa, 2002	0.60	0.36	0.24	0.39
Spain, 1967	0.41	0.30	0.11	0.26
Taiwan, 1977	0.39	0.27	0.12	0.30
Thailand, 2004	0.36	0.27	0.10	0.27
Average	**0.46**	**0.30**	**0.17**	**0.36**

LSS and HSS stand for low- and high-skill-intensive services, respectively.
GDP per capita is in international dollar and is computed from Penn World Tables 8.1.
Employment shares other than in the U.S. are constructed from GGDC 10-Sector Database.
Employment share in the U.S. are constructed from U.S. Census accessed through IPUMS.

Table A.1.4: Sectoral Employment Shares at similar GDP pc as in China in 2009 – Government Services excluded from HSS

Country, Year	Services / Total	LSS / Total	HSS / Total	HSS / Services
Argentina, 1994	0.46	0.39	0.07	0.15
Brazil, 2005	0.48	0.38	0.09	0.20
China, 2009	**0.29**	**0.28**	**0.01**	**0.05**
Costa Rica, 2004	0.50	0.40	0.10	0.21
Denmark, 1951	0.34	0.30	0.04	0.11
France, 1957	0.25	0.21	0.05	0.18
Germany, 1959	0.30	0.26	0.04	0.14
Italy, 1966	0.26	0.23	0.03	0.12
Japan, 1966	0.34	0.28	0.06	0.18
Malaysia, 1991	0.36	0.30	0.06	0.15
Mauritius, 1988	0.31	0.28	0.03	0.09
Mexico, 1973	0.25	0.23	0.02	0.07
South Africa, 2002	0.43	0.34	0.09	0.20
Spain, 1967	0.33	0.30	0.03	0.10
Taiwan, 1977	0.29	0.27	0.02	0.06
Thailand, 2004	0.30	0.27	0.03	0.09
United Kingdom, 1950	0.35	0.33	0.02	0.06
United Sates, 1940	0.38	0.33	0.05	0.13
Average	**0.35**	**0.30**	**0.05**	**0.13**

LSS and HSS stand for low- and high-skill-intensive services, respectively.
GDP per capita is in international dollar and is computed from Penn World Tables 8.1.
Employment shares other than in the U.S. are constructed from GGDC 10-Sector Database.
Employment share in the U.S. are constructed from U.S. Census accessed through IPUMS.

Table A.1.5: Industry Employment Shares in Total Employment (in %)

	China in 2010	U.S. in 1950
Business & Repair	0.01	0.03
Public Administration	0.03	0.06
Finance, Insurance, Real Estate	0.01	0.03
Professional Services	0.04	0.08

Employment Share for China are constructed from the Chinese 2010 Census.
Employment shares for the U.S. come from 1950 IPUMS Census.

A.2 Model Solution

We start with household's problem. Applying (10) to (3) from the main text gives:

$$
\begin{aligned}
c_{it} &= -\frac{\left(E_t B_t^{-1} - A_t\right)^{\varepsilon-1}\left(-E_t B_t^{-2} B_{pit} - A_{pit}\right) + D_{pit}}{\left(E_t B_t^{-1} - A_t\right)^{\varepsilon-1} B_t^{-1}} \\
&= A_{pit} B_t + E_t B_{pit} B_t^{-1} - \left(E_t B_t^{-1} - A_t\right)^{1-\varepsilon} D_{pit} B_t,
\end{aligned}
$$

where A_{pit}, B_{pit}, and D_{pit} were defined in the text to denote the derivatives of A_t, B_t, and D_t with respect to p_{it}. Hence, the expenditure shares are given by (11), as claimed in the main text. Calculating the partial derivatives of A_t, B_t and D_t with respect to p_{it} and plugging the results into (11) gives the closed-form solutions to the expenditure shares:

$$
\begin{aligned}
s_{gt}(\vec{P}_t, E_t) &= \phi_g + (\mu_g - \phi_g)\frac{A(\vec{P}_t)}{E_t/B(\vec{P}_t)} + \left(\frac{E_t}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{1-\epsilon} \frac{B(\vec{P}_t)}{E_t} \sum_{k\in\{l,h\}} \bar{D}\nu_k \left(\frac{p_{kt}}{p_{gt}}\right)^{\psi_k}, \\
s_{it}(\vec{P}_t, E_t) &= \phi_i + (\mu_i - \phi_i)\frac{A(\vec{P}_t)}{E_t/B(\vec{P}_t)} - \left(\frac{E_t}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{1-\epsilon} \frac{B(\vec{P}_t)}{E_t} \bar{D}\nu_i \left(\frac{p_{it}}{p_{gt}}\right)^{\psi_i}, \quad i \in \{l,h\}.
\end{aligned}
$$

Equation (17) from the main text implies market clearing for low-skilled labor can be written as:

$$
\begin{aligned}
\Omega_t^l &= \sum_{i\in\{g,l,h\}} \ell_{it} = \ell_{gt} \sum_{i\in\{g,l,h\}} \frac{\ell_{it}}{\ell_{gt}} \\
\implies \quad \ell_{gt} &= \frac{\Omega_t^l \left(1 - \alpha_{gt}\right) s_g(\vec{P}_t, E_t)\left[\varphi_{gt}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}{\sum_{i\in\{g,l,h\}} (1-\tau_{it})(1-\alpha_{it})\, s_i(\vec{P}_t, E_t)\left[\varphi_{it}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}.
\end{aligned}
\tag{A.1}
$$

Equations (14) and (17) from the main text imply that market clearing for high-skilled labor can be written as:

$$
\begin{aligned}
\Omega_t^h &= \sum_{i\in\{g,l,h\}} h_{it} = \ell_{gt} \sum_{i\in\{g,l,h\}} \frac{h_{it}}{\ell_{it}}\frac{\ell_{it}}{\ell_{gt}} \\
\implies \quad \ell_{gt} &= \frac{\Omega_t^h \hat{w}_t^\rho \left(1 - \alpha_{gt}\right) s_g(\vec{P}_t, E_t)\left[\varphi_{gt}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}{\sum_{i\in\{g,l,h\}} a_{it}^\rho (1-\tau_{it})(1-\alpha_{it})\, s_i(\vec{P}_t, E_t)\left[\varphi_{it}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}
\end{aligned}
\tag{A.2}
$$

The equilibrium can be reduced to two equations in the two unknowns $(\hat{w}_t, E_t)$. The first equation is obtained by equating (A.1) and (A.2) while using that equation (16) implies that relative prices are a function of $\hat{w}_t$:

$$\frac{\Omega_t^l}{\Omega_t^h} = \frac{\hat{w}_t^{\rho} \sum_{i \in \{g,l,h\}} (1-\tau_{it})(1-\alpha_{it})\, s_i\left(\vec{P}_t(\hat{w}_t), E_t\right) \left[\varphi_{it}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}{\sum_{i \in \{g,l,h\}} a_{it}^{\rho} (1-\tau_{it})(1-\alpha_{it})\, s_i\left(\vec{P}_t(\hat{w}_t), E_t\right) \left[\varphi_{it}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}.$$

The second equation follows from substituting (15), (16), and (A.1) into the identity $E_t = \sum p_{it} y_{it}$:

$$E_t = \frac{\Omega_t^l Z_{gt} \left(1-\alpha_{gt}\right) \left[\varphi_{gt}(\hat{w}_t)\right]^{\frac{1}{\rho}}}{\sum_{i \in \{g,l,h\}} (1-\tau_{it})(1-\alpha_{it})\, s_i\left(\vec{P}_t(\hat{w}_t), E_t\right) \left[\varphi_{it}(\hat{w}_t)\right]^{\frac{1-\rho}{\rho}}}.$$

Given equilibrium values of $(\hat{w}_t, E_t)$, the main text describes how to obtain the other endogenous variables.

A.3 Robustness of the Results with Respect to ρ

Table A.1.6: Determinants of the Employment Share of HSS for different ρ

Parameter Values	$\rho = 1$		$\rho = 1.42$		$\rho = 2$	
	n_h	n_l	n_h	n_l	n_h	n_l
Benchmark	0.07	0.27	0.07	0.27	0.07	0.27
$\tau_h = 0$	0.15	0.24	0.15	0.24	0.15	0.24
$Z_h = 1.5Z_{h,09}$	0.07	0.26	0.07	0.26	0.07	0.26
$Z_h = 2Z_{h,09}$	0.07	0.26	0.07	0.26	0.07	0.26
$\Omega^h = 1.5\Omega^h_{09}$	0.08	0.26	0.08	0.26	0.08	0.26
$\Omega^h = 2\Omega^h_{09}$	0.09	0.26	0.08	0.26	0.08	0.26

n_h and n_l are employment shares of HSS and LSS. "09" is for 2009 calibration.
$\rho = 1.42$ is value of Katz and Murphy (1992).

Table A.1.7: Effects of τ_h on GDP per capita for different ρ

Parameter Values	$\rho = 1$		$\rho = 1.42$		$\rho = 2$	
	Y	n_h	Y	n_h	Y	n_h
$\tau_{h,09}$	1	0.07	1	0.07	1	0.07
$0.75\tau_{h,09}$	1.01	0.08	1.01	0.08	1.01	0.08
$0.5\tau_{h,09}$	1.03	0.09	1.03	0.10	1.03	0.10
$0.25\tau_{h,09}$	1.04	0.11	1.04	0.12	1.04	0.12
0	1.05	0.15	1.05	0.15	1.05	0.15

Y is real GDP per capita an n_h is employment share of HSS.
"09" is for 2009 calibration. $\rho = 1.42$ is value of Katz and Murphy (1992).

A.4 Results for Calibration with Census Data

Figure A1: Census Calibration of Parameters – Production Side

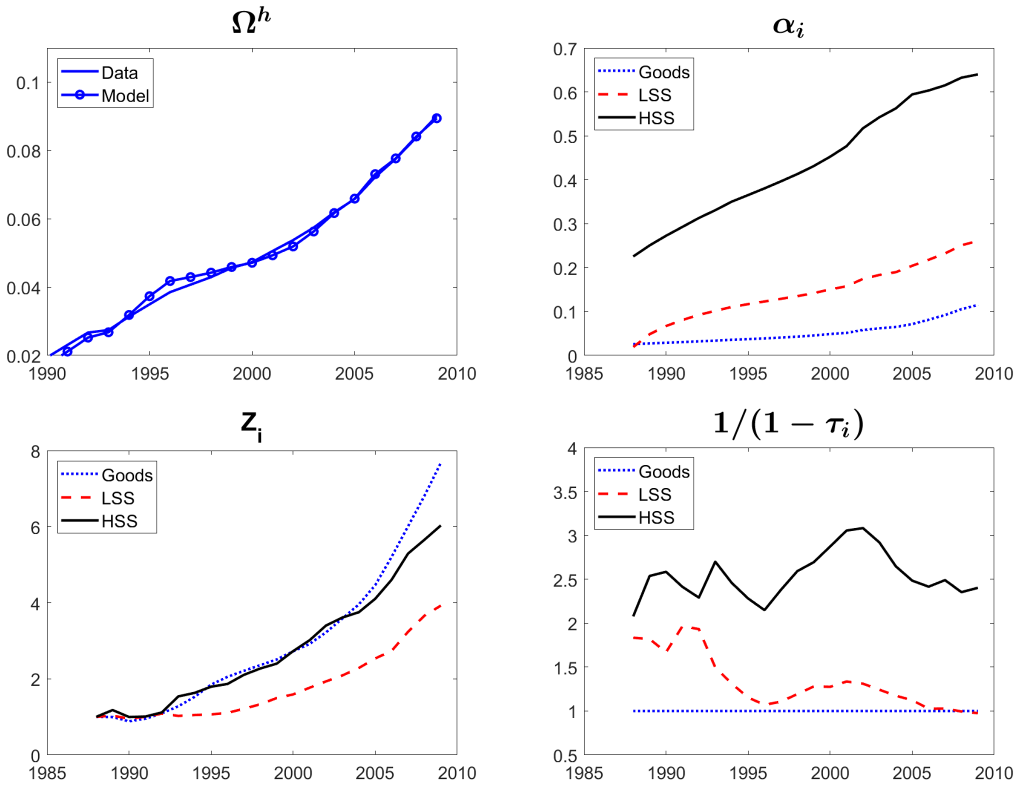

Figure A2: Non-targeted Variables in Model and Data – Census Calibration

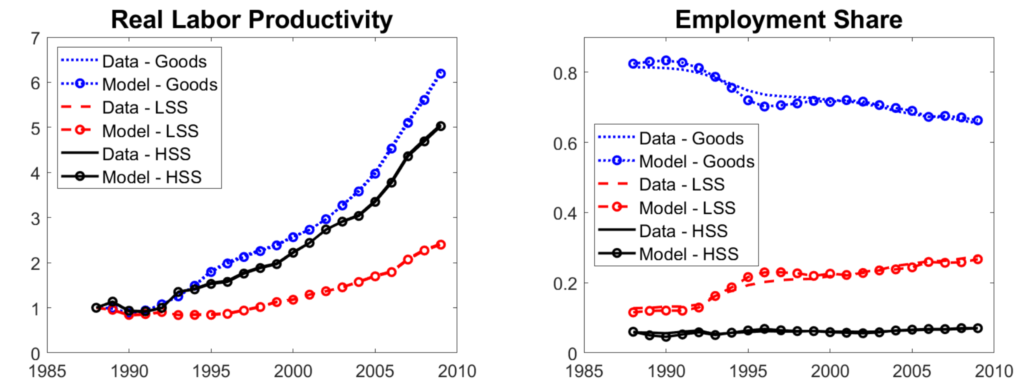

Figure A3: Targeted Variables in Model and Data – Census Calibration

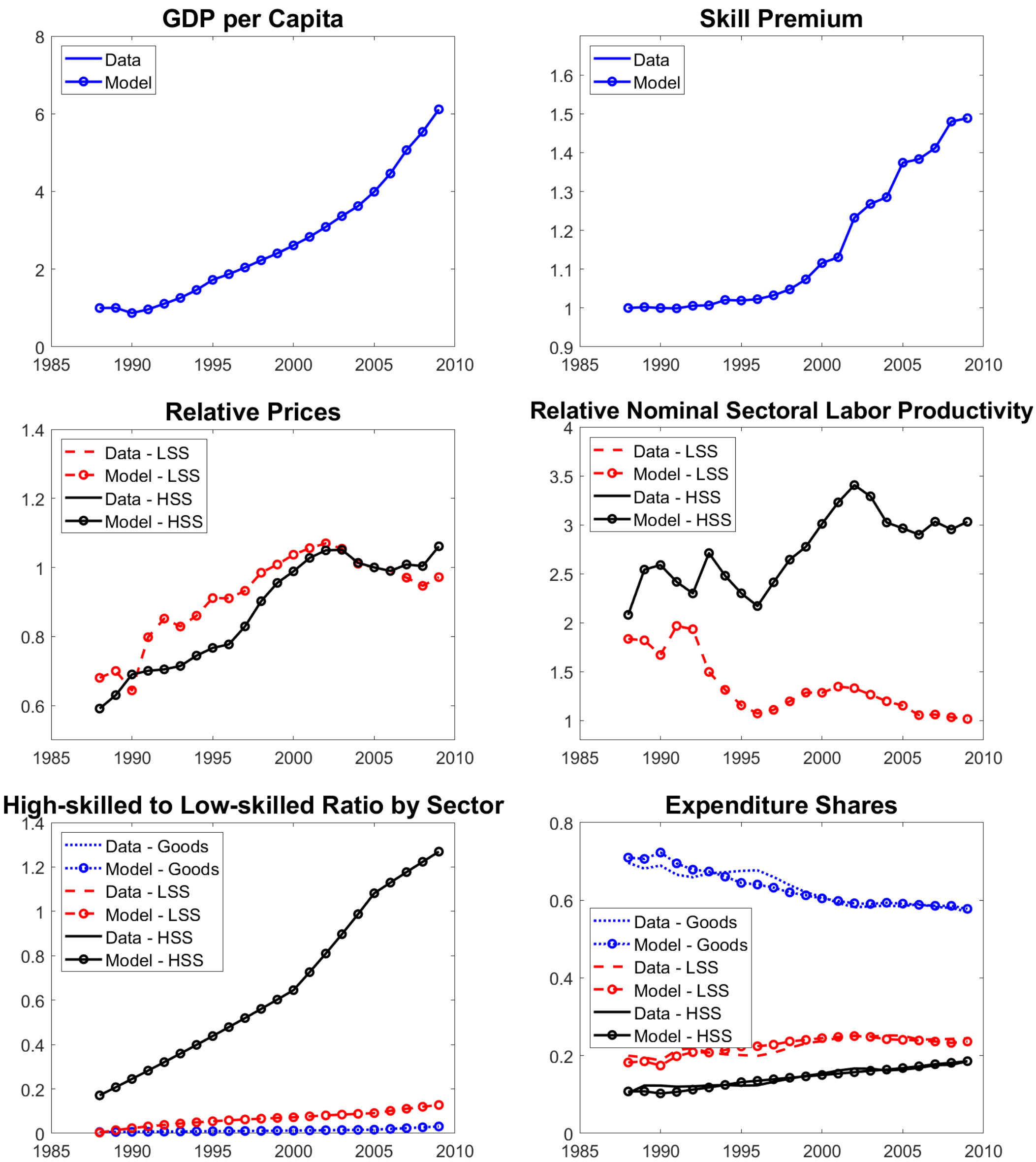

Figure A4: Counterfactual GDP per capita Keeping one Parameter Constant – Census Calibration

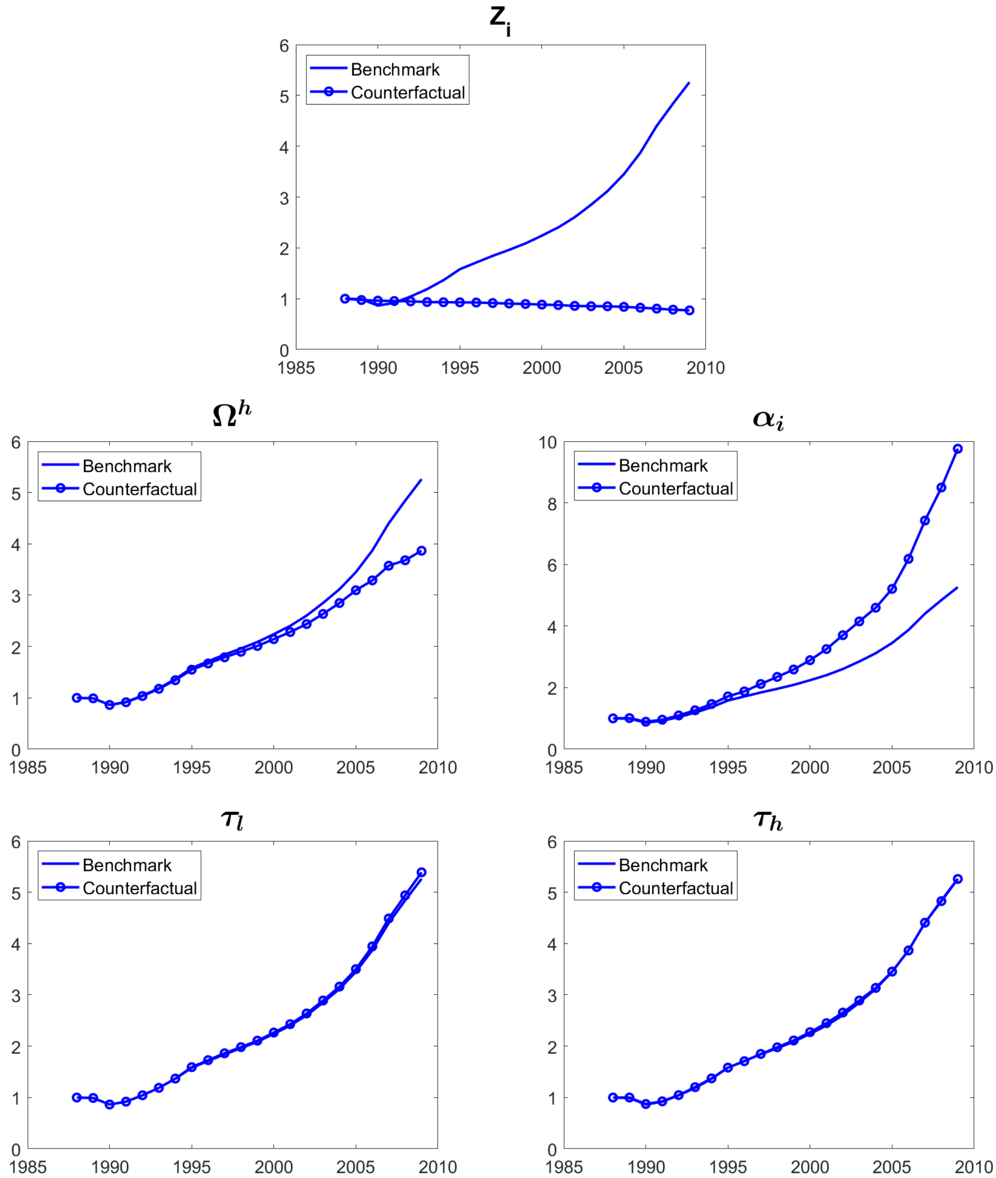

Table A.1.8: **Results about Sectoral Shares and Nominal Labor Productivity Gaps – Census Calibration**

Parameter Values	n_h	n_l	n_g	s_h	s_l	s_g	$\frac{p_h y_h/n_h}{p_g y_g/n_g}$	$\frac{p_l y_l/n_l}{p_g y_g/n_g}$
Benchmark	0.07	0.27	0.66	0.19	0.24	0.58	3.02	1.02
$\tau_h = 0$	**0.13**	**0.24**	**0.62**	**0.18**	**0.24**	**0.58**	**1.44**	**1.03**
$Z_h = 1.5Z_{h,09}$	0.07	0.26	0.67	0.18	0.23	0.58	3.01	1.01
$Z_h = 1.5Z_{h,09}$, $\tau_h = 0$	0.13	0.24	0.63	0.18	0.23	0.59	1.44	1.03
$Z_h = 2Z_{h,09}$	0.07	0.26	0.67	0.18	0.23	0.59	3.00	1.01
$Z_h = 2Z_{h,09}$, $\tau_h = 0$	0.13	0.24	0.63	0.18	0.23	0.59	1.44	1.03
$\Omega^h = 1.5\Omega^h_{09}$	0.08	0.26	0.66	0.18	0.23	0.59	2.47	0.98
$\Omega^h = 1.5\Omega^h_{09}$, $\tau_h = 0$	0.15	0.24	0.61	0.18	0.23	0.59	1.23	1.01
$\Omega^h = 2\Omega^h_{09}$	0.10	0.26	0.65	0.18	0.22	0.59	2.06	0.94
$\Omega^h = 2\Omega^h_{09}$, $\tau_h = 0$	0.17	0.23	0.60	0.18	0.22	0.60	1.05	0.98

"09" is for 2009 calibration. n_h, n_l and n_g are the employment shares and s_h, s_l and s_g are the value-added shares of high-skill-intensive services, low-skill-intensive services, and goods. $(p_i y_i/n_i)/(p_g y_g/n_g)$ and $(y_i/n_i)/(y_g/n_g)$ are nominal and real labor productivity for HSS and LSS relative to goods

Table A.1.9: **Results about Relative Productivities and GDP per capita – Census Calibration**

Parameter Values	$\frac{y_h/n_h}{y_g/n_g}$	$\frac{y_l/n_l}{y_g/n_g}$	Y
Benchmark	2.86	1.05	1
$\tau_h = 0$	**2.71**	**1.03**	**1.04**
$Z_h = 1.5Z_{h,09}$	4.29	1.05	1.08
$Z_h = 1.5Z_{h,09}$, $\tau_h = 0$	4.07	1.03	1.12
$Z_h = 2Z_{h,09}$	5.72	1.05	1.14
$Z_h = 2Z_{h,09}$, $\tau_h = 0$	5.43	1.03	1.18
$\Omega^h = 1.5\Omega^h_{09}$	2.92	1.06	1.03
$\Omega^h = 1.5\Omega^h_{09}$, $\tau_h = 0$	2.87	1.05	1.07
$\Omega^h = 2\Omega^h_{09}$	2.91	1.05	1.04
$\Omega^h = 2\Omega^h_{09}$, $\tau_h = 0$	2.92	1.06	1.08

"09" is for 2009 calibration. $(y_i/n_i)/(y_g/n_g)$ are real labor productivity for HSS and LSS relative to goods. Y is output.