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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 argue that this presence leads to important distortions.

JEL classification: O41, O47, O51

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

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1 Introduction

Since the economic reforms in 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 people 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 all of 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 low- and high-skill-intensive services.[2] Instead, China has a similar employment share of low-skill-intensive services as the average over the comparison countries but has a much lower employment share of high-skill-intensive services (7% in China versus close to 20% in the comparison countries). In other words, China's high-skill-intensive services sector is severely underdeveloped given China's stage of development.

We ask why the high-skilled-intensive services sector is underdeveloped in China and what it would take for it to develop in the future. Possible reasons for the 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 in our analysis.

We approach the question why the high-skill-intensive services sector is underdeveloped in China by building a model of structural change among goods, low-skill-intensive services, and high-skill-intensive services. Our model combines the utility function from Alder et al. (2017) with the production function from Buera et al. (2018). The utility function allows for time

[1] Dekle and Vandenbroucke (2012) and Cao and Birchenall (2013) offer detailed analyses of this first phase of structural change.

[2] High-skill-intensive services industries make intensive use of workers with at least some college education. We will be more specific below.

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. (2017). The production side features skilled and unskilled workers in all sectors, and allows the skill intensities to differ across sectors and to change over time. To capture that the nominal labor productivities differ across sectors in China even after controlling for sectoral differences in the skill intensity, we introduce labor wedges that increase the rental prices of labor in the sector to which they apply. The wedges stand in for factors that affect the allocation of labor among sectors. Examples are monopoly power in the product or labor market of particular sectors.

We calibrate our model to match salient features of the Chinese economy since 1988, 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 labor wedges in high-skill-intensive services sector that generate a high rental price of labor and a high output price. Removing the labor 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 comparison, increasing the share of skilled workers or the labor productivity in high-skill-intensive services has much smaller effects on the employment share of high-skill-intensive services. 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.

One possible explanation for the wedges we are finding is that state-owned enterprises ("SOEs") are much more prevalent in the high-skilled service sector than in the other sectors. We document that in China in 2016, SOEs employed more than half of the workers of the high-skill-intensive services sector, but fewer than one in twenty five of the workers of the other sectors. Since SOEs can dominate a whole sector of the economy only if they are sheltered from competition of private domestic and foreign firms, monopoly rights must be wide spread in Chinese services industries. While other observers have arrived at a similar conclusion, our analysis points to the *high-skill-intensive* services industries as being the severely distorted ones, and it shows that the distortion has quantitatively large effects.

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 did not separately analyze the situation in the high-skilled service sector. Several studies found severe misallocation of production factors in China and sizeable gains in productivity from eliminat-

ing 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 SOE create large distortions, 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 [Baumol et al. (1985) and 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) focused on services with high versus low productivity growth in the context of cost disease.

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 concludes. An Appendix contains the details of the solution of our model.

2 Facts about the Second Phase of Structural Change

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. We define high–skilled workers as having at least an associate degree (or two years of college), and low–skilled workers as the rest. High-skill-intensive services are the services industries that have a higher share of high-skilled workers than the median services industry. Using IPUMS Census data, for the U.S. these are: business and repair services; finance, insurance, and real estate; professional and related services (mainly education and health care);

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

Industry	1950	1960	1970	1980	1990	2000	2010
Low-skilled							
Transport & Telecommunication	2	8	12	22	22	26	29
Wholesale & Retail	4	11	13	21	19	20	24
Personal Services	3	6	9	20	22	24	28
Utilities	5	12	15	25	28	29	40
High-skilled							
Business and Repair	6	19	24	35	36	42	45
Public Administration	8	20	24	35	35	41	47
Finance, Insurance, Real Estate	8	24	29	39	39	45	53
Professional Services	24	51	50	55	53	55	59

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

public administration. The remaining services industries are low skill intensive: personal services; transportation and communication; utilities; wholesale and retail trade.[3]

We use the U.S. classification of services industries instead of the Chinese one because the U.S. is a natural benchmark in the group of comparison countries against which we contrast our results for China. Moreover, there is reliable information for the U.S. about the skill composition by industry over time, whereas for China we have only spotty survey evidence from the Chinese Household Income Project. It is reassuring that the most recent 2013 wave of the Chinese Household Survey (CHIP) leads to the same classification as the U.S. data. We note that the classification of U.S. services industries is also robust to changing the definition of skilled from two to three or four years of college. We also note that the classification of U.S. services industries is robust over time; see Table 1. Of course, the shares of high-skilled workers went up over time in all sectors, and there were some minor switches in the ranking of the different services industries. But all switches happened within the high- or low-skill-intensive services sector so that the assignments of the services industries to the two services sector are unaffected.

Table 1 shows that the utility industry is the most skill-intensive industry in low-skill-intensive services. Nonetheless, its skill intensity is still considerably below the median skill intensity of all services industries. We have verified that the assignment of the utility industry does not drive our results. In fact, in China and in the comparison countries, the utility industry is so small that it does not crucially affect the aggregate outcomes we care about here.[4]

Table 2 compares the Chinese sectoral composition with that of country-year pairs that are at a similar stage of development, which we define as having a ppp-adjusted GDP per

[3]This classification is essentially as in Buera et al. (2018).

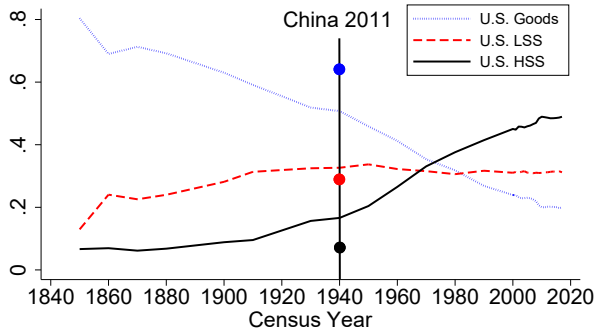
[4]The employment share of the utility industry is 0.5% in China at 2011 and averages at 0.8% in the comparable countries.

Table 2: Sectoral Employment Shares at similar GDP per capita

Country, Year	Services / Total	LSS / Total	HSS / Total	HSS / Services
Average	**0.49**	**0.31**	**0.18**	**0.36**
Argentina, 1995	0.67	0.38	0.29	0.43
Brazil, 2009	0.63	0.40	0.23	0.36
China, 2011	**0.36**	**0.29**	**0.07**	**0.20**
Costa Rica, 2006	0.65	0.41	0.24	0.36
Denmark, 1953	0.43	0.30	0.14	0.32
France, 1959	0.43	0.21	0.22	0.50
Germany, 1960	0.41	0.26	0.15	0.37
Hong Kong, 1975	0.47	0.35	0.12	0.25
Italy 1967	0.39	0.23	0.16	0.40
Japan, 1967	0.46	0.28	0.18	0.39
Malaysia, 1993	0.50	0.30	0.20	0.40
Mauritius, 1991	0.42	0.27	0.15	0.36
Mexico, 1995	0.54	0.35	0.19	0.35
South Africa, 2005	0.63	0.39	0.24	0.39
Spain, 1968	0.40	0.30	0.11	0.27
Taiwan, 1979	0.40	0.28	0.12	0.30
Thailand, 2006	0.38	0.27	0.11	0.28
United Kingdom, 1954	0.51	0.32	0.19	0.37
United States, 1940	0.50	0.33	0.17	0.34

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 Census data as reported by IPUMS.

Figure 1: U.S. Sectoral Labor Shares – Census data from IPUMS



LSS and HSS stand for low- and high-skill-intensive services, respectively.
Data for 1850–2000 constructed from Censuses reported by IPUMS.
Data for 2010 constructed from American Community Survey reported by IPUMS.
Data for China in 2011 constructed from GGDC 10-sector Database.

capita within plus/minus $300 of China's GDP per capita in 2011. The table 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 13 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 (0.29 versus 0.31), but a dramatically lower employment share of high-skill-intensive services (0.07 versus 0.18). 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.

Several remarks about the table are at order. First, we define being at the same stage of development as having a similar GDP per capita as China because that is the most commonly used and widely available measure of development. Of course, countries could differ on many other dimensions, but since we compare China with 18 countries other cross-country differences should wash out. Second, we use data for China in the year 2011, instead of a more recent year, because our main data source, the Groningen Growth and Development Center 10-sector Database, stops in 2011. We emphasize that the employment share of high-skill-intensive services has not increased much after 2011. In 2016, for example, it was just 9%. Third, in comparison to the other countries, China has low employment in both government and privately provided high-skill-intensive services. Moreover, the low ratio of high-to-low-skill-intensive employment in China in 2011 is not the result of business cycle fluctuations. This becomes clear from the time-series of the employment shares, which is drawn in the lower panel of Figure 6 later on in the body of the paper. Fourth, Yao and Zhu (2018) argued that the official Chinese data overstate agricultural employment, and that part of it should be re-classified as employment in manufacturing and low-skill-intensive services. We note that, if

anything, such a reclassification would strengthen our stylized fact, because it would further reduce the already low Chinese ratio of high- to low-skill-intensive services.

The previous facts imply that in China the second phase of structural change will likely involve the development of high-skill-intensive services. To get an idea about the possible extent of the future development of high-skill-intensive services, it is useful to bring in the U.S. experience. Figure 1 plots the U.S. employment shares of goods, low-skill-intensive services, and high-skill-intensive services during 1850–2017. 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 share of employment in low-skill-intensive services has been mostly flat. The high-skill-intensive services sector took off after World War II and has become the largest sector and the only sector that is still growing in share.[5] Moreover, although in terms of GDP per capita, China in 2011 was about where the U.S. was in 1940, in terms of the employment share of high-skill-intensive services, China was about where the U.S. was as far back as in the second half of the 19th century.

If the development experience of the U.S. is anything to go by, then there is a huge potential for the development of the Chinese high-skill-intensive services sector. Our paper is about why the development of the Chinese high-skill-intensive services sector has not yet happened and what it would take to make it happen.

3 Model

3.1 Production

There are three sectors producing goods, low-skill-intensive services, and high-skill-intensive services. We index them by g, l, and h, respectively. There are two types of workers: low- and high-skilled workers. Workers can move freely across sectors. While production in each sector uses both types of workers, the intensity of factor inputs may differ. In each sector, a representative firm uses a CES production function to combine low-skilled and high-skilled workers:

$$y_{it} = Z_{it}\left(\alpha_{it} h_{it}^{\frac{\rho-1}{\rho}} + (1-\alpha_{it})\ell_{it}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}, \qquad i \in \{g, l, h\}, \tag{1}$$

where 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 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 two

[5] These are essentially the same observations that Buera and Kaboski (2012) made before us.

labor inputs and is assumed to be constant and equal across sectors. To justify calling h high skill intensive and l low skill intensive, we impose that $\alpha_{ht} > \alpha_{lt}$.

Our production function is as in Buera et al. (2018), and so labor is the only input. This implies that 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 our results.

A key feature of the Chinese data is that nominal labor productivity differs across sectors. In our context, it is important to capture the differences because they will affect the sectoral allocation of labor, and thus the size of high-skill-intensive service sector. Different sectoral compositions of labor imply differences in value added per average worker, but it turns out that these differences are not sufficient to capture the differences in the data. Therefore, we introduce a sectoral labor wedge, τ_{it}. Specifically, firms must pay an additional amount τ_{it} per unit of their wage bill, and the revenue of the payments is lump-sum rebated back to all households. Assuming perfect competition in the product and labor markets, the problem of firm $i \in \{g, l, h\}$ is then given by:

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

We choose goods in each period as the numeraire, $p_{gt} = 1$. Since only relative wedges will matter for the equilibrium outcome, we also choose $\tau_{gt} = 0$.

3.2 Discussion

The wedges are a reduced-form way of capturing the implications of unmeasured determinants of the nominal sectoral labor productivity. Prominent examples are the distortions that arise from monopoly power in the product market and monopoly power in the labor market. In what follows, we elaborate on this statement.

We first think about monopoly power in the product market of any of the three sectors while assuming that the labor market is competitive and wages are the same in all sectors. The key insight is that the equilibrium allocation with monopoly power in the product market can be replicated by the equilibrium allocation with competition in the product market if we choose the value of the wedge appropriately. To see this, consider first the equilibrium allocation with monopoly power. The monopoly mark up increases the price of sector output above the marginal costs (wages), which generates monopoly profits for the firm and reduces output and

employment. Consider instead the case where the product and labor markets are both competitive but there is a wedge on labor. The wedge can be chosen so that the following variables are as in the monopoly case: the number of workers in the sector, the wage workers receive net of the wedge, real value added over the number of workers, the relative price of output of the sector, and the revenue the firm receives. The only difference between the two cases is that the firm does not make monopoly profits any longer because the wedge eats them up by increasing the factor costs.

Now, consider monopoly power in the labor market of any of the three sectors while the product market is competitive. Again, the equilibrium allocation with monopoly power in the labor market can be replicated by the equilibrium allocation with competition in the labor market if we choose the value of the wedge appropriately. Consider first the equilibrium allocation with monopoly power. The monopoly mark up increases the price of labor in the sector over the marginal costs (wages), which generates monopoly rents to the workers in the sector and reduces output and employment. Consider instead the case where the product and labor markets are both competitive but there is a wedge on labor in the sector. The size of the wedge can be chosen so that the following variables are as in the monopoly case: the number of workers in the sector, the wage including the wedge, the revenue the firm receives, real value added over the number of workers, and the relative price of the output of the sector. The only difference is that the workers do not get a monopoly profit because the wedge eats it up.

Several additional aspects of the wedges deserve discussion. In our model, each wedge applies uniformly to a whole sector's labor irrespective of whether it is high- or low-skilled. If a distortion within a sector's labor market affects high- and low-skilled workers differently, then the effects are captured by the labor weights α_{it}. Since we will find that differences in the sectoral α_{it} do not matter much for our results, abstracting from distortions within a sector's labor market is not of first-order importance for our conclusions. A second aspect of the wedges is that it does not matter for anything of relevance whether they are modelled as labor wedges or output wedges. Since that observation corresponds to a standard result in public finance, we leave showing it as an easy exercise to the interested reader. Third, Restuccia et al. (2008) are one of the first papers who used labor wedges, but they called them barriers (of moving between sectors).[6] There is a subtle difference between a wedge on wages in a sector and a barrier on moving to the sector. A wedge applies to every worker in the sector, but a barrier applies only to the workers who are moving to the sector. In a static model, one can assume that every worker moves, in which case wedge and barrier are the same. But that would not be true in a dynamic model where only some workers move in any given period.

[6]Subsequently, labor wedges have been widely used in macro development. See for example Herrendorf and Schoellman (2018).

3.3 Households

There is a measure one of households. In period t, a fraction Ω_t^h of the households is high skilled and a fraction Ω_t^l is low skilled. Each household is endowed with one unit of time in each period, which it supplies inelastically to the labor market. Hence, the total number of workers will equal the population in our model, and GDP per workers and GDP per capita will be the same.

We use the indirect utility function proposed by Alder et al. (2017) instead of the Stone-Geary utility, which is common in the earlier literature.[7] The reason for doing this is that the indirect utility of Alder et al. (2017) permits flexible and persistent income effects which are a feature of the data of several countries. In contrast, the income effects implied by the Stone-Geary utility are not persistent and vanish as the economy grows. Moreover, the indirect utility function of Alder et al. (2017) has nice aggregation properties. They imply that the distribution of wage income across the two skill groups does not to matter to a first-order for the aggregate outcomes of our economy. Therefore, it will not matter how we rebate the wedge revenues. These features will simplify our analysis.

The indirect utility function is a function of prices and income. Let p_{it} denote the price of good i with $\vec{P}_t \equiv (p_{gt}, p_{lt}, p_{ht})$ and e_t^n denote the income of the representative household with skill level $n = l, h$. Then, the indirect utility function can be written as:

$$v(e_t^n, \vec{P}_t) = \frac{1}{\varepsilon}\left(\frac{e_t^n}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{\varepsilon} - \frac{1}{\varepsilon} + D(\vec{P}_t), \tag{2}$$

where $A(\vec{P}_t)$ 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 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.

We adopt the functional forms from Alder et al. (2017):

$$\begin{aligned}
A(\vec{P}_t) &= \bar{A} \prod_{i\in\{g,l,h\}} p_{it}^{\mu_i - \phi_i}, \\
B(\vec{P}_t) &= \prod_{i\in\{g,l,h\}} p_{it}^{\phi_i}, \\
D(\vec{P}_t) &= \bar{D} \sum_{i\in\{l,h\}} \nu_i \frac{1}{\psi_i}\left(\frac{p_{it}}{p_{gt}}\right)^{\psi_i}.
\end{aligned}$$

The parameters satisfy the following restrictions:

[7] See for example Kongsamut et al. (2001) and Herrendorf et al. (2013).

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

Given the aggregation results from Alder et al. (2017), the aggregate expenditure share of category $i \in \{g, l, h\}$ can be written as a function of aggregate expenditures, E_t, and of the prices.[8] Because we are focused on understanding the sectoral allocation of labor and the resulting effects on GDP per capita, it suffices to solve for the aggregate expenditure shares and the allocations from the production side. Hence, we will define and solve the equilibrium without specifying the rebating rule separately for the two types of households.

3.4 Equilibrium

Let $s_{it}(\vec{P}_t, E_t)$ be the aggregate consumption expenditure share of sector i, T_t be the aggregate transfer, $Y_t \equiv \sum p_{it} y_{it}$ be the aggregate value-added, and $e_{it} \equiv (p_{it} y_{it})/E_t$ be the share of value-added from sector i.

Equilibrium Definition

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

$$\sum_{i \in \{g,l,h\}} h_{it} = \Omega_t^h \tag{3}$$

$$\sum_{i \in \{g,l,h\}} \ell_{it} = \Omega_t^l; \tag{4}$$

- Consistency:

$$E_t = Y_t, \tag{5}$$

$$e_{it} = \frac{p_{it} y_{it}}{E_t} = s_{it}(\vec{P}_t, E_t), \tag{6}$$

$$T_t = \sum_{i \in \{g,l,h\}} \tau_{it}(w_t^h h_{it} + w_t^l \ell_{it}). \tag{7}$$

The details of the solution for the equilibrium are in Appendix A.

[8] Appendix A contains more details of the derivation of the expenditure shares.

4 Calibration

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 uses annual data on GDP per capita, sectoral prices, and sectoral expenditure shares. We equate aggregate expenditures in the model with GDP per worker from the data. We choose goods as the numeraire in each period, implying that GDP per capita and prices from the data are expressed relative to goods. Since the expenditure shares add up to one, we choose the preference parameters to minimize the distance between two expenditure shares in the model and the data. Note that our procedure amounts to assuming that the economy is closed and households consume all production. Whether the assumption is appropriate in our context depends on whether our model can fit the Chinese data on the sectoral composition of GDP. We find that it does this well.

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 also applies to China. There are three reasons for doing this. First, the elasticity 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. Third, our results are robust to reasonable changes in the value of the elasticity. We have established this by varying the elasticity in the range between 1 and 2 and found that the results hardly change. See Appendix A.3 for the details.

Recall that we normalized $\tau_{gt} = 0$ for every year. The rest of the parameters, $\{\alpha_{gt}, \alpha_{lt}, \alpha_{ht}, Z_{gt}, Z_{lt}, Z_{ht}, \tau_{lt}, \tau_{ht}, \Omega^h_t\}_{t=0,1,2,\ldots}$, can be calibrated period by period.[9] We jointly target the following nine targets: the three ratios between high and low-skilled workers by sector, h_{it}/ℓ_{it}, the two relative sectoral nominal productivities, $(p_{it}y_{it}/n_{it})/(p_{gt}y_{gt}/n_{gt})$, the two relative sectoral prices, p_{it}/p_{gt}, GDP, Y_t, in units of goods, and the economy-wide skill premium $\hat{w}_t$. Note that it would be equivalent to target Ω^h instead of $\hat{w}_t$. We prefer to target $\hat{w}_t$ because it turns out to be easier computationally.

4.2 Identification

It is helpful to provide a sense for how the main parameters are identified in the calibration.

[9] Note that since $\Omega^l + \Omega^h = 1$, the share of high-skilled workers in all workers is $\Omega^h = \Omega^h/(\Omega^l + \Omega^h)$.

The identification of the share of high-skilled workers, Ω_t^h, and the level of one sectoral labor productivity, Z_{gt}, is straightforward. Ω_t^h is closely related to the observed economy-wide skill premium. Z_{gt} is closely related to the observed level of GDP in units of goods. Somewhat less obvious is the identification of α_{it} for $i = g, l, h$ and τ_{it} and Z_{it} for $i = l, h$. In what follows, we summarize the equations from the solutions of the firm problems that are key for the identification of these parameters. More details and the complete solution of the model can be found in Appendix A.2.

The identification of α_{it} works as follows. The first-order conditions to the firm's problem in sector i imply:

$$\frac{h_{it}}{\ell_{it}} = a_{it}^{\rho} \hat{w}_t^{-\rho}, \tag{8}$$

where $a_{it} \equiv \alpha_{it}/(1-\alpha_{it})$ and $\hat{w}_t \equiv w_t^h / w_t^l$ denotes the skill premium. Thus, given values for the skill premium and the elasticity of substitution, ρ, the value of α_{it} is pinned down by sector $i's$ high–to-low-skilled employment ratio, h_{it}/ℓ_{it}.

This leaves the identification of τ_{it} and Z_{it}, and in particular how the model distinguishes between them. Using equation (8), the production function can be written as:

$$y_{it} = Z_{it}\varphi_{it}(\hat{w}_t)\ell_{it}, \quad \text{where} \quad \varphi_{it}(\hat{w}_t) \equiv (1-\alpha_{it})^{\frac{\rho}{\rho-1}} \left(a_{it}^{\rho}\hat{w}_t^{1-\rho} + 1\right)^{\frac{\rho}{\rho-1}}.$$

The first-order conditions to the firm's problems in sector i and j then imply:

$$\frac{p_{it}}{p_{jt}} = \left(\frac{Z_{jt}}{Z_{it}}\right)\left(\frac{1+\tau_{it}}{1+\tau_{jt}}\right)\left(\frac{1-\alpha_{jt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{jt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1}{\rho}}. \tag{9}$$

This equation links the observed relative prices to the relative wedges and the relative labor productivities. To distinguish between the two, we need an additional equation. Combing the last two equations gives:

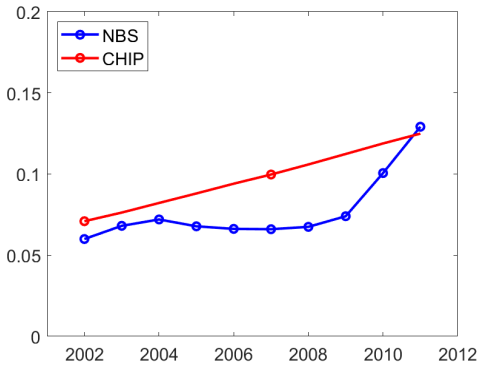
$$\frac{p_{it}y_{it}}{p_{jt}y_{jt}} = \left(\frac{1+\tau_{it}}{1+\tau_{jt}}\right)\left(\frac{1-\alpha_{jt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{jt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{\ell_{it}}{\ell_{jt}}\right). \tag{10}$$

Denoting the total labor inputs of sector i by $n_{it} \equiv h_{it} + \ell_{it}$, equations (8) and (10) imply that:

$$\frac{p_{it}y_{it}/n_{it}}{p_{jt}y_{jt}/n_{jt}} = \left(\frac{1+\tau_{it}}{1+\tau_{jt}}\right)\left(\frac{1-\alpha_{jt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{jt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{1+a_{jt}^{\rho}\hat{w}_t^{-\rho}}{1+a_{it}^{\rho}\hat{w}_t^{-\rho}}\right). \tag{11}$$

Given the calibrated values of α_{it} and ρ and the observed $\hat{w}_t$, equation (11) shows that the relative wedges are determined by the observed nominal labor productivity gaps. Given the relative wedges so determined, equation (9) shows that the relative labor productivities are determined by the observed relative prices.

Figure 2: Shares of High-skilled Workers in CHIP and NBS



In sum, the relative wedges are crucial for matching the observed gaps in *nominal* labor productivities in the data. The relative wedges are unrelated to differences in *real* labor productivities, which are given by the ratio of equations (9) and (11). The reason, of course, is that in a distortion-free economy with homogenous labor, differences in real labor productivities would be offset by opposing differences in relative prices while nominal labor productivities would be equalized. Given that differences in relative prices reflect differences in real sectoral labor productivities already, additional differences in *nominal* sectoral labor productivities reflect distortions.

4.3 Data Targets

We use the numbers from the Mincer wage regression of Meng (2012) for the Chinese skill premium during 1988–2009. We use the data from the GGDC 10-sector Database to construct the sector-level variables for China from 1988–2009.[10] 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 Thörnqvist 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 construct high- and low-skilled labor by sector ourselves. We start from the Chinese Household Income Project, or CHIP for short, which separately surveyed rural and urban households in 1988, 1995, 1999, 2002, 2007, 2008, 2013. From 2002 onwards, CHIP also separately surveyed migrant households. We do not use data for 1999 and 2008 because the 1999 wave only surveyed urban households and the 2008 survey has missing education information for many rural households. We restrict our 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

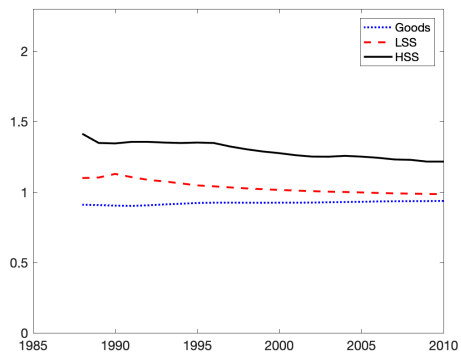
[10]The industry classification in the 10-sector data is similar to the classification in the Census Data.

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 from the National Bureau of Statistics (NBS). 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. As shown in the Figure 2, the resulting national share of high-skilled workers in the overall workforce is broadly consistent with that reported by the NBS. We are not too bothered by the fact that our national share does not replicate the drop in NBS data, because that drop was peculiar to begin with.

Table 3: Calibrated Preference Parameters

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

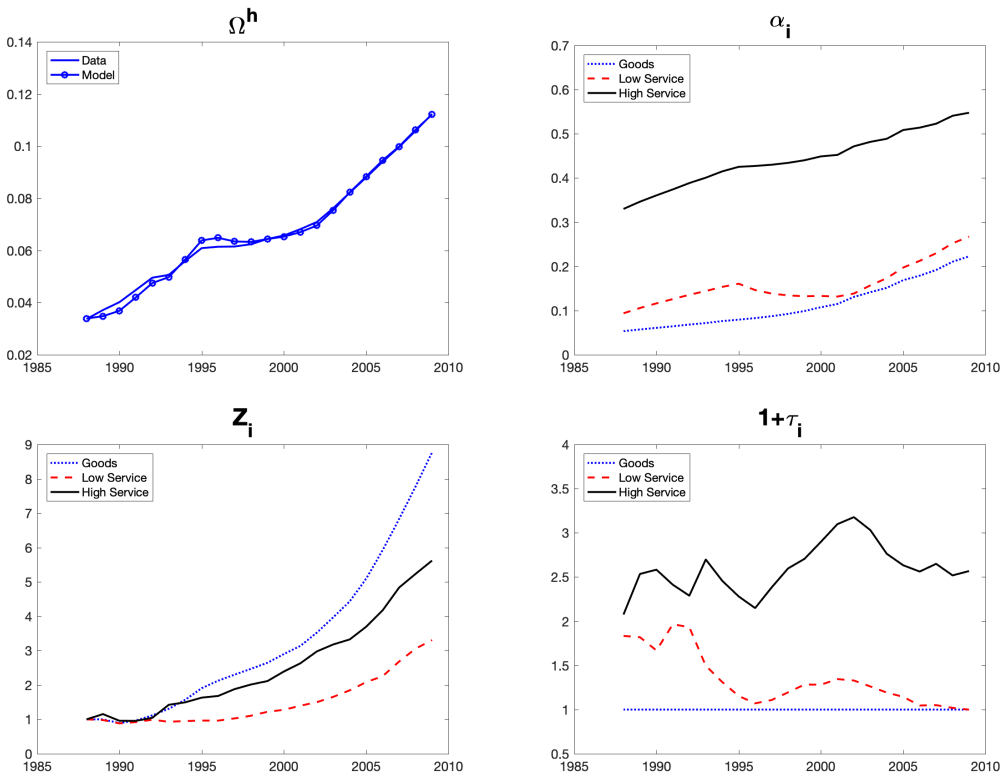
Figure 3: Calibrated Income Elasticities



4.4 Calibration Results

Table 3 reports the calibrated parameters from the household side. The individual parameters do not have much economic meaning, 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 combination and what they imply 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 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,

Figure 4: Calibrated Parameters – Production Side



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. Another 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 and the average elasticity between high and low-skill-intensive services is one.

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, τ_{lt}, declined to around zero whereas the wedge in high-skill-intensive services fluctuated around the large mean of 2.5 without showing a clear trend. Recall that the wedges are relative to the goods sector wedge so that $1+\tau_{gt} = 1$. The rise of the wedge in the high-skill-intensive services during 1997–2003 may therefore reflect the decrease in the distortions in the goods sector that resulted from the privatization of SOEs which happened since 1997 in goods but not in high-

Figure 5: Targeted Variables – Model and Data

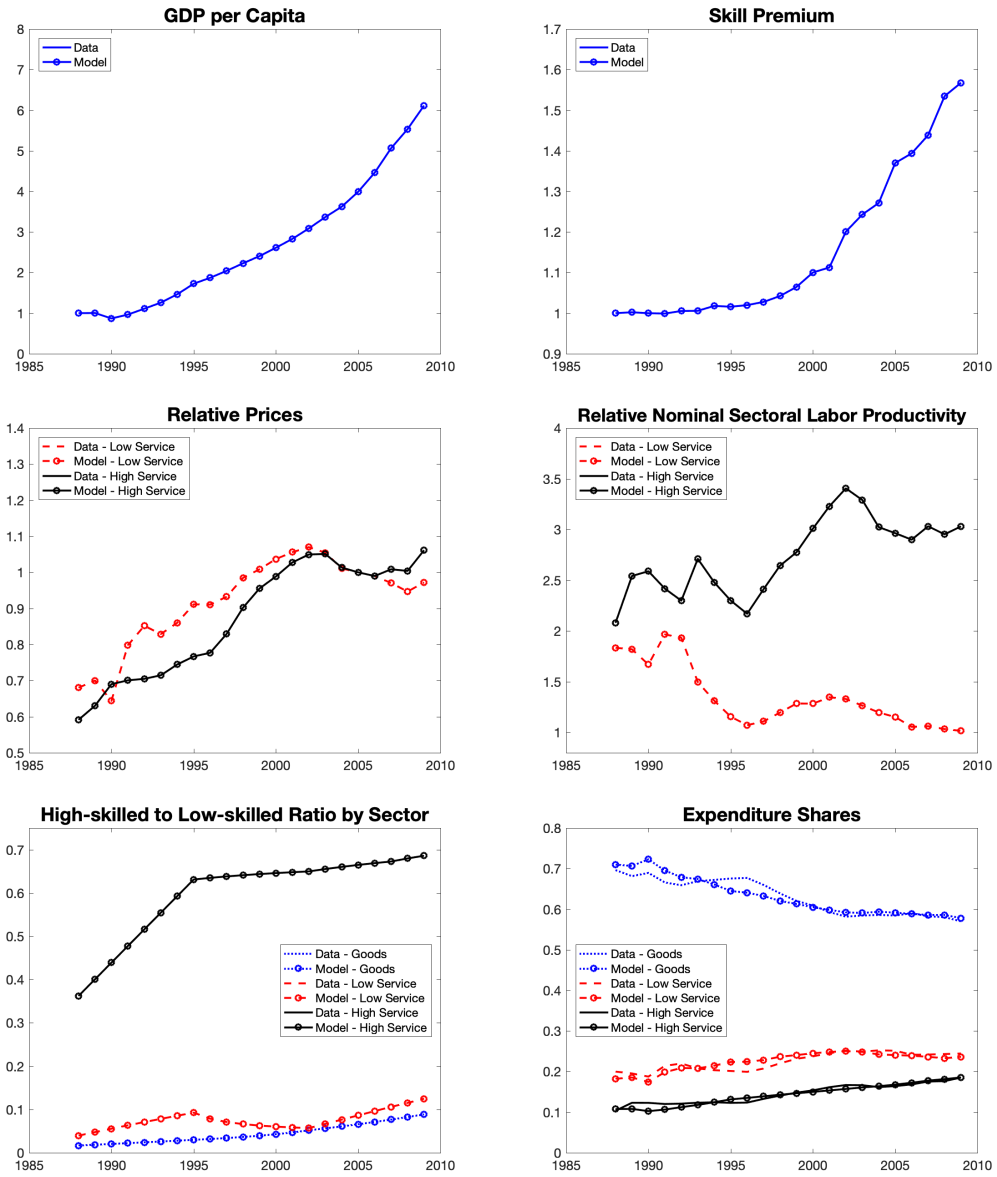
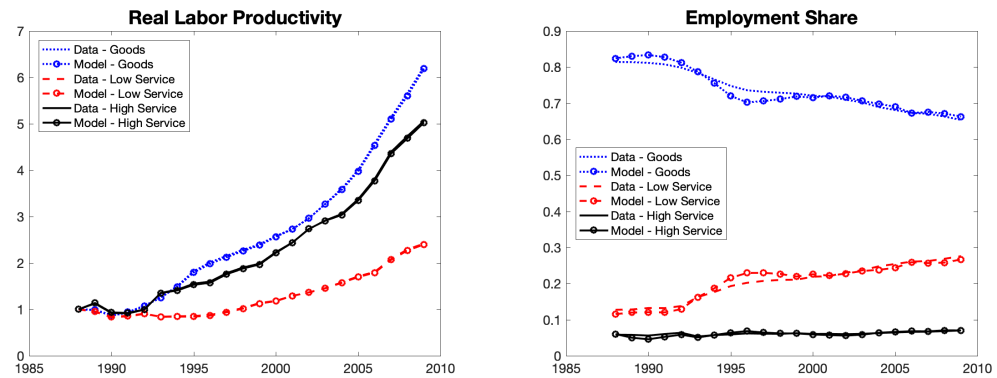


Figure 6: Non-targeted Variables – Model and Data



skilled services.

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 ratio by sector. In addition, the calibrated model also matches the expenditure shares well. Lastly, as shown in Figure 6, the calibration gets very close to the non-targeted sectoral real labor productivities and sectoral employment shares. Note that the employment shares are smooth over time, so there is no evidence that the low employment share of high-skill-intensive services in 2011 that we reported in Table 2 at the beginning is associated with business cycle fluctuations.[11]

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 during the past three decades. 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 services sector developed.

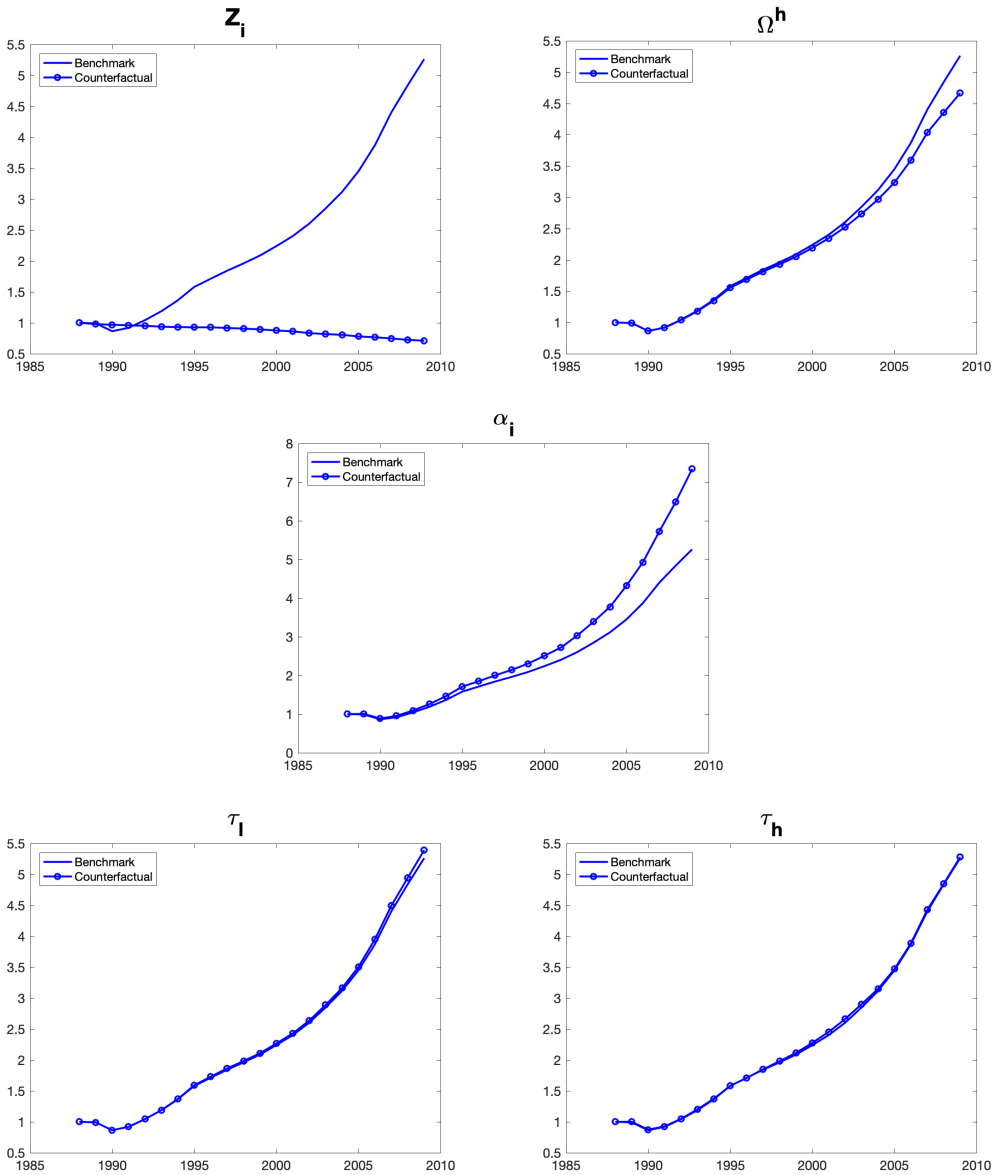
5.1 What Drove Chinese Growth during 1988–2009?

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. 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). 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.

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, we should point out that our labor productivity growth includes the effects

[11]For recent analyses of the interaction between structural change and business cycles in China, see Tan et al. (2017) and Yao and Zhu (2018).

Figure 7: Counterfactual GDP per capita Keeping one Parameter Constant



of capital accumulation whereas Zhu's TFP growth did not.

In sharp contrast to the results on labor productivity and education, the effects of increases in the skill intensity, α_{it}, and decreases in the wedge in low-skill-intensive services, τ_{lt}, are *negative* and *decrease* real GDP per capita. While these results 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.

Table 4: Share of College-educated Workers at similar GDP per capita

Country, Year	Education Year	Some College / Employment	College / Employment
Average		**0.11**	**0.06**
Argentina, 1995	1991	0.09	0.06
Brazil, 2009	2010	0.17	0.03
China, 2011	**2011**	**0.13**	**0.06**
Costa Rica, 2006	2000	0.21	0.12
France, 1959	1968	0.05	0.05
Malaysia, 1993	1991	0.06	0.06
Mexico, 1995	1995	0.12	0.07
South Africa, 2005	2007	0.07	0.07
Thailand, 2006	2000	0.08	0.04
United States, 1940	1940	0.12	0.06

GDP per capita is in international dollar and is computed from Penn World Tables 8.1.
Years of schooling are computed from IPUMS International where available.
Some college corresponds to at least two years of college.

5.2 Why is the Chinese High-skilled 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-skilled services (i.e., low Z_{ht}), and 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 2 for which we have data, Table 4 shows that in China 13% of the population have at least an associates degree (at least two years of college) and 6% have a completed college degree. These numbers are very close to the country averages of 11% and 6%. Judging by this comparison, workers in China are not at all "undereducated" given China's stage of development. Our formal analysis will confirm this impression.

Table 5: Determinants of the Employment Share of the HSS Sector

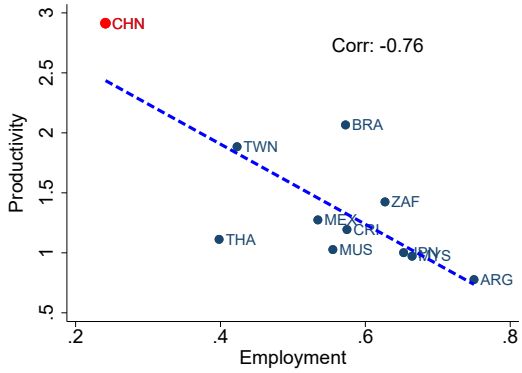
Parameter Values	n_h	n_l
Benchmark	0.07	0.27
$\boldsymbol{\tau_h = 0}$	**0.15**	0.24
$Z_h = 1.5 \cdot Z_{h,09}$	0.07	0.26
$Z_h = 2 \cdot Z_{h,09}$	0.07	0.26
$\Omega^h = 1.5 \cdot \Omega^h_{09}$	0.08	0.26
$\Omega^h = 2 \cdot \Omega^h_{09}$	0.08	0.26

"09" is for 2009 calibration.
n_h and n_l are employment shares of HSS and LSS.

We approach the question why the high-skill-intensive services sector is underdeveloped in China by asking how the sectoral composition is affected by: changes in the wedge in high-skill-intensive services; changes in the sectoral labor productivities; changes in the skill composition. Guided by the calibration results, we consider three scenarios: set the wedge in high-skill-intensive services to zero; increase the labor productivity of high-skilled services by 50 and 100%; increase the economy-wide ratio of high- to low-skilled workers by 50% and 100%. Table 5 shows 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 eliminated just the wedge in high-skill-intensive services (second row), then employment in high-skill-intensive services would rise to 15%, which is close to the 18% average share over the comparable countries listed in Table 2. It is remarkable that removing just the wedge in high-skill-intensive services sector brings us most of the way to the average over the comparable countries. In contrast, if we doubled the labor productivity in high-skilled services or doubled the share of skilled workers (last row), then the share of high-skilled employment would not change much. We conclude that neither low productivity in high-skilled services nor a shortage of high-skilled workers are the primary reasons for the abnormal sectoral composition of China.

The intuition for why the wedge suppresses employment in high-skill-intensive services is straightforward. Removing the wedge decreases the relative price of high-skill-intensive services and increases overall income. Since the substitution elasticities are close to one and high-skill-intensive services are luxuries, the net effect is that the value-added share of high-

Figure 8: Ratios of Nominal Productivity and of Employment in HSS versus LSS



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

skill-intensive services increases. Since the other terms of the wedges equation (11) do not change much quantitatively, this means that n_{gt}/n_{ht} must decrease:

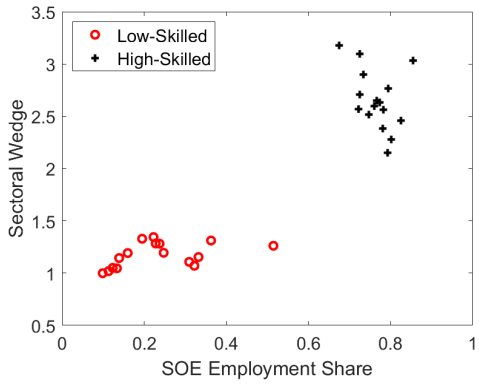
$$\frac{n_{gt}}{n_{ht}} = \underbrace{(1+\tau_{ht})}_{\downarrow}\underbrace{\frac{p_{gt}y_{gt}}{p_{ht}y_{ht}}}_{\downarrow}\underbrace{\left(\frac{1-\alpha_{gt}}{1-\alpha_{ht}}\right)\left(\frac{\varphi_{gt}(\hat{w}_t)}{\varphi_{ht}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{1+a_{gt}^{\rho}\hat{w}_t^{-\rho}}{1+a_{ht}^{\rho}\hat{w}_t^{-\rho}}\right)}_{\text{no big changes}}.$$

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 (11) 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 8 shows that the negative correlation is strongly present in the subset of our comparison countries for which we have sectoral nominal value added data. We interpret this as evidence for the validity of our model.

5.3 Discussion

A natural question to ask at this point is what nature the wedges in high-skill-intensive services have in reality. One obvious possibility is that they are related to the presence of state-owned enterprises (SOEs) in high-skill-intensive services. Table 6 shows that, indeed, SOEs employ more than half of the workers in high-skill-intensive services, but less than one in twenty five of the workers in the other two sectors. Note that the high employment share of SOEs in high-skill-intensive services industries is not mainly driven by public administration, which constitutes only 2.3% of overall employment in China. Note too that the correlation between wedges and SOEs is not restricted to 2016. To show this, we plot the relative wedges in the two services sectors against the employment shares of SOEs for all years for which we have

Figure 9: Sectoral Wedges versus Sectoral SOE Employment Shares



SOE employment share constructed from the Chinese NBS data 1994–2009.

observations. Figure 9 shows that indeed there is a strong positive relationship between the two.

The evidence reported above suggests to take seriously the possibility that the large employment share of SOEs in high-skill-intensive services is symptomatic of large distortions. One obvious link between the two is that usually SOEs can survive at such a large scale only if entry restrictions protect them from the competition by privately-owned enterprises that tend to be more productive. Brandt et al. (2017) establish that local variations in the dynamics of entry barriers are the key for understanding the growth and convergence of the non-state sector in China. Zhu (2012), in the second paragraph of the last page, argues: *"Protected by barriers to entry of 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."*

Our formal analysis goes beyond these observations by showing that, in recent times, the main problem has been in *high-skill-intensive* services, instead of more broadly in all services industries. It might be helpful to give some concrete examples of entry restrictions in high-skill-intensive services in China that are captured by our wedges. The banking and insurance industry is accessible to foreign investors only through joint venture structures with Chinese companies. Moreover, until 2018, foreign banks were allowed only minority share holdings and had limited influence over big decisions. Hence, the large Western banks are largely absent in China. Another example is that, until recently, foreign hospitals were not allowed to operate in China, and now they are allowed only in a handful of very large cities.

There are three possible, alternative explanations for why the high-skill-intensive services sector is underdeveloped in China. First, it might be that the Chinese economy imports many high-skill-intensive services and runs a large trade deficit in this part of the economy. We have found no evidence for this possibility in the Chinese trade data. In fact, trade in high-skill-intensive services is balanced, by and large. Second, in independent work, Lu et al. (2019) put forth the thesis that migration barriers from the country side to the city are an explanation

Table 6: Share of Employment in SOEs in China in 2016 (in %)

Goods	**1.7**
Agriculture, Forestry, Fishing	1.1
Manufacturing	1.5
Construction	4.4
Mining	9.0
Low-Skilled Services	**4.0**
Wholesale and Retail	0.6
Household Services	1.2
Hotels and Restaurants	1.4
Transport and Post	24.0
Utilities	45.0
High-Skilled Services	**51.5**
Leasing and Business Service	4.0
Real Estate	7.4
Information Technology	9.2
Finance and Insurance	22.0
Scientific Research and Technical Services	51.0
Health Care	87.0
Education	92.0
Public Administration	99.0

SOE employment shares are constructed from the Chinese NBS data.

for the high employment share of agriculture and the low employment share of services in China. They name the hukou system as a prominent example for such migration barriers. While one might think that our wedges capture the effects of migration barriers in a reduced-form way, this is unlikely to be the case because the migration barriers modelled in Lu et al. (2019) affect all services whereas our wedges affect mostly high-skill-intensive services. Third, an underdeveloped high-skill-intensive services sector might somehow result as a by product of fast catch up growth. This thesis is consistent with the fact that in Table 2 above the East Asian countries Taiwan and Thailand also show much lower than average employment shares of high-skill-intensive services, although their shares are not quite as low as in China. Things are not quite as simple though because the Table also shows that in Japan in 1967 the employment shares of high-skill-intensive services did not differ much from the average over all comparison countries.

5.4 How Wedges Affect GDP per capita

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.

Before we delve into the details, it is necessary to spend a moment on how to measure counterfactual changes in GDP per capita. In the modeling part and the counterfactuals, 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 Data Base. Instead of using a numeraire from each period, it is built around Thörnqvist 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 Thörnqvist index. The growth rate between periods t and $t+1$ of GDP per capita is then defined as:[12]

$$\Delta \log Y_t = \sum_{i=g,l,h} S(p_{it}y_{it})(\log y_{i,t+1} - \log y_{it}). \tag{12}$$

y_{it} denotes value added in sector i and $S(p_{it}y_{it})$ denotes the shares of sector i's nominal value added in the economy-wide total. The Törnqvist indexes uses the average share over the adjacent periods between which the growth rates are calculated. In our model with numeraire goods, the average share is defined as:

$$S(p_{it}y_{it}) \equiv \frac{1}{2}\left(\frac{(p_{it}/p_{gt})y_{it}}{\sum_{i=g,l,h}(p_{it}/p_{gt})y_{it}} + \frac{(p_{i,t+1}/p_{g,t+1})y_{it+1}}{\sum_{i=g,l,h}(p_{i,t+1}/p_{g,t+1})y_{it+1}}\right). \tag{13}$$

Table 7 reports the effects of wedges in high-skill-intensive services on GDP per capita. The

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

table shows that removing the wedges leads to an increase in GDP per capita by 5%. This is a large gain! 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%, which we have already reported in the previous section.

Table 7: Effects of τ_h on GDP per capita

τ_h	Y	n_h
$\tau_{h,09}$	1	0.07
$0.75 \cdot \tau_{h,09}$	1.01	0.08
$0.5 \cdot \tau_{h,09}$	1.03	0.10
$0.25 \cdot \tau_{h,09}$	1.04	0.12
0	1.05	0.15

"09" is for 2009 calibration.
Y is real GDP per capita an n_h is employment share of HSS.

For several reasons, our gains of removing the distortions are likely to be a lower bound of the actual gains. A first reason is that we rebate the revenues accruing from the labor wedges. If instead we assumed that they are thrown away, then the output gains from removing the wedge would include both the gains we measured and the gains from not wasting the wedge revenues. A second reason is that our model does not feature physical capital accumulation, and so our gains arise exclusively from the static misallocation of labor among sectors. Herrendorf and Teixeira (2011) developed an environment with monopoly power and rent extraction in which physical capital accumulation importantly amplifies the GDP effects of removing barriers to entry. A third reason why our gains are likely to be a lower bound is that our model does not explicitly consider the effects on GDP per capita that result from the entry of additional firms after the reduction of entry barriers. Using a Hopenhayn model, Asturia et al. (2019) showed that this effect can considerably increase GDP per capita. 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 this effect can further increase GDP per capita. A last reason why our gains are likely to be a lower bound is that human capital accumulation can react as well to the removal of barriers to entry. For example, the incentive to obtain a degree in finance increases if China's financial sector is liberalized and Western banks are allowed to operate in China without severe constraints. Note the side effect that a liberalized financial sector can also improve the allocation of credit, which in itself increases GDP per capita further.

To summarize, this section has established that labor productivity growth was the main driver of the growth in Chinese GDP per capita in the past decades. It then has identified large wedges in high-skill-intensive services as the main cause of the under-development of high-skill-intensive services in China. Lastly, it has shown that removing the wedges in high-

skill-intensive services leads to sizeable gains in Chinese GDP per capita.

6 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.

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".[13] 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.

Our results raise the question what nature the distortions in high-skill-intensive services take. We have established that SOEs are much more prevalent in the high-skill-intensive services industries than elsewhere. Since SOEs can dominate high-skill-intensive services industries only if they are sheltered by entry barriers, our results are consistent with the broader view that barriers to entry and monopoly rights distort the high-skill-intensive services sectors.

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

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[13] Imrohoroglu and Zhao (2018) find that a sizeable part of the high Chinese savings rate is accounted for by demographic factors, suggesting that less re-balancing will be required than is often claimed.

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A Appendix

A.1 Solving for the Demand System

Let c_{it}^n be the consumption of good i by household n. From Roy's identity:

$$c_{it}^n = -\frac{\partial v(e_t^n, \vec{P}_t)/\partial p_{it}}{\partial v(e_t^n, \vec{P}_t)/\partial e_t^n}.$$

Applying this to (2) gives:

$$c_{it}^n = -\frac{\left(e_t^n B_t^{-1} - A_t\right)^{\varepsilon-1}\left(-e_t^n B_t^{-2} B_{it} - A_{it}\right) + D_{it}}{\left(e_t^n B_t^{-1} - A_t\right)^{\varepsilon-1} B_t^{-1}} = A_{it}B_t + e_t^n B_{it} B_t^{-1} - \left(e_t^n B_t^{-1} - A_t\right)^{1-\varepsilon} D_{it} B_t,$$

where A_{it}, B_{it} and D_{it} are the derivatives with respect to p_{it}, respectively. Hence, we get the expenditure shares:

$$\frac{p_{it}c_{it}^n}{e_t^n} = \frac{B_t}{e_t^n} p_{it}A_{it} + B_t^{-1} p_{it} B_{it} - \frac{B_t}{e_t^n}\left(e_t^n B_t^{-1} - A_t\right)^{1-\varepsilon} p_{it} D_{it}.$$

Following Proposition 3 in Alder et al. (2017), we can aggregate the expenditure shares for all households and derive $s_{it}(\vec{P}_t, E_t)$:

$$s_{it}(\vec{P}_t, E_t) = \frac{p_{it}\sum_n c_{it}^n}{E_t} = \frac{B_t}{E_t} p_{it}A_{it} + B_t^{-1} p_{it} B_{it} - \frac{B_t}{E_t}\left(E_t B_t^{-1} - A_t\right)^{1-\varepsilon} p_{it} D_{it}\kappa, \tag{A.1}$$

where

$$\kappa \equiv \frac{\sum_n \partial v(\vec{P}_t, E_t)/\partial e}{\partial v(\vec{P}_t, e_t^n)/\partial e}.$$

Deriving A_{it}, B_{it} and D_{it} and plugging the results into (A.1) gives:

$$s_{gt}(\vec{P}_t, E_t) = \phi_g + (\mu_g - \phi_g)\frac{A(\vec{P}_t)}{E_t/B(\vec{P}_t)} + \left(\frac{E_t}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{1-\epsilon}\frac{B(\vec{P}_t)}{E_t}\sum_{k\in\{h,l\}}\bar{D}\nu_k\left(\frac{p_{kt}}{p_{gt}}\right)^{\psi_k}\kappa,$$

$$s_{it}(\vec{P}_t, E_t) = \phi_i + (\mu_i - \phi_i)\frac{A(\vec{P}_t)}{E_t/B(\vec{P}_t)} - \left(\frac{E_t}{B(\vec{P}_t)} - A(\vec{P}_t)\right)^{1-\epsilon}\frac{B(\vec{P}_t)}{E_t}\bar{D}\nu_i\left(\frac{p_{it}}{p_{gt}}\right)^{\psi_i}\kappa, \quad i \in \{h, l\},$$

$$\kappa = \frac{\Omega_t^l(e_t^l/B_t - A_t)^{1-\epsilon} + \Omega_t^h(e_t^h/B_t - A_t)^{1-\epsilon}}{(E_t/B_t - A_t)^{1-\epsilon}}.$$

A.2 Solving the Production Side

The representative firm $i's$ problem is given by:

$$\max p_{it}y_{it} - (1+\tau_{it})(w_t^h h_{it} + w_t^l \ell_{it}).$$

The first-order conditions are:

$$p_{it}Z_{it}\alpha_{it}\left(\frac{L_{it}}{h_{it}}\right)^{\frac{1}{\rho}} = w_t^h(1+\tau_{it}), \tag{A.2}$$

$$p_{it}Z_{it}(1-\alpha_{it})\left(\frac{L_{it}}{\ell_{it}}\right)^{\frac{1}{\rho}} = w_t^l(1+\tau_{it}). \tag{A.3}$$

Dividing equations (A.2) and (A.3) by each other gives:

$$\frac{h_{it}}{\ell_{it}} = \left(\frac{\alpha_{it}}{1-\alpha_{it}}\right)^{\rho}\left(\frac{w_t^l}{w_t^h}\right)^{\rho}. \tag{A.4}$$

Defining $a_{it} \equiv \alpha_{it}/(1-\alpha_{it})$ and $\hat{w}_t \equiv w_t^h/w_t^l$, the above ratio becomes:

$$\frac{h_{it}}{\ell_{it}} = a_{it}^{\rho}\hat{w}_t^{-\rho}. \tag{A.5}$$

Using (A.5), the production function can be rewritten as:

$$y_{it} = Z_{it}(1-\alpha_{it})^{\frac{\rho}{\rho-1}}\left(a_{it}^{\rho}\hat{w}_t^{1-\rho}+1\right)^{\frac{\rho}{\rho-1}}\ell_{it}.$$

Defining:

$$\varphi_{it}(\hat{w}_t) \equiv (1-\alpha_{it})^{\frac{\rho}{\rho-1}}\left(a_{it}^{\rho}\hat{w}_t^{1-\rho}+1\right)^{\frac{\rho}{\rho-1}}, \tag{A.6}$$

y_{it} can be further rewritten as:

$$y_{it} = Z_{it}\varphi_{it}(\hat{w}_t)\ell_{it}. \tag{A.7}$$

Plugging (A.7) into the first-order condition (A.3) gives relative sectoral prices:

$$p_{it} = \frac{(1+\tau_{it})w_t^l}{Z_{it}(1-\alpha_{it})}\varphi_{it}(\hat{w}_t)^{-\frac{1}{\rho}}, \tag{A.8}$$

$$\frac{p_{it}}{p_{jt}} = \left(\frac{1+\tau_{it}}{1+\tau_{jt}}\right)\left(\frac{1-\alpha_{jt}}{1-\alpha_{it}}\right)\left(\frac{Z_{jt}}{Z_{it}}\right)\left(\frac{\varphi_{jt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1}{\rho}}. \tag{A.9}$$

From (A.7) and (A.9), it now follows that:

$$\frac{p_{it}y_{it}}{p_{jt}y_{jt}} = \left(\frac{1+\tau_{it}}{1+\tau_{jt}}\right)\left(\frac{1-\alpha_{jt}}{1-\alpha_{it}}\right)\left(\frac{\varphi_{jt}(\hat{w}_t)}{\varphi_{it}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\left(\frac{\ell_{it}}{\ell_{jt}}\right).$$

From the households' problems we know $s_i(\vec{P}_t, E_t)$. Hence, the above equation can be rewritten as:

$$\frac{\ell_{it}}{\ell_{jt}} = \left(\frac{1+\tau_{jt}}{1+\tau_{it}}\right)\left(\frac{1-\alpha_{it}}{1-\alpha_{jt}}\right)\left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{jt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\frac{s_i(\vec{P}_t, E_t)}{s_j(\vec{P}_t, E_t)}. \tag{A.10}$$

(A.10) implies market clearing for low-skilled labor can be written as:

$$\begin{aligned}
\Omega_t^l &= \sum \ell_{it}, \\
\Omega_t^l &= \ell_{gt}\sum \frac{\ell_{it}}{\ell_{gt}}, \\
\frac{\ell_{gt}}{\Omega_t^l} &= \frac{1}{\sum\left(\frac{1+\tau_{gt}}{1+\tau_{it}}\right)\left(\frac{1-\alpha_{it}}{1-\alpha_{gt}}\right)\left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\frac{s_i(\vec{P}_t, E_t)}{s_1(\vec{P}_t, E_t)}}.
\end{aligned} \tag{A.11}$$

(A.5) and (A.10) imply that market clearing for high-skilled labor can be written as:

$$\begin{aligned}
\Omega_t^h &= \sum h_{it}, \\
\frac{\Omega_t^h}{\Omega_t^l} &= \frac{\ell_{gt}}{\Omega_t^l}\sum \frac{h_{it}}{\ell_{it}}\frac{\ell_{it}}{\ell_{gt}}, \\
\frac{\ell_{gt}}{\Omega_t^l} &= \frac{\Omega_t^h/\Omega_t^l}{\sum a_{it}^{\rho}\hat{w}_t^{-\rho}\left(\frac{1+\tau_{gt}}{1+\tau_{it}}\right)\left(\frac{1-\alpha_{it}}{1-\alpha_{gt}}\right)\left(\frac{\varphi_{it}(\hat{w}_t)}{\varphi_{gt}(\hat{w}_t)}\right)^{\frac{1-\rho}{\rho}}\frac{s_i(\vec{P}_t, E_t)}{s_1(\vec{P}_t, E_t)}}.
\end{aligned} \tag{A.12}$$

The equilibrium is characterized by two equations in the two unknowns $(\hat{w}_t, E_t)$. The first equation is obtained by equating (A.11) and (A.12). The second equation is $E_t = \sum p_{it}y_{it}$.

A.3 Robustness with Respect to ρ

Table A1: 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
$Z_h = 1.5 \cdot Z_{h,09}$	0.07	0.26	0.07	0.26	0.07	0.26
$Z_h = 2 \cdot Z_{h,09}$	0.07	0.26	0.07	0.26	0.07	0.26
$\Omega^h = 1.5 \cdot \Omega^h_{09}$	0.08	0.26	0.08	0.26	0.08	0.26
$\Omega^h = 2 \cdot \Omega^h_{09}$	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 A2: Effects of τ_h on GDP per capita for different ρ

τ_h	$\rho = 1$		$\rho = 1.42$		$\rho = 2$	
	Y	n_h	Y	n_h	Y	n_h
$\tau_{h,09}$	1	0.07	1	0.07	1	0.07
$0.75 \cdot \tau_{h,09}$	1.01	0.08	1.01	0.08	1.01	0.08
$0.5 \cdot \tau_{h,09}$	1.03	0.09	1.03	0.10	1.03	0.10
$0.25 \cdot \tau_{h,09}$	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).