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STRUCTURAL TRANSFORMATION IN INDIA: THE ROLE OF THE SERVICE SECTOR

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Title: Structural transformation in India: The Role of the Service Sector

Abstract:

Contrary to the experience of industrialized countries, productivity growth of Indian services has been consistently faster than manufacturing. In this paper, I document that (i) the fastest growing industries in services grow faster than in manufacturing; (ii) faster productivity growth in services than in manufacturing is not because of sluggish manufacturing productivity; (iii) the supply of skilled workers in India is skewed towards tertiary education and (iv) the service sector is the most skill intensive; (v) returns to schooling are larger for the high-productivity services. To quantify and rationalize these facts, I construct a multi-sector model of structural change with high and low-skilled workers. The calibrated model suggests that the large supply of high-skill workers combined with higher skill intensity in the service sector seem to be behind the services take-off. The data imply that service sub-sectors are gross substitutes while manufacturing sub-sectors are gross complements. This will accelerate productivity growth in services and decelerate productivity growth in manufacturing.

JEL Codes: O41, O47, O51.

Keywords: Structural transformation, Productivity, Human Capital, India

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Structural transformation in India: The Role of the Service Sector *

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LATEST VERSION

Abstract

Services led development strategies have raised concerns based on the historically low productivity growth of services. In this paper, I investigate which conditions make these strategies successful by looking at the most prominent example, India. I show that (i) the fastest growing industries in services grow faster than in manufacturing; (ii) services grow faster than manufacturing not because of sluggish manufacturing productivity; (iii) the distribution of educational attainment is skewed towards tertiary educated workers and (iv) the service sector is the most skill intensive; (v) returns to schooling are larger for the high-productivity services. To quantify and rationalize these facts, I construct a multi-sector model of structural change with high and low-skilled workers that takes into account heterogeneity in productivity growth within manufacturing and services. The calibrated model suggests that the large supply of high-skill workers combined with higher skill intensity in the most productive industries in the service sector seem to be behind the take-off in services productivity.

Keywords: Structural transformation; Productivity; Human Capital; India
JEL Classification: O41; O47; O51

*I am thankful to Fidel Pérez-Sebastián and Ákos Valentinyi for their guidance, comments, and support. I also thank Javier Andrés Santiago, Gaaitzen de Vries, Luis Franjo, and Francesco Turino for their very helpful comments, as well as the audiences of presentations at the University of Barcelona, University of Navarra, Corvinus University, University of the Balearic Islands, University of Groningen, and University of Alicante. Also audiences at STEG 2021 Annual Conference, 44th Simposio de la Asociación Española de Economía, and NWSSDTP PhD Conference 2019. Financial support from Spanish Ministry of Science, Innovation, and Universities (ECO2015-70540-P), is gratefully acknowledged. All possible mistakes are my own.

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1 Introduction

The pattern of structural transformation that has characterized industrialized countries involved a process of industrialization with fast productivity growth in manufacturing.[1] However, the experience of low and middle income countries today shows that they are deindustrializing at lower levels of income than developed countries, which has created a concern about whether they are running out of opportunities for development (Rodrik, 2016).

The main concern about premature deindustrialization is that, historically, manufacturing has been the main engine of development absorbing low skilled workers and allowing them to move from the agricultural sector. Technologically, it is also a dynamic sector exhibiting unconditional convergence in productivity (Rodrik, 2012) which suggests that industrialization is key for developing countries. On the contrary, services have traditionally exhibited slow productivity growth and its expansion was driven by rising incomes that altered relative demands.

In this paper, I look at the case of India, one of the most prominent examples of services-led development that virtually skipped the process of industrialization while undergoing one of the most stable and long standing processes of development in modern history (Lamba and Subramanian, 2020). Understanding how these fast and sustained rates of growth emerge from a process of services led development is the main objective of this paper. In particular, I ask why productivity has grown at a faster pace in services than in manufacturing. I also document five stylized facts that empirically motivate the analysis and guide the model.

(i) The fastest growing industries in services grow at faster rates than their manufacturing counterparts. I divide the industries in the manufacturing and service sectors as in Duernecker et al. (2023) by assigning them to either high-productivity or low-productivity growth subsectors. In the US, the high-productivity growth manufacturing subsector is, by far, the fastest growing sector while the low-productivity service is the slowest growing one. In India, however, high-productivity services show the fastest productivity growth, even faster than that of high-productivity growth manufacturing. Furthermore, within the low-productivity subsectors, services still grow faster than manufacturing.

(ii) I show that the faster productivity growth in services is not because of sluggish manufacturing. In fact, controlling by the stage of development and population, productivity growth in Indian services is 1.77 percentage points faster than the average country while there are no differences for productivity growth in manufacturing. Controlling for the stage of development is crucial since faster productivity growth could be a result of convergence to the international norm (Eichengreen and Gupta, 2011). Finding no differences in productivity growth in manufacturing goes in line with Ziebarth (2013) who argues that the degree of misallocation in India and China is not different from that of the US at a similar stage of development.

[1] Baumol (1967); Kuznets (1966) and Kuznets (1973) already connected productivity growth and structural transformation. More recently, Echevarria (1997); Kongsamut et al. (2001); Ngai and Pissarides (2007); Acemoglu and Guerrieri (2008) have proposed the main theoretical mechanisms behind the process of structural change. Empirically, productivity differences seem to be one of the key elements to account for structural change (Święcki, 2017) and the decline in the agricultural employment share (Álvarez-Cuadrado and Poschke, 2011; Teignier, 2018). Herrendorf et al. (2014) provide an extensive literature review on structural transformation.

(*iii*) The distribution of educational attainment in India is skewed towards tertiary education. Roy (1996) and Sivasubramonian (2004) suggest that the distribution of educational attainment (and government efforts) in India have historically been skewed towards tertiary education. Furthermore, on the demand side, education was biased towards certain social groups. Certain castes and communities were associated with occupations from the literate services, which in turn, caused certain regions (port cities mostly) to be more intensive in this type of services. [2] The percentage of workers with some university education in India grew from 3 percent in 1983 to 9.6 percent in 2009. For comparison, In China, only 0.87 percent of workers had some university education in 1982 while in 2000 this number rose to 4.7 percent. Although small, the numbers for India are significantly larger than for China even when the differences in GDP are accounted for.

(*iv*) Using census data, I show that the service sector is the most skilled intensive, especially, the high-productivity industries.

(*v*) Returns to schooling are larger for the service sectors and services provide a sectoral wage premium. I estimate the returns to schooling for each of the sectors as in Herrendorf and Schoellman (2018) and I find high-productivity services offer the highest wage premium with larger returns to schooling than in the rest of the sectors.

These facts suggest that a services-led development strategy where high-productivity services absorb the highest skilled individuals and the rest of services absorb the lower skilled individuals, might be a more successful development strategy than previously thought.

To rationalize these facts and quantify the relative importance of each source of growth, I build a model of structural transformation that explicitly divides the manufacturing and service sectors into high and low-productivity subsectors and incorporate high and low-skilled workers. The division of the sectors into high and low-productivity subsectors is important due to the substantial heterogeneity in productivity growth rates but it will also be useful to identify the differential sources of growth that matter for the observed productivity dynamics.[3] The model is most similar to that of Buera et al. (2021) and Fang and Herrendorf (2021) but departs from them by modelling the manufacturing and service subsectors as CES aggregates of the high-productivity and low-productivity subsectors.

The calibrated model suggests that high and low-productivity growth manufacturing subsectors are gross complements while services subsectors are gross substitutes. This implies that, conditional on labor flowing into the manufacturing sector, labor will flow relatively more into the low-productivity growth one. If, instead, labor flows into the service sector, labor will flow into the high-productivity growth one. That will further increase differences in labor productivity growth between the aggregate manufacturing and service sectors.

In the model there are several sources of growth. First, a sectoral Hicks-neutral techno-

[2] Roy (2011) also notes that these castes were still dominating the entrance on the telecommunications sector in during the 1990s. Kochhar et al. (2006) shows that India has focused on skill intensive manufacturing as well.

[3] Jorgenson and Timmer (2011); Eichengreen and Gupta (2011); Buera and Kaboski (2012) and Bridgman et al. (2018) divide the service sector by considering traditional and modern industries or home and market services. Duarte and Restuccia (2019) classify services into traditional and non-traditional based on the income elasticity of relative prices.

logical component that captures TFP growth. Second, a skill-intensity parameter that captures both the intensity of sectoral high-skill labor use and the sectoral increase in the demand for high-skilled labor. In turn, it measures some form of skill bias technical change at the sector level. Third, the aggregate relative supply of high skilled workers, and fourth, a sector specific distortion that firms need to pay as an additional cost for each unit of labor hired. These distortions will work as wedges reflecting all additional costs besides wages firms have to incur in order to hire an additional worker (skilled or unskilled).[4]

The calibrated Hicks-neutral terms cannot be driving the differences in productivity growth between high-productivity growth manufacturing and services subsectors since their growth rates are very similar. The decomposition into high and low-productivity growth subsectors is crucial for this result since, as Verma (2012) shows, the main differences between services and manufacturing on aggregate come from TFP growth. Instead, what drives the differences between the high-productivity growth subsectors is their skill-intensity. High productivity growth services are far more intensive in high-skilled workers thus attracting more workers of this type, and showing a faster labor productivity growth.

Closely related to this paper, Fan et al. (2021) find that productivity growth in consumer services has been an important driver of living standards but that service gains were localized in urbanized regions. This paper complements their analysis by disaggregating further manufacturing and services sectors, accounting for skill intensity differences, and identifying the main driver of divergence in labor productivity between manufacturing and services.

International trade could be a potentially important mechanism to explain the documented patterns. To address this, I introduce unbalanced trade as in Fang and Herrendorf (2021) but to account for productivity differences the drivers highlighted above are still necessary. Service subsectors are gross substitutes while manufacturing subsectors are gross complements; and what drives the differences in labor productivity growth between high-productivity manufacturing and services is the skill intensity.[5]

A crucial implication of the model is that high-productivity sectors both in manufacturing and services face large distortions. I explore two sources of distortions, barriers to female employment and complementarities between education and migration costs. In India, female labor market participation is very low (20.5% in 2019 according to World Bank Data) and female employment is mostly concentrated in the least productive sectors (66.75% work in agriculture). This is a barrier that affects mostly the high-productivity sectors.

To explore migration costs and educational complementarities, I regress the sectoral employment share at the municipality level at a given time period on an interaction between

[4] Buera and Kaboski (2009) show that to account for differences between employment and output shares, different sectoral wages are necessary. Wedges are a way of accommodating this, an alternative could be a mobility cost paid by the workers moving into another sector (Alonso-Carrera and Raurich, 2018).

[5] The literature on structural change and its relationship with international trade is large and growing. Matsuyama (1992) analyzes the effect of trade for agricultural productivity in a two-sector model and Matsuyama (2009) analytically studies how trade affects the movements of consumption and value added shares. Uy et al. (2013); Teignier (2018) and Sposi (2019) are more recent papers analyzing the role of trade in structural transformation.

distance to the city and average educational attainment controlling for other municipality characteristics. The results from this set of regressions show that the high-productivity employment share increases both because of proximity to a large city and because of increases in average years of schooling, and these two factors complement each other. However, for high-productivity manufacturing, there is no such complementarity. This suggests that barriers to entry in high-productivity services are larger than in high-productivity manufacturing.

The remainder of the paper is organized as follows. Section 2 documents the different patterns in sectoral labor productivity dynamics, compares sectoral labor productivity growth with the rest of countries in the sample, and sheds light on some other countries that could enjoy a similar development process as India. In Section 2.3 I analyze educational data for India and China and estimate sectoral Mincer returns to schooling and the economy wide skill-premium. Section 3 presents the theoretical model of structural change and its main implications. In Section 4 I show the quantitative analysis of the model. Section 5 concludes.

2 Labor Productivity Trends

I start by documenting differences in sectoral labor productivity trends observed in India and the United States, then I compare growth rates of labor productivity in India with a set of 41 countries at all stages of development, and finally look at sectoral skill composition.

2.1 Labor Productivity Growth

The main data source for India's sectoral accounts is the India KLEMS database (version from July 2019) from the Reserve Bank of India, which compiles according to the KLEMS standard, industry accounts that comprise the full economy. The data covers 27 industries from 1981 up to 2017. The data for the United States is taken from World KLEMS (March 2017) which covers 65 industries from 1947 up to 2014. The fact that these two datasets follow the same compiling methodology makes comparison across these two countries sensible.

Let labor productivity[6] in sector j (agriculture, manufacturing, or services) be defined as the real value added in sector j divided by the quality-adjusted labor employed by that sector.[7] The growth rate is calculated in log differences. Thus

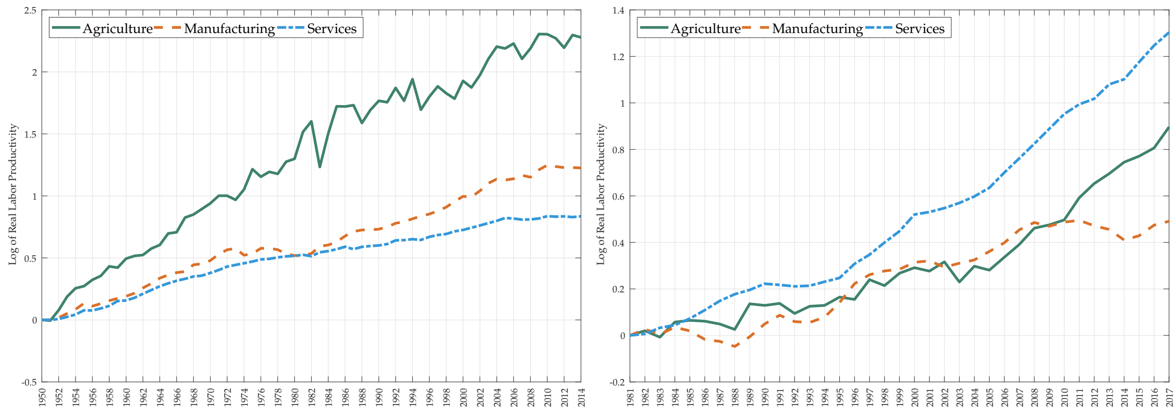
$$\log\left(LP_{jt}\right) \equiv \log\left(\frac{Y_{jt}}{H_{jt}}\right)$$

[6] I focus on labor productivity but in Figure E.10a in Appendix E I show the decline in relative prices which is another measure of productivity and the qualitative pattern is the same.

[7] The labor input for the US World KLEMS Series is defined as a Törnqvist index of the hours worked by different worker types where the shares are the value or compensation of each type of labor. For the India KLEMS the definition is the same except they use persons employed rather than hours. The quality or composition of labor in the Indian case takes into account differences in education, age, and earnings of self-employed workers. In the US case they also take into account gender. The construction of the quality of labor index is explained in Jorgenson et al. (2014) available at the World KLEMS website.

where Y_{jt} is value added in that sector and H_{jt} the quality-adjusted labor employed.[8]

Since the interest is on sectoral productivity growth, I normalize labor productivities in the US and India to the initial period and show in Figure 1 the logs of these series so the slope indicates its growth rate.[9]



(a) United States (b) India

Figure 1: Labor Productivities in Logs. Initial = 0

The pattern that arises for the United States is what would be expected from a standard model *à la* Ngai and Pissarides (2007). Agriculture is the fastest growing sector, manufacturing follows, and services is the lagging sector. This is the pattern shown in most industrialized countries and is consistent with the theory that fast productivity growth in agriculture frees people from that sector and moves them towards manufacturing and services. While services being the lagging sector is in line with the evidence on the Baumol's cost disease (Duernecker et al., 2023). However, for India the pattern is reversed, services is the fastest growing sector at least since 1984, with agriculture and manufacturing growing at similar rates.

Given the degree of heterogeneity in productivity growth rates within manufacturing and services, I disaggregate both sectors to differentiate between those industries that experienced faster growth from those that did not grow as fast. To do so, I compute the average growth rate over the full period for each industry within each sector. If the average growth rate of an industry i is higher than the average growth rate of the sector it belongs to, then that industry is considered *"high-productivity"*, otherwise, it is a low-productivity industry. This decomposition follows Duernecker et al. (2023). After classifiying industries into these two subgroups, I aggregate them to obtain a high-productivity and a low-productivity service (manufacturing) sector. Tables 1 and 2 show the service and manufacturing industry classification, respectively, and their average growth rate. Figure 2 shows the same plot as before in Figure 1 but for the

[8] One key issue is that of aggregating industries into sectors since the KLEMS accounting framework uses Törnqvist indices and these are not additive, thus, real value added in sector j is not equal to the sum of real value added of the industries that belong to sector j. Appendix A shows the aggregation details, but intuitively, it consists on adding-up industry-growth rates weighted by their nominal shares (in value added or efficiency units of labor).

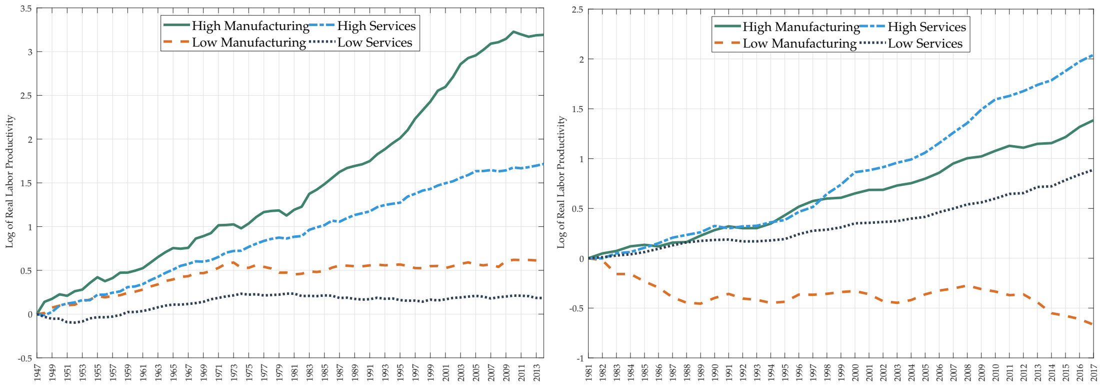
[9] The plot for labor productivity growth in the United States normalized at 1981 instead of at 1947 shows agriculture and manufacturing growing at similar rates and services growing at a signficantly slower rate. However, the same qualitative pattern holds.

disaggregated manufacturing and service sectors.[10]

Table 1: Division of Services by Labor Productivity Growth

High Productivity Services	
Post and Telecommunication	8.5416
Public Administration and Defense; Compulsory Social Security	4.6582
Business Service	3.9885
Financial Services	3.9528
Overall Service Sector	**3.6198**
Low Productivity Services	
Trade	3.4951
Health and Social Work	2.9357
Education	2.8785
Hotels and Restaurants	2.7428
Transport and Storage	2.1658
Other services	1.3643

Note: All numbers are in percentages (%). Labor productivity is the ratio of real value added to quality-adjusted labor, the numbers represent averages for the full period (1981-2017). Overall Service Sector represents the growth rate of labor productivity in the aggregated service sector.



(a) United States (b) India

Figure 2: Labor Productivities in Logs. Initial = 0

Once again, the pattern observed for the US is what one would expect, in line with the evidence from Rodrik (2012). High-productivity manufacturing industries are the fastest growing ones in the economy. While high-productivity services still grow at fast rates, these are significantly below that of high-productivity manufacturing industries. Among the low-productivity, still manufacturing grows at a faster rate than services.

Surprisingly, for India the pattern reverses once again. High productivity services are the fastest growing of all, but even low productivity services still grow faster than low productivity manufacturing. In summary, the service sector grows faster than the manufacturing sector

[10] I classify industries into high and low productivity for each country separately. Tables E.4 and E.5 in Appendix E show the classification of services and manufacturing for the US.

Table 2: Division of Manufacturing by Labor Productivity Growth

High Productivity Manufacturing	
Coke, Refined Petroleum Products and Nuclear fuel	6.0102
Chemicals and Chemical Products	5.5726
Textiles, Textile Products, Leather and Footwear	4.9469
Transport Equipment	4.8449
Other Non-Metallic Mineral Products	4.5473
Electricity, Gas and Water Supply	4.4339
Rubber and Plastic Products	4.0767
Manufacturing, nec; recycling	3.4973
Food Products,Beverages and Tobacco	3.0075
Pulp, Paper,Paper products,Printing and Publishing	2.8913
Mining and Quarrying	2.4697
Electrical and Optical Equipment	1.8890
Basic Metals and Fabricated Metal Products	1.6030
Overall Manufacturing Sector	**1.3643**
Low Productivity Manufacturing	
Machinery, nec.	1.1631
Wood and Products of wood	-0.5881
Construction	-1.9478

Note: All numbers are in percentages. Labor productivity is the ratio of real value added to quality-adjusted labor, the numbers represent averages for the full period (1981-2017). Overall Manufacturing Sector represents the growth rate of labor productivity in the aggregated manufacturing sector.

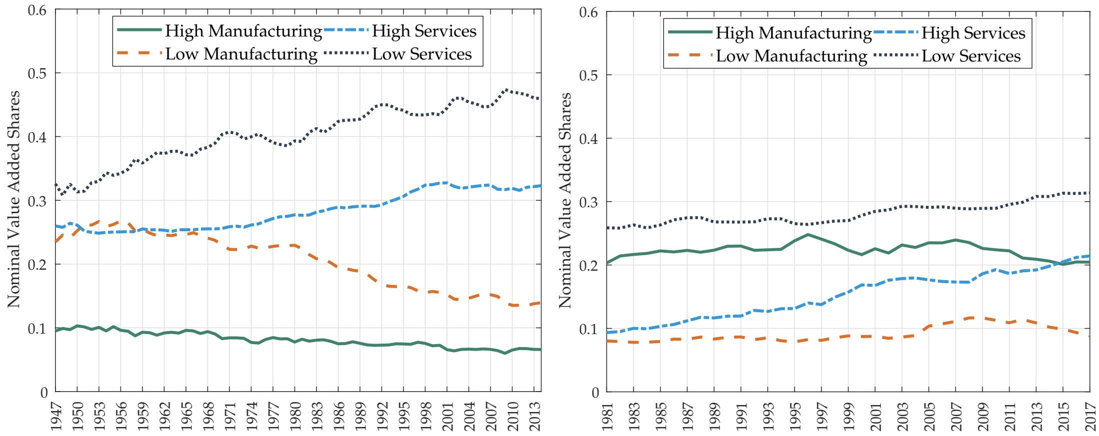
because both its high and low productivity industries grow faster than their manufacturing counterpart.

The aggregate gains of sectoral productivity will depend on the relative expansion and contraction of sectors. Figure 3 shows nominal value added shares for the United States and India with this sector classification.

Figure 3a shows that in the US both manufacturing subsectors show a slightly declining trend, consistent with deindustrialization in the later phases of development. At the same time, both services subsectors are expanding with the low-productivity services expanding at a faster rate, which is what the Baumol's cost disease implies. Duernecker et al. (2023) argue it is not likely that the Baumol's cost disease will be such a drag on aggregate productivity, since the two subsectors are gross substitutes.

For India, the pattern is again different. In Figure 3b both manufacturing subsectors are roughly constant, while both services subsectors are expanding. However, for India, the high-productivity subsector is the one expanding the fastest and its expansion is key for services-led growth to continue.

A potential concern of this classification is that the variation in average productivity growth in manufacturing is larger (from -1.9% to 6%) than in services (from 1.3 to 8.54%) and, thus, high-productivity manufacturing aggregates more industries. To consider another potential classification, I consider an industry high productivity if the average growth rate of the indus-



(a) United States

(b) India

Figure 3: Nominal Value Added Shares

try is larger than aggregate productivity growth (2.71%).[11] For the low productivity sectors there is no qualitative change, however, for the high productivity sectors, their growth rates are approximately equal. The high productivity manufacturing sector increases its average productivity growth from 3.85% to 4.65% while high productivity services see their growth rate reduced from 5.67% to 4.53%. If we compute the average growth rates of both subsectors for the 1999-2017 period, high productivity services would grow faster than high productivity manufacturing (5.87% vs 5.15%). This supports the claim that high productivity services are at least as productive as high productivity manufacturing.

There is evidence of a wage premia in public sectors relative to private sectors in India (Glinskaya and Lokshin, 2007) and other developing countries (Barton et al., 2017). Thus, to assess how much the Public Administration sector might affect these stylized facts, I drop completely this sector from the analysis. Then, the average growth rate of the aggregate service sector drops by 0.43 percentage points but still high productivity services grow faster than high productivity manufacturing (the growth rates are 4.21% and 3.85%, respectively). Furthermore, the employment share in this sector was low and declined from 2.75% to 1.87%. This suggests that the distortions of the public sector might not be significantly large for the purposes of this paper.[12]

2.2 Cross-Country Evidence

The analysis of previous section shows that India's structural transformation process and sectoral productivity dynamics differ from the standard experience of previously industrialized countries. However, this could be explained by manufacturing being too unproductive or services growing faster because of convergence to the international norm. This section now

[11] Figure E.10b shows the dynamics of sectoral labor productivities for this classification.

[12] I provide more evidence of faster productivity growth in high-productivity services compared to high-productivity manufacturing in Appendix B. I follow the KLEMS methodology for growth accounting and show that TFP grows faster in high-productivity services.

compares sectoral productivity growth in India with a set of countries to assess whether productivity growth in the three main sectors is different in some way.

The data comes from the 10-Sector Groningen Growth and Development Centre (GGDC) Database (Timmer et al., 2015), and cosists on 41 different countries that belong to four different regions (Africa, Asia, Latin America, and Western Countries), it is an unbalanced panel from 1950 to 2012 but most observations exist for the period 1960 to 2011. The purpose of this subsection is to compare labor productivity growth rates of India with that of the rest of countries in the sample, to see whether labor productivity is growing faster in services just within India or compared to other countries as well.

As the whole literature on structural transformation has shown, sectoral value added shares differ significantly with the stage of development. Ziebarth (2013) also shows that the missallocation levels also depend on the stage of development and thus it might be important to control for this when comparing sectoral labor productivities. The estimating equation (1) thus controls for the log of GDP per capita, log of GDP per capita squared, and the log of population.

$$\begin{aligned} \log(LP_{s,c,t}) = \alpha + \beta_1 \log(y_{c,t}) + \beta_2(\log(y_{c,t}))^2 + \beta_3 \log(pop_{c,t}) \\ + \varphi_c + \phi Time_t + \gamma Time_t \times IND_{c,t} + \varepsilon_{s,c,t} \end{aligned} \tag{1}$$

Where $LP_{s,c,t}$ denotes labor productivity in sector s, country c, at time t; $y_{c,t}$ denotes GDP per capita; $pop_{c,t}$ is the population level, φ_c denotes country fixed effects, $Time_t$ is a time trend, the term $Time_t \times IND_{c,t}$ is the time trend interacted with a dummy variable that takes value one if the observation corresponds to India, and finally $\varepsilon_{s,c,t}$ is an error term. If the coefficient of the interaction term is positive, that would tell us by how much labor productivity in India grows faster than in a comparable country (i.e. holding level of development and population constant). Table 3 shows the results from estimating three different regressions based on equation (1) one for each sector.[13]

Column 1 in Table 3 shows that labor productivity growth in agriculture is about 1.23 percentage points slower in India than in a comparable country. This result might be one of the possible explanations for why India still has a large fraction of its labor force employed in agriculture. Since labor productivity does not grow fast, it cannot free people from this sector to move them into manufacturing or services. In Column 2, the coefficient of the interaction term is not statistically significant which suggests that labor productivity growth in India is not different from what we would expect conditioning on population and the stage of development. This goes in line with the result of Ziebarth (2013). Finally, Column 3 shows that labor productivity growth in services is about 1.77 percentage points faster in India than in a similar country, thus suggesting that the service sector is in fact growing above the average and that this is not a result of manufacturing being very low-productivity nor a result of convergence to

[13]The data for GDP per capita and population used in these regressions is from the Maddison Database Project (Bolt et al., 2018). Tables E.6 and E.7 in Appendix E show the same set of regressions as in Tables 3, 4, and 5 using GDP per capita from the Penn World Tables (Feenstra et al., 2015), the pattern is still consistent but the coefficient for services labor productivity increases in magnitude, which gives even stronger support to my claims.

Table 3: Cross-country Comparison of Labor Productivity Growth

	(1) Agriculture	(2) Manufacturing	(3) Services
Time × India	-0.0123***	-0.00337	0.0177***
	(0.000941)	(0.00271)	(0.00153)
Time	0.0400***	0.0182***	-0.00277
	(0.00136)	(0.00203)	(0.00143)
Log of GDP per capita	-0.454*	2.559***	0.814***
	(0.204)	(0.414)	(0.240)
Log of GDP per capita squared	0.0433***	-0.106***	-0.0149
	(0.0121)	(0.0236)	(0.0135)
Log of Population	-1.139***	-1.014***	-0.175**
	(0.0595)	(0.0812)	(0.0660)
Country Fixed Effects	Yes	Yes	Yes
No. Countries	41	41	41
N	2158	2168	2168

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the international norm since I control for the stage of development.[14]

This set of regressions include 41 countries from four different regions and at different states of development, however, as Rodrik (2016) points out, different regions of the world seem to be more affected by premature deindustrialization than others which might also cause differences in labor productivity across regions. To explore how different India is compared to other countries, Table 4 shows the results of the same set of regressions from equation (1) but restricting the sample to the 11 Asian countries contained in the database.

Overall, a similar pattern emerges. Slower than average labor productivity growth in agriculture and faster than average labor productivity growth in services. However, the coefficient for the manufacturing sector is statistically significant and negative. Note also that the magnitude of the coefficient for the interaction term declines significantly for the service sector. This is due to the larger effect China has on the sample now. Labor productivity growth, both in services and manufacturing, is extremely rapid in China, although it is much faster in manufacturing. If we restrict the sample to Asian countries excluding China, same qualitative pattern emerges although the coefficient on manufacturing is positive and statistically significant, Table 5 shows the results.

India's comparative advantage in the service sector remains a robust result no matter which comparison group we take. In Appendix E, I estimate equation (1) using the World Development Indicators Database to increase the sample to 143 countries. I find productivity growth in

[14] In a standard Solow-type framework, the lower the stage of development the faster the growth rate when transitioning to the steady state. Controlling by the stage of development nets out this effect.

Table 4: Labor Productivity in India Within Asia

	(1) Agriculture	(2) Manufacturing	(3) Services
Time × India	-0.00779***	-0.0161***	0.00665***
	(0.000768)	(0.00392)	(0.00141)
Time	0.0122***	0.0293***	0.0131***
	(0.00276)	(0.00411)	(0.00187)
Log of GDP per capita	0.977***	2.693***	0.573***
	(0.180)	(0.371)	(0.165)
Log of GDP per capita squared	-0.0238*	-0.116***	-0.00595
	(0.00973)	(0.0229)	(0.00915)
Log of Population	-0.582***	-0.911***	-0.266**
	(0.110)	(0.110)	(0.0813)
Country Fixed Effects	Yes	Yes	Yes
No. Countries	11	11	11
N	520	522	522

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Labor Productivity in India Within Asia Excluding China

	(1) Agriculture	(2) Manufacturing	(3) Services
Time × India	-0.0110***	0.0101***	0.0153***
	(0.00109)	(0.00190)	(0.00145)
Time	0.0150***	0.00799***	0.00689***
	(0.00270)	(0.00182)	(0.00186)
Log of GDP per capita	1.363***	-0.778**	-0.798***
	(0.273)	(0.259)	(0.201)
Log of GDP per capita squared	-0.0471**	0.0872***	0.0711***
	(0.0150)	(0.0146)	(0.0108)
Log of Population	-0.612***	-0.576***	-0.0864
	(0.111)	(0.0825)	(0.0921)
Country Fixed Effects	Yes	Yes	Yes
No. Countries	10	10	10
N	461	462	462

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

agriculture to be slower than the average, manufacturing is also slower but marginally,[15] and services is 2.19 percentage points faster than the average. If we restrict the sample to 51 developing countries, services grow 2.16 percentage points faster while there is no difference for agriculture and manufacturing. These results are in Table E.8. To investigate further regional differences in labor productivity growth, Table E.9 shows the results from estimating equation (1) but replacing the dummy variable for India with an indicator for the region (Africa, Asia, Latin America, and Western Countries). Table E.10 shows the interaction term for services for each of the African countries in the region. These regressions show that a similar pattern could be ocurring for some of these countries.

2.3 Educational Attainment by Sector and Year

In parallel with the strong growth rate of labor productivity in services, the supply of high-skilled workers has also experience a pervasive increase. Not only it has increased at the aggregate level, but it has been consistently skewed towards the service sector.

For the analysis of education in India, I use data from the Integrated Public Use Microdata Series (IPUMS-I, 2018) for India and, for comparison purposes, for China. The data comprises individual and household level data through six waves that span from 1983 up to 2009. Tables 6 and 7 show the educational attainment at the aggregate level for each year of the survey for India and China respectively. Throughout the sample years, the share of people with at least some university education in India is larger than in China. Note however that India's GDP per capita was consistently below that of China since the 1990s. Even if the share of high-skilled workers is larger in India, average educational attainment is higher in China. This is because there are substantially less workers with primary or less than primary education and more workers with secondary education in China. In India, the share of workers with no schooling drops from 56% in 1983 to 30% in 2009, while in China 28% of workers had no education in 1982 and only 7.5% had no education in 2000.

The service sector in India is more intensive in skilled workers than the rest of sectors within India. Furthermore, the share of skilled workers in Indian services is also larger than the share employed by Chinese services. This is shown in Figure 4. Furthermore, when disaggregating in industries, those industries with larger share of university graduates coincide with the service industries labeled as high-productivity in previous sections. And these industries seem to be more intensive in high-skilled workers than the same industries in China as Figure E.11 shows.

As Herrendorf and Schoellman (2018) show, wages are not equalized across sectors in the data. As they point out, wages in agriculture are significantly lower than in other sectors and agriculture has less educated workers as well as lower returns to schooling. Figure E.12 in Appendix E shows this also occurs in the data for India. The figure shows the density of log wages for each sector and each year. For services in general this is shifted to the right, with larger gaps in between years which suggests that these sectors experienced the largest growth in wages. Agricultural wages display a density shifted to the left.

[15] The point estimate implies productivity in manufacturing is 0.4 percentage points slower than the average country.

Table 6: Educational Attainment in India

Panel A: Aggregate Educational Attainment (%)						
	1983	1987	1993	1999	2004	2009
Primary or less	79.19	77.65	71.36	65.43	62.12	54.72
Secondary	17.81	18.77	23.76	28.50	29.81	35.71
University	3.00	3.58	4.88	6.07	8.07	9.57
Total	100	100	100	100	100	100

Panel B: Detailed Educational Attainment (%)						
	1983	1987	1993	1999	2004	2009
No schooling	56.49	54.97	47.72	43.51	39.46	30.73
Some primary completed	9.5	9.42	11.36	10.12	8.75	9.52
Primary (5 yrs) completed	13.2	13.26	12.28	11.79	13.91	14.47
Lower secondary general completed	10.02	9.83	12.06	14.3	15.91	17.34
Secondary, general track completed	7.79	8.94	7.86	9.56	9.06	12.01
Some college completed	–	–	3.84	4.64	4.84	6.36
Post-secondary technical education	–	–	–	–	1.54	1.28
University completed	3.00	3.58	4.88	6.07	6.53	8.29
Total	100	100	100	100	100	100

Note: Data from IPUMS International. Panel A shows aggregated educational levels according to variable *educin*. Panel B is the comparable aggregate levels given by variable *edattaind*.

Table 7: Educational Attainment in China

Panel A: Aggregate Educational Attainment (%)			
	1982	1990	2000
Primary or less	62.45	54.18	40.30
Secondary	36.68	43.91	54.99
University	0.87	1.91	4.71
Total	100	100	100

Panel B: Detailed Educational Attainment (%)			
	1982	1990	2000
No schooling	28.02	16.52	7.49
Some primary completed	0.00	10.22	3.96
Primary (6 yrs) completed	34.43	31.68	30.68
Lower secondary general completed	26.10	28.82	40.61
Secondary, general track completed	10.58	8.77	8.92
Some college completed	0.06	0.07	0.04
Secondary, technical track completed	-	2.08	3.63
Post-secondary technical education	-	1.16	3.28
University completed	0.81	0.67	1.38
Total	100	100	100

Note: Data from IPUMS International. Panel A shows aggregated educational levels according to variable *educcn*. Panel B is the comparable aggregate levels given by variable *edattaind*.

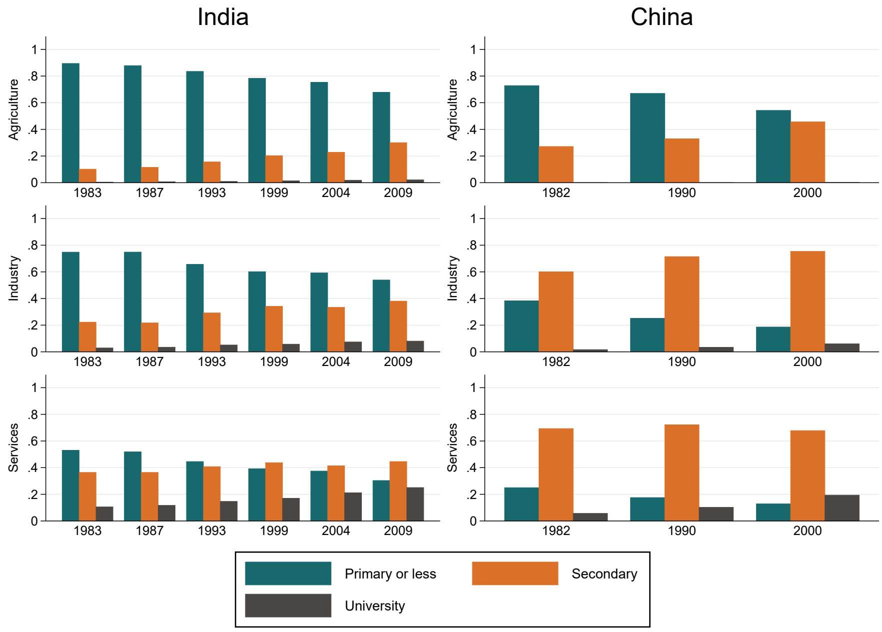


Figure 4: Educational Attainment by Sector

Following Herrendorf and Schoellman (2018) I estimate returns to schooling by sector and year. Figure 5 shows, in line with the evidence they provide, that agricultural wages have the lowest wages and the lowest returns.[16] When I separate the service sector into high and low productivity services, these regressions show that there is a premium for working the high-productivity service sector and that the low-productivity service sector has returns to schooling larger than those in high-productivity manufacturing. Furthermore, returns in the low-manufacturing sector seem to decline over time. Overall, wages are higher in the service sector as well as the returns to schooling. This suggests that high-skilled workers enjoy a comparative advantage in the service sector.

3 Model

The evidence shown in Section 2 has stablished five main stylized facts: namely, *(i)* high productivity industries show faster growth of labor productivity in services than in manufacturing, opposite to what has been the experience of traditional industrializers. *(ii)* Fast productivity growth in services is not because of sluggish productivity growth in manufacturing, but because services in fact grow faster in India than in a comparable country. *(iii)* Aggregate supply of skilled workers is high compared to that of China while China's GDP per capita is twice that of India since 1985. *(iv)* The service sector employs a higher share of high-skilled workers than manufacturing and *(v)* returns to schooling are larger. The purpose of the model presented in this Section is to rationalize and reproduce these stylized facts and shed light on how the elements of the model affect labor productivity growth.

[16] Table E.11 of Appendix E shows the coefficients for all these regressions controlling for age, age squared, and sex.

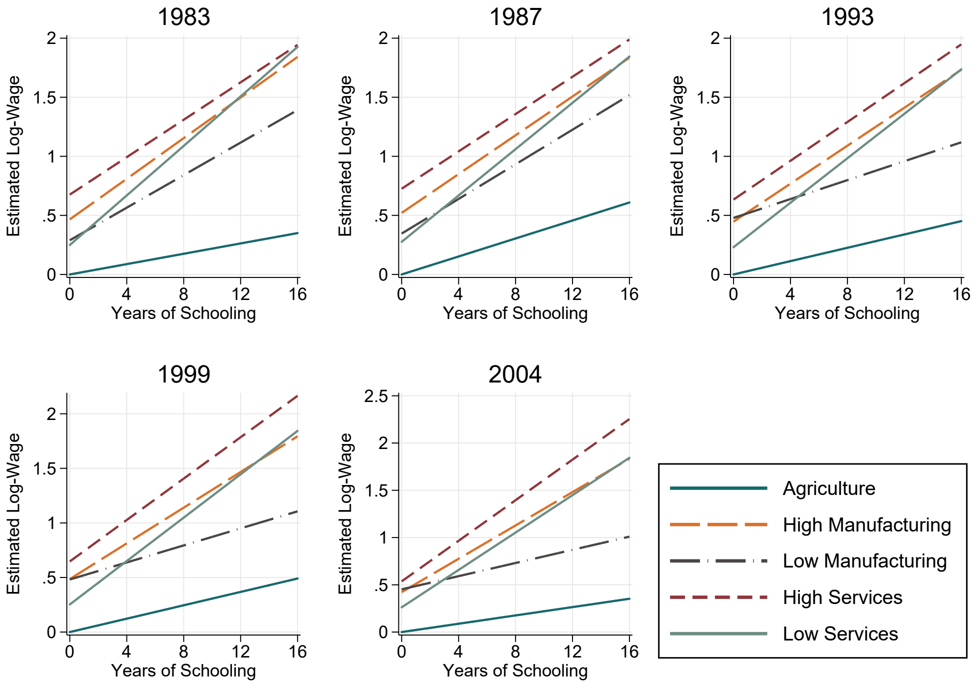


Figure 5: Log of Wages and Returns to Schooling by Sector

Note: *High Services:* Transportation, storage and communication, Financial services and insurance, Public administration and defense, Real estate and business services. *Low Services:* Wholesale and retail trade, Hotels and restaurants, Education, Health and social work, Other services, Private household services.

3.1 Household

Time is discrete and there are three major sectors of production indexed by j. The three sectors are agriculture, manufacturing, and services ($j = a, m, s$ respectively). However, the manufacturing and services sectors are divided into two subsectors each, a high-productivity and a low-productivity one ($i \in \{h, l\}$) to follow the disaggregation explained in Section 2.

The economy consists of an infinitely lived representative household formed by a continuum of members distributed along the $[0, 1]$ interval. A fraction M_{ht} of these members will be high-skilled individuals and a fraction M_{lt} will be low-skilled individuals. The preferences of the household are defined by a class of non-homothetic constant elasticity of substitution (CES) utility functions proposed originally by Hanoch (1975) and Sato (1975) but used more recently by Comin et al. (2020) and Duernecker et al. (2023). In particular, the consumption aggregator $\widetilde{C}_t$ is implicitly defined by function (2)

$$\omega_a^{1/\varepsilon}\left(\frac{c_{at}}{\widetilde{C}_t^{\nu_a}}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \omega_m^{1/\varepsilon}\left(\frac{c_{mt}}{\widetilde{C}_t^{\nu_m}}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \omega_s^{1/\varepsilon}\left(\frac{c_{st}}{\widetilde{C}_t^{\nu_s}}\right)^{\frac{\varepsilon-1}{\varepsilon}} = 1 \tag{2}$$

where parameters $\nu_j > 0$ control the income elasticity of demand for good j, the $\omega_j > 0$ terms are relative weights of each consumption good, and $\varepsilon > 0$ denotes the elasticity of substitution. Under this formulation, if all $\nu_j = 1$ the preferences become the standard CES utility function. The manufacturing consumption good and the service consumption are both CES aggregators of the high and low-productivity subsectors. The elasticity of substitution between these two subsectors is given by η_j which is potentially different for manufacturing and for services.

$$c_{mt} = \left[\left(\omega_m^h\right)^{\frac{1}{\eta_m}}\left(c_{mt}^h\right)^{\frac{\eta_m-1}{\eta_m}} + \left(1-\omega_m^h\right)^{\frac{1}{\eta_m}}\left(c_{mt}^l\right)^{\frac{\eta_m-1}{\eta_m}}\right]^{\frac{\eta_m}{\eta_m-1}} \tag{3}$$

$$c_{st} = \left[\left(\omega_s^h\right)^{\frac{1}{\eta_s}}\left(c_{st}^h\right)^{\frac{\eta_s-1}{\eta_s}} + \left(1-\omega_s^h\right)^{\frac{1}{\eta_s}}\left(c_{st}^l\right)^{\frac{\eta_s-1}{\eta_s}}\right]^{\frac{\eta_s}{\eta_s-1}} \tag{4}$$

The household's problem can be split into two layers. The first one is how much to allocate across agriculture, manufacturing, and services. That is, minimize total expenditure $\sum_{j\in\{a,m,s\}} p_{jt}c_{jt}$ subject to (2). The second is how much to allocate to the high and the low productivity goods given the total expenditure on manufacturing or services. That is, minimize $\sum_{i\in\{h,l\}} p_{jt}^i c_{jt}^i$ for $j \in \{m, s\}$ subject to (3) or (4).

From the second layer of the household's optimization problem, relative expenditure of high to low productivity good in sector j is given by (5). Thus, the relative expenditure depends on the relative price effect only.

$$\frac{p_{jt}^h c_{jt}^h}{p_{jt}^l c_{jt}^l} = \left(\frac{\omega_j^h}{1-\omega_j^h}\right)\left(\frac{p_{jt}^h}{p_{jt}^l}\right)^{1-\eta_j} \quad \text{for } j \in \{m, s\} \tag{5}$$

The data for India shows that, within services, value added in high-productivity industries is rising relative to the low-productivity ones and, at the same time, the relative price is declining. For manufacturing, both the relative expenditure and the relative price are declining. The calibration exercise will deliver parameter values for η_m and η_s consistent with this structural transformation pattern, yielding η_s larger than one while η_m will be lower than one. This is consistent with the interpretation that high-productivity services might be considered *luxuries* as Duernecker et al. (2023) document for the US.

From this layer of the problem we can obtain expressions for the ideal price indices of sectors $j \in \{m, s\}$ as functions of the prices in the two subsectors $i \in \{h, l\}$ (equation (6)). Using the ideal price index and the first order conditions of the optimization problem, total expenditure in sector $j \in \{m, s\}$ equals the product of the sectoral price index and the consumption aggregator c_{jt} as shown in equation (7).

$$p_{jt} = \left[\omega_j^h (p_{jt}^h)^{1-\eta_j} + (1-\omega_j^h)(p_{jt}^l)^{1-\eta_j}\right]^{\frac{1}{1-\eta_j}} \tag{6}$$

$$p_{jt}^h c_{jt}^h + p_{jt}^l c_{jt}^l = p_{jt} c_{jt} \tag{7}$$

From the first layer of the household's optimization problem, we obtain

$$\frac{p_{jt}c_{jt}}{p_{at}c_{at}} = \frac{\omega_{jt}}{\omega_{at}} \left(\frac{p_{jt}}{p_{at}}\right)^{1-\varepsilon} \widetilde{C}^{(1-\varepsilon)(\nu_j - \nu_a)} \tag{8}$$

$$\widetilde{P} = \left[\sum_{j\in\{a,m,s\}} \left(\omega_j p_{jt}^{1-\varepsilon}\right)^{\frac{1}{\nu_j}} \left(E_{jt} E_t^{1-\varepsilon}\right)^{\left(1-\frac{1}{\nu_j}\right)}\right]^{\frac{1}{1-\varepsilon}} \tag{9}$$

where equation (8) expresses expenditure on good j relative to agriculture, (9) shows the aggregate price index as a function of sectoral price indices given by (6), total expenditure E_t, and expenditure shares on good j E_{jt}. Appendix C provides all derivations for these expressions.

3.2 Firms and Technology

The production side of the model is similar to Buera et al. (2021) and Fang and Herrendorf (2021). Each sector $j \in \{a, m, s\}$ and subsector $i \in \{h, l\}$ is comprised by a large number of firms that produce output Y_{jt}^i using two types of labor, high and low skill, and pay a tax τ_{jt}^i. The role of sectoral taxes τ_{jt}^i is important to create differences in sectoral nominal labor productivities. As Restuccia et al. (2008) show, low labor productivity and high employment shares in agriculture are one of the main reasons why poor countries show low aggregate productivity. In particular, barriers to labor markets generate large differences across countries in terms of employment shares. Buera and Kaboski (2009) also note that to account for differences in value added and employment shares in the data, different sectoral wages are necessary, one way to accommodate this is to include this taxes. The precise role of the taxes in the model is to generate distortions in labor markets that affect nominal sectoral labor productivities. Although as I will show below, differences in sectoral real labor productivities are not directly driven by the taxes.

Since the production function (10b) is homogenous of degree one, we can restrict the attention to a representative firm with competitive behavior in each sector. The representative firm in sector $j \in \{a, m, s\}$ and subsector $i \in \{h, l\}$ thus solves the following maximization problem.

$$\max_{\{h^i_{jt}, l^i_{jt}\}} \quad p^i_{jt} Y^i_{jt} - (1 + \tau^i_{jt})(w^h_t h^i_{jt} + w^l_{jt} l^i_{jt}) \tag{10a}$$

$$\text{s.t.} \quad Y^i_{jt} = A^i_{jt} L^i_{jt} = A^i_{jt} \left[\pi^i_{jt} \left(h^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} + (1 - \pi^i_{jt}) \left(l^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{10b}$$

A^i_{jt} denotes Hicks-neutral (TFP) sectoral technology which grows exogenously, π^i_{jt} is a parameter that determines the comparative advantage of high-skilled labor in the different sectors and, since it grows exogenously over time, it also captures the increase in the relative demand for high-skilled labor. Suppose $\pi^h_s > \pi^l_s$, that would imply that high-skilled labor displays comparative advantage in the high-productivity service subsector compared to the low-productivity one. The elasticity of substitution between each type of labor is common across sectors and is given by σ. This specification is equivalent to a production function with factor-augmenting technical change. That is, a production function of the form:

$$Y^i_{jt} = \left[\tilde{\pi}^i_j \left(\Lambda^i_{jt} h^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} + (1 - \tilde{\pi}^i_{jt}) \left(\Gamma^i_{jt} l^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where Λ^i_{jt} and Γ^i_{jt} represent high-skill and low-skill labor-augmenting technical change, respectively. Note that we can express π^i_{jt} and A^i_{jt} as functions of the parameter $\tilde{\pi}^i_j$, the factor-augmenting technical change terms, and the elasticity, thus π^i_{jt} is capturing the effect of skill-biased technical change. In particular:

$$\pi^i_{jt} \equiv \frac{\tilde{\pi} \left(\Lambda^i_{jt} \right)^{\frac{\sigma-1}{\sigma}}}{\tilde{\pi} \left(\Lambda^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} + (1 - \tilde{\pi}) \left(\Gamma^i_{jt} \right)^{\frac{\sigma-1}{\sigma}}} \; ; \; A^i_{jt} \equiv \left(\tilde{\pi} \left(\Lambda^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} + (1 - \tilde{\pi}) \left(\Gamma^i_{jt} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

For clarity of exposition, I use the production function (10b) throughout the paper.

Profit maximization in each sector implies the following expression for the ratio of high-skill to low-skill wage rate for each sector j and subsector i.

$$\frac{w^h_t}{w^l_t} = \frac{\pi^i_{jt}}{1 - \pi^i_{jt}} \left(\frac{l^i_{jt}}{h^i_{jt}} \right)^{\frac{1}{\sigma}} \tag{11}$$

The assumption of common sectoral elasticities of substitution between high and low-skill labor might be somewhat restrictive, however, the elasticity mainly determines how changes in the relative prices of the factors of production affect relative demand. Since π^i_{jt} varies over time and precisely captures the changes in the relative demand of high to low-skill labor, the assumption of a common elasticity of substitution across sectors might not be as restrictive.

International trade might be a driver of structural change (Matsuyama, 1992, 2009; Teignier, 2018) and affect the expansion of each of the sectors. I introduce unbalanced trade as in Fang and Herrendorf (2021) which implies that the market clearing condition for sector j and subsector i is given by

$$Y^i_{jt} = c^i_{jt} + x^i_{jt} \tag{12}$$

where x^i_{jt} denotes net exports of sector j subsector i and is defined as

$$x^i_{jt} = \varphi^i_{jt} Y^i_{jt}$$

where φ^i_{jt} evolves exogenously. Then, nominal aggregate GDP is defined as in (13).

$$P_t Y_t = p_{at} Y_{at} + p^h_{mt} Y^h_{mt} + p^l_{mt} Y^l_{mt} + p^h_{st} Y^h_{st} + p^l_{st} Y^l_{st} \tag{13}$$

In this model, I abstract from capital accumulation but as Acemoglu and Guerrieri (2008) show, differences in factor intensity can be a source of structural change and, as shown in Appendix B, capital deepening is the main source of growth for the high-productivity manufacturing sector. In this case, abstracting from capital will imply that the TFP component A^i_{jt} will be capturing these differences. What is important is that the model will be able to capture increases in the relative demand for high-skilled workers through the π^i_{jt} terms, even if they are a result of capital-skill complementarity.

3.3 Equilibrium

Let us ommit time subscripts for clarity since all the components of the model have been introduced already. Appendix C shows the details of the equilibrium and solution of the model but the idea is to express all endogenous variables as functions of the skill premium and the consumption aggregator $\widetilde{C}$. The share of wages high-skill workers get in a given sector j and subsector i is given by equation (14).

$$\Omega^i_j \equiv \frac{w^h_t h^i_j}{w^h_t h^i_j + w^l_t l^i_j} = \left(1 + \left(\frac{w^h}{w^l}\right)^{\sigma-1} \left(\frac{1-\pi^i_j}{\pi^i_j}\right)^{\sigma}\right)^{-1} \tag{14}$$

Using the definition of L^i_j, (11) and (14), we get an expression for inverse of the ratio of high-skill workers over the total labor input.

$$\frac{L^i_j}{h^i_j} = \left(\frac{\pi^i_j}{\Omega^i_j}\right)^{\frac{\sigma}{\sigma-1}} \tag{15}$$

Since there are two types of labor and also sectoral labor market distortions, relative prices do not depend only on sectoral TFPs. Instead, they are also a function of relative taxes, the relative increase in high-skill labor demand, and of the relative sectoral wage share of high-skill workers.

$$\frac{p^i_j}{p_a} = \frac{A_a}{A^i_j} \left(\frac{1+\tau^i_j}{1+\tau_a}\right) \left(\frac{\pi_a}{\pi^i_j}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{\Omega_a}{\Omega^i_j}\right)^{\frac{1}{1-\sigma}} \tag{16}$$

Appendix C shows the details of the expressions for the expenditure on the high relative to the low-productivity good within sector j (E^{hl}_j), and the expenditure on sector j subsector i good relative to the agricultural good (E^i_{ja}). All these ratios are ultimately functions of the skill-premium and exogenous parameters only.

The amount of high-skill workers in sector j subsector i relative to those in agriculture (equation 17) is a function of the relative net exports and taxes, the relative sectoral wage share in high-skill workers and also on the relative expenditure.

$$\frac{h_j^i}{h_a} = \left(\frac{1-\varphi_j^i}{1-\varphi_a}\right)\left(\frac{1+\tau_a}{1+\tau_j^i}\right)\left(\frac{\Omega_j^i}{\Omega_a}\right) E_{ja}^i \tag{17}$$

Relatively higher distortions in sector j subsector i reduce the proportion of high-skilled workers in that sector relative to those in agriculture. As shown in Appendix C, the share of high-skilled workers in agriculture over the total supply of high-skilled workers is obtained as a function of all relative expenditures, relative sectoral high-skill wage shares, and relative taxes by equation (18)

$$\frac{h_a}{M_h} = \frac{1}{\sum_{j\in\{a,m,s\}} \sum_{i\in\{h,l\}} \left(\frac{1-\varphi_j^i}{1-\varphi_a}\right)\left(\frac{1+\tau_a}{1+\tau_j^i}\right)\left(\frac{\Omega_j^i}{\Omega_a}\right) E_{ja}^i} \tag{18}$$

Although relative taxes matter for matching differences in nominal labor productivity, differences in real labor productivity are not directly determined by these taxes, instead, real labor productivity depends on skill-biased technical change, sectoral TFP, and the skill-premium. Equation (19) shows that taxes do not enter in the determination of real labor productivity.

$$\frac{Y_j^i}{l_j^i + h_j^i} = \frac{1}{1+\left(\frac{w^h}{w^l}\right)^{\sigma}\left(\frac{1-\pi_j^i}{\pi_j^i}\right)^{\sigma}} A_j^i \left(\frac{\pi_j^i}{\Omega_j^i}\right)^{\frac{\sigma}{\sigma-1}} \tag{19}$$

4 Quantitative Analysis

The purpose of the model presented in Section 3 is to analyze labor productivity trends in India over the period 1981-2017 and understand the causes behind the fact that labor productivity growth is faster in high-productivity services than in high-productivity manufacturing industries. In the model there are three main exogenous variables that affect labor productivity at the sector level; sectoral TFP (A_{jt}^i), the parameters governing sectoral increase in the demand for high-skill labor (π_{jt}^i), and labor market distortions (τ_{jt}^i). At the aggregate level, apart from the productivity effects of the process of structural transformation itself, the aggregate supply of high-skill workers relative to low-skill workers (M_{ht}/M_{lt}) also plays an important role in the process of economic development.

In this section, I calibrate the model to match salient features of the Indian economy for the 1981-2017 period and perform a set of counterfactual experiments. These experiments will be useful to assess the relative importance of the forces governing the process of structural transformation and development.

4.1 Calibration

The model solution requires calibrating four elasticities $\{\varepsilon, \eta_m, \eta_s, \sigma\}$, three parameters that control the strength of income effects $\{\nu_a, \nu_m, \nu_s\}$, five weights in the utility function $\{\omega_a, \omega_m, \omega_s, \omega_m^h, \omega_s^h\}$, the five parameters governing changes in the demand for high-skill labor $\{\pi_{at}, \pi_{mt}^h, \pi_{mt}^l, \pi_{st}^h, \pi_{st}^l\}$, the five sectoral TFP components $\{A_{at}, A_{mt}^h, A_{mt}^l, A_{st}^h, A_{st}^l\}$, and the aggregate ratio of high to low-skill labor supply $\{M_{ht}/M_{lt}\}$. I set exogenously $\sigma = 1.42$ following Katz and Murphy (1992) and $\varepsilon = 0.5$ while the rest of the parameters are calibrated using data for India from the KLEMS Database 2019 Version and data from the OECD Trade in Value Added Database together with total exports and imports from the World Bank Indicators.

Following Fang and Herrendorf (2021) and Yao and Zhu (2021), I use the data on trade in value added and aggregate imports and exports to compute the ratio of net exports to sectoral value added. This will enter the model as an exogenous wedge that will affect how much production of value added is consumed nationally and how much is (net) exported. Until 1991, India was a closed country but turned to a process of openness to trade and liberalization of certain sectors after a balanced of payments crisis. The policies adopted ranged from reduction of tariffs to reduction of export controls and import licensing. However, these liberalization policies affected relatively more the manufacturing sector although with significant impacts on services (Gordon and Gupta, 2005).[17] Furthermore, high-productivity services in particular are partially tradeable which allows these sectors circumvent in some degree the limitations of domestic demand.

I calibrate simultaneously the rest of the utility function parameters $\{\omega_a, \omega_m, \omega_s, \omega_m^h, \omega_s^h\}$, and $\{\eta_m, \eta_s, \nu_a, \nu_m, \nu_s\}$ imposing $\omega_s = 1 - \omega_a - \omega_m$ and $\nu_m = 1$ since what matters for income effects are the relative sizes. I calibrate these parameters minimizing the sum of the squared difference implied by the demand system from the model and the relative nominal value added data. Note that we can express the aggregate consumption index $\widetilde{C}_t$ as

$$\widetilde{C}^{1-\varepsilon} = \left(\frac{E_{mt}}{\omega_m}\right)^{\frac{1}{\nu_m}} \left(\frac{E_t}{p_{mt}}\right)^{\frac{1-\varepsilon}{\nu_m}}$$

and substitute it into (C.10) so that we can express relative expenditure shares as

$$\frac{E_{jt}}{E_{mt}} = \frac{\omega_a}{\omega_m^{\nu_j/\nu_m}} \left(\frac{p_{jt}}{p_{mt}}\right)^{1-\varepsilon} E_{mt}^{\frac{\nu_j}{\nu_m}-1} \left(\frac{E_t}{p_{mt}}\right)^{(1-\varepsilon)\left(\frac{\nu_m}{\nu_a}-1\right)} \tag{20}$$

I use equation (20) for $j \in \{a, s\}$. For the preference parameters in subsectors $i \in \{h, l\}$, I use equation (5) for $j \in \{m, s\}$. Note that from the market clearing condition for the consumption goods we can separate net exports from consumption of value added. The values obtained for the elasticities are $\eta_m = 0.81$, and $\eta_s = 2.02$.[18] Table 8 shows the values of the calibrated parameters.

[17] Arnold et al. (2016) also find that the improvement in manufacturing performance in India was affected by services as an input, however, I consider productivity in value added which abstracts from connections across sectors.

[18] I also follow a similar approach as Acemoglu and Guerrieri (2008) and estimate the elasticities η_j by regressing the ratios of nominal value added on a constant and on the relative price indices for sectors $j = \{m, s\}$ and $i = \{h, l\}$. I obtain $\eta_m = 0.4054$ and $\eta_s = 1.6145$ both statistically significant at the 0.1%.

Table 8: Calibrated Parameter Values for the Non-Homothetic CES Model with Trade

Weights		Elasticities	
ω_a	0.681	ν_a	0.001
ω_m	0.200	ν_m	1.000
ω_s	0.119	ν_s	1.286
ω_m^h	0.736	η_m	0.807
ω_s^h	0.389	η_s	2.021
		ε	0.500
		σ	1.420

Note: The table shows the calibrated values of the utility function parameters from 1981 to 2017 summarizing the calibration for the non-homothetic CES utility function.

As commented before, since the relative price of high to low-productivity manufacturing good is declining and so is the relative nominal value added, equation (5) implies that η_m should be lower than one. The opposite trends are observed for high and low-productivity services, thus implying $\eta_s > 1$, consistent with the calibration results. An implication is that high-productivity services are luxuries while low-productivity are necessities.

Regarding the strength of income effects, the parameter values yield sensible values. The difference $\nu_a - \nu_m$ is -0.99 which suggests there is a strong income effect. While the difference $\nu_s - \nu_m$ is calibrated to be 0.29. These are in the ranges estimated by Comin et al. (2020) when they use relative employment shares (proportional to value added). They find these ranges to be $(-0.99, -0.80)$ for agriculture and $(0.17, 0.37)$ for services.

The remaining parameters are calibrated period by period following Duernecker et al. (2023) and Fang and Herrendorf (2021). These parameters are calibrated to match the four relative prices of high and low productivity manufacturing and services with respect to agriculture; the four relative nominal labor productivities; the five high-to-low skill ratios; the aggregate skill premium; and aggregate nominal GDP. Since a price can always be normalized, I choose to keep p_{at} from the data as the numeraire.

The skill-bias technical change parameters π_{jt}^i are identified from the high to low skill ratios in each sector. Taxes in the agricultural sector are set to 0 for all the periods (i.e. $\tau_{at} = 0 \; \forall t \geq 0$), since what matters for equilibrium are relative taxes. Notice that relative taxes affect both relative prices and relative nominal labor productivities. Thus, they are identified from these equations. Nominal relative labor productivities and nominal GDP also pin down the TFPs in each sector. The relative aggregate supply of high-to-low skill workers is identified from the skill premium.

Figure 6 shows the results of the time-varying parameters calibrated for the period 1981-2017. The first panel shows the log of the normalized sectoral TFPs to compare average growth rates. In terms of TFP growth, I find high-productivity services and manufacturing to be quite similar which, given the differences observed in the data, tells us that labor productivity in the high-productivity services grows faster than in their manufacturing counterpart not because of faster TFP. However, Verma (2012) finds that most of the difference in growth between manufacturing and services as aggregated sectors is due to TFP growth thus, it seems that disaggregating these subsectors might be of importance. In particular, when comparing the low-productivity subsectors, there are clear differences in TFP growth. The service subsector grows significantly faster in TFP than the low-productivity manufacturing subsector but still slower than agricultural TFP.

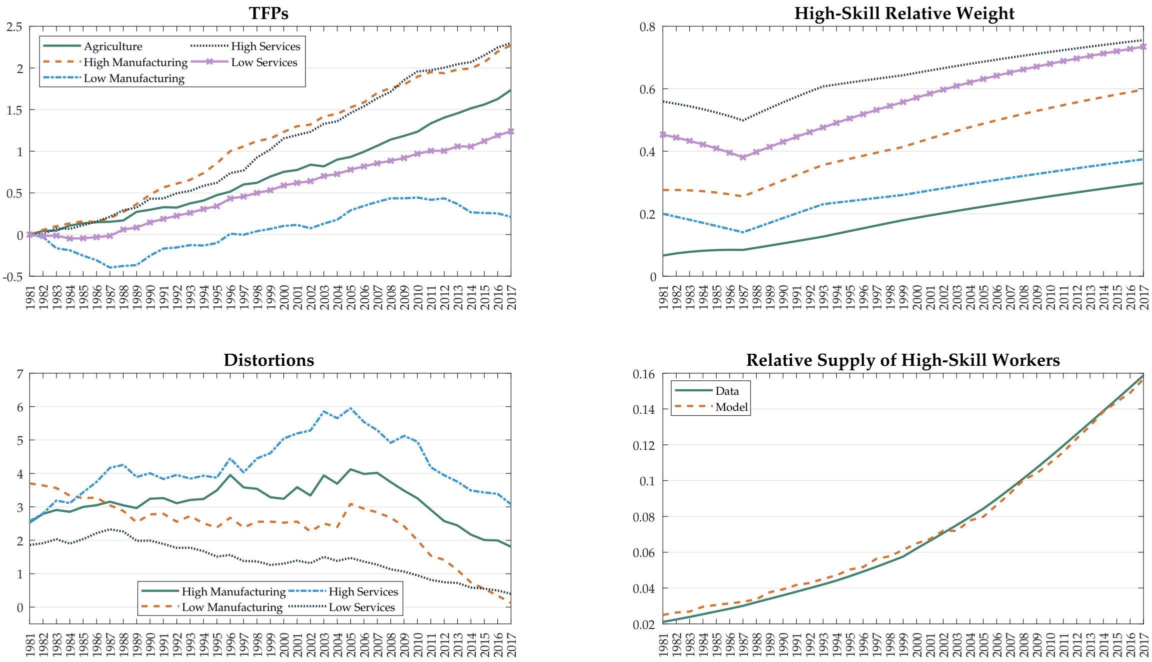


Figure 6: Calibrated Parameters

The sectoral production function parameters reflect two features of the data that were observed before when the returns to schooling by sector were estimated (Figure 5). In levels, both service subsectors show larger parameters than the rest with agriculture being the lowest in magnitude. This reflects the sectoral premium or comparative advantage of high-skilled workers in the service sector as an aggregate. However, in terms of growth, both service subsectors show the slowest increase in the demand for high-skilled workers. This is not so surprising if we note that these subsectors show, in levels, quite high values for the parameters. Table 9 shows the average growth rates for the sectoral TFPs and the parameters π^i_{jt}.

Table 9: Growth Rates of Sectoral Technology (in percentages)

	Agriculture	High Manufacturing	Low Manufacturing	High Services	Low Services
A^i_j	4.82	6.31	0.59	6.39	3.44
π^i_j	4.17	2.15	1.74	0.84	1.34

Note: The table shows the growth rates of each sectoral technology in percentages. These growth rates are computed as the averages for the full period.

The distortion parameters τ^i_j show that barriers to entry in the high-productivity subsectors are the largest relative to agriculture. Furthermore, these barriers seem to be trendless. However, for both of the low-productivity subsectors, the distortions seem to be declining over time. These distortions capture all the additional costs that stem from moving from one sector to another (e.g. costs of moving from rural to urban areas) and the relative distortions firms in those sectors face (e.g. subsidies or protectionist policies that manufacturing industries received).

Finally, the relative supply of total high-skill workers matches the growth in the data quite closely. The data shows a ratio of high-skilled to low-skilled workers of 2.11% in 1981 and 15.87% in 2017, while the calibrated values are 2.44% in 1981 and 16.70% in 2017. The model predicts a faster growth of the high-to-low skill ratio. It is important to mention how the data values have been computed. The data on education is obtained from IPUMS-I Database, while the sectoral level of workers and the total amount of workers in the economy is obtained from KLEMS Database 2019. These figures for the total amount of high-skilled workers are obtained by taking first the percentage of high-skilled workers in each sector from IPUMS-I and computing the amount of workers using these percentages and the KLEMS data. Then, the total amount of high-skilled workers in the economy is given by the sum of sectoral high-skilled workers, computed as explained before.[19]

4.2 Benchmark Simulation

With the calibrated parameters in hand, the solution of the model is determined with two equations in two unknowns, the skill premium and the consumption aggregator (details in Appendix C.4). Figure 7 shows the targeted variables as a solution of the model and the match of the model. The model matches the targets very closely.

Figure 8 shows in Panels A and B the data and the model-implied values for the log of the normalized sectoral real labor productivities. The model accurately captures the long-run trends of the sectoral labor productivities. In particular, it reproduces accurately the stylized facts documented in Section 2.1. High-productivity services perform better than manufacturing, and low-productivity services better than agriculture and manufacturing. The model can also reproduce the relative constancy of labor productivity in the low-productivity subsector of manufacturing. At the aggregate level, the model reproduces the observed growth in Real per capita GDP as well, shown in Panel C of Figure 8.

In terms of value added and employment shares, the model reproduces the overall behavior shown in the data in Figure 9. In particular, the increase in value added shares in high-productivity services and the relative constancy of the manufacturing value added shares in general. In terms of employment shares, the model overpredicts employment in both manufacturing subsectors but captures quite closely the behavior of the shares in the service subsectors. Finally, the model can reproduce the decline observed in agriculture in both value added and

[19]These values are similar to the ones computed directly from the IPUMS-I Database however, they are not exactly equal for several reasons. First, IPUMS-I provides weights for the observations so that the data is representative of the population in question thus the total amount of high-skilled workers is not simply the sum. Second, for the analysis of the IPUMS-I Data, some observations that do not have information on educational attainment, income from wages, or industry of work have been dropped. These reasons might lead to disparities between the total amount of workers in IPUMS-I and KLEMS Data.

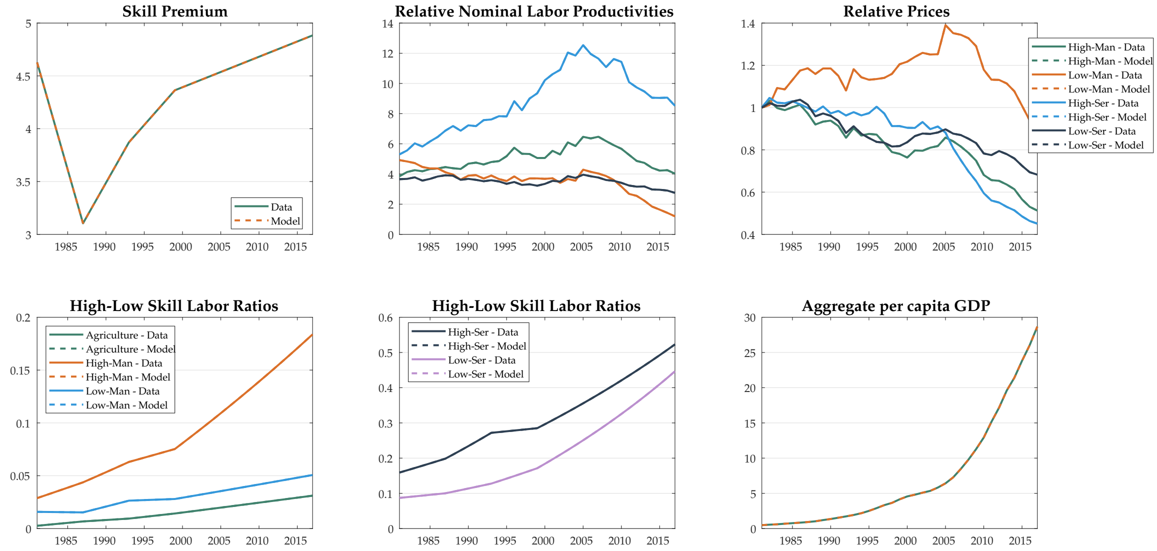


Figure 7: Targeted Variables

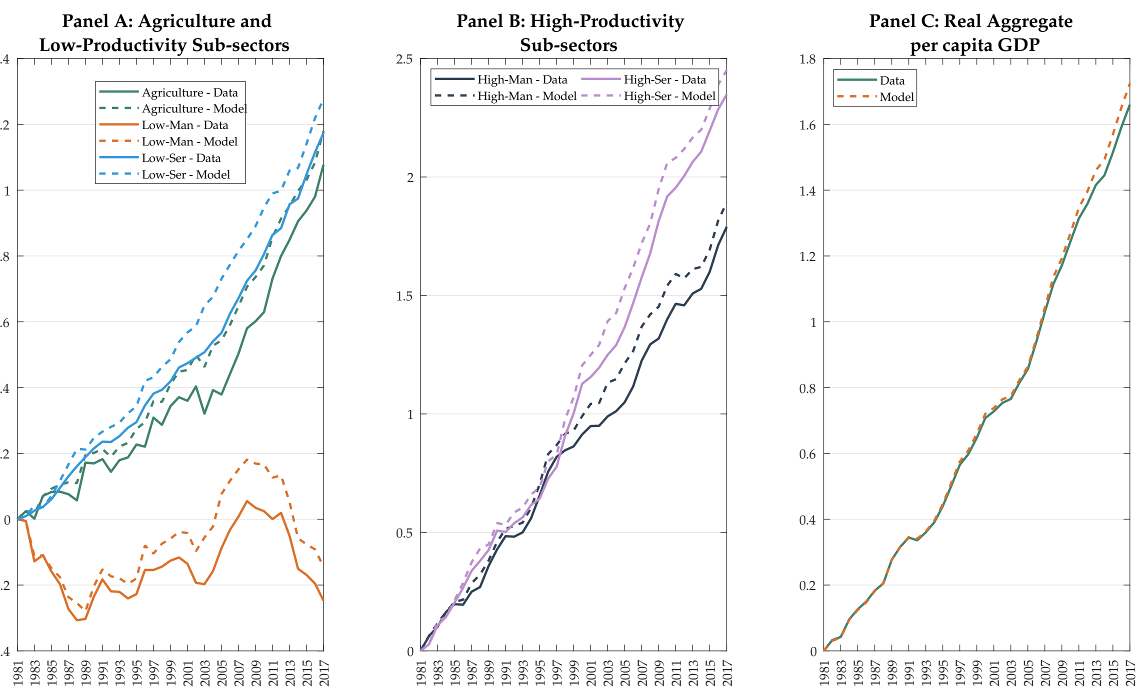


Figure 8: **Benchmark:** Sectoral Productivities and Aggregate Growth

Note: Each panel shows the log of the variables normalized to 1 in the first period. Sectoral real labor productivity is computed in the model from equation (19). Real aggregate per capita GDP is computed in the model from equation (C.25).

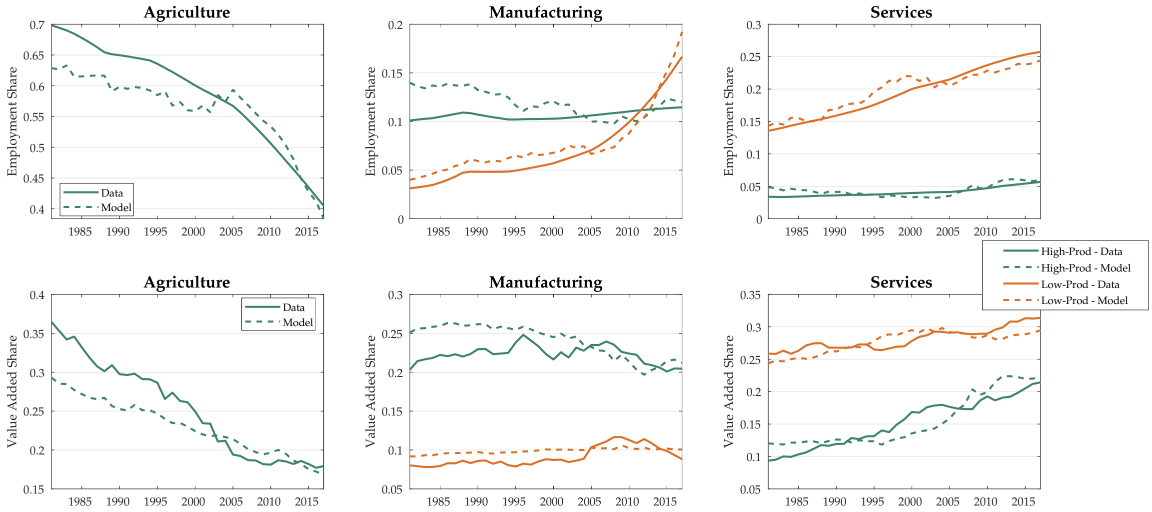


Figure 9: **Benchmark:** Value Added and Employment Shares

employment shares. However, the model predicts slightly less employment and value added in this sector.

4.3 Sources of Growth

The purpose of the model is to identify the causes of sectoral labor productivity growth and aggregate growth. To tackle those questions, in this subsection I switch off the different mechanisms of growth one by one in the model and evaluate their contribution to overall growth. Part of the observed growth in India comes from the process of structural transformation itself and part of it comes from the exogenous variables with steady increase. To separate between these effects, I start by analyzing the roles of the exogenously growing variables of the model (i.e. relative supply of high-skill to low-skill workers, sectoral TFP growth, and the increase in sectoral demand for high-skill labor) and then, by analyzing the role of distortions in the allocation of labor and how that process affects sectoral labor productivity.

(i) **The Role of Relative Supply of High-Skill Workers** In this experiment, I keep the relative supply of high-skilled workers constant at the 1981 values throughout the entire period for which we have data keeping the rest of the parameters as in the benchmark calibration.

Figure 10 shows that sectoral real output declines with respect to the benchmark calibration for all sectors except agriculture. Furthermore, real labor productivity also declines for all sectors. It is particularly dramatic the decline in high-productivity services (61% decline). This is because it is the most intensive sector in high-skill labor and note that the sectoral demand for high-skill workers is kept as in the benchmark calibration. Thus, as the sectoral demand for high-skill labor increases over time, the relative supply of high-skill workers does not increase. Therefore, real output in the subsectors that are most intensive in high-skill workers suffer more this decline. For the same reason, the skill premium rises dramatically. In terms of aggregate growth, the effects of keeping the supply of high-skill workers fixed has significant effects as Figure 11 shows (51% decline). This summarized in the first row of Table 10.

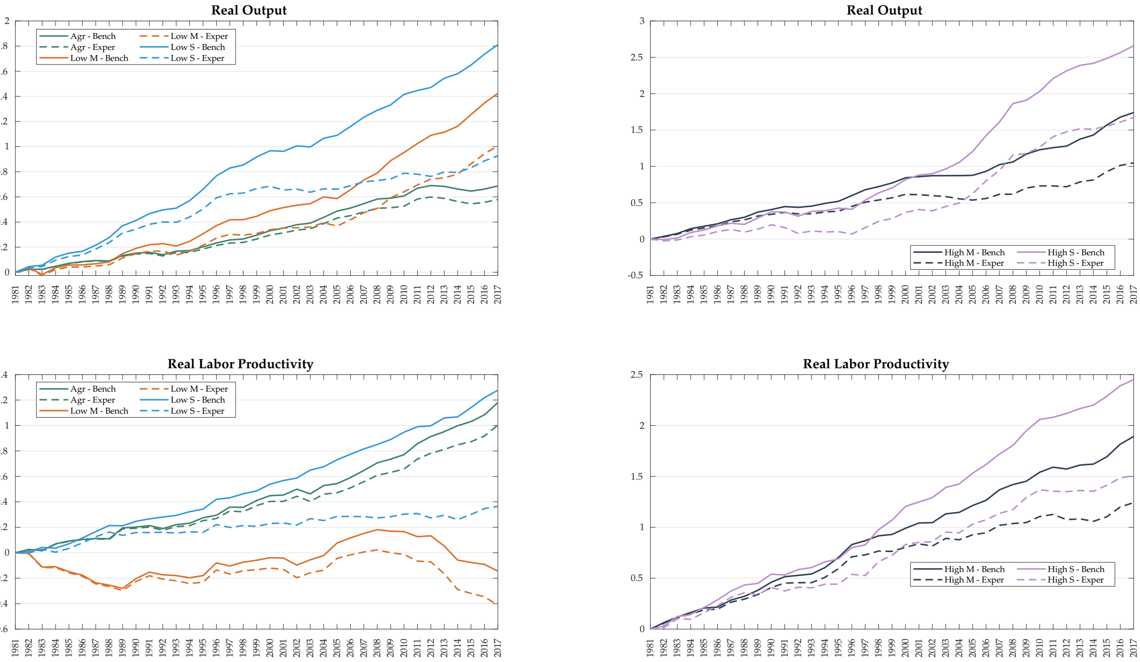


Figure 10: **Counterfactual:** Constant M_h/M_l

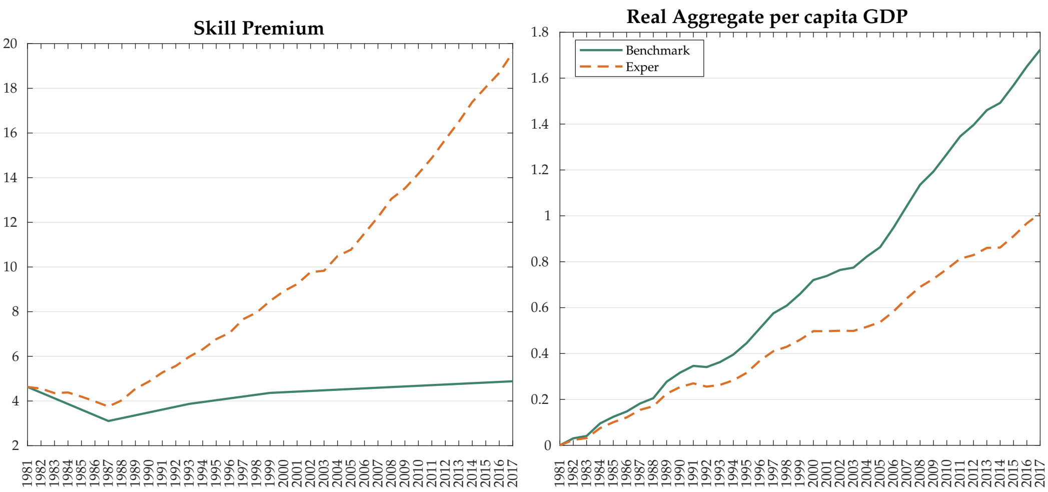


Figure 11: **Counterfactual:** Constant M_h/M_l

(ii) **The Role of Sectoral TFP Growth** To evaluate the role of sectoral TFPs, this experiment holds sectoral TFPs at their levels in 1981 without growth. The rest of the parameters are kept at their benchmark values. Holding constant sectoral TFPs shows this is the main source of growth in India. Both real sectoral outputs and labor productivities decline over time and aggregate GDP is mostly flat. This summarized in the second row of Table 10. Figures E.13 and E.14 in Appendix E.3 show the evolution of these variables.

(iii) **The Role of the Sectoral Demand for High-Skill Labor** The sectoral skill-biased technical change parameters π_j^i are crucial to replicate the behavior of the skill premium. The relative increase over time of these parameters reflects the increase in the sectoral demand for high-skill labor over time. Holding constant these parameters tells us how much they contribute to economic growth in India. The experiment sets the values constant at their 1981 levels for the entire period, that is, I assume there is no increase in the demand for high-skill workers over time. Figures 12 and 13 show the results.

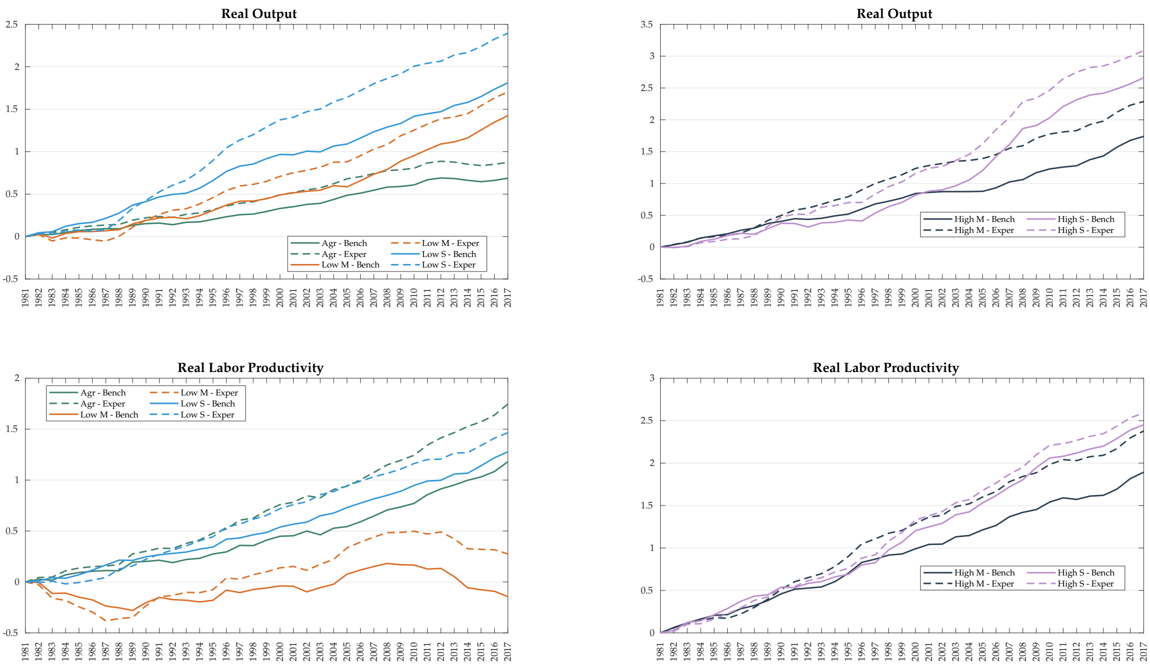


Figure 12: **Counterfactual:** Constant π_j^i

The results indicate an increase in real output and labor productivity for all sectors, an increase in real GDP per capita, and a steady decline in the skill premium. The rationale behind the results is that keeping constant these parameters holds constant the demand for high-skilled workers. However, the supply increases over time. This explains why the skill premium declines. To see why there are productivity gains and output increases, note that the level of the parameter reflects the sectoral skill-intensity, while the demand remains unchanged. The most skill-intensive sectors are the ones with fastest growing productivities, which results in high-skill labor moving in a larger proportion to those sectors. Thus, causing structural change to be growth-enhancing. That explains the gains in GDP per capita and real labor productivities. . The third row of Table 10 shows these effects.

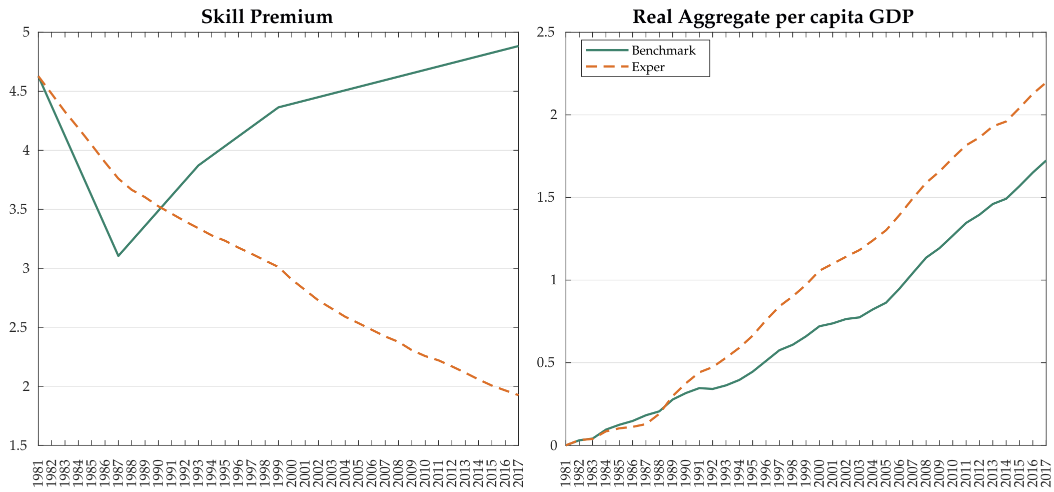


Figure 13: **Counterfactual:** Constant π_j^i

(iv) **The Role of Distortions** This experiment consists on reducing all distortions to the level of τ_m^l. That is, keep the taxes of $\tau_a = 0$ and lower the rest to the level of the low-productivity manufacturing which is the sector with the smallest distortions. Figures E.15 and E.16 in Appendix E.3 show the results.

Reducing the distortions radically as in this experiment results in the share of people working in the low-productivity services to drop substantially, while getting a significant increase in the high-productivity services subsector. This is because the service sector faces larger barriers than the manufacturing sector. However, in the manufacturing sector, high-productivity manufacturing employment shares increase substantially, while low-productivity manufacturing shares do not increase much. This is because the low-productivity manufacturing sector remains as in the benchmark relative to agriculture, while high-productivity manufacturing experiences a drop in barriers. Although real output increases for both high-productivity subsectors, the inflow of labor they receive causes labor productivity to drop. Note that this reduction in barriers increases real output for high-productivity subsectors but decreases for agriculture and low-productivity subsectors. This increases real aggregate per capita GDP. The fourth row in Table 10 summarizes these results.

(v) **Industrial Policies** Rows five and six of Table 10 show what would happen if only the high-productivity subsectors would see their barriers reduced. The fifth row shows that if only the high-productivity manufacturing would see its barriers reduced to the level of low-productivity manufacturing, aggregate GDP would increase by a factor of 1.24. If, instead, the high-productivity subsector would have less distortions, this number would rise up to 2.11. This reflects how different aggregate outcomes can be depending on which subsectors are targeted.

(vi) **International Trade** India was by 2014 the largest exporter in the world of Computer and Information Services (Loungani et al., 2017) and this can have direct consequences for structural change and development.[20] In the data, India is a net exporter of high and low-productivity services and agricultural goods while being a net importer of manufacturing goods. In this counterfactual, I set net exports in all sectors equal to 0. The last row in Table 10 shows this counterfactual.

There are small aggregate gains in GDP per capita and virtually no changes in the skill premium or labor productivity. This does not mean that international trade is not an important ingredient to understand structural transformation in India. In this experiment, the employment share in high-productivity manufacturing remains larger. This is because domestic demand must be served by national production only. This implies that the agricultural employment shares is reduced compared to the benchmark case with very small changes in the employment shares in services. What this experiment shows, though, is that trade cannot be the main reason for the productivity surge in services and, in particular, to explain why high-productivity services grow faster than high-productivity manufacturing industries.

Table 10: Experiments and Benchmark Calibration

	Agriculture		High-Manufacturing		Low-Manufacturing		High-Services		Low-Services		Aggregate	
	Labor Productivity	Real Output	Labor Productivity	Real Output	Labor Productivity	Real Output	Labor Productivity	Real Output	Labor Productivity	Real Output	Skill Premium	Real Output
M_h/M_l	0.838	0.898	0.522	0.501	0.765	0.659	0.390	0.373	0.402	0.413	4.014	0.490
A_j^i	0.190	0.350	0.127	0.080	0.899	0.378	0.125	0.022	0.364	0.184	0.604	0.139
π_j^i	1.762	1.206	1.625	1.729	1.522	1.323	1.150	1.532	1.206	1.793	0.394	1.603
τ_j^i	0.982	0.892	0.944	1.447	0.974	0.711	0.933	3.461	0.933	0.401	1.133	1.400
$\tau_{mt}^h = \tau_{mt}^l$	0.994	0.924	0.981	1.613	0.991	0.779	0.977	0.946	0.977	0.948	1.043	1.236
$\tau_{st}^h = \tau_{mt}^l$	0.983	0.907	0.948	0.920	0.976	0.944	0.938	4.120	0.938	0.308	1.123	2.112
$\varphi_j^i = 0$	1.001	0.919	1.002	1.373	1.001	1.044	1.002	0.840	1.002	0.955	0.996	1.026

Note: The table shows the ratio of the variable evaluated in the last period of the experiment simulation by the variable in the last period of the benchmark simulation.

4.4 Future Growth

The model presented serves as a framework to assess the future dynamics of growth and structural transformation. To do so, I pose two main questions. First, how will growth, employment, and value added shares evolve in the future if exogenous variables keep growing as up to now? Second, what would be the growth rates of the sectoral TFPs to achieve a 2.5% growth in aggregate GDP per capita? The first question highlights the importance of complementariy in manufacturing and substitutability in services, and the role of structural transformation in aggregate growth. The second question shows the necessary decline in sectoral TFPs to converge to a plausible standard value of developed countries. The model is simulated until 2075, which seems a reasonable period although the same qualitative patterns would remain if we chose 2055 (roughly same years as in the data).

For the first experiment I assume that the exogenous sectoral TFPs and the relative supply of high-skilled workers grow at their past average growth rate (1980-2017) until the ratio M_h/M_l reaches 25%, then it remains constant. while the labor market distortions (τ_{jt}^i) stay at the past

[20] Matsuyama (1992) analyzes the effect of trade for agricultural productivity in a two-sector model and Matsuyama (2009) analytically studies how trade affects the movements of consumption and value added shares. Uy et al. (2013); Teignier (2018) and Sposi (2019) are more recent papers analyzing the role of trade in structural transformation.

average value. The skill-bias technical change parameters (π^i_{jt}) and net exports parameters (φ^i_j) are kept constant at the value obtained for the year 2017.[21] This is obviously not realistic but this would give a conservative estimate for what could happen in the future since the skill-bias technical change is the main source of divergence between high-productivity manufacturing and services. Furthermore, since π^i_{jt} needs to be smaller than one, it is not obvious how to make assumptions about its evolution.

Figure 14 shows the employment and value added shares of high and low-productivity subsectors over the total sector. This reflects the relative importance of the high-productivity subsector within the sector. What the Figure shows is that the high-productivity services, both in terms of employment and value added shares, increase while the opposite happens for manufacturing. This implies that the service sector will become more productive over time, while the manufacturing sector will become less productive.

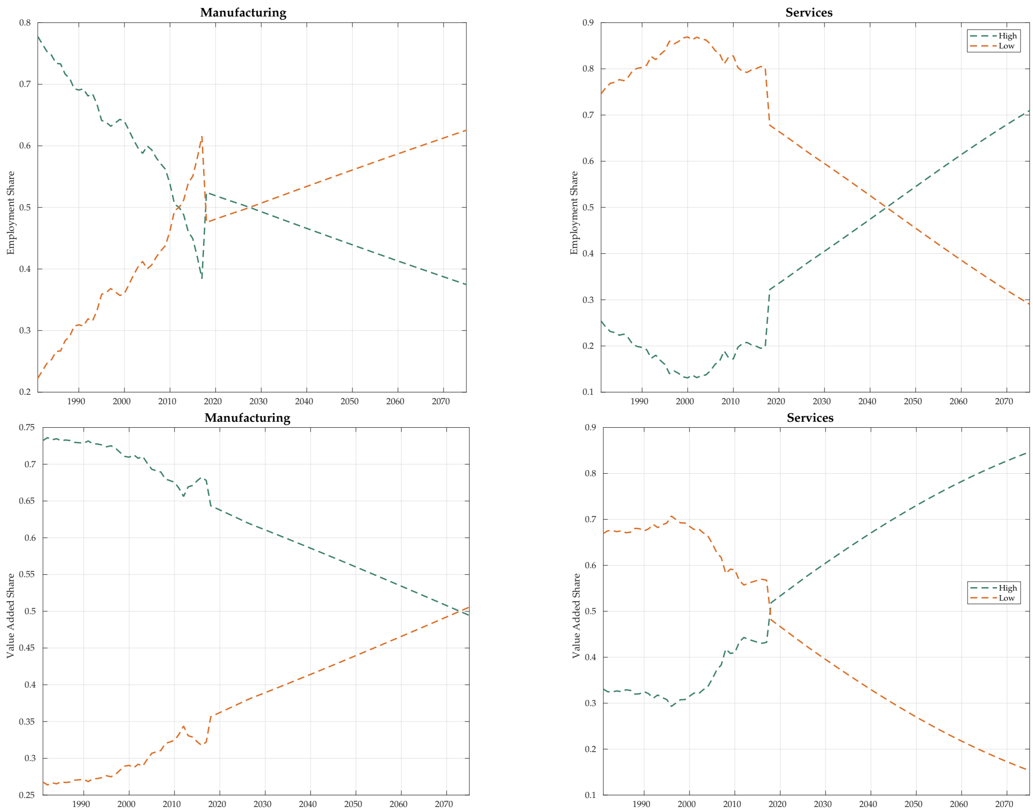


Figure 14: Evolution of Employment and Value Added Shares

Note: The Figure shows the employment and value added share of each subsector over the total of the sector.

The reason behind this is that manufacturing subsectors are gross complements while services are gross substitutes, this implies that, conditioning on labor flowing into services (manufacturing) as an aggregate, it will flow relatively more to the most (least) productive subsector

[21] In Appendix D I perform an experiment in which I allow for growth in skill-bias technical change parameters assuming they grow according to a logistic growth function. Assuming TFPs grow as in this current section, GDP grows faster by 0.2 percentage points. This gain comes from improvements in labor productivity in the agriculture and high manufacturing sectors. The results are shown in Table D.2.

which increases (decreases) the employment share in the high-productivity subsector. A natural question that follows is how will the process of structural transformation affect future productivity growth? Table 11 shows the average yearly growth rates of sectoral labor productivity and aggregate productivity growth for both periods under different scenarios. The second column corresponds to the values obtained for the sample period, the third and fourth columns correspond to this experiment. Last two columns correspond to the experiment in which the purpose is to obtain an average yearly GDP growth rate of 2.5%.

Table 11: Growth Rates of Sectoral Labor Productivity (in percentages)

		Averages		*Convergence to* 2.5%	
	1980-2017	2017-2075	Difference	2017-2075	Difference
Agriculture	3.278	4.824	1.546	4.019	0.741
High Manufacturing	5.257	6.249	0.992	1.585	−3.673
Low Manufacturing	−0.402	0.537	0.938	0.067	0.468
High Services	6.809	6.309	−0.500	1.551	−5.258
Low Services	3.548	3.543	−0.005	0.913	−2.635
GDP	4.789	7.321	2.532	2.501	−2.288

Note: The table shows the average growth rates of sectoral labor productivity in percentages for both time periods and the difference for both. Labor productivity is defined as real value added over total labor employed. Columns 3 and 4 under the title *Averages* correspond to the average growth rates in the experiment where exogenous variables take their past average values. Columns 5 and 6 correspond to the experiment in which the sectoral TFP growth rates are set to match a 2.5% growth rate of GDP per capita.

From the third and fourth columns in Table 11, the model suggests that if the exogenous variables keep growing as they did in the past, the growth rate of GDP per capita can increase in 2.5 percentage points. This increase comes from the process of structural transformation itself through which labor flows into the most productive sectors and, assuming that the pool of skilled workers keeps increasing, these workers become more productive. Note further that the average growth rate of labor productivity in low-productivity manufacturing turns positive and that the sector that improves the most is agriculture. This is because the employment share in agriculture keeps falling. Note further that the sector with the highest productivity growth is still the high-services, however, there is a reduction in the growth rate of labor productivity of 0.5 percentage points. This suggests that this sector absorbs more labor, thus the larger employment share.

Now I turn to the question of what are the sectoral TFP growth rates compatible with a 2.5% growth of aggregate GDP. For this experiment, I calibrate sectoral TFP growth rates to match an average GDP per capita growth of 2.5% in the period 2017-2075. I impose some additional constraints. First, the difference between the growth rates in the high-productivity and the low-productivity subsectors must remain the same as in the data for both manufacturing and services. Second, the difference between the growth rates of the high-productivity manufacturing and services must also remain as in the data. The rest of the parameters are kept as in previous experiment. The calibrated growth rates in percentages are $\{3.98, 1.43, 0.13, 1.41, 0.76\}$ for agriculture, high and low manufacturing, and high and low services, respectively. The resulting average growth rates of sectoral labor productivity for both periods is shown in columns 5 and 6 of Table 11.

The results from the model show that labor productivity growth is faster in the 2017-2075 period for agriculture and low-productivity manufacturing and slower in the rest. Agriculture's labor productivity growth increases because it is the sector with the fastest TFP growth and the non-homotheticities imply that less labor is needed over time.

The implied reductions in TFPs for both services and the high-productivity manufacturing result into lower labor productivity growth in each sector. Nevertheless, the necessary decline in high-productivity services to achieve the 2.5% aggregate growth is of 5.26 percentage points, while for the high-productivity manufacturing it is of 3.67. Thus, the reduction necessary in the high-productivity services is much larger than in the manufacturing counterpart.

4.5 Potential Explanations for Distortions

The calibration exercise reveals an important role of distortions in the allocation of labor across sectors and, especially, in the most productive sectors. In this subsection I assess what are the distortions that the wedges are capturing. A natural starting point is to ask whether the caste system has contributed to specialization of certain castes in specific sectors. Roy (2011) notes that the demand for education was biased towards certain castes and social groups, and, furthermore, these social groups were dominating the entrance on the telecommunications sector during the 1990s. However, Hnatkovska et al. (2012) shows that scheduled castes and tribes have converged in terms of educational achievement, occupation distribution, wages, and consumption in the period 1983-2005. Hnatkovska et al. (2013) also show that these social groups have also converged in terms of inter-generational mobility.

Rodrik and Subramanian (2004) suggest that what spurred economic growth during the 1980s was in fact a *pro-business* attitudinal change in the government reducing corporate taxes and removing price controls affecting the incumbents more than new entrants. They argue that this attitudinal change started with the return to power of Indira Gandhi in 1980 and continued with Rajiv Gandhi in 1984. The data I use starts in 1981 so I cannot test wether there was a trend break in distortions pre-1980. However, the distortions for the high-productivity subsectors are trendless throughout the period and, if anything, they increase during the 1980s, thus it is not likely that the distortions are capturing this attitudinal change.

I explore other two potential explanations for the high distortions in the most productive sectors, one is the distribution of female employment and, the second one, migration costs and educational complementarities. First, I document that the distribution of female employment in India is largely concentrated in the non-service sector while, within the service sector, they tend to work significantly more in the low productivity services. Table 12 shows the disproportionate concentration in the non-services sector and that even at the end of the sample in 2009, only 2.25% of employed women worked in high-productivity services. But, furthermore, out of the non-services, the large majority work in agriculture (66.75% in 2009).

Table 12: Distribution of Female Employment in India (in %)

	1983	1987	1993	1999	2004	2009
Non-Services	86.89	87.20	85.55	84.73	83.25	82.56
High services	1.63	1.86	2.48	2.21	2.25	2.94
Low services	11.48	10.94	11.97	13.06	14.50	14.50

Note: Data from IPUMS International. The table shows the distribution of female employment across sectors for the period 1983-2009.

Furthermore, from World Bank data, female labor force participation in India is substantially low and what is more surprising, declining in the last years falling from the peak in 2005 at 31.8% to 20.5% in 2019. These figures suggest that women tend to face larger costs of working and, especially, of working in high-productivity sectors.[22] These costs are partly explained by cultural norms. Jensen (2012) provided with education in recruiting services young women in rural areas of India finding that treated women were less likely to get married and reported wanting to have less children. This could highlight that women face larger costs of acquiring education than men, and thus, they face larger barriers of entry in high-productivity sectors.

The second explanation I investigate are migration costs and the complementarity with average years of schooling. Alonso-Carrera and Raurich (2018) show that migration costs can limit the process of structural change since the presence of the cost constraints the allocation of labor across sectors. Furthermore, Fan et al. (2021) show that benefits from services-led growth were skewed towards to urbanized locations, thus sectoral employment shares will depend substantially on their geographical location. To see how employment shares and migration costs are related, I estimate the following equation

$$
\begin{aligned}
N^s_{d,t} = \alpha + \beta_1 \log(City_d) + \beta_2 \log(Railroad_d) &+ \beta_3 S_{d,t} + \beta_4 S_{d,t} \times \log(City_d) \\
&+ \gamma_1 Longitude_d + \gamma_2 Latitude_d + \mu_t + \varepsilon_{d,t}
\end{aligned}
\tag{21}
$$

where $N^s_{d,t}$ is the sector s employment share in district d at time t, $City_d$ is the distance from district d to the closest city with more than 1 million inhabitants,[23] $Railroad_d$ is the distance to the closest railroad, $S_{d,t}$ is average years of schooling in district d at time t, $Longitude$ and $Latitude$ are proxies for geographical characteristics such as temperature or rainfall, and μ_t denote year fixed effects. I estimate this regression for the five sectors separately. Figure 15 shows the distribution of these cities together with the railroads distribution.

From column (1) in Table 13, we see that the results for agriculture are not surprising. Those districts further away from large cities or with less average years of schooling are associated with larger employment shares in agriculture. However, this Table highlights one important

[22]Evidence suggests that female labor force participation is linked to the stage of development. At early stages women tend to participate on the agricultural labor market and as the economy industrializes, labor force participation falls. Ngai and Petrongolo (2017) show that a sizeable share of observed trends in hours and relative wages is accounted for by the inclusion of women in services jobs which benefited from marketization of home production.

[23]Data for the population of the cities comes from the *2018 Revision of World Urbanization Prospects* by the United Nations. Data for railroads comes from the *Global Map Version 2* accessible here.

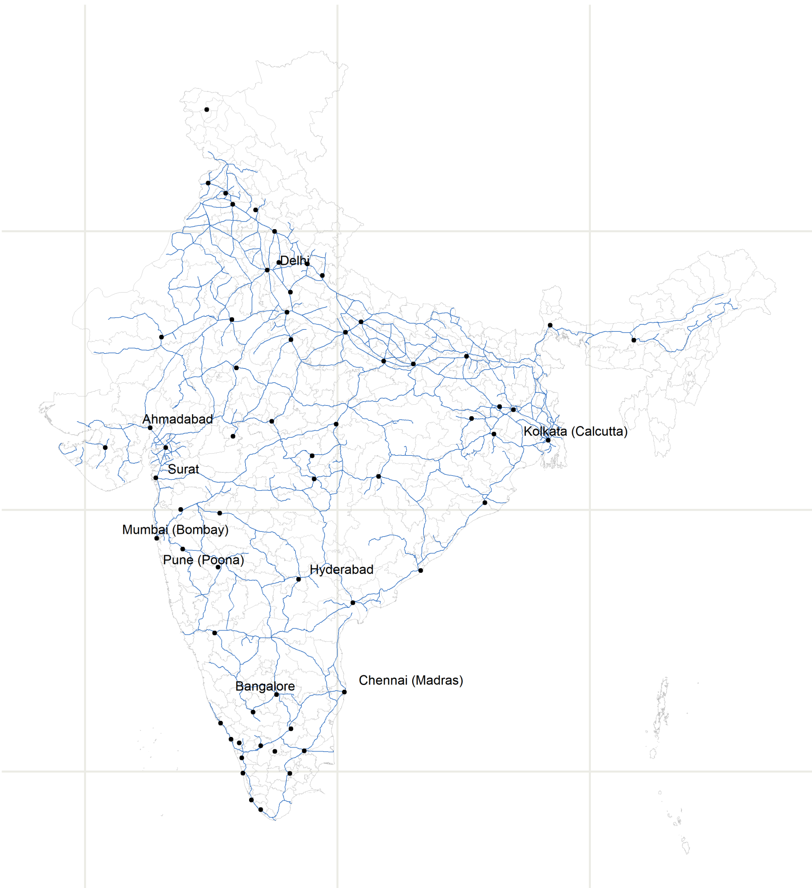


Figure 15: Distribution of Large Cities and Railroads

Note: Each point is a city with more than 1 million inhabitants. Names of the city are displayed for those cities with more than 4 million inhabitants. Lines in blue show the distribution of railroads.

Table 13: Employment Shares and Distance to Railroads, Roads, and Large Cities

	Agriculture	High Manufacturing	Low Manufacturing	High Services	Low Services
	(1)	(2)	(3)	(4)	(5)
Distance to Large Cities (logs)	0.034***	-0.019***	0.004	-0.004**	-0.015***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)
Distance to Rails (logs)	0.002	-0.007***	0.003*	0.005***	-0.002**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Average years of schooling	-0.067***	0.011***	0.002	0.028***	0.027***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
City × School	0.013***	-0.001	-0.004***	-0.004**	-0.005***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1648	1648	1648	1648	1648
R^2	0.482	0.273	0.170	0.410	0.449

Data: IPUMS-I. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include longitude, latitude, and year fixed effects. Large cities are those cities with more than one million inhabitants. The interaction term is computed by first de-meaning each of the variables and then computing the product. Distance to large cities is computed as the minimum distance from the centroid of the district to all cities with more than 1 million inhabitants.

difference between high-productivity manufacturing and high-productivity services (columns (2) and (4)). For both high-productivity subsectors, being closer to large cities or more average years of schooling is associated with larger employment shares. However, being closer to a railroad only increases employment shares for the high-productivity manufacturing. One possible explanation is that railroads are mostly used for freight transport which is mostly important for manufacturing rather than for services.

However, Table 13 also suggest a potential explanation for why distortions are larger in high-productivity services than in high-productivity manufacturing. From column (2), the interaction between distance to a large city and average years of schooling is not statistically significant, however, for high-productivity services, it is significant and negative. This implies that being closer to a large city is associated with higher employment shares in high-productivity services and that this association is strengthened with the average years of schooling. Note that the association between the employment share and average years of schooling is also strengthened with shortest distances to large cities. This highlights why entry costs in the high-productivity services are higher since it is not sufficient to be close to a large city but it is necessary to have high education. Thus, the entry cost comes from the costs associated to migration and the costs of acquiring education. While for the high-productivity manufacturing sector, most of the cost is from migrating only.

Another potential problem is whether high-skilled workers perform high-skill tasks or to which extent there is high-skilled labor misallocated and performing low-skill tasks. To check this, I follow the International Standard Classification of Occupations (ISCO) and map the occupations in ISCO with major skill levels associated.[24] With this classification, I compute the proportion of high-skilled workers within each sector that are assigned to the lowest ranked

[24]This mapping can be found in International Labour Office (2012).

occupations. These proportions are presented in Table 14.

Table 14: Percentage of High-Skill Workers in Low-Rank Occupations

	1983	1987	1993	1999	2004	2009
Agriculture	2.90	4.24	8.07	4.97	5.87	6.82
High Manufacturing	1.51	1.33	0.85	1.52	1.07	3.41
Low Manufacturing	1.11	3.24	2.14	9.43	3.75	13.92
High Services	0.79	0.82	0.78	2.00	1.24	1.07
Low Services	0.26	0.46	0.69	1.04	1.06	0.77
Aggregate	0.86	1.20	1.63	2.09	1.77	2.44

Note: Based on IPUMS-International Data and ISCO Classification (International Labour Office, 2012).

Table 14 shows that, overall, very few high-skilled workers tend to work in lower ranked occupations. In the low-productivity subsector however, the proportion of high-skilled workers performing low-ranked occupations rises up to almost 14% which might help explain the poor performance in productivity of this subsector. Nevertheless, the proportions in both service subsectors and on aggregate are low and stable over time.

5 Conclusion

Services-led development has been controversial as a development strategy. In this paper, I provide a plausible explanation for how services have been the main engine of growth in one of the most successful stories of development, India. In particular, I show why productivity in manufacturing and services have been diverging based on skill-intensity differences at the sectoral level. Through the proposed model, I find skill-biased technical change to be the main factor differencing high-productivity services from high-productivity manufacturing. Furthermore, the calibrated model implies that since services are gross substitutes and manufacturing are gross complements, the high productivity subsector will take over services while the least productive sector will take over manufacturing which will perpetuate differences in labor productivity across the two sectors.

The findings of the model are further supported by reduced form evidence from cross-country regressions and from census data. In a set of cross-country regressions, I show that labor productivity in services has grown faster than the rest of countries after controlling for the stage of development and population, which suggests there is more to it than just converging to the international norm. The evidence from census data shows that returns to schooling are higher in services and that there is a sectoral premium for working in the service sector. I conclude that services-led growth seems to be rooted in the skewed distribution of educational attainment and the skill intensity of fast growing services. However, the model also shows that there are large labor market distortions in most productive sectors, which could potentially limit the effect of increasing the presence of these sectors in the Indian economy.

Services-led growth appears to be a story of success in the case of India but it is crucially affected by the pool of high-skilled workers and the intensity with which services employ them. Strategies based on the development of services might be more successful than previously thought but without a sufficient pool of high-skilled workers that keeps increasing over time, premature deindustrialization might be blocking the road towards economic convergence.

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Appendix A Industry Aggregations

In this section I briefly describe the process of aggregation across industries which follows the KLEMS methodology closely. I define nominal value added shares as

$$\nu\left(P_{j,t}Y_{j,t}\right) = \frac{1}{2}\left(\frac{P_{j,t}Y_{j,t}}{\sum_{j=1}^{N} P_{j,t}Y_{j,t}} + \frac{P_{j,t+1}Y_{j,t+1}}{\sum_{j=1}^{N} P_{j,t+1}Y_{j,t+1}}\right)$$

where j is the industry subscript. Note that the base year for the KLEMS Database 2018 Release is 2012, thus, for $t = 2012$ $P_{j,t}Y_{j,t} = Y_{j,t}$ for every j. Then, $Y_{i,2012} = \sum_{l\in L} P_{l,2012}Y_{l,2012}$ for $j = \{a, m, s\}$ denotes real value added in 2012 for sector i composed of L industries. Where l indicates the industries that belong to sector i. Then, real value added in sector i is the Törnqvist index given by

$$Y_{i,t+1} = Y_{i,t}\exp\left\{\sum_{l\in L}\nu\left(P_{l,t}Y_{l,t}\right)\log\left(\frac{Y_{l,t+1}}{Y_{l,t}}\right)\right\}$$

In a similar way, it is possible to aggregate quality-adjusted labor and capital, only changing the weights in the aggregation by:

$$\nu\left(W_{j,t}H_{j,t}\right) = \frac{1}{2}\left(\frac{W_{j,t}H_{j,t}}{\sum_{j=1}^{N} W_{j,t}H_{j,t}} + \frac{W_{j,t+1}H_{j,t+1}}{\sum_{j=1}^{N} W_{j,t+1}H_{j,t+1}}\right)$$

$$\nu\left(R_{j,t}K_{j,t}\right) = \frac{1}{2}\left(\frac{R_{j,t}K_{j,t}}{\sum_{j=1}^{N} R_{j,t}K_{j,t}} + \frac{R_{j,t+1}K_{j,t+1}}{\sum_{j=1}^{N} R_{j,t+1}K_{j,t+1}}\right)$$

Appendix B Growth Accounting

To provide further evidence of the faster productivity growth in high-productivity services than in high-productivity manufacturing, I follow the KLEMS methodology for growth accounting with value added production functions. This is based on the following equation

$$\Delta\log(Y_{j,t}) = \nu(R_{j,t}, K_{j,t})\Delta\log(K_{j,t}) + \nu(W_{j,t}, H_{j,t})\Delta\log(H_{j,t}) + \Delta\log(A_{j,t})$$

where $A_{j,t}$ is the total factor productivity, the shares $\nu(R_{j,t}, K_{j,t})$ and $\nu(W_{j,t}, H_{j,t})$ are defined as before, and $\Delta\log(X)$ is defined as the log differences between periods t and $t-1$. I use this

Table B.1: Growth Accounting

	Agriculture	High-Manufacturing	Low-Manufacturing	High-Services	Low-Services
Real Value Added	2.96	6.80	5.44	9.44	6.52
Capital	2.04	5.52	3.10	3.55	3.58
Labor	0.24	0.95	4.90	2.14	2.14
TFP	0.68	0.33	−2.56	3.75	0.81
			Pre-Liberalization (1980-1990)		
Real Value Added	3.05	7.26	4.48	7.73	6.11
Capital	1.67	5.93	2.69	2.75	1.83
Labor	0.87	1.48	5.19	3.06	2.29
TFP	0.50	−0.14	−3.40	1.93	1.99
			Post-Liberalization (1990-2017)		
Real Value Added	2.94	6.63	5.88	9.83	6.67
Capital	2.19	5.36	3.24	3.81	4.20
Labor	0.05	0.76	4.70	1.85	2.12
TFP	0.70	0.51	−2.07	4.18	0.34

Note: The numbers are the average growth rates for the period of each factor in percentages.

procedure to recover total factor productivity for the five sector classification. Table B.1 shows the growth rates of each component.

This exercise provides further evidence of the faster productivity growth of high productivity services. These industries have a TFP growth of 4.18% per year for the post-liberalization period with fast capital and labor accumulation. TFP growth for high productivity manufacturing is significantly slower and approximately 81% of the growth in real value added is explained by capital accumulation. Following the arguments in Acemoglu and Guerrieri (2008), capital deepening in the most capital-intensive sector should imply faster growth rates of output. In this case, the most capital intensive sector is high-productivity manufacturing and it also experiences faster capital deepening than services. However, it is not the fastest growing sector.

Appendix C Deriving the Competitive Equilibrium

C.1 Household

This appendix shows how to derive the competitive equilibrium and all expressions that appear in the main text. I omit time indices for clarity and simplicity. The first layer of the household problem consists of minimizing total expenditure across $j \in \{a, m, s\}$ sectors subject to (2). That is

$$\min_{c_a, c_m, c_s} \sum_{j \in \{a,m,s\}} p_j c_j \tag{C.1}$$

$$\text{subject to} \quad \omega_a^{1/\varepsilon} \left(\frac{c_{at}}{\widetilde{C}_t^{\nu_a}} \right)^{\frac{\varepsilon-1}{\varepsilon}} + \omega_m^{1/\varepsilon} \left(\frac{c_{mt}}{\widetilde{C}_t^{\nu_m}} \right)^{\frac{\varepsilon-1}{\varepsilon}} + \omega_s^{1/\varepsilon} \left(\frac{c_{st}}{\widetilde{C}_t^{\nu_s}} \right)^{\frac{\varepsilon-1}{\varepsilon}} = 1 \tag{C.2}$$

The first order conditions for the three goods can be expressed as

$$p_j = \lambda \omega_j^{\frac{1}{\varepsilon}} \frac{\varepsilon - 1}{\varepsilon} c_j^{-\frac{1}{\varepsilon}} \widetilde{C}^{\nu_j \frac{1-\varepsilon}{\varepsilon}} \tag{C.3}$$

Using (C.3) we can obtain (8) as

$$\frac{p_{jt}c_{jt}}{p_{at}c_{at}} = \frac{\omega_j}{\omega_a} \left(\frac{p_{jt}}{p_{at}} \right)^{1-\varepsilon} \widetilde{C}^{(1-\varepsilon)(\nu_j - \nu_a)}$$

Multiplying (C.3) by c_j and aggregating across sectors, we get $E = \widetilde{P}\widetilde{C} = \sum_{j \in \{a,m,s\}} p_j c_j = \lambda \frac{\varepsilon - 1}{\varepsilon}$ which can be substituted back into (C.3) to obtain expenditure shares as

$$E_j \equiv \frac{p_j c_j}{E} = \omega_j \left(\frac{p_j}{E} \right)^{1-\varepsilon} \widetilde{C}^{\nu_j (1-\varepsilon)} \tag{C.4}$$

We can substitute $\widetilde{C}$ in (C.3) and use the relationship between E and $\widetilde{C}$ to get

$$p_j c_j = \omega_j p_j^{1-\varepsilon} E^{\varepsilon} \left(\frac{E}{\widetilde{P}} \right)^{\nu_j (1-\varepsilon)}$$

Note that $p_j c_j = E_j E$ so simplifying previous expression

$$\widetilde{P}^{1-\varepsilon} E_j = \left(\omega_j p_j^{1-\varepsilon} \right)^{\frac{1}{\nu_j}} \left(E_j E^{1-\varepsilon} \right)^{(1-\frac{1}{\nu_j})}$$

Adding up across j sectors, we obtain the expression for the aggregate price index (9). The budget constraint (C.5) determines total expenditure E

$$p_a c_a + p_{mt}^h c_{mt}^h + p_{mt}^l c_{mt}^l + p_{st}^h c_{st}^h + p_{st}^l c_{st}^l = w_t^h M_{ht} + w_t^l M_{lt} + T_t \tag{C.5}$$

where T_t is a lump-sum rebated tax from firms. The labor market clearing conditions are given by (C.6) and (C.7).

$$M_{ht} = h_{at} + h_{mt}^h + h_{mt}^l + h_{st}^h + h_{st}^l \tag{C.6}$$

$$M_{lt} = l_{at} + l_{mt}^h + l_{mt}^l + l_{st}^h + l_{st}^l \tag{C.7}$$

The second layer of the problem allocates a given amount c_j across the high and the low productivity goods. That is the household solves the problem

$$\min_{c_j^h, c_j^l} \quad p_j^h c_j^h + p_j^l c_j^l \tag{C.8}$$

$$\text{subject to} \quad c_j = \left[\left(\omega_j^h \right)^{\frac{1}{\eta_j}} \left(c_{jt}^h \right)^{\frac{\eta_j - 1}{\eta_j}} + \left(1 - \omega_j^h \right)^{\frac{1}{\eta_j}} \left(c_{jt}^l \right)^{\frac{\eta_j - 1}{\eta_j}} \right]^{\frac{\eta_j}{\eta_j - 1}} \tag{C.9}$$

The first order conditions for this problem are given by

$$p_j^h = \mu \left(\omega_j^h \right)^{\frac{1}{\eta_j}} \left(\frac{c_j^h}{c_j} \right)^{-\frac{1}{\eta_j}}$$

$$p_j^l = \mu \left(1 - \omega_j^h \right)^{\frac{1}{\eta_j}} \left(\frac{c_j^l}{c_j} \right)^{-\frac{1}{\eta_j}}$$

The ratio of these two first order conditions yields equation (5). To obtain the price index (6) multiply each previous first order condition by c_j^h and c_j^l respectively and add them up. This implies that $p_j c_j \equiv p_j^h c_j^h + p_j^l c_j^l = \mu_j c_j$. Raising previous first order conditions to the power of $1-\eta_j$, adding them up, and using $p_j = \mu_j$ yields (6). By dividing the two first order conditions we obtain

$$\frac{c_j^h}{c_j^l} = \left(\frac{\omega_j^h}{1-\omega_j^h}\right)\left(\frac{p_j^h}{p_j^l}\right)^{-\eta_j} \quad \text{for } j \in \{m,s\} \tag{C.10}$$

C.2 Firms

Firms produce using high-skill and low-skill labor only and pay a tax τ_{jt}^i per unit of labor which is independent of the skill-type of labor employed. The representative firm in sector $j \in \{a, m, s\}$ and subsector $i \in \{h, l\}$ solves the following problem.

$$\begin{aligned} &\max_{\{h_{jt}^i, l_{jt}^i\}} \quad p_{jt}^i Y_{jt}^i - (1+\tau_{jt}^i)(w_t^h h_{jt}^i + w_{jt}^l l_{jt}^i) \\ &\text{s.t.} \quad Y_{jt}^i = A_{jt}^i L_{jt}^i = A_{jt}^i \left[\pi_{jt}^i \left(h_{jt}^i\right)^{\frac{\sigma-1}{\sigma}} + (1-\pi_{jt}^i)\left(l_{jt}^i\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{C.11}$$

Profit maximization yields the first order conditions

$$p_j^i A_j^i \left[\pi_{jt}^i \left(h_{jt}^i\right)^{\frac{\sigma-1}{\sigma}} + (1-\pi_{jt}^i)\left(l_{jt}^i\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \pi_j^i \left(h_j^i\right)^{-\frac{1}{\sigma}} = (1+\tau_j^i) w^h$$

$$p_j^i A_j^i \left[\pi_{jt}^i \left(h_{jt}^i\right)^{\frac{\sigma-1}{\sigma}} + (1-\pi_{jt}^i)\left(l_{jt}^i\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (1-\pi_j^i) \left(l_j^i\right)^{-\frac{1}{\sigma}} = (1+\tau_j^i) w^l$$

Using the first order condition for h_j^i, noting that the wage rate w^h must equalize across sectors we get

$$\frac{p_j^i}{p_a} = \left(\frac{1+\tau_j^i}{1+\tau_a}\right)\frac{A_a}{A_j^i}\frac{\pi_a}{\pi_j^i}\left(\frac{h_j^i}{L_j^i}\frac{L_a}{h_a}\right)^{\frac{1}{\sigma}}$$

using (15) in previous expression yields (16). To get (11) use the ratio of the two first order conditions of the firms' problem.

C.3 Expenditure Ratios

From the household's FOCs for the two types of manufacturing and service goods, and the expression for prices (16) we get the relative expenditure ratios of high-to-low productivity goods of sectors $j \in \{m,s\}$.

$$E_j^{hl} \equiv \frac{p_j^h c_j^h}{p_j^l c_j^l} = \left(\frac{\omega_j^h}{1-\omega_j^h}\right)\left(\frac{A_j^l}{A_j^h}\right)^{1-\eta_j}\left(\frac{1+\tau_j^h}{1+\tau_j^l}\right)^{1-\eta_j}\left[\left(\frac{\pi_j^l}{\pi_j^h}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{\Omega_j^l}{\Omega_j^h}\right)^{\frac{1}{1-\sigma}}\right]^{1-\eta_j} \tag{C.12}$$

Using (C.10) into the definition of c_j (equation (C.9)) we get the inverse of the share of high productivity consumption of sector j on total consumption of sector j.

$$\frac{c_j}{c_j^h} = \left(\omega_j^h\right)^{\frac{1}{\eta_j - 1}} \left(1 + \left(\frac{1-\omega_j^h}{\omega_j^h}\right)\left(\frac{p_j^l}{p_j^h}\right)^{1-\eta_j}\right)^{\frac{\eta_j}{\eta_j-1}} \tag{C.13}$$

From (C.10) we can solve for p_j^h/p_j^l in terms of E_j^{hl} and substitute into (C.13) to get the share in terms of the expenditure ratio E_j^{hl}.

$$\frac{c_j}{c_j^h} = \left(\omega_j^h\right)^{\frac{1}{\eta_j - 1}} \left(1 + \frac{1}{E_j^{hl}}\right)^{\frac{\eta_j}{\eta_j-1}} \tag{C.14}$$

Note that $\mu_j = p_j$ so we can combine the first order conditions from the two layers of the household's problem. In particular, we can substitute the first order condition for c_j into that of c_j^h to obtain

$$p_j^h = \lambda \frac{\varepsilon - 1}{\varepsilon} \omega_j^{\frac{1}{\varepsilon}} c_j^{-\frac{1}{\varepsilon}} \widetilde{C}^{\nu_j \frac{1-\varepsilon}{\varepsilon}} \left(\omega_j^h\right)^{\frac{1}{\eta_j}} c_j^{\frac{1}{\eta_j}} \left(c_j^h\right)^{-\frac{1}{\eta_j}}$$

which we can combine with the first order condition for c_a to obtain

$$\frac{p_j^h}{p_a} = \left(\frac{\omega_j}{\omega_a}\right)^{\frac{1}{\varepsilon}} \left(\frac{c_j}{c_a}\right)^{-\frac{1}{\varepsilon}} \widetilde{C}^{\frac{1-\varepsilon}{\varepsilon}(\nu_j - \nu_a)} (\omega_j^h)^{\frac{1}{\eta_j}} \left(\frac{c_j}{c_j^h}\right)^{\frac{1}{\eta_j}}$$

Solving for c_j/c_a

$$\frac{c_j}{c_a} = \left(\frac{p_j^h}{p_a}\right)^{-\varepsilon} \left(\omega_j^h\right)^{\frac{\varepsilon}{\eta_j}} \left(\frac{\omega_j}{\omega_a}\right) \left(\frac{c_j}{c_j^h}\right)^{\frac{\varepsilon}{\eta_j}} \widetilde{C}^{(1-\varepsilon)(\nu_j-\nu_a)} \tag{C.15}$$

Substituting (16) and (C.14) into (C.15)

$$\frac{c_j}{c_a} = \left(\frac{\omega_j}{\omega_a}\right) \left[\left(\frac{A_j^h}{A_a}\right)\left(\frac{1+\tau_a}{1+\tau_j^h}\right)\left(\frac{\pi_j^h}{\pi_a}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{\Omega_j^h}{\Omega_a}\right)^{\frac{1}{1-\sigma}}\right]^{\varepsilon} \left[\omega_j^h \left(1 + \frac{1}{E_j^{hl}}\right)\right]^{\frac{\varepsilon}{\eta_j - 1}} \widetilde{C}^{(\nu_j-\nu_a)(1-\varepsilon)} \tag{C.16}$$

Note that $c_j^h/c_a = (c_j^h/c_j)(c_j/c_a)$ which we have expressions for these two ratios. Furthermore, we can use (16) to get E_{ja}^h.

$$E_{ja}^h \equiv \frac{p_j^h c_j^h}{p_a c_a} = (\omega_j^h)^{\frac{\varepsilon-1}{\eta_j-1}} \left(\frac{\omega_j}{\omega_a}\right)\left(\frac{p_j^h}{p_a}\right)^{1-\varepsilon} \left(1 + \frac{1}{E_j^{hl}}\right)^{\frac{\varepsilon-\eta_j}{\eta_j-1}} (\widetilde{C})^{(1-\varepsilon)(\nu_j-\nu_a)} \tag{C.17}$$

A similar procedure can be used to find E_{ja}^l.

$$E_{ja}^l \equiv \frac{p_j^l c_j^l}{p_a c_a} = (1-\omega_j^h)^{\frac{\varepsilon-1}{\eta_j-1}} \left(\frac{\omega_j}{\omega_a}\right)\left(\frac{p_j^l}{p_a}\right)^{1-\varepsilon} \left(1 + E_j^{hl}\right)^{\frac{\varepsilon-\eta_j}{\eta_j-1}} (\widetilde{C})^{(1-\varepsilon)(\nu_j-\nu_a)} \tag{C.18}$$

Thus, we have expressed the expenditure ratios $\{E_m^{hl}, E_s^{hl}, E_{ma}^h, E_{sa}^h, E_{ma}^l, E_{sa}^l\}$ as functions of the skill premium and the consumption aggregator $\widetilde{C}$. Finally, note that using (12) we can express the expenditure in sector j subsector i relative to agriculture as

$$\tilde{E}_{ja}^i = E_{ja}^i \left(\frac{1-\varphi_a}{1-\varphi_j^i}\right)$$

where $\tilde{E}^i_{ja}$ is defined as $p^i_j Y^i_j / p_a Y_a$.

C.4 Labor Allocations

Note that we can re-write E^i_{ja} using the market clearing condition (12) and the production function (C.11) as follows:

$$E^i_{ja} \equiv \frac{p^i_j c^i_j}{p_a c_a} = \frac{1-\varphi^i_j}{1-\varphi_a}\frac{p^i_j Y^i_j}{p_a Y_a} = \left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)\frac{p^i_j A^i_j L^i_j}{p_a A_a L_a} = \left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)\frac{p^i_j A^i_j L^i_j h^i_j h_a}{p_a A_a L_a h_a h^i_j}$$

Substituting (15)

$$E^i_{ja} = \left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)\frac{p^i_j}{p_a}\frac{A^i_j}{A_a}\left(\frac{\pi^i_j}{\Omega^i_j}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{\Omega_a}{\pi_a}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{h^i_j}{h_a}\right)$$

Substituting (16)

$$E^i_{ja} = \left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)\left(\frac{1+\tau^i_j}{1+\tau_a}\right)\left(\frac{\Omega_a}{\Omega^i_j}\right)\left(\frac{h^i_j}{h_a}\right)$$

which solving for h^i_j/h_a yields

$$\frac{h^i_j}{h_a} = \left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)E^i_{ja}\left(\frac{1+\tau_a}{1+\tau^i_j}\right)\left(\frac{\Omega^i_j}{\Omega_a}\right) \tag{C.19}$$

From the market clearing condition of high-skilled workers and substituting (C.19)

$$\frac{M_h}{h_a} = \sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}}\frac{h^i_j}{h_a} = \sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}}\left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)E^i_{ja}\left(\frac{1+\tau_a}{1+\tau^i_j}\right)\left(\frac{\Omega^i_j}{\Omega_a}\right)$$

Finally, the share of high-skilled workers in the agricultural sector is given by

$$\frac{h_a}{M_h} = \frac{1}{\sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}}\left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)E^i_{ja}\left(\frac{1+\tau_a}{1+\tau^i_j}\right)\left(\frac{\Omega^i_j}{\Omega_a}\right)} \tag{C.20}$$

Similarly, for low-skilled labor in agriculture:

$$\frac{M_l}{M_h} = \frac{1}{M_h}\sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}} l^i_j = \frac{h_a}{M_h}\sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}}\frac{l^i_j}{h^i_j}\frac{h^i_j}{h_a}$$

Solving for h_a/M_h and substituting (11) and (C.19) we get

$$\frac{h_a}{M_h} = \frac{M_l/M_h}{\sum_{j\in\{a,m,s\}}\sum_{i\in\{h,l\}}\left(\frac{w^h}{w^l}\right)^{\sigma}\left(\frac{1-\pi^i_j}{\pi^i_j}\right)^{\sigma}\left(\frac{1-\varphi^i_j}{1-\varphi_a}\right)E^i_{ja}\left(\frac{1+\tau_a}{1+\tau^i_j}\right)\left(\frac{\Omega^i_j}{\Omega_a}\right)} \tag{C.21}$$

The equilibrium is characterized by two equations in two unknowns; the skill premium (w^h/w^l) and the consumption aggregator $(\widetilde{C})$ which are obtained by equating (C.20) and (C.21) and with the implicit definition of $\widetilde{C}$ in equation (2). The skill premium depends on the relative expenditure shares with respect to the agricultural good, and these expenditure shares are given by (C.12), (C.17), and (C.18).

Once the relative expenditure shares have been obtained, we can get employment shares as follows. Let employment share of sector j subsector i be N_j^i, then, by definition

$$N_j^i = \frac{l_j^i + h_j^i}{\sum_{k\in\{a,m,s\}} \sum_{s\in\{h,l\}} l_k^s + h_k^s} = \frac{l_j^i + h_j^i}{M_h + M_l}$$

This can be rewritten as

$$N_j^i = \frac{\frac{l_j^i}{h_j^i} + 1}{\frac{M_h}{h_j^i} + \frac{M_l}{h_j^i}} = \frac{\frac{l_j^i}{h_j^i} + 1}{\frac{M_h}{h_j^i}\left(1 + \frac{M_l}{M_h}\right)} = \frac{\frac{l_j^i}{h_j^i} + 1}{\frac{M_h}{h_a}\frac{h_a}{h_j^i}\left(1 + \frac{M_l}{M_h}\right)} \tag{C.22}$$

Note that l_j^i/h_j^i is obtained from (11), M_h/h_a from (C.20), h_j^i/h_a ratio from (C.19), and M_l/M_h is exogenous.

To get real labor productivity, we first define it as the ratio of real value added in sector j subsector i divided by the total employment of sector j subsector i, i.e. $Y_j^i/(l_j^i + h_j^i)$. Before obtaining an expression for labor productivity, note we can rewrite the production function as

$$Y_j^i = h_j^i A_j^i \left(\frac{\pi_j^i}{\Omega_j^i}\right)^{\frac{\sigma}{\sigma-1}}$$

Dividing now by $(l_j^i + h_j^i)$ and inverting it we get

$$\frac{l_j^i + h_j^i}{Y_j^i} = \frac{l_j^i + h_j^i}{h_j^i}\frac{1}{A_j^i}\left(\frac{\Omega_j^i}{\pi_j^i}\right)^{\frac{\sigma}{\sigma-1}}$$

Using (11) and inverting again, we obtain real labor productivity as (C.23) which is (19) in the main text.

$$\frac{Y_j^i}{l_j^i + h_j^i} = \frac{1}{1 + \left(\frac{w^h}{w^l}\right)^{\sigma}\left(\frac{1-\pi_j^i}{\pi_j^i}\right)^{\sigma}} A_j^i \left(\frac{\pi_j^i}{\Omega_j^i}\right)^{\frac{\sigma}{\sigma-1}} \tag{C.23}$$

Thus, differences in sectoral real labor productivities are not driven directly from wedges introduced by the taxes.

Aggregate GDP in the model corresponds to aggregate value added per capita in the data since we do not include population growth. To obtain aggregate GDP in the model, let us start by computing first sectoral employment levels. From the equalization of wages across sectors, we can solve for l_j^i in terms of l_a/h_a and h_j^i as

$$l_j^i = l_a \left(\frac{\pi_a}{1-\pi_a}\frac{1-\pi_j^i}{\pi_j^i}\right)^{\sigma} \frac{h_j^i}{h_a}$$

The sum of sectoral low-skill labor is equal to M_l and thus, adding-up sectors in previous equation and solving for l_a we get

$$l_a = \frac{M_l}{\left(\frac{\pi_a}{1-\pi_a}\right)^{\sigma} \sum_{j\{a,m,s\}} \sum_{i\{h,l\}} \left(\frac{\pi_j^i}{1-\pi_j^i}\right)^{\sigma} \frac{h_j^i}{h_a}} \tag{C.24}$$

Note that M_l is exogenous and we can solve for h_j/h_a using (C.19). From the firm's first order condition (11) and from (C.24) we obtain h_a. To solve for h_j^i we use our solution of h_a into (C.19). Finally, l_j^i is obtained from (11) and the solution for h_j^i. Since we have solved for all employment levels, we can construct production functions and use (16) to get nominal GDP in the model given by (13). Real GDP in the model is defined as (C.25).

$$Y_t \equiv p_{a0}Y_{at} + p_{m0}^h Y_{mt}^h + p_{m0}^l Y_{mt}^l + p_{s0}^h Y_{st}^h + p_{s0}^l Y_{st}^l \tag{C.25}$$

Appendix D Future Growth with Skill-Bias Technical Change

This section presents the same set of results as in Section 4.4 but assuming that the sectoral skill-biased technical change parameters present bounded growth. Since these parameters cannot be larger than one, I choose to simulate forward these parameters assuming they grow according to a logistic growth function shown in equation (D.26)

$$\pi_{jt}^i = \frac{1}{1+e^{-g_j^i(t-t_{j0}^i)}} \tag{D.26}$$

where g_j^i is the parameter controlling growth and t_{j0}^i is where the function takes the midpoint. The value for t_{j0}^i is computed so that the function predicts the same value for the parameter in the last period of the data. Figure D.1 shows the simulated parameters up to 2075.

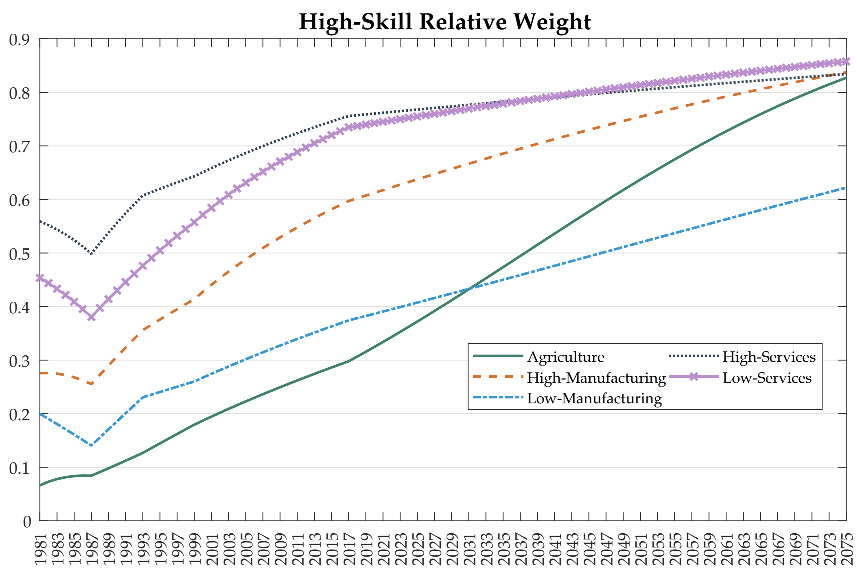


Figure D.1: Simulated Sectoral Skill-biased Technical Change

Looking at the second and third columns of Table D.2 we can see that sectoral labor productivity growth rates are larger than when we do not allow for skill-biased technical change except for the low-manufacturing sector, for which labor productivity increases in 0.2 percentage points rather than 0.6 percentage points in the case without skill biased technical change. This is explained by the evolution of the parameters shown in Figure D.1 where the agriculture skill-biased technical change is the one increasing the fastest, and where the low-manufacturing lags significantly behind the others.

Table D.2: Growth Rates of Sectoral Labor Productivity with SBTC (in percentages)

		Averages		*Convergence to* 2.5%*	
	1980-2017	2017-2075	Difference	2017-2075	Difference
Agriculture	3.008	5.052	2.045	5.077	2.070
High Manufacturing	4.987	7.005	2.018	7.028	2.042
Low Manufacturing	−0.672	0.458	1.130	0.501	1.173
High Services	6.539	6.738	0.199	1.710	−4.829
Low Services	3.278	4.127	0.849	1.570	−1.708
GDP	4.847	8.710	3.863	2.732	−2.115

Note: The table shows the average growth rates of sectoral labor productivity in percentages for both time periods and the difference for both. Labor productivity is defined as real value added over total labor employed. Columns 3 and 4 under the title *Averages* correspond to the average growth rates in the experiment where exogenous variables take their past average values. Columns 5 and 6 correspond to the experiment in which the TFP growth rate of the services subsectors is set to get a 2% growth rate of GDP per capita.

* This experiment keeps the TFPs in the service sector as in previous experiment, not to achieve a 2.5% aggregate growth rate.

In the last two columns of Table D.2 we can see that reducing the TFP growth rates of service sectors to the same values as in Section 4.4 yields a growth rate of aggregate GDP per capita of 2.7% instead of the 2.5% that was achieved before. This is a significant amount that comes mostly through improvements in the labor productivity of the agriculture and high-manufacturing sectors. That is because they are the sectors with fastest TFP growth and because of the skill-bias technical change, they can attract more high-skilled workers.

Appendix E Additional Tables and Graphs

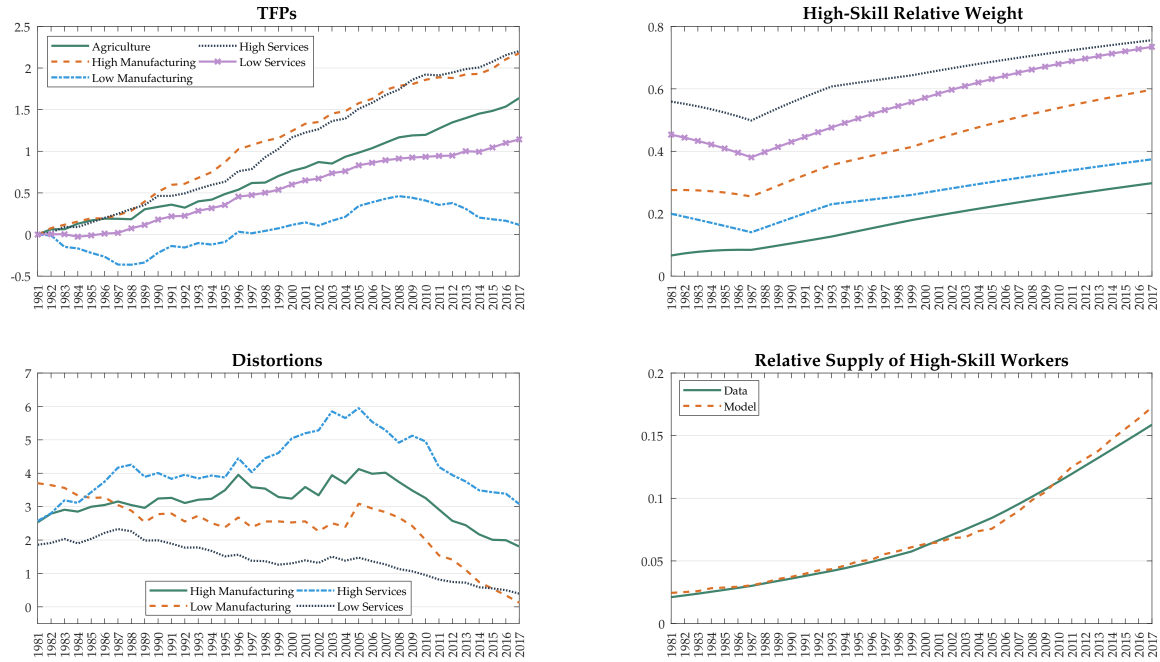


Figure D.2: **Non-Homothetic CES:** Calibrated Parameters

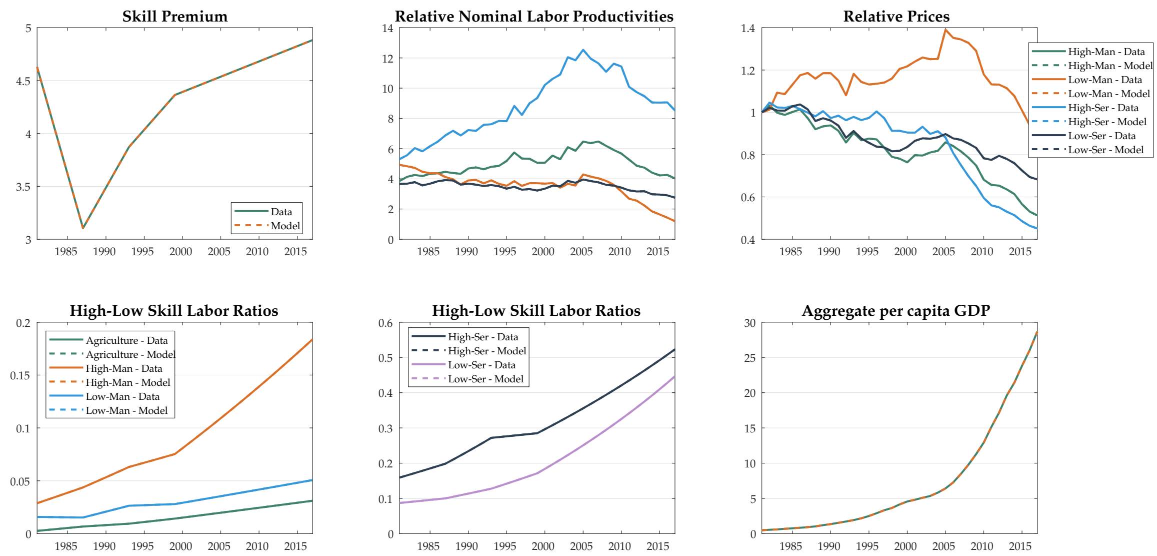


Figure D.3: **Non-Homothetic CES:** Targeted Variables

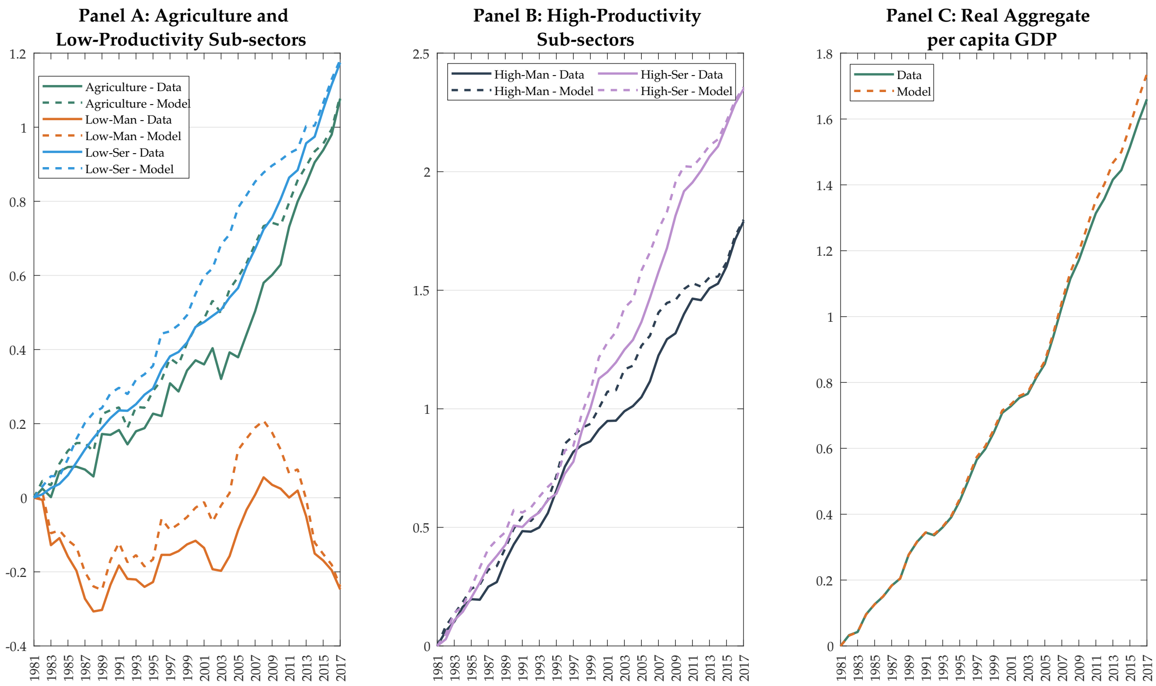


Figure D.4: **Non-Homothetic CES:** Sectoral Productivities and Aggregate Growth

<u>Note:</u> Each panel shows the log of the variables normalized to 1 in the first period. Sectoral real labor productivity is computed in the model from equation (19). Real aggregate per capita GDP is computed in the model from equation (C.25).

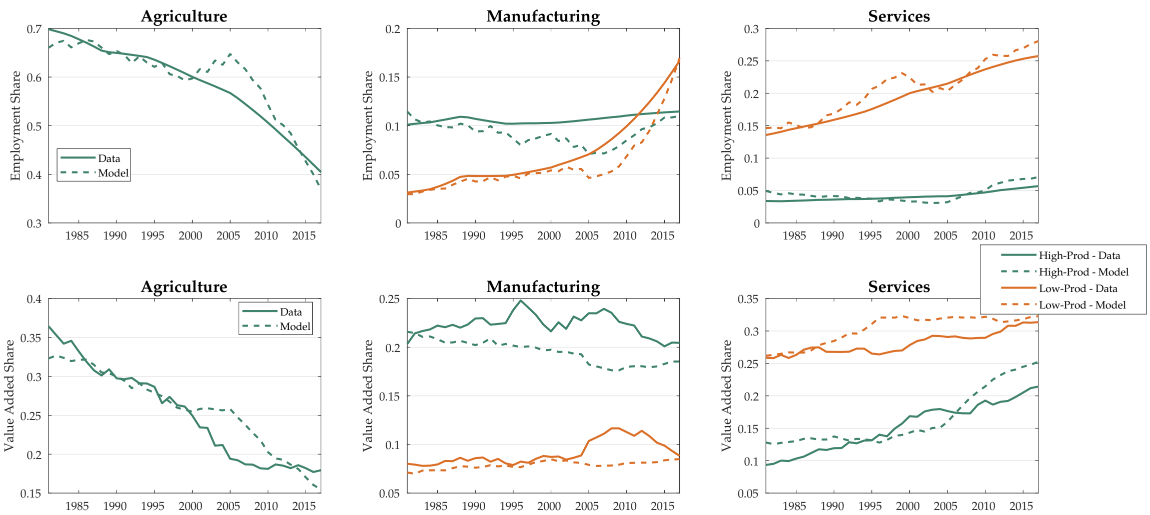


Figure D.5: **Non-Homothetic CES:** Value Added and Employment Shares

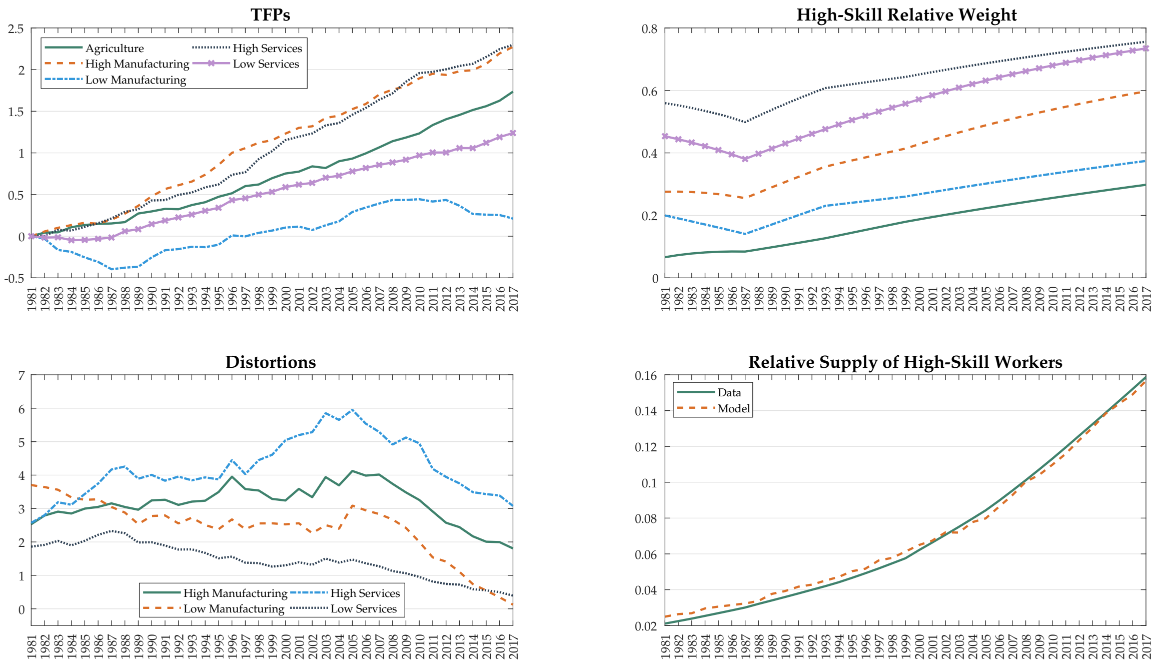


Figure D.6: **Non-Homothetic CES and Trade:** Calibrated Parameters

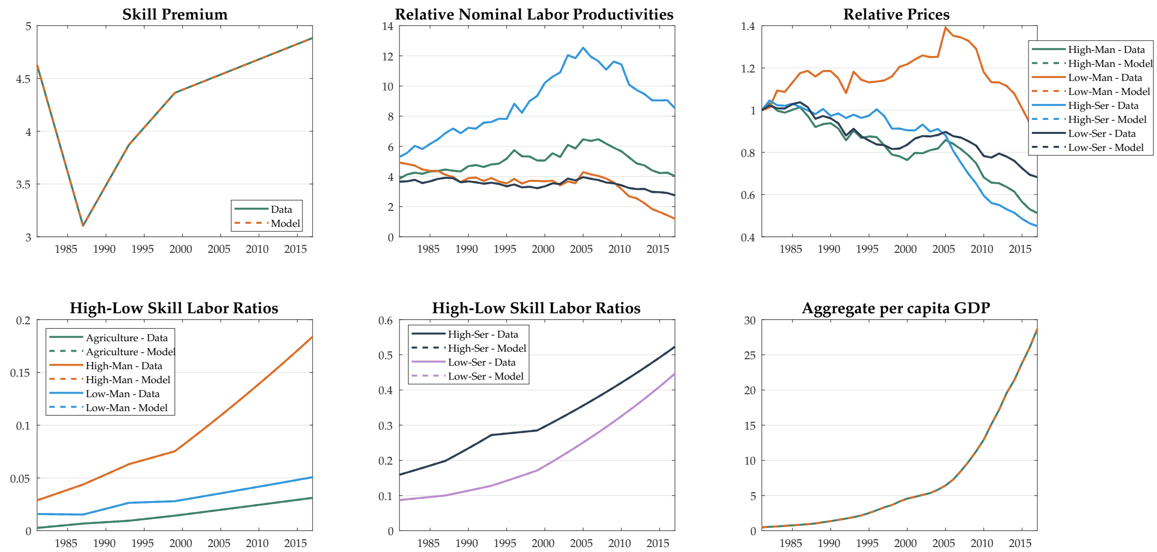


Figure D.7: **Non-Homothetic CES and Trade:** Targeted Variables

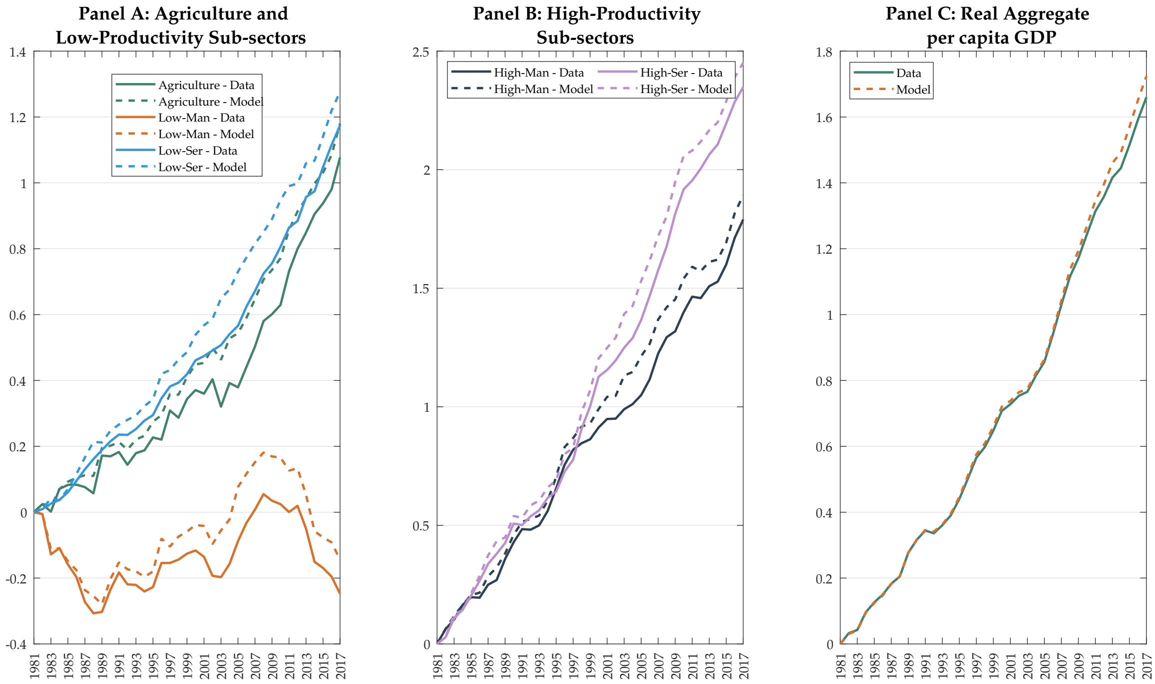


Figure D.8: **Non-Homothetic CES and Trade:** Sectoral Productivities and Aggregate Growth

Note: Each panel shows the log of the variables normalized to 1 in the first period. Sectoral real labor productivity is computed in the model from equation (19). Real aggregate per capita GDP is computed in the model from equation (C.25).

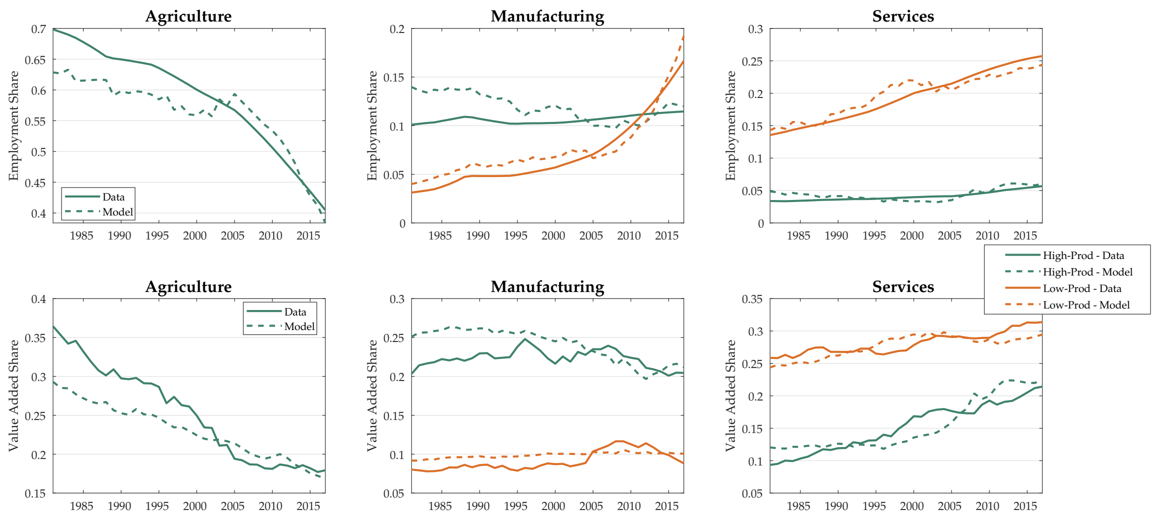
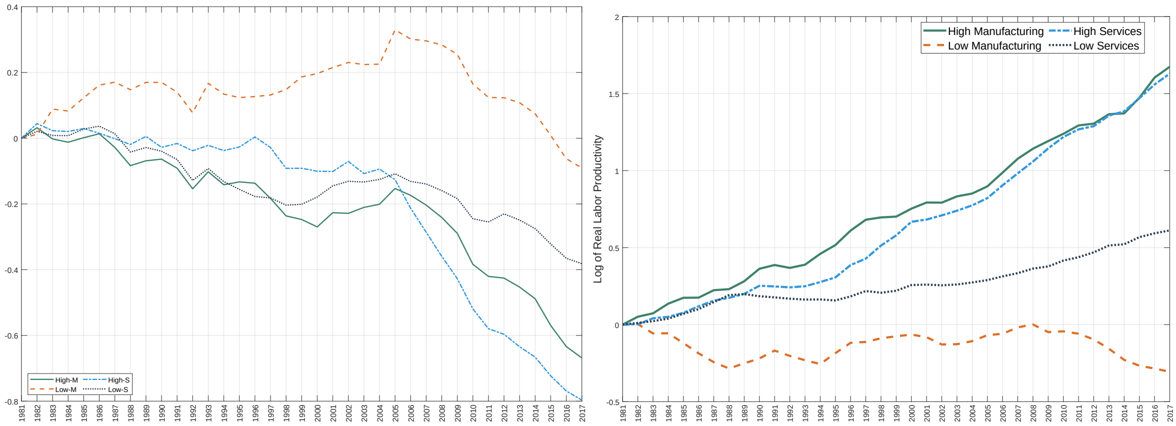


Figure D.9: **Non-Homothetic CES and Trade:** Value Added and Employment Shares



(a) Sectoral Relative Prices

(b) Labor Productivities in Logs. Initial = 0

Figure E.10: Sectoral Prices and Alternative Classification of Sectors

Table E.3: Three-Sector Split

AGRICULTURE	MANUFACTURING		SERVICES
Agriculture,Hunting,Forestry and Fishing	Mining and Quarrying	Other Non-Metallic Mineral Products	Trade
	Food Products,Beverages and Tobacco	Basic Metals and Fabricated Metal Products	Hotels and Restaurants
	Textiles, Textile Products, Leather and Footwear	Machinery, nec.	Transport and Storage
	Wood and Products of wood	Electrical and Optical Equipment	Post and Telecommunication
	Pulp, Paper,Paper products,Printing and Publishing	Transport Equipment	Financial Services
	Coke, Refined Petroleum Products and Nuclear fuel	Manufacturing, nec; recycling	Business Service
	Chemicals and Chemical Products	Electricity, Gas and Water Supply	Public Administration and Defense; Compulsory Social Security
	Rubber and Plastic Products	Construction	Education
			Health and Social Work
			Other services

Table E.4: Division of Services by Labor Productivity Growth (US)

High Productivity Services	
Pipeline transportation	5.605
Air transportation	4.58
Broadcasting and telecommunications	4.392
Wholesale Trade	3.077
Water transportation	2.933
Waste management and remediation services	2.768
Securities commodity contracts and investments	2.752
Publishing industries (includes software)	2.602
Social assistance	2.592
Rental and leasing services and lessors of intangible assets	2.463
Administrative and support services	2.445
Rail transportation	2.429
Truck transportation	2.201
Retail Trade	2.082
Insurance carriers and related activities	1.627
Motion picture and sound recording industries	1.59
Warehousing and storage	1.545
Performing arts spectator sports museums and related activities	1.504
Miscellaneous professional scientific and technical services	1.327
Management of companies and enterprises	1.305
Overall Service Sector	1.29
Low Productivity Services	
Federal Reserve banks credit intermediation and related activities	1.14
Accommodation	1.095
Federal General government	1.084
Real estate	0.8778
Educational services	0.7757
Ambulatory health care services	0.6399
Computer systems design and related services	0.5503
Funds trusts and other financial vehicles	0.5023
Legal services	0.2841
Hospitals Nursing and residential care facilities	0.2018
Information and data processing services	0.1029
Federal Government enterprises	0.09619
S&L General Government	−0.03914
Amusements gambling and recreation industries	−0.1332
Other transportation and support activities	−0.3179
S&L Government enterprises	−0.4192
Food services and drinking places	−0.5297
Other services except government	−0.6435
Transit and ground passenger transportation	−0.665

Note: All numbers are in percentages (%). Labor productivity is the ratio of real value added to quality-adjusted labor, the numbers represent averages for the full period (1947-2014). Overall Service Sector represents the growth rate of labor productivity in the aggregated service sector.

Table E.5: Division of Manufacturing by Labor Productivity Growth (US)

High Productivity Manufacturing	
Computer and electronic products	9.274
Petroleum and coal products	6.397
Textile mills and textile product mills	3.575
Miscellaneous manufacturing	3.236
Chemical products	2.802
Motor vehicles bodies and trailers and parts	2.777
Apparel and leather and allied products	2.655
Support activities for mining	2.268
Overall Manufacturing Sector	2.028
Low Productivity Manufacturing	
Machinery	1.952
Mining except oil and gas	1.671
Plastics and rubber products	1.583
Food and beverage and tobacco products	1.498
Wood products	1.379
Furniture and related products	1.373
Utilities	1.35
Nonmetallic mineral products	1.268
Fabricated metal products	1.17
Other transportation equipment	1.128
Paper products	1.09
Printing and related support activities	1.041
Electrical equipment appliances and components	1.015
Primary metals	0.9067
Construction	0.2722
Oil and gas extraction	−0.5773

Note: All numbers are in percentages (%). Labor productivity is the ratio of real value added to quality-adjusted labor, the numbers represent averages for the full period (1947-2014). Overall Service Sector represents the growth rate of labor productivity in the aggregated service sector.

Table E.6: Cross-country Comparison of Labor Productivity Growth

	(1) Agriculture	(2) Manufacturing	(3) Services
Time × India	-0.0114***	0.0139***	0.0265***
	(0.000713)	(0.00173)	(0.00123)
Time	0.0429***	0.0156***	-0.00255
	(0.00141)	(0.00235)	(0.00160)
Log of GDP per capita	-0.292*	-0.493	-0.502*
	(0.136)	(0.311)	(0.195)
Log of GDP per capita squared	0.0285***	0.0508**	0.0488***
	(0.00857)	(0.0182)	(0.0116)
Log of Population	-1.188***	-0.670***	-0.0313
	(0.0592)	(0.0855)	(0.0657)
Country Fixed Effects	Yes	Yes	Yes
No. Countries	41	41	41
N	2158	2168	2168

Data: GGDC 10-Sector Database, Maddison Project Database, and Penn World Tables. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.7: Labor Productivity in India Within Asia

	Asian Countries			Excluding China		
	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
Time × India	-0.00446***	-0.0118**	0.00704***	-0.00409***	0.0140***	0.0144***
	(0.00106)	(0.00424)	(0.00157)	(0.00119)	(0.00175)	(0.00152)
Time	0.0155***	0.0415***	0.0215***	0.0145***	0.00560*	0.0103***
	(0.00252)	(0.00586)	(0.00257)	(0.00297)	(0.00244)	(0.00244)
Log of GDP per capita (PWT)	1.019***	1.643***	0.227	0.842***	-0.913***	-0.758***
	(0.183)	(0.336)	(0.178)	(0.211)	(0.220)	(0.175)
Log of GDP per capita squared (PWT)	-0.0314**	-0.0739***	0.00219	-0.0220	0.0913***	0.0622***
	(0.0100)	(0.0212)	(0.00997)	(0.0120)	(0.0126)	(0.0102)
Log of Population	-0.605***	-0.949***	-0.286**	-0.537***	-0.372***	-0.0178
	(0.113)	(0.162)	(0.109)	(0.124)	(0.105)	(0.112)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Countries	11	11	11	10	10	10
N	520	522	522	461	462	462

Data: GGDC 10-Sector Database, Maddison Project Database, and Penn World Tables. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regressions in columns (4) to (6) exclude China from the sample keeping the rest of Asian countries.

Table E.8: Labor Productivity in India

	Full Sample			Low-Income Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
Time×India	-0.00714***	-0.00396**	0.0219***	-0.00315	-0.000482	0.0216***
	(0.00134)	(0.00143)	(0.000945)	(0.00186)	(0.00167)	(0.00120)
Time	0.0191***	-0.00261*	-0.00154**	-0.0000983	-0.0108***	0.00341
	(0.00191)	(0.00105)	(0.000596)	(0.00341)	(0.00239)	(0.00189)
Log of GDP per capita	1.711***	-0.471**	0.465***	2.191***	-0.339	0.0979
	(0.272)	(0.178)	(0.107)	(0.313)	(0.316)	(0.261)
Log of GDP per capita squared	-0.0671***	0.0752***	0.00934	-0.0897***	0.0644**	0.0268
	(0.0171)	(0.0101)	(0.00589)	(0.0213)	(0.0195)	(0.0165)
Log of Population	-0.875***	-0.0901	-0.0666*	-0.237	0.354***	-0.118
	(0.0818)	(0.0525)	(0.0299)	(0.127)	(0.104)	(0.0728)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Countries	146	147	143	51	51	51
N	3681	3671	3504	1275	1261	1196

Data: World Development Indicators. These regressions exclude oil-exporting countries as classified by the IMF. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.Regressions in columns (4) to (6) include only those countries considered as low-income countries by the World Bank in the year 2000.

E.1 Cross-Country Regressions for Regions and African Countries

Each regression controls for stage of development, population, and country fixed effects as in equation (1) but only the time trend and the interaction coefficients are shown.

Table E.9: Differential Labor Productivity Growth by Region

	Agriculture	Manufacturing	Services
Panel A: Africa			
Time × Region	-0.00721***	-0.00116	0.0121***
	(0.000964)	(0.00134)	(0.00135)
Time	0.0391***	0.0179***	-0.00159
	(0.00130)	(0.00190)	(0.00145)
Panel B: Asia			
Time × Region	-0.0174***	0.0173***	0.0207***
	(0.000934)	(0.00174)	(0.00130)
Time	0.0380***	0.0189***	-0.000165
	(0.00119)	(0.00172)	(0.00122)
Panel C: Latin America			
Time × Region	0.00813***	-0.00548***	-0.0159***
	(0.000688)	(0.00117)	(0.00129)
Time	0.0378***	0.0186***	0.000779
	(0.00126)	(0.00194)	(0.00133)
Panel D: Western Countries			
Time × Region	0.0173***	-0.00900***	-0.0112***
	(0.00121)	(0.00142)	(0.00138)
Time	0.0235***	0.0260***	0.00876***
	(0.00165)	(0.00234)	(0.00196)

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each panel shows the result of a separate regression in which the dummy variable Region takes value equal to one if the region corresponds to that of the panel and zero otherwise. All regressions include country fixed effects and control for log of GDP per capita, log of GDP per capita squared, and population

Table E.9 shows that there are significant differences across regions. African countries in the sample show the same qualitative pattern as India when compared with the full sample. Slower than average labor productivity growth in agriculture and faster than average in services with no differences in manufacturing. Asian countries overall grow faster than average in manufacturing and services (the influence of China, Korea, Japan, and India is crucial for this result).

Latin american countries, however, seem to have slower than average labor productivity growth in manufacturing and services but faster than average in agriculture. Bustos et al. (2016) show that the introduction of genetically engineered soy beans in Brazil led to industrial growth through freeing workers in agriculture since this new technology turned out to be labor-saving. Bustos et al. (2019) show in an endogenous growth model that improvements in agricultural technology can facilitate movement of unskilled workers into the manufacturing sector. However, these workers move into less innovative industries, which might in fact end up causing a decline in the long-run growth rate of the economy. Thus, improvements in agricultural technology might end up harming the growth rate of other sectors.

For western countries, labor productivity growth in agriculture is faster than for other countries, however, labor productivity growth is slower in manufacturing and services. The reason for this is mostly due to the fact that these countries are already developed countries closer to the technology frontier. Furthermore, because these are industrialized countries, the weight of the service sector is larger and it is likely that the Baumol's cost disease plays a larger role.

From the regional regressions, African countries seem to show a similar pattern to that of India, to investigate further which countries are driving this result Table E.10 shows the interaction of the country dummy and time variable for each of the african countries in the sample. Once again, all regressions include country fixed effects, controls for the stage of development and population, and a time trend. Egypt, Ghana, Nigeria, Mauritius, Zambia, and South Africa show positive and statistically significant coefficients for labor productivity growth in services. However, countries like Malawi, Senegal, or Kenya show large negative coefficients. McMillan et al. (2014) show that since the 2000s structural change in Africa has been growth-enhancing with labor flowing from low-productivity to high-productivity industries, however there is significant heterogeneity across countries within Africa.

Table E.10: Differential Labor Productivity in Services by Country (Africa)

Botswana	0.00219	**Ghana**	0.0143***	**Kenya**	-0.0147***	**South Africa**	0.00917***
	(0.00405)		(0.00141)		(0.00140)		(0.00109)
Egypt	0.0250***	**Nigeria**	0.0219***	**Morocco**	-0.00579***		
	(0.00117)		(0.00262)		(0.00112)		
Ethiopia	0.00388	**Senegal**	-0.0152***	**Zambia**	0.0492***		
	(0.00213)		(0.00146)		(0.00132)		
Malawi	-0.0170***	**Mauritius**	0.00976***	**Tanzania**	-0.00649**		
	(0.00297)		(0.00166)		(0.00224)		

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each coefficient is from a separate regression comparing the country with the rest of the countries in the sample, the coefficient corresponds to the interaction of the country dummy and the time trend. All regressions include country fixed effects and control for log of GDP per capita, log of GDP per capita squared, and population.

Out of the five countries with a positive and significant coefficient, three of them (Ghana, Mauritius, and South Africa) show strong growth in services employment share while Nigeria shows an increasing trend up to 1985 approximately where the employment share reverses and the agricultural labor share is its mirror image. Zambia has approximately constant employment share in services and manufacturing with the agricultural labor share being the largest at around 70%. It is out of the scope of this paper to investigate further the patterns of structural change in Africa, however, these regressions suggest similar stories could be happening in African countries.

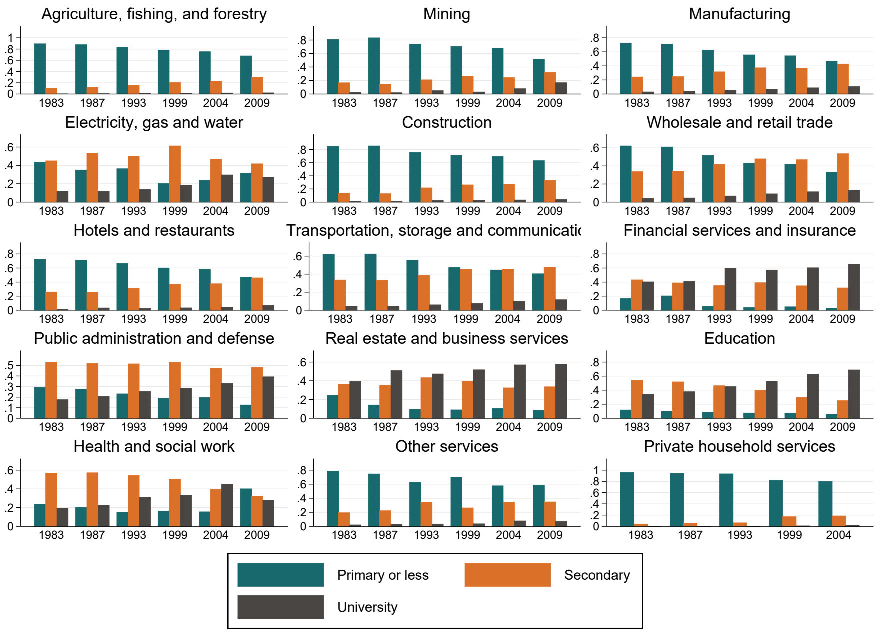
E.2 Education in India

Table E.11: Returns to Schooling by Sector and Year

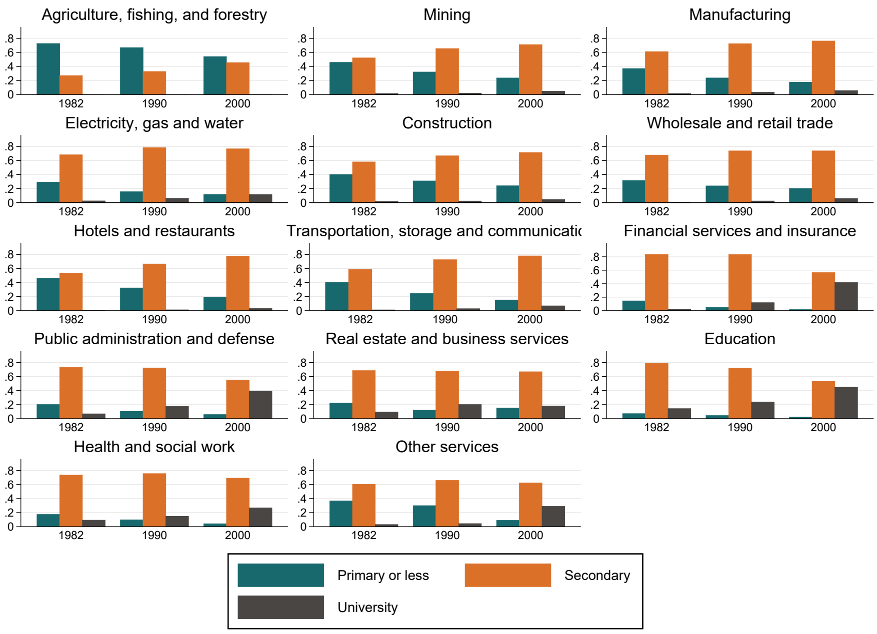
Wave:	1983	1987	1993	1999	2004
Sector Intercept:					
Agriculture	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
High-Manufacturing	0.466***	0.521***	0.447***	0.486***	0.422***
	(0.012)	(0.018)	(0.014)	(0.016)	(0.016)
Low-Manufacturing	0.290***	0.346***	0.478***	0.482***	0.452***
	(0.013)	(0.017)	(0.016)	(0.012)	(0.013)
High-Services	0.676***	0.726***	0.634***	0.647***	0.536***
	(0.020)	(0.020)	(0.019)	(0.027)	(0.023)
Low-Services	0.249***	0.276***	0.231***	0.253***	0.262***
	(0.014)	(0.019)	(0.018)	(0.017)	(0.017)
Sector Returns to Schooling:					
Agriculture	0.022***	0.038***	0.028***	0.031***	0.022***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
High-Manufacturing	0.086***	0.082***	0.080***	0.082***	0.088***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Low-Manufacturing	0.069***	0.073***	0.040***	0.039***	0.035***
	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)
High-Services	0.079***	0.079***	0.082***	0.095***	0.107***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Low-Services	0.105***	0.098***	0.094***	0.099***	0.099***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.502	0.580	0.425	0.553	0.558
Observations	83842	49750	79695	85601	82157

Data: IPUMS-I. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include age, age squared, and sex.

E.3 Additional Graphs from Counterfactuals



(a) India



(b) China

Figure E.11: Educational Attainment by Industry

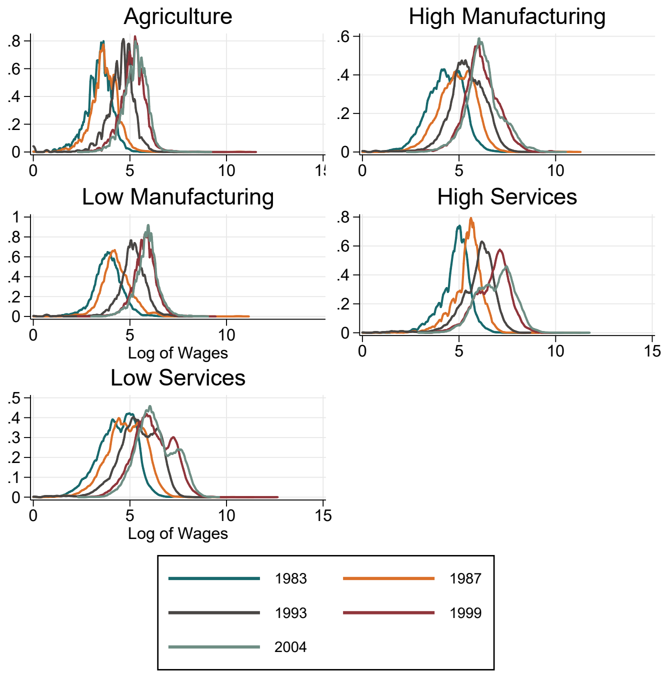


Figure E.12: Density of Log of Wages by Sector and Years in India

Note: *High Services:* Transportation, storage and communication, Financial services and insurance, Public administration and defense, Real estate and business services. *Low Services:* Wholesale and retail trade, Hotels and restaurants, Education, Health and social work, Other services, Private household services,

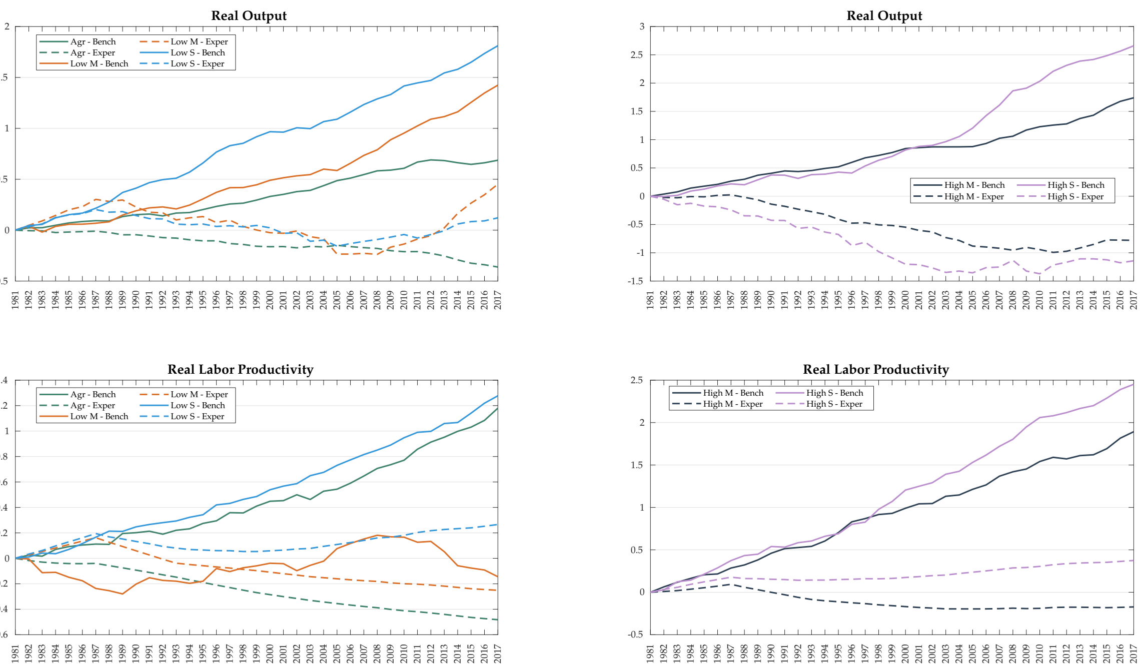


Figure E.13: **Counterfactual:** Decline in A_j^i

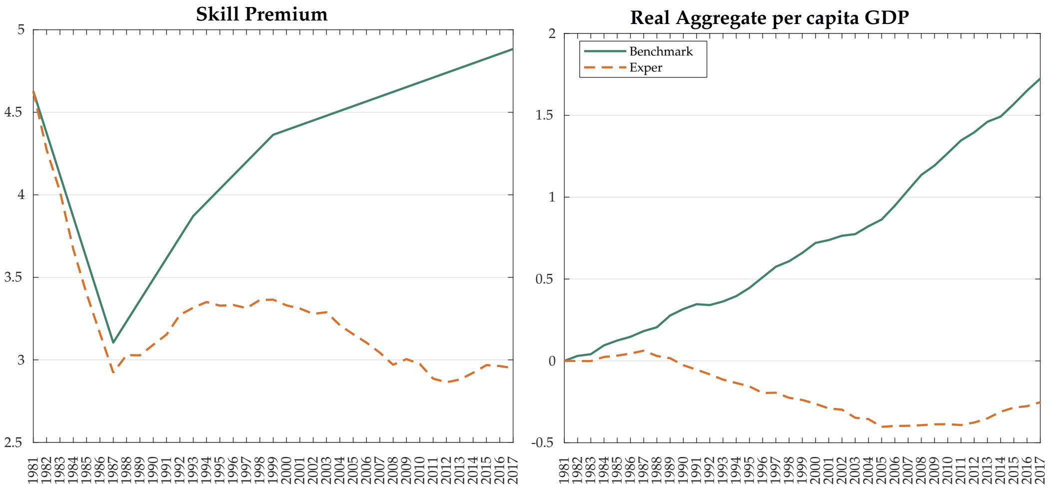


Figure E.14: **Counterfactual:** Decline in A_j^i

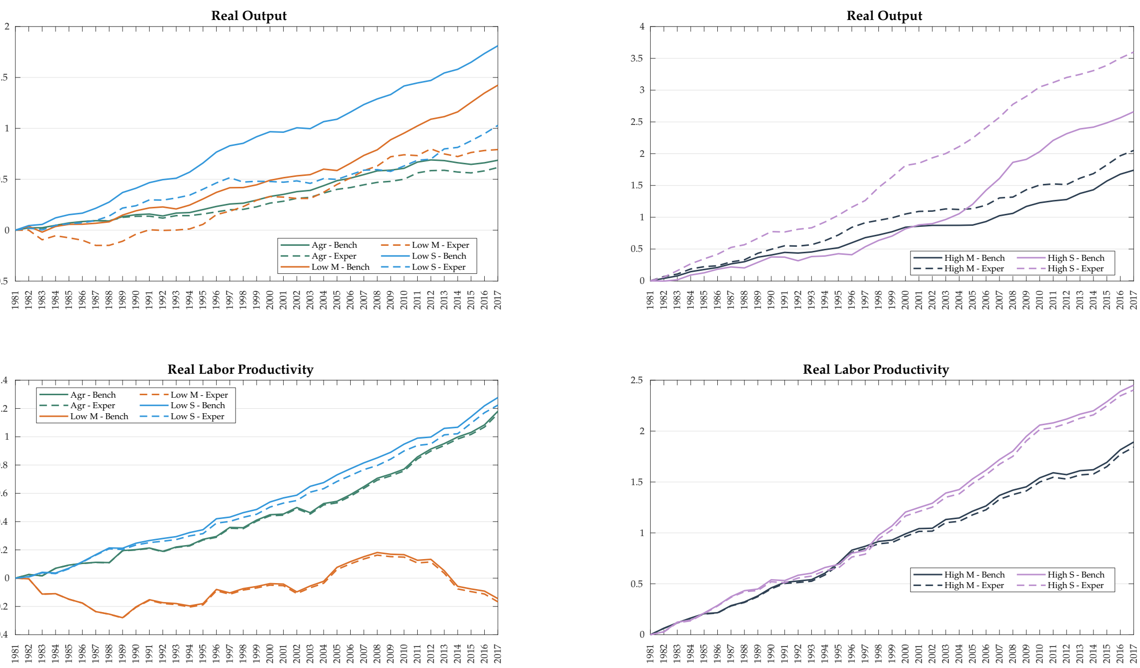


Figure E.15: **Counterfactual:** Declining Taxes

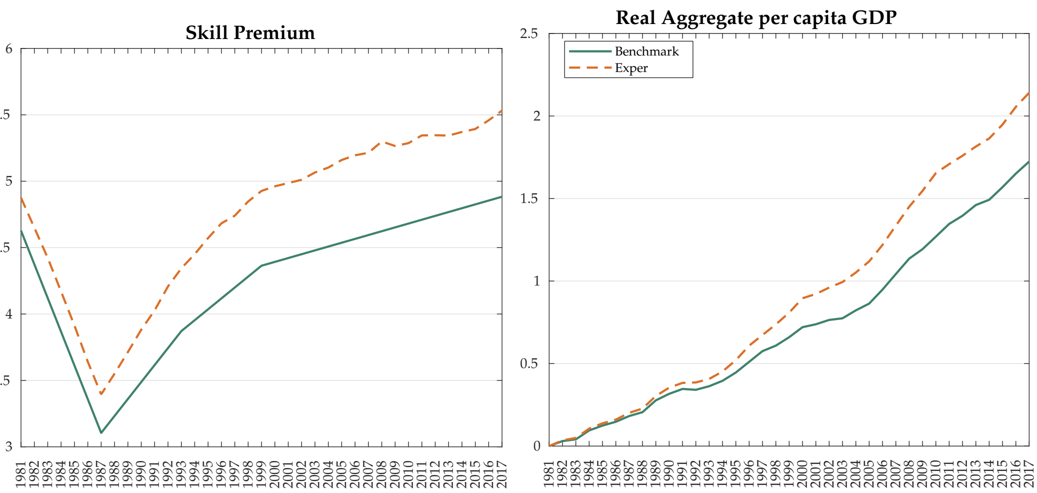


Figure E.16: **Counterfactual:** Declining Taxes