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

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Abstract

Labor productivity growth in India has been the fastest in the service sector. However, there is substantial heterogeneity within manufacturing and services. I disaggregate both sectors into high and low productivity growth sub-sectors. The data show that high productivity growth services grow faster than its manufacturing counterpart, contrary to the experience of industrialized countries. Furthermore, India’s supply of high-skilled workers is larger than that of other countries at similar stages of development. To understand the sources of differences in sectoral labor productivity growth, I construct a five-sector model of structural change with high and low-skilled workers including agriculture, two manufacturing and two service sub-sectors. 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. Furthermore, 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.

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1 Introduction

Modern economic growth is characterized by substantial changes in sectoral composition. As countries develop, the agricultural sector declines steadily, manufacturing first increases and then declines showing a hump-shaped pattern, and services tend to grow. Differences in sectoral productivity growth is one of the classic mechanisms proposed by the literature.¹ Sector-biased productivity growth creates differences in relative prices which, depending on whether final goods are gross complements or substitutes, generates movements in employment and output shares. The current paper investigates differences in sectoral productivity growth in India to understand why, contrary to the experience of industrialized countries, productivity growth is much faster in services than in manufacturing.

Nevertheless, industries within the manufacturing and service sectors are substantially heterogeneous with respect to their average productivity growth rates. To address this heterogeneity, I divide industries in the manufacturing and services sectors into two sub-groups. In a similar fashion as Duernecker et al. (2017),² if the industry’s average productivity growth rate is above that of the aggregate sector, I consider it as a high-productivity growth industry. Otherwise, it is a low-productivity growth industry. Comparing these high and low-productivity growth sub-sectors in India and the U.S. shows striking differences.

In the U.S. the high-productivity growth manufacturing sub-sector is, by far, the fastest growing sector while the low-productivity service sub-sector 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 sub-sectors, services still grow faster than manufacturing.

To further explore the causes of services productivity surge, I make use of the Indian and Chinese Census data from the Integrated Public Use Microdata Series (IPUMS-I, 2018) to explore educational attainment at the aggregate and at the sector level. The percentage of workers with some university education in India was about 3 percent in 1983, 6.1 percent in 1999, and 9.6 percent in 2009. In China, however, 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 though real GDP per capita in India was roughly 65% and 49% that of China in 1980 and 2000 respectively.

¹Baumol (1967) already connected productivity growth and structural transformation noting that reallocation of economic activity can even happen towards stagnant sectors. Kuznets (1966) and Kuznets (1973) defined structural transformation as one of the main features of modern growth. 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, Álvarez-Cuadrado and Poschke (2011) find that since the 1960s improvements in agricultural technology seem to be the main mechanism driving the agricultural employment share downwards. Święcki (2017) suggests and calibrates a model with several sources of structural change to address the importance of each one. He finds differences in sectoral productivity growth to be the most important mechanism to account for structural change. Herrendorf et al. (2014) provide an extensive literature review on the theoretical and empirical papers that study the process of structural transformation.

²Duernecker et al. (2017) only divide the service sector into high and low-productivity growth while aggregating agriculture and manufacturing into a single goods sector.
This does not imply that average educational attainment is higher in India, instead it goes in line with Roy (1996) and Sivasubramonian (2004) suggesting that the distribution of educational attainment as well as government efforts in India have historically been skewed towards tertiary education. If on top of having a relatively large supply of skilled workers, different sectors use them with different intensities, an education-based explanation for this productivity surge could be plausible. In Section 2.3 I document that high-productivity services are more intensive in high-skillwed workers than the rest of sectors, that services provide a sectoral wage premium, and that returns to schooling are larger for the service sectors than for the non-service sectors. This suggests that high-skilled workers have a comparative advantage in services, in particular in the high-productivity growth sub-sector.

To understand the sources of differential productivity growth in India and put to test the education-based explanation, I build a model of structural change with the three traditional sectors, and allow manufacturing and services to be CES aggregates of two sub-sectors. A high-productivity one and a low-productivity growth one. Furthermore, the model incorporates two types of workers, skilled and unskilled, and allows every sector to use both of them. The model is most similar to that of Buera et al. (2018) and Herrendorf and Fang (2019) but departs from them in allowing further heterogeneity within sectors.

The sub-division into high and low-productivity growth sub-sectors has crucial implications for development. The calibrated model suggests that high and low-productivity growth manufacturing sub-sectors are gross complements while services sub-sectors are gross substitutes. This implies that, conditional on labor flowing into the manufacturing sector, labor will flow 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 technological 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. Third, the aggregate relative supply of high skilled workers, and fourth, a sector specific tax that firms need to pay for each unit of labor hired. These taxes reflect all additional costs besides wages firms have to incur in order to hire an additional worker. From the calibration, the Hicks-neutral terms cannot be the elements driving the differences in productivity growth between high-productivity growth manufacturing and services sub-sectors since they grow at very similar rates. The decomposition into high and low-productivity growth sub-sectors is crucial for this result since, as Verma (2012) shows, the main differences between

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3 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. Roy (2011) also notes that these castes were still dominating the entrance on the telecommunications sector in during the 1990s.

4 These taxes account for all the additional costs besides wages that firms need to incur in order to hire more workers. Buera and Kaboski (2009) show that to account for differences between employment and output shares, different sectoral wages are necessary. Taxes are a way of accommodating this. A wage gap can also be generated by including a mobility cost paid by the workers moving into another sector as Alonso-Carrera and Raurich (2018) show.
services and manufacturing on aggregate come from TFP growth.

What drives the differences between the high-productivity growth sub-sectors is the skill-intensity parameter. 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.

Regarding the labor market distortions implied by the sectoral taxes, the high-productivity growth sub-sectors seem to be the most affected ones; especially the service sub-sector. Removing these barriers would imply sizeable gains in aggregate GDP growth. If all barriers were set at the values calibrated for the low-productivity manufacturing sub-sector (the sector with the largest declines in barriers), GDP per capita would be twice as much as in the benchmark model for 2017. If, instead, only barriers in the high-productivity growth manufacturing sector would decline to this level, GDP per capita would increase by a factor of 1.5. The same experiment for high-productivity growth services would increase GDP per capita by a factor of 2.6.

Although fast TFP growth is the most important factor for aggregate development, the relatively large supply of high-skilled workers also plays an important role. Keeping it constant at 1981 values would imply that real aggregate GDP per capita in 2017 would be 46.4% of the GDP per capita predicted by the benchmark model in the same year. Thus, for aggregate growth, the model suggests that the aggregate supply of high-skill workers is at least as important as the labor market barriers.

The results from the model highlight the importance high skilled workers have had in labor productivity growth of the service sector and captures the fact that intensity in high skilled workers has increased for all sectors. However, there is still a sceptic view regarding productivity growth in services. Eichengreen and Gupta (2011) point out correctly, that India started from very low levels and that it has been converging to the international norm which could imply a reduction in future growth. In Section 2.2 I address this concern by comparing labor productivity growth in India with a set of countries of all levels of development. In the benchmark regressions, I make use of the Groningen Growth and Development Center (GGDC) 10-Sector Database (Timmer et al., 2015) which provides data for a set of 41 countries at all stages of development on employment, nominal value added, and real value added for ten broad sectors comprising the whole economy. Controlling for country fixed effects, the stage of development, and population levels, labor productivity of Indian services grows around 1.77 percentage points faster than the average country. However, labor productivity growth in manufacturing does not seem to be different from the average country.\footnote{This result is in line with Ziebarth (2013) who argues that the degree of misallocation in India and China is not different from that of the U.S. at a similar stage of development.}

I perform several robustness checks by comparing India with other Asian countries only or by excluding China, the same conclusion remains. When using the World Development Indicators (WDI) Database including approximately 145 countries does not change the conclusions. Using only low-income countries only does not seem to affect the results either. This is suggestive that Indian services have an intrinsically fast labor productivity growth above that of other similar countries.
It is still a matter of discussion why Indian services have experienced such fast and sustained growth for several decades but there is still no consensus on what are the consequences for economic development and about the sustainability of services-led growth. Rodrik (2016), for example, argues that developing countries are prematurely deindustrializing, which might hurt potential future growth since manufacturing has traditionally been the most technologically dynamic sector, exportable, and a sector that can absorb unskilled labor. In Section 4.4 I simulate the model forward into the future up to 2075 to investigate the possible effects of services-led development. The question I pose is, what should be the growth rates of the Hicks-neutral terms in the services sub-sectors to achieve a 2% growth rate of GDP per capita?

A possible answer is 0.7% and 0.5% for the high and the low-productivity growth sub-sectors respectively. Those values imply a decline in the growth rate of the Hicks-neutral terms of 5.3 and 2.5 percentage points, respectively. Although this exercise imposes many unrealistic assumptions and the limitations are clear, it gives an idea of how big the change in overall productivity of the service sector needs to be to achieve a growth rate similar to that of developed countries.

This exercise also shows how important the gross complementarity of the manufacturing sub-sectors and the gross substitutability of the service sub-sectors are. The manufacturing and services sectors would not diverge forever in terms of labor productivity, since the least productive manufacturing sub-sector would take over in the limit, and the most productive service sub-sector would take over in the limit. In these simulations, the growth rates of labor productivity of the manufacturing and service sectors will be the same around 2066. From that point on, labor productivity of the service sector as an aggregate will grow faster than manufacturing.

The remainder of the paper is organized as follows. Section 2 describes and 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 Sections 4.1, 4.2, and 4.3 I calibrate the model, simulate the benchmark model, and evaluate the different channels of growth and distortions introduced. Section 4.4 presents the predictions about future growth obtained through 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

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6The services-led growth in India appears to be a very long-run phenomenon. Broadberry and Gupta (2010) show that Indian services pre-colonization already showed convergence in productivity to UK services, which signals to the historical specialization in services in India.

7For this simulations, I impose that the skill intensity, the sectoral labor market distortions, and the growth rate of the relative supply of skilled workers stay constant at their corresponding sample average values.
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 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. The growth rate is calculated in log differences. Thus

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

Where $Y_{jt}$ is value added in that sector and $H_{jt}$ the quality-adjusted labor employed. 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).

Since the interest is on sectoral productivity growth, I normalize labor productivities in the U.S. and India to the initial period. Figure 1 plots the logs of sectoral labor productivities for the U.S. and India normalized at the initial period, thus the slope indicates the growth rate of the series.

![Figure 1: Labor Productivities in Logs. Initial = 0](image)

The pattern that arises for the United States is what would be expected from a standard

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8The 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 significantly slower rate.
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 disease (Duerrnecker et al., 2017). 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.

This might not be too surprising since Broadberry and Gupta (2010) for example, show that the service sector is the only one converging in terms of labor productivity to the U.K., and Eichengreen and Gupta (2011) document that growth in the service sector has been unusually rapid in the last decades. However, as Eichengreen and Gupta (2011) argue, services labor productivity started from very low levels and by 2011 it already converged to international standards, and thus, the question was on whether it was going to continue its rapid expansion.

Rapid growth in services would depend on whether the fastest growing service industries could continue their expansion. To look into that, I disaggregate both the service and manufacturing 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 Duerrnecker et al. (2017). After classifying 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 disaggregated manufacturing and service sectors.

Once again, the pattern observed for the U.S. 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.
### Table 1: Division of Services by Labor Productivity Growth

<table>
<thead>
<tr>
<th>High Productivity Services</th>
<th>Percentage Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post and Telecommunication</td>
<td>8.5416</td>
</tr>
<tr>
<td>Public Administration and Defense;</td>
<td>4.6582</td>
</tr>
<tr>
<td>Compulsory Social Security</td>
<td></td>
</tr>
<tr>
<td>Business Service</td>
<td>3.9885</td>
</tr>
<tr>
<td>Financial Services</td>
<td>3.9528</td>
</tr>
</tbody>
</table>

**Overall Service Sector** 3.6198

<table>
<thead>
<tr>
<th>Low Productivity Services</th>
<th>Percentage Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade</td>
<td>3.4951</td>
</tr>
<tr>
<td>Health and Social Work</td>
<td>2.9357</td>
</tr>
<tr>
<td>Education</td>
<td>2.8785</td>
</tr>
<tr>
<td>Hotels and Restaurants</td>
<td>2.7428</td>
</tr>
<tr>
<td>Transport and Storage</td>
<td>2.1658</td>
</tr>
<tr>
<td>Other services</td>
<td>1.3643</td>
</tr>
</tbody>
</table>

*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.

### Table 2: Division of Manufacturing by Labor Productivity Growth

<table>
<thead>
<tr>
<th>High Productivity Manufacturing</th>
<th>Percentage Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coke, Refined Petroleum Products and Nuclear fuel</td>
<td>6.0102</td>
</tr>
<tr>
<td>Chemicals and Chemical Products</td>
<td>5.5726</td>
</tr>
<tr>
<td>Textiles, Textile Products, Leather and Footwear</td>
<td>4.9469</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>4.8449</td>
</tr>
<tr>
<td>Other Non-Metallic Mineral Products</td>
<td>4.5473</td>
</tr>
<tr>
<td>Electricity, Gas and Water Supply</td>
<td>4.4339</td>
</tr>
<tr>
<td>Rubber and Plastic Products</td>
<td>4.0767</td>
</tr>
<tr>
<td>Manufacturing, nec; recycling</td>
<td>3.4973</td>
</tr>
<tr>
<td>Food Products,Beverages and Tobacco</td>
<td>3.0075</td>
</tr>
<tr>
<td>Pulp, Paper,Paper products,Printing and Publishing</td>
<td>2.8913</td>
</tr>
<tr>
<td>Mining and Quarrying</td>
<td>2.4697</td>
</tr>
<tr>
<td>Electrical and Optical Equipment</td>
<td>1.8890</td>
</tr>
<tr>
<td>Basic Metals and Fabricated Metal Products</td>
<td>1.6030</td>
</tr>
</tbody>
</table>

**Overall Manufacturing Sector** 1.3643

<table>
<thead>
<tr>
<th>Low Productivity Manufacturing</th>
<th>Percentage Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machinery, nec.</td>
<td>1.1631</td>
</tr>
<tr>
<td>Wood and Products of wood</td>
<td>-0.5881</td>
</tr>
<tr>
<td>Construction</td>
<td>-1.9478</td>
</tr>
</tbody>
</table>

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

Nevertheless, it is also of major importance to see whether the high-productivity sectors are expanding and how fast. Figure 3 shows nominal value added shares for the United States and India with this sector split.

Figure 3: Nominal Value Added Shares

Figure 3 shows that in the U.S. both manufacturing subsectors show a slightly declining trend, consistent with deindustrialization in the later phases of development. At the same time, both services subsectors grow but the fastest growing share is the low-productivity services, which is what the Baumol’s cost disease implies. Duernecker et al. (2017) argue it is not likely that the Baumol’s cost disease will be such a drag on aggregate productivity, since the two sub-sectors are gross substitutes.

For India, the pattern is again different. Both manufacturing subsectors are roughly constant, while both services subsectors are growing. However, for India, the high-productivity subsector is the one that grows the fastest, implying that those fast-growing industries are also expanding the fastest. This seems to suggest that services-led growth might not have come to an end for India.

2.2 Cross-Country Evidence

The analysis of previous section shows that India’s structural transformation process and sectoral productivity dynamics differ from the experience of previously industrialized countries. This section now compares sectoral productivity growth in India with a set of countries to assess whether sectoral labor productivity growth is different in some way.

The data comes from the 10-Sector Groningen Growth and Development Centre (GGDC)
Database (Timmer et al., 2015), and consists of 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.

\[
\log(LP_{s,c,t}) = \alpha + \beta_1 \log(y_{c,t}) + \beta_2(\log(y_{c,t}))^2 + \beta_3 \log(pop_{c,t}) + \phi + \gamma Time_t \times IND_{c,t} + \epsilon_{s,c,t} 
\]  

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, \(\phi\) 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 \(\epsilon_{s,c,t}\) 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.

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.

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 coun-

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9 The data for GDP per capita and population used in these regressions is from the Maddison Database Project (Bolt et al., 2018). Tables 14 and 15 in Appendix C 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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agriculture</td>
<td>Manufacturing</td>
<td>Services</td>
</tr>
<tr>
<td>Time × India</td>
<td>-0.0123***</td>
<td>-0.00337</td>
<td>0.0177***</td>
</tr>
<tr>
<td></td>
<td>(0.000941)</td>
<td>(0.00271)</td>
<td>(0.00153)</td>
</tr>
<tr>
<td>Time</td>
<td>0.0400***</td>
<td>0.0182***</td>
<td>-0.00277</td>
</tr>
<tr>
<td></td>
<td>(0.00136)</td>
<td>(0.00203)</td>
<td>(0.00143)</td>
</tr>
<tr>
<td>Log of GDP per capita</td>
<td>-0.454*</td>
<td>2.559***</td>
<td>0.814***</td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
<td>(0.414)</td>
<td>(0.240)</td>
</tr>
<tr>
<td>Log of GDP per capita squared</td>
<td>0.0433***</td>
<td>-0.106***</td>
<td>-0.0149</td>
</tr>
<tr>
<td></td>
<td>(0.0121)</td>
<td>(0.0236)</td>
<td>(0.0135)</td>
</tr>
<tr>
<td>Log of Population</td>
<td>-1.139***</td>
<td>-1.014***</td>
<td>-0.175**</td>
</tr>
<tr>
<td></td>
<td>(0.0595)</td>
<td>(0.0812)</td>
<td>(0.0660)</td>
</tr>
</tbody>
</table>

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.

tries, 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.

Overall, India’s comparative advantage in the service sector remains a robust result no matter which comparison group we take. To investigate further regional differences in labor productivity growth, Table 6 shows the results from estimating equation (1) but replacing the dummy variable for India with an indicator for region. Each regression controls for stage of development, population, and country fixed effects as before but only the time trend and the

10The same specification as in equation (1) is estimated using the World Development Indicators Database using 143 countries. As before, labor productivity growth in agriculture is estimated to be below that of comparable countries; for manufacturing the coefficient is negative and significant but very small; and the coefficient for services is positive, statistically significant, and larger in magnitude than the estimated using the 10-Sector GGDC Database. Restricting the sample to low-income countries shows the same result, but the coefficient for manufacturing is no longer statistically significant. These results are shown in Table 16 in Appendix C.
Table 4: Labor Productivity in India Within Asia

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

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

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

Data: GGDC 10-Sector Database and Maddison Project Database. Robust standard errors in parenthesis. ∗ p < 0.05, ∗∗ p < 0.01, ∗∗∗ p < 0.001.
interaction coefficients are shown.

Table 6: Differential Labor Productivity Growth by Region

<table>
<thead>
<tr>
<th>Panel A: Africa</th>
<th>Agriculture</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time × Region</td>
<td>-0.00721***</td>
<td>-0.00116</td>
<td>0.0121***</td>
</tr>
<tr>
<td></td>
<td>(0.000964)</td>
<td>(0.00134)</td>
<td>(0.00135)</td>
</tr>
<tr>
<td>Time</td>
<td>0.0391***</td>
<td>0.0179***</td>
<td>-0.00159</td>
</tr>
<tr>
<td></td>
<td>(0.00130)</td>
<td>(0.00190)</td>
<td>(0.00145)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Asia</th>
<th>Agriculture</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time × Region</td>
<td>-0.0174***</td>
<td>0.0173***</td>
<td>0.0207***</td>
</tr>
<tr>
<td></td>
<td>(0.000934)</td>
<td>(0.00174)</td>
<td>(0.00130)</td>
</tr>
<tr>
<td>Time</td>
<td>0.0380***</td>
<td>0.0189***</td>
<td>-0.000165</td>
</tr>
<tr>
<td></td>
<td>(0.00119)</td>
<td>(0.00172)</td>
<td>(0.00122)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Latin America</th>
<th>Agriculture</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time × Region</td>
<td>0.00813***</td>
<td>-0.00548***</td>
<td>-0.0159***</td>
</tr>
<tr>
<td></td>
<td>(0.000688)</td>
<td>(0.00117)</td>
<td>(0.00129)</td>
</tr>
<tr>
<td>Time</td>
<td>0.0378***</td>
<td>0.0186***</td>
<td>0.000779</td>
</tr>
<tr>
<td></td>
<td>(0.00126)</td>
<td>(0.00194)</td>
<td>(0.00133)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Western Countries</th>
<th>Agriculture</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time × Region</td>
<td>0.0173***</td>
<td>-0.00900***</td>
<td>-0.0112***</td>
</tr>
<tr>
<td></td>
<td>(0.00121)</td>
<td>(0.00142)</td>
<td>(0.00138)</td>
</tr>
<tr>
<td>Time</td>
<td>0.0235***</td>
<td>0.0260***</td>
<td>0.00876***</td>
</tr>
<tr>
<td></td>
<td>(0.00165)</td>
<td>(0.00234)</td>
<td>(0.00196)</td>
</tr>
</tbody>
</table>

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 6 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 7 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 7: Differential Labor Productivity in Services by Country (Africa)

<table>
<thead>
<tr>
<th>Country</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>Country</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>Country</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>Country</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Botswana</td>
<td>0.00219</td>
<td>(0.00405)</td>
<td>Ghana</td>
<td>0.0143***</td>
<td>(0.00141)</td>
<td>Kenya</td>
<td>-0.0147***</td>
<td>(0.00140)</td>
<td>South Africa</td>
<td>0.00917***</td>
<td>(0.00109)</td>
</tr>
<tr>
<td>Egypt</td>
<td>0.0250***</td>
<td>(0.00117)</td>
<td>Nigeria</td>
<td>0.0219***</td>
<td>(0.00262)</td>
<td>Morocco</td>
<td>-0.00579***</td>
<td>(0.00112)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ethiopia</td>
<td>0.00388</td>
<td>(0.00213)</td>
<td>Senegal</td>
<td>-0.0152***</td>
<td>(0.00146)</td>
<td>Zambia</td>
<td>0.0492***</td>
<td>(0.00132)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Malawi</td>
<td>-0.0170***</td>
<td>(0.00297)</td>
<td>Mauritius</td>
<td>0.00976***</td>
<td>(0.00166)</td>
<td>Tanzania</td>
<td>-0.00649**</td>
<td>(0.00224)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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%.
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 experienced a pervasive increase. Not only has it 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 8 and 9 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.

Table 8: Educational Attainment in India

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary or less</td>
<td>79.19</td>
<td>77.65</td>
<td>71.36</td>
<td>65.43</td>
<td>62.12</td>
<td>54.72</td>
</tr>
<tr>
<td>Secondary</td>
<td>17.81</td>
<td>18.77</td>
<td>23.76</td>
<td>28.50</td>
<td>29.81</td>
<td>35.71</td>
</tr>
<tr>
<td>University</td>
<td>3.00</td>
<td>3.58</td>
<td>4.88</td>
<td>6.07</td>
<td>8.07</td>
<td>9.57</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No schooling</td>
<td>56.49</td>
<td>54.97</td>
<td>47.72</td>
<td>43.51</td>
<td>39.46</td>
<td>30.73</td>
</tr>
<tr>
<td>Some primary completed</td>
<td>9.5</td>
<td>9.42</td>
<td>11.36</td>
<td>10.12</td>
<td>8.75</td>
<td>9.52</td>
</tr>
<tr>
<td>Primary (5 yrs) completed</td>
<td>13.2</td>
<td>13.26</td>
<td>12.28</td>
<td>11.79</td>
<td>13.91</td>
<td>14.47</td>
</tr>
<tr>
<td>Lower secondary general completed</td>
<td>10.02</td>
<td>9.83</td>
<td>12.06</td>
<td>14.3</td>
<td>15.91</td>
<td>17.34</td>
</tr>
<tr>
<td>Secondary, general track completed</td>
<td>7.79</td>
<td>8.94</td>
<td>7.86</td>
<td>9.56</td>
<td>9.06</td>
<td>12.01</td>
</tr>
<tr>
<td>Some college completed</td>
<td>–</td>
<td>–</td>
<td>3.84</td>
<td>4.64</td>
<td>4.84</td>
<td>6.36</td>
</tr>
<tr>
<td>Post-secondary technical education</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>1.54</td>
<td>1.28</td>
</tr>
<tr>
<td>University completed</td>
<td>3.00</td>
<td>3.58</td>
<td>4.88</td>
<td>6.07</td>
<td>6.53</td>
<td>8.29</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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.

The service sector in India is both more intensive in skilled workers than the rest of sectors within India, but the share of skilled workers in Indian services is also higher than the share employed by Chinese services. This is shown in Figure 4. Furthermore, when disaggregating in industries, those industries with a 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 5 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...
Table 9: Educational Attainment in China

Panel A: Aggregate Educational Attainment (%)

<table>
<thead>
<tr>
<th></th>
<th>1982</th>
<th>1990</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary or less</td>
<td>62.45</td>
<td>54.18</td>
<td>40.30</td>
</tr>
<tr>
<td>Secondary</td>
<td>36.68</td>
<td>43.91</td>
<td>54.99</td>
</tr>
<tr>
<td>University</td>
<td>0.87</td>
<td>1.91</td>
<td>4.71</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Panel B: Detailed Educational Attainment (%)

<table>
<thead>
<tr>
<th></th>
<th>1982</th>
<th>1990</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>No schooling</td>
<td>28.02</td>
<td>16.52</td>
<td>7.49</td>
</tr>
<tr>
<td>Some primary completed</td>
<td>0.00</td>
<td>10.22</td>
<td>3.96</td>
</tr>
<tr>
<td>Primary (6 yrs) completed</td>
<td>34.43</td>
<td>31.68</td>
<td>30.68</td>
</tr>
<tr>
<td>Lower secondary general completed</td>
<td>26.10</td>
<td>28.82</td>
<td>40.61</td>
</tr>
<tr>
<td>Secondary, general track completed</td>
<td>10.58</td>
<td>8.77</td>
<td>8.92</td>
</tr>
<tr>
<td>Some college completed</td>
<td>0.06</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Secondary, technical track completed</td>
<td>-</td>
<td>2.08</td>
<td>3.63</td>
</tr>
<tr>
<td>Post-secondary technical education</td>
<td>-</td>
<td>1.16</td>
<td>3.28</td>
</tr>
<tr>
<td>University completed</td>
<td>0.81</td>
<td>0.67</td>
<td>1.38</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

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
Figure 5: Educational Attainment by Industry
agriculture has less educated workers as well as lower returns to schooling. Figure C.1 in Appendix C 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.

Following Herrendorf and Schoellman (2018) I estimate returns to schooling by sector and year. Figure 6 shows\(^{11}\) in line with the evidence they provide that agricultural wages have the lowest wages and the lowest returns. 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.

![Figure 6: Log of Wages and Returns to Schooling by Sector](image)

**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.

\(^{11}\)In Table 17 of Appendix C the coefficients of these regressions are shown.
3 Model

The evidence shown in Section 2 has established five main stylized facts: namely, high productivity industries show faster growth of labor productivity in services than in manufacturing, opposite to what has been the experience of traditional industrializers. 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. 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. And the service sector employs a higher share of high-skilled workers than manufacturing and 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.

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 sub-sectors 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 $M_h$ of these members will be high-skilled individuals and a fraction $M_l$ will be low-skilled individuals. The lifetime utility of the household is given by (2).

$$U = \sum_{t=0}^{\infty} \beta^t \log(\tilde{C}_t)$$ (2)

Where $\beta$ is the discount factor and $\tilde{C}_t$ an aggregator of agricultural ($c_{at}$), manufacturing ($c_{mt}$), and service ($c_{st}$) consumption given by equation (3).

$$\tilde{C}_t = \left[ (\omega_a)^{\frac{1}{\varepsilon}} (c_{at})^{\frac{\varepsilon-1}{\varepsilon}} + (\omega_m)^{\frac{1}{\varepsilon}} (c_{mt})^{\frac{\varepsilon-1}{\varepsilon}} + (\omega_s)^{\frac{1}{\varepsilon}} (c_{st})^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{1}{\varepsilon}}$$ (3)

Where the $\omega_j > 0$ terms are the weights of each consumption good and $\varepsilon > 0$ is the elasticity of substitution between the aggregate consumption goods. As explained before, the manufacturing and service consumption are both CES aggregators of the high and low-productivity subsectors. The elasticity of substitution between these two sub-sectors is given by $\eta_j$ which is potentially different for manufacturing and for services.

$$c_{mt} = \left[ (\omega_m^h)^{\frac{1}{\eta_m}} (c_{mt}^h)^{\eta_m-1} + (1 - \omega_m^h)^{\frac{1}{\eta_m}} (c_{mt}^l)^{\eta_m-1} \right]^{\frac{1}{\eta_m}}$$ (4)

$$c_{st} = \left[ (\omega_s^h)^{\frac{1}{\eta_s}} (c_{st}^h)^{\eta_s-1} + (1 - \omega_s^h)^{\frac{1}{\eta_s}} (c_{st}^l)^{\eta_s-1} \right]^{\frac{1}{\eta_s}}$$ (5)

The household maximizes (2) subject to (3), (4), (5) and (6).
\[ p_i c_{i} + p_{i}^{h} c_{i}^{h} + p_{i}^{l} c_{i}^{l} + p_{i}^{j} C_{i}^{j} = w_{i}^{h} M_{i} + w_{i}^{l} M_{i} + T_{i} \] (6)

The budget constraint sets the sum of consumption expenditure in sectors \( j \) and sub-sectors \( i \) \( (p_{i}^{j} C_{i}^{j}) \) equal to total income. Total income is the sum of the high-skill wage \( w_{i}^{h} \) earned by the fraction \( M_{i}^{h} \) of high-skilled workers and the low-skill wage \( w_{i}^{l} \) earned by the fraction \( M_{i}^{l} \) of the low-skilled workers, and a lump-sum rebated tax from firms \( T_{i} \).

From the household’s optimization problem, relative expenditure of high to low-productivity good in sector \( j \) is given by (7). Thus, the relative expenditure depends on the relative price effect only. The reason for this is that I abstract from non-homotheticities that might also affect the process of structural transformation. This is because the focus of the paper is on differential sectoral productivity and the effects it has on structural transformation.

\[ \frac{p_{j}^{h} c_{j}^{h}}{p_{j}^{l} c_{j}^{l}} = \left( \frac{\omega_{j}^{h}}{1 - \omega_{j}^{h}} \right) \left( \frac{p_{j}^{h}}{p_{j}^{l}} \right)^{1-\eta_{j}} \quad \text{for } j \in \{ m, s \} \] (7)

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 \( \eta_{m} \) and \( \eta_{s} \) consistent with this structural transformation pattern, yielding \( \eta_{s} \) larger than one while \( \eta_{m} \) will be lower than one. This is consistent with the interpretation that high-productivity services might be considered luxuries as Duernecker et al. (2017) document for the U.S.

The maximization problem also yields expressions for the ideal price indices of sectors \( j \in \{ m, s \} \) as functions of the prices in the two sub-sectors \( i \in \{ h, l \} \) (equation (8)). Using the ideal price index and the first order conditions of the maximization problem, total expenditure in sector \( j \in \{ m, s \} \) equals the product of the sectoral price index and the consumption aggregator \( c_{j} \) as shown in equation (9).

\[ p_{j} = \left[ \omega_{j}^{h} (p_{j}^{h})^{1-\eta_{j}} + (1 - \omega_{j}^{h}) (p_{j}^{l})^{1-\eta_{j}} \right]^{\frac{1}{1-\eta_{j}}} \] (8)

\[ p_{j}^{h} c_{j}^{h} + p_{j}^{l} c_{j}^{l} = p_{j} c_{j} \] (9)

Similarly, an aggregate price index can be obtained as a function of the sectoral prices as in (10).

\[ \tilde{P}_{t} = \left[ \omega_{a} (p_{at})^{1-\epsilon} + \omega_{m} (p_{mt})^{1-\epsilon} + \omega_{s} (p_{st})^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} \] (10)

### 3.2 Firms and Technology

The production side of the model is similar to Buera et al. (2018) and Herrendorf and Fang (2019). Each sector \( j \in \{ a, m, s \} \) and sub-sector \( i \in \{ h, l \} \) is comprised by a large number of firms that produce output \( Y_{j}^{i} \) using two types of labor, high and low skill, and pay a tax \( \tau_{j}^{i} \).
The role of sectoral taxes $\tau_{jt}^i$ 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 these 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 (11b) 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 sub-sector $i \in \{h, l\}$ thus solves the following maximization problem.

$$\max_{\{h_{jt}^i, l_{jt}^i\}} p_{jt}^i Y_{jt}^i - (1 + \tau_{jt}^i)(w_{jt}^h h_{jt}^i + w_{jt}^l l_{jt}^i)$$  \hspace{1cm} (11a)

s.t. $Y_{jt}^i = A_{jt}^i L_{jt}^i = A_{jt}^i \left[ \pi_{jt}^i \left( h_{jt}^i \right)^{\sigma\over(\sigma-1)} + (1 - \pi_{jt}^i) \left( l_{jt}^i \right)^{\sigma\over(\sigma-1)} \right]^{1\over\sigma}$ \hspace{1cm} (11b)

$A_{jt}^i$ denotes Hicks-neutral (TFP) sectoral technology which grows exogenously, $\pi_{jt}^i$ 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.\(^{12}\) Suppose $\pi_{jt}^h > \pi_{jt}^l$, that would imply that high-skilled labor displays comparative advantage in the high-productivity service sub-sector compared to the low-productivity one. The elasticity of substitution between each type of labor is common across sectors and is given by $\sigma$. 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 sub-sector $i$.

$$w_{jt}^h \over w_{jt}^l = \frac{\pi_{jt}^h}{1 - \pi_{jt}^h} \left( \frac{l_{jt}^i}{h_{jt}^i} \right)^{1\over\sigma}$$ \hspace{1cm} (12)

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

\(^{12}\)This specification is equivalent to a production function with factor-augmenting technical change. That is, a production function of the form:

$$Y_{jt}^i = \left[ \bar{\pi}_{jt}^i \left( \Lambda_{jt}^i h_{jt}^i \right)^{\sigma\over(\sigma-1)} + (1 - \bar{\pi}_{jt}^i) \left( \Gamma_{jt}^i l_{jt}^i \right)^{\sigma\over(\sigma-1)} \right]^{1\over\sigma}$$

Where $\Lambda_{jt}^i$ and $\Gamma_{jt}^i$ represent high-skill and low-skill labor-augmenting technical change, respectively. Note that we can express $\pi_{jt}^i$ and $A_{jt}^i$ as functions of the parameter $\bar{\pi}_{jt}^i$, the factor-augmenting technical change terms, and the elasticity. In particular:

$$\pi_{jt}^i \equiv \bar{\pi}_{jt}^i \left( \Lambda_{jt}^i \right)^{\sigma\over(\sigma-1)}; \ A_{jt}^i \equiv \left( \bar{\pi}_{jt}^i \left( \Lambda_{jt}^i \right)^{\sigma\over(\sigma-1)} + (1 - \bar{\pi}_{jt}^i) \left( \Gamma_{jt}^i \right)^{\sigma\over(\sigma-1)} \right)^{1\over\sigma}$$

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in the relative prices of the factors of production affect relative demand. Since \( \pi_{jt} \) 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.

The market clearing condition for goods is \( Y_{jt} = c_{jt} \) thus, we can define nominal aggregate GDP as in (13) by using the market clearing conditions for goods and the first order conditions from the household’s problem.

\[
P_t Y_t = p_{at} Y_{at} + p^h_{mt} Y^h_{mt} + p^l_{mt} Y^l_{mt} + p^h_{st} Y^h_{st} + p^l_{st} Y^l_{st}
\]

(13)

### 3.3 Equilibrium

Let us omit time subscripts for clarity. Appendix B shows the details of the equilibrium and solution of the model. The share of wages high-skill workers get in a given sector \( j \) and sub-sector \( i \) is given by equation (14).

\[
\Omega_{ij} \equiv \frac{w^h_{i} h^i_{j}}{w^h_{i} h^i_{j} + w^l_{i} I^i_{j}} = \left( 1 + \left( \frac{w^h_{i}}{w^l_{i}} \right)^{\sigma - 1} \left( 1 - \frac{\pi_{ij}}{1 - \pi_{ij}} \right) \right)^{-1}
\]

(14)

Using the definition of \( L_{ij} \) (12) and (14), we get an expression for inverse of the ratio of high-skill workers over the total labor input.

\[
\frac{L_{ij}}{h_{ij}} = \left( \frac{\pi_{ij}}{\Omega_{ij}} \right)^{\frac{1}{\sigma - 1}}
\]

(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.

\[
\frac{p^i_{i} h_{i}}{p^a_{a}} = \frac{A_a}{A^j_{ij}} \left( 1 + \tau_a \right) \left( \frac{\pi_a}{\pi_{ij}} \right)^{\frac{1}{\sigma - 1}} \left( \frac{\Omega_a}{\Omega_{ij}} \right)^{\frac{1}{\sigma - 1}}
\]

(16)

Appendix B shows the details of the expressions for the expenditure on the high relative to the low-productivity good within sector \( j \) \( (E^h_{ij}) \), and the expenditure on sector \( j \) sub-sector \( i \) 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 \( j \) sub-sector \( i \) relative to those in agriculture (equation 17) is a function of the relative taxes, the relative sectoral wage share in high-skill workers and also on the relative expenditure.

\[
\frac{h^i_{j}}{h^a_{j}} = E^i_{ja} \left( 1 + \tau_j \right) \left( \frac{\Omega_j}{\Omega_a} \right)
\]

(17)

Relatively higher distortions in sector \( j \) sub-sector \( i \) reduce the proportion of high-skilled workers in that sector relative to those in agriculture. As shown in Appendix B, 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)

\[
\frac{h_a}{M_{ht}} = \frac{1}{\sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} E^j_{ia} \left( \frac{1 + \tau_a}{1 + \tau^j_i} \right) \left( \frac{\Omega^j_i}{\Omega^j_a} \right) (18)}
\]

Although relative taxes matter for matching differences in nominal labor productivity, differences in real labor productivity are not directly determined by these taxes. Appendix B shows in detail that real labor productivity defined as total output produced in sector j sub-sector i divided by total labor employed in that sector depends on the parameter driving changes in the demand for high-skill labor, the skill premium, sectoral TFP, and the wage bill of high-skill workers in that sector. Equation (19) shows that taxes do not enter in the determination of real labor productivity.

\[
\frac{Y^j_{i}}{l^j_{i} + h^j_{i}} = \frac{1}{1 + \left( \frac{w^h_{i}}{w^l_{i}} \right) ^{\sigma} \left( \frac{1 - \pi^j_{i} \pi^j_{i}}{\pi^j_{i}} \right) ^{\sigma} A^j_{i} \left( \frac{\pi^j_{i}}{\Omega^j_{i}} \right) ^{\sigma}} (19)
\]

**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 \( (A^j_{i}) \), the parameters governing sectoral increase in the demand for high-skill labor \( (\pi^j_{i}) \), and labor market distortions \( (\tau^j_{i}) \). 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 throughout this 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 \( \{\varepsilon, \eta_m, \eta_s, \sigma\} \), five weights in the utility function \( \{\omega_{a}, \omega_{m}, \omega_{s}, \omega_{ht}^{h}, \omega_{lt}^{h}\} \), the five parameters governing changes in the demand for high-skill labor \( \{\pi_{at}, \pi_{mit}, \pi_{lit}, \pi_{st}^{h}, \pi_{st}^{l}\} \), the five sectoral TFP components \( \{A_{at}, A_{mit}^{h}, A_{mit}^{l}, A_{st}^{h}, A_{st}^{l}\} \), 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) the rest of the parameters are calibrated using data for India from the KLEMS Database 2019 Version.
I start by calibrating simultaneously the utility function parameters \( \{ \omega_a, \omega_m, \omega_s, \omega_{hm}, \omega_{hs}, \epsilon, \eta_m, \eta_s \} \) imposing \( \omega_s = 1 - \omega_a - \omega_m \). 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 using equations (7) for manufacturing and services, and the ratio of equations (B.7a) and (B.9) for both manufacturing and services. Note that the market clearing condition for the consumption goods imply that \( c_i = Y_i \). The values obtained for the elasticities are \( \epsilon = 3.32, \eta_m = 0.41, \) and \( \eta_s = 2.11 \). Table 10 shows the values of the calibrated parameters.

Table 10: Calibrated Parameter Values for the Benchmark Model

<table>
<thead>
<tr>
<th>Weights</th>
<th>Elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \omega_a )</td>
<td>0.177</td>
</tr>
<tr>
<td>( \omega_m )</td>
<td>0.325</td>
</tr>
<tr>
<td>( \omega_{hm} )</td>
<td>0.687</td>
</tr>
<tr>
<td>( \omega_{hs} )</td>
<td>0.423</td>
</tr>
<tr>
<td>( \omega_s )</td>
<td>0.498</td>
</tr>
</tbody>
</table>

*Note:* The table shows the calibrated values of the utility function parameters from 1981 to 2017 summarizing the benchmark calibration.

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 (7) implies that \( \eta_m \) 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.

The value obtained for \( \epsilon \) requires more consideration. Verma (2012) constructs a three-sector general equilibrium model for India and calibrates this elasticity through a regression approach where she finds the elasticity to be 5.26. In a recent paper, Storesletten et al. (2019) estimate an elasticity of substitution between agricultural and non-agricultural consumption for China of 3.60 with their baseline model and, when they allow for non-homotheticities, they find a lower value of this elasticity but still substantially larger than one at 3.36. However, the empirical literature on other countries have found values for \( \epsilon < 1 \) (Herrendorf et al., 2013).

The remaining parameters are calibrated period by period following Duernecker et al. (2017) and Herrendorf and Fang (2019). 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.

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13I also follow a similar approach as Acemoglu and Guerrieri (2008) and estimate the elasticities \( \eta_j \) 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%. I estimate \( \epsilon \) via Seemingly Unrelated Regressions using the ratio of nominal value added in manufacturing and services relative to agriculture, and imposing that the coefficient is equal in both equations. The SUR approach yields an estimate for \( \epsilon = 2.8035 \). If instead of the relative price indices the ratio of real value added is used, the estimate for \( \epsilon \) is 3.4468 instead.
The skill-bias technical change parameters $\pi_{jt}$ 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. $\tau_{jt} = 0 \forall t \geq 0$), 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 7 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 sub-sectors might be of importance. In particular, when comparing the low-productivity subsectors, there are clear differences in TFP growth. The service sub-sector grows significantly faster in TFP than the low-productivity manufacturing sub-sector but still slower than agricultural TFP.

Figure 7: 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 6). 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 sub-sectors show the slowest increase in the demand for high-skilled workers. This is not so surprising if
we note that these sub-sectors show, in levels, quite high values for the parameters. Table 11 shows the average growth rates for the sectoral TFPs and the parameters $\pi_{ij}$.

Table 11: Growth Rates of Sectoral Technology (in percentages)

<table>
<thead>
<tr>
<th>Sector</th>
<th>Agriculture</th>
<th>High Manufacturing</th>
<th>Low Manufacturing</th>
<th>High Services</th>
<th>Low Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{ij}$</td>
<td>4.549</td>
<td>6.042</td>
<td>0.318</td>
<td>6.116</td>
<td>3.169</td>
</tr>
<tr>
<td>$\pi_{ij}$</td>
<td>4.178</td>
<td>2.146</td>
<td>1.744</td>
<td>0.8372</td>
<td>1.34</td>
</tr>
</tbody>
</table>

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 $\tau_{ij}$ show that barriers to entry in the high-productivity sub-sectors are the largest relative to agriculture. Furthermore, these barriers seem to be trendless. However, for both of the low-productivity sub-sectors, 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.\footnote{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.}

4.2 Benchmark Simulation

With the calibrated parameters in hand, the solution of the model is determined with one equation in one unknown, the skill premium (details in Appendix B.4). Figure 8 shows the targeted variables as a solution of the model and the match of the model. The model matches the targets very closely.

Figure 9 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 sub-sector 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 9.

In terms of value added and employment shares, the model reproduces the overall behavior shown in the data in Figure 10. 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 sub-sectors 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 employment shares. However, the model predicts slightly less employment and value added in this sector. As another

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 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.
Figure 9: 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 (B.30).

Figure 10: Benchmark: Value Added and Employment Shares
The Role of Relative Supply of High-Skill Workers  This experiment holds the relative supply of high-skilled workers constant at the 1981 values throughout the entire period for which we have data holding the rest of the parameters as in the benchmark calibration.

Figure 11: Counterfactual: Constant $M_h/M_l$

Figure 11 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 (51% 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 12 shows (53.6% decline).

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 leading cause for growth in India. Both real sectoral outputs and labor productivities decline over time and aggregate GDP is mostly flat as shown in Figures 13 and 14.

The Role of the Sectoral Demand for High-Skill Labor  An important parameter to replicate the behavior of the skill premium is the skill-bias technical change parameters $\pi^{ij}$. 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
Figure 12: **Counterfactual**: Constant $M_h/M_l$
economic growth in India. The experiment sets the values constant at their 1981 levels for the entire period. Figures 15 and 16 show the results.

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 Role of Distortions  This experiment consists on reducing all distortions to the level of \( \tau_{lm}^L \). 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 17 and 18 show the results.
ing 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 sub-sectors, the inflow of labor they receive causes labor productivity to drop. Note that this reduction in barriers increases real output for all sectors except agriculture, which overall causes aggregate real GDP per capita to increase significantly.

**Industrial Policies**  Table 12 summarizes the results of previous experiments and adds two additional experiments. The last two rows of the table show what would happen if only the high-productivity sub-sectors would see their barriers reduced. 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 1.5. If, instead, the high-productivity sub-sector would have less distortions, this number would rise up to 2.6. This reflects how different aggregate outcomes can be depending on which sub-sectors are targeted.

**Table 12: Experiments and Benchmark Calibration**

<table>
<thead>
<tr>
<th></th>
<th>Agriculture</th>
<th>High-Manufacturing</th>
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<th>High-Services</th>
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<td></td>
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<tr>
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<tr>
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<td>1.667</td>
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<tr>
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*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

TO BE COMPLETED. RESULTS AVAILABLE UPON REQUEST.

### 5 Conclusion

TO BE COMPLETED

### References


Appendix A Industry Aggregations

This section shows the exercise of decomposing growth rates in the real value added of each sector by factor of production. In particular, the decomposition shows growth rates of the capital stock, labor, quality of labor, and TFP. Before showing results of the growth decomposition, I briefly describe the process of aggregation across industries.

Let me start by defining nominal value added shares as follows:

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

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, simply aggregating growth rates of individual industries in sector $i$, real value added in sector $i$ is given by

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

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

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

$$v(R_{j,t}K_{j,t}) = \frac{1}{2} \left( \sum_{j=1}^{N} R_{j,t}K_{j,t} + \sum_{j=1}^{N} R_{j,t+1}K_{j,t+1} \right)$$
Appendix B  Deriving the Competitive Equilibrium

B.1 Household

Households consume five types of goods; an agricultural good, two types of manufacturing goods, and two types of services. The two types of manufacturing goods and services are high-productivity and low-productivity. The utility function of the household is given by

\[ U = \log(\tilde{C}_t) \]

\[ \tilde{C}_t = \left( (\omega_s)^{\frac{1}{\eta_s}} (c_{at})^{\frac{1-\xi}{\xi}} + (\omega_m)^{\frac{1}{\eta_m}} (c_{mt})^{\frac{1-\xi}{\xi}} + (\omega_h)^{\frac{1}{\eta_h}} (c_{ht})^{\frac{1-\xi}{\xi}} \right)^{\frac{1}{1-\xi}} \quad (B.1) \]

\[ c_{mt} = \left[ (\omega_m^h)^{\frac{1}{\eta_m}} (c_{mt}^h)^{\frac{\eta_m-1}{\eta_m}} + (1 - \omega_m^h)^{\frac{1}{\eta_m}} (c_{mt}^l)^{\frac{\eta_m-1}{\eta_m}} \right]^{\frac{\eta_m}{\eta_m-1}} \quad (B.2) \]

\[ c_{st} = \left[ (\omega_s^h)^{\frac{1}{\eta_s}} (c_{st}^h)^{\frac{\eta_s-1}{\eta_s}} + (1 - \omega_s^h)^{\frac{1}{\eta_s}} (c_{st}^l)^{\frac{\eta_s-1}{\eta_s}} \right]^{\frac{\eta_s}{\eta_s-1}} \quad (B.3) \]

And the budget constraint

\[ p_{at} c_{at} + p_{mt}^h c_{mt}^h + p_{st}^h c_{st}^h + p_{st}^l c_{st}^l = \tilde{w}_t^h M_{ht} + \tilde{w}_t^l M_{lt} + T_t \quad (B.4) \]

Where \( T_t \) is a lump-sum rebated tax from firms and the labor market clearing conditions are given by (B.5) and (B.6).

\[ M_{ht} = h_{at}^h + h_{mt}^h + h_{st}^h + h_{lt}^l \quad (B.5) \]
\[ M_{lt} = l_{at}^l + l_{mt}^l + l_{st}^l + l_{lt}^l \quad (B.6) \]

The household’s first order conditions are given by:

\[ \lambda p_{at} = \left( \tilde{C}_t \right)^{\frac{1-\xi}{\xi}} (\omega_s)^{\frac{1}{\eta_s}} (c_{at})^{-\frac{1}{\xi}} \quad (B.7a) \]

\[ \lambda p_{mt}^h = \left( \tilde{C}_t \right)^{\frac{1-\xi}{\xi}} (\omega_m)^{\frac{1}{\eta_m}} (c_{mt})^{-\frac{1}{\xi}} \left( \omega_m^h \right)^{\frac{1}{\eta_m}} \left( \frac{c_{mt}}{c_{mt}^h} \right)^{\frac{1}{\eta_m}} \quad (B.7b) \]

\[ \lambda p_{mt}^l = \left( \tilde{C}_t \right)^{\frac{1-\xi}{\xi}} (\omega_m)^{\frac{1}{\eta_m}} (c_{mt})^{-\frac{1}{\xi}} \left( 1 - \omega_m^h \right)^{\frac{1}{\eta_m}} \left( \frac{c_{mt}}{c_{mt}^l} \right)^{\frac{1}{\eta_m}} \quad (B.7c) \]

\[ \lambda p_{st}^h = \left( \tilde{C}_t \right)^{\frac{1-\xi}{\xi}} (\omega_s)^{\frac{1}{\eta_s}} (c_{st})^{-\frac{1}{\xi}} \left( \omega_s^h \right)^{\frac{1}{\eta_s}} \left( \frac{c_{st}}{c_{st}^h} \right)^{\frac{1}{\eta_s}} \quad (B.7d) \]

\[ \lambda p_{st}^l = \left( \tilde{C}_t \right)^{\frac{1-\xi}{\xi}} (\omega_s)^{\frac{1}{\eta_s}} (c_{st})^{-\frac{1}{\xi}} \left( 1 - \omega_s^h \right)^{\frac{1}{\eta_s}} \left( \frac{c_{st}}{c_{st}^l} \right)^{\frac{1}{\eta_s}} \quad (B.7e) \]

Dividing (B.7b) by (B.7c), and (B.7d) by (B.7e) we obtain (B.8) which is equation (7) in the main text.
\[ \frac{c_{ht}^j}{c_{lt}^j} = \left( \frac{\omega_j^h}{1 - \omega_j^h} \right) \left( \frac{p_{ht}^j}{p_{lt}^j} \right)^{-\eta_j} \quad \text{for } j \in \{m, s\} \]  

(B.8)

Raising equations (B.7b), (B.7c), (B.7d) and (B.7e) to the power of \(1 - \eta_j\) and adding them up yields the ideal price index (B.10) which correspond to equation (8) in the main text. These also yield two first order conditions for the composite manufacturing and service good (B.9).

\[ \lambda_t p_{jlt} = \left( \frac{\tilde{C}_t}{\eta_{jlt}} \right)^{\frac{1}{1 - \eta_j}} (\omega_j^h)^{\frac{1}{1 - \eta_j}} (c_{jlt})^{-\frac{1}{1 - \eta_j}} \]  

(B.9)

\[ p_{jlt} = \left[ \omega_j^h(p_{jlt}^{1-\eta_j}) + (1 - \omega_j^h)(p_{jlt}^{1-\eta_j}) \right]^{\frac{1}{1 - \eta_j}} \]  

(B.10)

Adding up equations (B.7b), (B.7c), (B.7d), and (B.7e) and using the definition of \(p_{jlt}\) and (B.9), we obtain that expenditure in high and low productivity manufacturing or service goods is equal to the product of the ideal sectoral price index and the sectoral consumption aggregator, which is (9).

\[ p_{jht} c_{jht} + p_{jl} c_{jl} = p_{jlt} c_{jlt} \]  

(B.11)

Raising equations (B.7a), and (B.9) to \(1 - \varepsilon\) and adding them up, we obtain an expression for a first order condition for aggregate consumption and for the ideal aggregate price index (\(\tilde{P}_t\)).

\[ \lambda_t \tilde{P}_t = \frac{1}{\tilde{C}_t} \]  

(B.12)

\[ \tilde{P}_t = \left[ \omega_a^h(p_{at}^{1-\varepsilon}) + \omega_m(p_{mt}^{1-\varepsilon}) + \omega_s(p_{st}^{1-\varepsilon}) \right]^{\frac{1}{1 - \varepsilon}} \]  

(B.13)

**B.2 Firms**

Firms produce using high-skill and low-skill labor only and pay a tax \(\tau_{ji}\) 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 sub-sector \(i \in \{h, l\}\) solves the following problem.

\[ \max_{(h_{ji}, l_{ji})} p_{ji} Y_{ji} - (1 + \tau_{ji})(w_{ji}^h h_{ji}^i + w_{ji}^l l_{ji}^i) \]  

s.t. \(Y_{ji} = A_{ji}^h L_{ji}^h = A_{ji}^l \left[ (\tau_{ji}^h)^{\frac{\varepsilon - 1}{\varepsilon}} + (1 - \tau_{ji}^h) \left( l_{ji}^h \right)^{\frac{\varepsilon - 1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon - 1}} \)  

(B.14)

From the firm’s profit maximization problem we get (12) in the main text:

\[ \frac{w_{ji}^h}{w_{ji}^l} = \frac{\tau_{ji}^h}{1 - \tau_{ji}^h} \left( l_{ji}^h \right)^{\frac{1}{\varepsilon - 1}} \]  

(B.15)

To obtain (13), I add up equations (B.7a) and (B.9). Noting that

\[ \lambda_t (p_{at} c_{at} + p_{mt} c_{mt} + p_{st} c_{st}) = 1 \]
And using (B.12), $1/\lambda_t = P_t \tilde{C}_t$, (B.11), and (B.16) we get (13) in the main text. Where the market clearing condition is given by:

$$Y_{jt}^i = c_{jt}^i \quad \text{(B.16)}$$

### B.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 $j \in \{m, s\}$.

$$E_{hl}^j \equiv \frac{p_{hl}^j c_{hl}^j}{p_{la}^j c_{la}^j} = \left( \frac{\omega_h^j}{1 - \omega_h^j} \right) \left( \frac{A_h^j}{A_h^j} \right)^{1-%eta_j} \left( \frac{1 + \tau_h^j}{1 + \tau_l^j} \right)^{1-%eta_j} \left[ \left( \frac{\pi_h^j}{\pi_l^j} \right)^{\frac{\sigma - 1}{\sigma}} \left( \frac{\Omega_h^j}{\Omega_l^j} \right)^{1-\sigma} \right]^{1-%eta_j} \quad \text{(B.17)}$$

Using (B.8) into the definition of $c_j$ (equations (B.2) and (B.3)) we get the inverse of the share of high productivity consumption of sector $j$ on total consumption of sector $j$.

$$\frac{c_j}{c_j^h} = \left( \frac{\omega_j}{\omega_h^j} \right)^{1-%eta_j} \left( 1 + \frac{1 - \omega_j}{\omega_h^j} \right)^{1-%eta_j} \left( \frac{p_h^j}{p_l^j} \right)^{1-%eta_j} \quad \text{(B.18)}$$

From (B.8) we can solve for $p_h^j / p_l^j$ in terms of $E_{hl}^j$ and substitute into (B.18) to get the share in terms of the expenditure ratio $E_{hl}^j$.

$$\frac{c_j}{c_j^h} = \left( \frac{\omega_j}{\omega_h^j} \right)^{1-%eta_j} \left( 1 + \frac{1}{E_{hl}^j} \right)^{1-%eta_j} \quad \text{(B.19)}$$

From the household’s FOC for $c_j$ and solving for $p_h^j$.

$$\frac{p_h^j}{p_a^j} = \left( \frac{\omega_j}{\omega_a^j} \right)^{\frac{1}{\epsilon}} \left( \frac{c_j}{c_a} \right)^{1-\frac{1}{\epsilon}} \left( \frac{p_h^j}{p_a^j} \right)^{\frac{1}{\epsilon}} \left( \frac{c_j}{c_a} \right)^{1-\frac{1}{\epsilon}}$$

Solving for $c_j / c_a$.

$$\frac{c_j}{c_a} = \left( \frac{p_h^j}{p_a^j} \right)^{-\epsilon} \left( \frac{\omega_j}{\omega_a^j} \right)^{\frac{\epsilon}{\omega_j}} \left( \frac{c_j}{c_a} \right)^{\frac{1}{1-\epsilon}} \left( \frac{c_j}{c_a} \right)^{\frac{\epsilon}{\omega_j}} \quad \text{(B.20)}$$

Substituting (16) and (B.19) into (B.20)

$$\frac{c_j}{c_a} = \left( \frac{\omega_j}{\omega_a^j} \right)^{\frac{1}{\omega_j}} \left( \frac{\omega_j}{\omega_a^j} \right)^{\frac{1}{\omega_j}} \left( \frac{A_h^j}{A_h^j} \right)^{\frac{\epsilon}{1 + \tau_a^j}} \left( \frac{\pi_h^j}{\pi_a^j} \right)^{\frac{\sigma - 1}{\sigma}} \left( \frac{\Omega_h^j}{\Omega_a^j} \right)^{\frac{1}{1-\sigma}} \left( 1 + \frac{1}{E_{hl}^j} \right)^{\frac{\sigma - 1}{\sigma}} \quad \text{(B.21)}$$

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 $E_{hl}^j$. 39
Note that we can re-write the skill premium only.

\[ E_{ja}^h \equiv \frac{p_j^h c_j^h}{p_a c_a} = (\omega_j^h)^{\frac{1}{1-\tau_j^h}} \left( \frac{\omega_j}{\omega_a} \right) \left( \frac{a_j^h}{a_j^e} \right) \left( 1 + \tau_j^h \right)^{-1-\varepsilon} \left( \frac{\tau_a}{\pi_j^h} \right) \left( \frac{\Omega_a}{\pi_j^h} \right)^{-\frac{\varepsilon}{1-\varepsilon}} \left( 1 + 1 - \frac{1}{E_j^h} \right)^{\frac{1-\varepsilon}{\eta_j^h}} \]  

(B.22)

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

\[ E_{ja}^l \equiv \frac{p_j^l c_j^l}{p_a c_a} = (1 - \omega_j^l)^{\frac{1}{1-\tau_j^l}} \left( \frac{\omega_j}{\omega_a} \right) \left( \frac{a_j^l}{a_j^e} \right) \left( 1 + \tau_j^l \right)^{-1-\varepsilon} \left( \frac{\tau_a}{\pi_j^l} \right) \left( \frac{\Omega_a}{\pi_j^l} \right)^{-\frac{\varepsilon}{1-\varepsilon}} \left( 1 + 1 - \frac{1}{E_j^l} \right)^{\frac{1-\varepsilon}{\eta_j^l}} \]  

(B.23)

Thus, we have expressed the expenditure ratios \( \{E_m^h, E_k^h, E_m^l, E_k^l\} \) as functions of the skill premium only.

### B.4 Labor Allocations

Note that we can re-write \( E_{ja} \) using (B.16) and (B.14) as follows:

\[ E_{ja} = \frac{p_j^h c_j^h}{p_a c_a} = \frac{p_j^h A_j^h L_j^h h_j}{p_a A_a L_a} = \frac{p_j^h A_j^h L_j^h h_j}{p_a A_a L_a h_a h_j} \]

Substituting (15)

\[ E_{ja} = \frac{p_j^h A_j^h}{p_a A_a} \left( \frac{\tau_j^h}{\Omega_j^h} \right)^{\frac{1}{1-\tau_j^h}} \left( \frac{\Omega_a}{\pi_j^h} \right)^{\frac{\varepsilon}{1-\varepsilon}} \left( \frac{h_j}{h_a} \right) \]

Substituting (16)

\[ E_{ja} = \left( \frac{1 + \tau_j^l}{1 + \tau_a} \right) \left( \frac{\Omega_j^l}{\Omega_a} \right) \left( \frac{h_j}{h_a} \right) \]

Which solving for \( h_j^l / h_a \) yields

\[ \frac{h_j^l}{h_a} = E_{ja} \left( \frac{1 + \tau_a}{1 + \tau_j^l} \right) \left( \frac{\Omega_j^l}{\Omega_a} \right) \]  

(B.24)

From the market clearing condition of high-skilled workers and substituting (B.24)

\[ \frac{M_h}{h_a} = \sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} h_j^i \frac{h_a}{h_a} = \sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} E_{ja} \left( \frac{1 + \tau_a}{1 + \tau_j^l} \right) \left( \frac{\Omega_j^l}{\Omega_a} \right) \]

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

\[ \frac{h_a}{M_{h}} = \frac{1}{\sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} E_{ja} \left( \frac{1 + \tau_a}{1 + \tau_j^l} \right) \left( \frac{\Omega_j^l}{\Omega_a} \right) \]

(B.25)

Similarly, for low-skilled labor in agriculture:
\[ \frac{M_l}{M_h} = \frac{1}{M_h} \sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} l_{ij} = \frac{h_a}{M_h} \sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} l_{ij} h_{ij} \]

Solving for \( \frac{h_a}{M_h} \) and substituting (B.15) and (B.24) we get

\[ \frac{h_a}{M_h} = \sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} \left( \frac{w^h}{w^l} \right)^\sigma \left( \frac{1 - \pi_{ij}^a \Omega_j}{\pi_{ij}} \right)^\sigma \left( \frac{1 + \tau_a}{1 + \tau_l} \right) \left( \frac{\Omega_j^l}{\Omega_a^l} \right) \]

(B.26)

The equilibrium is characterized by one equation in one unknown \( \left( \frac{w^h}{w^l} \right) \) which is obtained by equating (B.25) and (B.26). The skill premium depends on the relative expenditure shares with respect to the agricultural good, and these expenditure shares are given by (B.17), (B.22), and (B.23).

Once the relative expenditure shares have been obtained, we can get employment shares as follows. Let employment share of sector \( j \) subsector \( i \) be \( N_{ij}^l \), then, by definition

\[ N_{ij}^l = \frac{l_{ij}^l + h_{ij}^l}{\sum_{k \in \{a,m,s\}} \sum_{s \in \{h,l\}} l_{ik}^s + h_{is}^s} = \frac{l_{ij}^l + h_{ij}^l}{M_h + M_l} \]

This can be rewritten as

\[ N_{ij}^l = \frac{l_{ij}^l + h_{ij}^l}{M_h + M_l} = \frac{h_a}{M_h} \left( \frac{1}{1 + \frac{M_l}{M_h}} \right) = \frac{h_a}{M_h} \left( \frac{M_h}{h_a} \right) \left( \frac{1 + \frac{M_l}{M_h}}{1 + \frac{M_h}{M_l}} \right) \]

(B.27)

Note that \( \frac{l_{ij}^l}{h_{ij}^l} \) is obtained from (B.15), \( M_h/h_a \) from (B.25), \( h_{ij}^l/h_a \) ratio from (B.24), 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. \( Y_{ij}^l / (l_{ij}^l + h_{ij}^l) \). Before obtaining an expression for labor productivity, note we can rewrite the production function as

\[ Y_{ij}^l = h_{ij}^l \xi_j^l \left( \frac{\pi_{ij}^l}{\Omega_j^l} \right) \]

Dividing now by \( (l_{ij}^l + h_{ij}^l) \) and inverting it we get

\[ \frac{l_{ij}^l + h_{ij}^l}{Y_{ij}^l} = \frac{l_{ij}^l + h_{ij}^l}{h_{ij}^l} \frac{1}{\xi_j^l} \left( \frac{\Omega_j^l}{\pi_{ij}^l} \right) \]

Using (B.15) and inverting again, we obtain real labor productivity as (B.28) which is (19) in the main text.

\[ \frac{Y_{ij}^l}{l_{ij}^l + h_{ij}^l} = \frac{1}{1 + \left( \frac{w^h}{w^l} \right)^\sigma \left( \frac{1 - \pi_{ij}^l \Omega_j}{\pi_{ij}^l} \right)^\sigma \left( \frac{1 + \tau_a}{1 + \tau_l} \right) \left( \frac{\Omega_j^l}{\Omega_a^l} \right)} \]

(B.28)
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 $l_{ij}$ in terms of $l_a/h_a$ and $h_{ij}$ as

$$l_{ij} = l_a \left( \frac{\pi_a - 1 - \pi_{ij}}{\pi_a - 1 - \pi_{ij}} \right)^{\sigma} \frac{h_{ij}}{h_a}$$

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

$$l_a = \left( \frac{\pi_a - 1 - \pi_{ij}}{\pi_a - 1 - \pi_{ij}} \right)^{\sigma} \frac{M_l}{\sum_{j \in \{a,m,s\}} \sum_{i \in \{h,l\}} \left( \frac{\pi_i - 1 - \pi_{ij}}{1 - \pi_{ij}} \right)^{\sigma} \frac{h_{ij}}{h_a}}$$

(B.29)

Note that $M_l$ is exogenous and we can solve for $h_{ij}/h_a$ using (B.24). From the firm’s first order condition (B.15) and from (B.29) we obtain $h_a$. To solve for $h_{ij}$ we use our solution of $h_a$ into (B.24). Finally, $l_{ij}$ is obtained from (B.15) and the solution for $h_{ij}$. 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 (B.30).

$$Y_t = p_{a0}Y_{at} + p_{m0}Y_{mt} + p_{s0}Y_{st} + p_{h0}Y_{ht} + p_{l0}Y_{lt}$$

(B.30)

Appendix C Additional Tables and Graphs

Table 13: Three-Sector Split

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<th>SERVICES</th>
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<td>Hotels and Restaurants</td>
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<td>Transport and Storage</td>
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<td>Manufacturing, nec, recycling</td>
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Table 14: Cross-country Comparison of Labor Productivity Growth

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<td>(0.00141)</td>
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<tr>
<td>Log of GDP per capita</td>
<td>-0.292*</td>
<td>-0.493</td>
<td>-0.502*</td>
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<td>(0.311)</td>
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<td>Log of GDP per capita squared</td>
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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 15: Labor Productivity in India Within Asia

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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 16: Labor Productivity in India

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<td>Services</td>
<td>Agriculture</td>
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<td>0.0219***</td>
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<td>-0.00154**</td>
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<td>Log of GDP per capita</td>
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<td>(0.313)</td>
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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.
Figure C.1: 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,
Table 17: Returns to Schooling by Sector and Year

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<td>0.000</td>
<td>0.000</td>
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<td>High-Manufacturing</td>
<td>0.466*** (0.012)</td>
<td>0.521*** (0.018)</td>
<td>0.447*** (0.014)</td>
<td>0.486*** (0.016)</td>
<td>0.422*** (0.016)</td>
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<td>0.346*** (0.017)</td>
<td>0.478*** (0.016)</td>
<td>0.482*** (0.012)</td>
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<td>0.726*** (0.020)</td>
<td>0.634*** (0.019)</td>
<td>0.647*** (0.027)</td>
<td>0.536*** (0.023)</td>
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<td>0.038*** (0.004)</td>
<td>0.028*** (0.002)</td>
<td>0.031*** (0.002)</td>
<td>0.022*** (0.002)</td>
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<td>0.082*** (0.002)</td>
<td>0.080*** (0.002)</td>
<td>0.082*** (0.002)</td>
<td>0.088*** (0.002)</td>
</tr>
<tr>
<td>Low-Manufacturing</td>
<td>0.069*** (0.004)</td>
<td>0.073*** (0.005)</td>
<td>0.040*** (0.004)</td>
<td>0.039*** (0.002)</td>
<td>0.035*** (0.002)</td>
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<td>High-Services</td>
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<td>0.079*** (0.002)</td>
<td>0.082*** (0.002)</td>
<td>0.095*** (0.003)</td>
<td>0.107*** (0.002)</td>
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<td>0.098*** (0.002)</td>
<td>0.094*** (0.002)</td>
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Data: IPUMS-I. Robust standard errors in parenthesis. * p < 0.05, ** p < 0.01, *** p < 0.001. Controls include age, age squared, and sex.