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# SERVICE-LED OR SERVICE-BIASED GROWTH? EQUILIBRIUM DEVELOPMENT ACCOUNTING ACROSS INDIAN DISTRICTS

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**ABSTRACT**

In many developing countries today, the structural transformation is a shift of employment out of agriculture into the service sector. By contrast, industrial employment is mostly stagnant. Is the service sector an engine of growth and hence growth service led? Or is its expansion a mere corollary of growth, where rising incomes stemming from productivity growth in goods-producing industries increases the demand for services? To determine whether growth is service led or service biased, we estimate a spatial equilibrium model with nonhomothetic preferences. Our methodology is in the spirit of development accounting and lends itself to a quantitative assessment of both the aggregate and the heterogenous welfare effects of sectoral productivity growth. In an application to India, we find that productivity growth in consumer services such as retail and hospitality was an important driver of rising living standards between 1987 and 2011. However, such benefits were highly skewed and accrued mostly to high-income households living in urbanized locations.

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# Service-Led or Service-Biased Growth?

## Equilibrium Development Accounting across Indian Districts

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**Abstract**

In many developing countries today, the structural transformation is a shift of employment out of agriculture into the service sector. By contrast, industrial employment is mostly stagnant. Is the service sector an engine of growth and hence growth service led? Or is its expansion a mere corollary of growth, where rising incomes stemming from productivity growth in goods-producing industries increases the demand for services? To determine whether growth is service led or service biased, we estimate a spatial equilibrium model with nonhomothetic preferences. Our methodology is in the spirit of development accounting and lends itself to a quantitative assessment of both the aggregate and the heterogenous welfare effects of sectoral productivity growth. In an application to India, we find that productivity growth in consumer services such as retail and hospitality was an important driver of rising living standards between 1987 and 2011. However, such benefits were highly skewed and accrued mostly to high-income households living in urbanized locations.

# 1 Introduction

The major industrialized countries have undergone a similar pattern of structural transformation. At an early stage of development, a growing industrial sector drew labor from a declining agricultural sector. At a later stage, the employment shares of both agriculture and manufacturing fell, while the service sector became the main source of employment growth. This pattern fits the experience of most Western and East-Asian economies. However, in other parts of the globe, economic development appears to have taken a different turn. Over the last four decades, the share of manufacturing jobs has barely grown in most developing countries, including fast-growing economies such as India and sub-Saharan Africa. There, the structural transformation has taken the form of a shift from agriculture to services.

To many scholars (e.g., McMillan and Rodrik (2011) or Rodrik (2015)), the absence of employment growth in the manufacturing sector is a cause of concern. Traditionally, technical progress in manufacturing is seen as the engine of growth. By contrast, the expansion of the service sector is often interpreted as a by-product of growth driven by rising incomes. Hence, growth is often characterized as service biased, but not service led.

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A key hurdle to resolving this controversy is measurement: quantifying productivity growth in service industries is difficult. In this paper, we propose a novel structural methodology that allows us to estimate productivity in the service sector and quantitatively assess its importance for the development process. We then apply this methodology to the growth process of India since 1987. Our results go against this pessimistic view. We find substantial productivity growth in consumer services such as retail or hospitality that can account for about one third of aggregate welfare gains. In short: Indian growth was to a large extent service led.

**Methodology: Equilibrium Development Accounting.** Our approach follows the tradition of the development accounting literature. We do not attempt to explain the determinants of productivity growth but provide a method to measure sectoral productivity through the lens of a structural model. The estimation is disciplined by a theory that stands on two building blocks: (i) nonhomothetic preferences, and (ii) a spatial multisector equilibrium model with inter-regional trade where firms have heterogeneous productivities in different locations. These two ingredients allow us to capture two important features of services: the possibility of service-biased growth if services are luxuries and the fact that services are non-tradable and hence depend on local demand.

Because the service sector is broad and heterogeneous, we split it into two parts. Many services improve households' access to consumption goods (e.g., restaurants or retail) or directly enter their consumption basket (e.g., leisure services). We call these services *consumer services (CS)*. Other services are predominantly inputs to the production of goods, mostly in the industrial sector, and include, among others, business services, corporate law services, and part of transport services. We refer to such services as *producer services (PS)*. To capture this distinction, we model CS as directly entering the households' consumption basket so that consumers' preferences are defined over three final items: *food*, *industrial goods*, and *CS*. By contrast, PS are inputs into the production of industrial goods so that people can work in four sectors of activity: agriculture, manufacturing, PS and CS.

To highlight the fact that restaurant visits and personal services are local goods, we assume food and industrial goods are freely traded, whereas CS have to be purchased locally. Local CS productivity therefore directly affects the price and availability of CS in each market. Similarly, local income directly affects the demand for the local provision of CS. By contrast, PS are embedded in industrial goods so that their value added is tradable. To close the model, we assume labor is the only productive factor and is perfectly mobile across industries although immobile across locations. Thus, there is a single wage per effective unit of labor in each location, although wages differ across locations. These assumptions are extreme but can be relaxed by introducing non-prohibitive labor-mobility frictions across both sectors and space.

Our model allows us to disentangle the relative importance of service-biased versus service-led growth by estimating the variation in sectoral productivity across space and time. Conditional on a set of preference and technology parameters, regional endowments of human capital, and sectoral labor productivity in each region, the model yields a unique equilibrium vector of wages and sectoral labor allocations. Conversely, if we have data for the allocation of labor across sectors in each district and for local earnings, we can retrieve a unique set of labor productivity for each region-sector pair that rationalizes the data.

The main identification challenge emerges because of non-homothetic preferences. For example, imagine two small districts $R$ (rich) and $P$ (poor), which are part of a large multi-district economy, and abstract for simplicity from PS. Let $A_{rs}$ denote labor productivity in district $r$ and sector $s$. Consider two polar opposite scenarios. In the first scenario, $A_{RF} > A_{PF}$ and $A_{RM} > A_{PM}$; that is, the productivity of the tradable sectors food and manufacturing are larger in $R$ than in $P$. Instead, the productivity of CS is the same in both districts, $A_{RCS} = A_{PCS}$. In equilibrium, workers in district $R$ earn a higher wage. If food is a necessity and CS is a luxury, consumers in $R$ will spend a higher share of their income on CS, whereas consumers in $P$ will spend a higher share of their income on food. Because CS is nontradable, district $R$ will also have a larger employment share in CS, whereas $P$ will specialize in the production of goods.[1] In this scenario, spatial differences in expenditure and employment shares are entirely driven by income effects in demand. We refer to this case as *service-biased growth*.

The second scenario is one in which productivity in the tradable sectors is identical in $R$ and $P$, whereas $A_{RCS} > A_{PCS}$. As before, district $R$ is richer, has a larger service sector, and consumers spend a smaller share of their budget on food. However, in this case, any difference stems from a technological gap in the CS sector. We refer to this scenario as *service-led* growth.

Although the example highlights the difference across space, the same argument applies to the analysis of a given district at two points in time. Under *service-biased growth*, the growth of the service sector would be entirely a consequence of the productivity growth in the goods-producing sectors. Under *service-led growth*, productivity growth in the service sector would be the sole cause of productivity growth and structural change.

To solve this identification problem, we estimate the aggregate demand system for consumer services and directly measure the strength of the income effect. The key aspect of the demand system is the income elasticity. If service demand is very income elastic, growth tends to be service biased, because rising incomes sharply increase service demand. If, by contrast, this income elasticity is small, changes in employment indicate changes in productivity.

Given the pivotal role of this elasticity, we estimate it from Engel curves using microdata on income and expenditure. To link this empirical estimate to the aggregate demand system of our theory, we have to address two challenges. First, in the presence of nonhomothetic preferences, the income elasticity at the micro level is not necessarily informative about the elasticity of aggregate demand. Second, as stressed in Herrendorf et al. (2013), in general, no direct mapping exists between the preference parameters estimated from data on final expenditure to the ones of the value-added demand system used in our theory.

The preference specification we opt for overcomes both of these difficulties. We model preference as belonging to the PIGL class, which was first introduced by Muellbauer (1976) and has been recently popularized in the literature on growth and structural change by Boppart (2014) and Alder et al. (2019). The PIGL preference class has a crucial aggregation property: the choice of a set of agents endowed with PIGL preferences facing a common price vector can be rationalized as the choice of a representative agent whose preferences also fall into the PIGL class. In particular, the parameter governing the income elasticity for aggregate value added coincides with the micro elasticity. Moreover, we also show this parameter can be estimated from data on final expenditure.

Our methodology allows us quantify the extent to which the growth of the service sector is either a source or a consequence of the development process. First, it provides us with an estimate of sectoral productivity growth at the regional level so that we can directly determine whether productivity in the service sector actually grew. Second, it lends itself to a quantitative assessment of both the aggregate and the heterogenous welfare impact of service-led growth. In particular, when agents have nonhomothetic preferences and live in different locations characterized by different provision of local services, the growth of different sectors benefits people differentially–rich versus poor as well as urban versus rural residents. Using our model, we can quantify the heterogeneous welfare gains of service-led growth both across the income distribution and across space. We view this as important, because growth theory is often criticized for glossing over the distributional implications of economic growth.

**Application: Service-led growth in India (1987-2011).** We apply our methodology to India, a fast-growing economy, with an average annual growth rate of 4.2% during 1987–2011. In this period, the lion's share of the

[1] Because food and industrial goods are tradable, whether $P$ specializes in agriculture or industry depends on its comparative advantages.

process of structural change was a shift from agriculture to services. Our estimation exploits individual geolocalized consumption and employment data, and we estimate sectoral productivity growth for almost 400 Indian districts.

Our results are interesting in several respects. First, at the spatial level, there are large sectoral productivity differences. In particular, the CS sector features a large productivity gap between urban and rural districts. Thus, urban districts have a higher service employment share not only because their inhabitants are richer, but also because the market provides them more efficiently.

Second, we document a very important role for service-led growth. At the aggregate level, rising efficiency in the provision of consumer services accounts for almost one third of the increase in living standard since 1987. For comparison, the impact of agricultural productivity growth is roughly similar, but growth in the industrial sector was substantially less important. To the best of our knowledge, this paper is the first to quantify the importance of the consumer-service sector for a developing economy such as India.

Third, service-led growth is very unequal. Productivity growth in CS is the main source of welfare gains for richer households, especially those in urbanized districts. The residents in the top quintile of urbanization would have been better off taking a 42% income cut in 2011 than moving back to the productivity that the CS sector had in 1987. By contrast, for poorer households living in rural districts, improvements in living standards hinge mostly on productivity growth in agriculture.

Finally, productivity growth in CS turns out to also be the key driver of structural change. Had productivity in the service sector stagnated, the employment share of agriculture would not have declined. By contrast, the effect of agricultural productivity growth is negligible.

**Related Literature.** Our paper contributes to the macroeconomic literature on the structural transformation including, among others, Ngai and Pissarides (2007), Herrendorf et al. (2013, 2014, and 2020), Gollin et al. (2014), Hobijn et al. (2019), and Garcia-Santana et al. (2020).

A recent literature focuses on the service sector, however, mostly with a focus on developed economies such as the US. Buera and Kaboski (2012) emphasize the importance of the (demand-driven) growth of a skill-intensive service industry in the post-1950s US economy. Hsieh and Rossi-Hansberg (2019) argue that in more recent years, ICT has triggered an industrial revolution and has been a major source of productivity growth. Their view is echoed by Eckert et al. (2020) who argue service-led growth is the main cause of the growing urban-rural gap in the US. An exception to this rich-country focus is Duarte and Restuccia (2010), who document large cross-country productivity differences in service industries, a finding broadly in line with our results across locations within India, and Gollin et al. (2015), who emphasize how urbanization often goes hand in hand with a booming consumption of non-tradable services, although their focus on such "consumption cities" in resource-rich African economies is very different from ours. Finally, our finding that service growth was decidedly pro-rich and pro-urban is consistent with Chatterjee and Giannone (2021), who use data on regional income growth for a large number of countries and document that rising productivity in services is associated with regional divergence.

On the methodological side we build on the large literature on development accounting; see, for example, Caselli (2005) and Hall and Jones (1999). This literature postulates aggregate production functions and uses information on the accumulation of productive factors to fit the data. Our methodology is closer to the structural development accounting of Gancia et al. (2013), who exploit the restrictions imposed by an equilibrium model to identify sectoral productivities. Similarly, Cheremukhin et al. (2015) and Cheremukhin et al. (2017) use an accounting approach in conjunction with a neoclassical growth to study the determinants of growth in China and Russia.

We perform our accounting exercise in the context of a model with inter-regional trade linkages, commonly used in the economic geography literature; see, for example, Redding and Rossi-Hansberg (2017) or Allen and Arkolakis (2014). In contrast to these papers, we abstract from labor mobility, even though one could extend our methodology to allow for it. Cravino and Sotelo (2019) is a recent example of an analysis of the structural transformation in the context of a model with international trade.

Non-homothetic preferences play a key role in our analysis. The classic reference for the service bias (and resulting cost disease) of economic growth is Baumol (1967). Earlier papers emphasizing their importance for the growth process include Foellmi and Zweimueller (2006), Kongsamut et al. (2001), and Matsuyama (2000). The more recent literature on structural change with nonhomothetic preferences includes, among others, Boppart (2014) and Alder et al. (2019) who, like us, propose generalizations of the PIGL preferences class proposed in Muellbauer (1976). Eckert and Peters (2020) is the first paper to incorporate these preferences in a spatial model of structural change. In contrast to us, they focus on the interaction between spatial mobility and the structural transformation. Instead, Matsuyama (2019) and Comin et al. (2020) use a class of generalized CES preferences related to Sato (2014). The authors show these preferences can account accurately for the patterns of structural transformation across several countries. In our paper, we use PIGL preferences because their tractable and transparent aggregation properties are especially suitable. Exploring a different class of preferences would certainly be interesting, but we leave it for future research.

We also contribute to the vast literature on economic development of India including, among others, Aghion et al. (2005, 2008), Akcigit et al. (2020), Basu (2008), Basu and Maertens (2007), Foster and Rosenzweig (1996, 2004), Goldberg et al. (2010), Kochhar et al. (2006), and Martin et al. (2017).

**Road Map.** The structure of the paper is as follows. Section 2 presents some stylized facts of the role of services in India. Section 3 lays out the theoretical framework. Section 4 describes the data and the main empirical patterns in India. Section 5 discusses the estimation method. Section 6 discusses the main results. Section 7 performs robustness analysis. Section 8 concludes. The Appendix contains technical details, a description of the data sources, and additional tables and figures.

# 2 Structural Change and Service Growth in India: 1987-2011

Between 1987 and 2011, the Indian economy experienced a remarkable transformation. Not only did income per capita grow by a factor of 3, but the employment structure also changed markedly. In Figure 1, we show the time-series evolution of sectoral employment shares.[2] Panel (a) is based on the standard ISIC classification. Two facts are apparent: First, agriculture is the largest employment source, accounting for almost half of total employment in 2011. Second, the structural transformation in India is mostly an outflow of agriculture and an inflow into services and construction. Today, the service sector accounts for one third of aggregate employment. By contrast, employment in the manufacturing sector is stagnant. Panel (b) relies on a model-based classification of activities to which we return in Section 4.

The service sector encompasses a set of heterogeneous activities. In Figure 2, we decompose it into five subsectors: (1) Wholesale, Retail, Hotel and Restaurant; (2) Health and Community Services; (3) Financial, Business, and Transport; (4) ICT, and (5) Education and Public Administration (PA). The first and second subsectors, which serve mostly consumers, employed well over half of all Indian service workers in 2011. The third and fourth subsectors sell part of their services to industrial firms. Finance, business, and transport services accounted for

[2] The figure is constructed using micro data on employment from the NSS whose description is deferred to Section 4.

Panel a: Structural Change in India (ISIC class.) Panel b: Structural Change in India (our sample)

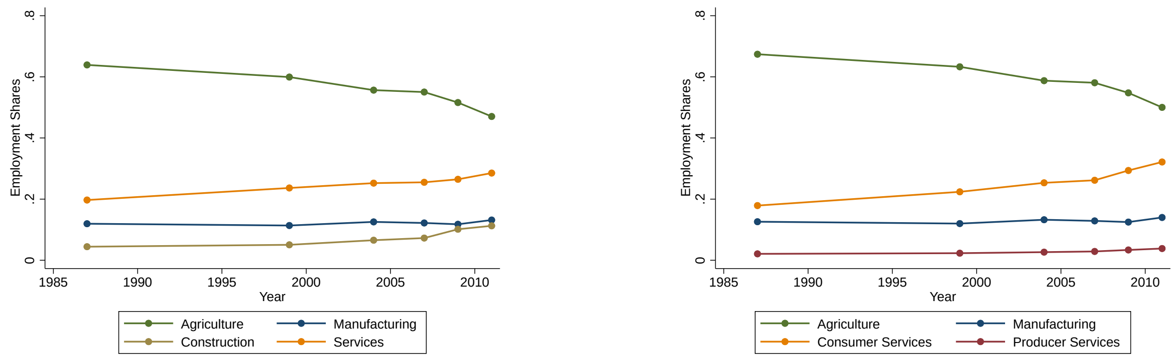


Figure 1: Structural Change in India: 1987–2011. The figure shows the evolution of sectoral employment shares over time. Panel (a) is based on a standard ISIC classification. Panel (b) is based on the classification we use in our analysis—see Section 4.

about a quarter of service sector employment in 2011. Although the growth rate of employment in the ICT sector was especially fast, this sector accounts for a mere 3.1% of service employment in 2011. Education and PA are mostly government-run activities. The share of the Indian labor force employed in this subsector is constant over time—in contrast to all other subsectors that grew rapidly during the period studied.[3] Thus, the expansion of services in India is not confined to business-oriented service industries, such as finance and ICT services. The vast majority of employment gains are found in consumer services such as retail, hospitality, and health.

Figure 2 also highlights important differences across local labor markets in India. We split India into rural and urban districts, broken down so that approximately half of the workers belong to rural districts and urban districts, respectively. Service activities are more prevalent in urban than in rural areas, especially so in business-oriented activities such as financial services and ICT.

Was this expansion of the service sector shown in Figures 1 and 2 a source or a corollary of Indian growth? In the remainder of the paper, we argue that rising service productivity was indeed an important source.

# 3 Theory

We consider a general equilibrium environment with $R$ regions. Consumers have preferences over three goods: agricultural goods (F for *food*), industrial goods (G for *goods*), and consumer services (CS). A single factor of production—labor— is inelastically supplied. Whereas goods and food are tradable, CS are not traded and must be provided locally. All markets are frictionless and competitive.

Our theory reflects the three salient aspects highlighted in Figures 1 and 2. First, we allow consumer preferences to be non-homothetic. Hence, the increase in retail employment can be driven both by income effects and by rising productivity in the retail sector. Second, we break down services into CS that—like retail—directly enter consumers' utility functions and PS that—like corporate legal services—are inputs to the production of goods. Finally, we assume services to be non-tradable across space so that some locations (e.g., cities) specialize in services because they are efficient in providing them or because their inhabitants are rich (or both).

[3] In absolute terms, employment in the first and second subsectors increased by approximately 32 million in 1987–2011. Employment in the third and fourth subsectors increased by approximately 20 million. Finally, employment in education and PA increased by approximately 7 million—proportionally to the growth of the labor force.

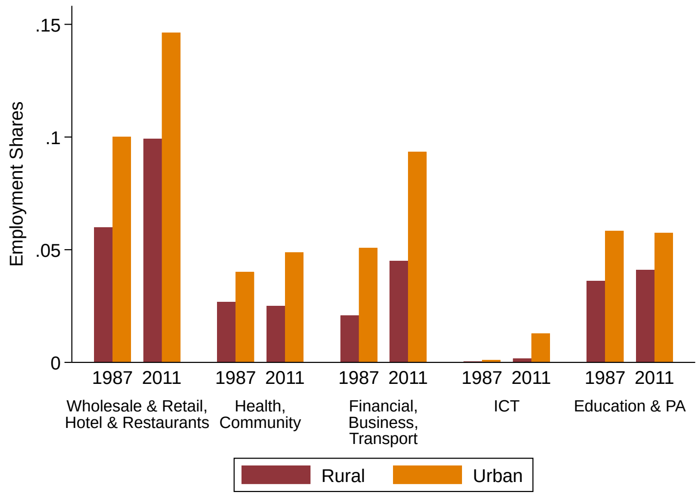


Figure 2: Service Industries. The figure displays the employment shares in 1987 and 2011 of five groups of service industries: (1) Wholesale, Retail, Hotel, and Restaurants; (2) Health and Community Services; (3) Financial, Business, and Transport Services; (4) ICT Services; and (5) Education and Public Administration.

## 3.1 Technology and Preferences

**Technology.** All goods and services are produced under constant return technologies such that

$$Y_{rst} = A_{rst} H_{rst} \quad \text{for } s = F, CS, G,$$

where $H_{rst}$ denotes the amount of human capital employed in sector $s$ in region $r$ at time $t$. Whereas we take total productivity in agriculture, $A_{rFt}$, and CS, $A_{rCSt}$, as exogenous, productivity in the industrial sector, $A_{rGt}$, is endogenously determined. However, in Section 3.5, we show the equilibrium allocation in the industrial sector implies $Y_{rGt} = A_{rGt} H_{rGt}$, where $A_{rGt}$ is a function of structural parameters that does not depend on equilibrium prices. Therefore, we can characterize the general equilibrium taking $A_{rGt}$ as if it were a primitive, and then solve for the equilibrium in the industrial sector.

**Preferences.** We assume consumers' preferences to be in the PIGL class. PIGL preferences have two important advantages for us. First, they allow us to parameterize the extent of nonhomotheticity in a flexible way, which we can estimate from individual data. Second, they have simple and transparent aggregation properties that allow us to take a district-level demand system to the data.

PIGL preferences do not have an explicit utility representation but are represented by an indirect utility function of the form

$$V(e, \mathbf{p}) = \frac{1}{\varepsilon} \left( \frac{e}{B(\mathbf{p})} \right)^{\varepsilon} - D(\mathbf{p}), \tag{1}$$

where $e$ denotes total spending and $\mathbf{p}$ the vector of prices of goods. The function $D(\mathbf{p})$ and $B(\mathbf{p})$ are homogeneous of degree zero and one, respectively.

For the traded commodities, consumers buy a CES aggregate of differentiated regional varieties with an elasticity of substitution $\sigma$. We parameterize the functions $B(\mathbf{p})$ and $D(\mathbf{p})$ in (1) as

$$B(\mathbf{p}) = \prod_{s\in\{F,G,CS\}} p_s^{\omega_s} \quad \text{and} \quad D(\mathbf{p}) = \left(\sum_{s\in\{F,G,CS\}} \tilde{\nu}_s \ln p_s\right),$$

with $\sum_s \omega_s = 1$ and $\sum_s \tilde{\nu}_s = 0$. This specification yields the indirect utility function

$$V(e,\mathbf{p}) = \frac{1}{\varepsilon}\left(\frac{e}{\prod_s p_s^{\omega_s}}\right)^{\varepsilon} - \sum_s \tilde{\nu}_s \ln p_s. \tag{2}$$

Roy's Identity implies the sectoral expenditure shares associated with $V(e,p)$ (see Section A-1 in the Appendix) are given by

$$\vartheta_s^h(e,\mathbf{p}) = \omega_s + \tilde{\nu}_s\left(\frac{e}{\prod_s p_s^{\omega_s}}\right)^{-\varepsilon}. \tag{3}$$

Equation (3) highlights income and price effects. The expenditure share on $s$ is increasing in income (i.e., $s$ is a luxury) if and only if $\tilde{\nu}_s < 0$. For instance, if food is a necessity, $\tilde{\nu}_F > 0$ and its expenditure share converges to $\omega_F$ from above. Likewise, if CS is a luxury, $\tilde{\nu}_{CS} < 0$ and $\vartheta_{CS}^h$ increases toward $\omega_{CS}$ from below. The strength of nonhomotheticities is governed by the parameter $\varepsilon$, which, with a slight abuse of terminology, we label the "income elasticity". This income elasticity $\varepsilon$ turns out to be the crucial parameter in our analysis.

### 3.2 Heterogeneity, Aggregate Demand, and Welfare

As already mentioned, PIGL preferences have nice aggregation properties. Suppose individuals have heterogeneous abilities, and let $w_{rt}$ denote the wage per efficiency unit of labor. Income (and expenditure) for individual $h$ is then given by $e_{rt}^h = q^h w_{rt}$, where $q^h$ is the number of efficiency units of labor. Let $F_{rt}(q)$ denote the distribution function of $q$ in region $r$ at the $t$. Empirically, we will relate the spatial variation in the distribution of $q$ to observable differences in human capital. Using (3), the *aggregate* spending share on goods in sector $s$ in region $r$ is then given by

$$\vartheta_{rs}(w_{rt},\mathbf{p_{rt}}) \equiv \frac{L_{rt}\int \vartheta_s^h(qw_{rt},p_{rt})\, qw_{rt}dF_{rt}(q)}{L_{rt}\int qw_{rt}dF_{rt}(q)} \quad = \quad \omega_s + \nu_{rs}\left(\frac{E_{rt}[q]\,w_{rt}}{p_F^{\omega_F}p_G^{\omega_G}p_{CSr}^{\omega_{CS}}}\right)^{-\varepsilon}, \tag{4}$$

where

$$\nu_{rs} \equiv \frac{E_{rt}\left[q^{1-\varepsilon}\right]}{E_{rt}[q]^{1-\varepsilon}}\tilde{\nu}_s. \tag{5}$$

Comparing (4) and (3) highlights in what sense PIGL allows for a representative household: the aggregate demand system is isomorphic to that of a representative consumer in region $r$ who earns the average income $E_{rt}[q]\,w_{rt}$, and has the inequality-adjusted preference parameter $\nu_{rs}$ instead of the primitive parameter $\tilde{\nu}_s$.

The correct inequality-adjustment to go from the micro preferences $\tilde{\nu}_s$ to the market demand parameters $\nu_{rs}$ is given by $E_{rt}\left[q^{1-\varepsilon}\right]/E_{rt}[q]^{1-\varepsilon}$ and hence depends, in general, on the local income distribution. The analysis simplifies further if we assume $q$ follows a Pareto distribution with c.d.f. $F_{rt}(q) = 1 - \left(\underline{q}_{rt}/q\right)^{\zeta}$, with a region-invariant tail parameter $\zeta$. Then, $E_r[q] = \frac{\zeta}{\zeta-1}\underline{q}_r$ and $E_r\left[q^{1-\varepsilon}\right] = \frac{\frac{\zeta}{1-\varepsilon}}{\frac{\zeta}{1-\varepsilon}-1}\underline{q}_r^{1-\varepsilon}$, so that equation (5) simplifies to $\nu_{rs} = \nu_s \equiv \frac{\zeta^{\varepsilon}(\zeta-1)^{1-\varepsilon}}{\zeta+\varepsilon-1}\tilde{\nu}_s$. Thus, if income is Pareto distributed with a common tail parameter, all regions have the same "aggregate" parameter $\nu_s$, which is proportional to the primitive individual preference parameter $\tilde{\nu}_s$. In this case, regional demand differences are solely driven by local prices, wages, and human capital $E_{rt}[q] \propto \underline{q}_{rt}$, and we can write $\vartheta_{rs}(w_{rt}, \mathbf{p_{rt}}) = \vartheta_s\left(\underline{q}_{rt} w_{rt}, \mathbf{p_{rt}}\right)$. Hence, despite heterogeneity in income and non-homothetic preferences, we can express aggregate demand as a function of wages, prices, and the average level of efficiency.

A similar aggregation property also allows us to calculate utilitarian welfare in location $r$. Given the local skill distribution $F_{rt}$ and a vector of local wages and prices, utilitarian welfare is defined as $\mathcal{U}_{rt}(w_{rt}, \mathbf{p_{rt}}) \equiv \int V(qw_{rt}, p_{rt})\, dF_{rt}(q)$. Using the indirect utility function in (2), $\mathcal{U}_{rt}(w_{rt}, \mathbf{p_{rt}})$ has the simple closed-form expression

$$\mathcal{U}_{rt}(w_{rt}, \mathbf{p_{rt}}) = \mathcal{U}(E_{rt}[q] w_{rt}, \mathbf{p_{rt}}) = \frac{\zeta^{1-\varepsilon}(\zeta-1)^{\varepsilon}}{\zeta-\varepsilon} \times \left(\frac{1}{\varepsilon}\left(\frac{E_{rt}[q] w_{rt}}{p_{Ft}^{\omega_F} p_{Gt}^{\omega_G} p_{rCSt}^{\omega_{CS}}}\right)^{\varepsilon} - \sum_s \nu_s^{\mathcal{U}} \ln p_{rst}\right), \tag{6}$$

where $\nu_s^{\mathcal{U}} \equiv \nu_s \times ((\zeta-\varepsilon)(\zeta-(1-\varepsilon)))/(\zeta(\zeta-1))$. Hence, utilitarian welfare is akin to the indirect utility of a representative agent with average income $E_{rt}[q] w_{rt}$ and a scaled taste parameter $\nu_s^{\mathcal{U}}$ that accounts for the income distribution ($\zeta$) and the income elasticity ($\epsilon$). Note that given this scaled taste parameter, the distribution $F_{rt}$ only enters through the average income term $E_{rt}[q] w_{rt}$. Hence, we also write $\mathcal{U}_{rt}(w_{rt}, \mathbf{p_{rt}}) = \mathcal{U}(E_{rt}[q] w_{rt}, \mathbf{p_{rt}})$ to stress that welfare differences across time and space depend entirely on wages $w_{rt}$, prices $p_{rt}$, and average human capital $E_{rt}[q]$.

Importantly, because CS are a luxury and productivity growth in CS lowers their price, the welfare benefits of an increase in the local productivity of CS is skewed toward the rich. The expenditure share $\vartheta_{CS}(e, \mathbf{p_{rt}})$ exactly measures the welfare exposure of a change in prices at the individual level.[4] Hence, richer households, that is, households with high human capital $q$ and households living in high-productivity locations benefit more from service-led growth. Below, we show the heterogeneity in the welfare impact across the income distribution is quantitatively large and makes service-led growth significantly pro rich.

### 3.3 Equilibrium

To characterize the equilibrium, recall that each variety of food and industrial goods is traded in the national market, whereas the market for CS clears locally. The CES demand structure and the fact that the competitive prices are given by $p_{rst} = A_{rst}^{-1} w_{rt}$ implies a set of nationwide market-clearing conditions for the two tradable goods

$$w_{rt} H_{rst} = \left(\frac{w_{rt}^{1-\sigma} A_{rst}^{\sigma-1}}{\sum_{j=1}^{R} w_{jt}^{1-\sigma} A_{jst}^{\sigma-1}}\right) \times \sum_{j=1}^{R} \vartheta_s\left(\underline{q}_{jt} w_{jt}, \mathbf{p_{rt}}\right) w_{jt} H_{jt} \qquad \text{for } s = F, G, \tag{7}$$

and a set of district-specific market-clearing conditions for nontradable CS,

$$w_{rt} H_{rCSt} = \vartheta_{CS}\left(\underline{q}_{rt} w_{rt}, \mathbf{p_{rt}}\right) w_{rt} H_{rt}. \tag{8}$$

Together with the market-clearing conditions for local labor markets, $H_{rF} + H_{rG} + H_{rCS} = H_r$, these equations fully describe the equilibrium.

[4] Formally, letting $e(\mathbf{p_{rt}}, V)$ denote the expenditure function of achieving a utility level of $V$ given prices $\mathbf{p_{rt}}$, $\partial \ln e(\mathbf{p_{rt}}, V)/\partial \ln p_{rCSt} = \vartheta_{CS}(e, \mathbf{p_{rt}})$.

### 3.4 Service-Led or Service-Biased Growth?

The equilibrium condition for the CS sector in (8) highlights the focal point of our analysis: Is growth service led or service biased? Using the definition of the expenditure share $\vartheta_{CS}$ in (4), the local CS employment share implied by(8) is given by

$$\frac{H_{rCSt}}{H_{rt}} = \omega_{CS} + \nu_{CS} p_F^{\varepsilon \omega_F} p_G^{\varepsilon \omega_G} \times \left( \underbrace{E_{rt}\left[q\right]}_{\text{Skills}} \times \underbrace{w_{rt}^{1-\omega_{CS}}}_{\text{Wages}} \times \underbrace{A_{rCSt}^{\omega_{CS}}}_{\text{Productivity}} \right)^{-\varepsilon}, \tag{9}$$

where we have eliminated $p_{rCS}$ using the competitive equilibrium condition $p_{rCS} = w_{rt}/A_{rCSt}$.

Equation (9) highlights how our theory encompasses both the possibility that growth was service-led and that growth was service-biased. Because preferences are nonhomothetic and CS are not tradable, employment depends on the local supply of skills ($E_{rt}\left[q\right]$), local wages ($w_{rt}$), and local productivity ($A_{rCSt}$). Hence, locations such as Delhi or Bangalore might have a large employment in the retail service industry either because consumers living there are, on average, rich or because the local retail sector is highly productive. Similarly, rising educational attainment and factor prices or rising productivity can increase CS employment over time. The former channel describes a *service-biased* growth scenario: the rise of service employment is due to income effects. The latter channel captures a *service-led* growth scenario where rising service employment is driven by rising productivity and the CS sector is a source rather than a corollary of growth.

To solve this identification problem, we leverage both the structure imposed by our theory and additional data. First, the data on earnings, schooling, and an estimate of the returns to schooling allow us to measure local skills and their price. Given an income elasticity $\varepsilon$ and the (endogenous) prices of tradable goods $p_F$ and $p_G$, we can use (9) to identify $A_{rCS}$. Similar to the traditional approach in development accounting, we use a set of structural parameters to identify productivity in a model-consistent way. However, our inference hinges on solving for a set of equilibrium prices, $p_F, p_G$, and $w_r$. For this reason, we label our methodology *equilibrium development accounting.*

### 3.5 Equilibrium in the Industrial Sector

Thus far, we have taken $A_{rG}$ as exogenous. In this section, we characterize the equilibrium of the industrial sector that determines $A_{rG}$. We assume each district's industrial good is produced by a continuum of firms using production workers and PS as inputs. PS are provided by a separate service sector comprising corporate law services, accounting, financial advising, and so on. Our theory explicitly allows for structural change to occur within the industrial sector in the form of an adoption of production techniques that are more intensive in PS over time.

**Environment.** We construct a model with heterogeneous firms where the demand of PS is related to firm size (or productivity). Intuitively, in small firms, activities such as accounting are carried out by the manager, whereas large firms outsource them to professional providers. We formalize this idea by positing a nonhomothetic production function of the following form:

$$y_i = z_i^{1-\alpha-\beta} H_{PMi}^{\alpha} \left(A_{rPS} H_{PSi} + \kappa\right)^{\beta}. \tag{10}$$

Here, $z_i$ is firm $i$'s productivity, and $H_{PMi}$ and $H_{PSi}$ denote the inputs of manufacturing production workers and PS, respectively. $A_{rPS}$ denotes the productivity of the PS sector in region $r$. The parameter $\kappa \geq 0$ governs the nonhomotheticity of firms' technology—if $\kappa > 0$, the input share of PS increases with firms' size. We assume

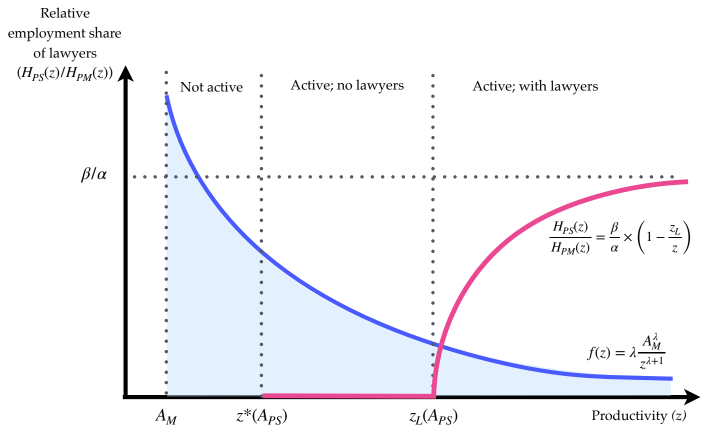


Figure 3: EQUILIBRIUM IN THE INDUSTRIAL SECTOR. The figure displays the main qualitative features of the industrial equilibrium. All firms with $z \geq z^*(A_{PS})$ are active. All firms with $z \geq z_L(A_{PS})$ demand PS. The shaded blue area represents the productivity distribution.

$\alpha + \beta < 1$, which captures a limited span of managerial control. Decreasing returns to scale guarantee firms earn profits in equilibrium.

The mass of active firms is endogenously determined via free entry. To enjoy the opportunity of drawing a realization from the productivity distribution, an entrant firm must pay a sunk labor cost of $f_E$ manufacturing workers. The productivity $z_i$ is drawn from a Pareto distribution $F_{rt}(z) = 1 - (A_{rMt}/z)^{\lambda}$, where $A_{rM}$ is a lower-bound productivity that parametrizes the state of technology in region $r$, and $\lambda > 1$ is the tail parameter of the Pareto distribution.

Active firms must hire $f_O$ manufacturing workers in order to start production. Some low-$z_i$ firms therefore might opt to remain inactive. In particular, we assume

$$\frac{f_O}{f_E} > \frac{\beta + (1-\alpha)(\lambda - 1)}{1 - \alpha - \beta}, \tag{11}$$

which ensures some low-productivity firms will choose not to be active. Although inessential, it simplifies the analysis and avoids a taxonomic presentation.

**Equilibrium.** In this section, we summarize—with the aid of Figure 3—the properties of the equilibrium, whose analytical characterization is deferred to Appendix Section A-2.

Under condition (11), two productivity thresholds, $z^*$ and $z_L(A_{PS})$, exist such that $A_M < z^* \leq z_L(A_{PS})$, defining three productivity ranges. Low-productivity firms with $z \in [A_M, z^*]$ are inactive; medium-productivity firms with $z \in [z^*, z_L(A_{PS})]$ produce using only production workers;[5] high-productivity firms with $z > z_L(A_{PS})$ demand both workers and lawyers.

High-productivity firms also specialize on PS on the intensive margin. Interestingly, the cutoff $z_L(A_{PS})$ fully

[5] The medium-productivity range may be empty. In particular, if $A_{PS} > \frac{1-\alpha}{\beta}\frac{\kappa}{f_0}$, all active firms hire lawyers, $A_M < z^* = z_L(A_{PS})$.

determines this intensive margin:

$$\frac{H_{PS}(z)}{H_{PM}(z)} = \frac{\beta}{\alpha} \times \left(1 - \frac{z}{z_L}\right).$$

As $z$ increases, the share of lawyers approaches $\beta/\alpha$. The following proposition summarizes the main properties of the equilibrium.

**Proposition 1.** *The equilibrium production level of the industrial-goods sector in region $r$ is given by $Y_{rG} = A_{rG}H_{rG}$, where $H_{rG} = H_{rM} + H_{rPS}$ and $A_{rG} = A_G(A_{rM}, A_{rPS})$ is given by*

$$A_G(A_M, A_{PS}) := \begin{cases} Q_1 A_M^{(1-\alpha-\beta)} \left( \left[ 1 + \frac{1}{\lambda-1}\frac{\beta}{1-\alpha}\left(\frac{1-\alpha}{\beta}\varsigma(A_{PS})\right)^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}} \right] \right)^{\frac{1-\alpha-\beta}{\lambda}} & \text{if } \varsigma(A_{PS}) > \frac{\beta}{1-\alpha} \\ Q_2 A_M^{(1-\alpha-\beta)} A_{PS}^{\beta} \left(1 - \varsigma(A_{PS})\right)^{\frac{(1-\lambda)(1-\alpha-\beta)}{\lambda}} & \text{if } \varsigma(A_{PS}) \leq \frac{\beta}{1-\alpha} \end{cases},$$

*where $\varsigma(A_{PS}) \equiv \frac{\kappa}{f_O A_{PS}}$, $Q_1$ and $Q_2$ are constant terms, and $A_G(A_M, A_{PS})$ is continuous and increasing in both arguments.*
*The employment share of PS is given by*

$$\frac{H_{PS}}{H_G} = \begin{cases} \frac{\beta}{\lambda}\frac{\beta+(\lambda-1)(1-\alpha)}{\beta+(1-\alpha)(\lambda-1)\left(\frac{1-\alpha}{\beta}\varsigma(A_{PS})\right)^{\frac{(\lambda-1)(1-\alpha)+\beta}{1-\alpha-\beta}}} & \text{if } \varsigma(A_{PS}) > \frac{\beta}{1-\alpha} \\ \left(\beta - (1-\alpha-\beta)\frac{\lambda-1}{\lambda}\frac{\varsigma(A_{PS})}{1-\varsigma(A_{PS})}\right) & \text{if } \varsigma(A_{PS}) \leq \frac{\beta}{1-\alpha} \end{cases}. \tag{12}$$

*$H_{PS}/H_G \in [0, \beta]$ is continuous and strictly increasing in $A_{PS}$.*

*Proof.* See Section A-2 in the Appendix. □

Proposition 1 contains three main results. First, it shows the aggregate production function of goods-producing sectors has indeed a simple form: it is linear in total employment, that is, PS and manufacturing employment, with a constant productivity $A_G$. Second, it provides a closed-form expression for $A_G$ that is increasing in both $A_M$ and $A_{PS}$. The comparative static of $A_{PS}$ reflects both the direct effect of lawyers being more productive and the indirect effect of selection: an increase in $A_{PS}$ *in*creases $z^*$ and *de*creases $z_L$, and hence induces a reallocation of resources toward more productive firms. Third, the proposition yields a closed-form expression for the aggregate PS employment share $H_{PS}/H_G$. Interestingly, the sole determinant of structural change within the industrial sector (i.e., of PS deepening) is the local productivity of the PS sector $A_{rPS}$. In particular, aggregate manufacturing productivity $A_{rM}$ does not affect the composition of employment. Free entry is key for this stark result. If manufacturing productivity $A_{rM}$ (or the demand for the regional industrial variety) were to increase, more entry would occur, whereas the technology choice of the active firms would remain unaffected.

In summary, the model has a tractable recursive structure. The trade equilibrium pins down the employment share of the industrial sector as a function of $A_{rM}$ and $A_{rPS}$, given preferences and technology in the other sectors. The employment breakdown into manufacturing and PS is then determined by $A_{rPS}$ only.

# 4 Empirical Analysis

We now turn to the empirical analysis. We first describe our main data sources. We then discuss measurement aspects.

## 4.1 Data

Our analysis relies on four datasets.[6]

1. The NSS Employment-Unemployment Schedule for the years 1987 and 2011, henceforth, the "NSS data."
2. The Economic Census for the years 1990, and 2013, henceforth, the "EC."
3. A Special Survey of the Indian Service Sector for the year 2006, henceforth, the "Service Survey."
4. The NSS Consumer-Expenditure Schedule, henceforth, the "Expenditure data."

The NSS data, which form the backbone of our analysis, are a household survey with detailed information on employment characteristics and households' location of residence. We use data for 1987 and 2011. The NSS data allow us to measure sectoral employment shares and average income at the district-year level. Consistent with our theory, we measure employment shares in four sectors: agriculture, manufacturing, PS, and CS. For agriculture and manufacturing, we follow the ISIC sectoral classification in the NSS data. As highlighted in Figure 2, the situation is more complicated in the service industry. Whereas, for example, retail workers are arguably part of the CS sector, the distinction is less clear for lawyers becuase this category includes both corporate lawyers and divorce lawyers, providing, respectively, PS and CS. To solve this problem, we combine information from the Economic Census and the Service Survey to estimate the extent to which particular subsectors within the service sector provide their value added to firms rather than consumers. We describe this procedure in detail in in Section 4.2 below. To measure income, we proxy earnings by average expenditure. We prefer this measure to direct information on wages to also capture informal employment.

The EC is a complete count of all establishments engaged in the production or distribution of goods and services in India. The census covers all sectors except crop production and plantation. The EC collects information on each firm's location, industry, employment, and the nature of ownership. It covers approximately 24 million and 60 million establishments in 1990 and 2013, respectively.[7] We use the EC to classify service employment into CS and PS.

The Service Survey was conducted in 2006 and is designed to be representative of India's service sector. It covers almost 200,000 private enterprises subdivided into six service industries. This relatively unexplored Service Survey allows us to estimate the size of PS within the service sector. In Appendix Section B-1, we compare it with the EC and document that it is representative of the distribution of firm size in India.

Finally, we use the NSS Consumer-Expenditure Schedule. This dataset contains detailed information on households' expenditure allocation across narrowly defined goods, and thus allows us to measure expenditure shares on food and CS. We refer to Section B-1.5 in the Appendix for details on the product classification. We leverage this information to estimate the income elasticity $\varepsilon$, which is the key preference parameter for our analysis.

To compare spatial units over time, we create a time-invariant definition of geography. We define regions as Indian districts. Because the boundaries of several districts changed over time, we harmonized them using GIS software, relying on maps for the years 1987, 1991, 2001, and 2011. We define regions so that they have the same boundaries over time. To keep the number of regions as large as possible, a region is always the smallest area that covers a single district or a set of districts with consistent boundaries over time. In the end, we obtain 370 regions

[6] A more detailed description of these datasets is deferred to Appendix Section B-1. Here, we highlight the main features.

[7] As shown in earlier studies, most Indian firms are very small, with an average size ranging between two and three employees, over half having a single employee, and only one in 1,000 firms employing more than 100 workers.

that cover all of India. For simplicity, we refer to these regions as "districts." Section B-3 in the Appendix describes in detail how we construct this crosswalk.

## 4.2 Measurement

**Consumer vs. Producer Services.** We aim to distinguish between PS and CS in a way that is consistent with our theory. Ideally, we would want to measure employment in PS and CS with the help of detailed input-output matrices so as to associate the value added of each firm to the identity of the buyers (either private individuals or firms). To the best of our knowledge, this information is not available.

We therefore leverage micro data on the firms' downstream trading partners contained in the Service Survey. Specifically, this data report whether a firm is selling mostly to consumers or to other firms. We could thus, in principle, calculate the share of employment in every service industry-district cell distinguishing between firms selling to other firms and those serving consumers. In practice, this procedure is not feasible, because the Service Survey contains too few firms to precisely estimate these employment shares for each service industry-district cell. Instead, we rely on the fact that the probability of a firm selling to other firms rather than to consumers is highly correlated with firm size—larger firms are more likely to sell to firms. We show this pattern in Table 1, which displays the share of firms that mainly sell to other firms by employment size. A clear pattern emerges: small firms with one or two employees sell almost exclusively to final consumers, whereas a significant share of large firms sell to other firms.

| | Firm size: Number of employees | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6-10 | 11-20 | 21-50 | 51+ |
| PS share | 5.0% | 3.8% | 6.2% | 8.5% | 11.5% | 12.6% | 11.8% | 27.6% | 42.5% |
| Number of firms | 97337 | 46571 | 13227 | 5156 | 2777 | 4841 | 2830 | 601 | 403 |

Table 1: Share of producer services by firm size. The table reports the share of firms selling to firms (rather than private individuals) in different size categories.

We use the pattern reported in Table 1 in the following way. First, we estimate the PS employment share by firm size for different industries within the service sector. We then use the *district*-specific size distribution from the EC to infer the aggregate PS employment share in district $r$. More formally, the PS employment share (relative to the total service sector) in subsector $k$ in region $r$ is given by $s_{rk}^{PS} = \sum_b \omega_{kb}^{PS} \ell_{kbr}$, where $\omega_{kb}^{PS}$ is the share of employment in firms selling to firms in sector $k$ in size class $b$, and $\ell_{kbr}$ is the employment share of firms of size $b$ in sector $k$ in region $r$. Note this procedure assumes the structure of production for firms of equal size to not vary across Indian districts. The regional variation in PS and CS employment stems from differences in (i) total service employment, (ii) the relative share of different service industries, and (iii) the distribution of firm size. We exclude from the analysis a subset of service industries for which the categorization into PS and CS is ambiguous. These industries include public administration and defense, compulsory social security, education, and extraterritorial organizations and bodies. In Section B-2.2 in the Appendix, we describe this procedure in more detail.

In Figure 4, we display the result of this exercise for different subsectors within the service sector. Within the retail and restaurant sector, only a few establishments cater to other firms. Hence, we estimate that more than 97% of employment in that industry is engaged in the production of CS. The situation is very different in the financial or the ICT sector, where roughly 26% of 53% of employment caters mainly to other firms.

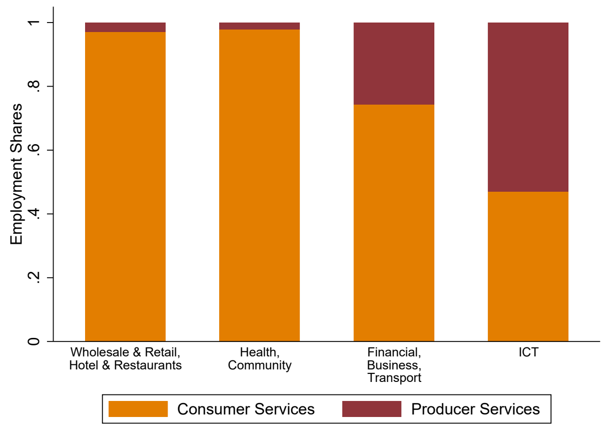


Figure 4: Producer vs consumer services in different industries. The figure shows the share of producer and CS in 2011 in different industries within the service sector.

Finally, we merge construction and utilities with the service sector. Although the construction sector is sometimes included in the industrial sector, the key distinction in our theory is that goods are tradable whereas services are nontradable. Because construction and utilities are local goods, we find it natural to merge them with services.[8] The construction sector serves both consumers (e.g., residential housing) and firms (e.g., business construction). To break these activities into PS and CS, we follow a procedure similar to that used for services. We exploit information from the "Informal Non-Agricultural Enterprises Survey 1999–2000" (INAES) dataset, which also reports whether a firm sells to consumers or other firms and which covers the construction sector. Given the sample size, splitting the destination of construction activities is possible only at the national, not the district level. We obtain the following breakdown. First, we remove 9.1% of the construction activity from the sample, which corresponds to the share of government activity (infrastructure and public goods). Then, based on the INAES data, we attribute 87.1% of what is left to CS and 12.9% to PS in every district-year. For more details, see Section B-2.2 in the Appendix.

Given these measurement choices, we are now in the position to quantify the structural transformation in India, across both time and space. Panel (b) of Figure 1 uses the sectoral classification we adopt in our analysis. Relative to Panel (a), we exclude the public sector, merge services with construction and utilities, and break down services into CS and PS, as discussed above. The time-series evolution of agricultural and manufacturing employment is essentially unchanged. Within the service sector, CS grow particularly quickly.[9]

In Figure 5, we turn to the spatial heterogeneity across Indian districts. We focus on urbanization as our measure of spatial heterogeneity. This as a mere descriptive device. In Section C-1 in the Appendix, we show a strong positive correlation between urbanization and the expenditure per capita in the NSS data for 2011. Thus, we take the urbanization rate as a proxy for economic development across Indian districts. Figure 5 displays sectoral employment shares by urbanization quintiles. The average urbanization rates of the five quintiles are, respectively, 6.4%, 12.1%, 19.5%, 29.2%, and 56.4%. Richer, urban locations have lower employment shares in agriculture and specialize in the production of services and industrial goods. Over time, the share of agriculture declines. Between

[8] In Section 7, we redo our analysis when we include construction in the manufacturing sector and show our results do not depend on this particular choice.

[9] Panel (b) of Figure 1 shows the employment share of education and PA remains constant over time at a 5% level. This finding suggests our choice to exclude them is largely inconsequential.

1987 and 2011 the structural transformation was especially fast in more urbanized districts. In 1987, agriculture was the main sector of activity even in the top quintile of urbanization. By contrast, in 2011, more than half of the working population was employed in CS and PS. This difference is even starker when one looks at earnings instead of employment (see Section C-1 in the Appendix.).

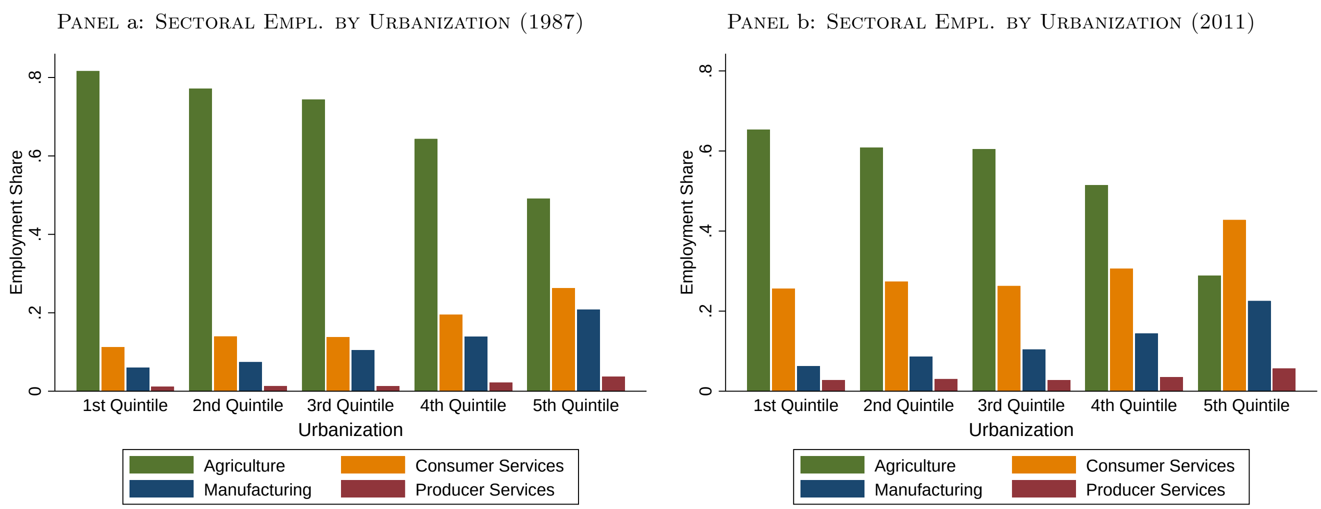


Figure 5: Sectoral Employment over Time and Space. The figure plots the sectoral employment shares by urbanization quintile in 1987 and 2011.

**Human Capital.** To be consistent with our theory, we measure each district's endowment of human-capital units $F_{rt}(q)$ and its distribution across sectors in terms of efficiency units of labor. To measure the distribution of human capital across sectors within a district, we rely on the sectoral distribution of earnings. Because local labor markets are frictionless, each district has a single wage per efficiency unit. Hence, differences in earnings must reflect heterogeneity in the endowment of effective units of labor.[10] To measure the distribution of human capital across districts, we follow the approach in the development accounting literature and leverage data on the regional distribution of schooling. We assume individual human capital $q_i$ as a function of schooling $s_i$ is given by $q_i = \exp(\rho s_i) \times \upsilon_i$, where $s_i$ denotes the number of years of education, $\rho$ is the annual return to schooling, and $\upsilon_i$ is an idiosyncratic shock, which we assume to be iid across districts and years and which satisfies $E[\upsilon_i] = 1$. To measure schooling attainment $s_i$, we classify people into four educational groups: (i) less than primary school, (ii) primary and upper primary/middle school, (iii) secondary school, and (iv) more than secondary school. We associate each step in the education ladder with three extra years of education, consistent with the organization of schools in India.

We estimate $\rho$ using Mincerian regressions—see Section 5.1. Given an estimate of $\rho$, we then calculate the average amount of human capital per region as $E_{rt}[q] = \sum_e \exp(\rho \times e)\ell_r(e)$, where $\ell_r(e)$ denotes the share of people in region $r$ with $e$ years of education. Hence, the distribution of educational attainment across space determines the spatial distribution of human capital. Finally, consistent with our assumption that $q$ follows a Pareto distribution with lower bound $\underline{q}_{rt}$, we use $E_{rt}[q_i] = E_{rt}[\exp(\rho s_i)] = \frac{\zeta}{\zeta-1}\underline{q}_{rt}$.

Table 2 shows why allowing for human capital differences across years, sectors, and space is important. First, the

[10] In Section 7.3.2 below, we extend our model to allow for imperfect substitution of skills across sectors.

level of schooling increased markedly between 1987 and 2011 and is itself a source of growth. Second, educational attainment differs across sectors. That agriculture is the least skill-intensive industry and educational attainment is highest in PS is not surprising. However, note the CS sector also employs lots of skilled individuals and is more skill intensive than the manufacturing sector.[11] Through the lens of our model, these patterns imply that the average number of efficiency units differs across sectors, and by using earnings shares rather than employment shares, our methodology takes such differences into account. Finally, there are large spatial differences whereby city dwellers are much more educated than the rural population. By explicitly measuring the local supply of human capital, we refrain from attributing these differences to differences in local TFP.

| | Less than primary | Primary, upper primary, and middle | Secondary | More than secondary |
|---|---|---|---|---|
| | | *Aggregate Economy (1987 - 2011)* | | |
| 1987 | 66.79% | 22.03% | 7.99% | 3.19% |
| 2011 | 40.32% | 30.10% | 18.79% | 10.79% |
| | | *By sector (2011)* | | |
| Agriculture | 53.72% | 29.23% | 14.45% | 2.60% |
| Manufacturing | 32.63% | 35.31% | 20.68% | 11.39% |
| CS | 25.16% | 31.99% | 27.94% | 14.90% |
| PS | 17.38% | 26.58% | 26.29% | 29.74% |
| | | *By Urbanization (2011)* | | |
| Rural | 46.97% | 30.00% | 16.30% | 6.84% |
| Urban | 33.69% | 30.30% | 21.27% | 14.73% |

Table 2: Educational Attainment. The table shows the distribution of the educational attainment. Wholesale, Retail, Hotel, Restaurants, Health, and Community Service are classified as CS. Financial, Business, Transport, and ICT Services are classified as PS. The breakdown of rural and urban districts is chosen in a way that approximately half of the population lives in rural and urban districts.

# 5 Estimation: Identification and Results

With the aforementioned data at hand, we can now turn to the estimation of our model. Our approach is in the tradition of development accounting, which has a long history in macro and development economics (see, e.g., Caselli (2005), Hall and Jones (1999), and Gancia et al. (2013)). Whereas these studies infer productivity at the country-level from an aggregate production function, we estimate the entire distribution of productivity $\{A_{rst}\}$ across sectors and space. We do so by relying on the entire equilibrium structure of our model, and hence refer to our method as *equilibrium development accounting*.

The centerpiece of our methodology is the distinction between structural parameters and local productivity. Our model is characterized by 14 structural parameters describing preferences, technologies, and the distribution of skills

$$\mathbf{\Omega} = \left\{ \underbrace{\varepsilon, \nu_{CS}, \nu_F, \omega_{CS}, \omega_F, \sigma,}_{\text{Preference parameters}} \underbrace{\lambda, \beta, \alpha, f_O, f_E, \kappa}_{\text{Manufacturing technology}}, \underbrace{\rho, \zeta}_{\text{Human capital}} \right\}.$$

[11] For ease of comparison with Figure 2, we classify CS and PS according to the NIC classification, that is, assign wholesale, retail, hotels, restaurants, health, and community services to CS and financial, business, transport and ICT services to PS.

In terms of local productivity, each region is characterized by a 3-tuple of regional productivity levels in agriculture, CS, and the goods-producing industry:

$$\mathbf{A_t} = \{A_{rFt}, A_{rCSt}, A_{rGt}\}.$$

The industry productivity $A_{rGt}$ in turn depends on manufacturing and PS productivity $A_{rMt}$ and $A_{rPSt}$.

In Section 5.1, we describe how we estimate the structural parameters in $\mathbf{\Omega}$. Given the parameters in $\mathbf{\Omega}$, a unique mapping exists from the equilibrium skill prices $\{w_{rt}\}$ and sectoral employment allocations $\{H_{rst}\}$ to the underlying productivity fundamentals in $\mathbf{A_t}$. In Section 5.2, we describe this procedure and our estimates of $\mathbf{A_t}$.

## 5.1 Estimation of Structural Parameters $\Omega$

**The Income Elasticity $\varepsilon$.**

The crucial parameter in our analysis is the income elasticity $\varepsilon$, which determines how quickly demand shifts away from agricultural goods as incomes rise. To estimate $\varepsilon$, we use the cross-sectional relationship between income and expenditure shares at the household level and estimate $\varepsilon$ via indirect inference. In particular, letting $\vartheta_{F,h}$ denote the observed expenditure share of food of household $h$ and $e_h$ total household spending, we estimate the following Engel curve using the data on household expenditure:

$$\ln \vartheta_{F,h} = \delta_r + \beta \times \ln e_h + x_h' \gamma + u_h, \tag{13}$$

where $\delta_r$ is a region fixed effect and $x_h$ contains household characteristics that could induce a correlation between total spending $\ln e_h$ and food shares. We then estimate $\varepsilon$ via indirect inference; that is, we estimate (13) in our model using the estimated coefficient $\hat{\beta}$ as a moment.[12]

Although $\beta$ is not an explicit structural parameter in our theory, the structural parameter $\varepsilon$ and the regression coefficient $\beta$ are tightly connected. Our theory implies

$$\ln \vartheta_F^h (e, \mathbf{p_r}) = \ln \left( \omega_F + \nu_F^h \left( \frac{e}{p_F^{\omega_F} \times p_G^{\omega_G} \times p_{CSr}^{\omega_{CS}}} \right)^{-\varepsilon} \right).$$

Hence, if $\omega_F \approx 0$ (which is the case in our structural estimation), our theory implies

$$\ln \vartheta_F^h (e, \mathbf{p_r}) = \ln \left( p_F^{\omega_F} p_G^{\omega_G} p_{CSr}^{\omega_{CS}} \right)^{\varepsilon} + \ln \nu_F^h - \varepsilon \times \ln e;$$

that is, the estimated income elasticity $\beta$ directly coincides with the structural parameter $\varepsilon$. Note that the region-specific price of CS, $p_{rCSt}$, is absorbed in the district fixed effect $\delta_r$ in (13) and that our additional household level controls $x_h$ aim to capture variation in preferences ($\nu_F^h$) which we abstract from in our theory.

Table 3 reports the results of estimating (13). The first column contains our baseline specification, where we control for a region fixed effect, a dummy for whether the household lives in an urban or rural area (within districts), a full set of fixed effects for household size and the number of workers within the household. We cluster standard

[12] To estimate (13) in our model, we randomly draw a sample of 1 million individuals from the region-specific income distribution $F_{rt}(q)$, calculate the model-implied food shares, and then run a regression of log food share against log income and region fixed effects. We draw our sample in a way to replicate the relative size of each district; that is, the share of observations from district $r$ is the same as observed in the data.

| | ln food expenditure share | | | |
|---|---|---|---|---|
| ln expenditure | -0.332*** | -0.318*** | -0.331*** | -0.366*** |
| | (0.008) | (0.007) | (0.008) | (0.010) |
| Winsorized (2%) | | ✓ | | |
| Addtl. Controls | | | ✓ | |
| IV | | | | ✓ |
| F-stat | | | | 2093.77 |
| $N$ | 101,654 | 101,654 | 101,601 | 94,436 |
| $R^2$ | 0.476 | 0.462 | 0.486 | 0.478 |

Table 3: INCOME ELASTICITY FOR FOOD. The table shows the estimated coefficient $\beta$ of the regression (13). In all specifications, we control for region fixed effects, an urban/rural dummy, a full set of fixed effects for household size, and the number of workers within the household. In column 2, we topcode household expenditure at the 98% quantile. In column 3, we control for the type of the household, the religion, the social class and whether the household receives rationing cards. In column 4, we instrument household expenditure with a set of three-digit occupation fixed effects. Standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

errors at the region level to account for the correlation spending shares through regional prices. We estimate an empirical elasticity of 0.332 that is precisely estimated.

In the remaining columns of Table 3, we report additional specifications to show the robustness of this estimate. In column 2, we winsorize the expenditure variable $\ln e_h$ at the top 2% level to limit the importance of measurement error. In column 3, we control for additional household-level controls. In particular, we control non-parametrically for differences in the household type, that is, whether the household is self-employed (in agriculture or non-agriculture), a regular wage earner or a casual laborer (in agriculture or non-agriculture), the household's religion, and social group and whether the household is eligible to purchase subsidised food grain from the Indian government. In both specifications, the estimate is indistinguishable from our baseline estimate.

In column 4, we present the results from an IV specification. We do so to address concerns about measurement error in $\ln e_h$ that would make our estimate for $\beta$ downward biased. We instrument total expenditure with a full set of three-digit occupation fixed effects.[13] Expectedly, these fixed effects strongly predict total expenditure as evidenced by the large F-statistic. The resulting estimate is slightly larger but quantitatively very similar to the OLS specifications reported in columns 1 - 3. In Section B-5 in the Appendix, we report additional specifications and also show the constant elasticity between expenditure and the expenditure share on food is a good approximation for a large part of the expenditure distribution.

For our baseline results we take an empirical elasticity of -0.33 as our target moment. In Section 7, we show that our results are robust to other choices for $\varepsilon$ in line with the results reported in Table 3.

**Value Added vs. Final Expenditure** To link the structural parameter in our theory ($\varepsilon$) to these empirical estimates, note that our theory specifies consumers' preferences over sectoral value added, whereas the data on household expenditure pertain to final expenditure. As stressed in Herrendorf et al. (2013), the structural parameters of the demand system based on final goods differ from the one based on value added. Although true in general, this is fortunately less of a concern for the elasticity parameter $\varepsilon$, the only parameter we estimate from the data on expenditure shares.

[13] The expenditure survey assign a unique occupation to each household by choosing the occupation of the household member with the highest earnings.

To see this formally, suppose the final-good demand system takes the form

$$\vartheta_s^{FE}(e,q) = \omega_s^{FE} + \tilde{\nu}_s^{FE} \left( \frac{e}{\prod_j q_j^{\omega_j^{FE}}} \right)^{-\varepsilon^{FE}},$$

where $q_j$ denotes the price of the final good of sector $j$, and we use the superscript "$FE$" to highlight that the respective structural parameters correspond to the final-expenditure demand system. Furthermore, suppose a unit of the final good in sector $s$ is produced with a Cobb-Douglas production function of sectoral value added:

$$y_s^{FE} = \prod_{j \in (A,CS,G)} \left( y_{js}^{VA} \right)^{\lambda_{js}}. \tag{14}$$

Hence, the matrix $[\lambda_{js}]_{js}$ describes the input-output matrix of the economy.

As we show in Section B-5 in the Appendix, these assumptions imply that the value-added share of sector $s$ is

$$\vartheta_s^{VA} = \omega_s^{VA} + \tilde{\nu}_s^{VA} \times \left( \frac{e}{\prod_j \left( p_j^{VA} \right)^{\omega_j^{VA}}} \right)^{-\varepsilon^{FE}},$$

where $\omega_s^{VA} = \sum_j \lambda_{js} \omega_j^{FE}$ and $\tilde{\nu}_s^{VA} = \sum_j \lambda_{js} \tilde{\nu}_j^{FE}$. Hence, the implied value-added demand system is *exactly* consistent with our theory. It is of the PIGL form and the final-good expenditure elasticity $\varepsilon^{FE}$ coincides with the value-added expenditure elasticity $\varepsilon$. This is different for the other parameters $\omega_j^{VA}$ and $\tilde{\nu}_j^{VA}$, both of which are expenditure-share weighted averages of the final-good structural parameters $\omega_j^{FE}$ and $\tilde{\nu}_j^{FE}$. Hence, as stressed by Herrendorf et al. (2013), in general, knowledge of the entire input-output structure $[\lambda_{js}]_{js}$ is required to identify the parameters of the value-added demand system. This, however, is not the case for the expenditure elasticity $\varepsilon$, which is the only parameter we estimate from the data on final-good expenditure.

In Section B-5 in the Appendix, we show that this intuition is more general than for the particular case of Cobb-Douglas aggregation embedded in (14) and extend this argument for a general CES production function.

**Other Preference Parameters $\nu_{CS}, \nu_F, \omega_{CS}, \omega_F$ and $\sigma$.**

The market-level demand system depends on the aggregate preference parameters $\nu_{CS}$ and $\nu_F$, which are in turn related to the primitive microlevel preference parameters $\tilde{\nu}_{CS}$ and $\tilde{\nu}_F$–cf. equation (5). We estimate $\nu_s$ directly from the data and infer the structural micro parameters $\nu_s^h$ given an estimate of the inequality parameter $\zeta$. Identifying $\nu_s^h$ separately from $\nu_s$ is only required to quantify the welfare consequences of service-led growth, not to estimate the model.

Equation (4) shows the taste shifters $\nu_{CS}$ and $\nu_F$ determine sectoral spending and employment when holding income and prices constant. In Section A-3 in the Appendix, we prove the taste shifter for CS $\nu_{CS}$ is not separately identified from the productivity in CS $A_{rCSt}$. Hence, without loss of generality, we can normalize it to -1. The taste shifter for agricultural products, $\nu_F$, can then be directly identified from the aggregate agricultural employment share in a given year. We opt to match it in the year 1987. Doing so yields $\nu_F = 1.277$. Given the normalization of $\nu_{CS} = -1$, $\nu_M = -(\nu_F + \nu_{CS}) = -0.277$. Hence, manufacturing products are also luxury goods, becuase their expenditure share is increasing in income. However, their income elasticity is below the one for CS.

| Parameter | Target | Value |
|---|---|---|
| | *Preference parameters* | |
| $\varepsilon$ | Engel curve | 0.34 |
| $\omega_F$ | Agricultural spending share US | 0.01 |
| $\omega_{CS}$ | Agricultural Employment share 2011 | 0.69 |
| $\nu_F$ | Agricultural Employment share 1987 | 1.28 |
| $\nu_{CS}$ | Normalization | -1 |
| $\sigma$ | Set exogenously | 3 |
| | *Production function parameters* | |
| $\lambda$ | Tail of the employment distribution | 1.42 |
| $\beta$ | Employment share of lawyers in the US | 0.7 |
| $\alpha$ | Profit share | 0.158 |
| $f_O$ | Normalization | 1 |
| $f_E$ | Normalization | 0.11 |
| $\kappa$ | Normalization | 1 |
| | *Skill parameters* | |
| $\rho$ | Mincerian schooling returns | 0.056 |
| $\zeta$ | Earnings distribution within regions | 3 |

Table 4: STRUCTURAL PARAMETERS. The table summarizes the estimated structural parameters. The details of the estimation are discussed in the text.

To identify the share parameters $\omega_{CS}$ and $\omega_F$, recall that $\vartheta_F^h(e,p) > \lim_{e\to\infty}\vartheta_F^h(e,p) = \omega_F$ and that $\vartheta_{CS}^h(e,p) < \lim_{e\to\infty}\vartheta_{CS}^h(e,p) = \omega_{CS}$. Hence, the expenditure share on food (CS) approaches $\omega_F$ ($\omega_{CS}$) from above (below) as income increases. In the US, which we take an example of a rich economy, where nonhomothetic demand is less important, the agricultural employment share is about 1%. Hence, we take $\omega_F = 0.01$. For $\omega_{CS}$, we follow a similar strategy as for $\nu_F$ and match the aggregate sectoral employment shares in a given year. Given our interest in the long-run growth experience of India, we opt to match sectoral employment in 2011, which implies $\omega_{CS} = 0.69$.[14] Finally, we set the inter-regional trade elasticity $\sigma$ to a consensus estimate in the literature and assume $\sigma = 3$.

**Skill Parameters $\zeta$ and $\rho$.**

Our specification of skills $q_i = exp(\rho s_i)\upsilon_i$ implies log earnings of individual $i$ in region $r$ at time $t$, $y_{irt}$ are given by the usual Mincerian regression $\ln y_{irt} = \ln w_{rt} + \rho s_i + \ln \upsilon_i$. Hence, we can estimate $\rho$ from the within-region variation between earnings and education, which we can measure from the NSS data. We estimate an average annual rate of return of 5.6%. Although this estimate is on the lower end of standard Mincerian regressions, recall that we are using data on consumption rather than income. In Section 7, we discuss the robustness of our results with respect to the Mincerian estimate.

We also estimate the tail parameter of the skill distribution $\zeta$. This parameter does not affect the equilibrium conditions given that we estimate the aggregate preference parameter $\nu_s$ directly. Hence, our estimate of regional productivity does not depend on the value of zeta. An estimate of $\zeta$ is only required once we want to calculate welfare. To estimate $\zeta$, recall that the distribution of income in region $r$ is given by $G_r(y) = 1 - \left(\frac{\underline{q}_r w_r}{y}\right)^{\zeta}$, implying $\ln(1 - G_r(y)) = \zeta \ln\left(\underline{q}_r w_r\right) - \zeta \ln y$. We therefore estimate $\zeta$ from a cross-sectional regression $\ln(1 - G_r(y_i)) =$

[14] Our model implies regional *employment* shares in CS are bounded by $\omega_{CS}$ from above. As we discuss in more detail in Section B-2.4 in the Appendix, our Indian data contains seven districts that feature employment shares in CS that exceed $\omega_{CS}$. Because these districts are very small and account for less than 1% of employment, we drop them from our analysis.

$\delta_r + \beta \ln y_i + u_{ir}$, where $\delta_r$ is a district fixed effect and $\{y_i\}$ is a grid of the income distribution. In practice, we pick a grid of 200 points and consider a support of regional incomes above the median, because the Pareto distribution is a better fit to the left tail of the income distribution. This procedure yields an estimate of $\zeta \approx 2$ (see Appendix Section B-7).

**Technology parameters: $\lambda, \beta, \alpha, f_O, f_E$, and $\kappa$.**

To decompose $A_{rG}$ into the $A_{rM}$ and $A_{rPS}$, we need to know the underlying parameters of the industrial sector. Proposition 1 establishes that all allocations only depend on $A_{rPSt} \times f_O/\kappa$. Hence, the parameters $\kappa$ and $f_O$ are not separately identified from $A_{rPSt}$, and we normalize $f_O = \kappa = 1$. This normalization entails no loss of generality, because the scale factor $f_O\kappa$ has no bearing on any of our results. Similarly, the entry cost $f_E$ is not separately identified from the level of productivity $A_{rMt}$ as long as some firms are "discarded" after their efficiency draw $z$ is observed, that is, condition (11) is satisfied. We therefore chose $f_E$ to satisfy (11). This leaves us with three parameters: $\lambda, \beta$, and $\alpha$.

We identify the tail of the productivity distribution $\lambda$ from the employment distribution of the EC. As we show in detail in Section B-8 in the Appendix, our model implies that, as for the distribution of productivity, the distribution of employment for large firms is also Pareto with shape $\lambda$. We find an estimate of $\lambda = 1.42$, which is very precisely estimated.

We then pick $\alpha$ and $\beta$ to jointly match a profit share of 10% and the long-run share of PS workers within the industrial sector. Consider a situation in which $A_{PS}$ becomes large. Our model implies $\lim_{A_{PS}\to\infty} H_{PS}/H_G = \beta$. In the US, PS account for about 28% of employment and production workers for 12%. This observation suggests $\beta = \frac{0.28}{0.28+0.12} = 0.7$. Given $\lambda$ and $\beta$, the parameter $\alpha$ is tied to the profit share because $\alpha + \beta$ determines the returns to scale and hence the share accruing to the fixed factor. In particular, our model implies the profit share equals $(1 - \alpha - \beta)/\lambda$. For $\beta = 0.7$ and $\lambda = 1.42$, a profit rate of 10% requires that $\alpha = 0.158$.

## The Demand for Consumer Services: Direct Evidence

In Table 3, we used data on food shares to estimate the income elasticity $\varepsilon$. In principle, we could use data on the expenditure share of CS. We choose food expenditures for two reasons. First, food expenditures might be better measured if these expenditures are more salient. Second, as argued above, the log-linear specification in (13) is particularly informative about $\varepsilon$ if $\omega_s$ is small, because our theory then exactly implies a log-linear relationship, and the distinction between final expenditure and value added becomes less important. Because CS are a luxury, $\omega_F \approx 0$ but $\omega_{CS} > 0$.

Reassuringly, our estimated model yields a nontargeted expenditure elasticity for CS that is broadly in line with the empirical evidence. Specifically, we ran—in the model and in the data—the same specification as in (13) except that we used households expenditure share on CS, $\ln \vartheta_{CS,h}$, as the dependent variable. We follow the official classification of the NSS expenditure module to assign expenditures to CS. These expenditures include, for example, domestic servants, barber shops, or tailor services. We also add entertainment expenses such as movie theaters, club fees, and cable TV. Again, we refer to Section B-1.5 in the Appendix for the exact list of expenses.

In Table 5, we report the estimates using the Indian expenditure data. The structure of the table is exactly the same as in Table 3 above; that is, in column 2, we winsorize the data; in column 3, we control for additional household characteristics; and in column 4, we report the IV specification, where we instrument total household expenditure with three-digit occupation dummies. Again, we cluster standard errors at the district level. Empirically, CS are

| | ln consumer service expenditure share | | | |
|---|---|---|---|---|
| ln expenditure | 0.268*** | 0.270*** | 0.214*** | 0.571*** |
| | (0.022) | (0.021) | (0.021) | (0.031) |
| Winsorized (2%) | | ✓ | | |
| Addtl. Controls | | | ✓ | |
| IV | | | | ✓ |
| F-stat | | | | 722.50 |
| $N$ | 100,383 | 100,383 | 100,334 | 93,571 |
| $R^2$ | 0.240 | 0.240 | 0.250 | 0.213 |

Table 5: Income elasticity for consumer services. The table shows the estimated income elasticity for the CS expenditure share (see (13)). In all specifications, we control for region fixed effects, an urban/rural dummy, a full set of fixed effects for household size and the number of workers within the household. In column 2, we topcode household expenditure at the 98% quantile. In column 3, we control for the type of household, the religion, the social class, and whether the household receives rationing cards. In column 4, we instrument household expenditure with a set of three-digit occupation fixed effects. Standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

indeed luxuries, because their spending shares are increasing in income. Quantitatively, this elasticity is estimated to be between between 0.25 and 0.3 for the OLS specification and around 0.55 in the IV case. When we estimate this specification in our model, we estimate a coefficient of about 0.4. Hence, even though we do not use the data on CS spending to estimate the model, the implied elasticities are consistent with what we see in the household data.

Our model also implies the price of CS varies across space and reflects differences in wages $w_r$ and CS productivity $A_{rCS}$. In particular, conditional on total expenditure $\ln e_h$, CS shares are predicted to be large in regions where prices are low, that is, where $A_{rCS}$ is large relative to the local wage. In the context of the regression in Table 5, this variation is captured by the regional fixed effects.

In Figure 6, we plot the correlation between our estimates of regional fixed effects and the regional urbanization rate. To visualize the relative size of districts, the size of the markers reflects the size of the population. Figure 6 shows a robust positive relationship: cities are particularly productive in CS (relative to the prevailing wage). As we show below, we find the same qualitative patterns in our structural analysis even though we do not use the information from the expenditure data.

Our estimated demand system also delivers estimates of the elasticity of substitution that are quantitatively broadly consistent with findings in the literature. For the class of PIGL preferences, the elasticity of substitution is not a structural parameter but depends on relative prices and total expenditure.[15] As we show in detail in Section B-6 in the Appendix, we find services and goods are complements, with an average elasticity of substitution of 0.7. By contrast, food and CS are, on average, substitutes with a substitution elasticity of around 1.3.

## 5.2 Estimation of Productivity Fundamentals $\mathbf{A_t}$

Given the structural parameter vector $\mathbf{\Omega}$, data on local wages and sectoral employment allocations as well as time-series data on relative prices and aggregate income, the equilibrium conditions uniquely identify a set of local

[15] The Allen Uzawa elasticity of substitution between goods $s$ and $k$ is given by $EOS_{sk} = 1 - \varepsilon \frac{(\vartheta_s - \omega_s)(\vartheta_k - \omega_k)}{\vartheta_s \vartheta_k}$. See Section A-4 in the Appendix.

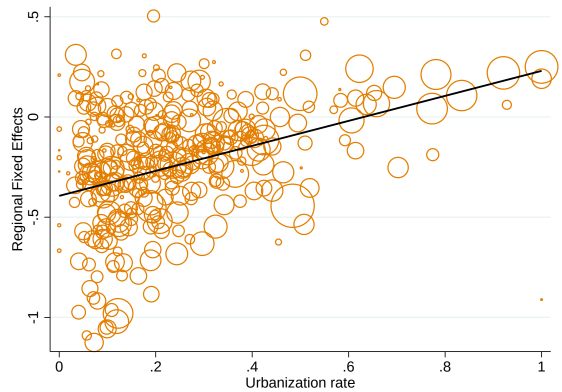


Figure 6: Urbanization and Regional Fixed Effects of Consumer Service Spending. The figures displays the correlation with the region fixed effects stemming from Table 5 (column 1) against the urbanization rate.

productivity fundamentals $\mathbf{A_t}$. We refer to Section A-3 in the Appendix for details, but we describe the main intuition here. Consider first the identification of $A_{rCSt}$, which we discussed in Section 3.4. Equation (9) implies we can uniquely solve for $A_{rCSt}$ as

$$A_{rCSt} = \left( \frac{(-\nu_{CS})}{\omega_{CS} - \frac{H_{rCSt}}{H_{rt}}} \right)^{\frac{1}{\omega_{CS}} \frac{1}{\varepsilon}} p_F^{\frac{\omega_F}{\omega_{CS}}} p_G^{\frac{\omega_G}{\omega_{CS}}} \left( E_{rt}\left[q\right] \times w_{rt}^{1-\omega_{CS}} \right)^{-\frac{1}{\omega_{CS}}}. \tag{15}$$

Controlling for the level of human capital $E_{rt}[q]$ and the equilibrium factor price $w_{rt}$, CS productivity is increasing in the observed employment share $\frac{H_{rCSt}}{H_{rt}}$.[16] Conversely, holding the employment share $\frac{H_{rCSt}}{H_{rt}}$ constant, CS productivity $A_{rCSt}$ is decreasing in both human capital and factor prices. Structurally decomposing the observed variation in employment shares into the part that is service led (i.e., $A_{rCSt}$) versus the part that is service biased because of income effects (i.e. $E_{rt}[q]\, w_{rt}^{1-\omega_{CS}}$) is a key aspect of our equilibrium accounting methodology.

The procedure to estimate productivity in tradable sectors is different. Equation (7) implies relative productivity across two locations is given by

$$\frac{A_{rs}}{A_{js}} = \left( \frac{H_{rs}}{H_{js}} \right)^{\frac{1}{\sigma-1}} \left( \frac{w_r}{w_j} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{for } s = F, G. \tag{16}$$

Hence, sectoral productivity differences can be inferred from relative skill prices and relative factor inputs (in units of human capital) given the elasticity of substitution $\sigma$. No other preference parameters are involved in this estimation, because food and industrial goods are tradable so that local demand is dissociated from local income.

Although we can use (16) to estimate relative sectoral productivity, we still need additional restrictions to estimate the level of productivity in agriculture and industry. As we show in the Appendix, we can exploit the time-series data on the relative price of food (relative to goods) and on aggregate GDP.[17]

[16] Recall that if CS are a luxury, $\nu_{CS} < 0$ and $\frac{H_{rCSt}}{H_{rt}} < \omega_{CS}$.

[17] We measure GDP in terms of the numeraire industrial good. Because of nonhomothetic preferences, we cannot define a standard

To finally decompose our estimates of productivity in the goods-producing sector $A_{rGt}$ into the manufacturing ($A_{rM}$) and PS ($A_{rPS}$) component, we rely on the regional employment share in PS. Specifically, equation (12) in Proposition 1 shows that—given $\alpha, \beta$, and $\lambda$—we can infer $\varsigma(A_{rPS})$ (and hence $A_{rPS}$) from the observed relative employment share of PS relative to manufacturing.[18]

This discussion underscores the sense in which our methodology is an accounting procedure: for given parameters, we estimate sectoral productivity that exactly rationalizes the observed data on wages and sectoral factor inputs as equilibrium outcomes. Our identification strategy leverages the recursive structure of Proposition 1: we can identify productivity in agriculture, CS, and the industrial sector independently of the particular microstructure of the industrial sector. Such structure is only required to decompose the overall productivity of the industrial sector into the part stemming from PS and the part stemming from manufacturing workers.

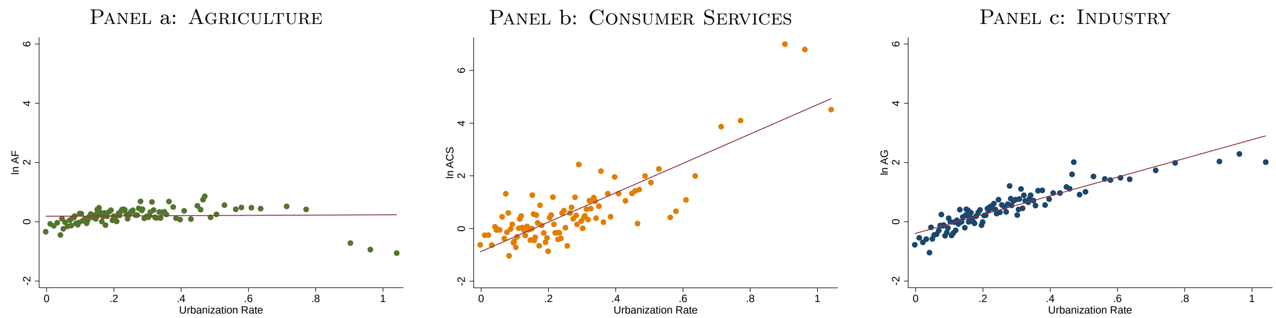


Figure 7: Estimated Sectoral Productivities. The figure shows a bin scatter plot of the estimated sectoral labor productivities in agriculture, CS, and industry across urbanization-rate bins. Each plot is constructed by pooling the estimates for 1987 and 2011 after absorbing year effects.

In Figure 7, we summarize the main cross-sectional pattern of our productivity estimates by displaying a bin scatter plot of the (logarithm of the) estimated labor productivities in the agricultural, industrial, and CS sector as functions of the urbanization rate. The relationship between productivity and urbanization is increasing for CS (Panel (b)) and in the industrial sector (Panel (c)). For agriculture, the relationship is relatively flat and slightly hump shaped. The declining portion corresponding to districts with an urbanization rate above 50% likely reflects the scarcity of land (a factor of production from which we abstract) in urban areas.

Remarkably, the productivity dispersion and its correlation with urbanization is strongest in the CS sector. Hence, the large employment share of CS in urbanized districts is not only a consequence of high wages (the Baumol effect) or of an abundance of human capital, but also of high CS productivity relative to rural areas. Qualitatively, this pattern is consistent with the estimated fixed effects in Figure 6 stemming from the CS-expenditure data: conditional on income, individuals in cities spend a larger share of their resources on CS.

Among the tradable goods, productivity is significantly more dispersed in the industrial than in the agricultural sector. To understand why, note a district's relative productivity is identified by its sectoral earning share relative

consumption price index. For comparison, we calculated wage growth for a fictitious agent endowed with the median wage and living in a district in which the supply of CS is at the median level. Based on the consumption basket of such an individual in 1987 and 2011, we calculated real wage growth using a Laspeyres and a Paasche index. The resulting real wage growth in the two cases is 1.82 and 4.85, respectively. Our calibration yields a wage growth factor of 2.60, which is in between.

[18] Our identification relies on the nonhomothetic factor demand functions. If $\kappa = 0$, equation (12) implies $\varsigma(A_{PS}) = 0$ irrespective of $A_{PS}$ and that the PS employment share would be constant and equal to $\beta$. Intuitively, with a Cobb-Douglas technology, the relative employment and expenditure shares would be independent of productivity. Moreover, $A_M$ and $A_{PS}$ would both be factor neutral, and the aggregate TFP $A_G$ would only depend on $A_M^{1-\alpha-\beta} A_{PS}^{\beta}$. Hence, $A_M$ and $A_{PS}$ could not be independently identified.

| | Sectoral productivity growth | | | | | |
|---|---|---|---|---|---|---|
| | 10th | 25th | 50th | 75th | 90th | Aggregate |
| | *Service-led growth* | | | | | |
| Consumer Services ($g_{rCS}$) | -1.4 | 0.7 | 3.4 | 8.1 | 14.0 | 5.0 |
| | *Growth in other sectors* | | | | | |
| Agriculture ($g_{rF}$) | 0.02 | 1.1 | 2.1 | 3.1 | 4.0 | 2.0 |
| Industry ($g_{rG}$) | 0.7 | 2.1 | 3.3 | 4.6 | 5.9 | 3.5 |

Table 6: Regional distribution of sectoral productivity growth. The table reports different moments of the distribution of growth rates in the different industries between 1987 and 2011. These growth rates are annualized and calculated as $g_{rs} = \frac{1}{2011-1987}(\ln A_{rs2011} - \ln A_{rs1987})$. Columns 1 - 5 report different quantiles. The "Aggregate" column reports the population-weighted average. All distributions are truncated at the top and bottom 3%.

to its skill price (see (16)). The "compressed" productivity distribution in agriculture reflects the observation that wages are negatively correlated with the employment share of agriculture across districts. By contrast, wages are positively correlated with the employment share of industry, implying a wider productivity dispersion.

# 6 The Importance of Service Led Growth

We now turn to our main question of interest: Was Indian growth service led? If so, did productivity growth in the provision of CS play a quantitatively important role for rising living standards and the structural transformation since 1987?

To answer these questions, we first use our sectoral productivity estimates $A_{rst}$ and calculate sectoral productivity growth between 1987 and 2011 for each district. We summarize these distributions of annualized productivity growth in Table 6. In the first row, we focus on CS-productivity growth; in the remaining rows, we report the distributions of growth rates in the tradable sectors. Two salient facts emerge. First and foremost, productivity in the CS sector grew in the majority of districts. Hence, the rise in CS employment was not merely driven by changes in demand driven by rising incomes or human-capital accumulation. Second, productivity growth was unequal across space and particularly so in the CS sector.[19]

To quantify the macroeconomic impact of these growth estimates reported in Table 6, we compute counterfactual equilibria where we set the respective sector's productivity growth to zero in all districts. The resulting changes in wages and employment allocations thus reflect the effect of sectoral productivity growth holding constant productivity growth in all other sectors. Our model then allows us to compute the welfare effects for consumers and how these effects vary across space and the income-distribution ladder. As we shall see in Section 6.1, our analysis uncovers a great deal of heterogeneity in both dimensions. In addition, we can also compute the implications for the structural transformation, and we do so in Section 6.2.

## 6.1 The Welfare Implications of Service Led Growth

To measure changes in welfare, we calculate equivalent variations relative to the *status quo* in 2011. We focus on three layers of heterogeneity: (i) across individuals differentiated by income, (ii) across districts differentiated by

[19] To account for measurement error, we winsorize the top and bottom 3% of the estimated productivity distributions. The details are discussed in the Appendix, where we also report robustness results to these choices (see Section B-9).

their rate of urbanization, and (iii) for the aggregate Indian economy.

As already discussed in Section 3.2 above, the PIGL demand system allows us to capture such heterogeneous welfare impacts in a tractable way. More specifically, suppose we want to compare the two vectors of wages and prices $\{w_r, \mathbf{p}_r\}_r$ and $\{w_r^{CF}, \mathbf{p}_r^{CF}\}_r$, where *CF* stands for *counterfactual*. Let $\varpi^h\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, q\right)$ be the income individual $h$ with skill level $q$ facing prices $\mathbf{p}_r$ requires to achieve the same level of utility as under $\{w_r^{CF}, \mathbf{p}_r^{CF}\}_r$. Using the indirect utility function $V$ given in (2), $\varpi^h$ is implicitly defined by

$$V(\varpi^h\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, q\right), \mathbf{p}_r) = V(qw_r^{CF}, \mathbf{p}_r^{CF}). \tag{17}$$

Thus, we can directly calculate the welfare-equivalent income $\varpi^h$ from $\{w_r^{CF}, \mathbf{p}_r^{CF}, \mathbf{p}_r\}_r$ for each level of human capital $q$. In a similar vein, we can calculate the utilitarian welfare consequences at the district level. Exploiting the aggregation result from Section 3.2, the appropriate representative agent in district $r$ facing prices $p_r$ would require a level of *regional* spending power $\varpi\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, E_r[q]\right)$ defined by

$$\mathcal{U}\left(\varpi\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, E_r[q]\right), \mathbf{p}_r\right) = \mathcal{U}(E_r[q]w_r^{CF}, \mathbf{p}_r^{CF}), \tag{18}$$

where $\mathcal{U}$ is defined in (6).[20]

Given $\varpi^h$ and $\varpi$ defined in (17) and (18), we calculate the respective welfare changes relative to 2011 as

$$\Delta\mathcal{W}_r^h(q) \equiv \frac{\varpi^h\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, q\right)}{qw_{r,2011}} - 1 \quad \text{and} \quad \Delta\mathcal{W}_r \equiv \frac{\varpi\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, E_r[q]\right)}{E_r[q]w_{r2011}} - 1. \tag{19}$$

Hence, $\Delta\mathcal{W}_r^h(q)$ is the change in income that an individual with human capital $q$ living in district $r$ in 2011 would require to achieve the same level of utility in the counterfactual allocation. If, for example, $\Delta\mathcal{W}_r^h(q) = -20\%$, the consumer would be indifferent between giving up 20% of her income in 2011 and an allocation in which productivity in a particular sector did not grow between 1987 and 2011. Similarly, $\Delta\mathcal{W}_r$ is the change in regional income required to achieve the same utilitarian welfare in district $r$.

Because these expressions vary across individuals and locations, they allow us to quantify the unequal effects of sectoral productivity growth. To gauge the welfare consequences at the aggregate level, we also report the change in aggregate welfare $\Delta\mathcal{W}$, which we compute as

$$\Delta\mathcal{W} = \frac{\sum_r \varpi\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, E_r[q]\right) L_{r2011}}{\sum_r E_r[q]w_{r2011}L_{r2011}} - 1 = \sum_r \Delta\mathcal{W}_r \frac{E_r[q]w_{r2011}L_{r2011}}{\sum_r E_r[q]w_{r2011}L_{r2011}}.$$

**Results: Sources of Welfare Growth in India (1987 - 2011)**

We now set to zero—for each sector—the distribution of productivity growth since 1987 shown in Table 6, recalculate the equilibrium, and then use the expressions above to calculate the implied welfare changes at the aggregate ($\Delta\mathcal{W}$),

[20] Using equations (17) and (2) and (18) and (6) we get that

$$\varpi^h\left(\left(w_r^{CF}, \mathbf{p}_r^{CF}\right)|\mathbf{p}_r, q\right) = \left(\left(\frac{qw_r^{CF}}{\prod\left(\frac{p_{rs}^{CF}}{p_{rs}}\right)^{\omega_s}}\right)^{\varepsilon} - \left(\prod p_{rs}^{\omega_s}\right)^{\varepsilon}\varepsilon\left(\sum \tilde{\nu}_s \ln \frac{p_{rs}^{CF}}{p_{rs}}\right)\right)^{1/\varepsilon}.$$

The expression for the aggregate variation $\varpi\left(w_r^{CF}, \mathbf{p}_r^{CF}|\mathbf{p}_r, E_r[q]\right)$ differs only in two ways: it uses $E_r[q]$ instead of $q$ and is evaluated using the scaled preference parameter $\nu_s^{\mathcal{U}}$ in lieu of the primitive parameter $\tilde{\nu}_s$.

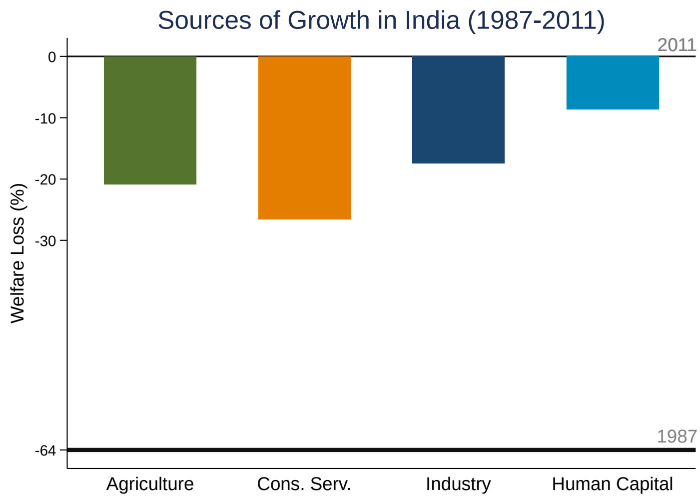


Figure 8: AGGREGATE WELFARE EFFECTS. The figure displays the average percentage welfare losses $\Delta\mathcal{W}$ associated with counterfactually setting productivity in agriculture, CS, and industry, as well as the level of human capital, to their respective levels in 1987 in all Indian districts. For comparison, the figure also shows the welfare loss of resetting all productivities and human capital to their 1987 level.

regional ($\Delta\mathcal{W}_r$), and individual ($\Delta\mathcal{W}_r^h(q)$) level.

**Aggregate Effects.** We first discuss the aggregate effects. Figure 8, which displays the change in aggregate welfare attributable to the different sectors, displays the first important results of our analysis: a substantial part of economic development in India since 1987 was indeed service led. On average, the Indian population would have been willing to reduce their income in 2011 by 26% in lieu of giving up the observed productivity growth originating in the CS sector. To put this number into perspective, the equivalent variation of the entirety of Indian income growth since 1987 is 64%. Hence, productivity growth in the CS sector accounts for roughly one third of the entire increase in economic well-being.

Figure 8 also shows that agricultural productivity was another important source of welfare improvement between 1987 and 2011. The salience of agriculture is hardly surprising given its large employment share in India. The relatively small welfare effects of productivity growth in the industrial sector is more surprising. The corresponding equivalent variation of productivity growth amounts to about 17%.[21] Hence, we find service-led growth has a larger welfare effect than productivity growth in the industrial sector. Finally, for comparison, we also report the welfare consequences of human-capital accumulation. At least as measured in the quantity of schooling, these welfare gains are relatively modest, namely a mere 9% of 2011 income.

In sum, Figure 8 shows service-led growth played an important role for economic development in India since 1987. In Section 7, we scrutinize this finding through a battery of sensitivity checks and show that the importance of service-led growth is a robust result.

**Heterogeneous Effects.** A centerpiece of our contribution is the quantification of the unequal effects of economic growth. Our analysis captures this inequality in two ways. First, as shown in Table 6, we estimate that regions differed in the productivity growth they experienced since 1987. Second, the non-homothetic nature of preferences

[21] We return below to the decomposition of the effects within the industrial sector—manufacturing versus PS.

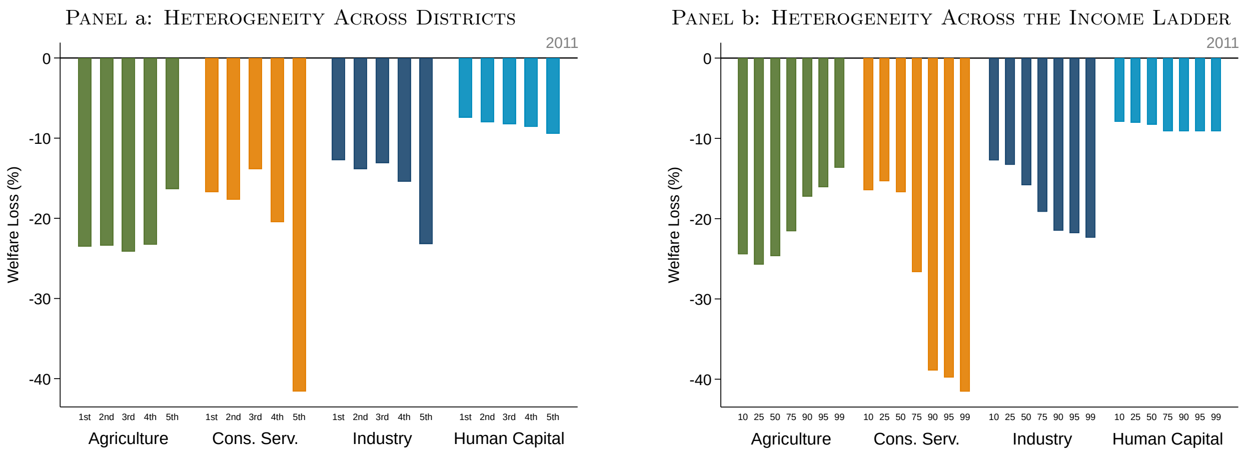


Figure 9: The Heterogeneous Welfare Impact of Service-Led Growth. The figure displays the average percentage welfare losses associated with counterfactually setting productivity in agriculture, CS, and industry, as well as human capital, at the respective 1987 level, broken down by urbanization quintile in 2011 (Panel (a)) and by the 10th, 20th, 50th, 75th, 90th, 95th, and 99th percentile of the income distribution in 2011 (Panel (b)).

implies consumers on different levels of the income ladder care differently about sectoral productivity growth: growth in CS and industrial goods is particularly beneficial for the rich, whereas growth in the agricultural sector mostly benefits the poor. Using the notation in (19), the former is mostly reflected in the regional welfare change $\Delta\mathcal{W}_r$, the latter mostly in the welfare change at the individual level $\Delta\mathcal{W}_r^h(q)$.

We first look at the spatial dimension and group districts by quintiles of the urbanization rate in 2011. We then calculate the (income-weighted) average welfare changes $\Delta\mathcal{W}_r$ within each urbanization quintile. These results are shown in the left panel of Figure 9.

The welfare consequences of productivity growth vary widely across space. Unsurprisingly, agricultural productivity growth is pro-rural. On average, households in the lowest quintile of urbanization are prepared to sacrifice 24% of their 2011 income to avoid going back to the 1987 productivity level in agriculture. This positive welfare change declines sharply in the top quintile, where productivity growth in agriculture is only worth 16% of the 2011 income. By contrast, productivity growth in CS and the industrial sector were decidedly pro-urban. This pattern is most pronounced for the CS sector whose productivity growth is worth 42% of the 2011 income for the most urbanized quintile.

Although these differences in the spatial incidence of sectoral productivity growth are partly driven by differences in productivity growth, they also reflect differences in income distribution. Because the population of cities is, on average, richer, their welfare is particularly reliant on the price of CS. The right panel of Figure 9 decomposes the welfare effects across the Indian income distribution. We focus on the 10th, 20th, 50th, 75th, 90th, 95th, and 99th percentiles. As expected, the benefits of productivity growth in CS and (to a lesser extent) industry are sharply increasing in income, whereas the opposite is true for agriculture. Interestingly, the welfare change for the top 99% attributable to CS productivity growth is smaller than for the average of the top quintile of the urbanization distribution, because not all the rich people live in cities.

In summary, the welfare effects of growth are heavily skewed. In urban areas and for rich households, the standards of living grew mostly because of productivity growth in CS and—to a lesser extent—in the industrial sector. By contrast, technical progress in agriculture is the main source of welfare gains for the poor, living in rural districts.

**Decomposing the Effects of Productivity Growth within the Industrial Sector.**

We have so far presented the welfare consequences of resetting productivity in the industrial sector to its 1987 level. As highlighted in Proposition 1, in our model, industrial productivity is not a primitive but is determined by the productivity of the manufacturing and the PS sector, and we can decompose the effect of industrial productivity growth into that of the two sectors. As we show in more detail in Section B-10 in the Appendix, when we implement this decomposition, we find productivity growth in the manufacturing sector accounts for the vast majority of the welfare impact of industrial growth. In our baseline calibration, productivity growth originating in the PS sector plays a minor role and accounts for less than 5% of the aggregate welfare gain of industrial productivity growth.

Our methodology infers a small role for PS productivity for two reasons. First, in the Indian micro data, the PS employment share is relatively small. Hence, productivity growth originating in that sector tends to have a quantitatively small effect. We expect this result to be different in more advanced economies, where PS play a quantitatively more important role (Eckert et al., 2020). Second, the decomposition depends on the parameters of the production function, in particular, $\beta$, which (see equation (10)) governs the importance of PS as an input of production and determines the share of PS workers in the long run.

Our results are robust with respect to both of these concerns. First, in Section 7.2, we explicitly address the concern that our methodology underestimates the employment share in PS, given the observation of a fast development in service industries such as ICT and show all our results are qualitatively robust to reasonable measurement choices that give a more prominent role for PS employment. Second, in Section B-10 in the Appendix, we study the extent to which our results depend on different calibrations of the production function, in particular, $\beta$. The effect of PS productivity growth remains small and accounts for at most one fifth of growth in the industrial sector.

## 6.2 Service Led Growth and Structural Change

Sectoral productivity growth is not only the driver of welfare growth, but is also at the heart of the sectoral reallocation of employment, that is, the structural transformation. We report these employment effects in Figure 10. Each of the three panels focuses on one sector and depicts the counterfactual sectoral employment share if productivity growth in agriculture (green bars), CS (orange bars), and the industrial sector (blue bars) had been zero since 1987. The dashed horizontal lines show the actual employment share in 1987 and 2011, for reference.[22]

Figure 10 has a clear message: productivity growth in CS was responsible for the largest part of the observed structural transformation. As seen in the left panel, in the absence of productivity growth in CS, the agricultural employment share would have been 60% instead of 50%. Hence, CS productivity growth accounts for more than half of the decline in agricultural employment between 1987 and 2011. The other panels show that employment in both CS and industry would have been lower if productivity had not grown in the CS sector.

Still, Figure 10 highlights an important role for service-*biased* growth: even in the absence of productivity growth in the CS sector, the employment share of CS would have grown by five percentage points between 1987 and 2011. However, its expansion would have been less spectacular than observed in the data.

The reason productivity in CS markedly affects agricultural employment is the following. In the absence of productivity growth, Indian consumers would be poorer and CS would be relatively more expensive. Given our

[22] The figure shows results for employment in effective units of labor, which we label employment with a slight abuse of terminology.

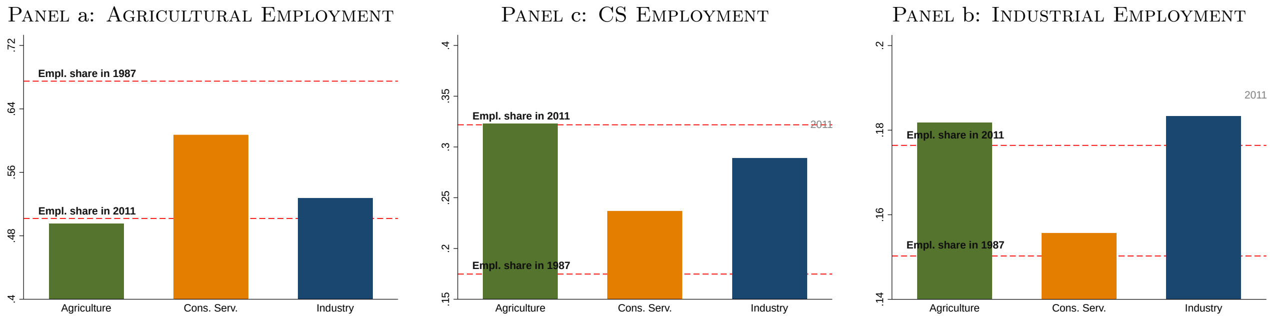


Figure 10: Sectoral Productivity Growth and Structural Change. Each panel in the figure shows the counterfactual employment shares in the one sector corresponding to setting the productivity in agriculture, CS, and industry (i.e., manufacturing and PS) at their respective 1987 levels. The dashed horizontal lines show employment in 1987 and 2011, for reference.

estimated demand system, both forces push toward an increase in the demand for agricultural goods. The income effect increases agricultural demand because food is a necessity. The substitution effect complements this force because we estimate food and CS to be slight substitutes.

By contrast, productivity growth in agriculture (green bars) appears to have marginally *increased* employment in agriculture and slowed down employment growth in industry and CS. This finding runs against the view that productivity growth in agriculture is a precondition for industrialization. It is instead in line with the findings of Foster and Rosenzweig (2004) on the effects of the Green Revolution and those of Kelly et al. (2020), who document a negative effect of agricultural productivity on the Industrial revolution across British regions.

In conclusion, service-led growth explains the lion's share of India's structural transformation between 1987 and 2011. Not only would India's consumers be substantially worse off in welfare terms, but India would also still resemble a much more agricultural economy, with industrial and service employment playing a less important role.

# 7 Robustness

In this section, we perform a robustness analysis of our results. We focus on the results concerning welfare reported in Figures 8 and 9.[23] We focus on three aspects. First, in Section 7.1, we study the sensitivity of the results to changes in the structural parameters. Next, in Section 7.2, we address some measurement issues. Finally, in Section 7.3, we discuss alternative modeling choices.

## 7.1 Sensitivity to Structural Parameters

Consider, first, the parameters governing preferences and skills. On the preference side, we focus on the asymptotic expenditure share on food $\omega_F$ and the income elasticity $\varepsilon$.[24] For the distribution of skills, we focus on the Mincerian returns $\rho$ and the tail parameter of the skill distribution $\zeta$. All results are based on re-estimating the entire model.

[23] The results for the structural transformation are available upon request.
[24] The other parameters $\nu_F$ and $\omega_{CS}$ are point identified in our theory.

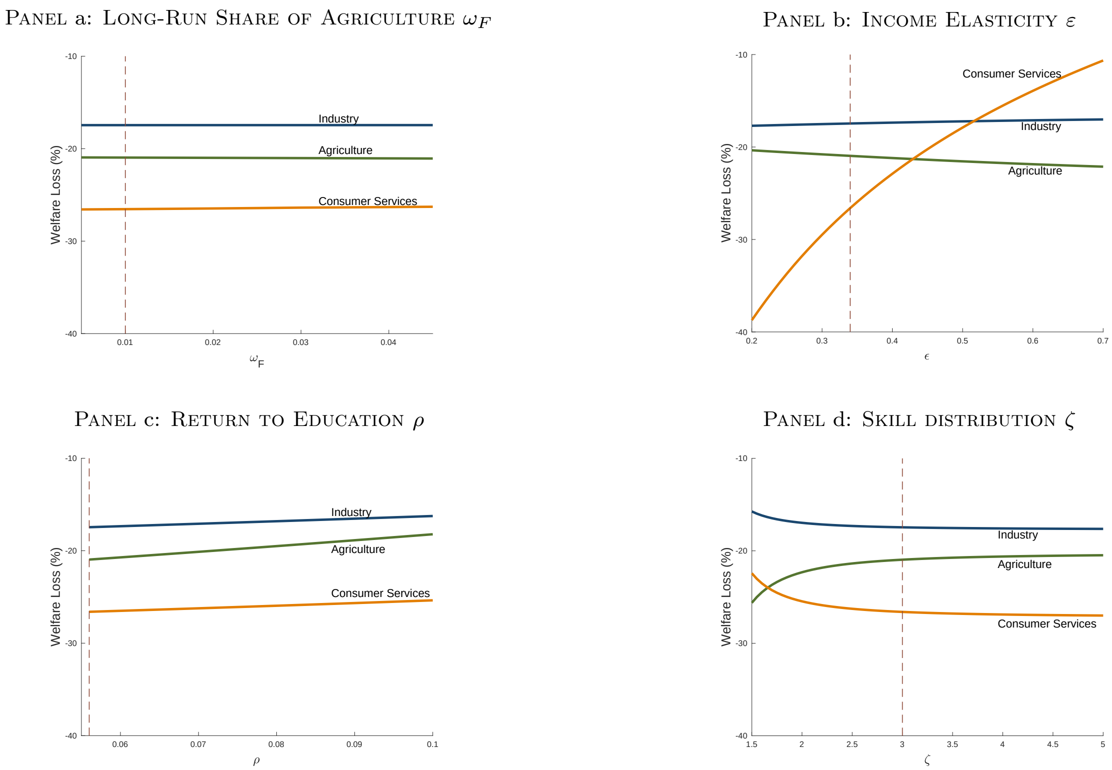


Figure 11: Robustness Analysis. Panels (a), (b), (c), and (d) show the aggregate welfare effects as a function of the preference parameters $\omega_F$, $\varepsilon$, the Mincerian rates of return to education $\rho$, and the tail parameter of the skill distribution $\zeta$. The vertical dashed line corresponds to the parameter value in our benchmark analysis.

**Preferences.** The parameter $\omega_F$ was calibrated so that the asymptotic GDP share of agriculture is 1%, corresponding to the output share of the US farming sector in 2017. However, the GDP share of agriculture is larger than 1% in many European countries, at about 2% in Italy and France, and 3% in Spain. Therefore, considering a range of larger values of $\omega_F$ is useful. Panel (a) of Figure 11 shows the implied welfare impact of sectoral productivity growth is essentially independent of $\omega_F$.

Panel (b) of Figure 11 focuses on the income elasticity $\varepsilon$. We expect our results to be sensitive to this parameter. In particular, a high income elasticity attributes a large share of the growth of the CS sector to income effects, scaling back productivity growth. Conversely, a low income elasticity would require large productivity growth to explain the observed expansion of the CS sector. Consequently, we expect the welfare effects of service-led growth to decrease in $\varepsilon$. The results shown in Panel (b) of Figure 11 confirm our expectation and show that changing $\varepsilon$ yields significant quantitative differences. For instance, if we set $\varepsilon = 0.7$, the aggregate welfare effect falls to a mere 10%. However, recall that the highest estimate of the food income elasticity was 0.366 (see Table 3) and that the parameter $\varepsilon$ approximately coincided with this elasticity. Figure 11 shows that for any $\varepsilon < 0.5$, a large share of Indian growth is service led. Hence, for growth to be preeminently service biased, the income elasticity should be much higher than what the household-level data suggest.

| | Aggregate Effects | | | | Effects by Urbanization Quantile | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Agriculture | CS | Industry | HC | Agriculture | | CS | | Industry | |
| | | | | | 1st | 5th | 1st | 5th | 1st | 5th |
| Baseline | -20.9 | -26.5 | -17.4 | -8.7 | -23.5 | -16.3 | -17.1 | -41.6 | -12.8 | -23.2 |
| | *Alternative measurement choices (Section 7.2)* | | | | | | | | | |
| Double PS | -20.9 | -23.1 | -20.2 | -8.7 | -22.5 | -17.8 | -19.4 | -30.1 | -14.7 | -27.1 |
| ICT & Business to PS | -21.2 | -20.2 | -18.8 | -8.6 | -23.3 | -17.6 | -19.9 | -23.8 | -13.3 | -25.9 |
| Construction to manufacturing | -20.2 | -24.0 | -22.6 | -8.7 | -26.3 | -12.3 | -3.8 | -50.3 | -13.1 | -33.3 |
| | *Alternative modelling assumptions (Section 7.3)* | | | | | | | | | |
| Open economy | -21.0 | -23.4 | -14.3 | -8.3 | -23.5 | -16.5 | -16.8 | -34.9 | -10.6 | -18.4 |
| Open economy (large ICT) | -20.4 | -19.3 | -14.2 | -8.3 | -22.8 | -16.4 | -18.5 | -22.7 | -10.5 | -17.8 |
| Imperfect skill substitution | -24.9 | -26.5 | -16.6 | -16.2 | -29.5 | -18.4 | -11.9 | -45.3 | -11.6 | -22.5 |

Table 7: THE IMPORTANCE OF SERVICE-LED GROWTH: ROBUSTNESS. In this table, we report a summary of our results from the robustness tests described in more detail in the main text. In the first four columns, we report the aggregate welfare loss in the absence of productivity growth (cols 1 - 3) or human-capital accumulation (col 4). In the remaining columns, we report the welfare loss for the 1st and 5th quintile of the urbanization distribution.

**Skills.** In the lower panels of Figure 11, we focus on the determinants of human capital. Our estimate of the return to education $\rho$ based on micro data is an annual 5.6% return. This estimate is on the lower end of typical Mincerian regressions. A potential concern is that we use data on consumption that might reflect consumption sharing within households with different skills and education levels. This might lead to attenuation bias. For this reason, we consider alternative calibrations in which the return to education is higher, up to an annual 10% that is an upper bound to the range of the typical estimates. As seen in Panel (c) of Figure 11, our main results are not sensitive to this parameter. The only exception is that a higher return to education increases the importance of human capital.

Panel (d) of Figure 11 shows the effect of the tail of the skill distribution $\zeta$. This parameter mostly affects our decomposition of productivity growth into agriculture and CS: the higher the $\zeta$, the higher the importance of CS growth relative to agricultural productivity. This result reflects the importance of nonhomothetic demand. The smaller $\zeta$, the higher the income inequality. And because higher inequality increases aggregate demand for CS for a given average wage, less productivity growth is "required" to explain the increase in CS employment if $\zeta$ were small. Figure 11 shows this intuition is borne out but that the effects are quantitatively moderate.

## 7.2 Measurement: Revisiting the PS-CS Split

Our classification of service employment into PS and CS hinges on whether firms in the service sector sell mostly to firms or consumers. For our baseline analysis, we use firm-level information contained in the service survey in this regard. According to this classification, the vast majority of service employment indeed caters to consumers. Even though sectors that sell in significant proportions to firms—such as ICT and business services—grow very quickly, the majority of the service sector continues to be in consumer-oriented industries such wholesale, retail, and restaurants.[25]

[25] To corroborate our results, we also measured aggregate employment from the Economic Census 2013; that is, we focused on the industry of firms rather than of the employees. In the Economic Census, industries such as wholesale, retail, restaurants, health and community services account for 37.9% of total employment, which compares with approximately 6.5% for financial, business, and ICT services. Note that even these sectors serve in part consumers as many lawyers (who are part of the business service industries) and banks sell their services to households.

Although we consider our data-driven approach an accurate way to separate CS from PS, our procedure could underestimate the PS sector if firms report sales to small firms as sales to individuals. To gauge the quantitative importance of such measurement concerns, we consider two alternative classifications. First, we assume the (human-capital-adjusted) employment share of PS is twice as large as in our benchmark estimate in each service industry shown in Figure 4. Second, we assume the entire ICT and business service industries serve manufacturing firms (while retaining our baseline approach for the remaining service industries). We regard both alternatives as generous upper bounds for the importance of PS employment.

The results are shown in rows 2 and 3 of Table 7. The first four columns report the aggregate welfare effect ($\Delta\mathcal{W}$), shown in Figure 8. The last six columns focus on the spatial heterogeneity ($\Delta\mathcal{W}_r$), shown in Figure 9. For parsimony, we only report the top and bottom urbanization quantiles. As expected, the importance of productivity growth in CS decreases when we attribute a larger share of the expanding service sector to PS. This is especially important for the most urban locations, because the spatial concentration of PS exceeds the one of CS. However, in all cases, Indian growth continues to be preeminently service led.

Finally, we explore the importance of the construction sector. Recall that we attributed construction to the service sector, given its non-tradable nature. Because, traditionally, construction is absorbed in the manufacturing sector, we also redid our analysis under this alternative measurement choice. We report the result in row 4 of Table 7. Although this reclassification reduces the importance of CS and increases the importance of the industrial sector, we still find CS to be the most important contributor to Indian growth. Construction plays a particularly important role for the spatial heterogeneity, because it is relatively pro rural. If we do not count the construction sector as part of the service sector, the spatial incidence of service-led growth is even more pro urban than in our baseline estimate. Specifically, the welfare effect of productivity growth in CS remains the same in the most urbanized districts, whereas it turns minuscule in the most rural districts.

## 7.3 Alternative Modeling Assumptions

Given the accounting nature of our methodology, a natural question concerns the extent to which our results are sensitive to our specific modeling assumptions. In this section, we consider two alternatives. First we extend our model to allow for international trade. Second, we consider an environment where skills are imperfectly substitutable.

### 7.3.1 Open Economy

Thus far, we have treated India as a closed economy. However, international trade, in particular exports of ICT services, has become increasingly important for India. In this section, we therefore extend our model to an open-economy environment. For brevity, we only summarize the main features of the extended model. The technical analysis can be found in Appendix Section A-5.

We assume consumers, both in India and in the rest of the world, consume industrial goods sourced from many countries. Different national varieties, which are in turn CES aggregates of regional varieties, enter into a CES utility function as imperfect substitutes. To capture that India might have a specific comparative advantage in ICT services, we assume India exports both domestic goods and ICT services. For simplicity, we assume ICT services are not sold in the Indian domestic market. In our estimation, we assume balanced trade, but we allow India to run a trade deficit in goods and a surplus in ICT services, which is in line with the empirical observation.

To calibrate this model, we need information on the revenue of ICT services, the exports and imports of goods, and an estimate of the trade elasticity. We measure ICT revenue from the income share of ICT workers. We classify as ICT service workers all those employed in the following service industries: (i) telecommunications, (ii) computer programming, (iii) consultancy and related activities software publishing, and (iv) information-service activities. In our NSS data, these activities constitute 0.72% of total employment in 2011 (in 1987, it was a less than 0.1%). ICT workers earn, on average, higher wages than other workers. When one considers the earning share, they account for 1.56% of total earnings in 2011 (in 1987, it was 0.11%). Given the small size of the ICT sector in 1987, we assume it was zero and target the earnings share in 2011. In terms of exports, according to the World Bank, the export of goods and merchandise increased from 11.3 billions (4.1% of GDP) in 1987 to 302.9 billions (16.6% of GDP) in current USD. The manufacturing sector accounted for 66% of such merchandise exports in 1987 and for 62% in 2011. According to the OECD, the domestic value added in gross exports amounts to 83.9% of exports for India and we assume this percentage to be constant over time. In accordance with these data, we assume the value-added export of trade increased from 13.9% in 1987 to 53.6% in 2011 as a share of the GDP in the manufacturing sector. Finally, we set the trade elasticity to 5 (Simonovska and Waugh, 2014).

The results of quantifying the sources of growth in this context are contained in rows 6 and 7 of Table 7. In row 6, we report the results from the measurement choices outlined above. In row 7, we report the results when the ICT sector is twice as large as actually observed. Expectedly, such choices reduce the importance of the CS, because they reduce measured employment growth in these industries. Again, this is particularly relevant for cities, which saw the fastest increase in ICT employment. Nevertheless, CS continue to play an important role for aggregate growth and for urban areas in particular. Adding foreign trade does not alter the result that Indian growth is largely service led.

#### 7.3.2 Imperfect Substitution and Skill Bias in Technology

In our model, we allow for individual heterogeneity in human capital but maintain that workers endowed with different efficiency units are perfect substitutes for one another. In this section, we generalize our model by assuming workers with different educational attainments are imperfect substitutes in production (see Section B-11 in the Appendix for details). As we showed in Table 2, agricultural workers have, on average, lower educational attainment that those employed in service industries. Thus, an increase in the skill endowment could be responsible for the reallocation of workers from agriculture to CS (see, e,.g., Porzio et al. (2020) or Schoellman and Hendricks (2020)). By ignoring such skill-based specialization, our Ricardian model could exaggerate the importance of technology for the development of the service sector.

For simplicity, we work with two skill groups and define workers to be skilled if they have completed secondary school. We assume the production functions to be of the usual CES form:

$$Y_{rs} = A_{rst}\left(\left(H_{rst}^{-}\right)^{\frac{\rho-1}{\rho}} + \left(Z_{rst}H_{rst}^{+}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \quad \text{for} \quad s = F, CS, G,$$

where $H^{+}$ and $H^{-}$ denote high- and low-skilled workers, respectively. Note that the technology admits differences in both TFP $A_{rst}$ and skill bias $Z_{rst}$ across sector-districts and time.[26] We assume the elasticity of substitution $\rho$ to be constant across sector-districts and externally calibrate $\rho = 1.8$, which is in the consensus region (see, e.g., Ciccone and Peri (2005) and Gancia et al. (2013)). Our conclusions do not hinge on the particular calibration of $\rho$.

[26] Allowing the skill bias of technology to vary across space is important. If $Z$ were constant across districts, the model would predict skill premia to be lower in skill-rich regions. However, this assumption contradicts the observation that both the relative supply of skills and the skill premium are positively correlated with urbanization.

We continue to allow for heterogeneous productivities across workers of the same educational group. A worker's wage is a draw from a skill-specific Pareto distribution with the same tail parameter as in our baseline analysis.[27] As in our baseline analysis, this model is exactly identified, and for given structural parameters, we can rationalize the data of sectoral earnings shares by skill group and average earnings by skill group for each region in India by choice of $A_{rst}$ and $Z_{rst}$ (see Section B-11 in the Appendix).

The results of this extension are reported in the last row of Table 7. Because productivity growth is now parametrized by changes in factor-neutral productivity $A_{rst}$ and the skill bias $Z_{rst}$, we set the respective growth rates in both sectors to zero. The quantitative role for the CS sector is very similar to the one of our baseline calibration. Interestingly, human capital now plays a more important role, owing to the increasing supply of high-skilled labor over time.

This extension also allows us to uncover additional facts about the skill bias in technology. In Figure 12, we plot our estimates of the skill bias $Z_{rst}$ as binned scatter plots. First, across districts, $Z_{rs}$ increases in the level of urbanization for all sectors. This increase reflects the empirical observation that the skill premium is higher in urban than in rural districts. Second, we find evidence for skill-biased technical change: over time, $Z_{rs}$ increases in all sectors. Although our accounting approach cannot uncover causal links, these patterns are consistent with models of directed technical change and directed technology adoption such as Acemoglu and Zilibotti (2001) and Gancia et al. (2013), where firms adopt more skill-intensive technologies in response to the wider availability of skilled workers.

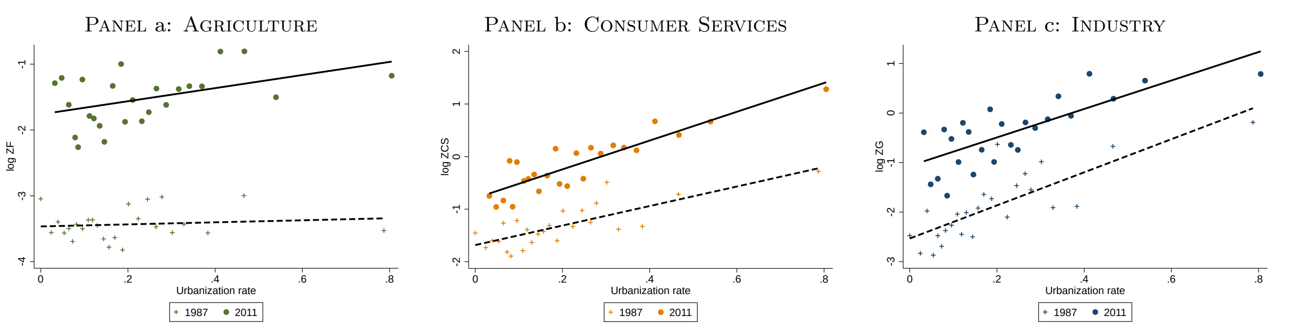


Figure 12: Skill Bias of Technology. The figure shows a binned scatter plot of $Z_{rF}$, $Z_{rCS}$, and $Z_{rG}$ as a function of the urbanization rate in 1987 (dashed line and "+" markers) and 2011 (solid line dots).

## 8 Conclusion

Although an expanding service sector is often seen as a rich-country phenomenon, tertiarization is well underway in most developing countries. In particular, rising employment in consumer services such as retail and restaurants accounts for the bulk of the decline in agricultural employment while industrial employment is often stagnant. Are these patterns a sign that services can be a source of productivity growth even at low levels of economic development? Or is rising service employment simply a corollary of rising incomes if services are luxury goods? In short: Is growth service led or service biased?

[27] Separately identifying the lower bound of the Pareto distribution of human-capital draws from the level of the technology parameters is impossible. Therefore, we normalize the lower bound to unity for both skill groups. Because we are only interested in changes over time in TFP, this normalization is immaterial.

In this paper, we developed a methodology to answer this question. Our approach is in the spirit of development accounting but uses the restrictions imposed by a spatial equilibrium model. The estimated model allows us to determine the importance of different sectors as an engine of growth and structural transformation. Moreover, it lends itself to a quantitative analysis of both the aggregate welfare effects of growth and its distributional consequences.

At the core of our identification strategy are consumers' preferences, in particular, the income elasticity of aggregate service demand. The higher this elasticity, the more service-biased economic growth is. Conversely, if the income elasticity of consumer demand is limited, rising employment in the consumer service sector is a sign that growth was service led. Given the importance of this parameter, we infer it directly using Indian household data. Importantly, we show that the income elasticity of consumers' observable demand system over final expenditure coincides with the one defined over value added that is relevant in our theory.

Our analysis delivers two main results. First and foremost, Indian growth was to a large extent service led. Quantitatively, productivity growth in sectors such as retail, hospitality, or transportation account for one third of welfare growth between 1987 and 2011. Second, the welfare impact of service-led growth was strikingly unequal and benefitted mostly wealth individuals in urbanized locations. The reasons are that service productivity grew particularly fast in urban areas and that richer consumers care more about the consumption of services owing to nonhomothetic preferences.

We also document that productivity growth in consumer services was the main driver of the structural transformation and accounts for almost half of the decline in agricultural employment. By contrast, technical progress in agriculture, did not promote structural change. This result is in line with a growing body of literature – including Kelly et al. (2020), Moscona (2019), or Foster and Rosenzweig (2004) – who document similar findings for India, within and across countries, and for the British Industrial Revolution.

Our approach has several limitations that we hope to overcome in future research. Two are particularly important. First, owing to our accounting approach, we took consumer service productivity as exogenous. Understanding the exact nature of productivity growth and how it materializes seems to us a question of first-order importance, in particular as far as potential policy-implications are concerned. Second, knowing whether service-led growth is unique to the Indian experience or also important in other developing countries would be interesting. If service-led growth is indeed an integral part of the growth trajectory of developing countries today, the absence of employment growth in the manufacturing sector might be less concerning than previously thought.

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# APPENDIX A: TECHNICAL DETAILS

In this section, we discuss the technical material referred to in the text.

## A-1 Derivation of the expenditure shares $\vartheta_s(e, \mathbf{p})$ (Equation (3))

Roy's Identity implies that the expenditure share on sector $s$ is given by

$$\vartheta_s(e, \mathbf{p}) = -\frac{\frac{\partial V(e(\mathbf{p},u),\mathbf{p})}{\partial p_s} p_s}{\frac{\partial V(e(\mathbf{p},u),\mathbf{p})}{\partial e} e}.$$

Using the indirect utility function in (2), $\vartheta_s(e, \mathbf{p})$ is given by

$$\vartheta_s(e, \mathbf{p}) = \omega_s + \nu_s \left( \frac{e}{\prod_s p_{st}^{\omega_s}} \right)^{-\varepsilon}$$

## A-2 Equilibrium in the Industrial Sector

In this section we characterize the equilibrium in the industrial sector. The technical details are contained in the Online Appendix. As highlighted in Proposition 1, we have to distinguish two cases. In particular, recall the definition

$$\varsigma(A_{PS}) \equiv \frac{\kappa}{f_O A_{PS}}. \tag{A-1}$$

Henceforth, we simply write $\varsigma$. Below we will show that some active firms do not hire lawyers if and only if

$$\varsigma \geq \frac{\beta}{1-\alpha}. \tag{A-2}$$

Note that $\varsigma$ is deceasing in $A_{PS}$ (see (A-1)). Hence, condition (A-2) requires the productivity of lawyers $A_{PS}$ to be low enough.

#### Firm-level allocations

We first solve for the firm-level allocations, i.e. firm profits, firm employment and the productivity cutoff $z^*$. Let $p_G$ denote the price of the industrial good. If active, firm $z_i$ solves the maximization problem

$$\pi(z_i) = \max_{H_{PMi}, H_{PSi} \geq 0} \left\{ p_G z_i^{1-\alpha-\beta} H_{PMi}^{\alpha} (A_{PS} H_{PSi} + \kappa)^{\beta} - w (H_{PMi} + H_{PSi}) - f_O w \right\}. \tag{A-3}$$

where $f_O w$ denotes the overhead costs. Note that we explicitly impose the constraint that $H_{PSi} \geq 0$. Firms operate if and only if $\pi(z_i) \geq 0$. We denote the productivity threshold by $z^*$, i.e., $\pi(z^*) = 0$. Under condition (11), $z^* > A_M$, that is there is a range of low-productivity firms that choose to be inactive.

**Proposition 2.** *Suppose that* $\varsigma \geq \frac{\beta}{1-\alpha}$*, where* $\varsigma$ *is given in* (A-1)*. Let* $z^*$ *denote the endogenous productivity threshold, such that firms with* $z_i \geq z^*$ *produce in equilibrium. Let* $z_L$ *denote the cutoff where firms start hiring producer services. Then:*

1. *The productivity threshold* $z^*$ *is given by*

$$z^* = \left( \frac{w}{p_G} \frac{1}{\kappa^{\beta} \alpha} \left( \frac{\alpha}{1-\alpha} f_O \right)^{1-\alpha} \right)^{\frac{1}{1-\alpha-\beta}}. \tag{A-4}$$

2. *The producer service cutoff* $z_L$ *is given by*

$$z_L = z^* \left(\frac{1-\alpha}{\beta}\varsigma\right)^{\frac{1-\alpha}{1-\alpha-\beta}} > z^* \tag{A-5}$$

3. *Optimal factor demands are given by*

$$H_{PS}\left(z_i\right) = \begin{cases} 0 & \text{if } z_i < z_L \\ \varsigma \frac{z_i - z_L}{z_L} f_O & \text{if } z_i \geq z_L \end{cases}, \tag{A-6}$$

*and*

$$H_{PM}\left(z_i\right) = \begin{cases} \frac{\alpha}{\beta} f_O \varsigma \left(\frac{z_i}{z_L}\right)^{\frac{1-\alpha-\beta}{1-\alpha}} & \text{if } z_i < z_L \\ \frac{\alpha}{\beta}\varsigma \frac{z_i}{z_L} f_O & \text{if } z_i \geq z_L \end{cases}. \tag{A-7}$$

4. *Firm-level profits are given by*

$$\pi\left(z_i\right) = \begin{cases} \left(\frac{1-\alpha}{\beta}\varsigma\left(\frac{z_i}{z_L}\right)^{\frac{1-\alpha-\beta}{1-\alpha}} - 1\right) f_O w & \text{if } z_i < z_L \\ \left(\varsigma\left(1 + \left(\frac{1-\alpha-\beta}{\beta}\right)\frac{z_i}{z_L}\right) - 1\right) f_O w & \text{if } z_i \geq z_L \end{cases}. \tag{A-8}$$

*Proof.* See Section OA-1.1 in the Online Appendix. □

Note that (A-5) determines $z_L$ directly as a function of $z^*$. Moreover, under our assumption that $\varsigma > \frac{\beta}{1-\alpha}$ indeed $z^* < z_L$ and all firms with $z_i \in [z^*, z_L]$ do not hire lawyers. As $\varsigma \to \frac{\beta}{1-\alpha}$, we have $z^* \to z_L$. Note also that the profit function in (A-8) is concave in $z$ as long firms do not hire lawyers but linear in $z$ once they hire lawyers.

**Proposition 3.** *Suppose that* $\varsigma < \frac{\beta}{1-\alpha}$*, where* $\varsigma$ *is given in* (A-1)*. Let* $\tilde{z}$ *denote the endogenous productivity threshold, such that firm with* $z_i \geq \tilde{z}$ *will produce in equilibrium. Then:*

1. *The productivity threshold is given by*

$$\tilde{z} = \frac{1}{1-\alpha-\beta}\left(\frac{w}{p_G}\right)^{\frac{1}{1-\alpha-\beta}}\left(\frac{1}{\alpha}\right)^{\frac{\alpha}{1-\alpha-\beta}}\left(\frac{1}{\beta A_{PS}}\right)^{\frac{\beta}{1-\alpha-\beta}} f_O\left(1-\varsigma\right). \tag{A-9}$$

2. *Optimal factor demands are given by*

$$\begin{aligned} H_{PMi} &= \frac{\alpha}{1-\alpha-\beta} f_O\left(1-\varsigma\right)\frac{z_i}{\tilde{z}} \\ H_{PSi} &= \frac{\beta}{1-\alpha-\beta} f_O\left(1-\varsigma\right)\frac{z_i}{\tilde{z}} - \frac{\kappa}{A_{PS}}. \end{aligned}$$

3. *Firm-level profits are given by*

$$\pi\left(z_i\right) = \pi\left(z_i\right) = \left(\frac{z-\tilde{z}}{\tilde{z}}\right) f_O\left(1-\varsigma\right) w. \tag{A-10}$$

*Proof.* See Section OA-1.1 in the Online Appendix. □

### Free Entry and the Equilibrium Wage

Free entry requires that the cost of entry are equal to the expected profits, i.e.

$$f_E w = E\left[\pi\right] = \int \pi\left(x\right) f\left(x\right) dx.$$

This condition allows us to solve for the equilibrium real wage $\frac{w}{p_G}$.

**Proposition 4.** *Suppose that* $\varsigma \geq \frac{\beta}{1-\alpha}$. *Then*

$$\left(\frac{z_L}{A_M}\right)^{\lambda} = \frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[\left(\varsigma\frac{1-\alpha}{\beta}\right)^{\lambda\frac{1-\alpha}{1-\alpha-\beta}} + \frac{\varsigma}{\lambda-1}\right]\frac{f_O}{f_E} \tag{A-11}$$

$$\left(\frac{z^*}{A_M}\right)^{\lambda} = \frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[1+\frac{1}{\lambda-1}\left(\frac{\beta}{1-\alpha}\right)^{\frac{(1-\alpha)\lambda}{1-\alpha-\beta}}\varsigma^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right]\frac{f_O}{f_E}, \tag{A-12}$$

*and*

$$\frac{w}{p_G} = \left(\frac{z_L}{\kappa}\right)^{1-\alpha-\beta}\alpha^{\alpha}\left(\beta A_{PS}\right)^{1-\alpha} \tag{A-13}$$

$$= \left(\frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[1+\frac{1}{\lambda-1}\left(\frac{\beta}{1-\alpha}\right)^{\frac{(1-\alpha)\lambda}{1-\alpha-\beta}}\varsigma^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right]\frac{f_O}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}} A_M^{1-\alpha-\beta}\kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha}{f_O}\right)^{1-\alpha} \tag{A-14}$$

*Suppose that* $\varsigma < \frac{\beta}{1-\alpha}$. *Then*

$$\left(\frac{\tilde{z}}{A_M}\right)^{\lambda} = \frac{1}{\lambda-1}\frac{f_O}{f_E}\left(1-\varsigma\right), \tag{A-15}$$

*and*

$$\frac{w}{p_G} = \left(\frac{\tilde{z}\left(1-\alpha-\beta\right)}{f_O\left(1-\varsigma\right)}\right)^{1-\alpha-\beta}\left(\beta A_{PS}\right)^{\beta}\left(\alpha\right)^{\alpha} \tag{A-16}$$

$$= \left(1-\alpha-\beta\right)^{1-\alpha-\beta}\left(\frac{1}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}\left(\frac{1}{f_O\left(1-\varsigma\right)}\right)^{\frac{\lambda-1}{\lambda}(1-\alpha-\beta)} A_M^{1-\alpha-\beta}\left(\beta\frac{\kappa}{f_O\varsigma}\right)^{\beta}\left(\alpha\right)^{\alpha}. \tag{A-17}$$

*Proof.* See Section OA-1.3 in the Online Appendix. □

Proposition 4 characterizes the cutoffs and the real wage in terms of parameters. In particular, all cutoffs $z_L$ are independent of the wage $w$. Note also that $\varsigma$ is decreasing in $A_{PS}$ so that $\frac{\partial z_L}{\partial A_{PS}} < 0$, i.e. if lawyers become more productive, the cutoff to hire lawyers declines. Moreover, $\frac{\partial z^*}{\partial A_{PS}} > 0$.[1] Because $\varsigma$ is decreasing in $A_{PS}$, the real wage is increasing in $A_{PS}$ (see Section OA-1.5 in the Online Appendix).

### Aggregate Labor Allocations

Now consider aggregate employment. In our economy, workers in the manufacturing sector are used for production work ($H_{PM}$), to provide PS ($H_{PS}$), pay for overhead ($H_{OM}$) and generate new business ideas ($H_{EM}$). Hence, labor market clearing requires that

$$H_G = H_{PS} + H_{PM} + H_{EM} + H_{OM}.$$

[1] Note that we assumed that $z^* > A_M$. Hence, we need to impose that

$$\frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[1+\frac{1}{\lambda-1}\left(\frac{\beta}{1-\alpha}\right)^{\frac{(1-\alpha)\lambda}{1-\alpha-\beta}}\varsigma^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right]\frac{f_O}{f_E} > 1$$

**Proposition 5.** *The number of entry and production workers is given by*

$$\begin{aligned} H_{EM} &= \frac{1-\alpha-\beta}{\lambda} H_G \\ H_{PM} &= \alpha H_G \end{aligned}$$

*independent of* $\varsigma$*. The number of firms,* $M$*, is given by*

$$M = \frac{1-\alpha-\beta}{\lambda} \frac{H_G}{f_E}.$$

*independent of* $\varsigma$*. The number of lawyers and overhead workers is given by*

$$H_{PS} = \begin{cases} \frac{\sigma(\varsigma)}{1+\sigma(\varsigma)} \frac{\beta+(\lambda-1)(1-\alpha)}{\lambda} H_G & \text{if } \varsigma \geq \frac{\beta}{1-\alpha} \\ \left(\beta - (1-\alpha-\beta) \frac{\lambda-1}{\lambda} \frac{\varsigma}{1-\varsigma}\right) H_G & \text{if } \varsigma < \frac{\beta}{1-\alpha} \end{cases}$$

*and*

$$H_{OM} = \begin{cases} \frac{1}{1+\sigma(\varsigma)} \times \frac{\beta+(\lambda-1)(1-\alpha)}{\lambda} H_G & \text{if } \varsigma \geq \frac{\beta}{1-\alpha} \\ (1-\alpha-\beta) \frac{\lambda-1}{\lambda} \frac{1}{1-\varsigma} H_G & \text{if } \varsigma < \frac{\beta}{1-\alpha} \end{cases},$$

*where*

$$\sigma(\varsigma) \equiv \frac{1}{\lambda-1} \left(\frac{\beta}{1-\alpha}\right)^{\lambda \frac{1-\alpha}{1-\alpha-\beta}} \varsigma^{-\frac{(\lambda-1)(1-\alpha)+\beta}{1-\alpha-\beta}}.$$

*Proof.* See Section OA-1.4 in the Online Appendix. □

Proposition 5 implies that $H_{PS}$ is increasing in $A_{PS}$, whereas $H_{OM}$ is decreasing in $A_{PS}$. Interestingly, their sum is independent of $A_{PS}$, i.e.

$$\frac{H_{OM}+H_{PS}}{M} = \left(\frac{\beta+(\lambda-1)(1-\alpha)}{1-\alpha-\beta}\right) f_E.$$

Proposition 5 also implies that the endogenous number of firms that are created, $M$, is independent of $A_{PS}$ conditional on total industrial employment $H_G$. But the number of ideas, that actually produce, $M(1-F(z^*)$, is decreasing in $A_{PS}$ as the production cutoff $z^*$ is increasing in $A_{PS}$. Hence, improvements in the productivity of lawyers induce selection by truncating the productivity distribution. Note that all these allocations are independent of aggregate manufacturing productivity $A_M$. This is in contrast to the micro-level, where employment shares vary systematically with firm productivity $z$. In particular, (A-6) and (A-7) imply that for firms that hire lawyers (i.e. $z_i \geq z_L$) we have

$$\frac{H_{PS}(z)}{H_{PM}(z)} = \frac{\beta}{\alpha}\left(1-\frac{z_i}{z_L}\right),$$

i.e. more productive firms have a higher employment share of lawyers relative to production workers. However, the aggregate employment share of production workers hired by (large) firms who hire a positive share of lawyers (i.e. $z_i > z_L$) is given by

$$\frac{\int_{z\geq z_L} H_{PM}(z)\, dG(z)}{\int_{z\geq z_L} H_{PS}(z)\, dG(z)} = \lambda \frac{\alpha}{\beta}.$$

Hence, even though there is micro-heterogeneity in the intensity of hiring lawyers, the aggregate employment share of lawyers (among firms who hire lawyers) is constant and depends on the tail of the productivity distribution $\lambda$. A thicker tail, i.e. $\lambda$ smaller, *increases* the aggregate employment share of lawyers by shifting resources towards large firms, which are lawyer intensive.

Figure A-1 depicts the allocation of employment as a function of $\varsigma = \frac{\kappa}{A_{PS} f_O}$ for both cases discussed above. Note that all employments are continuous at the threshold $\varsigma = \frac{\beta}{1-\alpha}$.

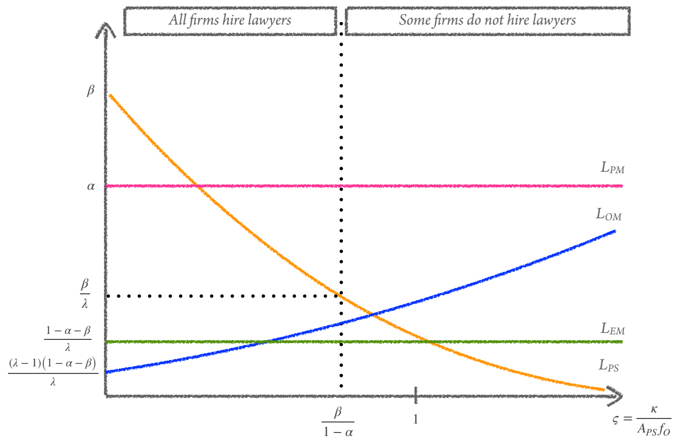


Figure A-1: Aggregate labor allocations

### Aggregate Manufacturing Productivity

The free entry condition ensures that the industrial sector as a whole does not generate any profits. Hence, aggregate revenue is equal to aggregate labor payments

$$p_G Y_G = w H_G.$$

**Proposition 6.** *Let aggregate productivity in the goods producing sector $A_G$ be defined by*

$$A_G \equiv \frac{Y_G}{H_G}.$$

*Then,*

$$A_G = \begin{cases} Q_2 \left(\frac{1}{1-\varsigma}\right)^{\frac{\lambda-1}{\lambda}(1-\alpha-\beta)} \left(\frac{1}{\varsigma}\right)^{\beta} A_M^{1-\alpha-\beta} & \text{if } \varsigma < \frac{\beta}{1-\alpha} \\ Q_1 \left(1 + \frac{1}{\lambda-1}\frac{\beta}{1-\alpha}\left(\frac{1-\alpha}{\beta}\varsigma\right)^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right)^{\frac{1-\alpha-\beta}{\lambda}} A_M^{1-\alpha-\beta} & \text{if } \varsigma \geq \frac{\beta}{1-\alpha} \end{cases},$$

*where*

$$Q_1 = \left(\frac{(1-\alpha-\beta)}{\beta + (1-\alpha)(\lambda-1)}\frac{f_O}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}} \kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha}{f_O}\right)^{1-\alpha}$$

*and*

$$Q_2 = \alpha^{\alpha}(1-\alpha-\beta)^{1-\alpha-\beta}\left(\frac{1}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}(\beta\kappa)^{\beta}\left(\frac{1}{f_O}\right)^{\frac{(\lambda-1)(1-\alpha)+\beta}{\lambda}}.$$

Proposition 6 follows directly from the fact that $A_G = w/p_G$ and the solution for $w/p_G$ from Proposition 4. The importance of Proposition 6 is that it shows that the manufacturing sector is characterized by an aggregate production function for the industrial good sector, where total productivity in industrial production $A_G$ is fully determined from parameters: the productivity of lawyers $A_{PS}$ (encapsulated in $\varsigma$), the level of productivity $A_M$, the overhead cost $f_O$ and the entry cost $f_E$ . Note that $A_G$ is continuous in $\varsigma$ and satisfies

$$\lim_{\varsigma\to\infty} A_G = \left(\frac{(\lambda-1)(1-\alpha)}{\beta+(1-\alpha)(\lambda-1)}\right)^{\frac{1-\alpha-\beta}{\lambda}} \kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha-\beta}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}\left(\frac{1-\alpha}{f_O}\right)^{\frac{(\lambda-1)(1-\alpha)+\beta}{\lambda}} A_M^{1-\alpha-\beta}$$

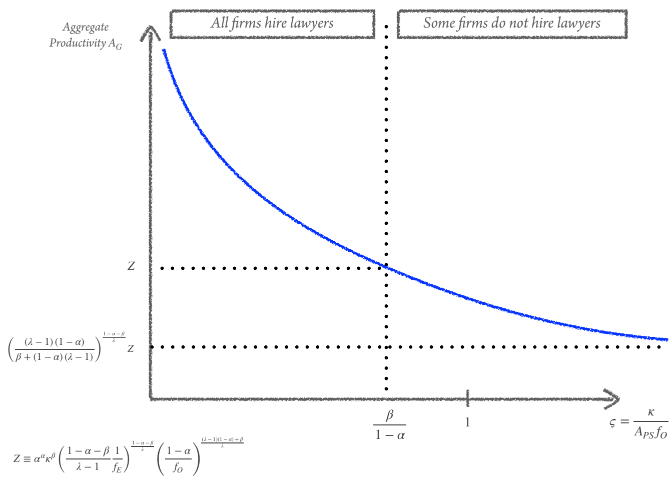


Figure A-2: Aggregate productivity $A_G$

and

$$A_G\left(\varsigma = \frac{\beta}{1-\alpha}\right) = \alpha^{\alpha}\kappa^{\beta}\left(\frac{1-\alpha-\beta}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}\left(\frac{1-\alpha}{f_O}\right)^{\frac{(\lambda-1)(1-\alpha)+\beta}{\lambda}} A_M^{1-\alpha-\beta}.$$

Figure A-2 depicts aggregate productivity $A_G$ as a function of $\varsigma = \frac{\kappa}{A_{PS} f_O}$ for both cases discussed above.

## A-3 Estimation of Productivity Fundamentals and Structural Parameters (Sections 5.2 and 5.1)

In this section we describe the details of our strategy to estimate the productivity fundamentals $\{A_{rst}\}$ and two structural parameters, $\omega_{CS}$ and $\nu_F$.

Consider a single time period. We observe $\left\{\left[w_r^D\right]_r, H_{rF}, H_{rG}, H_{rCS}\right\}_r$. We indicate the observed wages by $w_r^D$ to distinguish them from the model wages $w_r$ as we did not pick a numeraire yet - see below.

**Step 1: Estimating *relative* food productivity and *relative* manufacturing productivity** It is useful to write productivities as

$$\begin{aligned} A_{rF} &= A_F a_{rF} \text{ with } \sum_{r=1}^{R} a_{rF}^{\sigma-1} = 1 \\ A_{rG} &= A_G a_{rG} \text{ with } \sum_{r=1}^{R} a_{rG}^{\sigma-1} = 1. \end{aligned}$$

Here $A_s$ denotes the level of sectoral productivities and $a_{rs}$ denotes the relative productivity of region $r$. Using the market clearing conditions in (7), it is easy to show that

$$a_{rF} = \left(\frac{H_{rF} w_r^{\sigma}}{\sum_{r=1}^{R} (H_{rF}) w_r^{\sigma}}\right)^{\frac{1}{\sigma-1}} \tag{A-18}$$

$$a_{rG} = \left(\frac{H_{rG} w_r^{\sigma}}{\sum_{r=1}^{R} (H_{rG}) w_r^{\sigma}}\right)^{\frac{1}{\sigma-1}} \tag{A-19}$$

Note $a_{rF}$ and $a_{rG}$ are insensitive to the level of $w_r$.

**Step 2: Estimating $A_F$ and $A_G$** The two prices of the tradable goods are

$$p_{Ft} = \left(\sum_r \left(\frac{w_r}{A_{rF}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \frac{1}{A_F}\left(\sum_r \left(\frac{w_r}{a_{rF}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

$$p_{Gt} = \left(\sum_r \left(\frac{w_r}{A_{rG}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \frac{1}{A_G}\left(\sum_r \left(\frac{w_r}{a_{rG}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

Note that $\left(\sum_r \left(\frac{w_r}{a_{rF}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ and $\left(\sum_r \left(\frac{w_r}{a_{rG}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ are observable from (A-18) and (A-19). Hence, let us write

$$\Lambda_s^w \equiv \left(\sum_r \left(\frac{w_r}{a_{rs}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{A-20}$$

where $\Lambda_s^w$ is known. The superscript "$w$" indicates that this object is homogenous of degree one in the level of wages. To determine $A_F$ and $A_G$ we use two restrictions:

1. First we choose the manufacturing good as the numeraire. This determines $A_G$ because $p_{Gt} = 1$ implies that $A_G = \Lambda_G^w$. Note that an increase in $w$ by a common factor increases $A_G$ by the same amount.
2. Let the relative price of agricultural goods relative to manufacturing goods be $p_t^{AG}$. Then

$$p_t^{AG} = \frac{p_t^A}{p_t^G} = \frac{A_F^{-1}\Lambda_F^w}{A_G^{-1}\Lambda_G^w} = A_F^{-1}\Lambda_F^w.$$

   Given $p_t^{AG}$, we can thus identify $A_F$.

**Step 3: Estimating $\{A_{rCS}\}_{r=1}^R$ and the structural parameters $\omega_{CS}$ and $\nu_F$** To derive (A-18) and (A-19) we used $R-1$ equations for each sector. This means that we still have $R$ equations for the non-tradable CS sector and two aggregate resource constraints for the tradable goods. These are

$$\frac{H_{rCS}}{H_r} = \omega_{CS} + \nu_{CS}\left(p_{At}^{\omega_A} p_{rCSt}^{\omega_{CS}} p_{Gt}^{\omega_G}\right)^{\varepsilon} \left(E_{rt}[q] w_{rt}\right)^{-\varepsilon} \tag{A-21}$$

$$\sum_r w_r H_{rF} = \sum_{j=1}^{R} \left(\omega_A + \nu_A \left(p_{At}^{\omega_A} p_{CSjt}^{\omega_{CS}} p_{Gt}^{\omega_G}\right)^{\varepsilon} \left(E_{rt}[q] w_{rt}\right)^{-\varepsilon}\right) w_j H_j \tag{A-22}$$

$$\sum_r w_r H_{rG} = \sum_{j=1}^{R} \left((1-\omega_A-\omega_{CS}) - (\nu_A+\nu_{CS})\left(p_{At}^{\omega_A} p_{CSjt}^{\omega_{CS}} p_{Gt}^{\omega_G}\right)^{\varepsilon} \left(E_{rt}[q] w_{rt}\right)^{-\varepsilon}\right) w_j H_j \tag{A-23}$$

Equation (A-23) is redundant, it is implied by (A-21) and (A-22) due to Walras' Law. Substituting the numeraire assumption $p_{Gt}=1$, $p_{At}=p_t^{AG}$, where $p_t^{AG}$ is the observed relative price and $p_{rCSt}=\frac{w_{rt}}{A_{rCSt}}$ yields

$$\frac{H_{rCS}}{H_r} = \omega_{CS}+\nu_{CS}\left(p_t^{AG}\right)^{\varepsilon\omega_A}\left(\frac{w_{rt}}{A_{rCS}}\right)^{\varepsilon\omega_{CS}}\left(E_{rt}[q]w_{rt}\right)^{-\varepsilon} \tag{A-24}$$

$$\sum_r w_r H_{rF} = \omega_A\sum_{j=1}^{R}w_jH_j+\nu_A\left(p_t^{AG}\right)^{\varepsilon\omega_A}\sum_{j=1}^{R}\left(\frac{w_{jt}}{A_{CSj}}\right)^{\varepsilon\omega_{CS}}\left(E_{rt}[q]\right)^{-\epsilon}w_{jt}^{1-\varepsilon}H_j. \tag{A-25}$$

For a given year these are $R+1$ equations in $R$ productivities $\{A_{rCS}\}$ and 4 structural parameters $(\omega_{CS},\omega_F,\nu_F,\nu_{CS})$ (recall that we take $\varepsilon$ as given because we estimate it from the expenditure shares). If we have $T$ years, we have $TR+4$ unknowns and $TR+T$ equations. Thus, by insisting that preferences are constant over time, we add over-identifying restrictions to our analysis as we add additional years.

Note that (A-24) implies that

$$\left(p_t^{AG}\right)^{\varepsilon\omega_A}\left(\frac{w_{rt}}{A_{rCS}}\right)^{\varepsilon\omega_{CS}} = -\frac{1}{\nu_{CS}}\left(\omega_{CS}-\frac{H_{rCS}}{H_r}\right)\left(E_{rt}[q]w_{rt}\right)^{\varepsilon}.$$

Substituting this into (A-25) yields

$$\sum_r w_r H_{rF} = \omega_F\sum_{r=1}^{R}w_rH_r-\frac{\nu_F}{\nu_{CS}}\sum_{r=1}^{R}\left(\omega_{CS}-\frac{H_{rCS}}{H_r}\right)w_{rt}H_r. \tag{A-26}$$

Given the data on $\{w_r, H_{rs}\}$, this is - for a given year - a single equation in three unknowns: $\omega_F$, $\frac{\nu_F}{\nu_{CS}}$ and $\omega_{CS}$. This leaves us with $R$ equations for consumer service employment. From (A-24) it is apparent that $\nu_{CS}$ is not separately identified from the *level* of productivity in the consumer service sector: holding $\omega_{CS}$ and $\varepsilon$ fixed, the data on wages $w_{rt}$ and employment shares $\frac{H_{rCS}}{H_r}$ identifies $\nu_{CS}A_{rCS}^{-\varepsilon\omega_{CS}}$. Hence, under the assumption that consumer services are a luxury, we can wlog normalize $\nu_{CS}=-1$. For a given choice of $\omega_F$ we can therefore use (A-26) in 1987 and 2011 to uniquely solve for $\omega_{CS}$ and $\nu_F$.

## A-4 The Elasticity of Substitution

The Allen Uzawa elasticity of substitution between goods $s$ and $k$ is given by

$$EOS_{sk}=\frac{\frac{\partial^2 e(p,V)}{\partial p_s\partial p_k}e\left(p,V\right)}{\frac{\partial e(p,V)}{\partial p_s}\frac{\partial e(p,V)}{\partial p_k}}.$$

The expenditure function is given by

$$e\left(p,V\right) = \left(V+\sum_s\tilde{\nu}_s\ln p_s\right)^{1/\varepsilon}\varepsilon^{1/\varepsilon}\prod_{s\in\{F,G,CS\}}p_s^{\omega_s}.$$

This implies that

$$\begin{aligned}\frac{\partial e\left(p,V\right)}{\partial p_s} &= \left(V+\sum_s\tilde{\nu}_s\ln p_s\right)^{1/\varepsilon}\varepsilon^{1/\varepsilon}\prod_{s\in\{F,G,CS\}}p_s^{\omega_s}\left(\frac{\frac{1}{\varepsilon}\tilde{\nu}_s}{V+\sum_s\tilde{\nu}_s\ln p_s}+\omega_s\right)\frac{1}{p_s}\\ &= e\left(p,V\right)\left(\frac{\frac{1}{\varepsilon}\tilde{\nu}_s}{V+\sum_s\tilde{\nu}_s\ln p_s}+\omega_s\right)\frac{1}{p_s}.\end{aligned}$$

This also implies that

$$\begin{aligned}\frac{\partial^2 e(p,V)}{\partial p_s \partial p_k} &= \frac{\partial e(p,V)}{\partial p_k}\left(\frac{\frac{1}{\varepsilon}\tilde{\nu}_s}{V+\sum_s \tilde{\nu}_s \ln p_s}+\omega_s\right)\frac{1}{p_s} - e(p,V)\frac{\frac{1}{p_s}\frac{1}{\varepsilon}\tilde{\nu}_s\tilde{\nu}_k\frac{1}{p_k}}{\left(V+\sum_s \tilde{\nu}_s \ln p_s\right)^2} \\ &= e(p,V)\frac{1}{p_k}\frac{1}{p_s}\left\{\left(\frac{\frac{1}{\varepsilon}\tilde{\nu}_k}{V+\sum_s \tilde{\nu}_s \ln p_s}+\omega_k\right)\left(\frac{\frac{1}{\varepsilon}\tilde{\nu}_s}{V+\sum_s \tilde{\nu}_s \ln p_s}+\omega_s\right)-\varepsilon\frac{\frac{1}{\varepsilon}\tilde{\nu}_s\frac{1}{\varepsilon}\tilde{\nu}_k}{\left(V+\sum_s \tilde{\nu}_s \ln p_s\right)^2}\right\}.\end{aligned}$$

Now note that

$$\begin{aligned}\frac{\frac{1}{\varepsilon}\tilde{\nu}_k}{V+\sum_s \tilde{\nu}_s \ln p_s}+\omega_k &= \tilde{\nu}_k\frac{1}{\varepsilon}\left(V+\sum_s \tilde{\nu}_s \ln p_s\right)^{-1}+\omega_k \\ &= \tilde{\nu}_k\left(\frac{e(p,V)}{\prod_{s\in\{F,G,CS\}} p_s^{\omega_s}}\right)^{-\varepsilon}+\omega_k = \vartheta_k.\end{aligned}$$

Hence,

$$\begin{aligned}\frac{\partial e(p,V)}{\partial p_s} &= e(p,V)\,\vartheta_s\frac{1}{p_s} \\ \frac{\partial^2 e(p,V)}{\partial p_s \partial p_k} &= e(p,V)\frac{1}{p_k}\frac{1}{p_s}\left\{\vartheta_k\vartheta_s - \varepsilon\frac{\frac{1}{\varepsilon}\tilde{\nu}_s}{V+\sum_s \tilde{\nu}_s \ln p_s}\frac{\frac{1}{\varepsilon}\tilde{\nu}_k}{V+\sum_s \tilde{\nu}_s \ln p_s}\right\} \\ &= e(p,V)\frac{1}{p_k}\frac{1}{p_s}\left\{\vartheta_k\vartheta_s - \varepsilon(\vartheta_s-\omega_s)(\vartheta_k-\omega_k)\right\}.\end{aligned}$$

This implies that

$$\begin{aligned}EOS_{sk} &= \frac{e(p,V)\frac{1}{p_k}\frac{1}{p_s}\left\{\vartheta_k\vartheta_s - \varepsilon(\vartheta_s-\omega_s)(\vartheta_k-\omega_k)\right\}e(p,V)}{e(p,V)\,\vartheta_s\frac{1}{p_s}e(p,V)\,\vartheta_k\frac{1}{p_k}} \\ &= 1-\varepsilon\frac{(\vartheta_s-\omega_s)(\vartheta_k-\omega_k)}{\vartheta_s\vartheta_k}.\end{aligned}$$

## A-5 Open economy

In this model we present the formal analysis for the open economy extension discussed in Section 7.3.1.

### A-5.1 Environment and Equilibrium

We assume that the consumption of the physical good of consumers in India is a combination of domestic and imported goods with a constant elasticity of substitution $\eta$:

$$C_G = \left(C_{G,D}^{\frac{\eta-1}{\eta}} + \varphi C_{G,ROW}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}.$$

Here, $C_{G,D}$ and $C_{G,ROW}$ are the physical quantities of the domestic and imported physical good, $\varphi$ is a taste parameter capturing the preference for the imported good, and $\eta$ is the elasticity of substitution that we interpret as a trade elasticity.

Letting $p_{G,D}$ and $p_{G,ROW}$ denote the respective prices, the price index of the bundle $C_G$ is given by

$$P_G = \left(p_{G,D}^{1-\eta} + \varphi^{\eta} p_{G,ROW}^{1-\eta}\right)^{\frac{1}{1-\eta}}. \tag{A-27}$$

The expenditure share on Indian goods is $\frac{p_{G,D}C_G}{P_G C_G} = \left(\frac{P_{G,D}}{P_G}\right)^{1-\eta}$. Combining this expression with Equation (A-27) yields the expenditure shares

$$\begin{aligned}\frac{p_{G,D}C_{G,D}}{P_G C_G} &= \frac{\varphi^{-\eta}\left(\frac{P_{G,D}}{p_{G,ROW}}\right)^{1-\eta}}{1+\varphi^{-\eta}\left(\frac{P_{G,D}}{p_{G,ROW}}\right)^{1-\eta}},\\ \frac{p_{G,ROW}C_{G,ROW}}{P_G C_G} &= \frac{1}{1+\varphi^{-\eta}\left(\frac{P_{G,D}}{p_{G,ROW}}\right)^{1-\eta}}.\end{aligned}$$

For simplicity we subsume trade costs in the relative price of foreign goods.

The Indian economy is assumed to export both domestic goods and a special category of services that is traded internationally: ICT exports. Consider first the export of goods. We model total spending on Indian goods (in term of domestic goods) from the rest of the world (ROW) as

$$X_{G,D} = \frac{\varphi^{-\eta}\left(\frac{P_{G,D}}{p_{G,ROW}}\right)^{1-\eta}}{1+\varphi^{-\eta}\left(\frac{P_{G,D}}{p_{G,ROW}}\right)^{1-\eta}}\Upsilon_G,$$

i.e. $X_{G,D}$ are total exports from India, $\Upsilon_G$ is a demand shifter (for goods) and $p_{G,ROW}$ denotes the price of goods in the ROW. For simplicity we assume the price elasticity of exports and imports to be the same and equal to $\eta$. .

Consider, next, the exported ICT services.[2] We assume that the ROW buys a bundle of regional varieties ICT services

$$Y_{ICTt} = \left(\sum_{r=1}^{R}\left(y_{rICTt}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $y_{rICTt}$ denotes the quantity of services produced in region $r$ and exported to the rest of the world. ICT services are produced in region $r$ according to the production function $y_{rICTt} = A_{rICTt}H_{rt}$. Hence, the price of ICT services is given by

$$p_{ICTt} = \left(\sum_r p_{rICTt}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \left(\sum_r \left(\frac{w_{rt}}{A_{rICTt}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

As we do for goods, we model the import demand for ICT services as

$$X_{ICT} = p_{ICTt}^{1-\eta}\Upsilon_{ICT}.$$

Again, any trade costs are subsumed in the demand shifter $\Upsilon_{ICT}$.

### Equilibrium

The equilibrium with trade is pinned down by the following equilibrium conditions:

1. Market clearing for agricultural goods:

$$w_r H_{rF} = \left(\frac{w_r^{1-\sigma}A_{rF}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma}A_{jF}^{\sigma-1}}\right) \times \left(\sum_{j=1}^{R}\vartheta_{jF}w_j H_j\right)$$

[2] For simplicity, we assume that ICT services are not sold in the domestic market but only internationally.

2. Market clearing for manufacturing goods:

$$w_r H_{rG} \quad = \quad \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}}\right) \times$$
$$\underbrace{\left( \underbrace{\frac{\varphi^{-\eta}\left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}}\right)^{1-\eta}}{\varphi^{-\eta}\left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}}\right)^{1-\eta}+1} \sum_{j=1}^{R} \vartheta_{jG} w_j H_j}_{\text{Domestic spending}} + \underbrace{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G}_{\text{Total exports}} \right)}_{\text{Aggregate demand for physical goods}}$$

3. Market clearing for local CS:

$$w_r H_{rCS} = \vartheta_{rCS} w_r H_r.$$

4. Market clearing for local ICT services:

$$w_r H_{rICT} = \left(\frac{w_r^{1-\sigma} A_{rICT}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jICT}^{\sigma-1}}\right) \times \underbrace{\left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT}}_{\text{ICT exports}}$$

5. Labor market clearing:

$$H_{rF} + H_{rG} + H_{rCS} + H_{rICT} = H_r.$$

6. Balanced Trade:

$$\underbrace{\left(\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G + \left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT}\right)}_{\text{Exports}} = \underbrace{\frac{\sum_{j=1}^{R} \vartheta_{jG} w_j H_j}{\varphi^{-\eta}\left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}}\right)^{1-\eta}+1}}_{\text{Imports}}$$

Letting $x \equiv \varphi^{\eta} {p_{G,ROW}}^{1-\eta}$ denote the (scaled) terms of trade, these are $5R+1$ equations in $5R+1$ unknowns $\{x, \{w_r, H_{rF}, H_{rG}, H_{rCS}, H_{rICT}\}_r\}$. Again, we can pick a numeraire

$$p_{G,IND} = \left(\sum_r \left(\frac{w_r}{A_{rG}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = 1.$$

Given the productivities $\{A_{rF}, A_{rG}, A_{rCS}, A_{rICT}\}_r$, the population distribution $\{H_r\}_r$, the demand shilfters of the foreign sector $(\Upsilon_{ICT}, \Upsilon_G)$ and the other preference parameters of the model, we can calculate $\{x, \{w_r, H_{rF}, H_{rG}, H_{rCS}, H_{rICT}\}_r\}$.

### A-5.2 Identification of Productivity Fundamentals in the Open Economy Model

For the economy with trade we need to identify the following additional objects:

$$\left\{[A_{rICT}]_{r=1}^{R}, \Upsilon_G, \Upsilon_{ICT}\right\}.$$

There are $R+2$ unknowns. For these $R+2$ unknowns we have the following conditions

1. Relative ICT payments across localities for ICT exports:

$$\frac{w_r H_{rICT}}{w_j H_{jICT}} = \frac{w_r^{1-\sigma} A_{rICT}^{\sigma-1}}{w_j^{1-\sigma} A_{jICT}^{\sigma-1}}$$

   These are $R-1$ equations to determine $A_{rICT}$ up to scale, i.e.

$$A_{rICT} = A_{ICT} a_{rICT} \text{ with } \sum_r a_{rICT}^{\sigma-1} = 1$$

   yields

$$a_{rICT} = \left(\frac{H_{rICT} w_r^{\sigma}}{\sum_j H_{jICT} w_j^{\sigma}}\right)^{\frac{1}{\sigma-1}}$$

   Because the level of ICT productivity $A_{ICT}$ is not separately identified from the aggregate demand shifter $\Upsilon_{ICT}$, without loss of generality we can set $A_{ICT} = 1$.[3]

2. To identify $\Upsilon_{ICT}$ we use that

$$\begin{aligned}\sum_r w_r L_{rICT} &= \sum_r \left(\frac{w_r^{1-\sigma} A_{rICT}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jICT}^{\sigma-1}}\right)\left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT} \\ &= \left(\sum_j w_j^{1-\sigma} a_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT}. \qquad \text{(A-28)}\end{aligned}$$

   The RHS is total value added of the ICT sector, which we can calculate directly in the data. Given that $w_j$ and $a_{jICT}$ is observed, we can calculate $\Upsilon_{ICT}$.

3. To identify $\Upsilon_G$ we use a moment about the share of manufacturing value added that is exported. Our model implies that:

$$\text{Total value added in manufacturing} = \sum_r w_r H_{rG}$$

   and

$$\text{Total value added of exports} = \left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G$$

[3] To see this, note that the equilibrium condition for ICT exports implies that

$$w_r H_{rICT} = \left(\frac{w_r^{1-\sigma} A_{rICT}^{\sigma-1}}{\sum_j^R w_j^{1-\sigma} A_{jICT}^{\sigma-1}}\right)\left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT} = \left(\frac{w_r^{1-\sigma} a_{rICT}^{\sigma-1}}{\sum_j^R w_j^{1-\sigma} a_{jICT}^{\sigma-1}}\right)\left(\sum_j w_j^{1-\sigma} a_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} A_{ICT}^{\eta-1} \Upsilon_{ICT}$$

Hence, $\Upsilon_{ICT}$ and $A_{ICT}$ are not separately identified.

Hence, the share of value added in the manufacturing sector is

$$M_1 = \frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G}{\sum_r w_r H_{rG}} = \frac{P_{G,IND}^{1-\eta} \Upsilon_G}{\sum_r w_r H_{rG}} = \frac{\Upsilon_G}{\sum_r w_r H_{rG}} \tag{A-29}$$

Hence, for a given moment of the export share of manufacturing $M_1$ and data on $\{w_j, L_{jG}\}_j$ we can solve for $\Upsilon_G$.

# A-6 The Model with Imperfect Skill Substitution

In Section 7.3.2 we extended our analysis to a more general production function, where high and low skilled workers are imperfect substitutes. In this section we describe the details of this exercise.

## A-6.1 Environment and Equilibrium

Suppose that the technology in sector $s$ in region $r$ is given by

$$Y_{rs} = A_{rs} \left( \left(H_{rs}^{-}\right)^{\frac{\rho-1}{\rho}} + \left(Z_{rs} H_{rs}^{+}\right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}},$$

where $A_{rs}$ denotes factor neutral productivity, $Z_{rs}$ denotes the skill bias and $H_{rs}^{-}$ ($H_{rs}^{+}$) are the quantities of human capital of low (high) skilled individuals. Again we assume that individuals are heterogenous. Specifically, people of skill type $j \in \{-, +\}$ draw their efficiency level from a pareto with the same shape, i.e.

$$P\left(q_i^j \leq k\right) = 1 - \left(\frac{\underline{q}_{rt}^j}{k}\right)^{\zeta} \equiv F_{rt}^j(k).$$

Total income of an individual $i$ of skill type $j$ in region $r$ at time $t$ is therefore given by $y_{rt}^{i,j} = w_{rt}^j q_i^j$, where the skill price $w_{rt}^j$ is now skill-specific. The aggregate expenditure share on goods from sector $s$ goods in region $r$ is then given by

$$\vartheta_{rst} \equiv \frac{L_{rt}^{-} \int \vartheta_s^h \left(q w_{rt}^{-}, p_{rt}\right) q w_{rt}^{-} dF_{rt}^{-}(q) + L_{rt}^{+} \int \vartheta_s^h \left(q w_{rt}^{+}, p_{rt}\right) q w_{rt}^{+} dF_{rt}^{+}(q)}{L_{rt}^{-} \int q w_{rt}^{-} dF_{rt}^{-}(q) + L_{rt}^{+} \int q w_{rt}^{+} dF_{rt}^{+}(q)},$$

where $\vartheta_s^h\left(q w_{rt}^{-}, p_{rt}\right)$ denotes the sectoral expenditure share at the individual level. Substituting the expression for $\vartheta_s^h\left(q w_{rt}^{-}, p_{rt}\right)$ and using the fact that $y_{rt}^{i,j}$ is also pareto distributed yields

$$\vartheta_{rst} = \omega_s + \tilde{\nu}_s \frac{\zeta - 1}{\zeta - (1-\varepsilon)} \left(\frac{1}{\prod_s p_s^{\omega_s}}\right)^{-\varepsilon} \left( s_{rt}^{Y,-} \left(w_{rt}^{-} \underline{q}_{rt}^{-}\right)^{-\varepsilon} + \left(1 - s_{rt}^{Y,+}\right) \left(w_{rt}^{+} \underline{q}_{rt}^{+}\right)^{-\varepsilon} \right).$$

where $s_{rt}^{Y,-} = \frac{L_{rt}^{-} w_{rt}^{-} \underline{q}_{rt}^{-}}{L_{rt}^{-} w_{rt}^{-} \underline{q}_{rt}^{-} + L_{rt}^{+} w_{rt}^{+} \underline{q}_{rt}^{+}}$ is the income share of low skilled individuals in region $r$ at time $t$. Hence, the sectoral expenditure share is given by

$$\vartheta_{rst} = \vartheta_s \left( \underline{q}_{rt}^{-} w_{rt}^{-}, \underline{q}_{rt}^{+} w_{rt}^{+}, s_{rt}^{Y,-}, \mathbf{p_{rt}} \right),$$

i.e. sectoral spending varies at the regional level because of (i) differences in regional factor prices $w_{rt}^{-}$ and $w_{rt}^{+}$, (ii) differences in the prices of non-tradable goods $p_{rCSt}$ and (iii) differences in the skill composition $s_{rt}^{Y,-}$.

**Equilibrium** The equilibrium is characterized by the following conditions. The CES structure and perfect competition imply that prices are given by

$$p_{rs} = \frac{1}{A_{rs}}\left(\left(w_{rt}^{-}\right)^{1-\rho} + Z_{rs}^{\rho-1}\left(w_{rt}^{+}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}.$$

The relative skill demand for sector $s$ in region $r$is given by

$$\frac{w_{rt}^{+}H_{rst}^{+}}{w_{rt}^{-}H_{rst}^{-}} = Z_{rt}^{\rho-1}\left(\frac{w_{rt}^{+}}{w_{rt}^{-}}\right)^{1-\rho}.$$

The CES demand system across regional varieties implies the market clearing conditions

$$w_{rt}^{-}H_{rst}^{-} + w_{rt}^{+}H_{rst}^{+} \quad = \quad \left(\frac{p_{rs}}{p_s}\right)^{1-\sigma} \times \sum_{j=1}^{R}\vartheta_s\left(\underline{q}_{jt}^{-}w_{jt}^{-}, \underline{q}_{jt}^{+}w_{jt}^{+}, s_{jt}^{Y,-}, \mathbf{p_{jt}}\right)\overline{w}_{rt}L_{rt},$$

where $\overline{w}_{rt}$ denotes average income and $p_s = \left(\sum_{r=1}^{R} p_{rs}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. The market clearing condition for non-tradable CS implies

$$w_{rt}^{-}H_{rCSt}^{-} + w_{rt}^{+}H_{rCSt}^{+} = \vartheta_{CS}\left(\underline{q}_{jt}^{-}w_{jt}^{-}, \underline{q}_{jt}^{+}w_{jt}^{+}, s_{jt}^{Y,-}, \mathbf{p_{jt}}\right)\overline{w}_{rt}L_{rt}. \tag{A-30}$$

Finally, labor market clearing implies

$$H_{rF}^{j} + H_{rG}^{j} + H_{rCS}^{j} = H_{r}^{j} \text{ for } j \in \{-,+\}.$$

These equations uniquely determine the regional wages $\{w_{rt}^{-}, w_{rt}^{+}\}$ and the sectoral labor allocations $\{H_{rst}^{-}, H_{rst}^{+}\}$.

## A-6.2 Measurement and Equilibrium Accounting

As before we use these equations and the observable data to infer the productivity vector $\{A_{rst}, Z_{rst}\}$ for each region-sector pair. To connect our data to the objects in the model, we make the following measurement choices:

1. We classify individuals into high and low skill workers by their years of schooling. We assume workers with at least secondary schooling are high skill workers. In Figure A-3 we show the share of high skilled employment as a function of the urbanization rate. In rural regions, only 20% of workers are high-skilled. In cities, this share is twice as large.

2. As in our baseline model, we assume a Mincerian return $\rho = 5.6\%$ per year of schooling within skill groups. This allows us to measure the aggregate skill supplies $H_{rt}^{-}$ and $H_{rt}^{+}$ for each region.

3. As in our baseline model, we use the observed sectoral earnings shares by skill group to measure sectoral labor supplies. Specifically, for each skill group $j = \{-,+\}$ and sector $s$, we calculate

$$H_{rst}^{j} = \frac{\sum_i 1\left[i \in j \text{ and } i \in s\right] w_i}{\sum_i 1\left[i \in j\right] w_i} \times H_{rt}^{j}$$

   where $w_i$ is the wage of individual $i$.

4. We then calculate the regional skill prices as $w_r^j = \frac{1}{L_{rt}^j}\sum_{i=1}^{L_{rt}^j} y_{rti}^j$ where $y_{rti}^j$ denotes total income of individual $i$ in region $r$at time $t$ in skill group $j$.

These data are sufficient to uniquely solve for $\{A_{rst}, Z_{rst}\}$ and to perform the counterfactual analysis reported in Section 7.3.2.

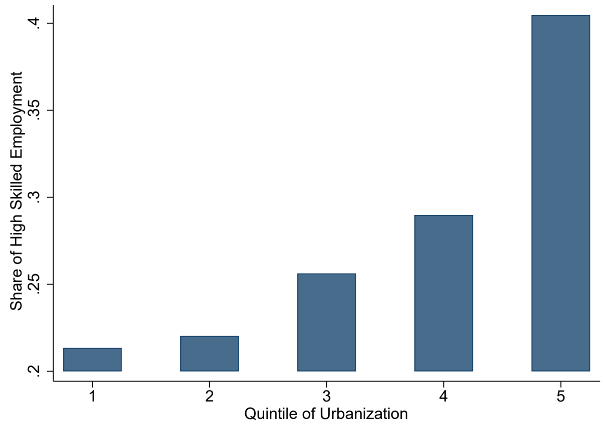


Figure A-3: Share of high skilled employment by urbanization. The figure shows the share of employment with at least secondary schooling for different quantiles of urbanization.

# APPENDIX B: DATA AND MEASUREMENT

In this section, we discuss the data and empirical issues discussed in the text.

## B-1 Data Sources

Our analysis relies on four data sets:

1. The national sample survey (NSS)
2. The Economic Census (EC)
3. The Service Sector in India: 2006-2007
4. The Informal Non-Agricultural Enterprises Survey 1999-2000 (INAES)
5. The Household Expenditure survey

In this section we describe these datasets in detail.

### B-1.1 National Sample Survey (NSS)

The National Sample Survey (NSS) is a representative survey conducted by the Government of India to collect socio-economic data at the household level since 1950. Each round of the survey consists of several schedules that cover different topics like “consumer expenditure”, “employment and unemployment”, “participation in education”, etc. We focus on the ”consumer expenditure” module and the ”employment and unemployment” module and use data from rounds 43, 55, 60, 64, 66 and 68 of NSS, which span the years 1987 to 2011. The survey covers the entirety of India except a few regions due to unfavorable field conditions.[4]

We use the “employment and unemployment” module to measure sectoral employment shares and total earnings. An individual is defined as being employed if his/her usual principal activity is one of the following: (i) worked in household enterprises (self-employed); (ii) worked as helper in household enterprises; (iii) worked as regular

[4] For example, Ladakh and Kargil districts of Jammu & Kashmir, some interior villages of Nagaland, and villages in Andaman and Nicobar Islands are not covered in some rounds of the survey.

salaried/wage employee; (iv) worked as casual wage labour in public works; (v) worked as casual wage labour in other types of work. We describe the details of our sectoral employment classification in Section B-2 below.

As our measure of income we focus on total expenditure. More specifically, we measure total household expenditure and divide it by household size. We do so to properly account for the relative income of self-employed of informally employed employees. In the main analysis, we winsorize the expenditure data at 98th percentiles to account for measurement error.

As we describe in more detail in Section B-1.5, the NSS provides two measures of expenditure. The so-called uniform reference period (URP) measure simply measures total expenditure as expenditure within the last 30 days. The mixed reference period (MRP) measure asks respondents for the total expenditure within the last year for a subset of durable goods to account for the lumpiness of purchases. For all years except 1987, expenditure is reported using the MRP classification. To make the results comparable across years, we merge the expenditure module (described in Section B-1.5) with the employment module in 1987 at the household-level and use the MRP measure contained in the expenditure module. In practice, this choice is inconsequential because the different measures are highly correlated. In Table B-1 we report the correlation between the monthly per capita expenditure (MPCE) measure reported in the employment module, the MPCE URP measure reported in the expenditure module and the URP and MRP measures after winsorizing. This correlation exceeds 0.9 for all measures and our results do not hinge on which measure we use for 1987.

| | MPCE Employment module | MPCE Expenditure module | MPCE_URP Authors' calculation | MPCE_MRP Authors' calculation |
|---|---|---|---|---|
| MPCE (Employment module) | 1 | | | |
| MPCE_URP (Expenditure module) | 0.968 | 1 | | |
| MPCE_URP (authors' calculation) | 0.967 | 0.998 | 1 | |
| MPCE_MRP (authors' calculation) | 0.916 | 0.939 | 0.941 | 1 |

Table B-1: Correlation Matrix of different expenditure measures. The table shows the correlation between household expenditure reported in the NSS employment schedule, NSS expenditure schedule, and calculated by authors. We trim the top 1% and bottom 1% of observations.

To measure human capital, we utilize information on educational attainment. We classify individual's education into four levels: (i) less than primary; (ii) primary, upper primary, and middle; (iii) secondary; (iv) more than secondary. We then associate different years of schooling to each category to estimate annual returns. Building on the official classification in India, we attribute 0, 3, 6, and 9 years respectively.

The "consumer expenditure" module collects information on households' consumption of various kinds of food, entertainment, sundry articles, consumer services and housing expenses during last 30 days and consumption of clothing, bedding, footwear, education and medical goods and services, and various durable goods during last 365 days. We measure total monthly household consumer expenditure as the sum of of all monthly-based expenditures and 30/365 of yearly-based expenditure.

In Table B-2 we report the summary statistics about the sample size of the NSS in the different years. Depending on the year, our data comprises between 60,000 and 120,000 household and between 300,000 and 600,000 individuals.

### B-1.2 Economic Census

The India Economic Census (EC) is a complete count of all establishments, i.e. production units engaged in production or distribution of goods and services not for the purpose of sole consumption, located within the country. The Censuses were conducted in the years 1977, 1980, 1990, 1998, 2005, 2013, 2019. The micro-level data in 1990, 1998, 2005, 2013 are publicly available.

The EC collects information such as firms' location, industry, ownership, employment, source of financing and the owner's social group. It covers all economic sectors excluding crop production and plantation. The EC in 2005 and 2013 exclude some public sectors like public administration, defense and social security. In terms of geography,

| Round | Year | Households | Individuals |
|---|---|---|---|
| 43 | 1987-1988 | 126,353 | 654,903 |
| 55 | 1999-2000 | 107,215 | 596,688 |
| 60 | 2004 | 59,042 | 303,233 |
| 64 | 2007-2008 | 125,578 | 572,254 |
| 66 | 2009-2010 | 100,957 | 459,784 |
| 68 | 2011-2012 | 101,717 | 456,970 |

Table B-2: National Sample Survey: Summary statistics.

the EC covers all States and Union Territories of the country except for the year 1990, which covers all states except Jammu and Kashmir.

In Table B-3 we report some summary statistics of the EC in various years. In the most recent year, 2013, the EC has information on almost 60m firms. As expected, the majority of such firms is very small. Average employment is around 2 and 55% firms have a single employee. The share of firms with more than 100 employees is 0.06%.

| Year | Number of firms | Total employment | Employment distribution | | | |
|---|---|---|---|---|---|---|
| | | | Avg. | 1 | empl. $< 5$ | $> 100$ |
| 1990 | 24216790 | 74570280 | 3.08 | 53.77% | 91.24% | 0.13% |
| 1998 | 30348881 | 83308504 | 2.75 | 51.18% | 91.71% | 0.11% |
| 2005 | 41826989 | 100904120 | 2.41 | 55.76% | 93.17% | 0.12% |
| 2013 | 58495359 | 131293872 | 2.24 | 55.47% | 93.44% | 0.06% |

Table B-3: The Economic Census: Summary Statistics. The table report the number of firms, total employment, average employment and the share of firms with 1, less than 5 and more than 100 employees.

### B-1.3 Service Sector in India: 2006-2007

The Service Sector in India (2006-2007) dataset is part of an integrated survey by the NSSO (National Sample Survey Organisation) in its 63rd round. In the 57th round (2001-2002), the dataset was called "Unorganized Service Sector". With the inclusion of the financial sector and large firms, the dataset was renamed as "Service Sector in India" and is designed to be representative for India's service sector. In Table B-4 we compare this Service Survey with the Economic Census for a variety of subsectors within the service sector. Table B-4 shows that the service survey is consistent with the EC, i.e. average firm size and the share of firms with less than 5 employees are quite comparable in most subsectors.

The Service Survey covers a broad range of service sectors, including hotels and restaurants (Section H of NIC 04); transport, storage and communication (I); financial intermediation (J); real estate, renting and business activities (K); education (M); health and social work (N) and other community, social and personal service activities (O). Excluded are the following subsectors: railways transportation, air transport, pipeline transport; monetary intermediation (central banks, commercial banks, etc); trade unions; government and public sector enterprises and firms that appeared in the Annual Survey of Industries frame (ASI 2004-2005). In terms of geography, the survey covers the whole of Indian Union except for 4 districts and some remote villages.[5] The survey was conducted in a total number of 5573 villages and 7698 urban blocks. A total of 190,282 enterprises were ultimately surveyed.

For our analysis we use two pieces of information: the number of employees and whether the main customer is another firm or a household.

[5] The survey covered the whole of India except (i) Leh (Ladakh), Kargil, Punch and the Rajauri districts of Jammu & Kashmir, (ii) interior villages situated beyond 5 km of a bus route in Nagaland, (iii) villages of the Andaman and Nicobar Islands, that remain inaccessible throughout the year.

| NIC2004 | Sector | Number of firms | | Average employment | | Less than 5 employees | |
|---|---|---|---|---|---|---|---|
| | | EC | Service Survey | EC | Service Survey | EC | Service Survey |
| 55 | Hotels and restaurants | 1499101 | 30744 | 2.52 | 2.49 | 90% | 91% |
| 60 | Land transport; transport via pipelines | 1317904 | 41065 | 1.67 | 1.24 | 97% | 99% |
| 61 | Water transport | 7914 | 174 | 4.35 | 1.92 | 0.90 | 0.98 |
| 63 | Transport activities; travel agencies | 188474 | 2101 | 3.40 | 3.33 | 86% | 85% |
| 64 | Post and telecommunications | 723119 | 22885 | 2.06 | 1.41 | 96% | 99% |
| 65-67 | Financial intermediation | 293489 | 16331 | 5.61 | 3.81 | 69% | 82% |
| 70 | Real estate activities | 70128 | 3648 | 2.18 | 1.64 | 93% | 96% |
| 71 | Renting of machinery and household goods | 365246 | 5387 | 2.00 | 1.77 | 94% | 97% |
| 72 | Computer and related activities | 66414 | 1060 | 6.01 | 13.45 | 83% | 86% |
| 73 | Research and development | 2097 | 5 | 16.66 | 4.58 | 66% | 89% |
| 74 | Other business activities | 519696 | 10610 | 2.81 | 1.92 | 90% | 95% |
| 85 | Health and social work | 783644 | 11930 | 3.39 | 1.99 | 88% | 95% |
| 91 | Activities of membership organizations | 1002996 | 2837 | 1.82 | 1.32 | 94% | 98% |
| 92 | Recreational, cultural and sporting activities | 222061 | 2698 | 2.95 | 2.91 | 85% | 82% |
| 93 | Other service activities | 1419685 | 26132 | 1.74 | 1.54 | 97% | 99% |

Table B-4: Economic Census and Service Survey. The table reports statistics about firms' number and employment from the Economic Census 2005 and Service Survey 2006.

### B-1.4 Informal Non-Agricultural Enterprises Survey 1999-2000 (INAES)

We use this dataset to allocate employment in the construction sector to either consumer or producer services. The Informal Non-Agricultural Enterprises Survey is part of the 55th survey round of the NSSO. It covers all informal enterprises in the non-agricultural sector of the economy, excluding those engaged in mining, quarrying and electricity, gas and water supply.[6] The Informal Non-Agricultural Enterprises Survey collects information on operational characteristics, expenses, value-added, fixed asset, loan and factor income. For our analysis we use two pieces of information: the number of employees and whether the main customer is another firm or a household.

### B-1.5 Household Expenditure Survey

To estimate the expenditure elasticity $\varepsilon$ we rely on data on consumer expenditure. This data is contained in the National Sample Survey, Round 68, Schedule 1.0. The dataset reports detailed information on a large set of spending categories. In Table B-5 we report the broad classifications. The data also contains a finer allocation of spending within each category. For the purpose of this paper, we rely only on the classification in Table B-5.

We classify consumers' spending on food as categories 1 - 17. We classify spending on consumer services as all spending in the consumer service category (category 24) and on entertainment (category 20). In Tables B-6 and B-7 we report the more detailed classification of the consumer service and entertainment spending categories.

Spending on category $c$ is measured as spending within a particular reference period. For all categories, subject report total spending during the last 30 days. For durable goods, and medical and educational spending (i.e. categories 29-34), the subjects additionally report total spending in the last year. This second concept of expenditure aims to account for the lumpiness of purchases. For this group we therefore take 1/12 of annual spending as our measure of monthly expenditure. We measure total spending as the sum of all spending across all categories to calculate the spending share on food and consumer services.

In Table B-8 we report a selected set of summary statistics for the main variables of interest. In total we have expenditure data for slghtly more than 100,000 households. In the first two rows we show the distribution of household expenditure for the case of measuring durable spending at the monthly frequency (the uniform reference

[6] The organized sector comprises all factories registered under Sections 2(m)(i) and 2(m)(ii) of the Factories Act, 1948, where 2(m)(i) includes manufacturing factories which employ 10 or more workers with electric power, and 2(m)(ii) includes manufacturing factories which 20 or more without electric power. The unorganized sector comprises all factories not covered in the organized sector. The informal sector is a subset of the unorganized sector. The unorganized sector includes four types of enterprises: (i) unincorporated proprietary enterprises; (ii) partnership enterprises;(iii) enterprises run by cooperative societies, trusts, private; (iv) public limited companies. The informal sector only includes firms in category (i) and (ii).

| No. | Description | No. | Description | No. | Description |
|---|---|---|---|---|---|
| 1 | Cereals | 13 | Served processed food | 25 | Conveyance |
| 2 | Cereal substitute | 14 | Packaged processed food | 26 | Rent |
| 3 | Pulses and products | 15 | Pan | 27 | Consumer taxes and cesses |
| 4 | Milk and milk products | 16 | Tobacco | **28** | **Sub-total (1 − 27)** |
| 5 | Salt and sugar | 17 | Intoxicants | 29 | Clothing |
| 6 | Edible oil | 18 | Fuel and light | 30 | Bedding |
| 7 | Egg, fish and meat | 19 | Medical (non-institutional) | 31 | Footwear |
| 8 | Vegetables | 20 | Entertainment | 32 | education |
| 9 | Fruits (fresh) | 21 | Minor durable-type goods | 33 | Medical (institutional) |
| 10 | Fruits (dry) | 22 | Toilet articles | 34 | Durable goods |
| 11 | Spices | 23 | Other household consumables | **35** | **Sub-total (29 − 34)** |
| 12 | Beverages | 24 | Consumer services excl. conveyance | | |

Table B-5: Broad classification of NSS expenditure survey. The table report the classification of broad expenditure items in the Expenditure Survey.

| No. | Description | No. | Description |
|---|---|---|---|
| 480 | Domestic servant/cook | 490 | Postage and telegram |
| 481 | Attendant | 491 | Miscellaneous expenses |
| 482 | Sweeper | 492 | Priest |
| 483 | Barber, beautician, etc. | 493 | Legal expenses |
| 484 | Washerman, laundry, ironing | 494 | Repair charges for non-durables |
| 485 | Tailor | 495 | Pet animals (incl. birds, fish) |
| 486 | Grinding charges | 496 | Internet expenses |
| 487 | Telephone charges: landline | 497 | Other consumer services excluding conveyance |
| 488 | Telephone charges: mobile | | |

Table B-6: Expenditure items within consumer services. This table reports the detailed expenditure items within the category consumer services (category 24 in Table B-5)

| No. | Description | No. | Description |
|---|---|---|---|
| 430 | Cinema, theatre | 435 | Photography |
| 431 | Mela, fair, picnic | 436 | VCD/ DVD hire (incl. instrument) |
| 432 | Sports goods, toys, etc. | 437 | Cable TV |
| 433 | Club fees | 438 | Other entertainment |
| 434 | Goods for recreation and hobbies | | |

Table B-7: Expenditure items within entertainment. This table reports the detailed expenditure items within the category entertainment (category 20 in Table B-5) period *URP*) and or at the annual frequency (the mixed reference period *MRP*). Table B-8 shows that the disperion is spending is much higher for URP case, especially in the right tail. We therefore use the MRP measure as our measure of total expenditure.

Table B-8 also reports a set of statistics for the distribution of food shares and consumer service spending shares. The full distribution is shown in Figure B-1. There is ample cross-sectional dispersion. Through the lens of our theory, this dispersion is generated through heterogeneity in income and relative prices.

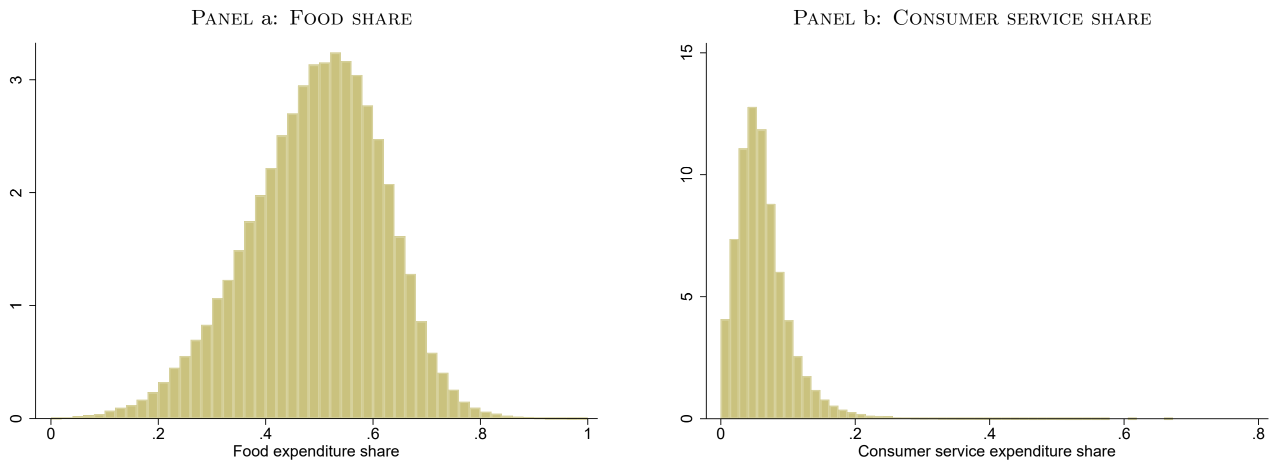


Figure B-1: Distributon of food and consumer service expenditure shares. The figure shows the unconditional distribution of the expenditure shares for food (left panel) and consumer services (right panel).

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| | N | mean | sd | min | median | p90 | p95 | max |
|---|---|---|---|---|---|---|---|---|
| Household expenditure (*URP*) | 101,662 | 8,226 | 12,784 | 40 | 6,264 | 14,475 | 19,081 | 1,239,930 |
| Household expenditure (*MRP*) | 101,662 | 8,316 | 7,438 | 44 | 6,572 | 14,960 | 19,433 | 339,832 |
| Household size | 101,662 | 4.57 | 2.25 | 1 | 4 | 7 | 9 | 39 |
| Food expenditure share | 101,662 | 0.49 | 0.13 | 0 | 0.50 | 0.64 | 0.68 | 1 |
| CS expenditure share | 101,662 | 0.06 | 0.04 | 0 | 0.06 | 0.11 | 0.14 | 0.67 |

Table B-8: NSS expenditure survey: Summary statistics. The table reports selected summary statistics from the NSS expenditure survey.

For our regression analysis reported in Tables 3 and 5 we control for additional household level of covariates. We control for the size of the household and the number of (potential) workers in the household which we define as all individuals between age 15 and 65. We also control for additional household demographics, namely

- the type of the household, which for rural areas is one of (i) self-employed in agriculture, (ii) self-employed in non-agriculture, (iii) regular wage/salary earner, (iv) casual worker in agriculture and (v) casual worker in non-agriculture, (vi) other and in urban areas one of (i) self-employed (ii) regular wage/salary earner, (iii) casual worker, (vi) other;
- the household's religion, which is one of Hinduism, Islam, Christianity, Sikhism, Jainism, Buddhism, Zoroastrianism and other;
- the household's social group, which is one of the following: scheduled tribe, scheduled case, backward class and other.

Finally, the survey also reports whether the household is eligible to receive a rationing card.

## B-2 Classification of Industries

At the heart of our analysis is the sectoral composition of regional employment. In our theory we distinguish between four sectors: Agriculture, Manufacturing, Consumer Services and Producer Services. To map these concepts to sectors in the data, we first construct six broad industries (see Section B-2.1). In a second step we then attribute employment in services and construction to consumer and producer services respectively - see Section B-2.2.

### B-2.1 Broad Industry Classification

We initially divide economic activities into six industries:

1. Agriculture
2. Manufacturing
3. Construction and Utilities
4. Services
5. Information and Communications Technology (ICT)
6. Public Administration and Education.

To do so we rely on India's official classification system National Industrial Classification (NIC). We report our classification of industries in Table B-9.

| Industry | NIC 2008 | Description |
|---|---|---|
| Agriculture | 01-03 | Agriculture, forestry and fishing |
| Manufacturing | 05-09 | Mining of coal and lignite |
| | 10-33 | Manufacturing |
| Construction & Utilities | 35 | Electricity, gas, steam and air conditioning supply |
| | 36-39 | Water supply; sewerage, waste management and remediation activities |
| | 41-43 | Construction |
| Services | 45-47 | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| | 49-53 | Transportation and storage |
| | 55-56 | Accommodation and Food service activities |
| | 581 | Publishing of books, periodicals and other publishing activities |
| | 64-66 | Financial and insurance activities |
| | 68 | Real estate activities |
| | 69-75 | Professional, scientific and technical activities |
| | 77-82 | Administrative and support service activities |
| | 86-88 | Human health and social work activities |
| | 90-93 | Arts, entertainment and recreation |
| | 94-96 | Other service activities |
| | 97 | Activities of households as employers of domestic personnel |
| ICT | 582-63 | Information and communication |
| Public Administration & Education | 84 | Public administration and defence; compulsory social security |
| | 85 | Education |
| | 99 | Activities of extraterritorial organizations and bodies |

Table B-9: Industrial Classification. The table reports the industrial classification into six broad sectors.

Because the NIC classification system changes over time, we construct a concordance table between 2-digit industries of different versions of the NIC based on official NIC documents and detailed sector descriptions. This concordance system allows to compare sectoral employment patterns over time. Our crosswalk is reported in Table B-10.

| sector | NIC-1987 | NIC-1998 & NIC-2004 | NIC-2008 |
|---|---|---|---|
| | **Agriculture** | | |
| Agriculture and hunting | 00-04 | 01 | 01 |
| Forestry and logging | 05 | 02 | 02 |
| Fishing and aquaculture | 06 | 05 | 03 |
| | **Manufacturing** | | |
| Coal, lignite, and peat | 10 | 10 | 05, 0892 |
| Crude petroleum and natural gas | 11,19 | 11 | 06, 091 |
| Metal ores | 12, 13, 14 | 12,13 | 07 |
| Other mining and quarrying | 15 | 14 | 08(except0892), 099 |
| Food products | 20,21, 220-224 | 15 | 10, 11 |
| Tobacco products | 225-229 | 16 | 12 |
| Textiles and wearing apparel | 23 24 | 17, 18 | 13, 14 |
| Leather products | 29(except 292) | 19 | 15 |
| Wood products | 27(except 276-277) | 20 | 16 |
| Paper products, printing and publishing | 28 | 21, 22 | 17, 18, 581 |
| Refined petroleum | 314-319 | 23 | 19 |
| Chemicals | 30 | 24 | 20, 21 |
| Rubber and plastics products | 310-313(except3134) | 25 | 22 |
| Other non-metallic mineral products | 32 | 26 | 23 |
| Basic metals | 33(except338) | 27 | 24 |
| Fabricated metal | 34(except342), 352, 391 | 28, 2927 | 25, 3311 |
| Machinery and equipment | 35-36(except352), 390, 392, 393, 395, 396, 399 | 29-32 (except2927) | 261-264, 268, 27, 28, 3312, 3314, 3319, 332, 9512 |
| Medical, precision and optical instruments | 380-382 | 33 | 265-267, 325, 3313 |
| Transport equipment | 37, 397 | 34, 35 | 29, 30, 3315 |
| Furniture | 276, 277, 3134, 342 | 361 | 31 |
| Other manufacturing | 383-389 | 369 | 32(except325) |
| | **Construction & Utilities** | | |
| Electricity, gas, steam supply | 40, 41, 43 | 40 | 35 |
| Water supply | 42 | 41 | 36 |
| Sewerage and waste treatment | 338, 6892, 91 | 37,90 | 37, 38, 39 |
| Construction | 50, 51 | 45 | 41, 42, 43 |
| | **Services** | | |
| Wholesale | 398, 60-64, 682, 686, 890, 974 | 50, 51(except51901) | 45, 46 |
| Retail | 65-68(except682,686,6892) | 52(except526,52591) | 47 |
| Repair services | 97(except974) | 526 | 952 |
| Land transport | 70 | 60 | 49 |
| Water transport | 71 | 61 | 50 |
| Air transport | 72 | 62 | 51 |
| Supporting and auxiliary transport activities | 730, 731, 732, 737, 738, 739, 74 | 63 | 52, 79 |
| Post and telecommunications | 75 | 64 | 53, 61 |
| Hotels | 691 | 551 | 55 |
| Restaurants | 690 | 552 | 56 |
| Computer and related activities | 394, 892, 897 | 72, 922 | 582, 62, 63, 9511 |
| Financial service | 80 | 65, 67 | 64, 66 |
| Insurance and pension | 81 | 66 | 65 |
| Real estate activities | 82 | 70 | 68 |
| Legal activities | 83 | 7411 | 691 |
| Accounting | 891 | 7412 | 692 |
| Business and management consultancy | 893 | 7413, 7414 | 70, 732 |
| Architecture and engineering | 894, 895 | 742 | 71 |
| Research and development | 922 | 73 | 72 |
| Advertising | 896 | 743 | 731 |
| Other business activities | 898, 899 | 749 | 74, 78, 80, 81, 82 |
| Renting | 733, 734, 735, 736, 85 | 71 | 77 |
| Health and social work | 93, 941 | 85 | 75, 86, 87, 88 |
| Recreational cultural and sporting activities | 95 | 92(except922) | 59, 60, 90, 91, 93 |
| Gambling | 84 | 51901, 52591 | 92 |
| Membership organizations | 94(except941) | 91 | 94 |
| Personal service | 96, 99 | 93, 95 | 96, 97 |
| goods-producing activities for own use | #N/A | 96 | 981 |
| services-producing activities for own use | #N/A | 97 | 982 |
| | **Public Administration & Education** | | |
| Public administration and defence | 90 | 75 | 84 |
| Education | 920-921 | 80 | 85 |
| Extraterritorial organizations | 98 | 99 | 99 |

Table B-10: Concordance between 2-digit industry Classes. The table report the classification of NIC codes in different years to the broad sectoral categories of Table B-9.

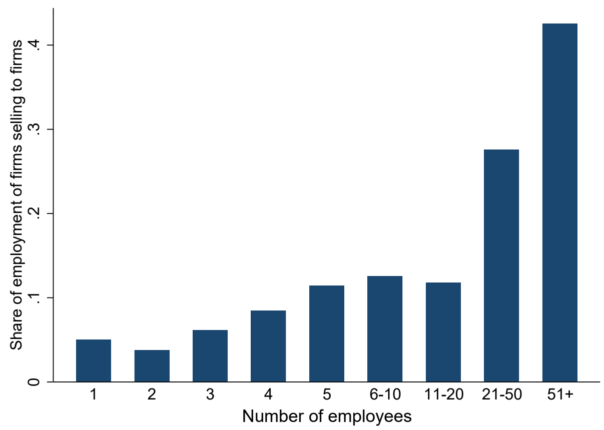


Figure B-2: Producer service share by firm size. The figure shows the share of service firms whose main customer are other firms (as opposed to private individuals) with breakdown by firm size.

### B-2.2 Attributing Employment to Producer and Consumer Services

Our theory highlights the difference between PS, that are inputs in the production of goods, and CS, that are bought directly by consumers and are luxuries. In terms of the data, see Table B-9, financial and insurance activities (NIC codes 64-66) are examples of the former while retail trade (NIC codes 45-47) is an example of the latter.

In order to arrive at a systematic classification, we rely on the Service Survey (see Section B-1.3) that reports the identify of the main *buyer* of a given firm. We therefore refer to firms that sell to other firms as PS-firms and firms that sell to consumers as CS-firms.

Ideally, we would calculate the employment share of PS-firms in each subsector of the service sectors and in each region. The regional variation is important because our theory stresses that CS and PS productivity varies at the regional level. Given the large number of regions and subsection, the sample size of the Service Survey is not sufficiently large to estimate these averages precisely.

We therefore generate the regional variation in employment shares by using regional variation in the firm-size distribution and differences in the employment share of PS firms by firm size. Empirically, large firms are - within their subsector - much more likely to sell to firms. To see this, consider Figure B-2 where we depict the employment share of PS firms as a function of firm size in the raw data. In Table B-11 we show that the same pattern is presents within two- and three-digit industries and whether or not we use sampling weights. In particular, we regress a dummy variable for whether the firm sells mainly to other firms on different firm size dummies. The coefficients are generally positive and increasing.

To exploit this size-dependence, we adopt the following procedure:

1. For each 2-digit subsector $k$ within the service sector listed in Table B-9 and size bin $b$ we calculate the employment share of PS firms as
$$\omega_{kb}^{PS} = \frac{\sum_{f\in(k,b)} 1\left\{f \in PS\right\} l_f}{\sum_{f\in(k,b)} l_f}.$$
Here, $f$ denotes a firm, $1\left\{f \in PS\right\}$ is an indicator that takes the value 1 if firm $f$ is a PS firm and $l_f$ denotes firm employment. In practice we take three size bins, namely "1 or 2 employees", "3-20 employees" and "more than 20" employees. We always weigh observations with the sampling weights provided in the Service Survey.[7]

[7] In some industries, there are not enough firms with more then 20 employees to estimate $\omega_{kb}^{PS}$ precisely. If there are less than 5 firms and $\omega_{kb}^{PS}$ is smaller than $\omega_{kb}^{PS}$ in the pre-ceding size bin (i.e. $\omega_{k3}^{PS} < \omega_{k2}^{PS}$), we set $\omega_{k3}^{PS} = \omega_{k2}^{PS}$. Hence, for cells with few firms we impose the the share of PS firms is monotonic in firm size.

| | Probability of selling to firms | | | |
|---|---|---|---|---|
| 2 employees | 0.013*** | 0.014*** | 0.014*** | 0.016*** |
| | (0.001) | (0.002) | (0.001) | (0.002) |
| 3 employees | 0.030*** | 0.028*** | 0.028*** | 0.029*** |
| | (0.002) | (0.006) | (0.002) | (0.005) |
| 4 employees | 0.055*** | 0.063*** | 0.049*** | 0.059*** |
| | (0.004) | (0.011) | (0.004) | (0.011) |
| 5 employees | 0.080*** | 0.074*** | 0.070*** | 0.072*** |
| | (0.006) | (0.011) | (0.006) | (0.010) |
| 6-10 employees | 0.090*** | 0.062*** | 0.080*** | 0.057*** |
| | (0.005) | (0.007) | (0.005) | (0.007) |
| 11-20 employees | 0.085*** | 0.042*** | 0.074*** | 0.039*** |
| | (0.006) | (0.008) | (0.006) | (0.008) |
| 21-50 employees | 0.192*** | 0.106*** | 0.164*** | 0.099*** |
| | (0.016) | (0.026) | (0.016) | (0.025) |
| more than 50 employees | 0.345*** | 0.159*** | 0.304*** | 0.137*** |
| | (0.023) | (0.044) | (0.022) | (0.034) |
| Industry FE (2 digit) | Yes | Yes | | |
| Industry FE (3 digit) | | | Yes | Yes |
| Sampling weights | No | Yes | No | Yes |
| N | 173743 | 173743 | 173743 | 173743 |
| $R^2$ | 0.100 | 0.077 | 0.133 | 0.104 |

Table B-11: Corporate Customers and Firm Size. *Notes:* Columns 1 and 2 (3 and 4) control for two (three) digit industry fixed effects. Columns 2 and 4 weigh each observation by the sampling weights. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2. We then use the Economic Census (see Section B-1.2) and calculate the share of employment of firms in size bin $b$ in subsector $k$ in region $r$ as

$$\ell_{kbr} = \frac{\sum_{f\in(k,b,r)} l_f}{\sum_{f\in(k,r)} l_f}$$

3. We then combine these two objects to calculate the share of employment of PS firms in region $r$ in subsector $k$ as

$$s_{rk}^{PS} = \sum_b \ell_{kbr}\omega_{kb}^{PS}$$

4. Finally, we use $s_{rk}^{PS}$ to calculate the share of employment in PS and CS in region $r$ as

$$\varpi_r^{PS} = \frac{\sum_k s_{rk}^{PS} l_{rk}^{NSS}}{l_{rk}^{NSS}} \quad \text{and} \quad \varpi_r^{CS} = \frac{\sum_k \left(1 - s_{rk}^{PS}\right) l_{rk}^{NSS}}{l_{rk}^{NSS}},$$

where $l_{rk}^{NSS}$ denotes total employment in subsector $k$ in region $r$ as measured from NSS.

Five subsectors within the service sector are not covered by the Service Survey. Table B-12 reports our approach to attribute the employment in these subsectors to the PS or CS sector respectively.

| NIC2004 | Industry | Approach |
|---|---|---|
| 22 | Publishing, printing and reproduction of recorded media | Attribute all employment to PS |
| 50 | Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel | Use average PS share (at firm-size bin level) from other sectors for which we have information |
| 51 | Wholesale trade and commission trade, except of motor vehicles and motorcycles | Use average PS share (at firm-size bin level) from other sectors for which we have information |
| 52 | Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods | Attribute all employment to CS |
| 62 | Air transport | Attribute all employment to PS |

Table B-12: Imputation of PS employment. This table reports our imputation of PS and CS employment for subsectors that are not covered by the service survey.

### B-2.3 Attributing employment in Construction & Utilities to PS and CS and the Public Sector

As explained in the text we also attribute employment in construction and utilities to either CS or PS. We follow a similar strategy as for the service sector. To do so, we use the Informal Non-Agricultural Enterprises Survey 1999-2000 (see Section B-1.4).

From the description of National Industry Classification, some subsectors are clearly for public purposes. We therefore classify 5-digit level industries within the construction sector into public and private. The results are reported in Table B-13.

We drop for our analysis all subsectors, that we classify as public. These account for roughly 9.2% of total construction employment (see below). For all subsectors attributed to the private sector, we estimate the CS and PS share based on the information in the Informal Non-Agricultural Enterprises Survey. The survey has information on firms in the construction sector and reports the identify of the main buyer of the firm. In particular, we observe in the data whether the firm sells to (i) the government, (ii) a cooperative or marketing society, (iii) a private enterprise, (iv) a contractor or intermediary, (v) a private individual and (vi) others. We associate all firms that

| NIC-2004 | Description | Public/Private |
|---|---|---|
| 45101 | Site preparation in connection with mining | Public |
| 45102 | Site preparation other than in connection with mining | Public |
| 45201 | General construction (including alteration, addition, repair and maintenance) of residential buildings. | Private |
| 45202 | General construction (including alteration, addition, repair and maintenance) of non-residential buildings. | Private |
| 45203 | Construction and maintenance of roads, rail-beds, bridges, tunnels, pipelines, rope-ways, ports, harbours and runways etc. | Public |
| 45204 | Construction/erection and maintenance of power, telecommunication and transmission lines | Public |
| 45205 | Construction and maintenance of waterways and water reservoirs | Public |
| 45206 | Construction and maintenance of hydro-electric projects | Public |
| 45207 | Construction and maintenance of power plants, other than hydro-electric power plants | Public |
| 45208 | Construction and maintenance of industrial plants other than power plants | Private |
| 45209 | Construction n.e.c. including special trade construction | Private |
| 45301 | Plumbing and drainage | Private |
| 45302 | Installation of heating and air-conditioning systems, antennas, elevators and escalators | Private |
| 45303 | Electrical installation work for constructions | Private |
| 45309 | "Other building installation n.e.c. | Private |
| 45401 | Setting of wall and floor tiles or covering with other materials like parquet, carpets, wall paper etc. | Private |
| 45402 | Glazing, plastering, painting and decorating, floor sanding and other similar finishing work | Private |
| 45403 | Finish carpentry such as fixing of doors, windows, panels etc. and other building finishing work n.e.c. | Private |
| 45500 | Renting of construction or demolition equipment with operator | Private |

Table B-13: Classification of the construction sector. The table reports how we classify different subsectors in the construction sector as either public or private sectors.

answer (ii), (iii) or (iv) with PS firms and all firms that answer (v) with CS firms. We then calculate the PS share of a given private subsector as total PS employment relative to total CS and PS employment in the respective subsector, i.e. for subsector $k$ we calculate the PS share as

$$\omega_k^{PS} = \frac{\sum_{f \in k} 1\{f \in PS\} l_f}{\sum_{f \in k} l_f},$$

where $l_f$ denotes firm employment and $1\{f \in PS\}$ is an indicator for whether firm $f$ is a PS firm.

In Table B-14 we report the relative employment shares of public employment (as classified in Table B-13), CS and PS in the construction sector as a whole. The share of public employment is around 10% with a slight bump in 2009, presumably a consequence of the financial crisis in 2008. Among the private subsectors, 12.9% of employment is associated with the provision of producer services.

| | 1999 | 2004 | 2007 | 2009 |
|---|---|---|---|---|
| Public employment | 0.073 | 0.102 | 0.073 | 0.136 |
| CS employment share | 0.806 | 0.781 | 0.809 | 0.755 |
| PS employment share | 0.121 | 0.116 | 0.118 | 0.109 |
| PS/(PS+CS) | 0.131 | 0.130 | 0.127 | 0.126 |

Table B-14: Composition of the construction sector. The table shows the relative employment shares of PS, CS and public employment in the construction sector in different years. We associate public employment to sectors classified as "public" in Table B-13. The classification of employment in the private subsectors to CS and PS is explained in the main text. The last row reports the relative employment share of PS within the private subsectors.

To calculate total employment in PS and CS industries within the private subsectors of the construction sector at the regional level, we apply the 5-digit PS shares $\omega_k^{PS}$ to the NSS employment data and calculate total as

$$\varpi_r^{PS} = \frac{\sum_k \omega_k^{PS} l_{rk}^{NSS}}{l_{rk}^{NSS}} \quad \text{and} \quad \varpi_r^{CS} = \frac{\sum_k \left(1 - \omega_k^{PS}\right) l_{rk}^{NSS}}{l_{rk}^{NSS}}.$$

Note that the regional variation in PS and CS shares within the construction sector only arises because regions differ in the relative size of the different private subsectors listed in Table B-13.

### B-2.4 Top-coding of CS and PS employment shares

Our model implies that regional CS expenditure shares (and hence employment shares) are bounded from above by $\omega_{CS}$. Similarly, our model implies that the share of producer service employment ("lawyers") relative to production workers is bounded from above by $\beta$. Given our estimated of $\omega_{CS} = 0.69$ and $\beta = 0.7$ reported in Table 4, 16 districts violate this requirement and we topcode them in our analysis. Topcoding such districts is entirely inconsequential because these districts are very small. In Table B-15 we report the aggregate population share of such districts by year. As can be seen, in almost all years, such districts account for less than 1% of the total population in India in almost all years.

| | Total share of population | |
|---|---|---|
| Year | CS empl. share $>\omega_{CS}$ | PS empl. share $>\beta$ |
| 1987 | 0.0013 | 0.0075 |
| 2011 | 0.0018 | 0.0092 |

Table B-15: Employment Shares of Top-Coded Districts. The table reports the aggregate population share of all districts whose employment share in CS exceeds $\omega_{CS}$ (column 1) or $\beta$ (column 2).

## B-3 Geography: Harmonizing Regional Borders

In this section we describe our procedure to harmonize the geographical boundaries to construct a consistent panel of time-invariant localities. This need arises because the borders of numerous Indian districts have changed between 1987 and 2011. This is for example seen in the left panel of Figure B-3 that plots the districts' boundaries in 2004 and 2011. The purple line represents the boundaries in 2004, the red line represents the boundaries in 2011.

The most common type of regional re-districting is a *partition* where one district has been separated into several districts in the subsequent years. The second type is a *border move*, where the shared border between two districts changes. The third is a *merge*, where two districts are merged into a single district. In Figure B-4 we plot two examples of such changes. The left panel shows a partition, where a district has been cut in half. The right district shows a border move, where one districts expands on behalf of the other district.

In order to carry out the analysis on a panel of districts with a consistent geography, we construct regions that have consistent borders in 1987 and 2011. To keep the number of regions as large as possible, a region is always the smallest area that covers a single district or a set of districts with consistent borders over time. For instance, in the case of a partition, the region is constructed as the district in the pre-partition year. In the case of a border move, a region is constructed as the union of two districts. We construct a regional map with consistent borders from 1987 to 2011. The right panel of Figure shows the official Indian districts in the year 2011 (dashed red lines) and the time-invariant geographical units, that we for simplicity also refer to as districts (solid blue lines).

## B-4 The relative price of agricultural goods

Our estimation uses the relative price of agricultural goods (relative to manufacturing goods) to identify the relative productivity in the agricultural sector (relative to manufacturing). The Ministry of Planning and Program Implementation (MOSPI) of the Government of India reports value added by 2-digit sectors at current prices and constant prices from 1950-2013[8] We then construct the sectoral price index by

$$p_i = \frac{\text{GDP at current price}_i}{\text{GDP at constant price}_i} \tag{B-1}$$

[8] The data is available at `http://www.mospi.gov.in/data`. See "Summary of macro economic aggregates at current prices, 1950-51 to 2013-14" and "Summary of macro economic aggregates at constant(2004-05) prices, 1950-51 to 2013-14".

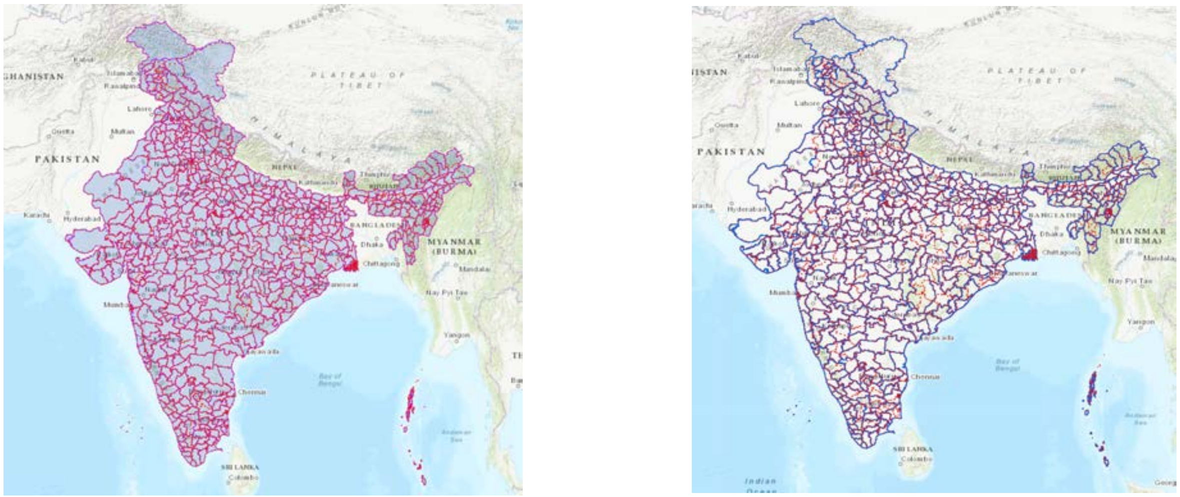


Figure B-3: District Borders in India: 1987 - 2011. The left figure plots the districts' boundaries in 2004 and 2011. The purple line represents the boundaries in 2004 and the red line represents the boundaries in 2011. The right figure shows the official Indian districts in the year 2011 (dashed red lines) and the time-invariant geographical units we construct (solid blue lines) upon which our analysis is based.

and normalize both price indexes in the year 2005 to unity. We then calculate the relative price of agricultural products as

$$p_{relative} = \frac{p_{agri}}{p_{manu}} \tag{B-2}$$

To check the validity of our results, we also use two additional data sources to calculate the relative price. The first is the GGDC 10-Sector Database[9], which provides long-run data on sectoral productivity performance in Africa, Asia, and Latin America. This data set reports the annual series of value-added at current national prices and value-added at constant 2005 national prices. We follow the same procedures to calculate the relative price.

The second is the Wholesale Price Index (WPI) reported by Office of the Economic Advisor[10]. The WPI tracks ex-factory price for manufactured products and market price for agricultural commodities. One issue with this is that the base year (and the basket of goods) changes during different time periods. Two series are relevant to our research. The first one is the series with the base year 1993, which is available from 1994 to 2009. The second one is the series with the base year 2004, which is available from 2005 to 2016. Again, we use the same method to calculate the relative price, and normalized the relative prize in the year 2005 to 1.

In Figure B-5 we plot the relative price of agricultural goods to manufacturing goods. Since the pattern from the different data sources are very similar, we use the results based on MOPSI in our analysis.

## B-5 Estimating the expenditure elasticity ($\varepsilon$)

In Table 3 in the main text we reported the estimated elasticity of agricultural expenditure shares with respect to total expenditure. In Figure B-6 we show the estimated Engel curve for the year 2011 graphically. As implied by the PIGL preference specification, the relationship is approximately linear for a large part of the expenditure distribution.

[9] The data is available at `https://www.rug.nl/ggdc/productivity/10-sector`
[10] The data is available at `https://eaindustry.nic.in/`


Figure B-4: Two Types of Boundary Change. The figure shows an example of a partition (left panel) and a border move (right panel).

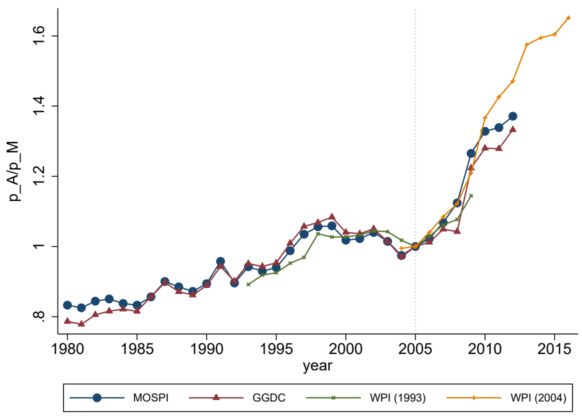


Figure B-5: Relative price of agricultural to manufacturing goods. The figure shows the relative price of agricultural products as calculated in (B-1) and (B-2) from the different sources mentioned in the main text. "MOSPI" refers to the data from the Indian Government is used in our analysis. "GGDC" stems from GGDC 10-Sector Database. "WPI (1993)" and "WPI (2004)" are based on the Wholesale Price Index with a 1993 base year and a 2004 base year respectively.

## Value added versus Final Expenditure

Our estimation of $\varepsilon$ relies on individual-level expenditure data. This data refers to consumer spending on final goods. Our theory, in contrast, is described in terms of value added. This raises the question whether we can identify the preference parameters of our value-added preferences from the data on final expenditure.

As shown in Herrendorf et al. (2013), the relevant parameters of consumers' preferences over final goods are in general distinct from the preference parameters consistent with the value-added interpretation. However, as we show now, this is less of a concern for the case of the income elasticity $\varepsilon$, which is the only parameter we estimate using data on expenditure.

To see this, suppose the consumer preferences over final goods are also of the PIGL form and given

$$V^{FE}(e,q) = \frac{1}{\varepsilon^{FE}}\left(\frac{e}{\prod_s q_j^{\omega_s^{FE}}}\right)^{\varepsilon^{FE}} - \sum_s \tilde{\nu}_s^{FE} \ln q_j. \tag{B-3}$$

Here $q_j$ denotes the price of the final good of sector $s \in \{F, CS, G\}$ and we denote the parameters with the superscript "$FE$" to highlight that these are parameters of the final expenditure specification. The associated

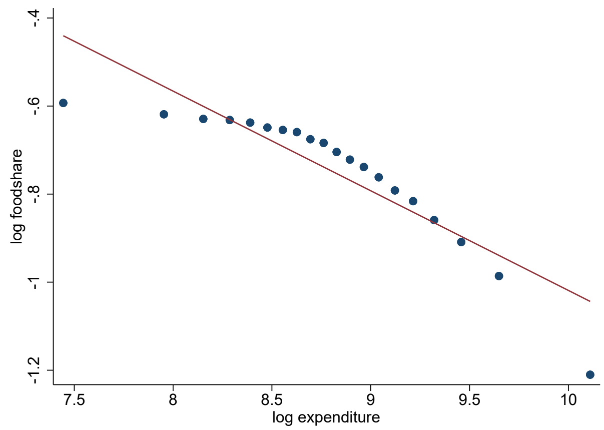


Figure B-6: ENGEL CURVES IN INDIA. The figure shows a binscatter plot of the log food shares and log expenditure for the year 2011 at the individual household level after absorbing district fixed effects.

expenditure share to (B-3) is given by

$$\vartheta_s^{FE}(e,q) = \omega_s^{FE} + \tilde{\nu}_s^{FE}\left(\frac{e}{\prod_j q_j^{\omega_j^{FE}}}\right)^{-\varepsilon^{FE}}. \tag{B-4}$$

The micro-data on expenditure in principle identifies the parameters $\left\{\left[\omega_j^{FE}\right]_j, \varepsilon^{FE}\right\}$.

To map these preference parameters to the demand system in terms of value added, we have have the technology to transform sectoral value added into final goods. Suppose first that the mapping from value added to final expenditure is given by a Cobb-Douglas technology

$$y_s^{FE} = \prod_{j\in(A,CS,G)} \left(y_{js}^{VA}\right)^{\lambda_{js}}, \tag{B-5}$$

where $\sum_j \lambda_{js} = 1$ for all $s$.[11] Here $y_s^{FE}$ is the total quantity of final goods in sector $s$ and $y_{js}^{VA}$ is the value added content of sector $j$ in the production of sector $s$ goods. Hence, the matrix $[\lambda_{js}]_{js}$ describes the input output matrix of the economy.

The specification in (B-5) implies that $\lambda_{js}$ is the cost share of sector $j$ value added in the production of final goods in sector $s$

$$p_j^{VA} y_{js}^{VA} = \lambda_{js} q_s^{FE} y_s^{FE}.$$

Furthermore, final good prices $q_s$ are given by$q_s = \prod_j \left(p_j^{VA}\right)^{\lambda_{js}}$. Total value added of sector $j$ is therefore given by

$$p_j^{VA} c_j^{VA} = \sum_s p_j^{VA} c_{js}^{VA} = \sum_s \lambda_{js} q_s^{FE} c_s^{FE}.$$

[11] Below we generalize our argument to a more general CES technology.

This implies that the value added share of sector $j$ is given by

$$
\begin{aligned}
\vartheta_j^{VA} = \frac{p_j^{VA} c_j^{VA}}{e} &= \sum_s \lambda_{js} \frac{q_s^{FE} c_s^{FE}}{e} = \sum_s \lambda_{js} \vartheta_j^{FE} \\
&= \sum_s \lambda_{js} \left( \omega_s^{FE} + \tilde{\nu}_s^{FE} \left( \frac{e}{\prod_m q_m^{\omega_m^{FE}}} \right)^{-\varepsilon^{FE}} \right) \\
&= \sum_s \lambda_{js} \omega_s^{FE} + \sum_s \lambda_{js} \tilde{\nu}_s^{FE} \times \left( \frac{e}{\prod_m \prod_j \left(p_j^{VA}\right)^{\lambda_{jm} \omega_m^{FE}}} \right)^{-\varepsilon^{FE}} \\
&= \sum_s \lambda_{js} \omega_s^{FE} + \sum_s \lambda_{js} \tilde{\nu}_s^{FE} \times \left( \frac{e}{\prod_s \left(p_s^{VA}\right)^{\sum_m \lambda_{sm} \omega_m^{FE}}} \right)^{-\varepsilon^{FE}} .
\end{aligned}
$$

Now define

$$
\begin{aligned}
\omega_j &\equiv \sum_s \lambda_{js} \omega_s^{FE} \\
\tilde{\nu}_j &\equiv \sum_s \lambda_{js} \tilde{\nu}_s^{FE} \\
\varepsilon &= \varepsilon^{FE}
\end{aligned}
$$

as the cost-share weighted averages of the respective final good parameters. Then,

$$
\vartheta_j^{VA} = \omega_j + \tilde{\nu}_j \left( \frac{e}{\prod_s \left(p_s^{VA}\right)^{\omega_j}} \right)^{-\varepsilon} . \tag{B-6}
$$

Note that (B-6) is exactly the value added demand system of our theory. In particular, the elasticity parameter $\varepsilon$ coincides exactly with the elasticity parameter of the final expenditure demand system in (B-4) and hence can be estimated from the data on final expenditure. This is not the case for the other preference parameters $\tilde{\nu}_j$ and $\omega_j$. In particular, knowledge of the input-output matrix $[\lambda_{js}]$ is required to translate the final good share $\left[\omega_s^{FE}\right]_s$ into the value added shares $[\omega_s]$. We therefore do not attempt to also estimate $\omega_F$ or $\tilde{\nu}_F$ from the expenditure data but only estimate $\varepsilon$.

The Cobb-Douglas specification in (B-5) is particularly convenient because it gives rise to the exact value added demand system of our theory. However, the results that the expenditure income elasticity $\varepsilon^{FE}$ and the value added elasticity $\varepsilon$ are closely linked is more general. Suppose that the final good production function in (B-5) is given by the more general CES form

$$
y_s^{FE} = \left( \sum_j \left(b_{js}\right)^{1/\eta_s} \left(c_{js}\right)^{\frac{\eta_s - 1}{\eta_s}} \right)^{\frac{\eta_s}{\eta_s - 1}} .
$$

Following the same steps as above, we then find that

$$
\begin{aligned}
\vartheta_j^{VA} &= \sum_{s\in} \frac{b_{js}\left(p_j^{VA}\right)^{1-\eta_s}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \vartheta_s^{FE} \\
&= \sum_s \frac{b_{js}\left(p_j^{VA}\right)^{1-\eta_s}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \left(\omega_s^{FE} + \tilde{\nu}_s^{FE}\left(\frac{e}{\prod_j q_j^{\omega_j^{FE}}}\right)^{-\varepsilon^{FE}}\right) \\
&= \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\omega_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}}\right) + \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\tilde{\nu}_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \times \left(\frac{1}{\prod_j q_j^{\omega_j^{FE}}}\right)^{-\varepsilon^{FE}}\right) \times e^{-\varepsilon^{FE}} \\
&= \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\omega_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}}\right) + \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\tilde{\nu}_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \times \left(\frac{1}{\prod_j q_j^{\omega_j^{FE}}}\right)^{-\varepsilon^{FE}}\right) \times \left(\frac{e}{-}\right)^{-\varepsilon^{FE}} \\
&= \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\omega_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}}\right) + \left(\frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\tilde{\nu}_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \times \prod_j \left(\sum_s b_{sj}\left(\left(p_s^{VA}\right)^{\omega_j^{FE}}\right)^{1-\eta_j}\right)^{\frac{\varepsilon^{FE}}{1-\eta_j}}\right) \times e^{-\varepsilon^{FE}}.
\end{aligned}
$$

Hence, define

$$
\begin{aligned}
\overline{\omega}_j\left(\left[p_s^{VA}\right]\right) &\equiv \overline{\omega}_{jrt} = \frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\omega_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \\
\overline{\tilde{\nu}}_j\left(\left[p_s^{VA}\right]\right) &\equiv \overline{\tilde{\nu}}_{jrt} = \frac{\sum_s b_{js}\left(p_j^{VA}\right)^{1-\eta_s}\tilde{\nu}_s^{FE}}{\sum_m b_{ms}\left(p_m^{VA}\right)^{1-\eta_s}} \times \prod_j \left(\sum_s b_{sj}\left(\left(p_s^{VA}\right)^{\omega_j^{FE}}\right)^{1-\eta_j}\right)^{\frac{\varepsilon^{FE}}{1-\eta_j}},
\end{aligned}
$$

where the dependence on sectoral prices $\left[p_{srt}^{VA}\right]$ implies that these functions vary across sectors, region and time. The value added expenditure shares are therefore given by

$$\vartheta_j^{VA} = \overline{\omega}_{jrt} + \overline{\tilde{\nu}}_{jrt} \times e^{-\varepsilon^{FE}}. \tag{B-7}$$

Hence, the derived demand system has the same functional form as the value added demand system in our theory. In particular, the final good expenditure elasticity $\varepsilon^{FE}$ again emerges as the value added expenditure elasticity. However, in contrast to (B-6), the "parameters" $\overline{\omega}_{jrt}$ and $\overline{\tilde{\nu}}_{jrt}$ explicitly depend on value added prices and hence vary across locations and time. Recall that we target the parameter $\beta$ from the regression

$$\ln \vartheta_{Frt}^i = \delta_{Frt} + \beta \times \ln e_{irt} + u_{irt},$$

i.e. we also identify the parameter $\beta$ from the cross-sectional variation within locations as dictated by (B-7).

## B-6 The Elasticity of Substitution and the Income Elasticity of Expenditure Shares

For the class of PIGL preferences, the elasticity of substitution is not a structural parameter but depends on relative prices and total expenditure. The Allen Uzawa elasticity of substitution between goods $s$ and $k$ is given by

$$EOS_{sk} = \frac{\frac{\partial^2 e(p,V)}{\partial p_s \partial p_k} e(p,V)}{\frac{\partial e(p,V)}{\partial p_s} \frac{\partial e(p,V)}{\partial p_k}},$$

where $e(p,V)$ denotes the expenditure function. As we show in Section A-4 in the Appendix, our preference specification implies that

$$EOS_{sk} = 1 - \varepsilon \frac{(\vartheta_s - \omega_s)(\vartheta_k - \omega_k)}{\vartheta_s \vartheta_k}.$$

In the left panel of Figure B-7 we report the implied elasticities of substitution as a function of the regional urbanization.[12] The substitution elasticities are relative to close to unity. Goods and consumer services are complements, in particular in poor, rural districts. Food and consumer services are slightly more substitutable than implied by a Cobb Douglas utility function. In the right panel we depict the elasticity of sectoral expenditure shares with respect to income. In our model, this elasticity if given by

$$\frac{\partial \ln \vartheta_s}{\partial \ln e} = -\varepsilon \frac{\vartheta_s - \omega_s}{\vartheta_s}.$$

Quantitatively, our estimated model predicts that the expenditure elasticity for agricultural products is close to -0.3. This is expected because $\varepsilon \approx -0.3$. The expenditure elasticities on goods and consumer services are both positive and between 0.2 and 0.5. The consumer service elasticity is particularly large in rural regions, that are on average poor and unproductive in consumer services.

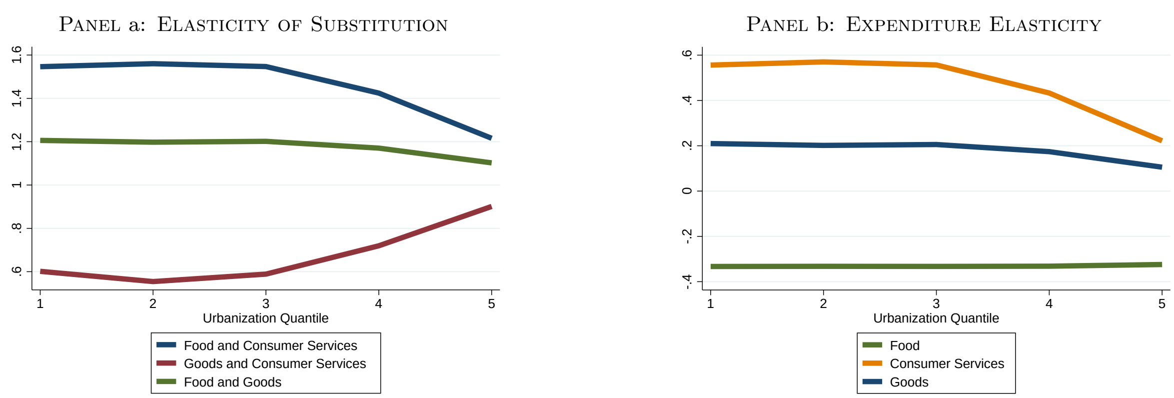


Figure B-7: Elasticities of Substitution and Expenditure Elasticities. The figure plots the elasticity of the substitution between the three goods (left panel) and the elasticity of expenditure shares with respect to expenditure (right panel) by urbanization quintile in 2011.

[12] More specifically, for each urban quintile we calculate the population weighted average of the respective regional elasticity of substitution for the region's representative household.

## B-7 Estimating the shape of the human capital distribution ($\zeta$)

We estimate the tail parameter of the distribution of efficiency units $\zeta$ from the distribution of income. Our model implies that total income and expenditure of individual $h$ is given by $e_{rt}^{h} = q^{h} w_{rt}$, where $q$ follows a Pareto distribution

$$f_{rt}(q) = \frac{\zeta \underline{q}_{rt}^{\zeta}}{q^{\zeta+1}}$$

This implies that

$$\ln\left(f_{rt}(q)\right) = \ln(\zeta \underline{q}_{rt}^{\zeta}) - (\zeta+1)\ln(q). \tag{B-8}$$

Hence, we estimate $\zeta$ from a regression of the (log of the) upper tail density on log efficiency units which we calculate as $q_{rt}^{h} = \frac{e_{rt}^{h}}{w_{rt}}$. In Table B-16 we report the estimated $\zeta$ based on (B-8). We report both the estimate based on the full sample (column 1) and the estimates by urbanization quintile (columns 2 - 6). We also report our estimates based on two measures of earnings: total expenditure by capita (which we use as our earnings measure for our main analysis) and total incomes, which is also reported in the NSS data.

Table B-16 contains two results. First, the estimated tail parameter for the aggregate economy is slightly below 3, stable across years and does not depend on the exact measure of earnings. Second, the estimated tail parameter is declining in the urbanization rate indicating that urban locations have higher inequality. Our estimates also indicate that inequality was lower in 2011 than in 1987. For our quantitative model we set $\zeta$ to an average value of 3. In Section 7 we show that our results are robust to a variety of choices for $\zeta$. Hence, for simplicity, we abstract from the heterogeneity in $\zeta$ across urbanization quantiles.

| | Variable | Full Sample | Quintiles of Urbanization | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1st | 2nd | 3rd | 4th | 5th |
| 1987 | Income | 2.82 | 3.11 | 3.06 | 3.25 | 2.93 | 2.92 |
| | Expenditure | 2.84 | 3.64 | 3.57 | 3.21 | 3.03 | 2.79 |
| 2011 | Income | 2.85 | 4.04 | 3.47 | 3.13 | 2.90 | 2.71 |
| | Expenditure | 2.90 | 3.80 | 3.57 | 3.16 | 2.96 | 2.63 |

Table B-16: Identification of $\zeta$. The table reports the estimate of $\zeta$ based on (B-8). In the first columns we report the estimates for the years 1987 and 2011. In the remaining columns we perform our estimation separately for different quantiles of the urbanization distribution.

## B-8 Estimating the shape of the productivity distribution ($\lambda$)

We identify the shape parameter $\lambda$ of the productivity distribution from the tail of the employment distribution. Our model implies that total employment of a firm with productivity $z$ is given by

$$l\left(z\right) = L_{PS}\left(z\right) + L_{PM}\left(z\right) = \frac{\beta+\alpha}{\beta}\varsigma\left(A_{PS}\right)\frac{z}{z_{L}}f_{0} - \varsigma\left(A_{PS}\right)f_{0}.$$

This implies that the employment distribution is given by

$$F_{l}\left(l\right) = P\left(l\left(z\right) \leq l\right) = 1 - \left(\frac{A_{rMt}\frac{\alpha+\beta}{\beta}\frac{\zeta(A_{PS})f_{0}}{z_{L}}}{l+\zeta\left(A_{PS}\right)f_{0}}\right)^{\lambda}.$$

Hence, for large firms (i.e. $l \to \infty$), the tail of the employment distribution is exactly equal to $\lambda$.

To estimate $\lambda$, note that

$$\ln\left(1-F_{l}(l)\right) = C_{0} - \lambda \ln l, \tag{B-9}$$

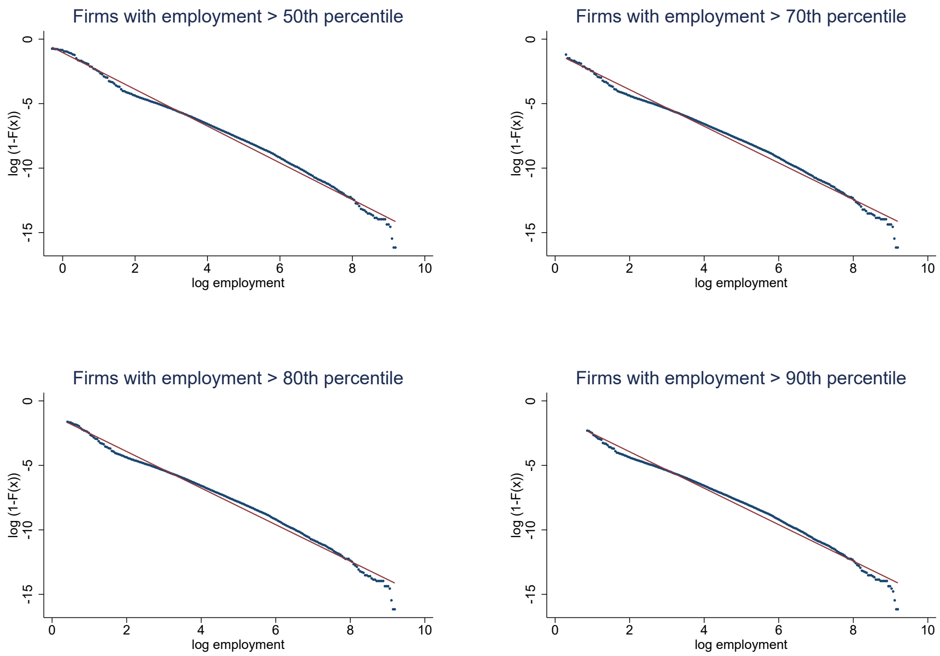


Figure B-8: IDENTIFICATION OF $\lambda$. The figures depicts the relationship between $\ln(1 - F_l(x))$ and $\ln x$ for different cutoffs of the employment distribution. We consider all firms with employment exceeding the 50%, 70%, 80% and 90% quantile. For each sample we consider a grid of 200 points the log employment distribution. The slope of the relationship coincides with $\lambda$ (see (B-9)).

where $C_0 = \ln\left(A_{rMt}\frac{\alpha+\beta}{\beta}\frac{\zeta f_0}{z_L}\right)^{\lambda}$. Hence, we estimate $\lambda$ from a regression of the log of the upper tail probability on log employment.

In Figure B-8 we depict the empirical relationship of (B-9) for the different sub samples of tail of the employment distribution. Specifically, we consider a grid of 200 points of the log employment distribution $\ln l$, calculate $F_l(l)$ for these grid points and then plot $\ln(1 - F_l(l))$ against $\ln l$. We consider four samples, namely all firms with employment exceeding the 50%, 70%, 80% and 90% quantiles.

Equation (B-9) implies that the relationship should be linear and that the slope should be equal $-\lambda$. Figure B-8 shows that the employment distribution in India indeed has a pareto tail and that the estimated slope does not depend markedly on the employment cutoff for the employment distribution.

In Table B-17 we report these results in a regression format. The four columns refer to the different subsamples of the tail of the employment distribution. We estimate a pareto tail of 1.42. Reassuringly, the slope is very precisely estimated and the estimates are almost identical across the different samples. We also find the economic magnitude plausible. The firm size distribution in the US is often found to have a tail of around 1.1. Given that the importance of large firms is larger in rich countries, an estimate of 1.42 strikes us as plausible.

## B-9 Outliers In Quantitative Analysis

For our quantitative analysis in Section 6 we winsorize a small number of outliers. For a small number of regions we estimate very large changes in CS productivity. Intuitively, because CS employment in our model is bounded by $\omega_{CS}$ from above, our theory can only rationalize employment shares close to $\omega_{CS}$ with an exceedingly high level

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $> 50\%$ | $> 70\%$ | $> 80\%$ | $> 90\%$ |
| log employment | -1.426*** | -1.420*** | -1.418*** | -1.414*** |
| | (0.010) | (0.011 | (0.011) | (0.012) |
| Industry FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.991 | 0.989 | 0.989 | 0.987 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B-17: Estimation of $\lambda$. The table reports the estimates of the tail of the productivity distribution $\lambda$. In the different columns we restrict the sample to firms with a size exceeding the 50%, 70%, 80% and 90% quantile of the size distribution.

| | Regional welfare changes (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Min | 1% | 2% | 3% | 5% | 95% | 97% | 98% | 99% | Max |
| Agriculture | -45.9 | -30.1 | -28.9 | -27.2 | -24.9 | -4.3 | -3.0 | -1.2 | 4.5 | 29.3 |
| Industry | -45.9 | -33.1 | -28.9 | -27.2 | -24.9 | -4.3 | -3.0 | -1.2 | 4.5 | 29.3 |
| Cons. Serv. | -98.5 | -97.4 | -95.1 | -91.6 | -84.9 | 23.1 | 59.9 | 338.6 | 2099.8 | $3.9 \times 10^4$ |
| Cons. Serv. (Baseline) | -96.4 | -96.1 | -94.2 | -91.5 | -84.9 | 23.1 | 49.7 | 62.4 | 109.9 | 144.4 |

Table B-18: Distribution of Welfare Losses. The table reports the lower and upper percentiles of the regional distributions of sectoral welfare losses.

of CS productivity.

This is seen Table B-19 where we report the upper and lower quantiles of the regional distribution of welfare changes for the different counterfactuals. Consider for example the agricultural sector. If agricultural productivity had not grown since 1987, the most adversely affected region would have seen its welfare decline by 56.9% in terms of an equivalent variation. Conversely, some regions would have gained. The region benefitting the most would have seen an increase in welfare by 57.2%. The last row of Table B-19 shows that some regions would have seen very large gains if CS productivity had not grown. These are regions where CS productivity *declined* between 1978 and 2011. As explained above, this pattern is entirely driven by few districts being close to the theoretical threshold of $\omega_{CS}$. For comparison, in the last row we also report the estimated distribution of the welfare effects in our baseline analysis, where we truncate the productivity growth distribution at the top and bottom 3%. This has large effects on the distribution of welfare effects in the right tail of the distribution.

These extreme values at the bottom of the regional productivity growth distribution have aggregate effects. For our baseline analysis we trim the top and bottom 3% of the productivity growth distribution and set regional productivity growth in such regions to the 3% and 97% quantile respectively. In Table B-19 we report the change in aggregate in the absence of CS productivity growth as a function of this trimming cutoff. Without any trimming, the aggregate effect is 32%, i.e. is positive due to the extreme outliers reported in Table B-19. Once such outliers are truncated, we recover our baseline results of a welfare loss of about -25%. In the last row of Table B-19 we report the aggregate employment share of the affected districts. The changes in the aggregate effects of CS growth are not driven by few large districts but by a small number of small districts with very large changes in CS productivity.

## B-10 Decomposing the Effects of Productivity Growth Within the Industrial Sector: Details

In this section we provide more details concerning the decomposition of productivity growth in the industrial sector into its two components: manufacturing productivity $A_{rMt}$ and PS productivity $A_{rPSt}$. In the left panel of Figure

| | | Trimming cutoff | | | | |
|---|---|---|---|---|---|---|
| | No trimming | 1% | 2% | 3% | 4% | 5% |
| Welfare Loss | 32.1% | -5.6% | -20.9% | -25.3% | -26.3% | -26.4% |
| Employment Share | 0 | 1.2% | 1.4% | 3.2% | 4.2% | 6.7% |

Table B-19: Welfare Losses with Different Trimming Cut-offs. The table reports the aggregate welfare effects of productivity growth in the CS sector for different trimming rules. A trimming cutoff $x\%$ means that we set the $x\%$ highest and lowest productivity growth rates to $x\%$ and $1-x\%$ respectively.

Panel a: Decomposition of industrial growth

Panel b:Decomposition as a function of $\beta$

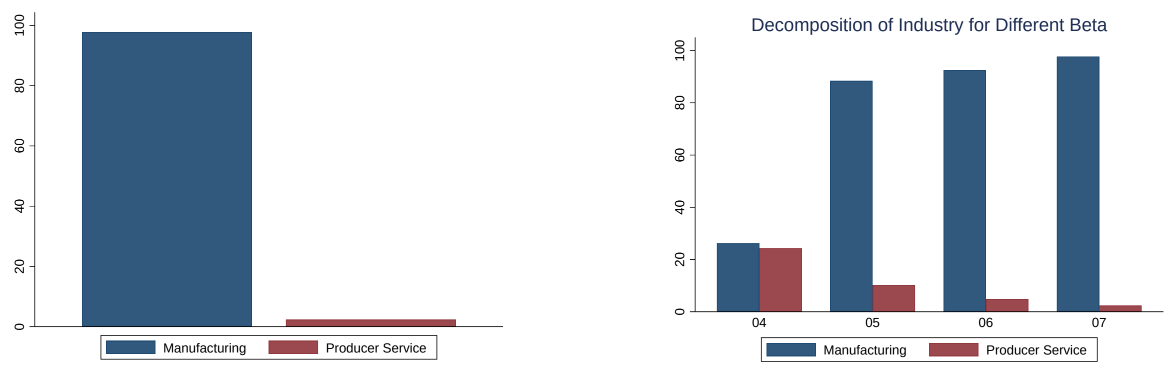


Figure B-9: Decomposition of Industrial Growth: Manufacturing vs Producer Services. The figure decomposes the effect of industrial productivity growth ($d\ln A_{rGt}$) into manufacturing ($d\ln A_{rMt}$) and producer service ($A_{rPSt}$) growth. In the left panel we display the decomposition in our baseline calibration. In the right panel we display the decomposition as a function of the PS share in the production function $\beta$.

B-9 we report the composition of the aggregate effect into the respective components in our baseline calibration. Clearly, manufacturing productivity accounts for the lion share of industrial growth.[13]

In the right panel, we study the sensitivity of our results with respect to $\beta$. In our baseline calibration, we choose $\beta = 0.7$ based on the observation of a large employment share of PS in the United States. However, we recognize that the calibration of $\beta = 0.7$ is subject to some uncertainty. For instance the asymptotic share of the PS sector could be smaller in India than in the United States—as it is in other large economies such as China and Germany. In the right panel of Figure B-9 we therefore replicate our decomposition as a function of $\beta$. The lower $\beta$, the higher the role for producer services. Intuitively: the closer the observed equilibrium to its asymptotic share of PS employment, the more sensitive are the employment allocations to $A_{PS}$. Hence, even modest increases in the PS intensity of production cause us to infer relative large changes in PS productivity. Still, manufacturing productivity accounts for more than 80% of productivity growth in the industrial sector.

For completeness, In Figure B-10, we decompose the welfare effect of the industrial sector into the manufacturing and PS component by urbanization quintile. As with the aggregate results reported in Figure B-9, the quantitative importance of producer service growth is small.

## B-11 Details of Robustness Analysis (Section 7)

This section contains additional results for our robustness analysis in Section 7.

[13] In this decomposition there is also a covariance component. Because the importance of this component is minuscule, we do not show it in Figure B-9.

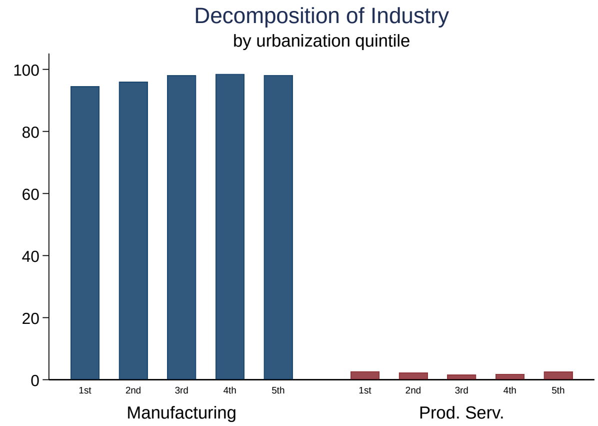


Figure B-10: Decomposition of Industrial Growth by urbanization. This figure report the decomposition of the aggregate welfare effect of productivity growth in the industrial sector between manufacturing (blue bars) and PS (red bars) for different urbanization quintiles.

### B-11.1 Sensitivity to Structural Parameters

In Figure B-11 we show the robustness of our results with respect to the elasticity of substitution across traded varieties $\sigma$ (left panel) and the trade elasticity $\eta$ used in the open economy extension of our theory (right panel). The structure of the graphs is the same as in Figure 11 in the main text.

The variety elasticity $\sigma$ has - quantitatively - a negligible effect on our results: the aggregate welfare effects of sectoral productivity do not depend much on the assumed value of $\sigma$. As far as the effects of consumer services is concerned, they are - if anything - increasing in $\sigma$, i.e. our benchmark value of $\sigma = 3$ (which is on the low end of the usual estimates) is conservative. The same is true for the trade elasticity $\eta$, shown in the right panel. Again, a higher level of $\eta$ increases the welfare gains of sectoral productivity growth but the quantitative effects are small. We therefore conclude that our main results are robust to our choices of $\sigma$ and $\eta$.

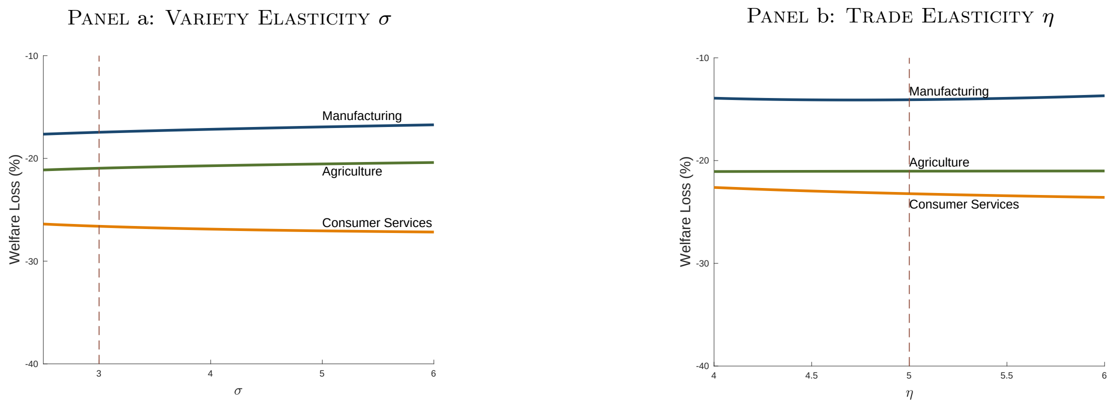


Figure B-11: Robustness Analysis. Panels (a) and (b) show the welfare effects as a function of the variety elasticity $\sigma$ and the trade elasticity $\eta$. The vertical dashed line corresponds to the parameter value in our benchmark analysis.

# APPENDIX C: FIGURES AND TABLES

In this section, we report additional tables and figures referred to in the main text.

## C-1 Additional empirical results

### Urbanization and Aggregate Growth

In Figure C-1 we report the time-series change in the urbanization rate (panel a) and in income per capita (panel b). The urbanization rate is the share of the population living in urban areas according to the definition of the NSS. The NSS defines an urban location in the following way: (i) all locations with a Municipality, Corporation or Cantonment and locations defined as a town area, (ii) all other locations that satisfy the following criteria: (a) a minimum population of 5000, (b) at least 75 percent of the male population are employed outside of agriculture, and (c) a density of population of at least 1000 per square mile. This share increased from around 22% in 1987 to 29% in 2010. Income per capita, shown in the right panel, stems from the World Bank. Between 1987 and 2010, income per capita increased by a factor of almost 3.

### Urbanization and Income per Capita

For some of our analysis we choose urbanization as our measure of spatial heterogeneity. We do so as a descriptive device and interpret urbanization as a broad proxy for regional economic development. Figure C-2 shows that there is a strong positive correlation between urbanization and expenditure per capita in the NSS data in 2011.

### Structural Change with Imperfect Substitution in Skills

Figure C-3 is the analogue of Figure 10 in the text for the extension of the model in Section 7.3.2.

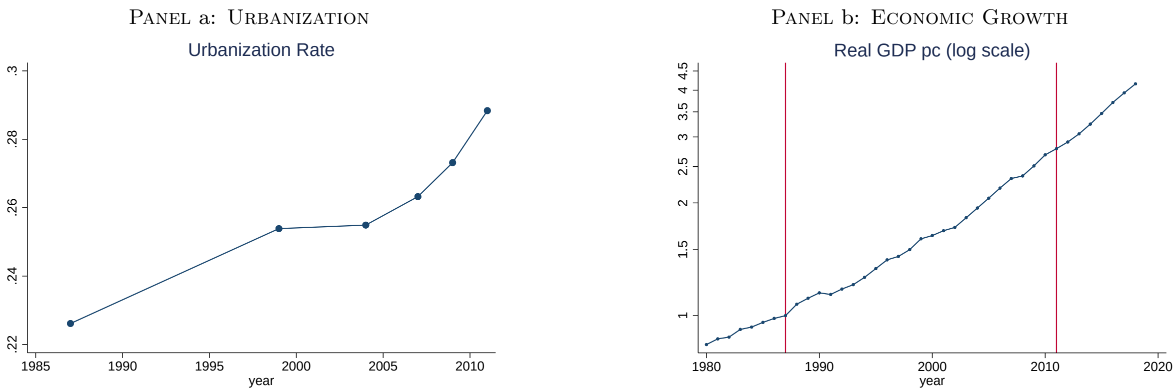


Figure C-1: Economic Growth in India: 1987 - 2011. This figure shows the evolution of the urbanization rate (Panel a) and income per capita (Panel b). The urbanization rate is the share of population living in urban areas according to the definition of the NSS. Income per capita stems from World Bank.

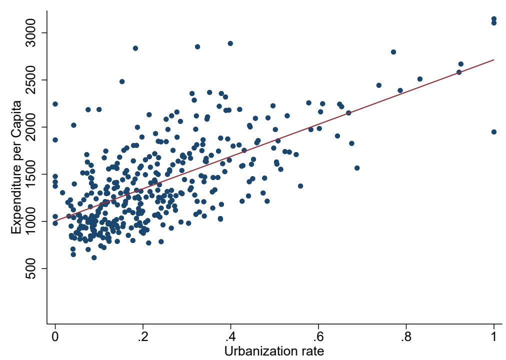


Figure C-2: Expenditure per capita vs. Urbanization. The figure shows a scatter plot of the average expenditure per capita in the NSS data across district-level urbanization rates in 2011.

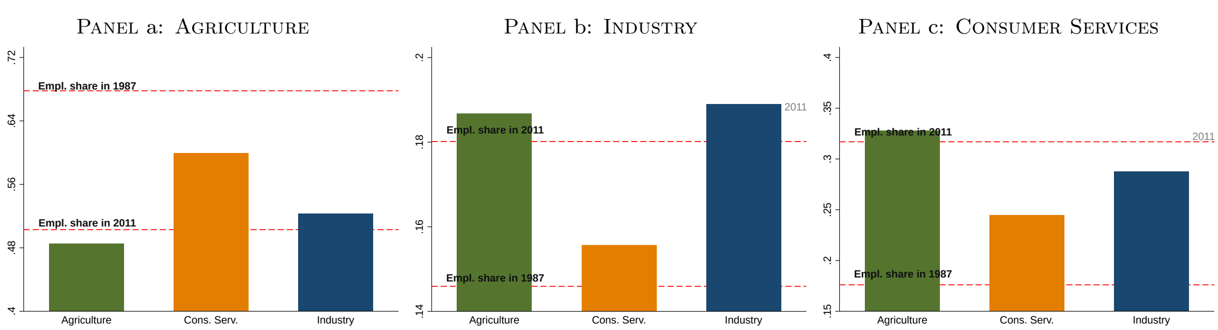


Figure C-3: Sectoral Productivity Growth and Structural Change with Imperfect Substitution in Skills. This figure is the analogue of Figure 10 in the extension allowing for imperfect substitution across skilled groups and for skill-biased technical change.