Service-Led or Service-Biased Growth? Equilibrium Development Accounting Across Indian Districts.

Tianyu Fan, Michael Peters, and Fabrizio Zilibotti

Yale University

September 2020

Abstract

In many developing countries, urbanization and structural change take the form of a declining agricultural sector and an increasing employment share of the service sector without a significant change in the size of the manufacturing sector. Is the growth of services an engine of growth or simply a consequence of the income effects stemming from productivity growth in the goods-producing sectors? In this paper we present a new methodology to estimate the productivity of the service sector exploiting the granularity of data on employment and expenditure shares. The structural estimation is a form of "equilibrium development accounting" and hinges on a spatial equilibrium model where the employment structure depends on the relative productivity of labor in different sector-regions and on the local demand. The key assumptions are non-homothetic preferences (of the PIGL class) and the assumption that services, different from goods, must be provided locally in each market. We apply our methodology to the economic development of India between 1987 and 2011. Our (preliminary) results suggest that productivity growth in consumer and producer services were important drivers of structural transformation and of an increase in the living standards of the more urbanized areas. The model also allow us to assess the unequal effects of growth at different ladders of the income distribution.

PRELIMINARY AND INCOMPLETE DRAFT

1 Introduction

Most industrialized countries have undergone a similar pattern of structural transformation over their development process. At an early stage, a growing industrial sector draws labor from a declining agriculture. At a later stage, the employment shares of both goods-producing sectors – agriculture and manufacturing – fall and the service sector becomes the main source of employment growth. In the US, for instance, the employment share of manufacturing has stayed above 30% until the mid 1950s and has declined thereafter falling below 10% during the most recent decade. In China, where large-scale industrialization only occurred much later, the manufacturing sector grew fast between the 1970s and 2014. Thereafter, the employment share of the industrial sector has started falling.

However, in other parts of the globe, the path of economic development appears to have taken a different turn. Over the last four decades, the share of manufacturing jobs has hardly grown in most developing countries, including fast-growing economies like India, Ethiopia, and other sub-Saharan African nations. In these countries, the structural transformation has taken the form of a shift from agriculture to services (see, e.g., Celasun and Gruss (2018)).

To many scholars (e.g., Mc Millan and Rodrik (2011)) the absence of industrialization is a cause of concern. The traditional view among development economists is that technical progress in manufacturing is the main engine of productivity growth. In contrast, the expansion of the service sector is a by-product of economic development: as countries grow richer, consumers spend an increasing share of their income on *luxuries*, and their demand triggers a growing provision of services. The proponents of this view are pessimistic about the service sector's capability to become a viable engine of growth. In his classical contribution, Baumol (1967) argues that wages can grow in service-sector jobs even in the absence of productivity gains because of the labor market competition from a dynamic manufacturing sector. However, in the absence of other forces that sustain productivity growth, living standards are bound to eventually stagnate.

These pessimistic conclusions rest on the assumption that technical progress is intrinsically slow in the service sector. This view is not undisputed. For instance, Hsieh and Rossi-Hansberg (2019) go as far as saying that ICT has triggered an industrial revolution in the service sector that has been a major source of productivity growth in mature economies during the last decades.[1] A hurdle to sorting out this controversy is measurement: it is often difficult to quantify the productivity of service-sector firms.

In this paper, we provide a novel structural methodology to estimate productivity in the service sector and to quantitatively assess its importance in the development process. Our approach is in the wake of the development accounting literature.[2] We do not attempt to explain the determinants of productivity growth but propose a method to measure sectoral productivity across sub-national geographical units (such as districts, provinces, MSAs, etc.) when the availability of data is limited. 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 location.

We assume that labor is the only productive factor and that people can work in four sectors of activity: agriculture, manufacturing, production services (PS) and consumer services (CS). Labor is perfectly mobile across industries and immobile across geographical units (*districts*). Thus, there is a single wage per effective unit of labor in each district while wages can differ across districts. These assumptions are extreme but can be easily relaxed by introducing non-prohibitive labor mobility frictions across both sectors and districts. Consumers have preferences defined over three final items: *food*, (industrial) *goods*, and *consumer services.*

Because the service sector is broad and heterogeneous, its growth may have different implications for consumers and producers. Part of the services produced improve the access of households to the consumption of goods (e.g., restaurants or retail) or enter directly their consumption basket (e.g., leisure services). This is what we call CS. Other services (PS) are predominantly inputs to the production of goods, mostly in the industrial sector. These include, among others, business services, corporate law services, and part of the transport services that increase the productivity of goods-producing firms. We model CS as final services that enter households' consumption and PS as inputs to the production of industrial goods.[3]

A key assumption in our theory is that food and industrial goods are traded across districts. In contrast, both PS and CS must be purchased locally. There is an important difference, though: CS must be consumed locally, so the local productivity impacts directly on the price and ultimately on the availability of CS in each market. In contrast, PS are embedded in industrial goods so their value added is tradable.

Without further assumptions, the equilibrium would feature perfect specialization in the production of tradable goods, based on Ricardian comparative advantages: some districts would only produce food while others would only produce industrial goods. Since full specialization is not appealing for a quantitative analysis, we introduce the common assumption in spatial equilibrium models that each district produces a differentiated variety of the traded goods. Preference for varieties are homothetic and are represented by a standard CES aggregator. This assumption ensures that in all districts consumers demand all varieties and all sectors have a positive employment share. For simplicity, we abstract from trade costs implying that all consumers will consume the same basket of

[1] The authors argue that ICT has made it possible for the most efficient service firms to replicate their superior production process in multiple locations close to consumers. This has granted large productivity gains in the provision of services.

[2] See, e.g. Caselli (2005) and Hall and Jones (1999). These papers use aggregate production functions and information on the accumulation of productive factors to fit the data. Our methodology is closer to the structural development accounting approach of Gancia et al. (2013) who use the restrictions imposed by a model of directed technical change to identify the sectoral productivities. However, in their model, spatial interactions are limited to technological spillovers. Moreover, our paper uses granular information about employment and expenditure shares in a novel fashion.

[3] If PS were the only source of productivity growth, one could argue that there is really nothing new under the sun. The technology in manufacturing is just becoming more intensive in services relative to other inputs, and the efficiency in the provision of business services has increased. However, ultimately, a properly defined goods-producing sector would continue to be the main growth engine. Our analysis show that such a description would miss important aspects of the growth process of developing countries like India.

tradable goods. The law of one price applies then to the baskets of agricultural and industrial goods, respectively.

The demand side of the economy is populated by consumers endowed with nonhomothetic preferences belonging to the PIGL class. This class of preferences 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). PIGL preferences do not admit in general an analytical representation of the utility function but can be represented in terms of an indirect utility function. Moreover, they have transparent aggregation properties: 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. In our model, this guarantees that we can derive district-level demand functions since, within each district, all agents face the same price vector. Moreover, it allows for a tractable characterization of the spatial equilibrium even though factor prices vary across space.

The ultimate goal of our analysis is to quantify the extent to which the growth of the service sector is either a source or a consequence of the development process. To clarify our conceptual framework, consider the following example. Imagine two small districts R (rich) and P (poor) which are part of a large multi-district economy, and abstract for simplicity from producer services.[4] Let A_{rs} denote labor productivity in district r and sector $s \in \{F, M, CS\}$. We consider two polar opposite scenarios.

In the first scenario, $\{A_{RF}, A_{RM}\} = \{\lambda A_{PF}, \lambda A_{PM}\}$, for $\lambda > 1$, i.e., the productivity of the tradable sectors are proportionally larger in R than in P by the factor λ. Instead, the productivity of consumer services 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 then spend a higher share of their income on CS while consumers in P while spend a higher share of their income on food. Since CS is nontradable, district R will also have a larger employment share in CS while P will specialize in the production of goods.[5] In this first scenario, spatial differences in expenditure and employment shares are entirely driven by income effects in demand. Note that workers in the CS sector earn higher wages in R than in P despite the fact that the productivity is identical in the two districts. This is a version of the canonical Balassa-Samuelson effect. To allude to the cost disease argument, we refer to this case as the *Baumol scenario* or *service-biased growth*.

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

While the example emphasizes a spatial difference across districts, the same argument applies to the analysis of a given district at two different 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.

Our model allows us to disentangle the relative importance of these two effects by estimating the variation in sectoral productivities across space and time. To see how, observe that, conditional on a set of structural (i.e., preference and technology) parameters, given a set of labor productivities $\{A_{rF}, A_{rM}, A_{rPS}, A_{rCS}\}$ and regional labor endowments $\{L_r\}$, it is possible to solve uniquely for the equilibrium wage vector $\{w_r\}$ and the allocation of labor $\{L_{rF}, L_{rM}, L_{rPS}, L_{rCS}\}$. Conversely, if we have data for the allocation of labor across sectors in each district and for the local real wage, we can retrieve a unique set of labor productivities $\{A_{rF}, A_{rM}, A_{rPS}, A_{rCS}\}$. After estimating the productivities, we can determine the extent to which growth is *service-biased* or *service-led* and run counterfactual experiments. The estimation hinges on a set structural parameters. Among them, those governing the income elasticities of demand are especially important because they determine the strength of income effects. We estimate these parameters from Engel curves using a mixture of micro and macro data as detailed below.

We apply our methodology to India. India is a fast-growing economy, with an average annual growth rate of 4.2% during 1987-2011. In this period, the employment share of agriculture declined substantially while that of manufacturing increased only marginally. The lion share of the process of structural change has then been a shift from agriculture to services.

Our estimation exploits individual geolocalized data on consumption, employment, and expenditure shares. The

[4]Although inessential, the assumption that R and P are small relative to the total economy is useful because it allows us to think of the price indexes for food and industrial goods as being exogenous.

[5]Because goods are tradable, whether P specializes in agriculture or manufacturing depends on its comparative advantage.

main data source is the Employment Schedule of the National Sample Survey (NSS) covering 400 Indian districts between 1987 and 2011. The NSS provides us with information on consumption per capita that we use as a proxy for district-level real wages. In order to split the employment in the service sector into consumer and production services, we use data from the Economic Census, a complete census of firms in India, and from the Survey of the Service Firms of India. The latter data source is particularly helpful because it reports whether services are bought by firms or consumers.

We estimate separately the cross-sectional distribution of productivities for 1987 and 2011. Then, we chain them so that the average growth rate implied by our model economy matches the national account statistics for GDP per capita growth India.[6] The results are interesting in several respects. At the spatial level, there are large productivity differences across districts in both manufacturing and CS. In the CS sector, the productivity gap is especially large between the most urbanized locations and the rest of the economy. Hence, urban location not only have higher employment shares in services because they their inhabitants are richer but the provision of such services is more productive.

We then use our model to quantify the importance of sectoral productivity growth for India's economic development between 1987 and 2011. We find that productivity growth in agriculture is the main driver of welfare changes in India between 1987 and 2011. This is not surprising, given the large size of the agricultural sector. However, productivity growth in the service sector is also very important, its average effect being quantitatively similar to the effect of technical progress in manufacturing. The welfare effects are especially large in the top quintile of the distribution of districts by urbanization. Consumers in highly urbanized districts would rather take a 30% wage cut in 2011 than moving back to the productivity distribution that the Indian CS sector had in 1987.

These effects also vary at different ladders of the income distribution within sectors. Because of non-homothetic preferences, the richer households are the main beneficiary of the growth of the consumer service sector in urban areas. The top quintile of the income distribution in urban district would rather renounce to the benefits accruing from the productivity gains in agriculture and industrial production altogether than to those accruing from technical progress in the service sector during the period 1987-2011. In sum, we find that a substantial share of Indian growth was indeed service-led.

Productivity growth in CS is also an important driver of structural change. Had productivity in the service sector stayed constant at the 1987 level, the structural transformation measured by the decline of the employment share in agriculture and the corresponding increase in the employment share of services would have been cut by two third. While income effects are important, our estimates suggest that the growth of services is far from being a mere corollary of growth as in the *Baumol scenario*. Another interesting observation is that productivity growth in agriculture, while being an important source of improvement in Indian people's living standards, plays no significant role in explaining structural change. Had productivity in agriculture remained at the 1987 level, the employment share of agriculture in 2011 would be lower than its actual share in 2011. Productivity growth in agriculture, if anything, slowed down the reduction of employment in agriculture over time. On the contrary, had productivity in CS remained at the 1987 level, the employment in agricultural sector would be 59%, close to its actual share in 1987. Thus, productivity growth in CS has been an important driver of structural change.

Our main analysis is based on a closed-economy environment. Since India–like the rest of the world–underwent a significant process of globalization throughout the period we study, we study in an extension the role of the international trade. We assume that industrial goods are also traded internationally and set the parameters of the model so as to match the increase in trade flows. In the case of India, services also play an important role in international trade. Since the main component of service export was the boom in ICT services, we treat this category as a separate sector that sells its services to the foreign sector. The results from the open-economy model broadly confirm the robustness of the results of the closed economy model.

In conclusion, our estimates indicate that the variations across time and space of productivity in the service sector are an important aspect of the recent economic development of India. Growth appears to be both service biased and service led. The service sector is by no means a mere ancillary force to development.

A more thorough review of the literature will follow. Here are some preliminary and incomplete references. We

[6] We could alternatively use the evolution of consumption from survey data to infer growth. This is notoriously problematic. First, we should compare Rupiah 2011 into Rupiah 1987 which is already complicated since our model doesn't lend to standard price indexes. Second, there are well-known discrepancies between consumption growth in survey data and national account statistics. We choose to use the national account statistics as an anchor, though alternative choices would simply amount to a rescaling of the results.

contribute to the macroeconomic literature on the structural transformation – see, e.g., Duarte and Restuccia (2010), Hobijn et al. (2019), Hansen and Prescott (2002), Herrendorf et al. (2013), Herrendorf et al. (2014), Herrendorf et al. (2017). Among recent papers emphasizing the role of nonhomothetic preferences, see Alder et al. (2019), Boppart (2014), Comin et al. (2017), Foellmi and Zweimüller (2006), Foellmi and Zweimüller (2008), Matsuyama (2000), and Matsuyama (2019). Our paper also embeds the role of differential technical progress across sectors, like Ngai and Pissarides (2007) and Storesletten et al. (2019).

The interaction between spatial equilibrium and structural change is studied by Eckert and Peters (2016), though their model is different and the focus is on migration within the United States. To model inter-regional trade linkages, we build on a large literature in economic geography, see e.g. Redding and Rossi-Hansberg (2017) or Allen and Arkolakis (2014).

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

A number of recent papers study more specifically the process of structural change in India and the role of the of service sector. Among them, Amirapu and Subramanian (2015), Eichengreen and Gupta (2011), Erumban et al. (2019), Ghose (2014), Gordon and Gupta (2005), Majid (2019), Mitra and Ural (2008), Mukherjee (2013), and Singh and Dasgupta (2016).

The structure of the paper is as follows. In Section 2 we describe our theoretical framework. In Section 3 we describe our data and the main empirical regularities about the structural transformation in India. Sections 4.1 and 4.2 contain the main quantitative analysis. Section 6 concludes.

2 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). There is a single factor of production, which is inelastically provided: labor. While goods and food are tradable, CS are non-traded and must be provided locally. All markets are frictionless and competitive.

2.1 Technology and Preferences

Technology. All goods are produced with constant return technologies such that

$$Y_{rst} = A_{rst} H_{rst}, \tag{1}$$

where H_{rst} denotes the amount of human capital employed in the production of sector s goods in region r. While we take total productivity in agriculture, A_{rFt}, and consumer service, A_{rCSt}, as exogenous, productivity in the industrial sector A_{rGt} is determined endogenously. However, in Section 2.4 below we show that the equilibrium allocations in the industrial sector yields a production function for goods as in (1), where A_{rGt} is only a function of structural parameters and does not depend on equilibrium prices. Therefore, we can characterize the trade equilibrium taking A_{rGt} as given and then solve for the industry equilibrium in the good-producing sector.

For the traded commodities food and goods, we assume that consumers buy a CES aggregate of differentiated regional varieties with an elasticity of substitution σ. Hence, the price of food and goods, which is common across localities due to free trade, is given by

$$p_{Ft} = \left(\sum_{r=1}^{R} p_{rFt}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \quad \text{and} \quad p_{Gt} = \left(\sum_{r=1}^{R} p_{rGt}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Preferences. We model consumers' preferences as stemming from the *PIGL* class (Price Independent Generalized Linear). These preferences have two key advantages, both of which feature prominently in our approach. First, they allow us to parameterize the extent of non-homotheticity in a flexible way, which we can easily take to the data.

Second, they still allow us to derive an aggregate demand system in a tractable way, which we can take directly to the data.

We represent preferences using the following indirect utility function:

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

where e denotes total spending and p the vector of prices of the three goods. Moreover, for $V(e,p)$ to be a well-defined indirect utility function, $\sum_s \tilde{\nu}_s = 0$ and $\sum_s \omega_s = 1$.

The sectoral expenditure shares associated with $V(e,p)$ are given by (see Section A-2 in the Appendix)

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

Equation 3 highlights consumers' expenditure shares feature both income and price effects. In particular, goods from sector s are luxuries if $\tilde{\nu}_s < 0$. The strength of this non-hometheticities is governed by the parameter ϵ, which, with a slight abuse of notation, we also refer to as the "income elasticity" as a short-hand. If agriculture is a necessity and consumer services are a luxury, then, $\tilde{\nu}_A > 0$ and $\tilde{\nu}_{CS} < 0$. In this case, the expenditure share in food CS are, respectively, decreasing and increasing in e. Moreover, $\lim_{e\to\infty}\vartheta_A^h(e,p) = \omega_A$ and $\lim_{e\to\infty}\vartheta_{CS}^h(e,p) = \omega_{CS}$.

2.2 Heterogeneity & Aggregate Demand

The PIGL preferences in 2 admit a tractable aggregation despite the fact that preferences are nonhomothetic. Suppose individuals have heterogeneous abilities, and let w_{rt} denote the wage per efficiency unit of labor. Then, the income and expenditure for individual i is given by $e_{irt} = q_i w_{rt}$, where q_i 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:

$$\vartheta_s(w_{rt},p_{rt}) \equiv \frac{L_{rt}\int \vartheta_s^h(qw_{rt},p_{rt})\, qw_{rt}dF_{rt}(q)}{L_{rt}\int qw_{rt}dF_{rt}(q)} \quad = \quad \omega_s + \nu_s^r\left(\frac{E_{rt}[q]\,w_{rt}}{\prod_s p_{rst}^{\omega_s}}\right)^{-\varepsilon}, \tag{4}$$

where

$$\nu_s^r \equiv \frac{E_{rt}\left[q^{1-\varepsilon}\right]}{E_{rt}[q]^{1-\varepsilon}}\tilde{\nu}_s,$$

If we compare the aggregate expenditure share in (4) with the individual share in (3), we can see that the aggregate demand 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 ν_s^r instead of the primitive preference parameter $\tilde{\nu}_s$. In general, ν_s^r depends on the local income distribution. However, one can introduce appropriate distributional assumptions that simplify the analysis further. In particular, suppose that q follows a Pareto distribution with CDF

$$F_r(q) = 1 - \left(\frac{\underline{q}_r}{q}\right)^{\zeta}.$$

While the lower threshold $\underline{q}_r$ varies across regions, the tail parameter ζ is region invariant. This implies that $E_r[q] = \frac{\zeta}{\zeta-1}\underline{q}_r$ and $E_r\left[q^{1-\varepsilon}\right] = \frac{\frac{\zeta}{1-\varepsilon}}{\frac{\zeta}{1-\varepsilon}-1}\underline{q}_r^{1-\varepsilon}$. Equation (2.2) therefore implies that

$$\nu_s^r = \nu_s \equiv \frac{\zeta^{\varepsilon}(\zeta-1)^{1-\varepsilon}}{\zeta+\varepsilon-1}\tilde{\nu}_s.$$

Thus, if income follows a Pareto distribution with a common tail parameter, all regions have the same parameter ν_s which is proportional to the primitive individual preference parameter $\tilde{\nu}_s$. In this case, regional differences in demand are solely driven by difference in prices, wages and the distribution of human capital. In particular, the demand for consumer services in region r is increasing both in the level of skill prices and average human capital.

2.3 Spatial Trade Equilibrium

In this section, we characterize the trade equilibrium. Recall that we assume there are single nationwide markets for each variety of food and industrial goods, whereas the markets for CS are segmented. This means that there are $3 \times R$ goods market and R labor markets to clear.

For notational simplicity we drop the t subscript if it does not cause any confusion. To characterize the equilibrium allocations note that prices are given by

$$p_{rs} = \frac{1}{A_{rs}} w_r.$$

Also, the CES demand structure implies the usual regional expenditure shares

$$\frac{\text{spending on food from } r \text{ in } j}{\text{spending on food in } j} = \left(\frac{p_{rF}}{p_F}\right)^{1-\sigma} = \frac{w_r^{1-\sigma} A_{F,r}^{\sigma-1}}{\sum_{m=1}^{R} w_m^{1-\sigma} A_{F,m}^{\sigma-1}}.$$

In the absence of trade costs, the expenditure shares on goods from a particular region r do not depend on the location of the buyer. Therefore, we have a set of nationwide goods market clearing conditions for the tradable products food and goods:

$$w_r H_{rs} = \left(\frac{w_r^{1-\sigma} A_{rs}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{js}^{\sigma-1}}\right) \times \left(\sum_{j=1}^{R} \vartheta_{js} w_j H_j\right) \qquad \text{for } s = F, G,$$

and a set of district-specific market clearing condition for the non-tradable consumer services

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

where ϑ_{rCS} are the aggregate spending shares given in (4). Together with the labor market clearing conditions

$$H_{rF} + H_{rG} + H_{rCS} = H_r,$$

and choosing the tradable physical good as the numeraire, i.e.

$$p_G = \left(\sum_r \left(\frac{w_r}{A_{rG}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = 1,$$

we have a total $4R+1$ equations. By Walras' Law, only $4R$ of them are independent. Given a set of productivities, these equations can be solved for the $4R$ unknowns $\{w_r, H_{rF}, H_{rG}, H_{rCS}\}_r$.

2.4 Equilibrium in the Industrial Sector

So far we have taken A_{rG} as exogenous. In this section, we characterize the equilibrium of the goods-producing industrial sector, where A_{rG} emerges as an endogenous outcome. We assume that industrial firms produce goods using as inputs both production workers and producer services provided by a separate industry comprising corporate law services, accounting, transport, financial advising, etc. Workers employed by this industry are service sector workers. The distinction between CS and PS is important because in many countries the employment share of PS has increased while employment in the manufacturing sector has stagnated or even declined. However, PS are arguably inputs to the production of final industrial goods. Our theory allows for structural change within the industrial sector in the form of a change over time towards production techniques that are more intensive in corporate services.

To study and quantify the effects this process, that we label PS deepening, we introduce a model with heterogeneous firms whose input demand functions have nonhomothetic features. The production technology for industrial goods is represented by the following production function:

$$y_i = z_i^{1-\alpha-\beta} H_{iPM}^{\alpha} \left(A_{rPS} H_{iPS} + \kappa\right)^{\beta}, \tag{5}$$

where z_i denotes productivity of firm i, and L_{iPM} and L_{iPS} denote the input of production (manufacturing) and PS workers, respectively. A_{rPS} denotes the labor productivity in the PS sector i region r. The parameter $\kappa \geq 0$ governs the nonhomotheticity of firms' technology. If $\kappa > 0$, the production function in (5) generates a complementarity between firm size and hiring lawyers so that the demand for lawyers and accounts stems from large firms. We assume that $\alpha + \beta < 1$ capturing a limited span of managerial control. Decreasing returns at the firm level guarantees that a positive share of the value added accrues to firms as profits.

We assume that there are two additional costs. First, in order to produce industrial firms must also pay f_O overhead workers. Second, there are entry costs: to enjoy the opportunity of drawing a realization from the productivity distribution, an entrant firm must pay a sunk labor cost of f_E workers. The total employment in the manufacturing sector (L_M) comprises then workers employed in production (L_{PM}), overhead (L_{OM}), and entry (L_{EM}) activities.[7] In turn, the industrial sector comprises manufacturing and PS workers, $L_G = L_M + L_{PS}$. In the rest of this section, we label the PS workers *lawyers*, and call simply *workers* those employed in the manufacturing sector.[8]

We assume z_i to be drawn from a Pareto distribution, i.e.

$$F_{rt}(z) = 1 - \left(\frac{A_{rMt}}{z}\right)^{\lambda}, \tag{6}$$

where A_M is a lower bound productivity that parametrizes the state of technology and $\lambda > 1$ is the tail parameter. Having drawn the productivity z_i, the firm can decide whether to produce and, if so, how many workers and lawyers to hire.

For technical reasons we assume that

$$\frac{f_O}{f_E} > \frac{\beta + (1-\alpha)(\lambda - 1)}{1 - \alpha - \beta}. \tag{7}$$

This assumes that overhead costs are large relative to entry costs and ensures that some low-productivity firms will not be active in equilibrium. This assumption is not essential but simplifies the algebra and avoids a taxonomic presentation.

Consider a set of firms competing in district r. For simplicity, we omit here the index r. Let p_G denote the price of the local variety of the industrial good. Conditional on being active, firm i solves the following maximization problem:

$$\pi(z_i) = \max_{L_{iPM}, L_{iPS} \geq 0} \left\{ p_G z_i^{1-\alpha-\beta} L_{iPS}^{\alpha} \left(A_{PS} L_{iPS} + \kappa_G\right)^{\beta} - w\left(L_{iPM} + L_{iPS}\right) - f_O w \right\}. \tag{8}$$

where we recall that $f_O w$ is the overhead cost.

In Section A-16 in the Appendix we provide a complete characterization of the equilibrium. Here, we summarize the main results. Under condition (7), there exist two threshold productivities $z^*, \tilde{z}(A_{PS})$, where $A_M < z^* \leq \tilde{z}(A_{PS})$ and $\tilde{z}$ is a decreasing function, such that:[9]

1. If $z \in [A_M, z^*]$, then, $\pi(z_i) \leq 0$, and the firm is not active.

2. If $z \in [z^*, \tilde{z}(A_{PS})]$, then $\pi(z_i) > 0$ and $\arg\max_{L_{iPS} \geq 0} \pi(z_i) = 0$. In this case, the firm produces but hire only production workers.

3. If $z \geq \tilde{z}(A_{PS})$, then, $\pi(z_i) > 0$ and $\arg\max_{L_{iPS} \geq 0} \pi(z_i) > 0$. In this case, the firm produce and hires both workers and lawyers.

Within each district, for given A_{PS}, it is the larger (i.e., more productive) firms that hire the services of lawyers.[10] An interesting property of the equilibrium (that hinges on the parametrization of the production function) is that,

[7] In the appendix, we provide a closed-form characterization of the breakdown of L_M into the three activities.

[8] Denote by M the number of active firms. Then, $L_{OM} = M \times f_O$ and $L_{EM} = M \times f_E$, where M is an endogenous variable. In the appendix, we prove that in equilibrium $M = \frac{1-\alpha-\beta}{\lambda} \times \frac{L_M}{f_E}$.

[9] The intermediate range may be empty. In particular, if $A_{PS} > \frac{1-\alpha}{\beta} \frac{\kappa}{f_0}$, then, all active firms hire lawyers.

[10] In the Appendix, we show that the profit function is concave in z as long firms do not hire lawyers but linear in z (see equation (A-27) once they hire lawyers. Hence, lawyers allow firms to leverage their innate productivity. Having access to efficient lawyers is therefore particularly valuable for efficient firms. The result echoes Akcigit et al. (2020) although in a very different model environment.

within the set of firms hiring lawyers (i.e., $z \geq \tilde{z}(A_{PS})$), more productive firms hire more lawyers relative to production workers. However, the *aggregate* employment share of lawyers relative production workers among the set of firms hiring lawyers is given by $\alpha\beta/\lambda$ and therefore constant and independent of A_{PS}. The labor productivity A_{PS} therefore affects the extent of PS deepening via two channels. First, a higher A_{PS} decreases $\tilde{z}$, namely, increases the proportion of firms that hire lawyers. As noted above, in districts where the productivity of PS is very high, all firms hire lawyers. Second, it shifts resources towards firms who produce with a technology that is more intensive in lawyers relative to workers.

Perhaps surprisingly, an increase in the total factor productivity A_M does not cause PS deepening. One might have expected that a higher A_M might imply larger firms and, hence, a more intensive use of PS. However, under a Pareto distribution, A_M shifts the productivity of all firms inducing a proportional increase in the demand for both workers and lawyers. Another interesting feature of the equilibrium is that neither the wage nor the price of the local variety of industrial good affects PS deepening. Similar to an increase in A_M, an exogenous increase in the demand for the local variety pushes up the price leading to an expansion of production and employment in the industrial goods sector. However, this has no effect on the relative demands for workers and lawyers. In short, in our tractable model, structural change (or PS deepening) within the industrial sector characterized must reflect technical progress in the PS sector.

The following proposition summarizes the results more formally.

Proposition 1. *The equilibrium production in the industrial goods sector of region r is given by*

$$Y_{rG} = A_{rG} \times L_{rG},$$

where $A_{rG} = A_G(A_{rM}, A_{rPS})$ and A_G is a continuous increasing function of its two arguments such that

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

$L_{rG} = L_{rM} + L_{rPS}$,and Q_1 and Q_2 are constant functions of the parameters $(\alpha, \beta, \lambda, f_O, f_E)$.

The employment split between the PS and the manufacturing sector is given by:

$$\begin{aligned} L_{rPS} &= \Xi(A_{rPS}) \times L_{rG}, \\ L_{rM} &= (1 - \Xi(A_{rPS}))) \times L_{rG}, \end{aligned}$$

where Ξ is a continuous increasing function such that

$$\Xi(x) := \begin{cases} \frac{1}{\lambda} \frac{\sigma(x)}{1+\sigma(x)} (\beta + (\lambda - 1)(1 - \alpha)) & \text{if } \frac{\kappa}{f_O A_{PS}} > \frac{\beta}{1-\alpha} \\ \beta - (1 - \alpha - \beta) \frac{\lambda-1}{\lambda} \frac{\kappa}{f_O x - \kappa} & \text{if } \frac{\kappa}{f_O A_{PS}} \leq \frac{\beta}{1-\alpha} \end{cases}$$

where

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

Proof. See Section (A-16) in the Appendix. □

Proposition 1 contains two important results. First, it provides an analytical expression for the labor productivity in the industrial sector where A_{rG} (that we took as exogenous in the trade equilibrium) is a simple increasing function of the primitive productivities A_{rPS} and A_{rM}, and L_G is determined by the trade equilibrium. Second, the employment allocation within the industrial sector (i.e., the shares of workers and lawyers) only depends on A_{rPS}.

In summary, the model has a nice recursive structure, whereby the trade equilibrium pins down the employment share of the industrial sector as a function of A_{rM} and A_{rPS}, given the productivities in the other sectors and in the rest of the economy. The employment breakdown into manufacturing and PS depends exclusively on A_{rPS}. When we invert the equilibrium, the district-level employment share of PS relative to manufacturing is a sufficient statistic to identify A_{rPS}.

3 Data and Estimation Method

3.1 Data

Our analysis relies on three datasets.

1. The NSS Employment-Unemployment Schedule, which we refer to as the "NSS data"

2. The Economic Census for the years 1990, 1998, 2005 and 2013, which we refer to as the "Economic Census".

3. A Special Survey about the Service Sector in India for the year 2006, which we refer to as the "Service Survey"

We describe these datasets in detail in the Appendix. Here, we highlight their main features. The NSS data forms the backbone of our analysis. It is a household survey with detailed information on employment characteristics and households' geographical location. We have access to the data for the years 1987, 1999, 2001, 2004 and 2011. The NSS data allows us to measure sectoral employment shares 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 sectoral classification in the NSS data. The situation is more subtle for the service industry. While for example retail workers are clearly part of the consumer service sector in the sense of our theory, the distinction is less clear for lawyers as corporate lawyers are providers of PS while divorce lawyers are providers of CS. We therefore rely on combined information from the Economic Census and the Service Survey to allocate service workers in the producer and consumer category (see Section 3.2 below).

The Economic Census is a complete count of all establishments, i.e. production units engaged in production or distribution of goods and services located within the country. We have access to the micro data for the years 1990, 1998, 2005 and 2013. The census covers all sectors except crop production and plantation and all states. The Economic Census collects information on the firms' location, its industry, employment and the nature of ownership. In Table A-2 we report a set of summary statistics of the Economic Census. It captures between 24m and almost 60m establishments in 1990 and 2013 respectively. As expected, the vast majority of firms is very small. The average size ranges between 2 and 3 employees, over half of all firms have a single employee and only 1 in 1000 firms has more than 100 employees.

Census	Year	Number of firms	Total employment	Employment distribution			
				Average	1 employee	Less than 5 employees	More than 100 employees
Third EC	1990	24216790	74570280	3.08	53.77%	91.24%	0.13%
Fourth EC	1998	30348881	83308504	2.75	51.18%	91.71%	0.11%
Fifth EC	2005	41826989	100904120	2.41	55.76%	93.17%	0.12%
Sixth EC	2013	58495359	131293872	2.24	55.47%	93.44%	0.06%

Table 1: The Economic Census: Summary Statistics

The Service Survey was conducted in 2006 and is designed to be representative for India's service sector. It covers the majority of service sectors, e.g. hotels and restaurants, transport, storage and communication, financial intermediation, real estate and health. The survey focuses on the private enterprises and hence does not contain information on government and public sector enterprises. In total, the survey contains information on 190,282 enterprises. To check that the survey is indeed representative of the firm size distribution in India, in Table A-3 we compare average firms size and the share of firms with less than 5 employees for different subsectors between the Economic Census and the Service Survey. Overall, these distributions are broadly comparable.

3.2 Measuring Producer and Consumer Services

We aim to distinguish between PS and CS in 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 that we can attribute value added to the identify of the buyer. To the best of our knowledge, this data is not available in India.

Sector	Number of firms		Average employment		Less than 5 employees	
	Census	Service Survey	Census	Service Survey	Census	Service Survey
Hotels and restaurants	1,499,101	30,744	2.52	2.49	0.90	0.91
Land transport; transport via pipelines	1,317,904	41,065	1.67	1.24	0.97	0.99
Post and telecommunications	723,119	22,885	2.06	1.41	0.96	0.99
Other business activities	519,696	10,610	2.81	1.92	0.90	0.95
Renting of machinery and household goods	365,246	5,387	2.00	1.77	0.94	0.97
Financial intermediation	221,953	12,984	6.27	4.15	0.63	0.79
Transport activities; travel agencies	188,474	2,101	3.40	3.33	0.86	0.85
Real estate activities	70,128	3,648	2.18	1.64	0.93	0.96
Computer and related activities	66,414	1,060	6.01	13.45	0.83	0.86
Activities auxiliary to financial intermediation	45,449	2,601	2.41	1.77	0.93	0.96
Insurance and pension funding	26,087	746	5.52	2.30	0.83	0.99
Water transport	7,914	174	4.35	1.92	0.90	0.98
Research and development	2,097	5	16.66	4.58	0.66	0.89

Table 2: Economic Census and Service Survey. The table reports statistics about firms' number and employment from the Economic Census 2005 and Service Survey 2006.

In the absence of such data, we exploit the fact that the Service Survey reports whether a firm is mostly selling to consumers or to other firms. We could therefore in principle calculate the share of employment in e.g. the real estate industry in region r that works in firms who sell to firms rather than consumers. We would then apply this weight to the total employment in the real estate sector in region r as observed in the NSS data. Summing over all service industries would yield total producer and consumer service employment in region r.

In practice, this procedure is not feasible because the Service Survey contains too few firms to precisely estimate these relative employment shares at the subsector-region level. Instead, we exploit the fact that the probability for a firm to sell to firms is highly correlated with firm size–larger firms are more likely to sell to firms rather than to consumers. To see this, consider Figure 1, displaying the share of firms who mainly sell to other firms by firm size. There is a clear pattern that small firms with one or two employees sell almost exclusively to final consumers, while a significant share of large firms sell to other firms. We classify these firms as providers of PS.

We exploit the pattern shown in Figure 1 in the following way. First, we estimate the PS employment share by firm size within subsectors. We then use the *region*-specific size distribution from the Economic Census to infer the aggregate producer service employment share in region r. Hence, this procedure assumes that the structure of production for firms of equal size does not vary across regions in India within subsectors. The regional variation in e.g. PS employment stems from regional variation in (i) total service employment, (ii) the relative share of different subsectors and (iii) in the distribution of firm size. In Section A-7 in the Appendix we describe this procedure in more detail.

We exclude from the analysis a subset of service industries for which the categorization into PS and CS is ambiguous. These include public administration and defence, compulsory social security, education, and extraterritorial organizations and bodies.[11]

Finally, we merge construction and utilities with the service sector. Although the construction sector is sometimes classified as affine to manufacturing, the identifying assumption in our theory is that goods are tradable while services are nontradable. Since construction and utilities are local goods, we find it natural to merge them with services.

Next, we must break down these activities into PS and CS. The construction sector serves both consumers (e.g., residential housing) and firms (e.g., business construction). We follow then a procedure similar to that used for services. We exploit information from the "Informal Non-Agricultural Enterprises Survey 1999-2000" (INAES) dataset , which reports the major destination for sale of final product/service. The details are discussed in the appendix. Because of tighter data limitation, it is only possible to split the destination of construction activities

[11] The public administration provides services to both individuals and firms. Education affects both households and labor productivity in goods-producing sectors. The development of these sectors is to a large extent determined by government policy rather than by market incentives.

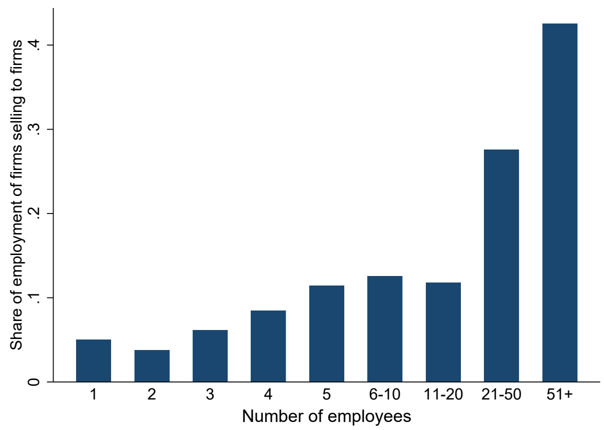

Figure 1: Producer service share by firm size. The figure shows the share of service firms whose main customer are other firms (as opposed to private individuals) with breakdown by firm size.

at the national level. Then, we assume that the same split applies across the board to all districts. With this *caveat*, we obtain the following break down. First, we remove 12.2% of the construction activity from the sample, corresponding to the share of government activity (infrastructure and public goods). Then, based on the INAES data, we attribute 86.9% of what is left to CS and 13.1% to PS in every district-year.

3.3 Geography

To compare spatial units over time, we need to create a time-invariant definition of geography. We start to define regions as Indian districts. Because the boundaries of some districts changed over time, we harmonized them using GIS software.[12] We rely on maps for the years 1991, 2001, and 2011 with 467, 593, and 641 districts respectively. In order to construct a panel to perform analysis in the consistent geography, we construct regions that have consistent boundaries across year. 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 total we arrive at a spatial classification of India, that covers 435 regions. In Figure 2 we show the map of India with the regions we constructed (in bold lines) and the official districts in 2011.

3.4 Human Capital

To be consistent with out theory, we measure each district's endowment of human capital units $F_{rt}(q)$ and its distribution across sectors in terms of effective units of labor, recognizing that individual workers possess heterogeneous skills.

To measure the distribution of human capital across sectors within a district, we rely on the sectoral distribution of earnings. Since local labor markets are frictionless, there is a single wage per efficiency units in each district. Hence, differences in earnings must reflect heterogeneity in the endowment of effective units of labor.

To measure the distribution of human capital across districts, we follow a large literature on development accounting and leverage the data on the regional distribution of schooling. More formally, we assume the individual human capital q_i is partly determined by the level of schooling s_i, i.e.

$$q_i = \tilde{q}\left(s_i, \upsilon_i\right) = \exp\left(\rho s_i\right) \times \upsilon_i \tag{9}$$

where s_i denotes the number of years education, ρ is the annual return to schooling and υ_i is an idiosyncratic shock, which we assume to be iid across districts and years. This specification implies that individual log earnings

[12]See Section A-3 in the Appendix for more details on how we constructed this crosswalk.

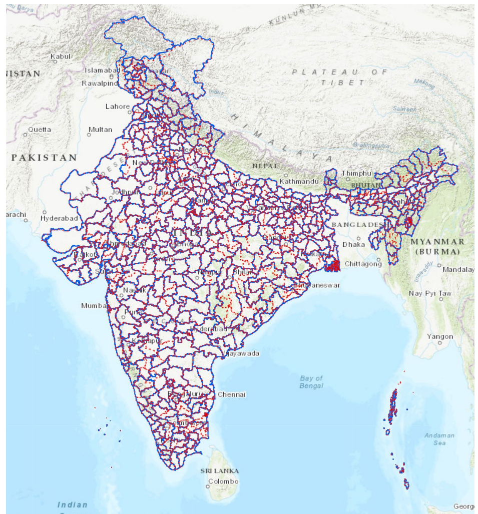

Figure 2: Indian Districts. The figure shows the official Indian districts in the year 2011 (dashed red lines) and the time-invariant geographical units (*districts* we construct (solid blue lines) upon which our analysis is based.

of individual i in region r at time t, y_{irt} are given by the usual Mincerian regression

$$\ln y_{irt} = \ln w_{rt} + \rho s_i + \ln \upsilon_i. \tag{10}$$

Hence, we can estimate ρ from the within-region variation between earnings and education, which we can measure from the NSS data.

We implement this procedure by classifying people in four educational groups: (i) less than primary school; (ii) primary and upper primary/middle school; (iii) secondary school; (iv) more than secondary school. We associate each step in the education ladder to three extra years of education, consistent with the organization of schools in India. We proxy earnings by individual consumption, and regress its logarithm on the education level controlling for year-district fixed effects. The estimated coefficients for educational categories (ii)-(iii)-(iv) are, respectively, 13%, 31%, and 69%–where (i) is the omitted category. This yields an average 5.6% annual rate of return. While this is in the lower end of standard Mincerian regressions, it is useful to recall that we are using data on consumption rather than income. In Section 5 we discuss the robustness of our results with respect to this estimate.

The Mincerian regressions allow us to decomposed the earning differences across district-time into observed human capital heterogeneity and residual productivity differences that we structurally estimate. We emphasize that in our procedure the key input to the estimation process is the distribution of earnings across district-industry-time rather than the distribution of employment measured as headcount of workers. Alternatively, we could estimate the model using a headcount employment approach which (falsely) assumes that human capital does not vary across industries within each district. The results would be qualitatively and quantitatively similar. Details are available upon request.

3.5 Structural Change in India: 1987 - 2011

Figures 3 and 5 display the main aspects of the structural transformation in India since 1987. Figure 3 focuses on the time-series dimension. Panels a and b display the evolution of the sectoral employment shares. Panel a uses a standard classification of sectors in the national account statistics. Note that we separate public services and education from other services, because these are the two categories we exclude from our analysis. The figure

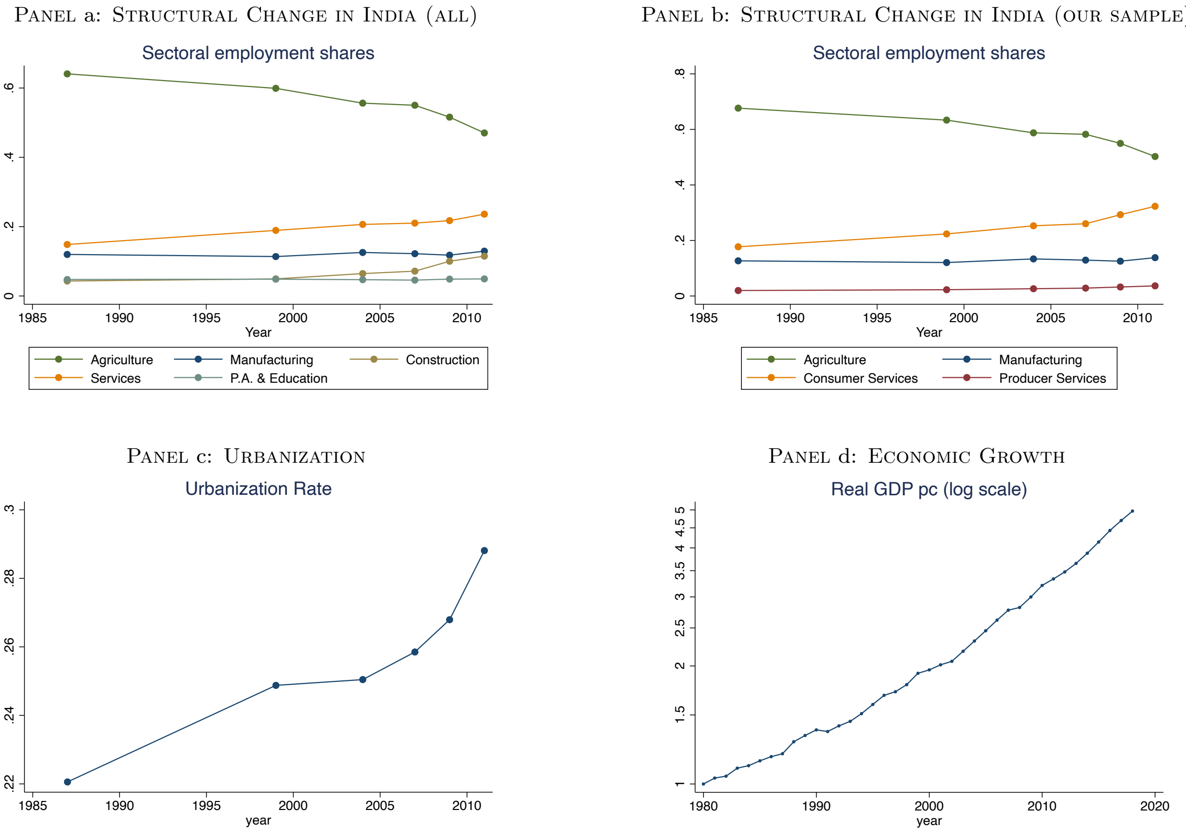

Figure 3: Structural Change in India: 1987 - 2011. This figure shows the evolution over time of sectoral employment shares (Panels a and b), urbanization rate (Panel c) and income per capita (Panel d). Panel a shows as separate categories Public Administration&Education and Construction&Utilities. Panel b excludes Public Administration and Education and merges Construction and Utilities with the service sector as described in the text. Panel b is based on the classification we use in our analysis. The urbanization rate is the share of population living in urban areas according to the definition of the NSS

suggests that excluding public services and education is inconsequential insofar as their employment share stays approximately constant over time at a 5% level. Panel b uses the sectoral classification we adopt in our analysis. Recall that services include here construction and utilities, with the break down into PS discussed in Section 3.2 above.

Two facts are apparent: First, agriculture is the largest employment source, accounting for more than 40% of total employment in 2011 (more than 50% in our sample of Panel b). Second, the structural transformation in India is mostly an outflow of agriculture and an inflow into CS. Employment in the manufacturing sector is essentially stagnant.

In panel c, we display one important spatial counterpart of Indian growth: the steep rise in urbanization.[13] In 2011, roughly a quarter of the Indian population lives in cities. Compared to 1987, the share of the urban population therefore increased by almost 50%. Finally, panel d shows the time-series of GDPpc. In the 4 decades between 1980 and 2020, income per capita increased almost by a factor of five.

We now turn to the spatial heterogeneity across Indian districts. We choose urbanization as our measure of

[13]The Indian statistical office defines "urban" in the following way: (i) all locations with a Municipality, Corporation or Cantonment and locations notified as 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.

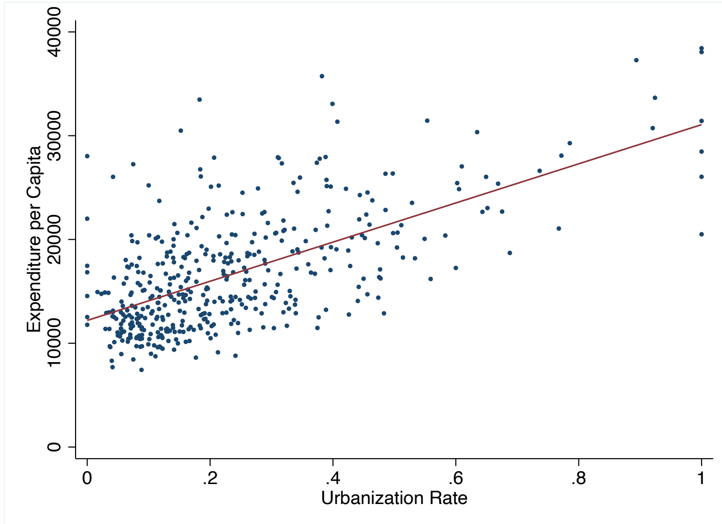

Figure 4: Expenditure per capita vs. Urbanization. The figure shows a binscatter plot of the average expenditure capita in the NSS data across district-level urbanization rates in 2011.

Panel a: Sectoral Empl. by Urbanization (1987)

Panel b: Sectoral Empl. by Urbanization (2011)

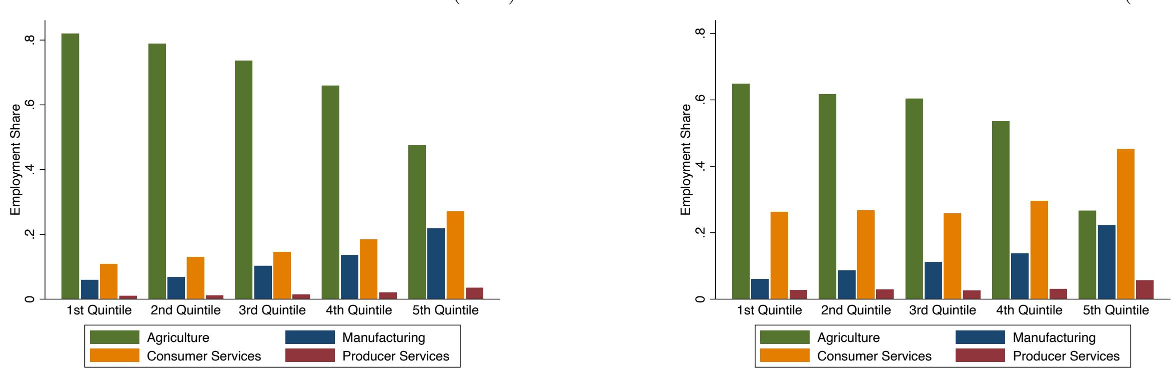

Figure 5: Spatial Structural Change in India. The figure plots plots the sectoral employment shares by urbanization quintile in 1987 (Panel a) and 2011 (Panel b).

spatial heterogeneity. This as a mere descriptive device. Since urbanization is in part the outcome of productivity growth, all results should be interpreted as correlations. Figure 4 shows that there is a strong positive correlation between urbanization and the expenditure per capita in the NSS data in 2011. Thus, urbanization rate is also a proxy for economic development across Indian districts.

In Figure 5 we display sectoral employment shares by urbanization quantiles. As expected, richer urban locations have lower employment shares in agriculture, being specialized in the production of services and manufacturing goods. Over time, the share of agriculture declines. Interestingly, between 1987 and 2011 the structural transformation has been especially fast in the most urbanized districts than in the rest of India. In 1987, agriculture was the main sector of activity even in the top quintile of urbanization. In contrast, in 2011, more than half of the working population is employed in the service sector. The difference is even larger when one looks at earnings instead of employment - see Section A-10 in the Appendix.

	$\ln \vartheta_F$					
	All	All	2004	2007	2009	2011
$\ln e$	-0.275***	-0.271***	-0.269***	-0.273***	-0.258***	-0.297***
	(0.00073)	(0.00072)	(0.00184)	(0.00128)	(0.00136)	(0.00150)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes				
Year×District FE	Yes					
Observations	570,511	570,511	98,763	188,920	143,401	139,427
R-squared	0.462	0.436	0.434	0.471	0.421	0.431

Table 3: Engel curves in India. The table shows the estimated coefficient β of the regression equation (12). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.6 Estimation of Structural Parameters

Our model is characterized by 12 structural parameters - see Table 4:

$$\left\{ \underbrace{\varepsilon, \nu_{CS}, \nu_F, \omega_{CS}, \omega_F, \sigma}_{\text{Preference parameters}}, \underbrace{\lambda, \beta, \alpha, f_O, f_E, \kappa}_{\text{Manufacturing technology}} \right\}. \tag{11}$$

While we estimate all parameters simultaneously, we here describe our identification strategy by referring to the main empirical moments, which identify a given parameter.

Preference Parameters $\varepsilon, \nu_{CS}, \nu_F, \omega_{CS}, \omega_F, \sigma$. An important parameter is the income-elasticity ε as it determines how quickly demand shifts away from agricultural goods as incomes rise. To estimate this parameter, we use the cross-sectional relationship between household income and household expenditure shares and estimate ε via indirect inference. In particular, we estimate the following Engel curve using the Indian household data:

$$\ln \vartheta_{F,i} = \delta_r + \beta \times \ln e_i + u_i \tag{12}$$

and estimate ε to target the income-elasticity β. Here, $\vartheta_{F,i}$ is the expenditure share on food of individual i, δ_r is a region fixed effect and $\ln e_i$ denotes total spending. While β is not an explicit structural parameter in our theory, there is a tight connection between the structural parameter ε and the regression coefficient β. Note that our theory implies that (see (3))

$$\ln \vartheta_F^h \left(e, p_r\right) = \ln \left(\omega_F + \nu_F^h \left(\prod_s p_{rs}^{\omega_s} \right)^{\varepsilon} e^{-\varepsilon} \right).$$

Hence, if $\omega_F \approx 0$ (which is going to be case in our structural estimation), our theory implies that

$$\ln \vartheta_F^h \left(e, p_r\right) = \ln \left(\nu_F^h \left(\prod_s p_{rs}^{\omega_s} \right)^{\varepsilon} \right) - \varepsilon \ln e.$$

The first term, which includes the region-specific price of consumer services p_{rCSt}, is absorbed in the district fixed effect δ_r in (12). The estimated income elasticity β directly coincides with the structural parameter ε.

The regression results from applying Equation (12) the the Indian data are reported in Table 3. The income elasticities is between -0.26 and -0.3 and very similar across years. In Figure 6 we show the estimated Engel curve graphically. A constant elasticity is a good approximation of the income-food-share relationship for a large part of the expenditure distribution.

The market-level demand system depends on the regional preference parameters ν_{CS}^r and ν_F^r, which are related to the primitive micro-level preference parameters $\tilde{\nu}_{CS}$ and $\tilde{\nu}_F$ via equation (2.2). In principle one can retrieve the

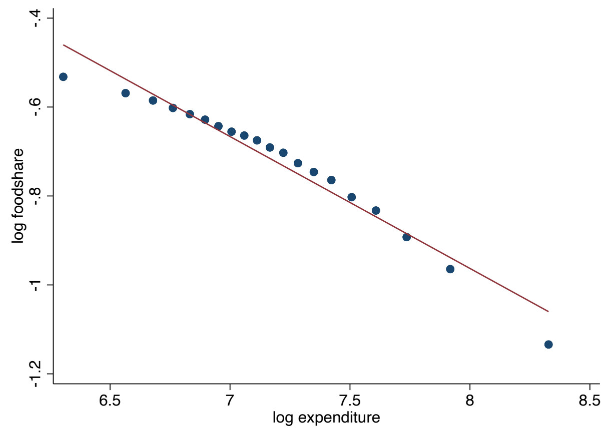

Figure 6: Engel curves in India. The figure shows a binscatter plot of the log food shares and log expenditure for the year 2011 at the individual household level after absorbing district fixed effects.

primitive parameters without further restrictions by allowing for regional variation in ν^r_{CS} and ν^r_F and estimating for each region the term $E\left[q^{1-\varepsilon}\right]/E\left[q\right]^{1-\varepsilon}$ from the data. Alternatively, one can impose restrictions on the income distribution ensuring that ν^r_F and ν^r_{CS} are constant over time and across space. As discussed in Section 2.2, a sufficient condition for this to hold true is that q be Pareto-distributed. We pursued both strategies finding very small differences–intuitively, the cross sectional variation in the term $E\left[q^{1-\varepsilon}\right]/E\left[q\right]^{1-\varepsilon}$ is small and has only a modest influence on the estimation results (details are available upon request). In the remainder of the paper, we focus on the latter strategy assuming that q follows a Pareto distribution with a region-invariant tail parameter ζ. This distributional form restriction becomes essential to quantify the welfare consequences of structural change in Section 4.2.1 below.[14]

Equation (4) shows that the taste shifters ν_{CS} and ν_F determine sectoral spending (and, hence, employment) holding income and prices constant. In Appendix Section A-13, we prove that the taste shifter for consumer services ν_{CS} is not separately identified from the productivity in consumer services A_{rCSt}. Hence, without loss of generality, we can normalize it to -1. The taste shifter for agricultural products, ν_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. This implies that $\nu_F = 1.315$. Given the normalization of $\nu_{CS} = -1$, this implies that $\nu_M = -(\nu_F + \nu_{CS}) = -0.315$. Hence, manufacturing products are also luxury goods as their expenditure share is increasing in income. However, their income elasticity is below the one for consumer services.

To identify the share parameters ω_{CS} and ω_F, recall that $\vartheta^h_F(e,p) > \lim_{e\to\infty}\vartheta^h_F(e,p) = \omega_F$ and that $\vartheta^h_{CS}(e,p) < \lim_{e\to\infty}\vartheta^h_{CS}(e,p) = \omega_{CS}$. Hence, the expenditure share on food (consumer services) approaches ω_F (ω_{CS}) from above (below) as income becomes large. In the US, which we take an example of a rich economy, where nonhomothetic demand is less important, the agricultural employment share is given by about 1%. Hence, we take $\omega_F = 0.01$. For ω_{CS}, we follow a similar strategy as for ν_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. This implies that $\omega_{CS} = 0.674$.[15]

Finally, we set the inter-regional trade elasticity σ to a consensus estimate in the literature. As our baseline estimate we assume that $\sigma = 3$ but we entertain different values in Section 5 where we discuss the robustness of our results.

[14]The value of the Pareto tail ζ is immaterial for the estimation, as it turns out to simply scale up or down the estimated $\tilde{\nu}_s$ terms. However, the value of ζ matters for welfare comparisons. For this reason, we return to it in Section 4.2.1.

[15]Note that our model implies that regional *employment* shares in consumer services are bounded by ω_{CS} from above. As we discuss in more detail in Section A-6 in the Appendix, there are only 7 districts in our Indian data, which feature employment shares in consumer services that exceed ω_{CS}. Because these districts are very small and account for less than 1% of employment, we drop them from our analysis.

Parameter	Target	Value
	Preference parameters	
ϵ	Engel Curve	0.297
ω_F	Agricultural spending share US	0.01
ω_{CS}	Agricultural Employment share 2011	0.688
ν_F	Agricultural Employment share 1987	1.269
ν_{CS}	Normalization	-1
σ	Set exogenously	3
	Production function parameters	
λ	Based on König et al. (2016)	2.5
β	Employment share of lawyers in the US	0.7
α	Profit share	0.05
f_O	Normalization	1
f_E	Normalization	1
κ	Normalization	1

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

Technology parameters $\lambda, \beta, \alpha, f_O, f_E$ and κ Note first that all allocations only depend on $A_{rPSt} \times f_O/\kappa$ (see Proposition 1) Hence, the parameters κ and f_O are not separately identified from A_{rPSt}. Since we are not interested in the scale of the average productivity, we normalize $f_O = \kappa = 1$. Similarly, the entry costs 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, i.e. condition (7) is satisfied.

For the tail of the productivity distribution λ, we follow König et al. (2016) and assume that $\lambda = 2.5$. We then pick α and β to jointly match a profit share of 10% and the long-run share of lawyers within the goods-producing sector. More specifically, consider a situation were the productivity of lawyers A_{PS} becomes large. Our model implies that $\lim_{A_{PS}\to\infty} L_S = \beta L_G$. In the US, lawyers account for about 28% of employment in the goods producing sector and production workers for 12%. This suggests that $\beta = \frac{0.28}{0.28+0.12} = 0.7$. Given λ and β the parameter α is tied to the profit share because $\alpha + \beta$ determine the returns to scale and hence the share accruing to the fixed factor. In particular, our model implies that

$$\text{Profit share} = \frac{1-\alpha-\beta}{\lambda}.$$

For $\beta = 0.7$ and $\lambda = 2.5$, a profit rate of 10% requires that $\alpha = 0.05$.

4 Estimation Results and Counterfactuals

4.1 Estimation Results

We estimate a full set of sector-district productivity separately for 1987 and 2011. Then, we chain them so as to ensure that the aggregate growth rate of GDP per capita matches the data for India.

Figure 7 displays a bin scatter plot of the distribution of the (logarithm of the) estimated sectoral labor productivities as a function of the urbanization rate. For agriculture, the relationship is hump-shaped. The limited falling portion likely reflects the scarcity of land (a factor of production from which we abstract) in highly urbanized districts. The productivity of manufacturing is increasing in urbanization.

Most importantly, we estimate that the productivity of the consumer service sector is also increasing in the urbanization rate. Hence, the high share of consumer service employment in cities is not only a consequence of high wages (the Baumol effect) or an abundance of human capital, but partly reflects higher levels of productivity.

Finally, the estimated productivity of PS activities is noisy and less systematically correlated with the rate of urbanization. This result is driven by two features. First, in many rural districts the employment share in producers

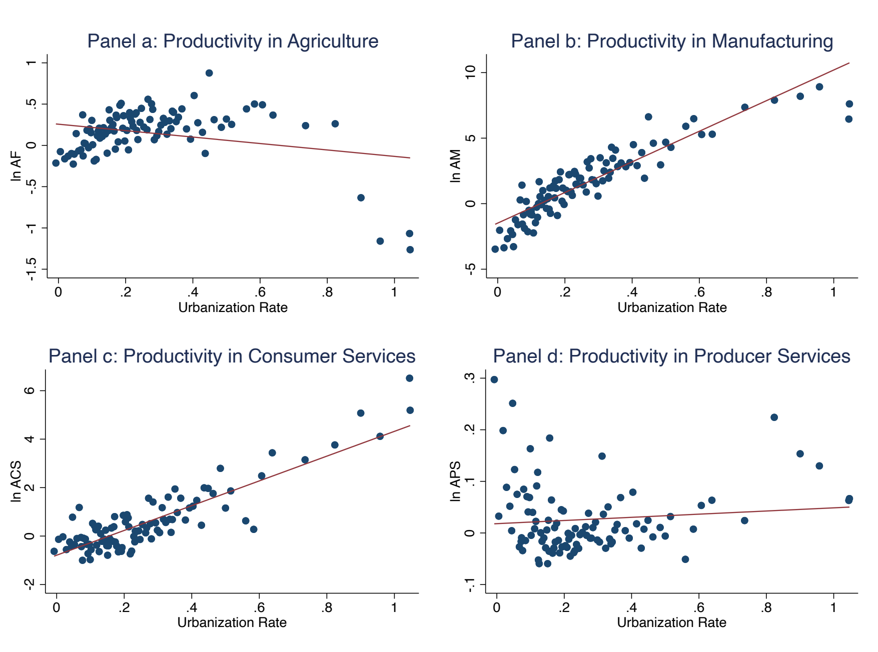

Figure 7: Estimated Sectoral Productivities. The figure shows a bin scatter plot of the estimated sectoral labor productivities in agriculture, manufacturing, consumer services, and producer services across urbanization rate bins. Each plot is constructed by pooling the estimates for 1987 and 2011 after absorbing the year effects and subtracting the (logarithm of) mean sectoral productivity.

services is small and hence susceptible to measurement error. If we exclude locations with an urbanization rate below 15%, the correlation is positive. Second, our treatment of the construction sector is important for this result. This sector has a significant share of producer services (ca. 13%) and a significant presence in rural districts. Recall that because of data limitations, we cannot break down construction activities into CS and PS at the district level. It is likely that this results in some misclassification of construction activities as PS rather than CS in rural areas. If we abstract from construction activities, the correlation turns positive and significant. Because, as we will document, the PS sector has a relatively small quantitative role in the process of growth and structural change of India, we do not investigate the issue further.

4.2 Quantifying the Role of Service for Indian Growth

In this section, we study the implications of sectoral productivity growth on welfare and on the structural transformation of the economy during the period 1987–2011. To this aim, we run counterfactual experiments in which we assume that each of the sectoral productivities is set back to its 1987 level. This allows us to assess the relative importance of technological progress in different sectors of the economy for the improvements of living standards and for structural change.

Out theory highlights two layers of heterogeneity: *spatial* heterogeneity, whereby differences in comparative advantages render some regions more exposed to changes in productivity in some sectors than others and *individual* heterogeneity, whereby consumers with different income care more about changes in prices and availability of some goods and services than others. As we shall see, our quantitative analysis uncovers a great deal of heterogeneity in both dimensions.

4.2.1 Counterfactual Welfare Effects: Methodology

To measure welfare changes, we calculate the equivalent variation at the district level. This is the lowest 2011 income that individuals (either a particularly-defined “representative agent” or a specific individual) would be willing to accept to avert setting back a particular sectoral productivity to its 1987 level. The lower such income, the more important productivity growth of a particular sector is for welfare. In some cases, we calculate measures of changes in social welfare by aggregating up results at the national level using a utilitarian welfare criterion.

Welfare Function. We now provide a formal definition of the equivalent variation in our model. The reader uninterested in the formal derivation can skip the rest of this section and go to the result section.

Given wages (income) w_{rt} and prices p_{rt}, the utilitarian welfare function in location r is given by

$$\mathcal{U}_{rt}\left(e_{rt}, p_{rt}\right) = \int V\left(q w_{rt}, p_{rt}\right) dF_{rt}\left(q\right).$$

Using the indirect utility function in (2), we obtain:

$$\mathcal{U}\left(e_{rt}, p_{rt}\right) \quad = \quad \frac{E_r\left[q^{\varepsilon}\right]}{E_r\left[q\right]^{\varepsilon}}\left(\frac{1}{\varepsilon}\left(\frac{E\left[q\right] h_r w_{rt}}{\prod_s p_{rst}^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s^{Welfare} \ln p_{rst}\right), \tag{13}$$

where

$$\nu_s^{Welfare} = \frac{E_r\left[q\right]^{\varepsilon}}{E_r\left[q^{\varepsilon}\right]}\tilde{\nu}_s = \frac{E\left[q\right]}{E\left[q^{1-\varepsilon}\right]E\left[q^{\varepsilon}\right]}\nu_s = \frac{\left(\zeta-\varepsilon\right)\left(\zeta-\left(1-\varepsilon\right)\right)}{\zeta(\zeta-1)}\nu_s. \tag{14}$$

Utilitarian welfare is akin to the indirect utility of a representative agent with average income $E\left[q\right] w_{rt}$ and a scaled taste parameter $\nu_s^{Welfare}$, that takes the distribution of income into account, see Section 2.2. The second equality in (14) uses the properties of the Pareto distribution. Note that the expression of $\nu_s^{Welfare}$ only depends on ζ, ε, and ν_s.

Until this point, we did not need a value for the tail parameter ζ. However, this becomes now necessary, because it affects the size of the average welfare effects. To estimate ζ, note that the distribution of income in region r is given by $G_r(y) = 1 - \left(\frac{\underline{q}_r w_{rt}}{y}\right)^{\zeta}$. This implies that

$$\ln\left(1 - G_r(y)\right) \quad = \quad \zeta \ln\left(\underline{q}_r w_{rt}\right) - \zeta \ln y.$$

We therefore estimate ζ, from a cross-sectional regression

$$\ln\left(1 - G_r(y_i)\right) \quad = \quad \delta_r + \beta \ln y_i + u_{ir},$$

where δ_r is a district fixed effect and $\{y_i\}$ is grid of the income distribution. In practice we pick a grid of 200 points and consider a support of regional incomes above the median as the pareto distribution is a better fit to the left tail of the income distribution. Doing so yields an estimate of $\zeta \approx 2$ (see Section A-15 in the Appendix for details of the estimation).

Measuring Welfare Differences. In order to compare two allocations with $\left\{e_{rt}, p_{rt}\right\}_r$ and $\left\{e_{rt}^{CF}, p_{rt}^{CF}\right\}_r$, where “CF” indicates a particular counterfactual, we focus on the equivalent income variation. More specifically, we define

$$\overline{\omega}\left(\left(e_{rt}^{CF}, p_{rt}^{CF}\right)|p_{rt}\right)$$

as the income which individuals in region r facing the equilibrium prices p_{rt} would require to achieve the same utility given in (13) as under $\left\{e_{rt}^{CF}, p_{rt}^{CF}\right\}_r$. Hence, $\overline{\omega}\left(\left(e_{rt}^{CF}, P_{rt}^{CF}\right)|P_{rt}\right)$ is defined by[16]

$$\mathcal{U}\left(\overline{\omega}\left(\left(e_{rt}^{CF}, p_{rt}^{CF}\right)|p_{rt}\right), p_{rt}\right) = \mathcal{U}\left(e_{rt}^{CF}, p_{rt}^{CF}\right).$$

[16]Equation (13) implies that

$$\frac{1}{\varepsilon}\left(\frac{E\left[q\right]\overline{\omega}\left(\left(e_{rt}^{CF}, p_{rt}^{CF}\right)|p_{rt}\right)}{\prod_s p_{rst}^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s^{Welfare} \ln p_{rst} = \frac{1}{\varepsilon}\left(\frac{E\left[q\right] e_{rt}^{CF}}{\prod_s \left(p_{rst}^{CF}\right)^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s^{Welfare} \ln p_{rst}^{CF},$$

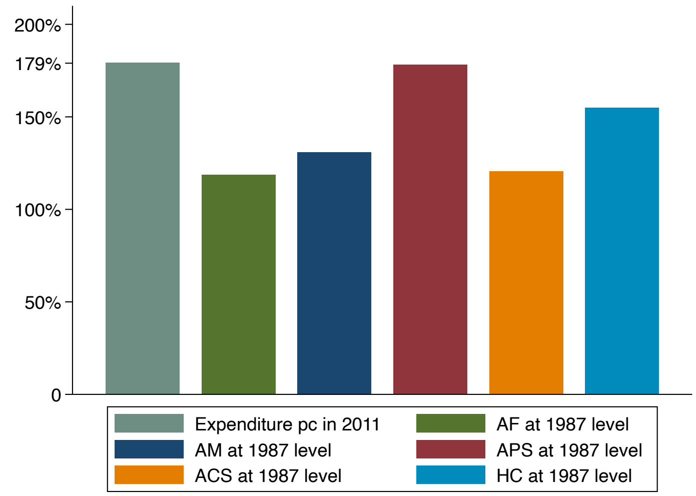

Figure 8: Aggregate Welfare Effects. The figure shows the expenditure per capita in India in 2011 (expenditure per capita in 1987 = 1) according to the NSS data and the welfare-equivalent expenditure in 2011 associated with setting productivity in agriculture, manufacturing, consumer services, producer services, and average human capital at the respective 1987 levels in all Indian districts.

Given the welfare-equivalent income $\varpi\left(\left(e_{rt}^{CF}, P_{rt}^{CF}\right)|P_{rt}\right)$, we can calculate aggregate welfare as follows:

1. Welfare in the calibrated model in 2011 is

$$Welfare^{2011} = \sum_{r} L_{r2011} e_{r2011}$$

   Note that this happens to be the same as "GDP" in 2011.

2. Then take a counterfactual say reducing A_{rF2011} to A_{rF1987}. Aggregate Welfare is the then given by

$$Welfare\left(A_{rF2011} \to A_{rF1987}\right) = \sum_{r} L_{r2011} \varpi\left(\left(e_{rt}^{CF}, P_{rt}^{CF}\right)|P_{r2011}\right)$$

   where e_{rt}^{CF} and P_{rt}^{CF} are the income and prices in the counterfactual.

4.2.2 Counterfactual Welfare Effects: Results

Figure 8 shows the average welfare effects of shutting down one-by-one each of the sectoral productivity growths in the entire economy. We also display the welfare effect of the changes in human capital that occurred between 1987 and 2011.

The figure shows that productivity growth in agriculture is the most important source of welfare improvement between 1987 and 2011. Shutting down agricultural productivity growth is equivalent to a 21% reduction in the 2011 income. The importance of agriculture is hardly surprising given the large employment share of this sector in India.

so that

$$E[q]\,\varpi\left(\left(e_{rt}^{CF}, p_{rt}^{CF}\right)|p_{rt}\right) = \left(\left(E[q]\,e_{rt}^{CF}\right)^{\varepsilon}\left(\frac{\prod_s p_{rst}^{\omega_s}}{\prod_s \left(p_{rst}^{CF}\right)^{\omega_s}}\right)^{\varepsilon} - \left(\prod_s p_{rst}^{\omega_s}\right)^{\varepsilon}\varepsilon\left(\sum_s \nu_s^{Welfare} \ln\frac{p_{rst}^{CF}}{p_{rst}}\right)\right)^{1/\varepsilon}.$$

Hence, given vectors of prices p_{rst}^{CF} and p_{rst} and incomes e_{rt}^{CF}, we can calculate $\varpi\left(\left(e_{rt}^{CF}, P_{rt}^{CF}\right)|P_{rt}\right)$ for a given distribution of q, $F(q)$.

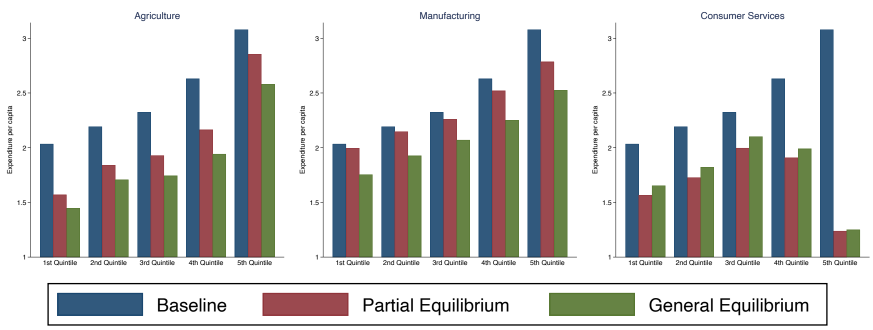

Figure 9: Welfare Effects By Urbanization Quintile. The figure shows the expenditure per capita in India in 2011 (where the average expenditure per capita in 1987 is set equal to unity) according to the NSS data and the welfare-equivalent expenditure in 2011 corresponding to partial and general equilibrium counterfactual experiments discussed the text for the representative median district in each quintile of urbanization. The counterfactual experiments consist of setting the productivity in agriculture, manufacturing, agriculture and manufacturing, and consumer services at the respective 1987 levels.

Maybe more surprising is the large role played by the consumer service sector. We find that in the absence of productivity growth in the consumer service sector, aggregate welfare growth would have been around 21 percentage points lower. Note that this is quantitatively comparable to growth in the manufacturing sector. The average welfare effect of productivity growth in the producer service sector is instead negligible, because of the small size of this sector. Finally, the effect of human capital accumulation are moderate, corresponding to a 9% of 2011 income.

Next, we break down the welfare effects across Indian districts. We group districts by quintiles of urbanization in 2011. The average urbanization rates of the five quintiles are, respectively: 0.07%, 0.12%, 0.19%, 0.29%, and 0.60%. Then, we construct a "representative" district for each quintile. Such a district is endowed with the median sectoral productivity (A_F, A_M, A_{PS}, A_{CS}) in the respective urbanization quintile. We do so to ensure that we consider a district that is broadly representative of an urbanization quintile in all four dimensions of productivity. In the data, the income per capita of these representative districts turns out to be very close to median income of the quintile they represent, except for the top quintile, where the median wage in the data is 15% larger than in the district with the median sectoral productivity.[17] Since this difference mitigates the results that we emphasize below, we take it as a conservative criterion.

We run two sets of counterfactual experiments and show the results (in terms of equivalent variations) in Figure 9. In the first experiment (red bars), we counterfactually change sectoral productivities only in the representative district under consideration, holding productivity constant in all other districts. With some abuse of terminology, we label these *partial equilibrium* experiments, because when productivity changes in only one district, there is no significant effect on the price indexes of the tradable goods. In the second set of experiments (green bars), we

[17] The income per capita of the fictitious districts are 2.03, 2.19, 2.32, 2.63, and 3.07, while the median income per capita in the data are 2.10, 2.26, 2.38, 2.62, and 3.47.

counterfactually change productivities simultaneously in all districts. Then, we report the welfare effects for each of the five representative districts.

Panels a and b focus on the traded good sectors (food and manufacturing). In the partial equilibrium experiments, lowering productivity in either sector reduces the expenditure share of the local variety in the national expenditure of India on that good (food or industrial good). In the general equilibrium experiment, the productivity falls across the board thereby increasing the price index of that good.

Consider the effect of productivity growth in agriculture (panel a). The welfare effect is maximum in the least urbanized district. In the partial equilibrium scenario, such district would be willing to sacrifice up to 23% of its 2011 income to avert going back to the 1987 productivity level in agriculture. In the general equilibrium scenario, the equivalent variation increases to 29% of the 2011 income.[18] The equivalent variation is also large for the second, third, and fourth quintile, while it plunges at the top quintile where productivity growth in agriculture between 1987 and 2011 is worth a mere 7% of the 2011 income in the partial equilibrium experiment. The gain increases to 16% in the general equilibrium experiment. The source of this heterogeneity is twofold: on the one hand, agriculture represents a small share of GDP in highly urbanized districts; on the other hand, food represents a small share of household consumption in rich districts.

The pattern is reversed in the case of manufacturing. There, the partial equilibrium effect of productivity growth is small in the three least urbanized districts–from a mere 2% for the first up to 10% for the richest district, where the welfare effect is the same as that of the agricultural counterfactual. The welfare effects are again larger in the general equilibrium experiment because the increase in the price index affects consumers. In the top quintile, the equivalent variation goes up to 18% of its 2011 income.

Most importantly, panel c shows the equivalent variations for counterfactual changes in the productivity of CS. In this experiment, the difference between the partial and general equilibrium experiments is smaller because consumer services are only sold in local markets. The welfare effects are moderate for the four less urbanized districts. Instead, the effect is large for the most urbanized district, where it is equivalent to 60% of the 2011 income. A hypothetical productivity set back to the 1987 level has two effects. On the one hand, it causes a reallocation towards the goods-producing sectors, which reduces real income through an adverse terms-of-trade effect. On the other hand, it reduces the availability of CS to consumers. These are especially valuable to the rich consumers in urbanized areas owing to non-homothetic preferences. Note that, for the top quintile, the productivity growth in CS is more important than the joint productivity gains in agriculture and manufacturing in the entire economy. We conclude that in urban districts there is a significant extent of service-led growth.

Figure 10 further decomposes the results across the income distribution ladder. We focus on the 20th, 50th and 80th percentile of the income distribution within each urbanization bin. In the fourth panel, the richest 20% in the most urbanized quintile is the main beneficiary of labor productivity growth in CS. This is the only group that would rather give up the joint productivity growth in agriculture and manufacturing than that in CS. This is in sharp contrast with the residents in less urbanized areas for whom productivity growth in CS is barely noticeable.

4.2.3 Counterfactual Structural Change

We now turn to the analysis of the process of structural change. Figure 11 displays the effects of sectoral technical progress on structural change nationwide. Each of the four panel focuses on one sector. The five bars show the actual employment share in 2011 and the counterfactual employment when each of the sectoral productivities is set to its 1987 level.[19]

Panel a displays results for the agricultural sector. Labor productivity in agriculture increases the employment share of agriculture. Thus, while important for welfare, productivity growth in agriculture is not a source of industrialization and structural change in India–rather, it slowed down it. The decline of agricultural employment observed between 1987 and 2011 hinges, instead, on productivity growth in manufacturing and consumer services.

[18]The general equilibrium effects are always larger than the partial equilibrium ones because in our model districts benefit from each other productivity gains.

[19]The results show employment in effective units of labor (which we label *employment* for simplicity). The results in terms of employment headcount are similar and are available upon request.

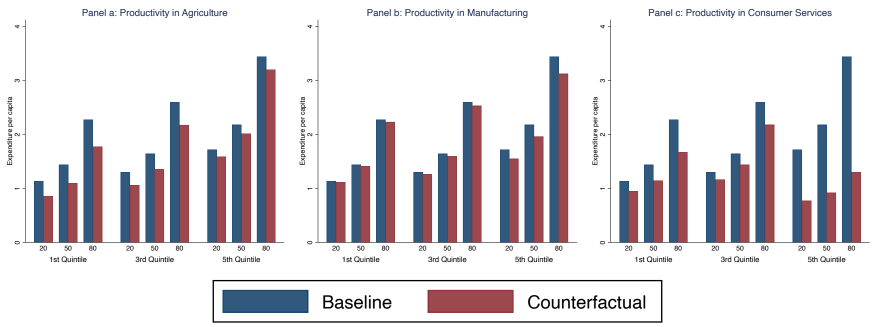

Figure 10: Welfare Effects: Heterogeneity. The figure shows the expenditure per capita in India in 2011 (average expenditure per capita in 1987 = 1) according to the NSS data and the welfare-equivalent expenditure in 2011 corresponding to partial equilibrium counterfactual experiments discussed in the text for households at different percentiles of the income distribution in the median district of the first, third, and fifth quintile of urbanization. The counterfactual experiments consist of setting the productivity in agriculture, manufacturing, agriculture and manufacturing, and CS at the respective 1987 levels.

Absent productivity growth in either of these sectors, the employment share of agriculture would have been close to 60% in 2011 Our finding goes against the common wisdom that high productivity in agriculture is a precondition for industrialization. They are instead in line with the findings of Foster and Rosenzweig (2004) on the effects of the Green Revolution.

Employment in manufacturing (panel b) is not affected significantly by any sectoral productivity growth, except from that in the CS sector. Without productivity growth in CS, the employment share in manufacturing would have been two percentage point lower, which is about the extent of the change we observe in the data thoroughout 1987–2017. Interestingly, productivity growth in PS, crowds out employment in manufacturing.

Panel c shows that employment growth in CS hinges on two sources of productivity growth: manufacturing and CS itself. Both are equally important and account for a four percentage point increase in the CS employment share. The reason why productivity growth in manufacturing has a significant positive effect on the development of CS (while agriculture has not) is that it has been especially strong in rich highly urbanized districts where the demand of CS is strong.

Next, we consider the disaggregated effect at the district level. For simplicity, we only focus on the partial equilibrium experiment and restrict attention to a comparison between the joint effect of productivity growth in the traded sectors with that in the CS sector. Figure 12 shows the result. The joint technical progress in agriculture and manufacturing (panel a) has a sizable effect on the level of consumer service employment. By making India poorer, bringing back labor productivity to the 1987 level would reduce the employment share of CS by 4 percentage points by way of an income effect. Setting productivity in CS back to the 1987 level (panel b) has an even larger impact on structural change in the most urbanized areas. In those districts, the employment share of CS would decrease by 12 percentage points.

Figure 11: Sectoral Productivity Growth and Structural Change. Each panel in the figure shows the 2011 employment share in one sector and the counterfactual employment shares in the same sector corresponding to setting the productivity in agriculture, manufacturing, consumer services, and producer services at the respective 1987 levels

In conclusion, structural change in urban areas appears to be largely driven by service-led growth. Interesting, productivity growth in CS is also responsible for a large share of the growth of CS in the least urbanized districts, being less important in areas of intermediate urbanization.

4.2.4 Spatial Counterfactuals

In this section, we consider counterfactual experiments in which we set all 2011 district-level productivities equal to the median productivity in the same year. As before, we run experiments one sector at a time. For brevity we report all figures in Section A-11 in the Appendix.

Figure A-5 shows the welfare effects broken down by quintiles of urbanization. Not surprisingly, poorer rural districts tend to fare better than do richer ones because they have lower productivities in the first place. More interestingly, panel c shows that counterfactually setting the productivity in both goods-producing sectors to the sample median reduces welfare significantly in all except the poorest quintile. The reason is that the counterfactual experiment reduces the strength of comparative advantages (especially, by reducing the productivity of manufacturing in more urbanized districts) thereby narrowing the gains from specialization and trade. Thus, the equalizing effect is dominated by an average welfare loss.

Panel d in Figure A-5 shows that equalizing productivity in the CS sector across districts causes large welfare losses in the most urbanized sector while the benefits for rural areas are marginal. The reason for this asymmetry is twofold. First, the productivity distribution is skewed, implying that the losses for high-productivity districts are larger than the gains for low-productivity districts. Second, poorer districts do not consume much CS because of income effects. Thus, consumers are not especially interested in seeing productivity improve in that sector. In contrast, CS represents an important share of the consumption basket in rich urban districts.

Figures A-6 shows the effect on structural change of counterfactually setting (simultaneously) the productivity of both goods-producing sector to the 2011 median. In this experiment, the less urbanized regions turn less agricultural while the more urbanized ones turn less industrial. While being more equal, this counterfactual Indian economy

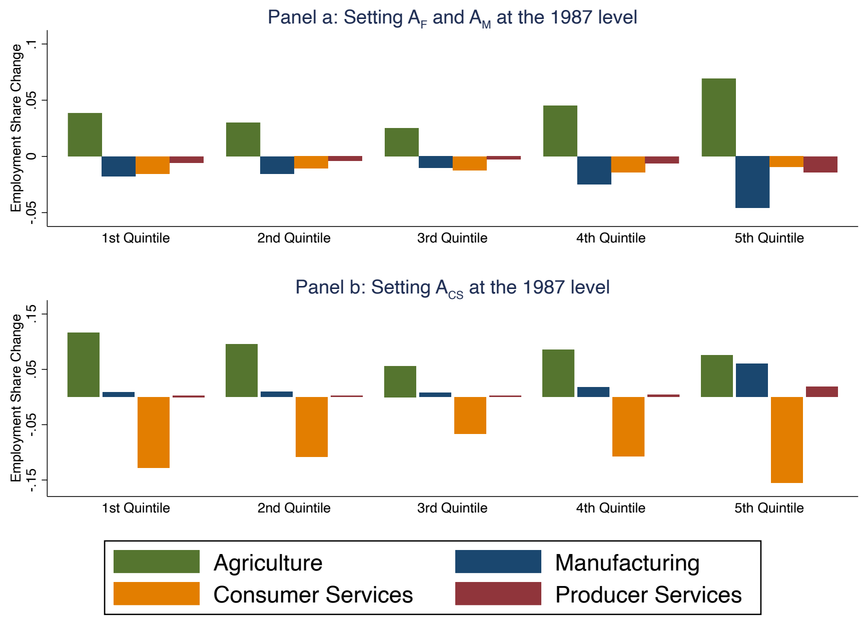

Figure 12: Sectoral Productivity Growth and Structural Change. Panel a shows the changes in sectoral employment share for five representative districts (by urbanization quintiles) when we counterfactually set both A_F and A_M at the 1987 levels. Panel b shows the same information when we counterfactually set A_{CS} at the 1987 level

would lose out on the benefits of specialization becoming on average poorer. As a result, the demand and production of consumer services falls throughout.

Figure A-7 shows the same experiment for the CS sector. When we set the productivity of CS in all districts to the median, we observe contrasting patterns across districts. In poor districts, the share of agriculture and (to a smaller extent) manufacturing falls, while employment in the CS increases. In the richest districts, the effects are opposite and much larger in size. The employment share in CS falls by three percentage points, being matched by a corresponding increase in the employment share of manufacturing and PS. This experiment shows that, if urbanized areas had a less productive CS service sector, cities would look more industrial and less rich in consumers' amenities.

5 Robustness

In this section we discuss the robustness of our results.

5.1 Open economy

Thus far, we have treated India as a closed economy. However, international trade has become increasingly important for India, which is today among the fifteen largest exporting nations worldwide. In this section we extend the model to an open economy environment. For brevity we only describe the main features of our treatment of the open economy. A detailed description can be found in Section A-12 in the Appendix.

We introduce trade by assuming that consumers, both in India and in the rest of the world, consume industrial goods sourcing from many countries. Different national varieties–which are in turn aggregations of regional varieties–enter as imperfect substitutes into a CES utility function. In addition, we recognize that India might have a comparative advantage in the trade of services. Because in our model services are local goods, this extension requires that we introduce a new separate category of services that is traded internationally.

	Welfare loss (%) if there was no growth in...							
	Agriculture	Manufacturing	Manufacturing + ICT Export	Cons. Serv.	Prod. Serv	Human Capital	Goods Trade	ICT Export
Closed Economy	21.7	17.4		21.0	0.35	8.71		
Open Economy	21.8		14.9	15.9	0.09	8.39	3.71	0.58

Table 5: Counterfactual Welfare Loss. The table compares the counterfactual welfare loss in benchmark and open economy

More specifically, we assume that India exports both domestic goods and a special category of services: ICT services. The foreign demand system for both these exported products is CES and as for other goods, the foreign sector purchases a bungle of regional varieties of ICT services. For simplicity, we assume that ICT services are not sold in the domestic market. In our estimation, we assume balanced trade, i.e. India runs a trade deficit in goods and a surplus in ICT services.

Estimating the model requires, as usual, to invert these relationships, so as to identify productivities, expenditure shares, and parameters from the observable distribution of employment and expenditure, and from the trade flows. Relative to the closed-economy environment, in the equilibrium with trade, we estimate the following additional parameters:

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

Here, A_{rICT} is the regional productivity in ICT productivity, Υ_{ICT} and Υ_G parametrize the foreign demand for ICT and Indian goods and η is the demand elasticity of international consumers. We externally calibrate η based on the evidence in the trade literature. Then, Υ_G and Υ_{ICT} are estimated to match the total trade flow and its composition between goods and services. The model nests the no-trade equilibrium as a special case in which $\Upsilon_G = \Upsilon_{ICT} = 0$.

Calibration We set the trade elasticity $\eta = 5$ in line with the estimates in the literature–see, e.g., Simonovska and Waugh (2011). According to the World Bank data, the export of goods and merchandise increased from 11.3bn USD (4.1% of GDP) in 1987 to 302.9bn USD (16.6% of GDP)–in current USD. The manufacturing sector accounted for 66% of such merchandise exports in 1987 for and 62% in 2011. According to the OECD, the domestic value added in gross exports amounts to 83.9% of exports in India (there is no time series, so we assume this to be constant). In accordance with these data, we assume that the value added export of trade has increased from 13.9% in 1987 to 53.6% in 2011 as a share of the GDP in the manufacturing sector.[20]

Next, we must determine the share of ICT exports. We classify as ICT service workers all those employed in the following service industries: telecommunications, computer programming, consultancy and related activities software publishing, and information service activities. In our NSS data, this comprises 2.16% of employment in the service sector and 0.67% of total employment in 2011 (in 1987, it was 0.1% of total employment). ICT workers earn on average higher wages than other workers. When one consider the earning share, they account for 3.85% of earnings in the service sector and 1.52% of total earnings in 2011 (in 1987, it was a 0.18% of total earnings).[21] Since ICT export was negligible in 1987, we assume it was zero. The target moment is then the revenue share of ICT in 2011. Again, we refer to Section A-12 in the Appendix for more details in the measurement.

Results Table 5 summarizes the results. In the first row we replicate the results from our baseline estimation. The second row contains the results from the calibrated model with international trade.

The table reports the welfare results of the counterfactual simulation in which we shut down productivity growth 1987-2011 in each of the sectors. The results of the closed-economy model are also displayed for comparison. The results of the estimation of the open-economy model are overall similar to those for the benchmark closed economy model. In the open economy model, shutting down productivity growth in the consumer service sector reduces average welfare by 16%, which compares with 21% in the closed economy model. The effect is larger than the joint effect of the increase in trade in goods and TFP growth in manufacturing.

[20] This corresponds to an increase in the value added of exports from 6.26bn USD to 157.6bn USD (in current USD).

[21] If we multiply 0.67% by the total size of the labor force in 2011, our estimate corresponds to 3.1 million workers being employed in the ICT sector. This is in the ballpark of the exisiting estimates.

The table displays the estimation results in which the ICT service accounts for 1% of total earnings in 2011, consistent with our NSS data. We have also run the counterfactual exercise for the alternative economy in which the ICT sector is twice as large as in our data–corresponding to a GDP share of ICT that is slightly larger than the value of ICT exports in the data. The results are again similar. In particular, resetting productivity in the consumer service sector at its 1987 level is equivalent to a 15% reduction in consumption in the open economy with a large ICT export sector.

The model also allows us to assess the welfare effects of international trade. To this aim, we counterfactually set $\Upsilon_G = \Upsilon_{ICT} = 0$, and $p_{G,ROW} \to \infty$, which corresponds to shutting down trade. The welfare effects are modest: they are equivalent to a fall in consumption of less than 5% in the open economy equilibrium for 2011.

6 Conclusion

In this paper, we propose a new methodology of structural development accounting using a spatial equilibrium model and granular data on employment and expenditure shares to estimate sectoral productivities across regions and over time. The building blocks are: (i) nonhomothetic PIGL preferences along the lines of Boppart (2014); (ii) a model of the industrial sector with endogenous entry where firms have heterogenous productivities and the more productive firms hire corporate services; (iii) the assumption that agricultural and industrial goods are tradable across Indian districts while production and consumption services must be provided locally.

We apply the methodology to India, a country whose growth is characterized by a pronounced transition from agriculture to services but only a modest role of the industrial sector. We are interested in both welfare effects and the impact of sectoral productivity growth on the process structural change. The analysis yields a number of novel insights. First, in spite of the stagnant employment share, productivity in manufacturing is an important driver of economic growth. Second, productivity growth in agriculture has large effects on the welfare of Indian households (especially in poor areas) but hardly any effect on structural change. It is not the case, in particular, that structural change originates from the agricultural sector shedding employment. The main source of structural change is productivity growth in the manufacturing and consumer service sector. Third, the analysis uncovers large asymmetric effects across districts. In particular, productivity growth in the CS sector has major consequences (larger than those of any other sectoral productivity growth) on both welfare and structural change in highly urbanized districts (top quintile). Had productivity in the CS stagnated at the 1987 level, cities would be more industrial and offer less amenities.

Our structural models has several limitations that we hope to overcome in future research. First, against our initial expectations, we find a limited role of producer services in India. These are likely to be more important in richer economies. Second, the Ricardian nature of the model prevented the possibility that human capital accumulation be an independent driver of technical change. To properly address this question, one might want to endogenize technical change and the location decision of workers with different skills. In spite of these and other limitations, our framework can become a useful tool of analysis for researchers planning to use survey data as the backbone of macroeconomic analyses of the development process.

References

Aghion, P., R. Burgess, S. Redding, and F. Zilibotti: 2005, ‘Entry Liberalization and Inequality in Industrial Performance’. *Journal of the European Economic Association* **3**(2-3), 291–302.

Aghion, P., R. Burgess, S. Redding, and F. Zilibotti: 2008, ‘The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India’. *American Economic Review* **98**(4), 1397–1412.

Akcigit, U., H. Alp, and M. Peters: 2020, ‘Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries’. Forthcoming in the *American Economic Review*.

Alder, S., T. Boppart, and A. Muller: 2019, ‘A Theory of Structural Change that Can Fit the Data’. CEPR Discussion Paper 13469.

Allen, T. and C. Arkolakis: 2014, 'Trade and the Topography of the Spatial Economy'. *The Quarterly Journal of Economics* **129**(3), 1085–1140.

Amirapu, A. and A. Subramanian: 2015, 'Manufacturing or Services? An Indian Illustration of a Development Dilemma'. Centre for Global Development Working Paper 409.

Basu, K.: 2008, 'The Enigma of India'. *Journal of Economic Literature* **46**(2), 396–406.

Basu, K. and A. Maertens: 2007, 'The pattern and causes of economic growth in India'. *Oxford Review of Economic Policy* **23**(2), 143–167.

Baumol, W.: 1967, 'Macroeconomics of unbalanced growth: the anatomy of urban crisis Macroeconomics of Unbalanced Growth: The Anatomy of the Urban Crisis'. *American Economic Review* **57**(3), 415–426.

Boppart, T.: 2014, 'Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non-Gorman Preferences'. *Econometrica* **82**(6), 2167–2196.

Caselli, F.: 2005, 'Accounting for Cross-Country Income Differences'. In: P. Aghion and S. Durlauf (eds.): *Handbook of Economic Growth*, Vol. 1A. Elsevier B.V., Chapt. 9, pp. 679–741.

Celasun, O. and B. Gruss: 2018, 'The declining share of manufacturing jobs'. Column published in vox.eu, CEPR Economic Portal, https://voxeu.org/article/declining-share-manufacturing-jobs.

Comin, D., D. Lashkari, and M. Mestieri: 2017, 'Structural Change with Long-Run Income and Price Effects'. Working Paper.

Duarte, M. and D. Restuccia: 2010, 'The Role of the Structural Transformation in Aggregate Productivity*'. *The Quarterly Journal of Economics* **125**(1), 129–173.

Eckert, F. and M. Peters: 2016, 'Spatial Structural Change'. Working Paper.

Eichengreen, B. and P. Gupta: 2011, 'The Service Sector as India's Road to Economic Growth'. *India Policy Forum, National Council of Applied Economic Research* **7**(1), 1–42.

Erumban, A. A., D. K. Das, S. Aggarwal, and P. C. Das: 2019, 'Structural change and economic growth in India'. *Structural Change and Economic Dynamics* **51**, 186 – 202.

Foellmi, R. and J. Zweimüller: 2006, 'Income Distribution and Demand-Induced Innovations'. *Review of Economic Studies* **73**(4), 941–960.

Foellmi, R. and J. Zweimüller: 2008, 'Structural change, Engel's consumption cycles and Kaldor's facts of economic growth'. *Journal of Monetary Economics* **55**(7), 1317 – 1328.

Foster, A. and M. Rosenzweig: 1996, 'Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution'. *American Economic Review* **86**(4), 931–953.

Foster, A. and M. Rosenzweig: 2004, 'Agricultural Productivity Growth, Rural Economic Diversity, and Economic Reforms: India, 1970-2000'. *Economic Development and Cultural Change* **52**(3), 509–542.

Gancia, G., , A. Müller, and F. Zilibotti: 2013, 'Structural Development Accounting'. In: D. Acemoglu, M. Arellano, and E. Dekel (eds.): *Advances in Economics and Econometrics: Theory and Applications (Tenth World Congress of the Econometric Society)*. Cambridge University Press, pp. 373–418.

Ghose, A.: 2014, 'India's services led growth'. Institute for Human Development New Delhi, Working Paper 01/2014.

Goldberg, P., A. K. Khandelwal, N. Pavcnik, and P. Topalova: 2010, 'Imported Intermediate Inputs and Domestic Product Growth: Evidence from India'. *The Quarterly Journal of Economics* **125**(4), 1727–1767.

Gordon, J. and P. Gupta: 2005, 'Understanding India's Services Revolution'. In: W. Tseng and C. David (eds.): *India's and China's Recent Experience with Reform and Growth. Procyclicality of Financial Systems in Asia.* Palgrave Macmillan, London, pp. 49–84.

Hall, R. and C. Jones: 1999, 'Why Do Some Countries Produce So Much More Ouput Per Worker Than Others?'. *Quarterly Journal of Economics* **114**(1), 83–116.

Hansen, G. D. and E. C. Prescott: 2002, 'Malthus to Solow'. *American Economic Review* **92**(4), 1205–1217.

Herrendorf, B., R. Rogerson, and A. Valentinyi: 2013, 'Two Perspectives on Preferences and Structural Transformation'. *American Economic Review* **103**(7), 2752–89.

Herrendorf, B., R. Rogerson, and A. Valentinyi: 2014, 'Growth and structural transformation'. In: *Handbook of economic growth*, Vol. 2. Elsevier, pp. 855–941.

Herrendorf, B., R. Rogerson, and A. Valentinyi: 2017, 'Structural Change in Investment and Consumption: A Unified Approach'. Working Paper.

Hobijn, B., T. Schoellman, and A. Vindas: 2019, 'Structural Transformation by Cohort'. Technical report, Technical Report, Arizona State University.

Hsieh, C.-T. and E. Rossi-Hansberg: 2019, 'The Industrial Revolution in Services'. NBER Working Paper No. 25968.

Kochhar, K., U. Kumar, R. Rajan, A. Subramanian, and I. Tokatlidis: 2006, 'India's pattern of development: What happened, what follows?'. *Journal of Monetary Economics* **53**(5), 981–2019.

König, M., J. Lorenz, and F. Zilibotti: 2016, 'Innovation vs. imitation and the evolution of productivity distributions'. *Theoretical Economics* **11**(3), 1053–1102.

Majid, N.: 2019, 'Structural Change and Employment in India'. ILO/SIDA Partnership on Employment Working Paper No.1.

Martin, L., S. Nataraj, and A. Harrison: 2017, 'In with the Big, Out with the Small: Removing Small-Scale Reservations in India'. *American Economic Review* **107**(2), 354–86.

Matsuyama, K.: 2000, 'A Ricardian Model with a Continuum of Goods under Nonhomothetic Preferences: Demand Complementarities, Income Distribution, and North-South Trade'. *Journal of Political Economy* **108**(6), 1093–1120.

Matsuyama, K.: 2019, 'Engel's Law in the Global Economy: Demand-Induced Patterns of Structural Change, Innovation, and Trade'. *Econometrica* **87**(2), 497–528.

Mc Millan, M. and D. Rodrik: 2011, 'Globalization, Structural Change, and Productivity Growth'. In: M. Bacchetta and M. Jansen (eds.): *Making Globalization Socially Sustainable.* International Labor Organization, pp. 49–84.

Mitra, D. and B. P. Ural: 2008, 'Indian manufacturing: A slow sector in a rapidly growing economy'. *The Journal of International Trade & Economic Development* **17**(4), 525–559.

Muellbauer, J.: 1976, 'Community Preferences and the Representative Consumer'. *Econometrica* **44**(5), 979 – 999.

Mukherjee, A.: 2013, 'The Service Sector in India'. Asian Development Bank Economics Working Paper Series No. 352.

Ngai, L. R. and C. A. Pissarides: 2007, 'Structural Change in a Multisector Model of Growth'. *American Economic Review* **97**(1), 429–443.

Redding, S. J. and E. Rossi-Hansberg: 2017, 'Quantitative Spatial Economics'. *Annual Review of Economics* **9**(1), 21–58.

Singh, A. and S. Dasgupta: 2016, 'Will services be the new engine of economic growth in India?'. Working Papers id:11176, eSocialSciences.

Storesletten, K., B. Zhao, and F. Zilibotti: 2019, 'Business Cycle during Structural Change: Arthur Lewis' Theory from a Neoclassical Perspective'. NBER Working Paper No. 26181.

Appendix

A-1 Technical Analysis of the Trade Equilibrium

For the economy with trade we need the following objects:

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

If we assume the trade is balanced, $T = 0$, There are $R+2$ unknowns. For these $R+2$ unknowns we have the following conditions

1. Relative ICT payments across localities for ICT exports:

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

These are $R-1$equations to determine A_{rICT} up to scale in the same way as we did before, i.e.

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

yields

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

2. Note that from the equilibrium condition for ICT exports we have

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

Hence, Υ_{ICT} and A_{ICT} are not separately identified so we can set

$$A_{ICT} = 1.$$

3. To identify Υ_{ICT} we use that

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

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

4. To identify Υ_G we use a moment about the share of manufacturing value added that is exported. Our model implies that:

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

and

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

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

$$M_1 = \frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G}{\sum_r w_r L_{rG}} = \frac{P_{G,IND}^{1-\eta} \Upsilon_G}{\sum_r w_r L_{rG}} = \frac{\Upsilon_G}{\sum_r w_r L_{rG}} \tag{A-2}$$

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 Υ_G.

Note that the market clearing for manufacturing varieties implies that

$$\begin{aligned}
w_r L_{rG} &= \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^R w_j^{1-\sigma} A_{jG}^{\sigma-1}} \right) \times \left(\frac{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta}}{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta} + 1} \sum_{j=1}^R \vartheta_{jG} w_j L_j + \left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G \right) \\
&= \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^R w_j^{1-\sigma} A_{jG}^{\sigma-1}} \right) \times \left(\frac{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta}}{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta} + 1} \sum_{j=1}^R \vartheta_{jG} w_j L_j + M_1 \left(\sum_r w_r L_{rG} \right) \right).
\end{aligned}$$

From (A-38) we know that

$$\begin{aligned}
&\frac{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta}}{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta} + 1} \\
&= 1 - \frac{\left(\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G + \left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT} \right)}{\sum_{j=1}^R \vartheta_{jG} w_j L_j} \\
&= 1 - \frac{\sum_r w_r L_{rG}}{\sum_{j=1}^R \vartheta_{jG} w_j L_j} M_1 - \frac{\sum_r w_r L_{rICT}}{\sum_{j=1}^R \vartheta_{jG} w_j L_j}.
\end{aligned}$$

Hence,

$$\begin{aligned}
&\frac{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta}}{\varphi^{-\eta} \left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1} \right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}} \right)^{1-\eta} + 1} \sum_{j=1}^R \vartheta_{jG} w_j L_j + M_1 \left(\sum_r w_r L_{rG} \right) \\
&= \left(1 - \frac{\sum_r w_r L_{rG}}{\sum_{j=1}^R \vartheta_{jG} w_j L_j} M_1 - \frac{\sum_r w_r L_{rICT}}{\sum_{j=1}^R \vartheta_{jG} w_j L_j} \right) \left(\sum_{j=1}^R \vartheta_{jG} w_j L_j \right) + M_1 \left(\sum_r w_r L_{rG} \right) \\
&= \sum_{j=1}^R \vartheta_{jG} w_j L_j - \sum_r w_r L_{rG} M_1 - \sum_r w_r L_{rICT} + M_1 \left(\sum_r w_r L_{rG} \right) \\
&= \sum_{j=1}^R \vartheta_{jG} w_j L_j - \sum_r w_r L_{rICT}.
\end{aligned}$$

Therefore

$$w_r L_{rG} = \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}} \right) \times \left(\sum_{j=1}^{R} \vartheta_{jG} w_j L_j - \sum_r w_r L_{rICT} \right),$$

Intuitively: if $\sum_r w_r L_{rICT} > 0$, India is an exporter of ICT services. With balanced trade this implies that this is exactly equal to net imports of manufacturing products. Hence, $\sum_{j=1}^{R} \vartheta_{jG} w_j L_j - \sum_r w_r L_{rICT}$ is exactly the manufacturing value added produced in India, which get distributed across regions according to the trade shares $\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}}$.

A-2 Derivation of Expenditure Shares (Equation

Using the definition of $B(p)$ and $D(p)$, the indirect utility function in (2) is given by

$$V(e,p) = (1-\varepsilon) \left[\frac{1}{\varepsilon} \left(\frac{e}{\prod_s p_{st}^{\omega_s}} \right)^{\varepsilon} - \left(\sum_s \nu_s \ln p_{st} \right) \right]. \tag{A-3}$$

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

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

Using (A-3), it follows that

$$\vartheta_s(e,p) = -\frac{(1-\varepsilon)\left(-\omega_s \left(\frac{e}{\prod_s p_{st}^{\omega_s}} \right)^{\varepsilon} - \nu_s \right)}{(1-\varepsilon)\left(\frac{e}{\prod_s p_{st}^{\omega_s}} \right)^{\varepsilon}} = \omega_s + \nu_s \left(\frac{e}{\prod_s p_{st}^{\omega_s}} \right)^{-\varepsilon}$$

A-3 Geography

There are many boundary changes at district level. The most common one is partition, namely, one district has been separated into several districts in the later year. The second type is boundary moving, the shared boundary of two districts has been moved. The third one is merge, two districts have been merged into one district. In addition, there were several complicated changes over the years.
To clearly see the changes, in figure A-1, we plot the districts' boundaries in 2004 and 2011 together. The purple line represents the boundaries in 2004 and the red line represents the boundaries in 2011, we can see boundary changes across the country. To see the details, in figure A-2, we plot two types of boundary changes: Partition (left panel) and Moving (right panel).

In order to construct a panel to perform analysis in the consistent geography, we construct regions that have consistent boundaries across year. 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. For instance, in the case of partition, the region is constructed as the district in the previous year. In the case of boundary moving, a region is constructed as the sum of two districts. We do it for three years' maps and arrive at a regional map with consistent boundaries from 1991 to 2011. Once we have regions with consistent boundaries, we can map our micro-data including NSS, Economic Census, and USS to the regions to construct panel data.

A-4 Data

We use the following datasets

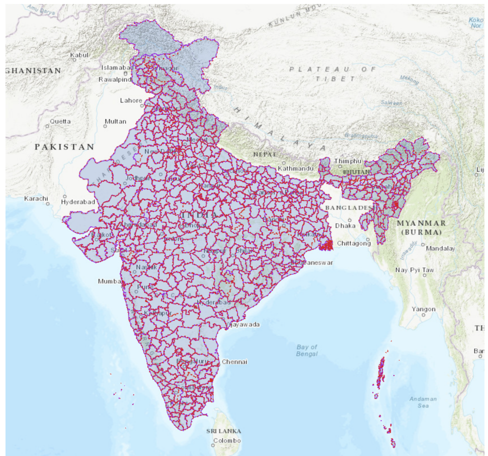

Figure A-1: District Boundary in India

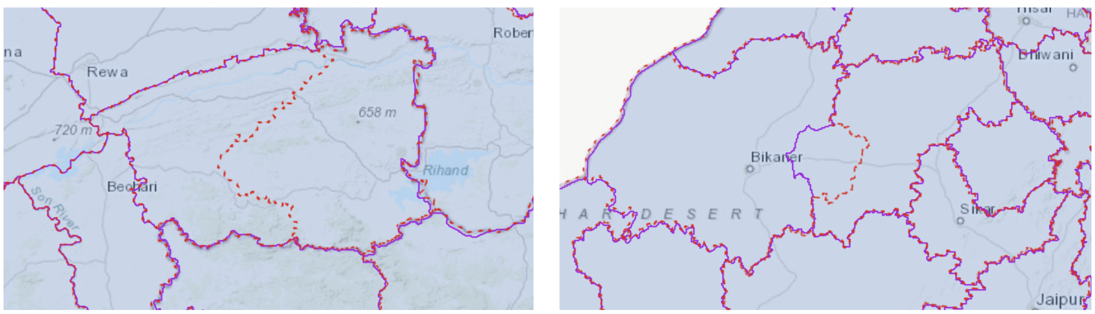

Figure A-2: Two Types of Boundary Change

A-4.1 NSS

(Description of NSS data; which years do we have; number of observations per year; we take the following variables ...., a table with important summary statistics)

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 survey consists of several schedules to cover different subjects like "Consumer Expenditure", "Employment and Unemployment", "Participation in Education", etc. We use data from rounds 43, 55, 60, 64, 66 and 68 of NSS, which span the years 1987 to 2011.

Geographical Coverage: The survey covers the whole of the Indian Union except a few regions due to unfavorable field conditions. 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.

Information Coverage: We mainly use the "Household Consumer Expenditure" schedule and "Employment and Unemployment" schedule. Both schedules collect Household characteristics (such as Household size, Household type (agriculture \non-agriculture\regular wage earning\casual labour\self-employed), land ownership, and religions) and Demographic particulars of household members (such as Sex, Age, Marital Status, and Education). In addition, the "Household Consumer Expenditure" schedule collects household expenditure information on different kinds of goods and services. The "Employment and Unemployment" schedule collects information such as employment status, occupation, job sectors, contract type, time disposition.

Concepts and Definitions:

Employment: An individual is defined as being employed if his/her usual principal activity status is one of the following: (i) worked in household enterprises (self-employed); (ii) worked as helper in household enterprises; (iii) worked as regular salaried/wage employee; (iv) worked as casual wage labour in public works; (v) worked as casual wage labour in other types of work

Education level: we classify individual's education into four levels: (i) Less than primary; (ii). Primary, upper primary, and middle; (iii). Secondary; (iv). More than secondary.

Household size The size of a household is the total number of persons in the household

Expenditure/Consumption: The survey collects households' consumption of various kinks of food, entertainment, sundry articles,consumer services, rent/ house rent and so on during last 30 days (monthly-based expenditure), and consumption of clothing, bedding, footwear, education and medical goods and services, and various kinds of durable goods during last 365 days (yearly-based expenditure). Total monthly household consumer expenditure is the sum of monthly-based expenditure and (30/365) * yearly-based expenditure

Expenditure per capita: Total household consumer expenditure divided by household size. In the main analysis, we top-code expenditure data at 98th percentiles to deal with extreme values.

Income: Total household consumer expenditure divided by the number of people between 15 and 65 in the household. In the main analysis, we top-code wage data at 98th percentiles to deal with extreme values.

Table A-1 reports important summary statistics of NSS.

Table A-1: National Sample Survey of India: summary statistics

round	Year	households	individuals	household size	employment rate	urbanization rate	expenditure per capita	Income per labor
43	1987-1988	126,353	654,903	5.18	36.89%	22.60%	2066.23	3873.32
55	1999-2000	107,215	596,688	5.57	36.53%	25.42%	6161.96	10929.28
60	2004	59,042	303,233	5.14	36.92%	25.51%	7318.92	12673.22
64	2007-2008	125,578	572,254	4.56	37.06%	26.32%	9713.66	16216.31
66	2009-2010	100,957	459,784	4.55	36.49%	27.32%	12987.22	21074.68
68	2011-2012	101,717	456,970	4.49	35.44%	28.84%	17507.15	28142.28

A-4.2 Economic Census

(Description of data; which years do we have; number of observations per year; we take the following variables .... a table with important summary statistics)

India Economic Census (EC) is the complete count of all establishments (i.e. 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. Micro-level data in 1990, 1998, 2005, 2013 are public available.

Industries Coverage: The Census covers all sectors excluding crop production and plantation. The Censuses in 2005 and 2013 exclude some public sectors like public administration, defence and compulsory social security.

Geographical Coverage: The Census covers all States and Union Territories of the country except for the year 1990, which covers all States/UTs except Jammu and Kashmir.

Information Coverage: The Census collects information such as firms' location, industry, ownership, owner's social Group, nature of operation, finance source, employment (male/female, hired/not hired). The following table reports important summary statistics of Censuses.

Census	Year	Number of firms	Total employment	Employment distribution			
				Average	1 employee	Less than 5 employees	More than 100 employees
Third EC	1990	24216790	74570280	3.08	53.77%	91.24%	0.13%
Fourth EC	1998	30348881	83308504	2.75	51.18%	91.71%	0.11%
Fifth EC	2005	41826989	100904120	2.41	55.76%	93.17%	0.12%
Sixth EC	2013	58495359	131293872	2.24	55.47%	93.44%	0.06%

Table A-2: The Economic Census: Summary Statistics

A-4.3 Service Sector in India: 2006-2007

The Service Sector in India (2006-2007) dataset was a part of an integrated survey under NSSO(National Sample Survey Organisation) in its 63rd round of survey of enterprises and households. In the 62nd round of NSSO(2001-2002), the dataset was called Unorganized Service Sector. With, the inclusion of financial sector and large firms, the dataset is renamed as Service Sector in India and is designed to be representative for India's service sector. Table 2 shows the consistency of Service Sector in India by comparing it's characteristic of firm sizes with that of the Economic Census dataset.

Industries Coverage (Covered): The Service Sector survey covers a broad ranges 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)

Industries Coverage (Not Covered): However, the industries does not cover the following industries: Railways Transportation, Air transport, Pipeline transport; Monetary intermediation(central banks, commercial banks, etc); Trade Unions. Moreover, the following units are not surveyed: Government and Public sector enterprises, Government aided education institutions, Service sector units appeared in the *Annual Survey of Industries frame(ASI 2004-2005).*

Geographical Coverage: The survey covers the whole of Indian Union except for 4 districts and some remote interior villages.

information Coverage: In the context of our analysis, the survey provides two important information:

- The number of employees in a surveyed unit
- Where is the major destination of output for a surveyed unit: Firm, Households, Non-resident, and so on

Locations and Number: The survey covered the whole of the Indian Union except (i) Leh (Ladakh), Kargil, Punch and Rajauri districts of Jammu & Kashmir, (ii) interior villages situated beyond 5 km of a bus route in Nagaland, (iii) villages of Andaman and Nicobar Islands, which remain inaccessible throughout the year. The survey was conducted in a total number of 5573 villages and 7698 urban blocks. A total of 1,90,282 enterprises (including 438 list frame enterprises) were ultimately surveyed.

To check the representativeness of this survey, we compare firm size from Economic Census 2005 and this survey. The following table reports the average firm size and the share of firms with less than 5 employees for both the Service Survey and the Economic Census.

Sector	Number of firms		Average employment		Less than 5 employees	
	Census	Service Survey	Census	Service Survey	Census	Service Survey
Hotels and restaurants	1,499,101	30,744	2.52	2.49	0.90	0.91
Land transport; transport via pipelines	1,317,904	41,065	1.67	1.24	0.97	0.99
Post and telecommunications	723,119	22,885	2.06	1.41	0.96	0.99
Other business activities	519,696	10,610	2.81	1.92	0.90	0.95
Renting of machinery and household goods	365,246	5,387	2.00	1.77	0.94	0.97
Financial intermediation	221,953	12,984	6.27	4.15	0.63	0.79
Transport activities; travel agencies	188,474	2,101	3.40	3.33	0.86	0.85
Real estate activities	70,128	3,648	2.18	1.64	0.93	0.96
Computer and related activities	66,414	1,060	6.01	13.45	0.83	0.86
Activities auxiliary to financial intermediation	45,449	2,601	2.41	1.77	0.93	0.96
Insurance and pension funding	26,087	746	5.52	2.30	0.83	0.99
Water transport	7,914	174	4.35	1.92	0.90	0.98
Research and development	2,097	5	16.66	4.58	0.66	0.89

Table A-3: ECONOMIC CENSUS AND SERVICE SURVEY. The table reports statistics about firms' number and employment from the Economic Census 2005 and Service Survey 2006.

A-4.4 Informal Non-Agricultural Enterprises Survey 1999-2000 (INAES)

We use this dataset when splitting the construction sector into consumer service and producer service. The enterprise survey is one schedule of NSS 55th round. It covers all informal enterprises in the non-agricultural sector of the economy, excluding those engaged in mining & quarrying and electricity, gas & water supply[22]. The survey collects information on operational characteristics, expenses, value-added, fixed asset, loan, factor income. In particular, the survey asks the major destination agency for sale of final product/service. This information helps us to identify if a construction firm is consumer-oriented or producer-oriented

A-5 Industry Classification

We divide economic activities into 6 industries: Agriculture, Manufacture, Construction and Utility, Service, Information and Communications Technology (ICT), and Public based on 2-digit (sometimes 3-digit) level of India National Industrial Classification (NIC). Table A-4 reports the broad structure of industry classification.

Table A-4: Broad Industries based on India National Industry Classification 2008

Industry	NIC 2008	Section
Agriculture	01-03	Agriculture, forestry and fishing
Manufacture	05-09	Mining of coal and lignite
	10-33	Manufacturing
Construction & Utility	35	Electricity, gas, steam and air conditioning supply
	36-39	Water supply; sewerage, waste management and remediation activities
	41-43	Construction
Service	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	84	Public administration and defence; compulsory social security
	85	Education
	99	Activities of extraterritorial organizations and bodies

Note: sector 98 is dropped.

What's more, data in different years use different versions of NIC. We construct a concordance table between 2-digit industries of different versions' NIC based on Official NIC documents and detailed sector descriptions. Sometimes we have to dig into 3 or 4 digit level to get a precise match.

[22]In India, organised and unorganised sectors are defined as follows:

organised sector: 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 power, and 2(m)(ii) includes manufacturing factories which 20 or more without power.

unorganised sector: all enterprises not covered in the organised sector

Informal sector is a subset of the unorganised sector. The unorganised sector includes four types of enterprises: 1) unincorporated proprietary enterprises; 2) partnership enterprises; 3) enterprises run by cooperative societies, trusts, private; 4) public limited companies; The informal sector only includes firms in category 1) and 2).

Table A-5: Concordance between 2-digit industry Classes of NICs

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
Manufacture			
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 & Utility			
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
Service			
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			
Public administration and defence	90	75	84
Education	920-921	80	85
Extraterritorial organizations	98	99	99

A-6 Bounding regional employment shares

Our model implies that regional consumer services expenditure shares and hence employment shares are bounded from above by ω_{CS}. Similarly, our model implies that the share of producer service employment ("lawyers") relative to production workers is bounded from above by β. Given our estimated of $\omega_{CS} = 0.607$ and $\beta = 0.7$ reported in Table 4, 7 districts violate this requirement and we drop them from our analysis. Dropping such districts is inconsequential because these districts are very small. In Table A-6 we report the aggregate population share of such districts by year. As can be seen, the aggregate importance of such districts is below 1% in almost all years

	Total share of population	
Year	CS empl. share >0.56	PS empl. share >0.7
1987	0	0.0031
1999	0.0039	0.0013
2004	0.0068	0.009
2007	0.0085	0.0027
2009	0.0071	0.0002
2011	0.0162	0.0054

Table A-6: Employment Shares of Top-Bottom Code Districts

A-7 Measuring Producer and Consumer Services

This section will start with an introduction on the general methodology of the measurement of Consumer and Producer Services, followed by detailed explanation and procedures. Since the 'Service Sector in India'(SS) dataset provides the information of major destination of firms, we utilized this information to calculate the approximated share of employment in Consumer Services and Producer Services sectors, respectively. This share is calculated industry-wise(at two digit level of NIC04) and is treated as proxies to the share of Producer services in India. The share from SS were later applied to the Economic Census(EC) dataset to calculate the total share of employment in each district. Every detail step of the procedure can be found in '[12] Prepare share of PS by district-year dataset.do' on 'Dropbox/India/Empirical Analysis/rawdata/Economic Census/dofile'

1. Calculating 2 digits division-firm size level PS share using USS 2005-2006 Information of different kinds(background, employment, etc) in the SS dataset are stored in different STATA files, with an unique key variable 'ID'. Therefore, the first step of the analysis is to merge dataset that contains information about employment with the dataset that contains the key variables of interest—Major destination of output. We then calculate the Producer Service share(PS share) from the constructed dataset. Specific decisions made are listed below:

   (a) Observations with missing value in employment or/and Major destination of output are dropped

   (b) All firms that has 'non-resident'(foreign) as their major destination of output are dropped

   (c) Generate firm size bins according to total employment(1-2, 3-20, 20+)

   (d) Generate the NIC industry indicator that classify industries using the first two-digit of NIC2004 Industrial Classification

   (e) If the 'Major destination of output' of a firm is resident financial enterprises or resident non-financial enterprises, we classified it as Producer Service firm

   (f) Formally, the PS share within a category of interest is the total employment of Producer Service firms within the category, divided by the total employment of that category. Here, we divide the SS dataset into different categories by firm size(see (c)) and industry(see (d)). The multiplier(weight) that comes with the SS dataset can be applied to calculate the PS share in this procedure.

   (g) We calculated the PS share per firm size per industry as stated in (f)

(h) For some industries, there are not enough data in some firm size bins. For example, there are some industries that has few/no firms with total employment larger than 20. Here, we apply the 'monotonic rule'

(i) 'monotonic rule': Within an industry, we posit that the larger a firm, the more likely that the firm will serve to producers. Therefore, if within a firm size bin(e.g. 20+) of an industry, there is fewer than 5 observations(5 included), then the PS share of this particular firm size bin should be at least as large as the PS share of the preceding level firm size bin(3-20 in this example)

(j) 'monotonic rule': Consequently, if there is no data within a firm size bin of an industry, we used the PS share of the preceding level firm size bin as a proxy. If there is less or equal to 5 observations within a firm size bin of an industry and the PS share is smaller to that of the preceding level firm size bin, we use the PS share of the preceding level firm size bin instead.

(k) The Economic Census dataset uses different NIC Industrial Classifications for different years. Since we only use the 'Service Sector in India' of year 2006-2007 dataset and apply the same PS share to Economic Census of different years, we need to convert NIC2004(used by SS 2006-2007) to NIC1987(used by EC1990) and NIC2008(used by EC2013) prior to the PS share calculation. We used the official document to create mapping between different NIC classifications. Check '[12] Prepare share of PS by district-year dataset.do' for detail mapping.

After these procedures, the firm size bin and industry level PS share is produced and will be applied to the Economic Census dataset

2. Applying these shares to corresponding division-firm size bin level employment from Economic Censuses. The specific procedures are:

   (a) generate firm size bins according to total employment(1-2, 3-20, 20+)
   (b) calculate total employment at 2 digits division-firm size bin-region level
   (c) merge division-firm size bin level employment with corresponding PS share information from SS dataset
   (d) fill in PS share for sectors not covered by SS dataset. Some service divisions are not covered by USS and therefore we cannot directly measure their PS shares. We handle these cases one by one to make our estimation as accurate as possible. The following table summarizes how we deal with divisions without PS share information.

Table A-7: Estimating PS share for divisions not covered by USS

NIC2004	Industry	Approach
22	Publishing, printing and reproduction of recorded media	attribute all employment to Producer Service
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	use the 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 the 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 Consumer Service
62	Air transport	attribute all employment to Producer Service

(e) Calculate Producer Service (Consumer Service) employment by multiplying total employment with PS (1-PS) share

(f) Aggregate Producer Service and Consumer Service employment into GIS region level

While Figure 1 showed the relationship between firm size and the probability of selling to other firms graphically, our procedure exploits this variation within industries. In Table A-8 we show that the same pattern is presents within two- and three-digit industries and whether or not we use sampling weights.

	(1) without multiplier	(2) with multiplier	(3) without multiplier	(4) with multiplier
employee_2	0.010***	0.013***	0.013***	0.015***
	(0.001)	(0.002)	(0.001)	(0.002)
employee_3	0.026***	0.025***	0.027***	0.028***
	(0.002)	(0.005)	(0.002)	(0.005)
employee_4	0.050***	0.060***	0.047***	0.058***
	(0.004)	(0.010)	(0.003)	(0.010)
employee_5	0.070***	0.064***	0.066***	0.065***
	(0.005)	(0.010)	(0.005)	(0.009)
employee_6_10	0.073***	0.048***	0.073***	0.051***
	(0.004)	(0.005)	(0.004)	(0.006)
employee_11_20	0.066***	0.033***	0.070***	0.037***
	(0.005)	(0.006)	(0.005)	(0.007)
employee_21_50	0.129***	0.066***	0.129***	0.073***
	(0.011)	(0.015)	(0.011)	(0.016)
employee_51_more	0.268***	0.076***	0.250***	0.082***
	(0.018)	(0.021)	(0.018)	(0.016)
_cons	0.039***	0.038***	0.038***	0.037***
	(0.001)	(0.001)	(0.001)	(0.001)
NIC2digits_FE	Yes	Yes		
NIC3digits_FE			Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A-8: 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

A-8 Breakdown of the Construction & Utility sector into PS and CS

This section explains how we split the construction & Utility sector into Consumer Service, Producers Service, and Public sectors. We obtain the information of major destinations for sale of final product/service from the "Informal Non-Agricultural Enterprises Survey 1999-2000" (INAES) dataset. Based on this information, we calculate the approximated share of employment in PS, CS, and Public, respectively at 5-digit industries level. We then apply these shares to NSS datasets to obtain the total PS/CS/Public share in the Construction sectors. For simplicity, we apply the same shares to the Utility sectors.

The following are detailed steps of how we calculate the PS shares in the construction sector.

1: Calculating 5-digits industry level PS/CS/PUBLIC share using INAES 1999-2000

The survey asks the following question: what is the destination agency for sale of final product/service? The choices are: 1-government; 2-cooperative / marketing society; 3-private enterprise; 4-contractor / middleman; 5-private individual / household; 6-no source agency; 9- others. We drop all firms that answer 6 or 9, and attribute firms that answer 1 into Public sector; firms that answer 2, 3 or 4 into PS sector; firms that answer 5 into CS sector. For each 5 digits industry, we calculate the relative employment shares of PS/CS/Public sectors.

2. Adjusting CS/PS/PUBLIC shares

From the description of National Industry Classification, some sectors are clearly for public purposes. We classify 5-digit level industries into Public and Private and the results are reported in table A-9. We assume that the new public share is 1 for Public construction, and is 0 for Private construction. For Private construction sectors, we calculate the revised PS/CS shares based on the relative magnitude of the old PS/CS shares.

Table A-9: National Sample Survey of India: summary statistics

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

3. Calculating the total sectoral employment based on revised shares

Finally, we apply the 5-digit industry level PS/CS/PUBLIC share to the employment data from the NSS datasets[23]. After summing across all 5-digit industries, we obtain total PS employment, CS employment, Public employment, and their relative shares. Table A-10 reports the results. We take the average across the shares comes from the NSS survey (round55, round60, round64, round66) weighted by the total construction employment of each round.To be concluded, 12.2% of employment belongs to the PUBLIC. In the remaining employment, 13.1% belong to PS and 86.9% belong to CS. We apply the same rule to the utility sector.

Table A-10: Sectoral employment share of the construction sector

	round 55-1999	round 60-2004	round 64-2007	round 66-2009
CS employment share	0.786	0.771	0.782	0.731
PS employment share	0.121	0.118	0.117	0.109
Public employment	0.093	0.111	0.101	0.160
PS/(PS+CS)	0.133	0.133	0.130	0.130
Total Construction employment	9921	5995	15356	17708

A-9 Relative Agricultural Price to Manufacturing

This section introduces how we calculate the relative prices of agricultural goods to manufacturing goods. Ministry of Planning and Program Implementation (MOSPI) of Government of India reports GDP by 2-digit sectors at current

[23](Shengqi: I will check if we can use NSS 43 and 68 with the new method) Conceptually, most residential construction firms belong to CS, and nonresidential construction firms belong to PS and Public, so we need to separate them. However, NSS 43rd round (uses NIC 1970) and NSS 68th round (uses NIC2008) do not distinguish between residential and nonresidential construction. So, we can only use NSS 55th, 60th (use NIC 1987), NSS 64th, and 66th round (use NIC 2004).

prices and constant prices from 1950-2013[24] We construct the price index for agricultural and manufacturing goods respectively by:

$$p_i = \frac{\text{GDP at current price}_i}{\text{GDP at constant price}_i}$$

We normalized both price indexes in the year 2005 to 1. Then we calculate the relative price by:

$$p_{relative} = \frac{p_{agri}}{p_{manu}}$$

To check the validity of our results, we also use two extra data sources to calculate the relative price. The first is the GGDC 10-Sector Database[25], which provides long-run data on sectoral productivity performance in Africa, Asia, and Latin America. Variables covered in the data set are annual series of value-added at current national prices, value-added at constant 2005 national prices, and persons employed for 10 broad sectors. 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[26]. The WPI tracks ex-factory price for manufactured products, agri-market (mandi) 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.

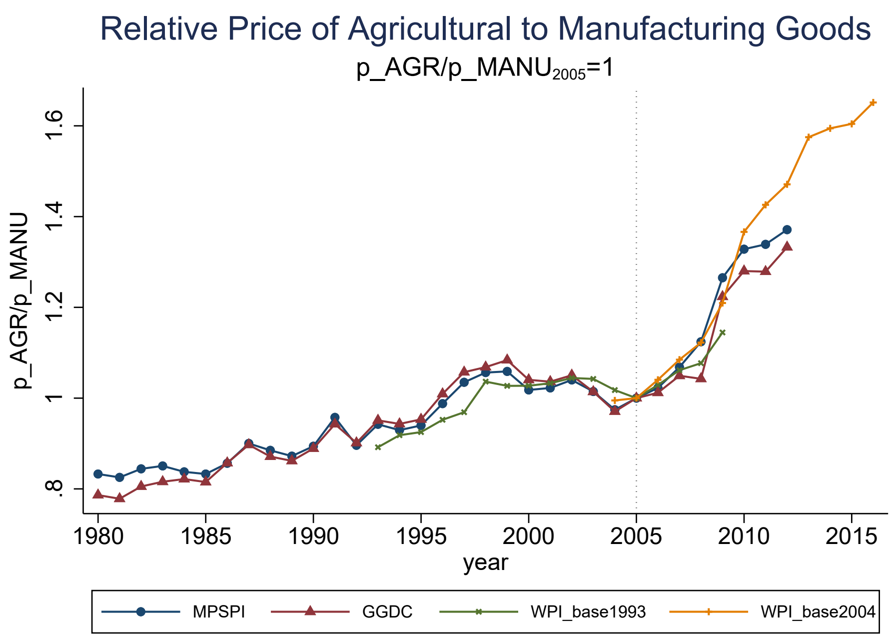

Figure A-3: Relative price of agricultural to manufacturing goods

In Figure A-3 we plot the relative price of agricultural goods to manufacturing goods. Since the pattern from different sources are very similar, we use the results based on MOPSI in the analysis.

[24]The data is available at `http://www.mospi.gov.in/data` 1. Summary of macro economic aggregates at current prices, 1950-51 to 2013-14

2. Summary of macro economic aggregates at constant(2004-05) prices, 1950-51 to 2013-14

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

[26]The data is available at `https://eaindustry.nic.in/`

Panel c: Sectoral Income by Urbanization (1987)　　Panel d: Sectoral Income by Urbanization (2011)

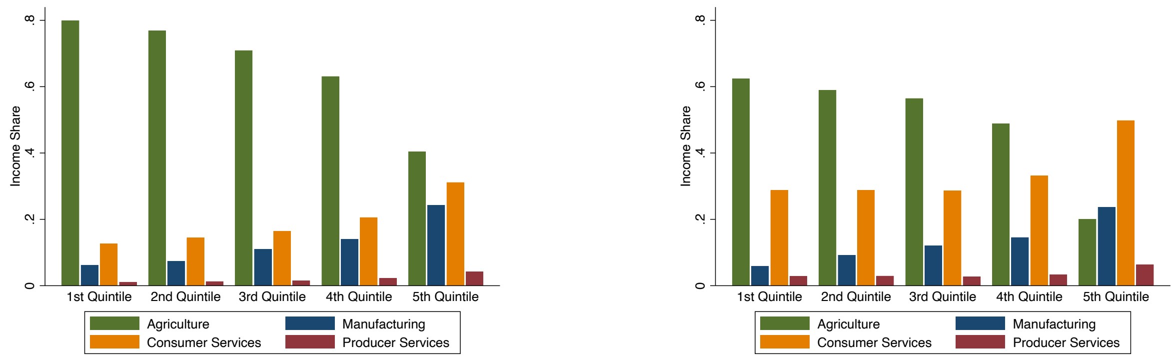

Figure A-4: Spatial Structural Change in India. The figure plots plots the sectoral income shares by urbanization quintile in 1987 and 2011.

A-10 Spatial Structural Change: Sectoral Income

A-11 Spatial Counterfactuals

A-12 Open economy

Thus far, we have treated India as a closed economy. However, international trade has become increasingly important for India, which is today among the fifteen largest exporting nations worldwide. In this section we extend the model to an open economy environment.

We introduce trade by assuming that consumers, both in India and in the rest of the world, consume industrial goods sourcing from many countries. Different national varieties–which are in turn aggregations of regional varieties–enter as imperfect substitutes into a CES utility function. In addition, we recognize that some international trade involves services. Because in our model services are local goods, this extension requires that we introduce a new separate category of services that is traded internationally.

Import of Goods We assume that the consumption of the physical good is a combination of domestic and imported goods with a constant elasticity of substitution:

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

Here, $C_{G,D}$ and $C_{G,ROW}$ are the physical quantities of the domestic and imported physical good, φ is a taste parameter capturing the preference for the imported good, and η 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

$$P_G = \left(p_{G,D}^{1-\eta} + \varphi^{\eta} p_{G,ROW}^{1-\eta} \right)^{\frac{1}{1-\eta}} . \tag{A-4}$$

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-4) yields the expenditure shares

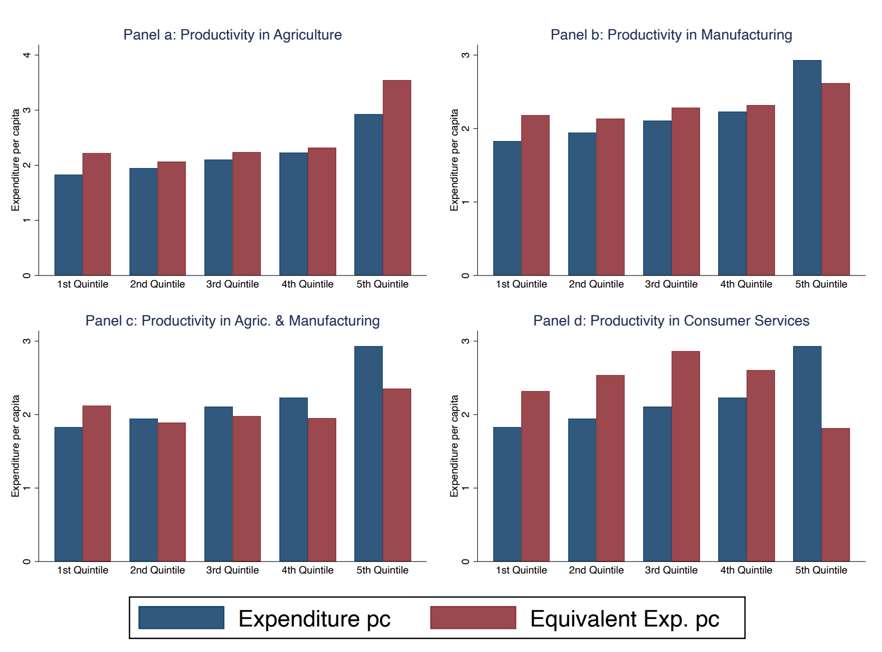

Figure A-5: Welfare Effects in Spatial Counterfactuals. The figure shows the expenditure per capita in India in 2011 by urbanization quintile (where the average expenditure per capita in 1987 is set equal to unity) according to the NSS data and the welfare-equivalent expenditure by urbanization quintile in 2011 corresponding to spatial counterfactual experiments. The spatial counterfactual experiments consist of setting the productivity in agriculture, manufacturing, agriculture and manufacturing, and consumer services to the respective national medians in 2011.

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

Although we do not model explicitly trade costs, these are reflected in the relative price of foreign goods.

Exports The domestic economy is assumed to export both domestic goods and a special category of services that is traded internationally. Adding such a category allows us to focus on the export of ICT services that is empirically important in the case of India.

Consider, first, the export of goods. We model total spending on domestic goods (in term of domestic goods) from the foreigner sector as

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

where Υ_G is a demand shifter for goods. For simplicity we assume the price elasticity of exports and imports to be the same. $X_{G,D}$ is the total sales of domestic goods exporters.

Figure A-6: Structural Change in Spatial Counterfactuals (A_F and A_M). The figure shows the changes in the 2011 sectoral employment shares in a counterfactual experiment setting A_F and A_M simultaneously to the respective national median in 2011.

Figure A-7: Structural Change in Spatial Counterfactuals (A_{CS}). The figure shows the changes in the 2011 sectoral employment shares in a counterfactual experiment setting A_{CS} to its national median in 2011.

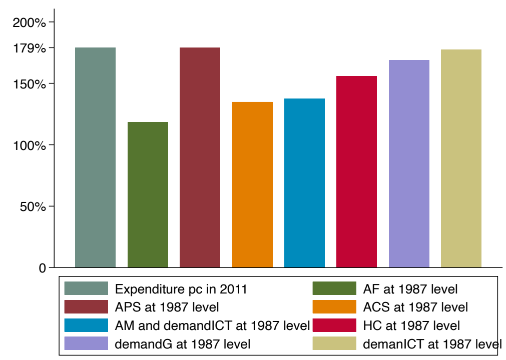

Figure A-8: Welfare In Open Economy. The figure plots plots the aggregate welfare changes for the model with international trade.

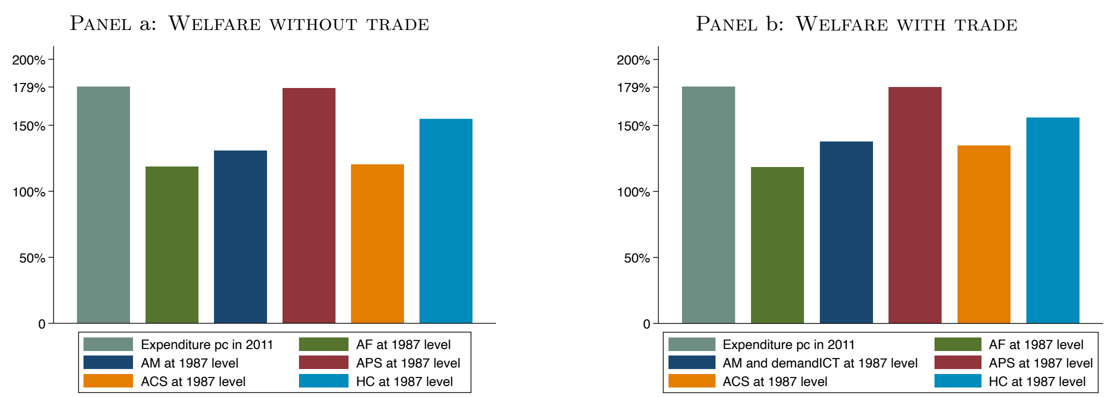

Figure A-9: Welfare In Open Economy. The figure plots the aggregate welfare changes for the closed-economy model (Panel a) and the model with international trade (Panel b).

Consider, next, the exported (ICT) services. For simplicity, we assume that ICT services are not sold in the domestic market.[27] We assume that the foreign sector buys a bundle of regional varieties ICT services

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

where y_{rICTt} denotes the quantity of services produced in region r and exported to the rest of the world. Suppose that ICT services are produced in region r according to the following production function:

$$y_{rICTt} = A_{rICTt} L_{rt}.$$

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

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

Trade Imbalance When trade is not balanced, household expenditure must be adjusted to clear the physical goods markets. Let T denotes the (possibly, negative) trade surplus. When $T \neq 0$, we redistribute T to households using wages as weights. More formally, we assume that households' expenditure in region r equals $e_r = w_r - \tau_r$, where $\tau_r = \frac{w_r L_r}{\sum_j w_j L_j} T$. A detailed description of the set of equilibrium conditions is provided in the appendix, see Section A-17.

In our estimation, we assume balanced trade. Under this assumption, market clearing for manufacturing varieties yields, for each region,

$$w_r L_{rG} = \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}} \right) \times \left(\sum_{j=1}^{R} \vartheta_{jG} w_j L_j - \sum_{r} w_r L_{rICT} \right). \tag{A-5}$$

An inspection of (A-5) shows that it is identical to the analogue no-trade equilibrium condition, except for the term $\sum_r w_r L_{rICT}$ that is subtracted on the RHS. Thus, conditional on the expenditure share ϑ_{jG}, it identifies a set of relative $a_{rG} \equiv A_{rG}/A_G$ exactly as it did in the no-trade equilibrium. Intuitively: if the domestic economy exports ICT services and trade is balanced, the value added of ICT exports is exactly equal to the net imports of manufacturing products. Hence, $\sum_{j=1}^{R} \vartheta_{jG} w_j L_j - \sum_r w_r L_{rICT}$ is exactly the manufacturing value added produced domestically, which gets distributed across regions according to the trade shares $\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}}$.

Estimating the model requires, as usual, to invert these relationships, so as to identify productivities, expenditure shares, and parameters from the observable distribution of employment and expenditure, and from the trade flows. Relative to the closed-economy environment, in the equilibrium with trade, we estimate the following additional $R+4$ parameters:

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

We externally calibrate η, based on the evidence in the trade literature. Then, Υ_G and Υ_{ICT} are estimated to match the total trade flow and its composition between goods and services. The model nests the no-trade equilibrium as a special case in which $\Upsilon_G = \Upsilon_{ICT} = 0$, and $p_{G,ROW} \to \infty$.

[27]We could model ICT as tradable services that are also consumed domestically , similar to the manufacturing good. Because ICT accounts for a very small share of employment, this alternative approach would not alter our main results.

A-12.1 Calibration

We set the trade elasticity $\eta = 5$ in line with the estimates in the literature–see, e.g., Simonovska and Waugh (2011).

In our quantitative analysis, we focus on trade in goods and ICT services. We ignore trade in services other than ICT, because this would require additional modifications of the model. If we abstract from the export of ICT, the import and export of other services is approximately balanced.

According to the World Bank data, the export of goods and merchandise increased from 11.3bn USD (4.1% of GDP) in 1987 to 302.9bn USD (16.6% of GDP)–in current USD. The manufacturing sector accounted for 66% of such merchandise exports in 1987 for and 62% in 2011. According to the OECD, the domestic value added in gross exports amounts to 83.9% of exports in India (there is no time series, so we assume this to be constant). In accordance with these data, we assume that the value added export of trade has increased from 13.9% in 1987 to 53.6% in 2011 as a share of the GDP in the manufacturing sector.[28]

Next, we must determine the share of ICT exports. We classify as ICT service workers all those employed in the following service industries: telecommunications, computer programming, consultancy and related activities software publishing, and information service activities. In our NSS data, this comprises 2.16% of employment in the service sector and 0.67% of total employment in 2011 (in 1987, it was 0.1% of total employment). ICT workers earn on average higher wages than other workers. When one consider the earning share, they account for 3.85% of earnings in the service sector and 1.52% of total earnings in 2011 (in 1987, it was a 0.18% of total earnings).[29] Since ICT export was negligible in 1987, we assume it was zero. The target moment is then the revenue share of ICT in 2011. To this aim, we consider two alternatives.

1. We follow the NSS data and assume that all services produced by ICT workers and only those are exported. This choice trades off different error margins. On the one hand, not all the services produced by these sector are exported. On the other hand, there are other services that are exported. This approach appears to underestimate the value added component of ICT services. Total ICT export amounts to 62.1 billion USD in 2011. Multiplying this gross figure by 83.9% (to target domestic value added), we obtain an export share in ICT equal to 2.9% of the Indian GDP, almost twice as high as in our data.

2. We target directly the 2.9% earning share in the data. Then, we allocate the earnings across Indian districts proportionally to the share of ICT services in our NSS data.

Finally, we assume trade balance and determine imports residually. In reality, India run a balance of payment deficit in 2011. While it would not be difficult to incorporate a trade imbalance, we find it more natural to introduce the same resource constraint in the two years considered, since our model focuses on long-term issues.

A-12.2 Results

The results of the estimation of the open-economy model are overall similar to those for the benchmark closed-economy model. Figure A-9 shows the welfare results of the counterfactual simulation in which we shut down productivity growth 1987-2011 in each of the sectors. The results of the closed-economy model are also displayed for comparison. The differences between the closed and open economy models are barely noticeable. The figure displays the estimation results in which the ICT service accounts for 1% of total earnings in 2011, consistent with our NSS data. We have also run the counterfactual exercise for the alternative economy in which the ICT sector is twice as large as in our data–corresponding to a GDP share of ICT that is slightly larger than the value of ICT exports in the data. The results are again similar. In particular, resetting productivity in the consumer service sector at its 1987 level is equivalent to a 15% reduction in consumption in the closed economy, to a 6% reduction in the open economy, and to a to a **12% increase** in the open economy with a large ICT export sector.

The model also allows us to assess the welfare effects of international trade. To this aim, we counterfactually set $\Upsilon_G = \Upsilon_{ICT} = 0$, and $p_{G,ROW} \to \infty$, which corresponds to shutting down trade. The welfare effects are modest: they are equivalent to a fall in consumption by 6% in the open-economy equilibrium for 2011.

[28] This corresponds to an increase in the value added of exports from 6.26bn USD to 157.6bn USD (in current USD).

[29] If we multiply 0.67% by the total size of the labor force in 2011, our estimate corresponds to 3.1 million workers being employed in the ICT sector. This is in the ballpark of the exisiting estimates.

A-13 Spatial Accounting

Consider a single period for now. We observe $\left\{\left[w_r^D\right]_r, H_{F,r}, H_{M,r}, H_{CS,r}\right\}_r$. I 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. We want to infer $[A_{F,r}, A_{Mr}, A_{CS,r}]_r$.

Step 1: Getting *relative* food productivities and *relative* manufacturing productivities Again, it is useful to write productivities as

$$\begin{aligned} A_{Fr} &= A_F a_{Fr} \text{ with } \sum_{r=1}^{R} a_{Fr}^{\sigma-1} = 1 \\ A_{Mr} &= A_M a_{Mr} \text{ with } \sum_{r=1}^{R} a_{Fr}^{\sigma-1} = 1. \end{aligned}$$

Then,

$$a_{Fr} = \left(\frac{H_{F,r} w_r^\sigma}{\sum_{r=1}^R (H_{F,r}) w_r^\sigma}\right)^{\frac{1}{\sigma-1}} \tag{A-6}$$

$$a_{Mr} = \left(\frac{H_{M,r} w_r^\sigma}{\sum_{r=1}^R (H_{M,r}) w_r^\sigma}\right)^{\frac{1}{\sigma-1}} \tag{A-7}$$

This means we have $R+2$ unknowns left

$$A_F, A_M, \{A_{CSr}\}_{r=1}^R.$$

Note a_{Fr} and a_{Mr} are insensitive to the level of w_r.

Step 2: Getting A_F and A_M The two prices of the tradable goods are

$$\begin{aligned} p_{Ft} &= \left(\sum_r \left(\frac{w_r}{A_{F,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \frac{1}{A_F}\left(\sum_r \left(\frac{w_r}{a_{F,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \\ p_{Mt} &= \left(\sum_r \left(\frac{w_r}{A_{M,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \frac{1}{A_M}\left(\sum_r \left(\frac{w_r}{a_{M,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \end{aligned}$$

Note that $\left(\sum_r \left(\frac{w_r}{a_{F,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ and $\left(\sum_r \left(\frac{w_r}{a_{M,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ are observable from (A-6) and (A-7) and are homogenous of degree 1 as a_{Fr} and a_{Mr} is homogeneous of degree zero. Hence, let us write

$$\Lambda_F^w \equiv \left(\sum_r \left(\frac{w_r}{a_{F,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{A-8}$$

$$\Lambda_M^w \equiv \left(\sum_r \left(\frac{w_r}{a_{M,r}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{A-9}$$

where $\Lambda_s^w(w)$ is known. I put the superscript "w" to highlight that this is HD1 in the level of wages. To determine A_F and A_M we need two restrictions:

1. First we choose the manufacturing good as the numeraire. This determines A_M as

$$p_{Mt} = 1 \qquad \Longrightarrow \qquad A_M = \Lambda_M^w.$$

   Note that an increase in w by a common factor increases A_M by the same amount.

2. Now suppose we observe the relative price of agriculture relative to manufacturing p_t^{AM}. Then

$$p_t^{AM} = \frac{p_t^A}{p_t^M} = \frac{A_F^{-1}\Lambda_F^w}{A_M^{-1}\Lambda_M^w} = A_F^{-1}\Lambda_F^w.$$

Hence, given p_t^{AM}, we can identify A_F. For a given relative price p_t^{AM}, a common increase in wages w increases A_F by the same amount.

Step 3: Getting $\{A_{CSr}\}_{r=1}^R$ and the structural parameters To derive (A-6) and (A-7) we used $R-1$ equations, i.e. all relative trade shares in the tradable sectors. This means that we still have the R equations for the non-tradable CS sector and the two aggregate resource constraints for the traceable goods. These are **Edited**

$$\begin{aligned}
\frac{H_{CSr}}{H_r} &= \omega_{CS} + \tilde{\nu}_{CS}\left(p_{At}^{\omega_A} p_{CSrt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon} && \text{(A-10)}\\
\sum_r w_r H_{Fr} &= \sum_{j=1}^R \left(\omega_A + \tilde{\nu}_A\left(p_{At}^{\omega_A} p_{CSjt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_j H_j && \text{(A-11)}\\
\sum_r w_r H_{M,r} &= \sum_{j=1}^R \left(\left(1-\omega_A-\omega_{CS}\right) - \left(\tilde{\nu}_A+\tilde{\nu}_{CS}\right)\left(p_{At}^{\omega_A} p_{CSjt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_j H_j && \text{(A-12)}
\end{aligned}$$

Note first that equation (A-12) is redundant, it is implied by (A-10) and (A-11) due to Walras' Law.[30] Substituting the numeraire assumption $p_{Mt} = 1$ and the fact that $p_{At} = p_t^{AM}$, where p_t^{AM} is the relative price we are targeting and $p_{CSrt} = \frac{w_{rt}}{A_{CSrt}}$ yields **Edited**

$$\begin{aligned}
\frac{H_{CSr}}{H_r} &= \omega_{CS} + \tilde{\nu}_{CS}\left(p_t^{AM}\right)^{\varepsilon\omega_A}\left(\frac{w_{rt}}{A_{CSr}}\right)^{\varepsilon\omega_{CS}}\left(h_r w_{rt}\right)^{-\varepsilon} && \text{(A-13)}\\
\sum_r w_r H_{F,r} &= \omega_A \sum_{j=1}^R w_j H_j + \tilde{\nu}_A\left(p_t^{AM}\right)^{\varepsilon\omega_A}\sum_{j=1}^R\left(\frac{w_{jt}}{A_{CSj}}\right)^{\varepsilon\omega_{CS}} h_r^{-\epsilon} w_{jt}^{1-\varepsilon} H_j. && \text{(A-14)}
\end{aligned}$$

For a given year these are $R+1$ equations in R productivities $\{A_{CSr}\}$ and 4 structural parameters $(\omega_{CS}, \omega_A, \tilde{\nu}_A, \tilde{\nu}_{CS})$ (recall that we take ε as given because we estimate it from the expenditure shares). If we have T years, we have

$$\begin{aligned}
\text{Number of unknowns} &= TR + 4\\
\text{Number of equations} &= T\left(R+1\right) = TR + T.
\end{aligned}$$

Hence, by insisting that preferences are constant over time, we add over-identifying restrictions if we add additional years to our analysis. Note that (A-13) implies that **Edited**

30

$$\begin{aligned}
\sum_r w_r H_{M,r} + \sum_r w_r H_{CSr} &= \sum_{j=1}^R \left(\left(1-\omega_A-\omega_{CS}\right) - \left(\tilde{\nu}_A+\tilde{\nu}_{CS}\right)\left(p_{At}^{\omega_A} p_{CSrt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_j H_j\\
&+ \sum_r \left(\omega_{CS} + \tilde{\nu}_{CS}\left(p_{At}^{\omega_A} p_{CSrt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_r H_r\\
\sum_r w_r\left(H_{M,r} + H_{CSr}\right) &= \sum_{j=1}^R \left(\left(1-\omega_A\right) - \tilde{\nu}_A\left(p_{At}^{\omega_A} p_{CSjt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_j H_j\\
\sum_r w_r\left(H_r - H_{F,r}\right) &= \left(1-\omega_A\right)\sum_{j=1}^R w_j H_j - \sum_r \tilde{\nu}_A\left(p_{At}^{\omega_A} p_{CSrt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon} w_r H_r\\
\sum_r w_r H_{F,r} &= \sum_{r=1}^R \left(\omega_A + \tilde{\nu}_A\left(p_{At}^{\omega_A} p_{CSrt}^{\omega_{CS}} p_{Mt}^{\omega_M}\right)^{\varepsilon}\left(h_r w_{rt}\right)^{-\varepsilon}\right) w_r H_r
\end{aligned}$$

$$\left(p_t^{AM}\right)^{\varepsilon\omega_A}\left(\frac{w_{rt}}{A_{CSr}}\right)^{\varepsilon\omega_{CS}} = -\frac{1}{\tilde{\nu}_{CS}}\left(\omega_{CS}-\frac{H_{CSr}}{H_r}\right)\left(h_r w_{rt}\right)^{\varepsilon}.$$

Hence, substituting this into (A-14) yields

$$\sum_r w_r H_{F,r} \quad = \quad \omega_A \sum_{r=1}^{R} w_r H_r - \frac{\tilde{\nu}_A}{\tilde{\nu}_{CS}} \sum_{r=1}^{R}\left(\omega_{CS}-\frac{H_{CSr}}{H_r}\right) w_{rt} H_r. \tag{A-15}$$

Given the data this is a single equation in ω_A, $\frac{\tilde{\nu}_A}{\tilde{\nu}_{CS}}$ and ω_{CS}. Note that (A-15) is HDZ, i.e. a common increase in the level of wages will leave ω_A, $\frac{\tilde{\nu}_A}{\tilde{\nu}_{CS}}$ and ω_{CS} unchanged. This leaves us with R equations for consumer service employment **Edited**

$$\frac{H_{CSr}}{H_r} = \omega_{CS} + \tilde{\nu}_{CS}\left(p_t^{AM}\right)^{\varepsilon\omega_A}\left(\frac{w_{rt}}{A_{CSr}}\right)^{\varepsilon\omega_{CS}}\left(h_r w_{rt}\right)^{-\varepsilon} = \omega_{CS} + \tilde{\nu}_{CS} A_{CSr}^{-\varepsilon\omega_{CS}}\left(p_t^{AM}\right)^{\varepsilon\omega_A} h_r^{-\epsilon} w_{rt}^{-\varepsilon(1-\omega_{CS})}$$

From (A-13) it is seen that $\tilde{\nu}_{CS}$ is not separately identified from the *level* of productivity in the consumer service sector: holding ω_{CS} and ε fixed, the data on wages w_{rt} and employment shares $\frac{L_{CSr}}{L_r}$ identifies $\tilde{\nu}_{CS} A_{CSr}^{-\varepsilon\omega_{CS}}$.

A-14 The Computational Algorithm

Step 1: Clean Data: For each year perform the following steps:

1. Normalize the size of the population to unity

$$1 = \sum_r L_{rt}$$

2. Normalize the level of wages to unity

$$1 = \sum w_{rt} L_{rt} \tag{A-16}$$

Step 2: Calculate human capital levels H_{rst} and H_{rt} To calculate the total supply of human capital in region r at time t we use the information on education attainment. Let r^E denote the yearly return to education. Suppose we have G groups of education attainment and group g has s_g years of schooling. Let l_{rgt} denote the share of people in region r at time t in education group g. We then calculate average human capital in region r at time t as

$$h_{rt} = \sum_{g=1}^{G} \exp(r^E s_g) l_{rgt}. \tag{A-17}$$

The aggregate supply of human capital is then given

$$H_{rt} = h_{rt} L_{rt}. \tag{A-18}$$

To calculate the distribution of human capital units across sectors *within* a location, we rely sectoral earnings shares, which in our theory are proportional to human capital units. Hence, we calculate H_{rst} as

$$H_{rst} = \frac{\sum_{i\in s} w_{rt}^i}{\sum_i w_{rt}^i} \times H_{rt}. \tag{A-19}$$

Here, w_{rt}^i denotes total earnings individual i in region r at time t observed in the micro data. Hence, $\sum_{i\in s} w_{rt}^i$ are aggregate earnings in sector s in region r and $\sum_i w_{rt}^i$ are aggregate earnings in region r. Hence, we use the information in human capital (schooling) to measure human capital differences across space and time and information on relative earnings to measure human capital differences across sectors within a location. For the remainder we treat H_{rst} and H_{rt} as known.

Step 3: Pick structural parameters For now set the following parameters

$$\begin{aligned}\varepsilon &= 0.297 \\ \omega_A &= 0.01 \\ \tilde{\nu}_{CS} &= -1\end{aligned}$$

Step 4: Calibrate remaining structural parameters to ensure market clearing in 1987 and 2011 Consider the market clearing condition in (A-15). Using (A-16), this can be written as

$$\begin{aligned}\sum_r w_{rt} H_{rFt} &= \omega_A \sum_{r=1}^{R} w_{rt} H_{rt} + \tilde{\nu}_A \sum_{r=1}^{R} \left(\omega_{CS} - \frac{H_{rCSt}}{H_{rt}}\right) w_{rt} H_{rt} \\ &= \omega_A + \tilde{\nu}_A \omega_{CS} - \tilde{\nu}_A \sum_{r=1}^{R} H_{rCSt} w_{rt}.\end{aligned}$$

Given ω_A, chose $\tilde{\nu}_A$ and ω_{CS} to solve the two equations

$$\begin{aligned}\sum_r w_{r1987} H_{rF1987} &= \omega_A + \tilde{\nu}_A \omega_{CS} - \tilde{\nu}_A \sum_{r=1}^{R} H_{rCS1987} w_{r1987} \\ \sum_r w_{r2011} H_{rF2011} &= \omega_A + \tilde{\nu}_A \omega_{CS} - \tilde{\nu}_A \sum_{r=1}^{R} H_{rCS2011} w_{r2011}\end{aligned}$$

Step 5: Calibrate relative productivities a_{rFt} and a_{rMt} Equations (A-6) and (A-7) allows us measure a_{rFt} and a_{rMt} directly from the data. I replicate these equations here for convenience:

$$\begin{aligned}a_{rF} &= \left(\frac{L_{F,r} w_r^{\sigma}}{\sum_{r=1}^{R} (L_{F,r}) w_r^{\sigma}}\right)^{\frac{1}{\sigma-1}} \\ a_{rM} &= \left(\frac{L_{M,r} w_r^{\sigma}}{\sum_{r=1}^{R} (L_{M,r}) w_r^{\sigma}}\right)^{\frac{1}{\sigma-1}}\end{aligned}$$

Note that these are insensitive to the scale of w_{rt}

Step 6: Calculate the level of productivity in manufacturing and agriculture in 1987 Given the price normalization $p_{M1987} = 1$ and the observed relative price p_{1987}^{AM}, calculate A_{M1987} and A_{F1987} as

$$\begin{aligned}A_{M1987} &= \left(\sum_r \left(\frac{w_{r1987}}{a_{rM1987}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \\ A_{F1987} &= \frac{1}{p_{1987}^{AM}} \left(\sum_r \left(\frac{w_{r1987}}{a_{rF1987}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}\end{aligned}$$

Step 7: Calculate the level of productivity in consumer services in 1987 From (A-13) we get that $A_{rCS1987}$ solves the equation **Edited**

$$\frac{H_{rCS1987}}{H_r} = \omega_{CS} - \left(p_{1987}^{AM}\right)^{\varepsilon\omega_A} \left(\frac{w_{r1987}}{A_{rCS1987}}\right)^{\varepsilon\omega_{CS}} \left(h_{r1987} w_{r1987}\right)^{-\varepsilon}$$

Step 7: Calculate physical quantities in 1987 The physical quantities of consumption in 1987 are given by

$$
\begin{aligned}
y_{rCS1987} &= A_{rCS1987} L_{rCS1987} \\
y_{F1987} &= \frac{\text{Spending on agricultural goods}}{P_{A1987}} = \frac{\text{Income in agriculture}}{P_{A1987}} \\
&= \frac{\sum_r w_{r1987} L_{rF1987}}{p^{AM}_{1987}} \\
y_{M1987} &= \sum_r w_{r1987} L_{rM1987}
\end{aligned}
$$

Step 8: Find the right scale in 1999

- Pick a scalar λ^{1999}.
- Calculate A_{M1999} and A_{F1999} as

$$
\begin{aligned}
A_{M1999} &= \left(\sum_r \left(\frac{\lambda^{1999} w_{r1999}}{a_{rM1999}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = \lambda^{1999} \left(\sum_r \left(\frac{w_{r1999}}{a_{rM1999}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \\
A_{F1999} &= \frac{1}{p^{AM}_{1999}} \left(\sum_r \left(\frac{\lambda^{1999} w_{r1999}}{a_{rF1999}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = \frac{\lambda^{1999}}{p^{AM}_{1999}} \left(\sum_r \left(\frac{w_{r1999}}{a_{rF1999}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}
\end{aligned}
$$

- Calculate

A-15 Estimating the Pareto Tail ζ

A-16 Equilibrium in the Industrial Sector

In this section we characterize the equilibrium in the industrial sector. The technical details are deferred to Appendix B, available upon request from the authors. As highlighted in Proposition 1, we have to distinguish two cases. In particular, it is useful to define the statistic

$$\vartheta \equiv \frac{\kappa}{f_0 A_{PS}}. \tag{A-20}$$

Below we will show that some active firms do not hire lawyers if and only if

$$\vartheta \geq \frac{\beta}{1-\alpha}. \tag{A-21}$$

Note that ϑ is deceasing in A_{PS} (see (A-20)). Hence, condition (A-21) requires the productivity of lawyers A_{PS} to be low enough.

A-16.0.1 Firm-level allocations

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

$$\pi(z_i) = \max_{L_{PMi}, L_{PSi} \geq 0} \left\{ p_G z_i^{1-\alpha-\beta} L_{PMi}^{\alpha} \left(A_{PS} L_{PSi} + \kappa\right)^{\beta} - w\left(L_{PMi} + L_{PSi}\right) - f_O w \right\}. \tag{A-22}$$

where $f_O w$ denotes the overhead costs. Note that we explicitly impose the constraint that $L_{PSi} \geq 0$. Firms operate if and only if $\pi(z_i) \geq 0$. We denote the productivity threshold by z^*, i.e., $\pi(z^*) = 0$. Under the condition (7), $z^* > A_M$, namely, there is a range of low-productivity firms that choose to be inactive.

Proposition 2. *Suppose that $\vartheta \geq \frac{\beta}{1-\alpha}$, where ϑ is given in (A-20). Let z^* denote the endogenous productivity threshold, such that firm with $z_i \geq z^*$ will produce in equilibrium. Define*

$$z_L = z^* \left(\frac{1-\alpha}{\beta} \vartheta \right)^{\frac{1-\alpha}{1-\alpha-\beta}}, \tag{A-23}$$

Then:

1. *The productivity threshold is given by*

$$z^* = \left(\frac{w}{p_G} \frac{1}{\kappa^{\beta} \alpha} \left(\frac{\alpha}{1-\alpha} f_O \right)^{1-\alpha} \right)^{\frac{1}{1-\alpha-\beta}}. \tag{A-24}$$

2. *Optimal factor demands are given by*

$$L_{PS}(z_i) = \begin{cases} 0 & \text{if } z_i < z_L \\ \vartheta \frac{z_i - z_L}{z_L} f_0 & \text{if } z_i \geq z_L \end{cases}, \tag{A-25}$$

i.e. a firm hires lawyers if and only if $z \geq z_L$. Moreover,

$$L_{PM}(z_i) = \begin{cases} \frac{\alpha}{\beta} f_O \vartheta \left(\frac{z_i}{z_L} \right)^{\frac{1-\alpha-\beta}{1-\alpha}} & \text{if } z_i < z_L \\ \frac{\alpha}{\beta} \vartheta \frac{z_i}{z_L} f_0 & \text{if } z_i \geq z_L \end{cases}. \tag{A-26}$$

3. *Firm-level profits are given by*

$$\pi(z_i) = \begin{cases} \left(\frac{1-\alpha}{\beta} \vartheta \left(\frac{z_i}{z_L} \right)^{\frac{1-\alpha-\beta}{1-\alpha}} - 1 \right) f_O w & \text{if } z_i < z_L \\ \left(\vartheta \left(1 + \left(\frac{1-\alpha-\beta}{\beta} \right) \frac{z_i}{z_L} \right) - 1 \right) f_O w & \text{if } z_i \geq z_L \end{cases}. \tag{A-27}$$

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

Note that (A-23) determines z_L directly as a function of z^* and that under our assumption that $\vartheta > \frac{\beta}{1-\alpha}$ indeed $z^* < z_L$ and all firms with $z_i \in [z^*, z_L]$ do not hire lawyers. As $\vartheta \to \frac{\beta}{1-\alpha}$, we have $z^* \to z_L$. Note also that the profit function in (A-27) is concave in z as long firms do not hire lawyers but linear in z once they hire lawyers.

Proposition 3. *Suppose that* $\vartheta < \frac{\beta}{1-\alpha}$*, where* ϑ *is given in* (A-20)*. 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*

$$\tilde{z} = \frac{1}{1-\alpha-\beta}\left(\frac{w}{p_G}\right)^{\frac{1}{1-\alpha-\beta}}\left(\frac{1}{\alpha}\right)^{\frac{\alpha}{1-\alpha-\beta}}\left(\frac{1}{\beta A_{PS}}\right)^{\frac{\beta}{1-\alpha-\beta}} f_O\left(1-\vartheta\right). \tag{A-28}$$

2. *Optimal factor demands are given by*

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

3. *Firm-level profits are given by*

$$\pi\left(z_i\right) = \pi\left(z_i\right) = \left(\frac{z-\tilde{z}}{\tilde{z}}\right) f_O\left(1-\vartheta\right) w. \tag{A-29}$$

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

A-16.0.2 Free Entry and the Equilibrium Wage

Free entry requires that the cost of entry are equal 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* $\vartheta \geq \frac{\beta}{1-\alpha}$*. Then*

$$\left(\frac{z_L}{A_M}\right)^{\lambda} = \frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[\left(\vartheta\frac{1-\alpha}{\beta}\right)^{\lambda\frac{1-\alpha}{1-\alpha-\beta}} + \frac{\vartheta}{\lambda-1}\right]\frac{f_O}{f_E} \tag{A-30}$$

$$\left(\frac{z^*}{A_M}\right)^{\lambda} = \frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[1+\frac{1}{\lambda-1}\left(\frac{\beta}{1-\alpha}\right)^{\frac{(1-\alpha)\lambda}{1-\alpha-\beta}}\vartheta^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right]\frac{f_O}{f_E}, \tag{A-31}$$

and

$$\frac{w}{p_G} = \left(\frac{z_L}{\kappa}\right)^{1-\alpha-\beta}\alpha^{\alpha}\left(\beta A_{PS}\right)^{1-\alpha} \tag{A-32}$$

$$= \left(\frac{(1-\alpha-\beta)}{\beta+(1-\alpha)(\lambda-1)}\left[1+\frac{1}{\lambda-1}\left(\frac{\beta}{1-\alpha}\right)^{\frac{(1-\alpha)\lambda}{1-\alpha-\beta}}\vartheta^{-\frac{(1-\alpha)(\lambda-1)+\beta}{1-\alpha-\beta}}\right]\frac{f_O}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}} A_M^{1-\alpha-\beta}\kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha}{f_0}\right)^{1-\alpha} \tag{A-33}$$

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

$$\left(\frac{\tilde{z}}{A_M}\right)^{\lambda} = \frac{1}{\lambda-1}\frac{f_O}{f_E}\left(1-\vartheta\right), \tag{A-34}$$

and

$$\frac{w}{p_G} = \left(\frac{\tilde{z}\left(1-\alpha-\beta\right)}{f_O\left(1-\vartheta\right)}\right)^{1-\alpha-\beta}\left(\beta A_{PS}\right)^{\beta}\left(\alpha\right)^{\alpha} \tag{A-35}$$

$$= \left(1-\alpha-\beta\right)^{1-\alpha-\beta}\left(\frac{1}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}\left(\frac{1}{f_O\left(1-\vartheta\right)}\right)^{\frac{\lambda-1}{\lambda}\left(1-\alpha-\beta\right)} A_M^{1-\alpha-\beta}\left(\beta\frac{\kappa}{f_0\vartheta}\right)^{\beta}\left(\alpha\right)^{\alpha}. \tag{A-36}$$

Proof. See Section OA-1.3 in the 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 ϑ 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, $\frac{\partial z^*}{\partial A_{PS}} > 0$.[31] Because ϑ is decreasing in A_{PS}, the real wage is increasing in A_{PS}.[32]

A-16.0.3 Aggregate Labor Allocations

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

$$L_G = L_{PS} + L_{PM} + L_{EM} + L_{OM}.$$

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

$$L_{EM} = \frac{1-\alpha-\beta}{\lambda}L_G$$
$$L_{PM} = \alpha L_G$$

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

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

[32]Taking logs

$$\log\left(\frac{w}{p_G}\right) = \log\left(\left(\kappa\right)^{-(1-\alpha-\beta)}\alpha^{\alpha}\beta^{1-\alpha}\right) + \left(1-\alpha-\beta\right)\log\left(z_L\right) + \left(1-\alpha\right)\ln A_{PS},$$

where the first term is a constant. Note that z_L is decreasing in A_{PS} (as A_{PS} increases, more firms hire lawyers and the threshold falls), so there are in principle two opposite effects. However, we establish in the appendix that the positive (direct) effect dominates. More formally,

$$\begin{aligned}\frac{\partial}{\partial A_{PS}}\log\left(\frac{w}{p_G}\right) &= \left(1-\alpha-\beta\right)\frac{\partial\log\left(z_L\right)}{\partial A_{PS}} + \left(1-\alpha\right)\frac{1}{A_{PS}}\\ &= -\left(1-\alpha-\beta\right)\psi\left(A_{PS}\right)\frac{1}{A_{PS}} + \left(1-\alpha\right)\frac{1}{A_{PS}}\\ &= \beta\psi\left(A_{PS}\right)\frac{1}{A_{PS}} + \left(1-\alpha\right)\left(1-\psi\left(A_{PS}\right)\right)\frac{1}{A_{PS}} > 0\end{aligned}$$

where

$$\psi\left(A_{PS}\right) \equiv \frac{\lambda\frac{1-\alpha}{1-\alpha-\beta}f_O\left(\frac{\kappa(1-\alpha)}{\beta A_{PS}f_O}\right)^{\lambda\frac{1-\alpha}{1-\alpha-\beta}} + \frac{\kappa}{A_{PS}(\lambda-1)}}{\lambda f_O\left(\frac{\kappa(1-\alpha)}{\beta A_{PS}f_O}\right)^{\lambda\frac{1-\alpha}{1-\alpha-\beta}} + \lambda\frac{\kappa}{A_{PS}(\lambda-1)}} \in (0,1). \tag{A-37}$$

Thus, the wage is increasing in A_{PS}.

independent of ϑ. The number of firms, M, is given by

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

independent of ϑ. The number of lawyers and overhead workers is given by

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

and

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

where

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

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

Note that $L_{PS} = \Xi(A_{PS})$, where $\Xi(A_{PS})$ is consistent with the expression in Proposition 1 for the case in which $\frac{\kappa}{f_O A_{PS}} > \frac{\beta}{1-\alpha}$. In particular, L_{PS} is increasing in A_{PS}, whereas L_{OM} is decreasing in A_{PS}. Interestingly, their sum is independent of A_{PS}, i.e.

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

This also implies that the endogenous number of firms M is given by

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

Hence, the number of ideas, which is generated does not depend on A_{PS}. But the number of ideas, which are actually implemented 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 A_M. This is in contract to the the micro-level, where employment shares vary systematically with firm productivity. In particular, (A-25) and (A-26) imply that for firms that hire lawyers (i.e. $z_i \geq z_L$) we have

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

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

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

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 explicitly on the tail of the productivity distribution λ. A thicker tail, i.e. λ smaller, *increases* the aggregate employment share of lawyers by shifting resources towards large firms, which are lawyer intensive.

A-16.0.4 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

$$p_G Y_G = wL_G.$$

Proposition 6. *Let aggregate productivity A_G be defined by*

$$\frac{Y_G}{L_G} = A_G.$$

Then,

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

where

$$Q_1 = \left(\frac{(1-\alpha-\beta)}{\beta + (1-\alpha)(\lambda-1)}\frac{f_O}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}} \kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha}{f_0}\right)^{1-\alpha}$$

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 ϑ), the level of productivity A_M, the overhead cost f_O and the entry cost f_E . Note that A_G is continuous in ϑ and satisfies

$$\lim_{\vartheta\to\infty} A_G = \left(\frac{(\lambda-1)(1-\alpha)}{\beta+(1-\alpha)(\lambda-1)}\right)^{\frac{1-\alpha-\beta}{\lambda}} \kappa^{\beta}\alpha^{\alpha}\left(\frac{1-\alpha-\beta}{\lambda-1}\frac{1}{f_E}\right)^{\frac{1-\alpha-\beta}{\lambda}}\left(\frac{1-\alpha}{f_0}\right)^{\frac{(\lambda-1)(1-\alpha)+\beta}{\lambda}} A_M^{1-\alpha-\beta}$$

and

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

A-16.1 Equilibrium in the Industrial Sector: Summary

Figure A-10 depicts the allocation of employment as a function of $\vartheta = \frac{\kappa}{A_{PS} f_O}$ for both cases discussed above. Note that all employments are continuous at the threshold $\vartheta = \frac{\beta}{1-\alpha}$. Figure A-11 depicts aggregate productivity A_G as a function of $\vartheta = \frac{\kappa}{A_{PS} f_O}$ for both cases discussed above. As for the employment allocations, aggregate productivity A_G is also continuous in ϑ.

A-17 Equilibrium in Open Economy

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

1. Market clearing for agricultural goods

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

2. Market clearing for manufacturing goods

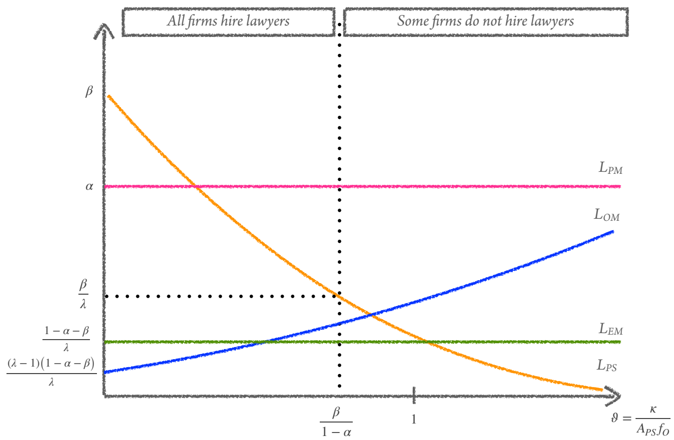

Figure A-10: Aggregate labor allocations

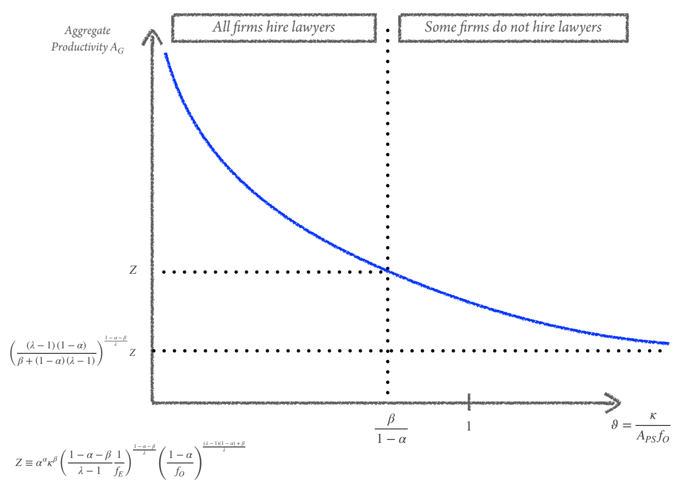

Figure A-11: Aggregate productivity A_G

$$w_r L_{rG} = \left(\frac{w_r^{1-\sigma} A_{rG}^{\sigma-1}}{\sum_{j=1}^{R} w_j^{1-\sigma} A_{jG}^{\sigma-1}}\right) \times$$

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

3. Market clearing for local consumer services

$$w_r L_{rCS} = \vartheta_{rCS}\left(w_j - \tau_j\right) L_r.$$

4. Market clearing for local ICT services

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

5. Labor market clearing

$$L_{rF} + L_{rG} + L_{rCS} + L_{rICT} = L_r.$$

6. Trade consistency equation

$$T = \left(\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G + \left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT}\right)$$

$$- \frac{1}{\varphi^{-\eta}\left(\frac{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1}{1-\sigma}}}{p_{G,ROW}}\right)^{1-\eta}+1} \sum_{j=1}^{R} \vartheta_{jG}\left(w_j - \tau_j\right) L_j$$

7. We can difine the followng term of trade

$$x \equiv \varphi^{\eta} {p_{G,ROW}}^{1-\eta}$$

These are $5R+1$ equations in $5R+1$ unknowns $\{x, \{w_r, L_{rF}, L_{rG}, L_{rCS}, L_{rICT}\}_r\}$. 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 $\{L_r\}_r$, the demand shilfters of the foreign sector $(\Upsilon_{ICT}, \Upsilon_G)$, total trade surplus (T) and the other preference parameters of the model, we can calculate $\{x, \{w_r, L_{rF}, L_{rG}, L_{rCS}, L_{rICT}\}_r\}$.

Term of Trade Note that the above equations treat the foreign sector, which is defined by $(\Upsilon_{ICT}, \Upsilon_G, T)$ as given. Hence, the term of trade $x \equiv \varphi^\eta {p_{G,ROW}}^{1-\eta}$ is determined endogenously

$$x^{-1} = \frac{1}{\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}}} \frac{\sum_{j=1}^{R} \vartheta_{jG} w_j L_j - \left(\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G + \left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT} - T\right)}{\left(\left(\sum_j w_j^{1-\sigma} A_{jG}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_G + \left(\sum_j w_j^{1-\sigma} A_{jICT}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICT} - T\right)} \tag{A-38}$$

As in the benchmark model, we set $p_G = 1$. Given the productivities $\{A_{rF}, A_{rG}, A_{rCS}, A_{rICT}\}_r$, the population distribution $\{L_r\}_r$, the parameters of the foreign sector $(\Upsilon_{ICT}, \Upsilon_G, T, \varphi, \eta)$, and the other preference parameters of the model, we can obtain $\{w_r, L_{rF}, L_{rG}, L_{rCS}, L_{rICT}, \vartheta_{rF}, \vartheta_{rG}, \vartheta_{rCS}\}_r$. Note that the expenditure shares $\vartheta_{rF}, \vartheta_{rG}$, and ϑ_{rCS} now depend on the foreign price $p_{G,ROW}$ which affects the price of the composite good comprising domestic and foreign varieties.

In an open economy environment, the equilibrium conditions above do not guarantee that expenditure equal domestic income. In other words, trade is not balanced. Given the long-run focus of our analysis, we close the model by assuming that $T = 0$.[33]

[33] More precisely, the adjustment pins down $\varphi^{\frac{\eta}{1-\eta}} \times p_{G,ROW}$. It is not possible to separately identify the taste parameter φ and the foreign price $p_{G,ROW}$. Thankfully, this distinction has no bearing on our analysis and we can simply normalize $\varphi = 1$.

To understand intuitively the equilibrating nature of the price adjustment, consider a low price $p_{G,ROW}$. When the industrial good is a luxury (as is the case under our estimates for India), a low (high) $p_{G,ROW}$ yields, *ceteris paribus*, a high (low) expenditure share in industrial goods causing a trade deficit (surplus)–a large (small) share of the domestic industrial production is absorbed by domestic demand. Increasing (decreasing) $p_{G,ROW}$ reduces (increases) the expenditure shares in industrial goods, thereby reducing (increasing) the trade deficit.