# Growing Like India:

## The Unequal Effects of Service-Led Growth

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**Abstract**

We study the welfare effects of productivity growth in the service sector in developing countries, emphasizing their variation across space and income distribution. To this aim, we construct a spatial equilibrium model in which agents have nonhomothetic preferences over final goods that differ in the intensity of the use of consumer services as production inputs. Over time, the expansion of employment in consumer services is both a consequence (income effects) and a cause (productivity growth) of the development process. We estimate the model using Indian household data from providing information on sectoral employment and consumption expenditure. We find that productivity growth in consumer services was an important driver of rising living standards between 1987 and 2011 accounting for one-third of aggregate welfare gains. However, these gains are heavily skewed toward high-income households living in cities because such individuals spend a large share of their budget on consumer service-intensive goods. Productivity growth in the service sector is also a powerful driver of the process of structural change that shifts employment out of agriculture and into the service sector with only limited industrialization.

# 1 Introduction

Urbanization and structural change are transforming the lives of hundreds of million of people across the globe. Consider India, the second most populous country in the world: Thirty years ago, only a quarter of the population resided in urban areas, and almost two-thirds of the labor force was employed in agriculture. Today, the share of people living in urban areas has increased by 10 percentage points while the employment share of agriculture is down to 42%. While economic development has improved living conditions across the board, the sources of welfare gains are diverse. In rural areas, poverty has fallen, mainly owing to productivity growth in agriculture. Meanwhile, the urban bourgeoisie has benefited not only from the availability of better and cheaper goods but also from the growing supply of local services that have changed the face of urban life.

This paper provides a framework to quantify the heterogeneous welfare effects of structural change across localities and the income distribution ladder, building a bridge between economic growth and economic development.

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We abandon the straightjacket of aggregate representative agent models and construct a multisectoral spatial equilibrium model in which people with heterogeneous purchasing power reside in different locations and consume different baskets of goods and services. This allows us to associate changes in the economic environment with their effects on the welfare of people with diverse socioeconomic characteristics.

**Building Blocks:** The theory has two main building blocks: (i) nonhomothetic preferences, and (ii) the assumption that—while manufacturing and agricultural goods are traded across regions—some services are of a local nature. We link these two aspects by assuming that final goods using intensively local services as inputs are luxuries, while goods with a low local service content are necessities. For instance, a large share of the value added of fashionable restaurants consists of the labor services of cooks, waiters, etc. In contrast, the value added of a basic homemade meal consists mainly of tradable goods. In the benchmark model, we assume labor is perfectly mobile across industries while labor is immobile across geographical locations (an assumption we relax in an extension).

Because the service sector is broad and heterogeneous, we split it into two parts. On the one hand, we label *consumer services* (henceforth, CS) services that contribute to households' local access to consumption goods (e.g., restaurants or retail shops) or directly enter their consumption basket (e.g., health or leisure services). On the other, we label *producer services (PS)* services that are used as inputs to the tradable goods, such as business services, corporate law services, and part of transport services.

Then, we use both micro and macro data to estimate the spatial and time variation of productivity in each sector. Our approach is in the wave of the development accounting literature. We do not attempt to explain the determinants of productivities but retrieve them from the equilibrium condition of a structural model. Finally, by means of counterfactual analysis, we evaluate the importance of different sources of productivity changes on structural change and on the welfare of people with different earnings living in different locations.

**PIGL Preferences:** We assume preferences parametrized by an indirect utility function in the Price-Independent Generalized-Linear (PIGL) class. This preference class was first introduced by Muellbauer (1976) and has been recently popularized in the literature on growth and structural change by Boppart (2014). PIGL has two important features. First, it allows aggregation: the choice of a set of agents endowed with PIGL preferences facing a common price vector can be rationalized as the choice of a representative agent whose preferences also fall into the PIGL class. The aggregation properties of PIGL preferences enable us to perform a variety of counterfactual welfare calculations based on the estimated model. In particular, because agents have nonhomothetic preferences and CS must be provided locally, productivity growth in different sectors benefits people differentially—rich versus poor as well as urban versus rural residents. Our estimated model allows us to quantify the heterogeneous welfare gains and development effects of service-led growth both across the income distribution and across space.

Second, PIGL preferences enable us to seamlessly go back and forth between preferences and demand defined over final expenditure or over the value added of three grand sectors: *food*, *industrial goods*, and *CS*. In this classification, we view PS as an integral part of the industrial goods sector. As such, their value added can be shipped across locations. In contrast, CS are neither directly nor indirectly traded. While the assumption that CS are consumed locally is stark, it is qualitatively consistent with Gervais and Jensen (2019), who estimate sector-specific trade costs and conclude that PS are as tradable as tangible goods, whereas trade costs in CS activities are substantially higher. This property of PIGL has important implications for our estimation procedure, to which we now turn.

**Identification:** The estimation of the productivity vector is subject to an identification problem. An increase in the employment share of CS could stem from demand forces (i.e., local income growth under nonhomothetic preferences) and supply forces (i.e., local productivity of CS). We refer to these two channels as *service-biased* and *service-led* growth, respectively. The identification of their relative importance hinges on the income elasticity of demand. Toward this aim, we estimate Engel curves using household expenditure data. This step is potentially treacherous. Our estimation of productivities uses sectoral employment data and a demand system defined over sectoral value added aggregates. As Herrendorf et al. (2013) show, the parameters of this demand system are in general different from those derived from preferences over final goods and services. The mapping between the two set of parameters depends in general on the input-output matrix. We formally establish that—under PIGL preferences—the key parameter governing the income elasticity is common to the value added and the final expenditure demand system, irrespective of input-output relations. While this equivalence does not extend to other parameters, we only use household expenditure to retrieve the parameter that is common in the two systems.

**Service-Led Growth in India:** We apply our methodology to India, a fast-growing economy, with an average annual 4.2% growth rate during 1987–2011, for which individual data of good quality are available. In this period, the lion's share of the process of structural change was a shift from agriculture to services with with the manufacturing sector playing only a minor role. India is not an exception in this respect. In recent years, structural change had similar features in many developing economies.

Our estimation exploits individual geolocalized consumption and employment data, and we estimate sectoral productivity growth for about 400 Indian districts. The results are interesting in several respects. First, at the spatial level, there are large sectoral productivity differences. In particular, the CS sector features a large productivity gap between urban and rural districts. Thus, urban districts have a higher service employment share not only because their inhabitants are richer but also because final goods are provided more efficiently (e.g., because of a better division of labor or for a market size effect that allows the entry of large more efficient retailers.)

Second, we document an important role of service-led growth for economic development. At the aggregate level, rising efficiency in the provision of CS accounts for almost one-third of the increase welfare since 1987. For comparison, the impact of agricultural productivity growth is roughly similar, but growth in the industrial sector was substantially less important. In fact, using a nonparametric bootstrap procedure to estimate the sampling uncertainty in our estimates, we show that the difference between service-led and industrial growth is statistically different. To the best of our knowledge, this paper is the first to quantify the importance of the consumer-service sector for a developing economy such as India.

Third, the welfare impact of service-led growth is strikingly unequal. Productivity growth in CS is the main source of welfare gains for richer households, especially those in urbanized districts. The residents in the top quintile of urbanization would have been better off taking a 41% income cut in 2011 than moving back to the productivity that the CS sector had in 1987. Similarly, service-led growth accounts for the vast majority of welfare gains the richest 20% of the Indian population experienced since 1987. By contrast, for poorer households living in rural districts, improvements in living standards hinge mostly on productivity growth in agriculture.

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

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

A recent literature focuses on the service sector, albeit, mostly with a focus on advanced economies. Buera and Kaboski (2012) emphasize the importance of the (demand-driven) growth of a skill-intensive service industry in the post-1950s US economy. Hsieh and Rossi-Hansberg (2019) argue that in more recent years, Information and Communication Technology (ICT) has triggered an industrial revolution and has been a major source of productivity growth. Their view is echoed by Eckert et al. (2020). An exception to this rich-country focus is Duarte and Restuccia (2010), who document large cross-country productivity differences in service industries, a finding that is broadly in line with our results across locations within India, and Gollin et al. (2015), who emphasize how urbanization often goes hand in hand with a booming consumption of nontradable services, although their focus on such *consumption cities* in resource-rich African economies is very different from ours. Desmet et al. (2015) and Dehejia and Panagariya (2016) also study the role of the service sector in India and document an important role for cities, in particular in the provision of PS. Our finding that service growth was decidedly pro-rich and pro-urban is consistent with Chatterjee and Giannone (2021), who use data on regional income growth for a large number of countries and document that rising productivity in services is associated with regional divergence. Atkin et al. (2018) study the welfare effects of the entry of global retail chains Mexico. They find that foreign retail entry causes large welfare gains for households that are associated with a reduction in the cost of CS, partly due to pro-competitive effects on the prices charged by domestic stores. Finally, our approach is close in spirit to Burstein et al. (2005), who emphasize in a different context the nontradable nature of CS and the large value added share of these services in final expenditure goods.

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

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

nonhomothetic preferences play a key role in our analysis. The classic reference for the service-biased growth is Baumol (1967). Earlier papers emphasizing their importance for the growth process include Foellmi and Zweimueller (2006), Kongsamut et al. (2001), and Matsuyama (2000). The more recent literature on structural change with nonhomothetic preferences includes, among others, Boppart (2014) and Alder et al. (2019) who, like us, propose generalizations of the PIGL preferences class proposed in Muellbauer (1976). Eckert and Peters (2020) is the first paper to incorporate these preferences in a spatial model of structural change. In contrast to us, they focus on the interaction between spatial mobility and the structural transformation. Instead, Matsuyama (2019) and Comin et al. (2020) use a class of generalized CES preferences related to Sato (2014). The authors show these preferences can account accurately for the patterns of structural transformation across several countries. In our paper, we use PIGL preferences because their tractable and transparent aggregation properties are especially suitable. Our results on the unequal gains from service growth are reminiscent of Fajgelbaum and Khandelwal (2016), who measure the unequal gains from trade in a setting with nonhomothetic preferences.

We also contribute to the vast literature on the economic development of India including, among others, Aghion

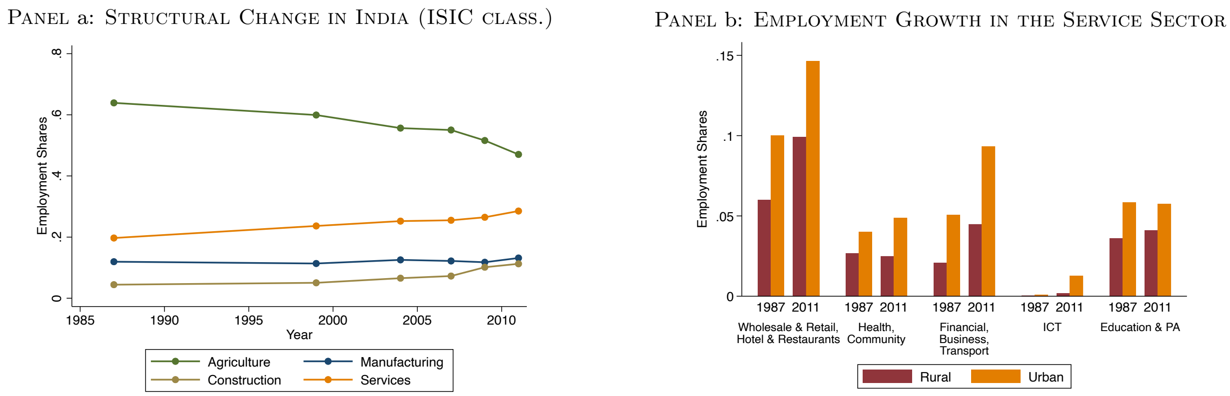


Figure 1: Structural Change in India: 1987–2011. The left panel shows the evolution of sectoral employment shares over time and is based on a standard ISIC classification. The right panel shows employment shares for different subsectors of the service sector independently for rural and urban localities. We rank districts by their urbanization rate and group them into rural and urban bins that account for roughly 50% of total employment.

et al. (2005, 2008), Akcigit et al. (2021), Basu (2008), Basu and Maertens (2007), Foster and Rosenzweig (1996, 2004), Goldberg et al. (2010), Kochhar et al. (2006), and Martin et al. (2017).

**Road Map:** The structure of the paper is as follows. Section 2 summarizes the key stylized facts of the growing role of services in India. Section 3 lays out our theoretical framework. Sections 4 and 5 describe the data and our empirical methodology. Our main results on the welfare effects of service-led growth are contained in Section 6. Section 7 performs a variety of robustness checks. Section 8 concludes. The Appendix contains details of the theoretical and empirical analysis.

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

Between 1987 and 2011, the Indian economy experienced a remarkable transformation. Not only did income per capita grow by a factor of three, but the employment structure also changed markedly. In the left panel of Figure 1, we show the time-series evolution of sectoral employment shares.[1] Two facts are apparent: First, agriculture is the largest employment source, accounting for almost half of total employment in 2011. Second, the structural transformation in India is mostly an outflow out of agriculture and an inflow into services and construction whose employment shares increased, respectively, by nine and seven percentage points. By contrast, employment in the manufacturing sector is stagnant. Today, the service sector accounts for about one-third of aggregate employment and almost one half of total value added in India.

The service sector encompasses a set of heterogeneous activities. In the right panel of Figure 1, we decompose it into five subsectors: (i) wholesale, retail, hotel and restaurants; (ii) health and community services; (iii) financial, business, and transport; (iv) ICT, and (v) education and Public Administration (PA). The first and second subsectors, which serve mostly consumers, employ well over half of all Indian service workers in 2011. The third and fourth subsectors sell part of their services to industrial firms. Finance, business, and transport services accounted for about a quarter of service sector employment in 2011. Although the growth rate of employment in the ICT sector was especially fast, this sector accounts for a mere 2.5% of service employment in 2011. Education and PA are mostly government-run activities. The share of the Indian labor force employed in this subsector is constant

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

over time—in contrast to all other subsectors that grew rapidly during the period studied.[2] Thus, the expansion of services in India has not been confined to business-oriented service industries, such as finance and ICT services. The vast majority of employment gains are found in CS such as retail, hospitality, and health.

The figure also highlights important differences across local labor markets in India. We split India into rural and urban districts, broken down so that approximately half of the workers belong to each type of district. Service activities are much more prevalent in urban areas than in rural ones, especially in business-oriented activities such as financial services and ICT. But service employment grew substantially in both localities. Was the rapid expansion of the service sector shown in Figure 1 a source or a corollary of Indian growth? And how did its development affect the different sectors of the Indian population? To answer these questions, we turn to a structural model that we present and estimate in the remainder of the paper.

# 3 Theory

The model economy comprises $R$ regions. Within each region there are three broad sectors of economic activity: agriculture (F for *food*), industry (G for *goods*), and CS. Consumers' preferences are defined over a continuum of products, and each product is a combination of the output of these three sectors. The main distinction between food and goods on the one hand and CS on the other hand is their tradability: while food and goods are tradable across regions (subject to iceberg costs), CS must be locally provided.[3] Throughout our analysis we assume that markets are frictionless and competitive.

In our benchmark model, we assume that the aggregate supply of labor is inelastically provided in each region, that workers' human capital is perfectly substitutable across the sectors, and that the economy is closed to international trade. Below we extend our model along all of these dimensions. First, we allow for spatial mobility and rationalize the geographic allocation of labor through the lens of a geography model with local amenities. This extension allows us to run experiments in which labor can move across regions in response to counterfactual changes in the environment. Second, we consider a setting in which workers with different education attainments are imperfect substitutes and sectoral technologies differ in the skill intensity. In that case, regional differences in the supply of skills emerge as a source of sectoral comparative advantage and specialization. Finally, we incorporate international trade, emphasizing the role of export of ICT services.

## 3.1 Technology

**Technology:** Each region $r$ produces a measure one continuum of differentiated final products that enter consumers' utility. Each good is produced using two physical inputs—food and goods—and local CS workers. For instance, a restaurant meal is a combination of food, kitchen tools, and the service provided by cooks and waiters. Formally, the production function for final good $n \in [0, 1]$ in region $r$ at time $t$ is given by

$$Y_{rnt} = \tilde{\lambda}_n x_{rFt}^{\lambda_{nF}} x_{rGt}^{\lambda_{nG}} \left(\mathcal{A}_{rnt} H_{rCSt}\right)^{\lambda_{nCS}}, \tag{1}$$

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

[3] As we describe in detail below, we assume that the industrial sector employs both production workers and workers producing production services (PS). Because the value added of corporate lawyers and consultants is embodied in industrial goods, PS are ultimately tradable.

where $x_F$, $x_G$, denote the inputs of food and goods in the production of commodity $n$, $H_{rCSt}$ is the mass of CS workers allocated to the production of good $n$, and $\mathcal{A}_{rnt}$ reflects the efficiency of providing the CS content for product $n$ in region $r$. We assume constant returns to scale: $\sum_s \lambda_{ns} = 1$ for $s \in \{F, G, CS\}$. The scalar $\tilde{\lambda}_n \equiv \lambda_{nF}^{-\lambda_{nF}} \lambda_{nG}^{-\lambda_{nG}} \lambda_{nCS}^{-\lambda_{nCS}}$ is an inconsequential normalization to simplify expressions.

Consumer goods are nontradable insofar as they require the input of local service workers. The elasticities $\lambda_{ns}$ determine the intensity of food, goods, and CS in the production of product $n$ and are thus akin to input-output coefficients. Intuitively, a home-cooked meal is a product with a large food content ($\lambda_{nF} \approx 1$) and a low content of CS (the retail store). A restaurant meal also requires food but has a larger CS content. Finally, personal services like haircuts or nanny services consist almost entirely of CS ($\lambda_{nCS} \approx 1$).

The tradable food and industrial good ($x_F$ and $x_G$) inputs are CES aggregates of differentiated varieties, each produced in a different region:

$$x_s = \left( \sum_{r=1}^{R} y_{rs}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{for} \quad s \in \{F, G\}. \tag{2}$$

The technology of all varieties features constant return to labor:

$$y_{rFt} = A_{rFt} H_{rFt} \quad \text{and} \quad y_{rGt} = A_{rGt} H_{rGt}, \tag{3}$$

where sectoral productivity (henceforth, TFP) $A_{rst}$ is allowed to differ across regions. $H_{rst}$ denotes the amount of human capital employed in the production of food and industrial goods.

**Manufacturing and PS:** When taking the model to the data, we have to take a stand on the mapping between value added created in different sectors and the three economic activities—food production, industrial goods production, and the provision of CS. We include the value added of PS in the industrial sector. More formally, we let $H_{rGt} = H_{rMt} + H_{rCSt}$ include labor services provided in both the manufacturing and PS sector. This specification does *not* restrict manufacturing and PS workers to being perfect substitute. To see why, suppose industrial firms combine the inputs of manufacturing ($M$) workers and PS to produce industrial goods using the technology $y_{rGt} = g_{rt}(H_{rMt}, H_{rPSt})$, where $g_{rt}$ is a linearly homogeneous function. Under this general specification, a region could enjoy high industrial productivity because of either an advanced manufacturing production technology or an efficient provision of accounting and legal services to firms. As long as firms maximize profits, the marginal product of $H_{rMt}$ and $H_{rPSt}$ is equalized. The assumption that the production function is linearly homogeneous implies then that $H_{rMt} \propto H_{rPSt}$. Thus, without loss of generality, we can express the constant-return technology in the form $y_{rGt} = A_{rGt} H_{rGt}$, where the cross-regional distribution of $A_{rGt}$ summarizes the heterogeneity in industrial productivity, which can stem either from a high productivity of production workers or a high productivity of the provision of PS (or both).[4] Hence, cities like Delhi or Mumbai, for example might have a comparative advantage in PS like finance or ICT and can then export the value added of such services to the rest of India. Moreover, the way PS enter the production of industrial goods can vary freely across locations.

[4] Linear homogeneity allows us to write $y_{rGt} = g_{rt}(1 - s_{rPSt}, s_{rPSt}) H_{rGt}$, where $s_{rPSt} = H_{rPSt}/H_{rGt}$ denotes the share of efficiency units of labor allocated to PS consistent with profit maximization. We can then write the industrial total factor productivity as $A_{rGt} \equiv \max_{s_{PS}} g_{rt}(1 - s_{PS}, s_{PS})$, which is independent on the total scale of industrial production. Although $A_{rGt}$, is not a primitive, it is fully determined from the production function $g_{rt}$. For instance, suppose $g$ takes the standard CES form $y_{rGt} = \left[ (A_{rMt} H_{rMt})^{\frac{\hat{\rho}-1}{\hat{\rho}}} + (A_{rPSt} H_{rPSt})^{(\hat{\rho}-1)/(\hat{\rho})} \right]^{\hat{\rho}/(\hat{\rho}-1)}$, where $\hat{\rho}$ is the elasticity of substitution. Then, $A_{rGt} = \left( A_{rMt}^{\hat{\rho}-1} + A_{rPSt}^{\hat{\rho}-1} \right)^{1/(\hat{\rho}-1)}$. For the purpose of our analysis, we directly estimate the distribution of $A_{rGt}$ from the data.

**Nontradable CS:** Equation (1) highlights the special role of the CS sector in our theory: its value added is combined with that of tradable commodities to turn the latter into final goods that local consumers can enjoy. Tradability is thus also the critical difference between PS and CS in our theory. While CS value added can only be supplied locally, PS value added embodied in goods is ultimately tradable.

Note that we refer to $\mathcal{A}_{rnt}$ as CS productivity even though in the Cobb-Douglas function (1)) $\mathcal{A}_{rnt}$ applies to all inputs and can as well be thought of as the productivity of the local final good sectors. We show below that the assumption that consumer goods must be supplied locally, while food and goods can be purchased in nationwide markets, allows us to separately identify $\mathcal{A}_{rnt}$ from $A_{rGt}$ and $A_{rFt}$.

### 3.2 Preferences and Demand System

Following Boppart (2014) and—more closely—Alder et al. (2019), we assume consumers' preferences over the continuum of final products are in the PIGL class. PIGL preferences have three appealing properties for our purposes. First, they have simple and transparent aggregation properties that allow us to take a spatial demand system to the data. Second, they allow us to derive analytic expressions for individual and aggregate welfare effects. Third, they provide a simple mapping of preferences over final goods into preferences over value added.[5]

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

$$\mathcal{V}^{FE}\left(e, \mathbf{p}_r\right) = \frac{1}{\varepsilon}\left(\frac{e}{B\left(\mathbf{p}_r\right)}\right)^{\varepsilon} - D\left(\mathbf{p}_r\right), \tag{4}$$

where $e$ denotes total spending and $\mathbf{p}_r$ the vector of prices in region $r$. The mnemonic "FE" highlights that this indirect utility function is defined over total expenditure and prices of final goods and hence corresponds to consumers' final expenditure. The functions $B\left(\mathbf{p}\right)$ and $P\left(\mathbf{p}\right)$ are homogeneous of degree one and zero, respectively. We parametrize them as

$$B\left(\mathbf{p}_r\right) = \exp\left(\int_{n=0}^{1} \beta_n \ln p_{rn} dn\right) \quad \text{and} \quad D\left(\mathbf{p}_r\right) = \left(\int_{n=0}^{1} \kappa_n \ln p_{rn} dn\right),$$

where $\int_0^1 \beta_n dn = 1$ and $\int_0^1 \kappa_n dn = 0$. This specification yields the indirect utility function

$$\mathcal{V}^{FE}\left(e, \mathbf{p}_r\right) = \frac{1}{\varepsilon}\left(\frac{e}{\exp\left(\int_n \beta_n \ln p_{rn} dn\right)}\right)^{\varepsilon} - \int_n \kappa_n \ln p_{rn} dn. \tag{5}$$

Roy's Identity implies that the expenditure share an individual allocates to final good $n$ given prices $\mathbf{p}_r$ and spending $e$, $\vartheta_n^{FE}\left(e, \mathbf{p}_r\right)$, is given by:

$$\vartheta_n^{FE}\left(e, \mathbf{p}_r\right) = \beta_n + \kappa_n \left(\frac{e}{\exp\left(\int_n \beta_n \ln p_{rn} dn\right)}\right)^{-\varepsilon}. \tag{6}$$

In this specification, prices $\mathbf{p}$ and spending $e$ conveniently enter only through a single summary statistic that resembles a notion of real income.

In Figure 2 we depict the expenditure share as a function of spending $e$. A good $n$ is a luxury if $\kappa_n < 0$

[5] An alternative class of nonhomothetic preferences recently proposed by Comin et al. (2020) has attractive properties for explaining long-run trends in the data. However, these preferences are less tractable when it comes to aggregation and moving between a value added to an expenditure approach. We leave to future research to explore how this class of preferences can be incorporated into the analysis.

and a necessity if $\kappa_n > 0$. Our class of preferences encompasses Cobb-Douglas preferences as a special case when $\kappa_n = 0$. Moreover, the parameter $\beta_n$ determines the long-run expenditure as incomes grow large. Equation (6) also highlights that the slope of the Engel curves and the strength of income effects is governed by the parameter $\varepsilon$. This parameter—that we label the *Engel elasticity*—plays a key role in our analysis.

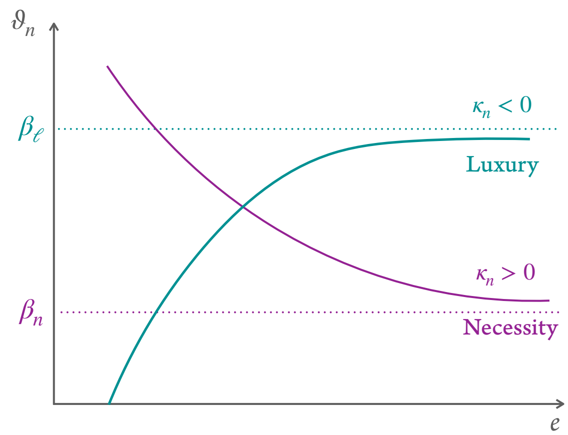


Figure 2: ENGEL CURVES. The figure shows the good-specific expenditure share as a function of income $e$ (see (6)). We depict the case of a luxury good and a nexessity.

### 3.2.1 Final Expenditure and Value Added

Equation (6) defines the expenditure share over final products $n \in [0, 1]$. Because the estimation methodology we adopt relies on sectoral employment data, it is useful to define a demand system in terms of the value added produced by the three grand sectors F, G, and CS. In this section, we show how the PIGL preference specification in (5) allows us to seamlessly go back and forth between preferences and demand defined over final expenditure or value added. Most important, the Engel elasticity $\varepsilon$ can be estimated using any of two approaches—a result that will prove very handy when we take the model to the data.

To derive the demand system over sectoral value added, we establish relationships between the price vector for final goods and price indexes for the tradable inputs. The price of final good $n$ in region $r$ is given by

$$p_{rnt} = P_{rFt}^{\lambda_{nF}} P_{rGt}^{\lambda_{nG}} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{\lambda_{nCS}} . \tag{7}$$

Here, $P_{rFt}$ and $P_{rGt}$ are the prices in region $r$ of the tradable food and industrial goods, and $w_{rt}$ is the wage per efficiency unit of human capital in region $r$ at $t$. Note that $\mathcal{A}_{rnt}^{-1} w_{rt}$ is the unit cost of the local CS input for producing the final good $n$.

Given perfect competition, the CES aggregation of regional varieties in (2), and the presence of trade costs, the price of tradable goods $s$ can be written as

$$P_{rst}^{1-\sigma} = \sum_{j=1}^{R} \tau_{rj}^{1-\sigma} A_{jst}^{\sigma-1} w_{jt}^{1-\sigma}, \qquad \text{for } s \in \{F, G\}, \tag{8}$$

where $\tau_{rj} \geq 1$ captures the iceberg cost of shipping variety $j$ to region $r$. Note that, absent trade costs, the price of tradable goods would be equalized across regions and the regional variation in final good prices $p_{rnt}$ would stem entirely from differences in local wages and in CS productivity. However, the presence of iceberg costs increases the price of tradable goods in remote locations *ceteris paribus*.

Combining (5) with (7) allows us to represent consumers' preferences directly over sectoral value added. The following proposition can be established.

**Proposition 1.** *The indirect utility function of consumers in region $r$ at time $t$ can be written as*

$$\mathcal{V}\left(e, \mathbf{P_{rt}}\right) = \frac{1}{\varepsilon}\left(\frac{e}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G} P_{rCSt}^{\omega_{CS}}}\right)^{\varepsilon} - \sum_{s\in\{F,G,CS\}} \nu_s \ln P_{rst}, \tag{9}$$

*where $\mathbf{P_{rt}} = (P_{rFt}, P_{rGt}, P_{rCSt})$, $P_{rCSt} \equiv A_{rCSt}^{-1} w_{rt}$, $P_{rFt}$ and $P_{rGt}$ are given by* (8),

$$\omega_s \equiv \int_{n=0}^{1} \lambda_{ns}\beta_n \, dn, \qquad \nu_s \equiv \int_{n=0}^{1} \lambda_{ns}\kappa_n \, dn, \quad \textit{for } s \in \{F, G, CS\}, \tag{10}$$

*and*

$$A_{rCSt} \equiv \exp\left(\int_n \frac{\beta_n \lambda_{CSn}}{\omega_{CS}} \ln \mathcal{A}_{rnt} \, dn\right). \tag{11}$$

*The associated expenditure shares over sectoral value added aggregates (compare* (6)*) are given by*

$$\vartheta_{rst}\left(e, \mathbf{P_{rt}}\right) = \omega_s + \nu_s \left(\frac{e}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G} P_{rCSt}^{\omega_{CS}}}\right)^{-\varepsilon}. \tag{12}$$

*Proof.* See Appendix Section A-1. □

Proposition 1 characterizes consumers' preferences and demand over sectoral value added. The indirect utility function (9) has the same functional form as in (5), which was defined over final goods. Equally important, the demand function over sectoral value added, $\vartheta_{rst}$ in (12), features the same Engel elasticity parameter $\varepsilon$ as the demand function over final goods, $\vartheta_{rnt}^{FE}$ in (6). This property of PIGL preferences enables us to estimate $\varepsilon$ from microdata on household expenditure shares (on final goods) and then use it in the demand system defined over sectoral value added that is the base of our estimation.[6]

The latter result may come as surprise because, as Herrendorf et al. (2013) point out, the mapping from the parameters of a final-expenditure demand to those of a value-added demand system generally involves the input-output matrix. In general, this is true in our model: while the two demand systems share the same elasticity $\varepsilon$, the parameters $\omega_s$ and $\nu_s$ are input-output weighted averages of the underlying final good demand parameters $\beta_n$ and $\kappa_n$; see Equation (10).

More specifically, whether the demand for sectoral value added is income elastic depends on the *correlation* of the good-specific demand parameters $\kappa_n$ with their factor intensities $\lambda_{ns}$. As seen in Equation (12), the expenditure share for sectoral value added is rising in income if and only if $\nu_s < 0$. Equation (10) shows that this in turn is the case if income elastic *products* have a large *sectoral* input requirement: rich individuals spend a large share of their income on value added created in the CS sector if income-elastic goods use CS inputs extensively. By

[6] In Section A-1 in the Appendix we also derive the analogue of (12), if the production function for final goods combines CS, food and goods in a CES fashion.

contrast, if all goods were produced with equal factor proportions, that is, $\lambda_{ns} = \lambda_s$, or more generally if $\lambda_{ns}$ were orthogonal to $\kappa_n$ for all $s$, the demand for sectoral value added would be homothetic and independent of prices (i.e., Cobb Douglas) even though the underlying demand for final goods was nonhomothetic. Formally, $\nu_s = \int_{n=0}^{1} \lambda_{ns}\kappa_n \, dn = \lambda_s \int_{n=0}^{1} \kappa_n \, dn = 0$, so that $\vartheta_{rst}^{VA} = \omega_s$; see Equation (12).

Finally, Proposition 1 shows that, holding constant the prices of tradable goods, local wages, and the level of spending $e$, the local CS sector enters the indirect utility function only through the productivity $A_{rCSt}$. This is an index constructed as the (geometric) average productivity of the technologies of all final goods weighted by their local CS content and by the demand share of each (nontradable) final good. $A_{rCSt}$ is a sufficient statistics to compute the welfare consequences of changes in the productivity of CS. In other words, knowing the evolution of $A_{rCSt}$ over time allows us to quantify the welfare consequences of productivity growth in the service sector using information on sectoral aggregates.

### 3.2.2 Heterogeneity and Aggregate Demand

In this section, we derive the aggregate demand system. Under general nonhomothetic preferences, aggregation requires the knowledge of the entire income distribution. However, PIGL preferences grant an analytical derivation of the aggregate demand system only in terms of prices, wages, and structural parameters.[7]

Suppose individuals have heterogeneous human capital that can be supplied to all sectors of production. Individual $h$'s income is then given by $e_{rt}^h = q^h w_{rt}$, where $q^h$ is the number of efficiency units of labor. Let $F_{rt}(q)$ denote the distribution function of $q$ in region $r$ at time $t$. Differences in human capital can reflect differences in both ability and education. Empirically, we will relate the spatial variation in the distribution of $q$ to observable differences in educational attainments.

Because our analysis abstracts from savings and capital accumulation, income equals expenditure. Then, Equation (6) implies that the *aggregate* spending share on value added produced in sector $s$ by consumers located in region $r$ is given by

$$\overline{\vartheta}_{rst} \equiv \frac{L_{rt} \int \vartheta_{rst}(q w_{rt})\, q w_{rt} dF_{rt}(q)}{L_{rt} \int q w_{rt} dF_{rt}(q)} = \omega_s + \overline{\nu}_{rst} \left( \frac{A_{rCSt}^{\omega_{CS}} \mathbb{E}_{rt}[q]\, w_{rt}^{1-\omega_{CS}}}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G}} \right)^{-\varepsilon}, \tag{13}$$

where

$$\overline{\nu}_{rst} \equiv \frac{\mathbb{E}_{rt}\left[q^{1-\varepsilon}\right]}{\mathbb{E}_{rt}[q]^{1-\varepsilon}} \nu_s, \tag{14}$$

having defined—with slight abuse of notation—the expectation operator $\mathbb{E}_{rt}[x] \equiv \mathbb{E}[x; F_{rt}(x)]$. Note that we have substituted away $P_rCSt$ using its definition. Comparing (13) with (6) highlights in what sense PIGL allows for a representative household: the *aggregate* demand system in (13) is isomorphic to that of a representative consumer in region $r$ who earns the average income $\mathbb{E}_{rt}[q]\, w_{rt}$ and has the inequality-adjusted preference parameter $\overline{\nu}_{rst}$ in (14) instead of the primitive parameter $\nu_s$. The inequality adjustment is the term $\mathbb{E}_{rt}\left[q^{1-\varepsilon}\right] / \mathbb{E}_{rt}[q]^{1-\varepsilon}$, which depends, in general, on the local distribution of efficiency units $F_{rt}$ and thus can vary across time and space.

The analysis further simplifies if we assume $q$ follows a Pareto distribution with c.d.f. $F_{rt}(q) = 1 - \left(\underline{q}_{rt}/q\right)^{\zeta}$, with a region-invariant tail parameter $\zeta$. In this case, $\mathbb{E}_r[q] = \frac{\zeta}{\zeta-1}\underline{q}_r$ and $\mathbb{E}_r\left[q^{1-\varepsilon}\right] = \frac{\zeta}{\zeta+\varepsilon-1}\underline{q}_r^{1-\varepsilon}$, so that Equation

[7] As we show in this chapter, even in PIGL the mapping from to individual and aggregate preferences parameters depends on the income distribution, but the relationship is simple and tractable.

(14) boils down to

$$\overline{\nu}_{rst} = \overline{\nu}_s = \frac{\zeta^{\varepsilon}\left(\zeta-1\right)^{1-\varepsilon}}{\zeta+\varepsilon-1}\nu_s. \tag{15}$$

Thus, if income is Pareto distributed with a common tail parameter and an intercept $\underline{q}_{rt}$ that can vary across space and time, all regions have the same "aggregate" parameter $\overline{\nu}_s$.

### 3.2.3 Welfare and Inequality

The aggregation properties of PIGL are especially useful to perform welfare analysis. For our purposes, we shall evaluate welfare both at the individual level and aggregated at the regional level. At the household level, we can use (9) to express the indirect utility of an individual living in region $r$ as a function of the local wage $w_{rt}$, the local productivity of CS $A_{rCSt}$, and the prices of the two tradable goods. At the regional level, we exploit the aggregation properties of PIGL to calculate utilitarian welfare $\mathcal{U}_{rt}\left(w_{rt},\mathbf{P_{rt}}\right) \equiv \int \mathcal{V}\left(qw_{rt},\mathbf{P_{rt}}\right)dF_{rt}\left(q\right)$. Note that this expression depends on the local skill distribution $F_{rt}$ and a vector of local wages and prices. Plugging in the indirect utility function in (9) yields

$$\mathcal{U}_{rt}\left(w_{rt},\mathbf{P_{rt}}\right) = \frac{\zeta^{1-\varepsilon}\left(\zeta-1\right)^{\varepsilon}}{\zeta-\varepsilon} \times \left(\frac{1}{\varepsilon}\left(\frac{\mathbb{E}_{rt}\left[q\right]w_{rt}}{P_{rFt}^{\omega_F}P_{rGt}^{\omega_G}P_{rCSt}^{\omega_{CS}}}\right)^{\varepsilon} - \sum_{s\in\{F,G,CS\}}\nu_s^{\mathcal{U}}\ln P_{rst}\right), \tag{16}$$

where $\nu_s^{\mathcal{U}} \equiv \nu_s \times \left(\left(\zeta-\varepsilon\right)\left(\zeta-\left(1-\varepsilon\right)\right)\right)/\left(\zeta(\zeta-1)\right)$. Hence, utilitarian welfare is akin to the indirect utility of a representative agent with average income $\mathbb{E}_{rt}\left[q\right]w_{rt}$ and a scaled taste parameter $\nu_s^{\mathcal{U}}$ that accounts for the income distribution ($\zeta$) and the income elasticity ($\epsilon$). Given this scaled taste parameter, the distribution $F_{rt}$ only enters through the average income term $\mathbb{E}_{rt}\left[q\right]w_{rt}$.

The welfare analysis is the core of our contribution. We will quantify the welfare consequences of productivity growth originating in the CS sector. Because preferences are nonhomothetic and CS are provided locally, productivity growth has heterogeneous welfare effects for consumers with different incomes and residing in different regions. If goods with a high CS content have a high income elasticity, the welfare effects of productivity growth in CS are skewed toward the rich. More precisely, the expenditure share $\vartheta_{CS}\left(e,\mathbf{P_{rt}}\right)$ exactly measures the welfare exposure of a change in prices at the individual level.[8] Note that the expenditure share can be high for two reasons—either because the individual is rich or because she lives in a location where the CS sector is very productive. Moreover, productivity growth in CS mostly benefits the location where it occurs, while, in contrast, large part of the benefits from productivity growth in tradable sectors is exported to other locations. Thus, if, for instance, urban districts experience fast growth in CS productivity $A_{rCSt}$ while it is stagnant in rural districts, city dwellers are going to be the exclusive beneficiaries of service-led growth.

## 3.3 Equilibrium

Having derived the aggregate demand functions, we can now fully characterize equilibrium.

**Proposition 2.** *The sectoral labor allocation* $\left\{H_{rFt}, H_{rGt}, H_{rCSt}\right\}_r$ *and local wages* $\left\{w_{rt}\right\}$ *are determined by the following equilibrium conditions:*

[8] Formally, letting $e(\mathbf{P_{rt}},V)$ denote the expenditure function associated with the utility level $V$ given the price vector $\mathbf{P_{rt}}$, $\partial \ln e(\mathbf{P_{rt}},V)/\partial \ln P_{rst} = \vartheta_{rst}\left(e,\mathbf{P_{rt}}\right)$.

1. *Market clearing for local CS:*

$$w_{rt}H_{rCSt} = \left(\omega_{CS} + \overline{\nu}_{CS}\left(\frac{A_{rCSt}^{\omega_{CS}}\mathbb{E}_{rt}[q]\,w_{rt}^{1-\omega_{CS}}}{P_{rFt}^{\omega_F}P_{rGt}^{\omega_G}}\right)^{-\varepsilon}\right)w_{rt}H_{rt}, \tag{17}$$

*where* $P_{rFt}$ *and* $P_{rGt}$ *are given by* (8).

2. *Market clearing for tradable goods:*

$$w_{rt}H_{rst} = \sum_{j=1}^{R}\pi_{rsjt}\left(\omega_s + \overline{\nu}_s\left(\frac{A_{jCSt}^{\omega_{CS}}\mathbb{E}_{jt}[q]\,w_{jt}^{1-\omega_{CS}}}{P_{jFt}^{\omega_F}P_{jGt}^{\omega_G}}\right)^{-\varepsilon}\right)w_{jt}H_{jt} \qquad \text{for } s = F, G, \tag{18}$$

*where* $\pi_{rsjt} = \tau_{rj}^{1-\sigma}A_{rst}^{\sigma-1}w_{rt}^{1-\sigma}/P_{jst}^{1-\sigma}$.

3. *Labor market clearing:* $H_{rFt} + H_{rGt} + H_{rCSt} = H_{rt}$.

Proposition 2 (proof in the text) fully characterizes the sectoral employment allocations across space and the local distribution of wages. The contrast between Equations (17) and (18) reflects the tradable nature of food and goods and the nontradable nature of CS. The local demand for CS value added hinges on local income—ultimately, wages, human capital, and local productivity. Instead, the demand for tradable goods originates from all localities. The spending shares on food and industrial goods $\pi_{rsot}$ follow from the CES demand structure across regional varieties subject to the set of bilateral iceberg costs $\tau_{ro}$.

The proposition also highlights that *sectoral* value added and employment are fully determined by the parameters $\overline{\nu}_s$ and $\omega_s$ in Equation (10) and by the aggregate CS TFP index $A_{rCSt}$ in (11). They do not directly separately depend on the preference parameters defined over local final consumption goods $[\beta_n, \kappa_n]_{n=0}^{1}$, nor on the product-specific productivity $[\mathcal{A}_{rnt}]_{n=0}^{1}$. Similarly, the size of the local industrial sector $H_{rGt}$ only depends on $A_{rGt}$, and we do not need to impose more structure on how PSs and manufacturing workers interact in production. Crucially, not only are $\overline{\nu}_s, \varepsilon$, $\omega_s$, and $A_{rst}$ necessary and sufficient to compute the equilibrium but they also determine individual and aggregate welfare.

Because tertiarization is the focal point of our analysis, we zoom in on the market clearing condition in the local CS market and show how it can be used to identify productivity and productivity growth in CS. In particular, (17) implies that the local CS employment share is given by

$$\frac{H_{rCSt}}{H_{rt}} = \omega_{CS} + \overline{\nu}_{CS}P_{rFt}^{\varepsilon\omega_F}P_{rGt}^{\varepsilon\omega_G} \times \left(\underbrace{\mathbb{E}_{rt}[q]}_{\text{Skills}} \times \underbrace{w_{rt}^{1-\omega_{CS}}}_{\text{Wages}} \times \underbrace{A_{rCSt}^{\omega_{CS}}}_{\text{Productivity}}\right)^{-\varepsilon}. \tag{19}$$

Note that $\overline{\nu}_{CS} < 0$ if value added in CS is a luxury.

Equation (19) highlights how our theory incorporates both income effects and service-led productivity growth. The equilibrium employment depends on the local supply of skills ($\mathbb{E}_{rt}[q]$), local wages ($w_{rt}$), the local prices of tradable goods ($P_{rFt}$ and $P_{rGt}$), and local productivity ($A_{rCSt}$). The retail sector could then be large in urban districts such as Delhi or Bangalore either because local consumers are, on average, more educated and richer, or because, in addition, the productivity of CS is larger than in less developed areas in the country. For instance, more-efficient department store chains open branches in large cities but not in rural districts where consumers must resort to smaller private retailers.

How does one separate the two growth sources? To attain identification, we leverage both the structure imposed by our theory and a variety of micro data. The data on earnings, schooling, and an estimate of the returns to schooling allow us to measure local skills $\mathbb{E}_{rt}[q]$ and their price $w_{rt}$. Given an income elasticity $\varepsilon$ (estimated below) and the prices of tradable goods that we retrieve from equilibrium conditions, we can use (19) to identify $A_{rCSt}$. Hence, similar to the traditional approach in development accounting, we use a set of structural parameters to identify productivity in a model-consistent way. However, our inference hinges on simultaneously solving for a set of equilibrium prices, specifically, $P_{rFt}$ and $P_{rGt}$.

# 4 Empirical Analysis

In this section, we describe our data sources and discuss measurement issues. An important feature of our approach is that covers people working in both the formal and informal sectors.

## 4.1 Data and Geography

We use four datasets.

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

A more detailed description of these datasets is deferred to Appendix Section B-1. In this section, we highlight the main features. The NSS, which provides the backbone for our analysis, is a household survey with detailed information on employment characteristics and households' location of residence. We use data for 1987 and 2011. The NSS yields measures of average consumption (income) and sectoral employment shares at the district-year level. To measure income, we proxy earnings by average expenditure. We prefer this measure to direct information on wages to also capture informal employment. Consistent with our theory, we measure employment shares in four sectors: agriculture, manufacturing, PS, and CS.

For agriculture and manufacturing, we follow the ISIC sectoral classification in the NSS data. In the service sector, we must separate CS from PS. For some service industries, the assignment is clearcut. For instance, it seems natural to classify hotels and restaurants as part of the CS sector. In other industries, the distinction is less sharp. For instance, within legal services, corporate lawyers provide PS whereas divorce lawyers provide CS. To solve this problem in a consistent way, we combine information from the Economic Census and the Service Survey to estimate the extent to which each service industry provides services to firms or to consumers. We describe this procedure in detail in in Section 4.2 below. We exclude from our analysis a subset of service industries for which the categorization into PS and CS is ambiguous. These industries include public administration and defense, compulsory social security, education, and extraterritorial organizations and bodies.

The EC is a complete count of all establishments engaged in the production or distribution of goods and services in India. It covers all sectors except crop production and plantation and collects information on each firm's location, industry, employment, and the nature of ownership. It contains approximately 24 million and 60 million establishments in 1990 and 2013, respectively.[9] The relatively unexplored Service Survey was conducted in 2006 and is designed to be representative of India's service sector. It covers almost 200,000 private enterprises subdivided into six service industries. We compared the Service Survey with the EC and document that it is representative of the distribution of firm size in India; see Appendix B. We use the EC and the Service Survey to classify service employment into CS and PS.

Finally, we use the NSS Consumer-Expenditure Schedule. This dataset contains detailed information on households' expenditure allocation across narrowly defined goods and thus allows us to measure expenditure shares on food and CS. We use this information to estimate the Engel elasticity $\varepsilon$.

**Geography:** To compare spatial units over time, we create a time-invariant definition of geography. We define regions as Indian districts. Because the boundaries of several districts changed over time, we harmonized them using GIS software, relying on maps for the years 1987, 1991, 2001, and 2011. We define regions so that they have the same boundaries over time. To keep the number of regions as large as possible, a region is always the smallest area that covers a single district or a set of districts with consistent boundaries over time. We exclude two small districts that existed in 2011 but did not exist in 1987. We also exclude districts with less than 50 observations because they do not allow us to precisely estimate sectoral employment shares. In the end, we obtain 360 regions that cover the vast majority of the Indian territory. We label these regions "districts." Appendix Section B-2 describes in detail how we construct this crosswalk.

## 4.2 Measurement

**Consumer versus Producer Services:** We distinguish between PS and CS in a way that is consistent with our theory. Our preferred criterion is to classify as PS firms selling to other firms and as CS firms selling to consumers.[10] We perform robustness analysis to alternative classification criteria. More details on the classification of industries can be found in Appendix Section B-3.

Ideally, we would want to measure employment in PS and CS with the help of detailed firm-level input-output matrices so as to associate the value added of each firm with the identity of the buyers—either private individuals or firms. To the best of our knowledge, this information is not available in India. We therefore leverage micro data on the firms' downstream trading partners contained in the Service Survey. Specifically, this data report whether a firm is selling mostly to consumers or to other firms. We could thus, in principle, calculate the share of employment in every service industry-district cell distinguishing between firms selling to other firms and those serving consumers. In practice, this procedure is not feasible because the Service Survey contains too few firms to precisely estimate these employment shares for each service industry-district cell. Instead, we rely on the fact that the probability of a firm selling to other firms rather than to consumers is highly correlated with firm size—larger firms are more likely to sell to firms. We show this pattern in Table 1, which displays the share of firms that mainly sell to other firms by employment size. A clear pattern emerges: small firms with one or two employees sell almost exclusively to final consumers, whereas a significant share of large firms sell to other firms. For example, among firms with

[9] As shown by Hsieh and Klenow (2014) and Akcigit et al. (2021), most Indian firms are very small, with an average size ranging between two and three employees. Over half have a single employee, and only one in 1,000 firms employs more than 100 workers.

[10] We recognize that this is an imperfect approximation. In particular, in our theory PS are only purchased by firms, while CS can also be purchased as inputs for the production of other CS. For instance, wholesale firms serving local retailers should be part of the CS sector even though they sell to firms. Measurement error is also a concern. Some firms might report selling to individuals, although some of these individuals are small entepreneurs using the services as inputs to production activities. In spite of these issues, we regard our criterion as a reasonable proxy measure to distinguish CS from PS in the data.

three employees, only 6.2% sell to other firms, while 42.5% of firms with more than 50 employees have other firms as their main customers.

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

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

We use the pattern reported in Table 1 in the following way. First, we estimate the PS employment share by firm size for different industries within the service sector. We then use the *district*-specific size distribution from the EC to infer the aggregate PS employment share in district $r$. More formally, the PS employment share (relative to the total service sector) in subsector $k$ in region $r$ is given by $s_{rk}^{PS} = \sum_b \omega_{kb}^{PS} \ell_{kbr}$, where $\omega_{kb}^{PS}$ is the share of employment in firms selling to firms in sector $k$ in size class $b$, and $\ell_{kbr}$ is the employment share of firms of size $b$ in sector $k$ in region $r$. Note this procedure assumes the structure of production for firms of equal size do not vary across Indian districts. The regional variation in PS and CS employment thus stems from differences in (i) total service employment, (ii) the relative share of different service industries, and (iii) the distribution of firm size. In Appendix Section B-3.2, we describe this procedure in more detail.

In Figure 3 we display the result of this exercise for different subsectors within the service sector. Within the retail and restaurant sector, only a few establishments cater to other firms. Hence, we estimate that more than 97% of employment in that industry is engaged in the production of CS. The situation is very different in the financial or the ICT sector, where, respectively, 26% and 53% of employment caters mainly to other firms.

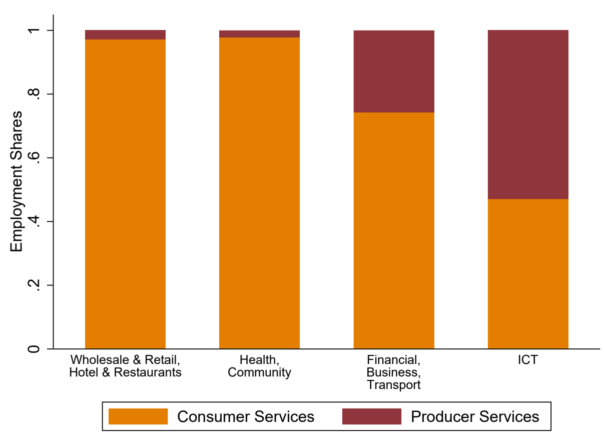


Figure 3: Producer vs. consumer services in different industries. The figure shows the share of PS and CS in 2011 in different industries within the service sector.

Finally, we merge construction and utilities with the service sector. Although the construction sector is sometimes included in the industrial sector, the key distinction in our theory is that goods are tradable whereas services are nontradable. Because construction and utilities are provided locally, we find it natural to merge them with services. However, in Section 7 we show that our results are similar when we include construction in the manufacturing sector.

The construction sector serves both consumers (e.g., residential housing) and firms (e.g., business construction). To break these activities into PS and CS, we follow a procedure similar to that used for services. We exploit information from the "Informal Non-Agricultural Enterprises Survey 1999–2000" (INAES) dataset, which also reports whether a firm sells to consumers or other firms and which covers the construction sector. Given the sample size, splitting the destination of construction activities is possible only at the national, not the district, level. We obtain the following breakdown. First, we remove 9.1% of the construction activity from the sample, which corresponds to the share of government activity (infrastructure and public goods). Then, based on the INAES data, we attribute 87.1% of what is left to CS and 12.9% to PS in every district-year. More details are provided in Appendix Section B-3.3.

Our model implies that regional CS value added shares cannot exceed the value of the parameter $\omega_{CS}$. Since we estimate below that $\omega_{CS} = 0.69$, twenty small districts violate the constraint. In these cases, we topcode the share of CS and split the excess proportionally between the other two sectors. In practice, this issue is inconsequential because these districts account altogether for a mere 0.12% and 0.18% of the total valued added of India in 1987 and 2011, respectively.

**Urbanization:** In Figure 4 we quantify the structural transformation in India across both time and space. We focus on urbanization as our measure of spatial heterogeneity. This as a mere descriptive device. In Appendix Section B-5, we document a strong positive correlation between urbanization and the expenditure per capita in the NSS data for 2011. Thus, we take the urbanization rate as a proxy for economic development across Indian districts. Figure 4 displays sectoral employment shares by urbanization quintiles. The average urbanization rates of the five quintiles are, respectively, 6.4%, 12.1%, 19.5%, 29.2%, and 56.4%. Richer urban districts have lower employment shares in agriculture and specialize in the production of services and industrial goods. Over time, the share of agriculture declines. Between 1987 and 2011 the structural transformation was especially fast in more-urbanized districts. In 1987, agriculture was the main sector of activity even in the top quintile of urbanization. By contrast, in 2011, more than half of the working population was employed in CS and PS. This difference is even starker when one looks at earnings instead of employment; see Appendix Figure B-6.

A concern is that our methodology might underestimate employment in PS relative to CS. In Section 7.2, we address this concern by showing that all our results are qualitatively robust to reasonable alternative measurement choices that give a more prominent role for PS employment.

**Human Capital:** To be consistent with our theory, we measure each district's endowment of human capital units $F_{rt}(q)$ and its distribution across sectors in terms of efficiency units of labor. To measure the distribution of human capital across sectors within a district, we rely on the sectoral distribution of earnings, which reflects differences in the endowment of effective units of labor.[11] To measure the distribution of human capital across districts, we follow the approach in the development accounting literature and leverage data on the regional distribution of schooling, together with an estimate of the Mincerian returns to schooling $\rho$ (see Section 5.1 below).

We classify people into four educational groups: (i) less than primary school, (ii) primary and upper primary/middle school, (iii) secondary school, and (iv) more than secondary school. We associate each step in the education ladder with three extra years of education, consistent with the organization of schools in India.

Table 2 shows why it is important to allow for human capital differences across years, sectors, and space. First, the level of schooling increased markedly between 1987 and 2011 and is itself a source of growth. Second,

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

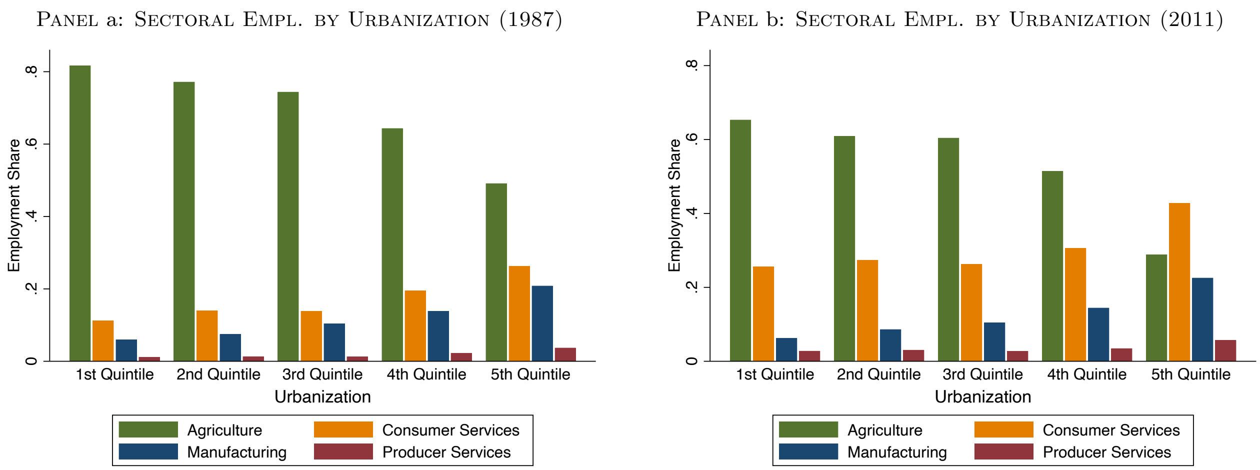


Figure 4: Sectoral Employment over Time and Space. The figure plots the sectoral employment shares by urbanization quintile in 1987 and 2011.

educational attainment differs vastly across sectors.[12] That agriculture is the least skill-intensive industry and educational attainment is the highest in PS is not surprising. However, note the CS sector also employs lots of skilled individuals and is more skill-intensive than the manufacturing sector. Through the lens of our model, these patterns imply that the average number of efficiency units differs across sectors, and by using earnings shares rather than employment shares, our methodology takes such differences into account. Finally, there are large spatial differences whereby city dwellers are much more educated than the rural population. By explicitly measuring the local supply of human capital, we refrain from attributing these differences to differences in local TFP.

| | Less than primary | Primary, upper primary, and middle | Secondary | More than secondary |
|---|---|---|---|---|
| | | *Aggregate Economy (1987–2011)* | | |
| 1987 | 66.79% | 22.03% | 7.99% | 3.19% |
| 2011 | 40.32% | 30.10% | 18.79% | 10.79% |
| | | *By Sector (2011)* | | |
| Agriculture | 53.72% | 29.23% | 14.45% | 2.60% |
| Manufacturing | 32.63% | 35.31% | 20.68% | 11.39% |
| CS | 29.85% | 32.24% | 23.40% | 14.51% |
| PS | 28.04% | 30.13% | 22.03% | 19.81% |
| | | *By Urbanization (2011)* | | |
| Rural | 46.97% | 30.00% | 16.30% | 6.84% |
| Urban | 33.69% | 30.30% | 21.27% | 14.73% |

Table 2: Educational Attainment. The table shows the distribution of the educational attainment over time (Panel A), by sector of employment (Panel B) and across space (Panel C). The breakdown of rural and urban districts is chosen so that approximately half of the population live in rural districts and half live in urban districts.

[12] In Table 2 we rely on our sectoral classification to associate workers with PS and CS. In Section B-4 in the Appendix, we report the analogue of Table 2 when we classify CS and PS according to the NIC classification, that is, assign wholesale, retail, hotels, restaurants, health, and community services to CS and financial, business, transport and ICT services to PS. This classification increases the relative skill content of both CS and PS.

# 5 Estimation: Identification and Results

We now turn to the estimation of the model. Our approach is in the tradition of development accounting; see, e.g., Caselli (2005), Hall and Jones (1999), and Gancia et al. (2013)). Whereas these studies infer productivity at the country level from an aggregate production function, we estimate the entire distribution of productivity $\{A_{rst}\}$ across sectors and space. Because we rely on the equilibrium structure of our model, we refer to our method as *equilibrium development accounting.*

The centerpiece of the methodology is the distinction between structural parameters and local productivities. The model has eight structural parameters describing preferences and the distribution of skills

$$\mathbf{\Omega} = \left\{ \underbrace{\varepsilon, \nu_{CS}, \nu_F, \omega_{CS}, \omega_F, \sigma}_{\text{Preference parameters}}, \underbrace{\rho, \zeta}_{\text{Human capital}} \right\}.$$

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

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

Given the parameter vector $\mathbf{\Omega}$, there exists a one-to-one mapping from the equilibrium skill prices $\{w_{rt}\}$ and sectoral employment allocations $\{H_{rst}\}$ to the underlying productivity fundamentals in $\mathbf{A_t}$. In Section 5.1, we describe how we estimate the vector of structural parameters $\mathbf{\Omega}$. In Section 5.2, we discuss the estimation procedure for $\mathbf{A_t}$ and its results.

## 5.1 Estimation of Preference and Human Capital Parameters

**The Engel Elasticity $\varepsilon$:** The crucial parameter in our analysis is the Engel elasticity $\varepsilon$, which determines how fast the expenditure on agricultural goods shrinks—and, conversely, how fast the expenditure for CS expands—as income rises. To estimate $\varepsilon$, we use the cross-sectional relationship between income and expenditure shares on different food items at the household level. Our estimation approach involves expenditure data. While in general this is not consistent with the value added approach based on employment data adopted in the rest of the paper, Proposition 1 establishes that under PIGL preferences, the two demand systems share the same Engel elasticity $\varepsilon$.

In terms of our theory, let the set $\mathcal{F}$ denote the subset of the product space $[0, 1]$, containing all products classified as food. According to our theory, the spending share on food item $j \in \mathcal{F}$ is then given by

$$\vartheta_j^{FE}(e, \mathbf{p_r}) = \beta_j + \kappa_n \left( \frac{e}{\exp\left(\int_n \beta_n \ln p_{rn} dn\right)} \right)^{-\varepsilon}. \tag{20}$$

Recall that $\beta_j$ is the asymptotic expenditure share on final good $j$ as income grows, namely, $\lim_{e\to\infty} \vartheta_j^{FE}(e, \mathbf{p_r}) = \beta_j$. If $\beta_j$ is small—which is reasonable to expect for food items— Equation (20) yields a log-linear approximate relationship between household income and expenditure shares on final good $j \in \mathcal{F}$:

$$\ln \vartheta_j^{FE}(e, \mathbf{p_r}) = \varepsilon \left( \int_n \beta_n \ln p_{rn} dn \right) - \varepsilon \times \ln e + \ln \kappa_j. \tag{21}$$

| | Y: log(food expenditure share) | | | | | | |
|---|---|---|---|---|---|---|---|
| log(household expenditure) | -0.367*** | -0.330*** | -0.321*** | -0.334*** | -0.371*** | | |
| | (0.062) | (0.070) | (0.007) | (0.066) | (0.103) | | |
| log(household expenditure) | | | | | | -0.265*** | |
| × below median | | | | | | (0.057) | |
| log(household expenditure) | | | | | | -0.418*** | |
| × above median | | | | | | (0.072) | |
| log(household expenditure) | | | | | | | -0.320*** |
| × low urbanization | | | | | | | (0.066) |
| log(household expenditure) | | | | | | | -0.363*** |
| × high urbanization | | | | | | | (0.064) |
| Trim (top & bottom 5%) | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Addtl. Controls | | | | ✓ | ✓ | ✓ | ✓ |
| IV | | | | | ✓ | | |
| Region-Food FE | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | | | | |
| N | 1245119 | 1130332 | 91495 | 1129730 | 1068038 | 1129730 | 1129730 |
| $R^2$ | 0.627 | 0.634 | 0.425 | 0.635 | 0.040 | 0.635 | 0.635 |

Table 3: Income elasticity for food. The table shows the estimated coefficient $\gamma$ of the regression (22). The dependent variable is the income share spent by each household on 17 different food items: beverages; cereals; cereal substitutes; dry fruit, edible oil; egg, fish and meat; fresh fruit; intoxicants; milk and milk products; pan; packaged processed food products; pulses and products; salt and sugar; served processed food; spices; tobacco; vegetables. In all specifications, we control for a (within-district) urban/rural dummy, a set of fixed effects for household size, and the number of workers within the household. Standard errors clustered at the district-food item level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We can thus estimate $\varepsilon$ from the regression

$$\ln \vartheta_j^h = \delta_{rj} + \varepsilon \times \ln e_h + x_h' \psi + u_{rjh}, \tag{22}$$

where $\vartheta_j^h$ denotes the observed expenditure share of household $h$ (living in region $r$) on food item $j$, $e_h$ denotes total household spending, $\delta_{rj}$ is a set of region-food item fixed effects, and $x_h$ is a set of household characteristics that could induce a correlation between total spending $\ln e_h$ and food shares.[13] Comparing (22) with (21) it is apparent that the terms $\left(\int_n \beta_n \ln p_{rn} dn\right)$ and $ln(\kappa_j)$ are absorbed in the region-food item fixed effects $\delta_{rj}$. Finally, the household-level controls $x_h$ capture cross-sectional variation in preferences (e.g., related to the size of the household) which—albeit abstracted from in the theory—could be correlated with household income $e$.

Our regression includes 17 food items; see the details in Table 3. The unit of observation is the individual expenditure on each food item. Table 3 reports the estimation results. We cluster standard errors at the region-food item level to account for the correlation of spending shares through regional prices. All regressions include region-food item fixed effects unless otherwise specified.

The first column refers to a specification that only controls for whether the household lives in an urban or rural area (within districts), a full set of fixed effects for household size, and the number of workers within the household (in addition to district-food item fixed effects). We estimate an elasticity of 0.37 that is precisely estimated. In column 2, we trim the top and bottom 5% income levels, since we suspect these observations can contain some

[13] The description in the text ignores formal details related to the continuum state space in the theory. These are irrelevant since in the data we observe a finite number of food items.

misreporting. The elasticity decreases to 0.33. In column 3, we run a regression in which the unit of observation is the individual expenditure on all food items rather than on each item.[14] This reduces the number of observations from over 1.2 million to ca. 91,000. In this regression, we can only control for district fixed effects. Interestingly—and reassuringly—the estimated elasticity is almost identical to that in column 2.

In the remaining columns of Table 3, we report additional specifications to show the robustness of this estimate. In column 4, we introduce additional household-level controls. In particular, we control nonparametrically for (i) differences in the household type, that is, whether the household is self-employed (in agriculture or non-agriculture), (ii) whether the household has a regular wage earner or a casual laborer (in agriculture or non-agriculture), (iii) the household's religion, (iv) the household's social group, and (v) whether the household is eligible to purchase subsidised food grain from the Indian government. The estimated value for the elasticity is very similar to the estimate in column 2.

In column 5, we present the results from an IV specification addressing concerns about measurement error in $\ln e_h$ that could bias the estimated Engel elasticity. We instrument total expenditure with a full set of three-digit occupation fixed effects.[15] As expected, these fixed effects strongly predict total expenditure as shown by the large F-statistic. The exclusion restriction is that occupational choices only affect spending shares through their effect on income.[16] The IV estimate is slightly larger than the OLS estimate.

In Figure 5 we show a binscatter plot of the data for log food expenditure shares versus log income after absorbing district-food item fixed effects. Our PIGL specification as well as the corresponding regression Equation (22) postulate a log-linear relationship. Indeed, a visual inspection of the figure confirms that the relationship across bins is approximately linear in the data. However, careful scrutiny reveals some mild concavity suggesting a higher elasticity for high-income levels. In column 6 of Table 3, we investigate this issue more formally by allowing different elasticities for households above and below the median income. The estimated elasticity is indeed larger for high-income households. The difference is statistically significant. However, neither of the estimated elasticities is significantly different from the point estimate in column 4—the *p-values* are 0.25 and 0.26, respectively.[17] Finally, in column 7 we analyze the extent to which the elasticity differs between rural and urban localities. We define urban locations as the ones in the top quartile of the distribution of urbanization. While urban locations have slightly higher elasticities, the differences are quantitatively small. For our baseline analysis we take the Engel elasticity $\varepsilon$ to be equal to 0.33. In Section 7, we check the robustness of our results to all estimates reported in Table 3.

**Other Preference Parameters** $(\nu_s, \omega_s)$**:** For the remaining parameters of the demand system, we follow the value added approach. The market-level demand system depends on the aggregate preference parameters $\overline{\nu}_{CS}$ and $\overline{\nu}_F$, which are in turn related to the primitive micro-level preference parameters $\nu_{CS}$ and $\nu_F$; see Equation (14). We estimate $\overline{\nu}_s$ directly from the data and then infer the micro parameters $\nu_s$ given an estimate of the inequality parameter $\zeta$. Identifying $\nu_s$ separately from $\overline{\nu}_s$ is only required to quantify the welfare consequences of service-led growth, not to estimate the model.

We identify the parameters $\omega_s$ and $\nu_s$ directly from the equilibrium conditions. In Appendix Section A-2, we

[14] More formally, in column 3 we run the regression $\ln \vartheta^h_{\mathcal{F}} = \delta_r + \varepsilon \times \ln e_h + x'_h \psi + u_{rh}$, where $\vartheta^h_{\mathcal{F}}$ denotes the observed food expenditure share of household $h$ on all food items in the set $\mathcal{F}$.

[15] The survey assigns the occupation of the household member with the highest earnings to the entire household.

[16] In this regression, we cannot include a full battery of region-food item fixed effects because we run short of degrees of freedom. Therefore, we control for district and for food item fixed effects but we do not interact them. Note that the two fixed effect strategies give very similar results in the specifications when we can run both.

[17] Allowing for the elasticity to vary with income in the theory would take us outside of the class of PIGL preferences we consider. We leave to future research to study generalizations of the class of preferences in this direction. In this paper, we maintain the assumption of a constant $\varepsilon$ and study a range of elasticities values in the robustness analysis in Section 7.

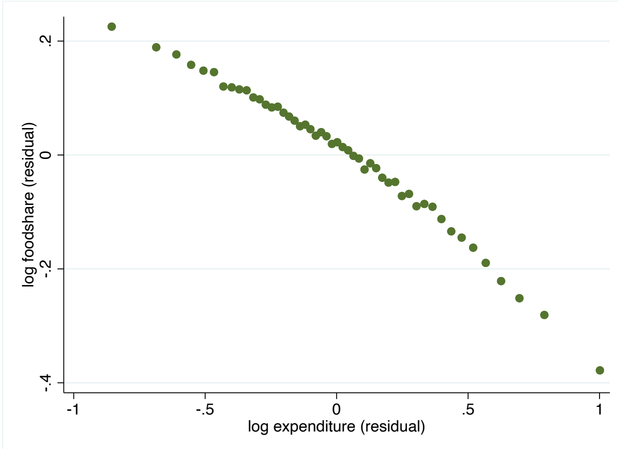


Figure 5: Engel curves in India. The figure shows a binscatter plot representation of the Engel elasticity for household-level data in 2011. It plots the residual of a regression of the log expenditure share on food item $j$ in region $r$ on region-product fixed effects against the residual of a regression of the log income (total expenditure) on the same set of fixed effects.

show that the set of market clearing conditions and Walras' law yield the following equation:

$$\sum_{r=1}^{R} w_{rt} H_{rFt} = \omega_F \sum_{r=1}^{R} w_{rt} H_{rt} + \overline{\nu}_F \sum_{r=1}^{R} \left( \omega_{CS} - \frac{H_{rCSt}}{H_{rt}} \right) w_{rt} H_{rt}, \tag{23}$$

which must hold for $t = 1987$ and $t = 2011$, assuming that preferences are stable over time. Since earnings and labor allocations are observable, this yields two equations in three unknown parameters, $\omega_F$, $\overline{\nu}_F$, and $\omega_{CS}$. Note in particular that (23) does not involve regional trade costs. Hence, our identification of preference parameters does not hinge on our correctly specifying the impediments to regional trade.

To identify $\omega_F$, $\overline{\nu}_F$, and $\omega_{CS}$, we use (23) for 1987 and 2011 and one long-run restriction. In particular, the parameter $\omega_F$ pins down the asymptotic expenditure share on agriculture goods to which $\vartheta_F$ declines as total expenditure grows. In the US, the agricultural employment share (as well as its value added share) is about 1%. Hence, we set $\omega_F = 0.01$. Incidentally, this implies that the structural Engel elasticity $\varepsilon$ is close to the empirical estimate $\hat{\gamma}$ in (21). Having set $\omega_F = 0.01$, Equation (23) yields then $\overline{\nu}_F = 1.276$ and $\omega_{CS} = 0.69$.

This implies an asymptotic expenditure share on CS of 69% that we view as reasonable. For instance, the value added share of the service sector in the US (that is not a targeted moment and includes PS and CS) has averaged 77% throughout the last decade.

Consider next $\overline{\nu}_{CS}$. In Appendix Section A-2, we show that $\overline{\nu}_{CS}$ is not separately identified from the productivity $A_{rCSt}$.[18] Hence, without loss of generality, we normalize it to -1. Given these estimates, the homotheticity restrictions imposed by PIGL preferences identify $\omega_G$ and $\overline{\nu}_G$. The asymptotic share of the good producing sector (that, recall, includes both manufacturing production and PS) is 30%. Moreover, $\overline{\nu}_M = -(\overline{\nu}_F + \overline{\nu}_{CS}) = -0.276$. This implies that industrial goods are also luxury goods, although their income elasticity is smaller than for the CS.

[18] This means that we cannot identify the level of $A_{rCSt}$. However, this is not important for our goals. Under the assumption of stable preferences, we can calculate the growth over time of $A_{rCSt}$ that is a focal point of our analysis.

| Parameter | | Target | Value |
|---|---|---|---|
| *Preference parameters* | $\varepsilon$ | Engel elasticity | 0.33 |
| | $\omega_F$ | Agricultural spending share US | 0.01 |
| | $\omega_{CS}$ | Agricultural Employment share 2011 | 0.69 |
| | $\overline{\nu}_F$ | Agricultural Employment share 1987 | 1.28 |
| | $\overline{\nu}_{CS}$ | Normalization | -1 |
| | $\sigma$ | Set exogenously | 5 |
| *Skill parameters* | $\rho$ | Mincerian schooling returns | 0.056 |
| | $\zeta$ | Earnings distribution within regions | 3 |

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

Finally, we set the inter-regional trade elasticity $\sigma$ to a consensus estimate in the literature and assume $\sigma = 5$.

**Skill Parameters $\zeta$ and $\rho$:** To link observable schooling $s_i$ to unobservable human capital $q_i$, we assume that $q_i = \exp(\rho s_i) \times \upsilon_i$, where $s_i$ denotes the number of years of education, $\rho$ is the annual return to schooling, and $\upsilon_i$ is an idiosyncratic shock, which we assume to be iid across districts and years and which satisfies $E[\upsilon_i] = 1$. Log earnings of individual $i$ in region $r$ at time $t$, $y_{irt}$ are thus given by a standard Mincerian regression $\ln y_{irt} = \ln w_{rt} + \rho s_i + \ln \upsilon_i$ and we can estimate $\rho$ from the within-region variation between earnings and education, which we can measure from the NSS data. This yields an average annual rate of return of 5.6%, which is on the lower end of standard Mincerian regressions, although broadly in line with the findings of recent studies for India using the NSS; see Singhari and Madheswaran (2016). In Section 7, we discuss the robustness of our results to using a higher return to education. Given this estimate of $\rho$, we then calculate the average amount of human capital per region as $\mathbb{E}_{rt}[q] = \sum_s \exp(\rho \times s)\ell_r(s)$, where $\ell_r(s)$ denotes the share of people in region $r$ with $s$ years of education. Hence, the distribution of educational attainment across districts determines the spatial distribution of human capital.

To estimate the tail parameter of the skill distribution $\zeta$, recall that the distribution of income in region $r$ is given by $G_r(y) = 1 - \left(\underline{q}_r w_r / y\right)^{\zeta}$, implying $\ln(1 - G_r(y)) = \zeta \ln\left(\underline{q}_r w_r\right) - \zeta \ln y$. We therefore estimate $\zeta$ from a cross-sectional regression $\ln(1 - G_r(y_i)) = \delta_r + \beta \ln y_i + u_{ir}$, where $\delta_r$ is a district fixed effect. In practice, we consider a support of regional incomes above the median, because the Pareto distribution is a better fit to the right tail of the income distribution. This procedure yields an estimate of $\zeta \approx 3$ (see Appendix Section C-1). With this estimate at hand, we can also compute the lower bound $\underline{q}_{rt}$ form $\mathbb{E}_{rt}[q_i] = \frac{\zeta}{\zeta - 1}\underline{q}_{rt}$.

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

Given the structural parameter vector $\mathbf{\Omega}$, data on local wages and sectoral employment allocations, as well as time-series data on relative prices and aggregate income, the equilibrium conditions uniquely identify a set of local productivity fundamentals $\mathbf{A_t}$. We summarize the methodology to estimate $\mathbf{A_t}$ in this section, referring the interested reader to Appendix Section A-2 for details. In particular, there we show that there is a unique set of sectoral prices $P_{srt}$ that rationalizes the observed data on skill prices and employment shares. For our discussion here, we can thus treat $P_{srt}$ as known, even though we want to stress that we do not directly use information on prices in our estimation.

**Productivity Distribution:** Consider first the identification of $A_{rCSt}$. Equation (19) implies we can uniquely solve for $A_{rCSt}$ as

$$A_{rCSt}=\left(\frac{(-\overline{\nu}_{CS})}{\omega_{CS}-\frac{H_{rCSt}}{H_{rt}}}\right)^{\frac{1}{\omega_{CS}}\frac{1}{\varepsilon}}P_{rFt}^{\frac{\omega_F}{\omega_{CS}}}P_{rGt}^{\frac{\omega_G}{\omega_{CS}}}\left(\mathbb{E}_{rt}\left[q\right]\times w_{rt}^{1-\omega_{CS}}\right)^{-\frac{1}{\omega_{CS}}}. \tag{24}$$

Controlling for the level of human capital $\mathbb{E}_{rt}[q]$, local tradable prices $P_{rGt}$ and $P_{rFt}$, and the equilibrium skill prices $w_{rt}$, CS productivity is increasing in the observed employment share $H_{rCSt}/H_{rt}$.[19] Conversely, holding the employment share $H_{rCSt}/H_{rt}$ constant, CS productivity $A_{rCSt}$ is decreasing in both human capital and factor prices. Structurally decomposing the observed variation in employment shares into the part that is service led (i.e., $A_{rCSt}$) versus the part that is driven by income effects (i.e., $\mathbb{E}_{rt}[q]\,w_{rt}^{1-\omega_{CS}}$ and $P_{rFt}^{\omega_F}P_{rGt}^{\omega_g}$) is a key step of our equilibrium accounting methodology.

The procedure to estimate productivity in tradable sectors is different. Equation (18) implies relative productivity across two locations is given by

$$\frac{A_{rs}}{A_{js}}=\left(\frac{H_{rs}}{H_{js}}\right)^{\frac{1}{\sigma-1}}\times\left(\frac{w_r}{w_j}\right)^{\frac{\sigma}{\sigma-1}}\times\left(\frac{\sum_{d=1}^{R}\tau_{rd}^{1-\sigma}P_{dst}^{\sigma-1}\overline{\vartheta}_{dst}w_{dt}H_{dt}}{\sum_{d=1}^{R}\tau_{jd}^{1-\sigma}P_{dst}^{\sigma-1}\overline{\vartheta}_{dst}w_{dt}H_{dt}}\right)^{\frac{1}{1-\sigma}}\quad\text{for } s=F,G. \tag{25}$$

Relative productivity $A_{rs}/A_{js}$ is driven by three factors: relative employment shares $H_{rs}/H_{js}$, relative factor prices $w_r/w_j$, and relative demand as summarized by producer market access. To understand (25), recall that a large employment share (holding wages fixed) and high wages (holding the employment share fixed) indicates that the location is able to provide its goods at low prices. The market access term in (25) is a correction term that summarizes the possibility that a location can have a high employment share in tradable goods not because of high efficiency but rather because it is close to centers of demand.[20]

**Sectoral Aggregate Productivity Growth:** Equations (24) and (25) determine the distribution of sectoral productivity across locations. To determine the level, we must pin down the average productivity growth for each sector between 1987 and 2011, which then determines the sectoral aggregate price levels. As we discuss in more detail in the Appendix, we target two aggregate moments to achieve identification. First, we target a 2.6 growth factor for real income per person, which matches real GDP per capita growth according to the World Bank (WDI).[21] Second, we target the change in the relative price of agricultural goods relative to industrial goods between 1987 and 2011 as reported by the Groningen Productivity Database (GGDC).[22] Empirically, agricultural prices rose by a factor of 1.42 relative to prices in the industrial sector. Given these moments, our model identifies all productivity levels $A_{rst}$. In particular, our estimated model endogenously generates a deflator for CS prices that is independent of its data analogue. We view this as an advantage given the notorious difficulty in measuring the price of services.

**Results:** Figure 6 summarizes the cross-sectional pattern of our productivity estimates $A_{rst}$ by displaying a bin-

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

[20] For the case of frictionless trade, $\tau_{rd}=1$, the last term disappears and productivity differences across regions can be inferred directly from relative skill prices and relative factor inputs given the elasticity of substitution $\sigma$. In this case, no preference parameters are required because food and industrial goods are tradable so that local demand is dissociated from local income.

[21] Note that we measure GDP in terms of the numeraire industrial good. Because of nonhomothetic preferences, we cannot define a standard consumption price index. For comparison, we calculated wage growth for a fictitious agent endowed with the median wage and living in a district in which the supply of CS is at the median level. Based on the consumption basket of such an individual in 1987 and 2011, we calculated real wage growth using a Laspeyres and a Paasche index. The resulting real wage growth in the two cases is 1.82 and 4.86, respectively. Our calibration yields an income growth factor of 2.60, which is in between.

[22] All sectoral average prices discussed in this section are constructed as weighted averages across Indian districts in a specific year, using the districts' income shares as weights.

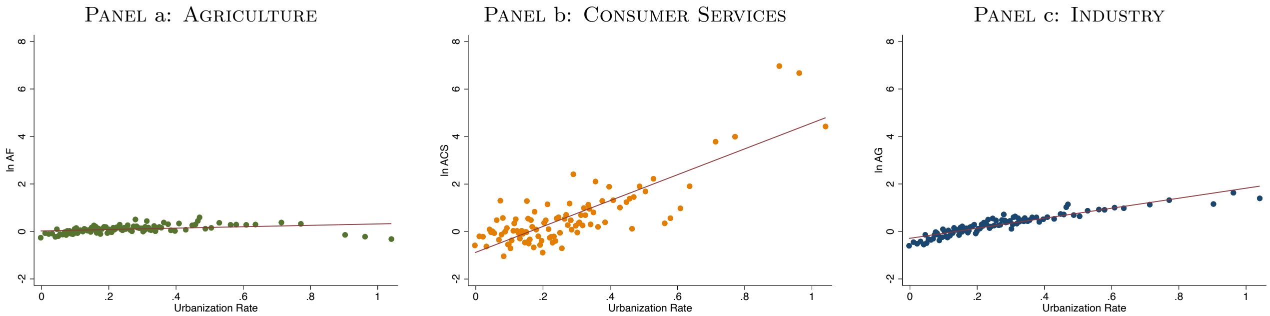


Figure 6: Estimated Sectoral Productivities. The figure shows a binscatter plot of the estimated sectoral labor productivities in agriculture, CS, and industry across urbanization-rate bins. Each plot is constructed by pooling the estimates for 1987 and 2011 after absorbing year effects.

scatter plot as a function of the observed urbanization rate. The relationship between productivity and urbanization is increasing for CS (Panel (b)) and in the industrial sector (Panel (c)). For agriculture, the relationship is relatively flat and slightly hump-shaped. The declining portion corresponding to districts with an urbanization rate above 50% likely reflects the scarcity of land (a factor of production from which we abstract) in urban areas.

Both the productivity dispersion and its correlation with urbanization is strongest in the CS sector. Hence, the large employment share of CS in urbanized districts is not only a consequence of high wages or of an abundance of human capital, but also of high CS productivity relative to rural areas. Among the tradable goods, productivity is significantly more dispersed in the industrial than in the agricultural sector. To understand why, note a district's relative productivity reflects its sectoral earning share relative to its skill price (see (25)). The "compressed" productivity distribution in agriculture reflects the observation that wages are negatively correlated with the employment share of agriculture across districts. By contrast, wages are positively correlated with the employment share of industry, implying a wider productivity dispersion.

Figure 6 describes the spatial variation in the *level* of sectoral productivity. We are equally interested in the distribution of sectoral productivity growth between 1987 and 2011. Using our estimates $A_{rst}$ we can calculate sectoral productivity growth between 1987 and 2011 for each district. We summarize the distributions of annualized productivity growth in Table 5.

In the first row, we focus on CS productivity growth; in the remaining rows, we report the distributions of growth rates in the tradable sectors. Two facts are salient. First and foremost, productivity in the CS sector grew in the vast majority of districts. In the median region, CS productivity grew by 3.5% annually between 1987 and 2011. This is comparable to productivity growth in the industrial sector and 1.3% higher than in agriculture. Second, productivity growth was unequal across space, particularly so in the CS sector.[23] In CS, the top 10% of locations experiences productivity growth exceeding 14%.

In Section C-3 in the Appendix we analyze the cross-sectional variation in productivity growth in more detail. In particular, we show that productivity growth is positively correlated with the urbanization rate in 1987, that is, cities experienced faster productivity growth. This correlation is also apparent in the last row of Table 5, which shows that the population-weighed average of productivity growth exceeds the growth experience of the median locality.

[23] To account for measurement error, we winsorize the top and bottom 3% of the estimated productivity distributions. The details are discussed in the Appendix, where we also report robustness results for these choices (see Section C-5).

| | Sectoral productivity growth | | | | | |
|---|---|---|---|---|---|---|
| | 10th | 25th | 50th | 75th | 90th | Aggregate |
| Consumer Services ($g_{rCS}$) | -1.4 | 0.8 | 3.5 | 8.3 | 14.0 | 5.1 |
| Agriculture ($g_{rF}$) | 0.6 | 1.4 | 2.2 | 3.0 | 3.5 | 2.3 |
| Industry ($g_{rG}$) | 1.6 | 2.6 | 3.4 | 4.3 | 5.8 | 3.6 |

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

### 5.3 nontargeted Moments

In this section, we highlight some implications of the estimated model for nontargeted data moments. In particular, we document that: (i) the predictions of our model for average productivity growth at the sectoral level line up well with existing estimates from the Groningen Productivity Database, (ii) the Engel elasticity $\varepsilon$ estimated from the food expenditure shares is also consistent with the expenditure shares of CS, (iii) the implied elasticites of substitution for the value added of different sectors are in line with existing estimates from other studies, and (iv) our model's predictions for the regional variation in food prices is consistent with the one observed empirically. For brevity, we summarize our main findings here and present a more detailed analysis in Section C-4 in the Appendix.

**Alternative Estimates of Sectoral Productivity Growth:** While we are not aware of productivity growth estimates at the regional level, the Groningen Productivity Database (GGDC) provides estimates of nationwide productivity growth at the sector level that can be compared with our estimates. In the left panel of Figure 7 we display the annual growth in value added per worker between 1987 and 2011 as reported in the GGDC data. The GGDC data highlights the important role of the service sector for Indian growth: productivity in services grew by 7.2%, manufacturing productivity grew by around 5%, and agricultural productivity grew by roughly 1%.

In the right panel, we display the results from our model. More specifically, we report the average regional growth rate of value added per worker weighted by the relative share of aggregate expenditure in each district. Our model-based accounting approach yields aggregate productivity growth rates that are in the same ballpark as the ones obtained from the GGDC.

It is important to note that the exact comparison is complicated because of the differences in the sectoral classification. First, as explained above, we allocate some business services (like financial services and ICT) and the construction sector partly to the industrial sector and partly to CS. Second, the GGDC data also includes government services—from which we abstract, and whose productivity growth is lower than for other service categories. However, at a finer level of disaggregation, the results are broadly consistent. As we show in Table C-3 in the Appendix, according to the GGDC data, productivity in the category of trade, restaurant, and hotels—which includes mostly CS—was above 7%. The category Finance, Insurance, etc.—which includes both PS and CS in our classification—attained the highest productivity growth, at 10%.

We can also compare the time evolution of the CS price implied by the model with the price index in the GGDC data. Recall that the two measures are totally independent because we do not use the price index for CS as a target in our estimation. In the period of 1987–2011, the average price of CS relative to industrial goods increased by a factor of 1.26 in our model, which compares with 1.12 in the published data. For comparison, the price of

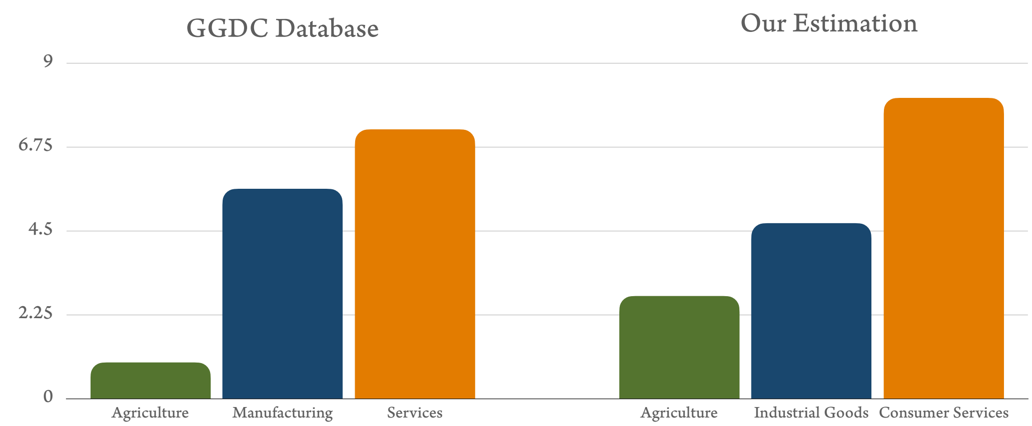


Figure 7: Aggregate Estimates of Productivity Growth. The figure shows the growth rates of sectoral value added as measured in the GGDC Data and the estimates from our model.

agricultural products relative to industrial goods increased by a factor of 1.42 both in the model and in the data (recall that in this case the relative price is targeted in the estimation and is matched by construction). Therefore, the ranking of the relative price changes is the same in the model as in the data, although the increase in the price of CS to relative to industrial goods is larger in the model than in the data.

While this aggregate evidence is, by construction, silent on the extent to which productivity growth is unbalanced across space, we find it reassuring that our model delivers estimates for productivity growth and prices that are broadly consistent with existing aggregate data.

**Spending on Consumer Services:** We have used data on food shares to estimate the Engel elasticity $\varepsilon$. Alternatively, we could have used data on the expenditure share of CS. We prefer food expenditures for two reasons. First, expenditure on food items is likely to be better measured. Second, the log-linear specification in (22) only recovers a consistent estimate of $\varepsilon$ if the asymptotic expenditure $\beta_n$ is small. While this is plausible for the case of food, the asymptotic spending share on CS intensive has to be positive if such goods are luxuries.

In Appendix Section C-4 we analyze the micro data on CS expenditure shares in more detail to validate our model along two dimensions. First, we run—in the model and in the data—the same specification as in (22) except that we use households' expenditure share on CS as the dependent variable. We follow the official classification of the NSS expenditure module to assign expenditures to CS. These expenditures include, for example, domestic servants, barber shops, or tailor services. We also add entertainment expenses such as movie theaters or club fees. We find that CS are luxuries: high-income households spend a higher share on CS. Quantitatively, we find the elasticity between the spending share on CS and individual income to be between between 0.25 and 0.3 for the OLS specification and around 0.55 in the IV case. When we estimate this specification in our model, we obtain a coefficient of about 0.4. Hence, even though we do not use the data on CS spending to estimate the model, the implied relationship between spending shares and income is broadly consistent with what we see in the household data.

Second, we use the CS expenditure share data to validate our estimates of regional CS productivity $A_{rCS}$. Our theory implies that, conditional on total expenditure, CS shares should be large in regions where prices are low, that is, where $A_{rCS}$ is large relative to the local wage. As we show in Appendix Section C-4, our estimates of $A_{rCS}$

are positively correlated with the estimated regional fixed effects of the CS expenditure system.

**Elasticities of Substitution:** Given our estimated preferences, we can calculate the elasticity of substitution between the value added of different sectors. For the class of PIGL preferences, the elasticity of substitution is not a constant structural parameter but varies with relative prices and total expenditure.[24] We defer the details of the analysis to Appendix Section C-4. The main finding is that services and industrial goods are complements, with an elasticity of substitution ranging between 0.6 and 0.9 across different urbanization quantiles. A relationship of complementarity is consistent with the common wisdom in the literature. On the other hand, we find that food and CS are, on average, substitutes with an elasticity of substitution elasticity ranging between 1.6 (least urbanized districts) and 1.2 (most urbanized districts). Finally, according to our estimates, agricultural and industrial value added are also substitutes but have lower elasticities ranging between 1.1 and 1.2.

**Regional Food Prices:** Our estimated model predicts local prices that can be compared with the data. The expenditure survey reports both the total expenditure and the total quantity bought for a variety of food items. We can thus compute the average price of product $n$ in region $r$, $p_{nr}$, as the ratio between total expenditure and quantity. Given this information, we compute the *average* food price in region $r$ as the regional fixed effect $\delta_r$ in the regression $\ln p_{nr} = \delta_r + \delta_n + u_{nr}$. Note that the product-specific fixed effect $\delta_n$ controls for differences in units of measurements across products. In Appendix Section C-4 we show that the estimated $\hat{\delta_r}$ is strongly correlated with the regional price of agricultural goods in the model, that is $\ln p_{rFt}$.[25]

# 6 The Unequal Welfare Effects of Service-Led Growth

This section contains the main results of the paper. We address the following related questions: (i) . How important was productivity growth in the service sector to rising living standards? (ii) How skewed were the benefits of service-led growth across different socioeconomic groups? (iii) How important was productivity growth in CS in promoting structural change in India?

To quantify the macroeconomic impact of these growth estimates reported in Table 5, we compute counterfactual equilibria where we set the respective sector's productivity growth to zero in all districts. The resulting changes in wages and employment allocations thus reflect the effect of sectoral productivity growth holding constant productivity growth in all other sectors. Our model allows us to compute the welfare effects for consumers and how these effects vary across space and the income distribution ladder. As we shall see in Section 6.1, we uncover a great deal of heterogeneity in both dimensions. In addition, we can also compute the implications for the structural transformation.

## 6.1 Methodology

To measure changes in welfare, we calculate equivalent variations relative to the *status quo* in 2011. We focus on two layers of heterogeneity: (i) across individuals differentiated by income, (ii) across districts differentiated by their rate of urbanization. We can also calculate aggregate effects for the entire Indian economy.

As discussed in Section 3.2.2, the PIGL demand system allows us to capture such heterogeneous welfare effects

[24] The Allen-Uzawa elasticity of substitution between goods $s$ and $k$ is given by $EOS_{sk} = 1 - \varepsilon\frac{(\vartheta_s - \omega_s)(\vartheta_k - \omega_k)}{\vartheta_s \vartheta_k}$.

[25] According to our model, the local price of good $n$ is given by $\ln p_{rnt} = \lambda_{Fn} \ln p_{rFt} + \lambda_{Gn} \ln p_{Grt} + \lambda_{CSn} \ln \frac{w_{rt}}{A_{rnt}}$. The local food price is the price of final goods that consist mostly of agricultural inputs, i.e. $\lambda_{nF} \approx 1$. Hence, $\ln p_{rnt} = \ln p_{rFt}$.

in a tractable way. More specifically, suppose we want to compare the two vectors of wages and prices $x_r = (w_r, \mathbf{P}_r)$ and $\hat{x}_r = \left(\hat{w}_r, \hat{\mathbf{P}}_r\right)$. Let $\varpi^q(\hat{x}_r|x_r)$ be the income an individual with skill level $q$ facing prices and wages $x_r$ requires to achieve the same level of utility as under $\hat{x}_r$. In our experiments below, the changes in wages and prices between $x_r$ and $\hat{x}_r$ are caused by counterfactual changes in sector-region-specific productivity.

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Using the indirect utility function $\mathcal{V}$ given in (5), $\varpi^q(\hat{x}_r|x_r)$ is implicitly defined by

$$\mathcal{V}(\varpi^q(\hat{x}_r|x_r), \mathbf{P}_r) \equiv \mathcal{V}(q\hat{w}_r, \hat{\mathbf{P}}_r). \tag{26}$$

Using (26), we can compute the welfare-equivalent income $\varpi^q(\hat{x}_r|x_r)$ for the entire income distribution (as parameterized by $q$) and for each location $r$. As we show in Section A-4 in the Appendix, $\varpi^q$ is given by

$$\frac{\varpi^q(\hat{x}_r|x_r)}{q\hat{w}_r} = \prod_s \left(\frac{P_{rs}}{\hat{P}_{rs}}\right)^{\omega_s} \times \left(1 - \left(\sum_s \nu_s \ln\left(\frac{\hat{P}_{rs}}{P_{rs}}\right)\right)\varepsilon\left(\frac{q\hat{w}_r}{\prod_s \hat{P}_{rs}^{\omega_s}}\right)^{-\varepsilon}\right)^{1/\varepsilon} \tag{27}$$

The expression in (27) highlights that the money-metric change in utility consists of two parts. The first part, $\prod_s \left(P_{rs}/\hat{P}_{rs}\right)^{\omega_s}$, is akin to the usual change in the Cobb-Douglas price index. Note that this is the only part that is present if preferences are homothetic, that is if $\nu_s = 0$. Because this change is common across all consumers within a location, this aspect of sectoral productivity growth is necessarily equal. The second part captures the presence of nonhomothetic preferences and induces unequal effects of productivity growth. Consider, for example, a decline in CS prices, that is, $\ln \hat{P}_{rs}/P_{rs} < 0$. This makes the consumer better off, that is, $\varpi^q < qw$. However, because CS are luxuries, $\sum_s \nu_s \ln\left(\hat{P}_{rs}/P_{rs}\right) > 0$ so that rich individuals for whom "real income" $\left(q\hat{w}_r \ \prod_s \hat{P}_{rs}^{\omega_s}\right)^{-\varepsilon}$ is small, have a higher willingness to pay for lower CS prices.

In a similar vein, we can calculate the utilitarian welfare effects at the district level. Exploiting the aggregation properties of PIGL, we can determine the level of *regional* spending power $\overline{\varpi}_r(\hat{x}_r|x_r)$ the representative agent in district $r$ facing prices $P_r$ would require to attain indifference. As before $\overline{\varpi}_r(\hat{x}_r|x_r)$ is implicitly defined by

$$\mathcal{U}(\overline{\varpi}_r(\hat{x}_r|x_r), \mathbf{P}_r) = \mathcal{U}(\mathbb{E}_r[q]\hat{w}_r, \hat{\mathbf{P}}_r), \tag{28}$$

where $\mathcal{U}$ is defined in (16).[26] One can show that $\overline{\varpi}_r(\hat{x}_r|x_r)$ satisfies an expression similar to the one given in (27).

Given $\varpi^q$ and $\overline{\varpi}_r$ defined in (26) and (28), we can calculate the equivalent variation of a given counterfactual $\hat{x}$ relative to 2011 as

$$\Delta\varpi_r^q \equiv \frac{\varpi^q(\hat{x}_r|x_{r2011})}{qw_{r2011}} - 1 \quad \text{and} \quad \Delta\overline{\varpi}_r \equiv \frac{\overline{\varpi}_r(\hat{x}_r|x_{r2011})}{\mathbb{E}_{r2011}[q]w_{r2011}} - 1. \tag{29}$$

Here, $\Delta\varpi_r^q$ is the percentage change in income that an individual with human capital $q$ living in district $r$ in 2011 would require to attain the same level of utility as in the counterfactual allocation. If, for example, $\Delta\varpi_r^q = -20\%$, the consumer would be indifferent between giving up 20% of her 2011 income and a counterfactual allocation in which productivity in a particular sector is reset to the 1987 level. Similarly, $\Delta\overline{\varpi}_r$ is the analogue equivalent variation for the representative agent in region $r$. The heterogeneity in the equivalent variations across individuals and districts allow us to quantify the unequal effects of sectoral productivity growth.

[26] Note that $\overline{\varpi}_r$ depends on the location $r$ conditional on $x_r$ and $\hat{x}_r$ because of the local human capital distribution.

To arrive at an aggregate level of welfare changes, we can also calculate the equivalent variation at the national level by averaging the local income variations using regional income shares as weights:

$$\Delta\varpi = \sum_r \Delta\overline{\varpi}_r \frac{\mathbb{E}_r[q] w_{r2011} L_{r2011}}{\sum_r \mathbb{E}_r[q] w_{r2011} L_{r2011}}.$$

## 6.2 Results: Sources of Welfare Growth in India

This section provides the main results in the paper. We construct counterfactual scenarios by sequentially setting to zero the productivity growth of each sector in the period of 1987–2011. In each experiment, we calculate the counterfactual equilibrium prices and income levels and use them to calculate the equivalent variations using the methodology discussed above. This allows us to derive heterogeneous welfare effects over the income ladder across 360 districts. We summarize our findings by first focusing on four districts with different characteristics (average income, urbanization, etc.). Then, we show equivalent variations at different levels of aggregation.

**Four Indian Districts:** We start by presenting the results for four selected districts: Delhi, Chengalpattu, Allahabad, and Bankura. Delhi is the area of the capital city, which comprises multiple administrative units. To keep the regional units consistent over time, we merge all of today's 11 districts into a single region. Chengalpattu is a dynamic industrial district in Tamil Nadu that includes the southern suburbs of the megacity of Chennai.[27] Allahabad is the largest and most populous district of Uttar Pradesh. It has a medium-low urbanization level. Finally, Bankura is a rural district in West Bengal, which is mostly dependent on agriculture and representative of rural India.

| District | State | Urbanization 2011 | Population 2011 (mil) | Avg. Income (2011 Rupees) | VA Share 2011 (%) | | | Prod. Growth (%) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Agr. | Ind. | CS | $A_F$ | $A_G$ | $A_{CS}$ |
| Delhi | Delhi | 0.92 | 12.8 | 3877 | 0.2 | 35 | 64 | 0.2 | 4.2 | 14.7 |
| Chengalpattu | Tamil Nadu | 0.67 | 8.1 | 2806 | 12 | 37 | 51 | 3.1 | 4.8 | 11.3 |
| Allahabad | Uttar Pradesh | 0.17 | 6.7 | 1595 | 51 | 17 | 32 | 1.6 | 2.6 | 4.3 |
| Bankura | West Bengal | 0.07 | 2.9 | 1597 | 64 | 7 | 29 | 1.9 | 1.7 | 3.5 |

Table 6: Descriptive Statistics of Four Selected Districts

Table 6 provides some descriptive statistics for the four districts. Household income is significantly higher in Delhi and Chengalpattu. Both the patterns of sectoral specialization and the estimated productivity growth are markedly different across districts. The 2011 value added share of CS is about 64% in Delhi, 50% in Chengalpattu, 32% in Allahabad, and 29% in Bankura. Chengalpattu is the most industrial among the four districts. Agriculture is totally gone by 2011 in Delhi. There are large differences in the productivity growth in CS—from a 3-4% growth in the two rural districts to 15% growth in Delhi. Industrial productivity growth is highest in Chengalpattu, consistent with the boom of manufacturing activity in the Chennai area. Productivity growth is lower across the board in Allahabad and Bankura.

Figure 8 displays the welfare effects of resetting productivity in agriculture (left panel), CS (center panel), and industry (right panel) to the respective 1987 levels simultaneously in all Indian districts. The figure displays estimated equivalent variations for households living in each of the four districts conditional on their income level. The horizontal axis shows nominal household income levels in 2011 normalized to 100 for the median Indian income.

[27] We use the border of Chengalpattu in 1987. This district was split into Kancheepuram and Thiruvallur between 1991 and 2001. A district of Chengalpattu has then be reunified in 2019.

Panel a: Agriculture Panel b: Consumer Services Panel c: Industry

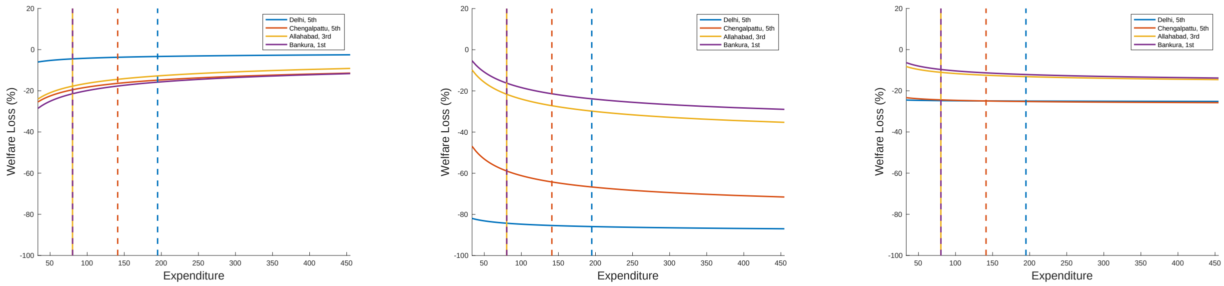


Figure 8: Counterfactual Welfare Change in Four Selected Districts. The figure displays the average percentage welfare losses associated with counterfactually setting productivity in agriculture, CS, and industry, at the respective 1987 level in all Indian districts for households with different income levels living in Delhi, Chengalpattu, Allahabad, and Bankura, respectively. The median income of Indian households is normalized to 100. The dashed lines indicate the average income for households who live in each of the four districts.

The figure also reports the income distribution for India and the average household income for each district (dashed vertical lines).

The center panel shows that the welfare effects associated of service-led growth vary dramatically both across space and the income ladder. The welfare effects of service-led growth are smaller in Allahabad and Bankura, especially, for very poor households. The first reason is that the provision of local CS—and, hence, the average expenditure share—is low in the two cities. Second, CS productivity grew significantly less than in the two urban districts during the 1987–2011 period. Third, the welfare effect of service-led growth is increasing in income because CS are luxuries. Even in Bankura—the most rural district—the equivalent variation for rich households exceeds 20% of their 2011 income, while it is negligible for very poor households. The welfare effect of service-led growth is much larger in Chengalpattu and even more so in Delhi, first and foremost because of the high local productivity in CS. The heterogeneity of welfare effects across income is still large in Chengalpattu, while it is narrower in Delhi. There, high productivity growth in $A_{CS}$ is responsible for a very large increase in real wages, which dwarfs the effect of nonhomothetic preferences.

The welfare effects follow an opposite pattern in the case of agriculture. They are large in rural districts like Bankura and negligible in Delhi. Very poor households in Bankura would rather sacrifice 30% of their 2011 income than experience the productivity setback in agriculture. The reason is not so much high local productivity growth in agriculture; rather the benefits for the poor accrue from agricultural productivity growth in the whole of India, which reduces the food price. In contrast, the benefits are modest for rich urban household. The left panel also shows a much smaller geographical spread in the welfare effects relative to the center panel. The reason is that food products are tradable, so the benefits of productivity growth diffuse to all regions. The graph might give the false impression that the welfare effects of productivity growth in agriculture are very similar in all districts. However, one should remember that there is an important composition effect: in the rural districts, households are on average poorer and consume a larger share of their income on food. The quantitative effect of such a composition effect will become clearer in the next section.

Finally, income effects are modest for industrial goods (right panel), consistent with a low estimated income elasticity. Differences across districts mostly hinge on different patterns of specialization and heterogeneity in productivity growth. The largest welfare effects accrue in Chengalpattu, an industrial district that experience fast

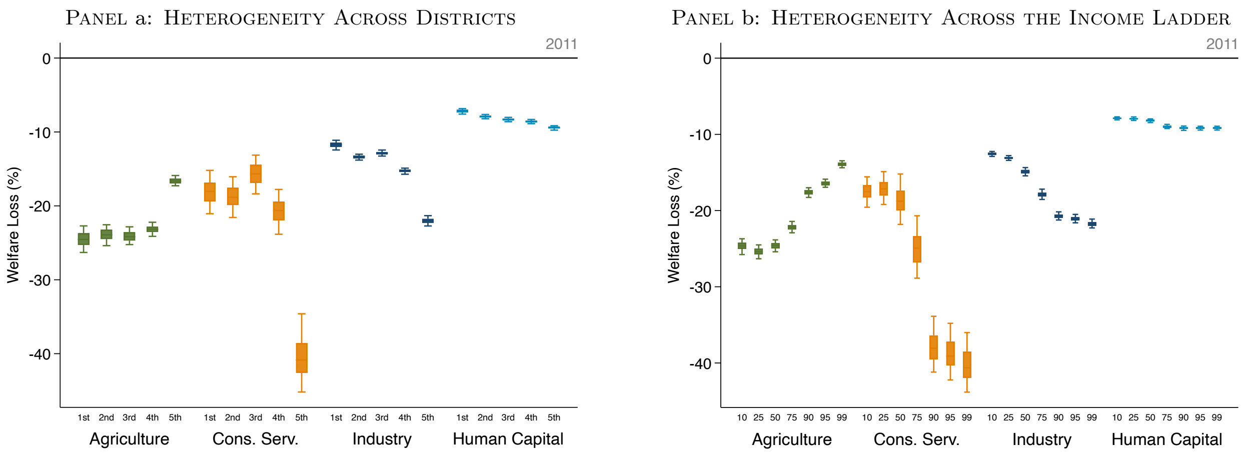


Figure 9: The Heterogeneous Welfare Impact of Service-Led Growth. The figure displays the average percentage welfare losses associated with counterfactually setting productivity in agriculture, CS, and industry, as well as human capital, at the respective 1987 level, broken down by urbanization quintile in 2011 (Panel (a)) and by the 10th, 20th, 50th, 75th, 90th, 95th, and 99th percentiles of the income distribution in 2011 (Panel (b)). We compute the distribution of such welfare losses using a nonparametric bootstrap. The respective boxes cover the 25%–75% quantile of the bootstrap distribution. The horizontal lines on the top and bottom refer to the 5% and 95% quantiles of the bootstrap distribution, respectively.

productivity growth in the industrial sector.

**Spatial Heterogeneity:** To gather more general lessons, we now show average welfare effects aggregated at the level of quintiles of urbanization. As in the previous section, we report the welfare change (equivalent variation) associated with counterfactually shutting down productivity growth in each sector. In addition, we construct a counterfactual in which we set to the 1987 level the human capital in all regions, as measured by educational attainment and by the estimated return to education.

These welfare implications stem from our estimated model and are therefore associated with sampling uncertainty. Intuitively, because the underlying micro data is a sample of individuals, the measured sectoral employment shares in each district are random variables. And given the accounting nature of our analysis, our estimates of productivity fundamentals $\mathbf{A_t}$ (and, in turn, the counterfactual exercises of shutting down sectoral productivity growth) inherit this sampling uncertainty. To quantify the extent of this uncertainty, we thus estimate the *distribution* of both the welfare effects and the sectoral reallocation of employment using a nonparametric bootstrap procedure (Horowitz, 2019).[28]

In Figure 9 we report these distributions as a boxplot. Each box shows the 25%–75% quantiles of the distribution of aggregate welfare gains. The line within the box indicates the median and the two vertical lines on the top and the bottom indicate the 5% and 95% quantiles, respectively. Note that the more negative the welfare loss in the plot, the larger the welfare gain associated with productivity growth in a sector.

In the left panel we group districts by quintiles of the urbanization rate in 2011. We then calculate the (income-

[28] Although we refer the reader to Section C-6 in the Appendix for the details of the implementation, the idea is conceptually simple. The nonparametric bootstrap treats the empirical distribution of the data as if it were the indeed the underlying population distribution. We can then construct a bootstrap sample with the same sample size from the Indian micro data by drawing households with replacement and redo our analysis. When we repeat this step $B$ times, we can calculate each statistic of interest $B$ times and hence estimate the entire distribution. Using this procedure we can calculate confidence intervals for all the outcomes we report. In practice, we take $B = 200$.

weighted) average welfare changes $\Delta \mathcal{W}_r$ within each urbanization quintile.[29] The welfare consequences of productivity growth vary widely across space. Unsurprisingly, the benefits of agricultural productivity growth are skewed toward rural areas. On average, households in the lowest quintile of urbanization are prepared to sacrifice 24% of their 2011 income to avoid going back to the 1987 productivity level in agriculture. The equivalent variation declines sharply in the top quintile, where productivity growth in agriculture is only worth 16% of the 2011 income. By contrast, the benefits from productivity growth in CS and the industrial sector are skewed toward urban locations. This pattern is most pronounced for the CS sector, whose productivity growth is worth 41% of the 2011 income for the most urbanized quintile. Our estimates of the distributions of these welfare gains make the urban-rural split of India also statistically precise. While we cannot reject that the welfare consequences of sectoral productivity growth are the same across the lower four quintiles of the distribution, the top urban quintile seems to be qualitatively different: there, welfare gains were mostly service led, while the benefits from agricultural productivity growth in India were modest.

The welfare gains from human capital accumulation are small. They range between 7% and 10% of 2011 income depending on the urbanization level. Note these differences are based on private returns to education. To the extent there is a wedge between the private and social returns to education, or a better-educated labor force favors technical progress, our calculation would underestimate the importance of human capital accumulation.

**Heterogeneity in Income:** In the right panel of Figure 9 we focus on inequality across people and decompose the welfare effects across the Indian income distribution. We focus on the 10th, 20th, 50th, 75th, 90th, 95th, and 99th percentiles. As expected, the benefits of productivity growth in CS and, to a lesser extent, industry are sharply increasing in income, whereas the opposite is true for agriculture. Interestingly, the welfare change for the top 99% attributable to CS productivity growth is smaller than for the average of the top quintile of the urbanization distribution because not all the rich people live in cities. Furthermore, our methodology uncovers statistically meaningful differences in the sources of welfare growth between the top 25% and the bottom 75% of the population. For the bottom 75% of the population, the welfare effects of productivity growth in agriculture, CS, and the industrial sector are roughly of the same size. For the top 25%, service-led growth was quantitatively much more important.

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

**Aggregate Effects:** Finally, in Figure 10 we aggregate welfare effects up to the nationwide level. We continue to weight districts by their value added. Even at the aggregate level, a substantial part of the total welfare gains appear to be service led. On average, the Indian population would have been willing to reduce its income in 2011 by 27% in lieu of giving up the observed productivity growth originating in the CS sector. Furthermore, with 90% probability, the welfare gains of service-led growth are between 22% and 29%. To put this number into perspective, the equivalent variation of the entirety of Indian income growth since 1987 is 64%. Hence, productivity growth in the CS sector accounts for roughly one-third of the entire increase in economic well-being.

Figure 10 also shows that agricultural productivity was an important source of welfare improvement. The salience of agriculture is hardly surprising given its large employment share in India. The smaller welfare effects

[29] In all experiments we perform, we shut down sectoral productivity growth simultaneously in all locations. Thus, part of the benefits spread around India through trade across districts.

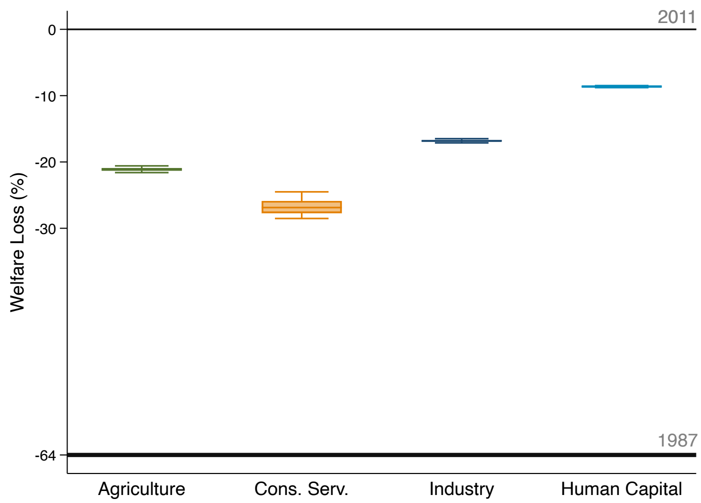


Figure 10: Aggregate Welfare Effects. The figure displays the percentage welfare losses $\Delta\mathcal{W}$ associated with counterfactually setting productivity in agriculture, CS, and industry, as well as the level of human capital, to their respective levels in 1987 in all Indian districts. We compute the distribution of such welfare losses using a nonparametric bootstrap. The respective boxes cover the 25%–75% quantile of the bootstrap distribution. The horizontal lines on the top and bottom refer to the 5% and 95% quantile of the bootstrap distribution, respectively. For comparison, the figure also shows the welfare loss of resetting all productivities and human capital to their 1987 levels as the horizontal line at the bottom.

of productivity growth in the industrial sector is perhaps more surprising. The equivalent variation amounts to 17% and is very precisely estimated. Hence, productivity growth in CS is more important in welfare terms than productivity growth in the industrial sector. These aggregate figures hide major heterogeneity across sectors of the population as discussed above.

## 6.3 Structural Change

Not only is sectoral productivity growth an important driver of welfare growth, it is also at the heart of the structural transformation. We report the effect of sectoral productivity growth on employment patterns in Figure 11. Each of the three panels focuses on one sector and depicts the counterfactual sectoral employment share if productivity growth in agriculture (green bars), CS (orange bars), and the industrial sector (blue bars) had been zero since 1987. The dashed horizontal lines show the actual employment share in 1987 and 2011, for reference.[30] Like in Figures 10 and 9 above, we again display the distribution of these effects through a boxplot. The aggregate employment effects are more precisely estimated than the welfare effects discussed above. Hence, sampling variation plays a minor role.

Figure 11 shows that productivity growth in CS was responsible for the lion's share of the observed structural transformation. The left panel shows that absent productivity growth in CS the agricultural employment share would have been 60% instead of 50%. Thus, CS productivity growth accounts for more than half of the decline in agricultural employment between 1987 and 2011. The other panels show that employment in both CS and industry would have been lower had productivity not grown in the CS sector.

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

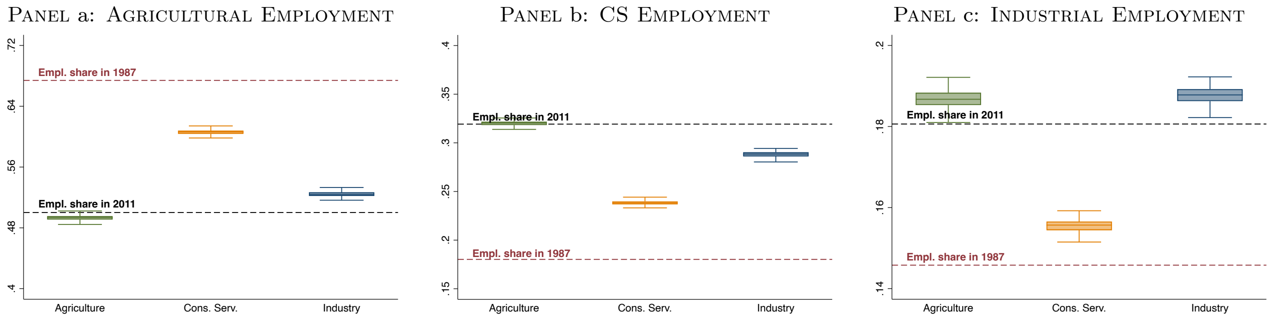


Figure 11: Sectoral Productivity Growth and Structural Change. Each panel shows the counterfactual employment share in the respective sector when we set productivity in agriculture, CS, and industry to their 1987 level. The dashed horizontal lines show employment in 1987 and 2011, for reference. We compute the distribution of such welfare losses using a nonparametric bootstrap. The respective boxes cover the 25%-75% quantile of the bootstrap distribution. The horizontal lines on the top and bottom refer to the 5% and 95% quantile of the bootstrap distribution.

Figure 11 also highlights an important role of income effects (service-*biased* growth.) Panel (b) shows that even without any productivity growth in the CS sector, the employment share of CS would have grown by five percentage points between 1987 and 2011. Yet, its expansion would have been less spectacular than observed in the data. The reason productivity growth in CS markedly affects agricultural employment is the following. In the absence of productivity growth, Indian consumers would be poorer and CS would be relatively more expensive. Given our estimated demand system, both forces push toward an increase in the demand for agricultural goods. The income effect increases agricultural demand because food is a necessity. The substitution effect complements this force because we estimate food and CS to be slight substitutes.

By contrast, productivity growth in agriculture (green bars) appears to have modest effects on structural change. If anything, it marginally *increased* employment in agriculture and slowed employment growth in industry and CS. This result is in line with the findings of Foster and Rosenzweig (2004) on the effects of the Green Revolution and those of Kelly et al. (2022), who document a negative effect of agricultural productivity on the Industrial Revolution across British regions.

In conclusion, service-led growth explains the lion's share of India's structural transformation between 1987 and 2011. Not only would India's consumers be substantially worse off in welfare terms, but India would also still be a more rural economy.

# 7 Robustness

In this section, we perform robustness analysis for the welfare effects reported in Figures 9 and 10. We consider three sets of issues. First, in Section 7.1, we study the sensitivity of the results to changes in the structural parameters. Next, in Section 7.2, we address some measurement issues. Finally, in Section 7.3, we study generalizations of the model. In particular, we extend our model to an open economy setting, we consider a production structure where skills are imperfectly substitutable, and we allow for workers to be mobile across space so that the spatial distribution of the population endogenously responds to changes in local wages and prices.

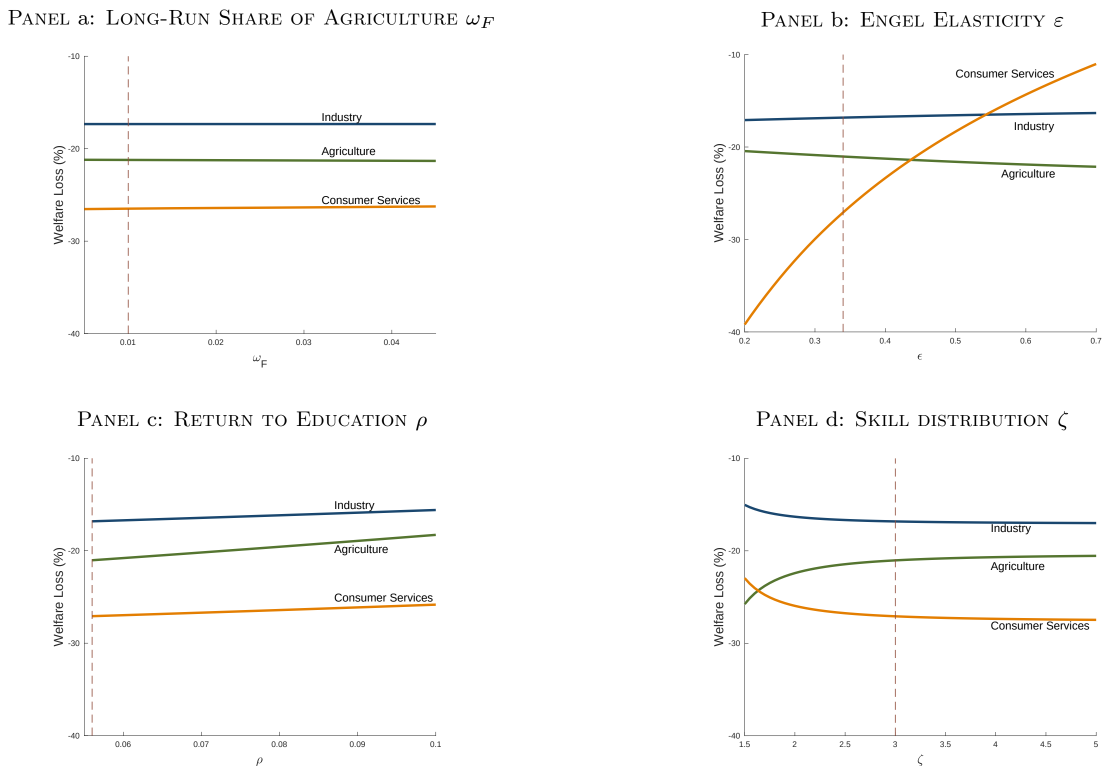


Figure 12: Robustness Analysis. Panels (a), (b), (c), and (d) show the aggregate welfare effects as a function of the preference parameters $\omega_F$, $\varepsilon$, the Mincerian rates of return to education $\rho$, and the tail parameter of the skill distribution $\zeta$. The vertical dashed line corresponds to the parameter value in our benchmark analysis.

## 7.1 Sensitivity to Structural Parameters

We consider the parameters governing preferences and skills. All results are based on re-estimating the entire model.

**Preferences:** We focus on $\omega_F$ and $\varepsilon$ that we calibrate or estimate outside of the theory. The other preference parameters are either point identified in our theory or pinned down by normalization.

We calibrate $\omega_F$ to 1% so as to match the value added (and employment) share of the US farming sector in 2017. However, the value added share of agriculture is larger than 1% in many industrial countries (e.g. 2% in Italy and France, 3% in Spain.) Therefore, we consider a range of larger $\omega_F$s. Panel (a) of Figure 12 shows the implied welfare impact of sectoral productivity growth is essentially independent of $\omega_F$.

Next, we consider the Engel elasticity $\varepsilon$. We expect our results to be sensitive to this parameter. In particular, a high Engel elasticity attributes a large share of the growth of the CS sector to income effects. Conversely, a low Engel elasticity would require large productivity growth to explain the observed expansion of the CS sector. The results shown in Panel (b) of Figure 12 show that the welfare effects of service-led growth are decreasing in $\varepsilon$. For instance, if we set $\varepsilon = 0.7$, the aggregate welfare effect would fall to a mere 10%. However, the highest estimate of $\varepsilon$ in Table 3 was 0.37. When we allow for heterogeneous income elasticities between low- and high-income households, the range of variation is between 0.27 and 0.42. There is also a smaller difference between less and more urbanized districts. The first observation is that if we stay within the range of variation of the estimates in Table 3, changes in $\varepsilon$ would not alter the main picture, in spite of somewhat affecting the quantitative results. Figure 12 shows that for any of the estimates reported in Table 3, the average welfare effects are those associated with productivity growth sourcing in the service sector. In other words, for the growth of the service sector to be preeminently driven by the income effect, we should believe in a much higher income elasticity than is indicated by the household-level data.

Because the main focus of our analysis is on the *unequal* welfare effects across space and income levels, we further explore how far heterogeneity in income elasticities could affect our conclusions. In our theory, it is in principle possible to assume different income elasticities across districts—though this assumption would become problematic once we allow for labor mobility as we do below. In the data, the Engel elasticity is larger in more-urbanized districts. This has two opposite implications on welfare: on the one hand, more of the expansion of CS activity is due to income effects, yielding a lower estimated productivity growth in CS. On the other hand, conditional on productivity, households' welfare is more sensitive to productivity growth in CS; remember that the welfare effect is approximately equal to the expenditure share on each sector. As long as productivity growth in services continues to be higher in urban districts, this points to higher spatial inequality. In Panel A of Appendix Figure C-8 we provide a tentative quantitative evaluation of these effects by assuming—in line with the estimates in column 7 of Table 3)—an elasticity of 0.363 in the highly urbanized Delhi district and 0.32 in the Bankura rural district. The goal of the experiment is to assess the impact of heterogeneity on spatial welfare inequality. As the figure shows, the experiment yields a mild reduction in inequality between Delhi and Bankura. However, the change is barely noticeable: the quantitative effect is very small. The conclusion that service-led growth is skewed towards urban districts is robust.

Next, we consider heterogeneity in $\varepsilon$ across income levels. Incorporating a variable income elasticity in our theory would be complicated and is beyond the scope of this paper. To gauge a sense of its potential quantitative effect, we run the following experiment. We estimate productivity growth in CS based on the benchmark income elasticity of 0.33. Then, we consider (a zero measure of) households with income above and below median with elasticities of 0.418 and 0.265, respectively, corresponding to the estimates of column 6 in Table 3. Panel B of Appendix Figure C-8 displays the results, focusing again on the districts of Delhi and Bankura. Here, we are interested in the differential effects within each district between rich and poor households. Clearly, welfare inequality—captured by the dashed lines—is now larger than in the benchmark case in which we assume all agents have the same preferences. The reason is intuitive: rich agents consume and care more about the provision of CS. The unequal differential effect is especially large in Delhi. While this exercise has important limitations, the lesson we draw is that a model allowing for increasing income elasticity is likely to deliver even more unequal welfare effects of service-led growth.

**Skills:** In the lower panels of Figure 12, we focus on the determinants of human capital. Our estimate of the return to education $\rho$ based on micro data is an annual 5.6% return. This estimate is on the lower end of typical Mincerian regressions. A potential concern is that we use data on consumption that might reflect consumption sharing within households with different skills and education levels. This might lead to attenuation bias. For this reason, we consider alternative calibrations in which the return to education is higher, up to an annual 10% that is an upper bound to the range of the typical estimates. As seen in Panel (c) of Figure 12, our main results are not sensitive to this parameter.

Panel (d) of Figure 12 shows the effect of the tail of the skill distribution $\zeta$. This parameter mostly affects our decomposition of productivity growth into agriculture and CS: the higher the $\zeta$, the higher the importance of CS growth relative to agricultural productivity. This result reflects the importance of nonhomothetic demand. The smaller the $\zeta$, the higher the income inequality. And because higher inequality increases aggregate demand for CS for a given average wage, less productivity growth is "required" to explain the increase in CS employment if $\zeta$ were small. Figure 12 shows this intuition is borne out but that the effects are quantitatively moderate.

## 7.2 Measurement: The PS-CS Split

Our classification of service employment into PS and CS hinges on whether firms in the service sector sell mostly to firms or consumers. For our baseline analysis, we use firm-level information contained in the service survey in this regard. According to this classification, the vast majority of service employment indeed caters to consumers. Even though sectors that sell in significant proportions to firms—such as ICT and business services—grow very quickly, the majority of the service sector continues to be in consumer-oriented industries such wholesale, retail, and restaurants.[31]

Our data-driven approach could underestimate the PS sector if firms report sales to small firms as sales to individuals. To address this concern, we consider two alternative classifications. First, we assume the true human capital-adjusted employment share of PS is twice as large as in our benchmark estimate in each service industry shown in Figure 3. Second, we assume the entire ICT and business service industries serve manufacturing firms, while retaining our baseline approach for the remaining service industries.

The results are shown in rows 2 and 3 of Table 7. The first four columns report the aggregate welfare effect ($\Delta\mathcal{W}$), shown in Figure 10. The last six columns focus on the spatial heterogeneity ($\Delta\mathcal{W}_r$), shown in Figure 9. For parsimony, we only report the top and bottom urbanization quantiles. As expected, the importance of productivity growth in CS decreases when we attribute a larger share of the expanding service sector to PS. This is especially important for the most urban locations, because the spatial concentration of PS exceeds the one of CS. However, in all cases, productivity growth in CS continues to be a large driver of welfare changes.

| | Aggregate Effects | | | | Effects by Urbanization Quantile | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Agriculture | CS | Industry | HC | Agriculture | | CS | | Industry | |
| | | | | | 1st | 5th | 1st | 5th | 1st | 5th |
| Baseline | -21.0 | -27.0 | -16.8 | -8.6 | -24.3 | -16.5 | -18.1 | -41.1 | -11.7 | -22.1 |
| | *Alternative measurement choices (Section 7.2)* | | | | | | | | | |
| Double PS | -21.3 | -22.8 | -19.2 | -8.7 | -25.1 | -18.1 | -20.7 | -27.7 | -12.8 | -25.6 |
| ICT & Business to PS | -21.4 | -20.7 | -18.2 | -8.6 | -24.9 | -17.8 | -20.7 | -23.3 | -12.2 | -24.4 |
| Construction to manufacturing | -20.0 | -23.2 | -21.9 | -8.7 | -24.3 | -12.6 | -3.3 | -48.5 | -13.1 | -32.0 |
| | *Alternative modeling assumptions (Section 7.3)* | | | | | | | | | |
| Open economy | -21.2 | -23.5 | -19.2 | -8.1 | -24.6 | -16.9 | -16.7 | -34.6 | -15.1 | -23.6 |
| Open economy (large ICT) | -20.7 | -19.5 | -19.2 | -8.0 | -24.9 | -16.7 | -18.2 | -22.3 | -14.9 | -23.6 |
| Imperfect skill substitution | -25.0 | -27.1 | -16.0 | -16.0 | -29.8 | -18.5 | -12.9 | -45.1 | -10.7 | -21.6 |
| Spatial labor mobility $\eta = \frac{2}{3}$ | -21.0 | -28.1 | -16.8 | -8.8 | -24.0 | -16.7 | -19.5 | -41.3 | -11.8 | -21.9 |
| Spatial labor mobility $\eta = \frac{4}{3}$ | -20.9 | -28.4 | -16.7 | -8.6 | -23.7 | -16.9 | -20.0 | -41.0 | -12.0 | -21.6 |
| Spatial labor mobility $\eta = 2$ | -20.8 | -28.4 | -16.7 | -8.6 | -23.3 | -17.0 | -20.1 | -40.5 | -12.0 | -21.4 |

Table 7: The importance of service-led growth—Robustness. In this table, we report a summary of our results from the robustness tests described in more detail in the main text. In the first four columns, we report the aggregate welfare loss in the absence of productivity growth (columns 1–3) or human capital accumulation (column 4). In the remaining columns, we report the welfare loss for the 1st and 5th quintile of the urbanization distribution.

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

Finally, we turn to the construction sector that we merge with to the service sector because of its nontradable nature. However, the traditional classification treats construction as part of the industrial sector. We report the result of following this traditional classification in row 4 of Table 7. Although this reclassification increases the importance of the industrial sector at the expense of CS, we still find CS to be the most important contributor to aggregate welfare growth. Interestingly, construction plays an important role for the spatial heterogeneity because it is relatively important in rural areas. If we aggregate construction with industrial activity, the welfare effect of CS is even more skewed in favor of urban districts than in our baseline estimate. Specifically, the effect remains about the same in the most-urbanized districts, whereas it turns minuscule in the least-urbanized districts.

## 7.3 Generalizations of the Theory

In this section, we consider three generalizations of the theory. First, we incorporate international trade. Second, we consider an environment where skills are imperfectly substitutable and skill-intensity varies across sectors. Third, we allow for workers to be spatially mobile.

### 7.3.1 Open Economy

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

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

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

The results of quantifying the sources of growth in this context are contained in rows 6 and 7 of Table 7. In row 6, we report the results from the measurement choices outlined above. In row 7, we report the results when the

ICT sector is twice as large as actually observed. Expectedly, such choices reduce the importance of the CS because they reduce measured employment growth in these industries. Again, this is particularly relevant for cities, which saw the fastest increase in ICT employment. Nevertheless, CS continue to play an important role for aggregate growth and for urban areas in particular. Adding foreign trade does not alter the result that Indian growth is largely service led.

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

In our model, we allow for individual heterogeneity in human capital but maintain that workers endowed with different efficiency units are perfect substitutes for one another. In this section, we generalize our model by assuming workers with different educational attainments are imperfect substitutes in production (see Section C-7 in the Appendix for details). As we showed in Table B-16, agricultural workers have, on average, lower educational attainment than those employed in service industries. Thus, an increase in the skill endowment could be responsible for the reallocation of workers from agriculture to CS (see, e,.g., Porzio et al. (2020) or Schoellman and Hendricks (2020)). By ignoring such skill-based specialization, our Ricardian model could exaggerate the importance of technology for the development of the service sector.

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

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

where $H^{+}$ and $H^{-}$ denote high- and low-skilled workers, respectively. Note that the technology admits differences in both TFP $A_{rst}$ and skill bias $Z_{rst}$ across sector-districts and time.[32] We assume the elasticity of substitution $\rho$ to be constant across sector-districts and externally calibrate $\rho = 1.8$, which is in the consensus region (see, e.g., Ciccone and Peri (2005) and Gancia et al. (2013)). Our conclusions do not hinge on the particular calibration of $\rho$.

We continue to allow for heterogeneous productivities across workers of the same educational group. A worker's wage is a draw from a skill-specific Pareto distribution with the same tail parameter as in our baseline analysis.[33] As in our baseline analysis, this model is exactly identified, and for given structural parameters, we can rationalize the data of sectoral earnings shares by skill group and average earnings by skill group for each region in India by choice of $A_{rst}$ and $Z_{rst}$ (see Section C-7 in the Appendix).

The results of this extension are reported in the last row of Table 7. Because productivity is now pinned down by two parameters, we set both $A_{rs}$ and $Z_{rs}$ to the respective 1987 level when running counterfactuals. The quantitative role for the CS sector is very similar to the one of our baseline calibration. Interestingly, human capital now plays a more important role, owing to the increasing supply of high-skilled labor over time.

This extension also allows us to uncover additional facts about the skill bias in technology. First, across districts, $Z_{rs}$ increases in the level of urbanization for all sectors. This increase reflects the empirical observation that the skill premium is higher in urban than in rural districts. Second, we find evidence for skill-biased technical change: over time, $Z_{rs}$ increases in all sectors. Although our accounting approach cannot uncover causal links, these patterns

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

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

are consistent with models of directed technical change and directed technology adoption such as Acemoglu and Zilibotti (2001) and Gancia et al. (2013), where firms adopt more skill-intensive technologies in response to the wider availability of skilled workers.

### 7.3.3 Spatially Mobile Workers

In our baseline model, workers are exogenously assigned to regions. In the counterfactual analysis, we assumed people to be spatially immobile. However, people could decide to leave urban areas in response to sector-region productivity changes. For instance, a counterfactual decline in CS productivity could lead people to move out of cities. To gauge the quantitative importance of labor mobility, we re-estimate our model in the presence of a migration choice. We model migration as a discrete choice problem, where individuals receive idiosyncratic preference shocks and locations differ in a scalar amenity. Formally, we assume that individual $h$'s value of living in location $r$ at time $t$ is given by

$$\mathcal{Q}_{rt}^{h} = \mathcal{B}_{rt}\overline{\omega}^{h}\left(w_{rt}, \mathbf{P}_{rt}|\mathbf{P}_{rt}, \overline{q}_{rt}\right) u_{rt}^{h}. \tag{30}$$

Here, $\mathcal{B}_{r}$ denotes the value of regional amenities, $\overline{\omega}^{h}\left(w_{rt}, \mathbf{P}_{rt}|\mathbf{P}_{rt}, \overline{q}_{rt}\right)$ describes the average utility of being in region $r$ in monetary terms, and $u_{rt}^{h}$ is an preference shock idiosyncratic to individual $h$ and location $r$, which we assume to to be Frechet distributed with parameter $\theta$.[34] Given these assumption, the share of people living in region $r$ at time $t$ is given by

$$\frac{L_{rt}}{L_{t}} = \frac{\left(\mathcal{B}_{rt}\overline{\omega}^{h}\left(w_{rt}, \mathbf{P}_{rt}|\mathbf{P}_{rt}, \overline{q}_{rt}\right)\right)^{\theta}}{\sum_{j}\left(\mathcal{B}_{jt}\overline{\omega}^{h}\left(w_{jt}, \mathbf{P}_{jt}|\mathbf{P}_{jt}, \overline{q}_{jt}\right)\right)^{\theta}}. \tag{31}$$

Except for the presence of nonhomothetic preferences, this setup is standard in most models of economic geography (see Redding and Rossi-Hansberg (2017)).

In Section A-7 in the Appendix we discuss the solution of this model in more detail. We first show that all our estimates of both structural parameters and sectoral productivities are the same as in the model with immobile labor. Intuitively, given the observed population, we can estimate the model exactly as in our baseline analysis. We can then residually estimate the spatial distribution of amenities $\mathcal{B}_{rt}$ to rationalize the observed population distribution as an equilibrium outcome.

To perform counterfactuals, we need an estimate of the spatial labor supply elasticity $\theta$, which in our context captures a long-run migration elasticity. In the absence of exogenous variation in local wages, this elasticity is hard to directly estimate. Therefore, we consider two scenarios: in our baseline scenario we pick $\theta$, such that in our CS counterfactual, the amount or spatial reallocation is as high as what occurred in India between 1987 and 2011 holding local amenities fixed. For robustness, we also consider a higher-elasticity scenario. Given that the empirical literature finds relatively low levels of regional mobility in India, we regard this to be a generous upper bound to how much mobility we can expect in response to counterfactual changes in productivity.

The results—reported in the last rows of Table 7—are both qualitatively and quantitatively similar to those in the baseline model (which the extended model encompasses as a particular case in which $\theta = 0$). We conclude that our results are robust to allowing quantitatively reasonable migration flows in response to counterfactual experiments.

[34] Recall that $\overline{\omega}^{h}$ describes the equivalent variation to achieve a given utility level.

# 8 Conclusion

Tertiarization is well underway not only in mature economies but also in most developing countries. In India, like in other economies, rising employment in local CS such as retail and restaurants accounts for the bulk of the decline in agricultural employment, while industrial employment growth is slow. This pattern of development raises two fundamental questions. First, can services be a source of productivity growth even at low levels of economic development? Second, if services are luxuries and must be enjoyed locally, how different are the welfare effects of service-led growth across different sectors of the population?

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

Our analysis delivers two main results. First, productivity growth in sectors such as retail, hospitality, and transportation accounts for one-third of the improvement in living standards between 1987 and 2011. Second, the welfare impact of service-led growth is strikingly unequal: it disproportionally benefited wealthy individuals in urban areas while leaving poor people almost unaffected. The reasons are that service productivity grew particularly fast in urban areas and that richer consumers care more about the consumption of services owing to nonhomothetic preferences. We also find that productivity growth in CS was the main driver of the structural transformation and accounts for almost half of the decline in agricultural employment.

Our approach has several limitations that we hope to overcome in future research. Two are particularly important. First, owing to our accounting approach, we take CS productivity as exogenous. Understanding the exact nature of productivity growth and how it materializes seems to us a question of first-order importance, in particular as far as potential policy implications are concerned. Second, it would be interesting to know the extent to which other developing countries are growing like India. If service-led growth is indeed an integral part of the growth trajectory of developing countries today, the absence of employment growth in the manufacturing sector might be less concerning than previously thought for the sustainability of growth. However, the distributional consequences of this type of growth could raise new concerns about inequality that remain invisible in aggregate statistics.

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# APPENDIX A: THEORY

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

## A-1 Proof of Proposition 1

To derive the expression in (9), note first that the definition of equilibrium prices $p_{rnt}$ in (7) implies that

$$\int_n \beta_n \ln p_{rn} dn = \ln P_{rFt} \int_n \beta_n \lambda_{nF} dn + \ln P_{rGt} \int_n \beta_n \lambda_{nG} dn + \ln w_{rt} \int_n \beta_n \lambda_{nCS} dn - \int_n \beta_n \lambda_{nCS} \ln \mathcal{A}_{rnt} dn.$$

Using the definitions of $\omega_s$ and $A_{rCSt}$ in (10) and (11), we get

$$\int_n \beta_n \ln p_{rn} dn = \omega_F \ln P_{rFt} + \omega_G \ln P_{rGt} + \omega_{CS} \ln \left(A_{rCSt}^{-1} w_{rt}\right).$$

Similarly,

$$\int_n \kappa_n \ln p_{rn} dn = \nu_F \ln P_{rFt} + \nu_G \ln P_{rGt} + \nu_{CS} \ln \left(A_{rCSt}^{-1} w_{rt}\right),$$

where $\nu_s$ is defined in (10).

Substituting these expression in the final-good indirect utility function $\mathcal{V}^{FE}$ in (5) yields

$$\begin{aligned} \mathcal{V}^{FE}(e, \mathbf{p}_r) &= \frac{1}{\varepsilon}\left(\frac{e}{\exp\left(\int_n \beta_n \ln p_{rn} dn\right)}\right)^{\varepsilon} - \int_n \kappa_n \ln p_{rn} dn \\ &= \frac{1}{\varepsilon}\left(\frac{e}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G} \left(A_{rCSt}^{-1} w_{rt}\right)^{\omega_{CS}}}\right)^{\varepsilon} - \nu_F \ln p_{rFt} - \nu_G \ln p_{rGt} - \nu_{CS} \ln \left(A_{rCSt}^{-1} w_{rt}\right), \end{aligned}$$

which is the expression in (9).

To derive the expenditure share over sectoral value added, $\vartheta_{rst}(e, \mathbf{P}_{rt})$ in (12), note that sector $s$ receives a share $\lambda_{ns}$ of total revenue of good $n$. Hence, given a spending level $e$ and prices $\mathbf{P}_{rt}$, sector $s$ receives a share

$$\begin{aligned} \vartheta(e, \mathbf{P}_{rt}) &= \frac{\int \lambda_{ns} e \vartheta_n^{FE}(e, \mathbf{p}_{rt}) dn}{e} \\ &= \int \lambda_{ns}\left(\beta_n + \kappa_n \left(\frac{e}{\exp\left(\int_n \beta_n \ln p_{rn} dn\right)}\right)^{-\varepsilon}\right) dn \\ &= \int \lambda_{ns} \beta_n dn + \int \lambda_{ns} \kappa_n dn \times \left(\frac{e}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G} \left(A_{rCSt}^{-1} w_{rt}\right)^{\omega_{CS}}}\right)^{-\varepsilon} \\ &= \omega_s + \nu_s \left(\frac{e}{P_{rFt}^{\omega_F} P_{rGt}^{\omega_G} \left(A_{rCSt}^{-1} w_{rt}\right)^{\omega_{CS}}}\right)^{-\varepsilon}, \end{aligned}$$

which is the expression in (12).

This analysis can be extended to the case, where the production of final goods combines tradable goods and local CS in a CES way. Specifically, suppose that

$$y_n = \left(\lambda_{nF} x_F^{\frac{\sigma-1}{\sigma}} + \lambda_{nG} x_G^{\frac{\sigma-1}{\sigma}} + \lambda_{nCS} \left(\mathcal{A}_{rnt} H_{nCS}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where the parameters $\lambda_{ns}$ are sectoral weights, which are specific to good $n$. The good-specific price index is then given by

$$p_{rnt} = \left(\lambda_{nF}^{\sigma} P_{rFt}^{1-\sigma} + \lambda_{nG}^{\sigma} P_{rGt}^{1-\sigma} + \lambda_{nCS}^{\sigma} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

Similarly, the cost shares of food, industrial goods, and CS for final good $n$ are given by

$$\varsigma_{rnt}^{F} = \lambda_{nF}^{\sigma} \left(\frac{P_{rFt}}{p_{rnt}}\right)^{1-\sigma} \quad \text{and} \quad \varsigma_{rnt}^{G} = \lambda_{nF}^{\sigma} \left(\frac{P_{rGt}}{p_{rnt}}\right)^{1-\sigma} \quad \text{and} \quad \varsigma_{rnt}^{CS} = \lambda_{nF}^{\sigma} \left(\frac{\mathcal{A}_{rnt}^{-1} w_{rt}}{p_{rnt}}\right)^{1-\sigma}. \tag{A-1}$$

This implies that

$$\int_n \kappa_n \ln p_{rn} dn = \int_n \ln \left(\lambda_{nF}^{\sigma} P_{rFt}^{1-\sigma} + \lambda_{nG}^{\sigma} P_{rGt}^{1-\sigma} + \lambda_{nCS}^{\sigma} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{1-\sigma}\right)^{\frac{\kappa_n}{1-\sigma}} dn$$

and

$$\exp\left(\int_n \beta_n \ln p_{rn} dn\right) = \exp\left(\int_n \ln \left(\lambda_{nF}^{\sigma} P_{rFt}^{1-\sigma} + \lambda_{nG}^{\sigma} P_{rGt}^{1-\sigma} + \lambda_{nCS}^{\sigma} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{1-\sigma}\right)^{\frac{\beta_n}{1-\sigma}} dn\right).$$

The indirect utility function (in terms of sectoral value added) can thus be written as

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

where

$$\begin{aligned} B\left(\mathbf{P}_{rt}\right) &= \exp\left(\int_n \ln \left(\lambda_{nF}^{\sigma} P_{rFt}^{1-\sigma} + \lambda_{nG}^{\sigma} P_{rGt}^{1-\sigma} + \lambda_{nCS}^{\sigma} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{1-\sigma}\right)^{\frac{\beta_n}{1-\sigma}} dn\right) \\ D\left(\mathbf{P}_{rt}\right) &= \int_n \ln \left(\lambda_{nF}^{\sigma} P_{rFt}^{1-\sigma} + \lambda_{nG}^{\sigma} P_{rGt}^{1-\sigma} + \lambda_{nCS}^{\sigma} \left(\mathcal{A}_{rnt}^{-1} w_{rt}\right)^{1-\sigma}\right)^{\frac{\kappa_n}{1-\sigma}} dn. \end{aligned}$$

The resulting expenditure shares on sectoral value added are then again given by $\vartheta_{rst} = -\frac{\partial V(e,\mathbf{P}_{rt})}{\partial P_{rst}} P_{rst} / \frac{\partial (e,\mathbf{P}_{rt})}{\partial e} e$. The expressions above imply

$$\vartheta_{rst} = \int_n \beta_n \varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right) dn + \left(\int_n \kappa_n \varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right) dn\right) \left(\frac{e}{B\left(\mathbf{P}_{rt}\right)}\right)^{-\varepsilon}, \tag{A-2}$$

where $\varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right)$ are the sectoral cost shares for good $n$ given in (A-1). The notation $\varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right)$ stresses that these shares depend on the regional prices of tradable goods and CS. Equation (A-2) is a direct generalization of the Cobb-Douglas structure considered in the main text. There, the spending shares $\varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right)$ are constant and given by $\varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right) = \lambda_{ns}$. In this more general formulation, the value added demand system still falls in the PIGL class (and has the same Engel elasticity $\varepsilon$ as the final good demand system), but the other parameters depend on regional prices. In particular, (A-2) can be written as

$$\vartheta_{rst} = \omega_{rst} + \nu_{rst} \left(\frac{e}{B\left(\mathbf{P}_{rt}\right)}\right)^{-\varepsilon}, \tag{A-3}$$

where $\omega_{rst} \equiv \int_n \beta_n \varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right) dn$ and $\nu_{rst} \equiv \int_n \kappa_n \varsigma_{rnt}^{s}\left(\mathbf{P}_{rt}\right) dn$. This is exactly the same representation as in our baseline analysis, except that $\omega_{rst}$ and $\nu_{rst}$ are no longer constant. Note, however, that it is still the case that $\sum_s \omega_{rst} = 1$ and $\sum_s \nu rst = 0$ as required.

## A-2 Estimation of Structural Parameters and Productivities (Sections 5.1 and 5.2)

In this section we describe the details of our strategy to estimate the productivity fundamentals $\{A_{rst}\}$ and two structural parameters, $\omega_{CS}$ and $\nu_F$. Consider a single time period. Given the regional distribution of human capital and the sectoral distribution of earnings, we can calculate $\{[w_r]_r, H_{rF}, H_{rG}, H_{rCS}\}_r$ in a model-consistent way. In particular, the supply of human capital in location $r$ is given by

$$H_{rt} = L_{rt} \sum_e exp(\rho \times s)\ell_{rt}(e),$$

where $\rho$ is the return to education, and $\ell_{rt}(e)$ denotes the share of people in region $r$ with $e$ years of education at time $t$.

We then use the observed sectoral earnings shares to measure sectoral labor supplies in region $r$. Specifically, for each sector $s$, we calculate

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

where $w_i$ is the wage of individual $i$ (in region $r$ at time $t$). The average regional skill price $w_r$ can be calculated as $w_r = \left(\sum_{i \in r} w_i\right)/H_{rt}$.

Given this data we can then infer sectoral productivity in the following way:

**Step 1: Estimate demand parameters $\omega_{CS}$ and $\nu_F$** The two structural parameters are jointly estimated from aggregate market clearing conditions. The local market clearing Equations (17) to (18), imply the two aggregate resources constraints for tradable goods

$$\sum_{r=1}^{R} w_{rt} H_{rst} = \sum_{r=1}^{R}\sum_{j=1}^{R} \pi_{rsjt} \left(\omega_s + \nu_s \left(\frac{A_{jCSt}^{\omega_{CS}} \mathbb{E}_{jt}\left[q\right] w_{jt}^{1-\omega_{CS}}}{P_{jFt}^{\omega_F} P_{jGt}^{\omega_G}}\right)^{-\varepsilon}\right) w_{jt} H_{jt} \qquad \text{for } s = F, G. \tag{A-4}$$

One of the aggregate resources constraints is redundant due to Walras' Law. We can substitute the local market clearing condition for CS (17) into the aggregate resources constraint for agriculture to arrive at

$$\sum_{r=1}^{R} w_{rt} H_{rFt} = \sum_{r=1}^{R}\sum_{j=1}^{R} \pi_{rFjt} \left(\omega_F - \frac{\nu_F}{\nu_{CS}} \left(\omega_{CS} - \frac{H_{jCSt}}{H_{jt}}\right)\right) w_{jt} H_{jt} \tag{A-5}$$

$$= \omega_F \sum_{r=1}^{R} w_{rt} H_{rt} - \frac{\nu_F}{\nu_{CS}} \sum_{r=1}^{R} \left(\omega_{CS} - \frac{H_{rCSt}}{H_{rt}}\right) w_{rt} H_{rt}. \tag{A-6}$$

Given the data on $\{w_r, H_{rs}\}$, this is, for a given year, a single equation in three unknowns: $\omega_F$, $\frac{\nu_F}{\nu_{CS}}$, and $\omega_{CS}$. In particular, note that prices do not appear in Equation (A-6). We thus achieve identification of the preference parameters directly from the data on sectoral employment and earnings. From the CS market clearing condition (17), it is apparent that $\nu_{CS}$ is not separately identified from the *level* of productivity in the consumer service sector, $A_{rCSt}$. Hence, under the assumption that consumer services are a luxury, we can wlog normalize $\nu_{CS} = -1$. For a given choice of $\omega_F$ we can therefore use (A-6) in 1987 and 2011 to uniquely solve for $\omega_{CS}$ and $\nu_F$.

**Step 2: Estimate the local price vector $\{p_{rFt}, p_{rGt}, p_{rCSt}\}_r$** Given the structural parameters, there is a unique local price vector that rationales all market clearing conditions from (17) to (18). We set the average level of the price of goods as the numeraire, i.e. $\left(\sum_r (p_{rGt})^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = 1$. In addition, one can show that all our results are insensitive to the level of food prices in 1987. Finally, we target the change in aggregate food prices (relative to goods prices)

$$\sum_{r=1}^{R} \frac{w_{rt} H_{rt}}{\sum_{j=1}^{R} w_{jt} H_{jt}} \times \frac{P_{rFt}}{P_{rGt}} = P_{FGt}^{\text{Data}}. \tag{A-7}$$

We compute the equilibrium price vector as the fixed point of these conditions.

**Step 3: Determine the level of the nominal wage** The NSS data on expenditure (our measure of income) is reported in rupees. Given the vector of prices computed in Step 2, we thus chose the level of earnings to match a given growth of the real GDP per capita. In our model, we use final goods as the numeraire, and thus take real GDP per capita to be denominated in goods. In particular, given the estimated local goods price, we have

$$\begin{aligned} \text{GDP}_t &= \sum_{r=1}^{R} \frac{w_{rt} H_{rt}}{\sum_{j=1}^{R} w_{jt} H_{jt}} \times \frac{w_{rt}}{P_{rGt}} \\ \frac{\text{GDP}_{2011}}{\text{GDP}_{1987}} &= 1 + g_{1987-2011}^{Data}, \end{aligned} \tag{A-8}$$

where $g_{1987-2011}^{Data}$ is the empirically observed growth rate of real GDP.

**Step 4: Estimate $\{A_{rst}\}_r$** Given the nominal wage and the local price vector, sectoral productivity is simply given by

$$A_{rst} = \frac{w_{rt}}{p_{rst}} \qquad \text{for } s = F, G, CS. \tag{A-9}$$

# A-3 The Allen-Uzawa Elasticity of Substitution (Section 5.3)

In this section we derive the implied elasticity of substitution. For notational simplicity we suppress the region and time subscripts and denote sectoral prices by $P_s$. The Allen Uzawa elasticity of substitution between sectoral output $s$ and $k$ is given by

$$EOS_{sk} = \frac{\frac{\partial^2 e(P,V)}{\partial P_s \partial P_k} e\left(P,V\right)}{\frac{\partial e(P,V)}{\partial P_s} \frac{\partial e(P,V)}{\partial P_k}}.$$

The expenditure function is given by

$$e\left(P,V\right) = \left(V + \sum_s \nu_s \ln P_s\right)^{1/\varepsilon} \varepsilon^{1/\varepsilon} \prod_{s \in \{F,G,CS\}} P_s^{\omega_s}.$$

This implies that

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

This also implies that

$$
\begin{aligned}
\frac{\partial^2 e(P,V)}{\partial P_s \partial P_k} &= \frac{\partial e(P,V)}{\partial p_k}\left(\frac{\frac{1}{\varepsilon}\nu_s}{V+\sum_s \nu_s \ln P_s}+\omega_s\right)\frac{1}{P_s} - e(P,V)\frac{\frac{1}{P_s}\frac{1}{\varepsilon}\nu_s\nu_k\frac{1}{P_k}}{\left(V+\sum_s \nu_s \ln P_s\right)^2} \\
&= e(P,V)\frac{1}{P_k}\frac{1}{P_s}\left\{\left(\frac{\frac{1}{\varepsilon}\nu_k}{V+\sum_s \nu_s \ln P_s}+\omega_k\right)\left(\frac{\frac{1}{\varepsilon}\nu_s}{V+\sum_s \nu_s \ln P_s}+\omega_s\right) - \varepsilon\frac{\frac{1}{\varepsilon}\nu_s\frac{1}{\varepsilon}\nu_k}{\left(V+\sum_s \nu_s \ln P_s\right)^2}\right\}.
\end{aligned}
$$

Now note that

$$
\begin{aligned}
\frac{\frac{1}{\varepsilon}\nu_k}{V+\sum_s \nu_s \ln P_s}+\omega_k &= \nu_k\frac{1}{\varepsilon}\left(V+\sum_s \nu_s \ln p_s\right)^{-1}+\omega_k \\
&= \nu_k\left(\frac{e(P,V)}{\prod_{s\in\{F,G,CS\}} P_s^{\omega_s}}\right)^{-\varepsilon}+\omega_k = \vartheta_k.
\end{aligned}
$$

Hence,

$$
\begin{aligned}
\frac{\partial e(P,V)}{\partial P_s} &= e(P,V)\,\vartheta_s\frac{1}{P_s} \\
\frac{\partial^2 e(P,V)}{\partial P_s \partial P_k} &= e(P,V)\frac{1}{P_k}\frac{1}{P_s}\left\{\vartheta_k\vartheta_s - \varepsilon\frac{\frac{1}{\varepsilon}\nu_s}{V+\sum_s \tilde{\nu}_s \ln P_s}\frac{\frac{1}{\varepsilon}\nu_k}{V+\sum_s \nu_s \ln P_s}\right\} \\
&= e(P,V)\frac{1}{P_k}\frac{1}{P_s}\left\{\vartheta_k\vartheta_s - \varepsilon(\vartheta_s-\omega_s)(\vartheta_k-\omega_k)\right\}.
\end{aligned}
$$

This implies that

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

## A-4 Equivalent Variation (Section 6.1)

In this section, we derive the equivalent variation money-metric welfare $\varpi$—see Section 6.1. Consider the indirect utility of an individual in $r$ with human capital $q$, given by

$$
\mathcal{V}(qw_r, \mathbf{P_r}) = \frac{1}{\varepsilon}\left(\frac{qw_r}{\prod_s P_{rs}^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s \ln P_{rs}. \tag{A-10}
$$

The equivalent variation for an individual with skills $q$, $\varpi^q(\hat{x}_r|x_r)$ is then implicitly defined by[1]

$$
\mathcal{V}(\varpi^q(\hat{x}_r|x_r), \mathbf{P_r}) \equiv \mathcal{V}\left(q\hat{w}_r, \hat{\mathbf{P}}_{\mathbf{r}}\right).
$$

Using (A-10), $\varpi^q(\hat{x}_r|x_r)$ solves

$$
\frac{1}{\varepsilon}\left(\frac{\varpi^q(\hat{x}_r|x_r)}{\prod_s P_{rs}^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s \ln P_{rs} = \frac{1}{\varepsilon}\left(\frac{q\hat{w}_r}{\prod_s \hat{P}_{rs}^{\omega_s}}\right)^{\varepsilon} - \sum_s \nu_s \ln \hat{P}_{rs}.
$$

[1] Recall that we defined $x_r = (w_r, \mathbf{P_r})$.

Rearranging terms, we can express $\varpi^q(\hat{x}_r|x_r)$ as

$$\frac{\varpi^q(\hat{x}_r|x_r)}{q\hat{w}_r} = \prod_s \left(\frac{P_{rs}}{\hat{P}_{rs}}\right)^{\omega_s} \times \left(1 - \left(\sum_s \nu_s \ln\left(\frac{\hat{P}_{rs}}{P_{rs}}\right)\right)\varepsilon\left(\frac{q\hat{w}_r}{\prod_s \hat{P}_{rs}^{\omega_s}}\right)^{-\varepsilon}\right)^{1/\varepsilon} \tag{A-11}$$

Note first that if $\nu_s = 0$, i.e. preferences are homothetic, we recover

$$\frac{\varpi^q(\hat{x}_r|x_r)}{q\hat{w}_r} = \prod_s \left(\frac{P_{rs}}{\hat{P}_{rs}}\right)^{\omega_s}$$

and the equivalent variation simply reflects the change in the Cobb-Douglas price index. Note also that (A-11) implies that all our welfare results are independent of the chosen level of the agricultural prices in 1987. As we show in (17), for a given choice of $P_{Ft}$, prices in the consumer service will adjust to keep the real prices index $\prod_s P_{rs}^{\omega_s}$ constant. (A-11) then shows that $\varpi^q(\hat{x}_r|x_r)$ is independent of the choice of the agricultural price level in 1987.

# A-5 Open economy (Section 7.3.1)

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

## A-5.1 Environment and Equilibrium

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

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

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

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

$$P_G = \left(p_{G,D}^{1-\eta} + \varphi^\eta p_{G,ROW}^{1-\eta}\right)^{\frac{1}{1-\eta}}. \tag{A-12}$$

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-12) yields the expenditure shares

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

For simplicity we subsume trade costs in the relative price of foreign goods and assume there are no intra-country shipment costs for exporting goods. We do, however, still assume (as in the baseline model) that there are intra-country trade costs for domestically consumed food and goods.

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

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

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

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

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

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

$$p_{ICT} = \left(\sum_r p_{rICT}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \left(\sum_r\left(\frac{w_r}{A_{rICT}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

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

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

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

## Trade Cost

We do allow for the international trade cost; however, it is not separately identified from the foreign demand shifter in our estimation. In addition, there is no ICT exporting cost.

### Equilibrium

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

1. Market clearing for agricultural goods:

$$w_{rt}H_{rFt} = \sum_{j=1}^{R}\pi_{rFjt}\left(\omega_F+\nu_F\left(\frac{A_{jCSt}^{\omega_{CS}}\mathbb{E}_{jt}\left[q\right]w_{jt}^{1-\omega_{CS}}}{P_{jFt}^{\omega_F}P_{jGt}^{\omega_G}}\right)^{-\varepsilon}\right)$$

   where $\pi_{rFot} = \tau_{ro}^{1-\sigma}A_{oFt}^{\sigma-1}w_{ot}^{1-\sigma}/P_{rFt}^{1-\sigma}$

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

2. Market clearing for manufacturing goods:

$$w_{rt}H_{rFt} = \sum_{j=1}^{R} \pi_{rGjt} \frac{P_{jGt}^{1-\eta}}{\left(P_{jGt}^{Agg}\right)^{1-\eta}} \left(\omega_G + \nu_G \left(\frac{A_{jCSt}^{\omega_{CS}} \mathbb{E}_{jt}[q] w_{jt}^{1-\omega_{CS}}}{P_{jFt}^{\omega_F} \left(P_{jGt}^{Agg}\right)^{\omega_G}}\right)^{-\varepsilon}\right) w_{jt}H_{jt}$$

$$+ \left(\frac{w_{rt}^{1-\sigma} A_{rGt}^{\sigma-1}}{\sum_{j=1}^{R} w_{jt}^{1-\sigma} A_{jGt}^{\sigma-1}}\right) \times \left(\sum_j w_{jt}^{1-\sigma} A_{jGt}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{Gt}$$

where $\left(P_{jGt}^{Agg}\right)^{1-\eta} = P_{jGt}^{1-\eta} + \varphi^{\eta} p_{G,ROW,t}^{1-\eta}$ and $\pi_{rGot} = \tau_{ro}^{1-\sigma} A_{oGt}^{\sigma-1} w_{ot}^{1-\sigma} / P_{rGt}^{1-\sigma}$

3. Market clearing for local CS:

$$w_{rt}H_{rCSt} \quad = \quad \left(\omega_{CS} + \nu_{CS} \left(\frac{A_{rCSt}^{\omega_{CS}} \mathbb{E}_{rt}\left[q\right] w_{rt}^{1-\omega_{CS}}}{P_{rFt}^{\omega_F} \left(P_{jGt}^{Agg}\right)^{\omega_G}}\right)^{-\varepsilon}\right) w_{rt}H_{rt}$$

4. Market clearing for local ICT services:

$$w_{rt}H_{rICTt} = \left(\frac{w_{rt}^{1-\sigma} A_{rICTt}^{\sigma-1}}{\sum_{j=1}^{R} w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}}\right) \times \underbrace{\left(\sum_j w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICTt}}_{\text{ICT exports}}$$

5. Labor market clearing:

$$H_{rFt} + H_{rGt} + H_{rCSt} + H_{rICTt} = H_{rt}$$

6. Balanced Trade:

$$\underbrace{\left(\left(\sum_j w_{jt}^{1-\sigma} A_{jGt}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{Gt} + \left(\sum_j w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICTt}\right)}_{\text{Exports}} = \underbrace{\sum_{j=1}^{R} \frac{\left(\omega_G + \nu_G \left(\frac{A_{jCSt}^{\omega_{CS}} \mathbb{E}_{jt}[q] w_{jt}^{1-\omega_{CS}}}{P_{jFt}^{\omega_F} \left(P_{jGt}^{Agg}\right)^{\omega_G}}\right)^{-\varepsilon}\right) w_{jt}H_{jt}}{\varphi^{-\eta} \left(\frac{P_{rGt}}{p_{G,ROW,t}}\right)^{1-\eta} + 1}}_{\text{Imports}}$$

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

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

Given the productivities $\{A_{rFt}, A_{rGt}, A_{rCSt}, A_{rICTt}\}_r$, the population distribution $\{H_{rt}\}_r$, the demand shifters of the foreign sector $(\Upsilon_{ICTt}, \Upsilon_{Gt})$ and the other preference parameters of the model, we can calculate

$$\{x_t, \{w_{rt}, H_{rFt}, H_{rGt}, H_{rCSt}, H_{rICTt}\}_r\}.$$

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

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

$$\left\{ [A_{rICTt}]_{r=1}^{R}, \Upsilon_{Gt}, \Upsilon_{ICTt} \right\}.$$

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

1. Relative ICT payments across localities for ICT exports:

$$\frac{w_{rt} H_{rICTt}}{w_{jt} H_{jICTt}} = \frac{w_{rt}^{1-\sigma} A_{rICTt}^{\sigma-1}}{w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}}.$$

These are $R-1$ equations to determine $A_{rICTt}$ up to scale, that is,

$$A_{rICTt} = A_{ICTt} a_{rICTt} \text{ with } \sum_r a_{rICTt}^{\sigma-1} = 1$$

yields

$$a_{rICTt} = \left( \frac{H_{rICTt} w_r^{\sigma}}{\sum_j H_{jICTt} w_{jt}^{\sigma}} \right)^{\frac{1}{\sigma-1}}.$$

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

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

$$\begin{aligned} \sum_r w_r H_{rICTt} &= \sum_{rt} \left( \frac{w_{rt}^{1-\sigma} A_{rICTt}^{\sigma-1}}{\sum_{j=1}^{R} w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}} \right) \left( \sum_j w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICTt} \\ &= \left( \sum_j w_j^{1-\sigma} a_{jICTt}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICTt}. \end{aligned} \quad \text{(A-13)}$$

The right hand-side is total value added of the ICT sector, which we can calculate directly in the data. Given that $w_{jt}$ and $a_{jICTt}$ are observed, we can calculate $\Upsilon_{ICTt}$.

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

$$\text{Total value added in manufacturing} = \sum_r w_{rt} H_{rGt}$$

and

$$\text{Total value added of exports} = \left( \sum_j w_{jt}^{1-\sigma} A_{jGt}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{Gt}.$$

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

$$w_{rt} H_{rICTt} = \left( \frac{w_{rt}^{1-\sigma} A_{rICTt}^{\sigma-1}}{\sum_j^R w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1}} \right) \left( \sum_j w_{jt}^{1-\sigma} A_{jICTt}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{ICTt} = \left( \frac{w_{rt}^{1-\sigma} a_{rICTt}^{\sigma-1}}{\sum_j^R w_{jt}^{1-\sigma} a_{jICTt}^{\sigma-1}} \right) \left( \sum_j w_{jt}^{1-\sigma} a_{jICTt}^{\sigma-1} \right)^{\frac{1-\eta}{1-\sigma}} A_{ICTt}^{\eta-1} \Upsilon_{ICTt}$$

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

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

$$M_{1t} = \frac{\left(\sum_j w_{jt}^{1-\sigma} A_{jGt}^{\sigma-1}\right)^{\frac{1-\eta}{1-\sigma}} \Upsilon_{Gt}}{\sum_r w_{rt} H_{rGt}} = \frac{P_{G,IND}^{1-\eta} \Upsilon_{Gt}}{\sum_r w_{rt} H_{rGt}} = \frac{\Upsilon_{Gt}}{\sum_r w_{rt} H_{rGt}}. \tag{A-14}$$

Therefore, for a given moment of the export share of manufacturing $M_{1t}$ and data on $\{w_{jt}, L_{jGt}\}_j$ we can solve for $\Upsilon_{Gt}$.

# A-6 Imperfect Skill Substitution (Section 7.3.2)

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

## A-6.1 Environment and Equilibrium

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where $\overline{w}_{rt}$ denotes average income, $\pi_{rsot} = \tau_{ro}^{1-\sigma} p_{rst}^{1-\sigma} / P_{rst}^{1-\sigma}$, and $P_{rst}^{1-\sigma} = \sum_o \tau_{ro}^{1-\sigma} p_{rst}^{1-\sigma}$. The market clearing condition for non-tradable CS implies

$$w_{rt}^{-} H_{rCSt}^{-} + w_{rt}^{+} H_{rCSt}^{+} = \vartheta_{CS} \left( \underline{q}_{jt}^{-} w_{jt}^{-}, \underline{q}_{jt}^{+} w_{jt}^{+}, s_{jt}^{Y,-}, \mathbf{p_{jt}} \right) \overline{w}_{rt} L_{rt}. \tag{A-15}$$

Finally, labor market clearing implies

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

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

### A-6.2 Measurement and Equilibrium Accounting

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

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

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

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

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

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

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

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

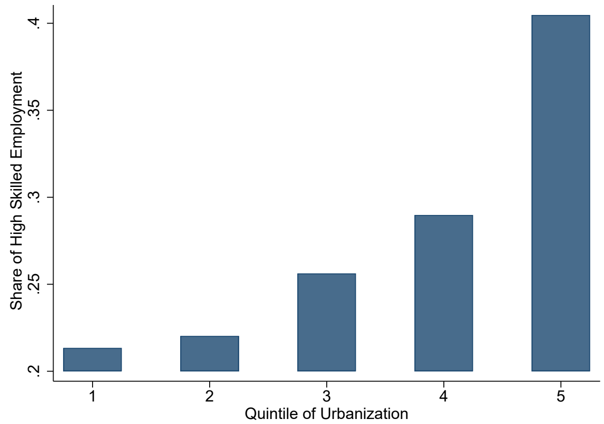


Figure A-1: Share of high-skill employment by urbanization. The figure shows the share of employment with at least secondary schooling for different quantiles of urbanization.

# A-7 Spatial Mobility (Section 7.3.3)

## A-7.1 Model Setting

In this section, we describe how we incorporate spatial labor mobility into the baseline model. We assume that individuals are free to locate in the region of their choosing. Given the long-run focus of our analysis, we assume that individuals learn their productivity $q$ after settling in region $r$. This productivity is drawn from the location-specific distribution $F_{rt}(q)$. Intuitively, by settling in location $r$, individuals have access to the local schooling system and they take this form of local human capital accumulation into account when making their location choice.

Formally, we assume that the utility of individual $i$ to settle in location $r$ at time $t$ given the wage vector $\hat{w}_{rt}$ and the price vector $\hat{\mathbf{P}}_{\mathbf{rst}}$ is given by

$$V_{rt}^{i} \equiv \mathcal{B}_{rt}\overline{\varpi}_{rt}\left(\hat{w}_{rt}, \hat{\mathbf{P}}_{\mathbf{rst}}|w_{rt}, \mathbf{P}_{\mathbf{rst}}\right)u_{rt}^{i},$$

where $\overline{\varpi}_{rt}$ is the money-metric average utility, $w_{rt}, \mathbf{P}_{\mathbf{rst}}$ are the wages and prices in the calibrated equilibrium in 2011, $\mathcal{B}_{rt}$ is a location amenity, and $u_{rt}^{i}$ is an idiosyncratic preference shock for location $r$.[4] By cardinalizing consumers' spatial preferences with $\overline{\varpi}_{rt}$, we measure spatial amenities $\mathcal{B}$ and $u_r$ in money terms. As a result, the overall utility of a location in the original equilibrium is simply $\mathcal{U}_{rt}^{i} = \mathcal{B}_{rt}E_{rt}[q]w_{rt}u_{rt}^{i}$.

We assume that workers' idiosyncratic preference shocks for each location $u_{rt}^{i}$ are Frechet distributed with parameter $\eta$, that is, $P\left(u_{rt}^{i} \leq u\right) = e^{-u^{-\eta}}$. Under these assumptions, one can show that the spatial allocation of labor is given by

$$L_{rt} = \frac{\left(\overline{\varpi}_{rt}\mathcal{B}_{rt}\right)^{\eta}}{\sum_{j}\left(\overline{\varpi}_{jt}\mathcal{B}_{jt}\right)^{\eta}}L. \tag{A-16}$$

Holding $\sum_{j}\left(\overline{\varpi}_{jt}^{h}\mathcal{B}_{jt}\right)^{\eta}$ constant, the partial elasticity with respect to the money-metric utility is given by

$$\frac{d\ln L_{rt}}{d\ln\overline{\varpi}_{rt}} = \eta.$$

Hence, labor supply is very elastic if the dispersion of idiosyncratic shocks is small (i.e. $\eta$ is large).[5] Note that $\eta$

[4] Note that individuals evaluate locations based on the average money-metric utility $\overline{\varpi}_{rt}$, because they do not know their specific human capital realization $q$ when making their location choice.

[5] It is also possible to explicitly allow for congestion externalities, where local amenities depend on the size of the population. If, for

is not equal to the empirically estimated labor supply elasticity with respect to local wages due to the presence of non-homothetic preferences.

### A-7.2 Estimation

Allowing for spatial mobility requires us to estimate additional parameters. First, we need to estimate the level of exogenous amenities $B_{rt}$. Second, we need the labor supply elasticity $\eta$.

Using the set of Equations (A-16), we can identify $B_{rt}$ given the observed allocation of labor and wages. This also implies that we cannot separately identify $\eta$ without additional information. Because we are specifically interested in understanding how the option of labor mobility affects our welfare counterfactuals, we discipline $\eta$ by their implied migration response. For our main exercise we chose $\eta$ so that the cross-sectional standard deviation of employment growth induced by a counterfactual is the same as the one observed in the data between 1987 and 2011.

| Counterfactual | Target Moment | $\eta$ |
|---|---|---|
| $A_{CS}$ | $sd(\Delta L_{r,1999-2011})$ | 0.55 |
| All $A_s$ | $sd(\Delta L_{r,1999-2011})$ | 0.61 |
| $A_{CS}$ | $2 \times sd(\Delta L_{r,1999-2011})$ | 1.93 |
| All $A_s$ | $2 \times sd(\Delta L_{r,1999-2011})$ | 2.05 |

Table A-1: Frechet Parameter

In table A-1, we report the corresponding values for $\eta$ for different counterfactuals. In the first two rows we show the implied levels of $\eta$ for the $A_{CS}$ counterfactual (row 1) and for the counterfactual of taking all productivity back to 1987 (row 2). In particular, the implied cross-sectional standard deviation of local population growth is the same as in the data, if $\eta$ is around 0.6. In the last two rows, we replicate this exercise for the case in which we target twice the empirically observed standard deviation of population growth. This implies a value of $\eta$ of about 2.

example, amenities were given by $\mathcal{B}_{rt} = B_{rt} L_{rt}^{-\delta}$ with $B_{rt}$ being a time-varying, exogenous district characteristic, the parameter $\delta$ would parameterize the strength of local congestion through housing prices or the reduced availability of public goods. In our setup without moving costs, $\delta$ plays a very similar role to $\eta$ as they both affect the aggregate labor supply.

# APPENDIX B: DATA AND MEASUREMENT

In this section, we discuss details of the data and measurement issues discussed in Section 4.

## B-1 Data Sources

Our analysis relies on four datasets:

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

In this section we describe these datasets in detail.

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

The National Sample Survey (NSS) is a representative survey that has been conducted by the government of India to collect socioeconomic data at the household level since 1950. Each round of the survey consists of several schedules that cover different topics like consumer expenditure, employment and unemployment, participation in education, etc. We focus on the *consumer expenditure module* and the *employment and unemployment module* and use data from rounds 43, 55, 60, 64, 66, and 68 of NSS, which span the years 1987 to 2011. The survey covers the entirety of India except for a few regions due to unfavorable field conditions.[6]

We use the "employment and unemployment" module to measure sectoral employment shares and total earnings. An individual is defined as being employed if his/her usual principal activity is one of the following: (i) worked in household enterprises (self-employed); (ii) worked as a helper in household enterprises; (iii) worked as a regular salaried/wage employee; (iv) worked as a casual wage labor in public works; (v) worked as casual wage labour in other types of work. We describe the details of our sectoral employment classification in Section B-3 below.

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

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

To measure human capital, we utilize information on educational attainment. We classify individuals' education into four levels: (i) less than primary; (ii) primary, upper primary, and middle; (iii) secondary; (iv) more than

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

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

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

secondary. We then associate different years of schooling to each category to estimate annual returns. Building on the official classification in India, we attribute 0, 3, 6, and 9 years respectively.

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

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

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

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

### B-1.2 Economic Census

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

The EC collects information such as firms' location, industry, ownership, employment, source of financing and the owner's social group. It covers all economic sectors excluding crop production and plantation. The EC in 2005 and 2013 excludes some public sectors like public administration, defense, and social security. In terms of geography, the EC covers all states and Union Territories of the country except for the year 1990, which covers all states except Jammu and Kashmir.

In Table B-3 we report some summary statistics of the EC in various years. In the most recent year, 2013, the EC has information on almost 60 million firms. The majority of them is very small: they employ on average around two employees, and 55% of them have a single employee. The share of firms with more than 100 employees is 0.06%.

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

Table B-3: THE ECONOMIC CENSUS: SUMMARY STATISTICS. The table reports the number of firms, total employment, average employment, and the share of firms with one, less than five, and more than 100 employees.

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

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

The Service Survey covers a broad range of service sectors, including hotels and restaurants (Section H of NIC 04); transport, storage and communication (I); financial intermediation (J); real estate, renting and business activities (K); education (M); health and social work (N); and other community, social and personal service activities (O). Excluded are the following subsectors: railways transportation; air transport; pipeline transport; monetary intermediation (central banks, commercial banks, etc); trade unions; government and public sector enterprises; and firms that appeared in the Annual Survey of Industries frame (ASI 2004–2005). In terms of geography, the survey covers the whole of the Indian Union except for four districts and some remote villages.[7] The survey was conducted in a total number of 5573 villages and 7698 urban blocks. A total of 190,282 enterprises were ultimately surveyed.

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

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

We use this dataset to allocate employment in the construction sector to either consumer or producer services. The Informal Non-Agricultural Enterprises Survey is part of the 55th survey round of the NSSO. It covers all informal enterprises in the non-agricultural sector of the economy, excluding those engaged in mining, quarrying and electricity, gas and water supply.[8] The Informal Non-Agricultural Enterprises Survey collects information on operational characteristics, expenses, value added, fixed asset, loans, and factor income. For our analysis we use two pieces of information: the number of employees and whether the main customer is another firm or a household.

### B-1.5 Household Expenditure Survey

To estimate the expenditure elasticity $\varepsilon$ we rely on data on consumer expenditure. This data is contained in the National Sample Survey, Round 68, Schedule 1.0. The dataset reports detailed information on a large set of

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

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

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

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

spending categories. In Table B-5 we report the broad classifications. The data also contains a finer allocation of spending within each category. For the purpose of this paper, we rely only on the classification in Table B-5.

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

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

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

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

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

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

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

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

Table B-7: Expenditure items within entertainment. This table reports the detailed expenditure items within the category entertainment (category 20 in Table B-5)

period $URP$) and or at the annual frequency (the mixed reference period $MRP$). Table B-8 shows that the dispersion in spending is much higher for the URP case, especially in the right tail. We therefore use the MRP measure as our measure of total expenditure.

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

.

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

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

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

- the type of the household, which for rural areas is one of (i) self-employed in agriculture, (ii) self-employed in non-agriculture, (iii) regular wage/salary earner, (iv) casual worker in agriculture, and (v) casual worker in non-agriculture, (vi) other and in urban areas one of (i) self-employed (ii) regular wage/salary earner, (iii) casual worker, (vi) other;

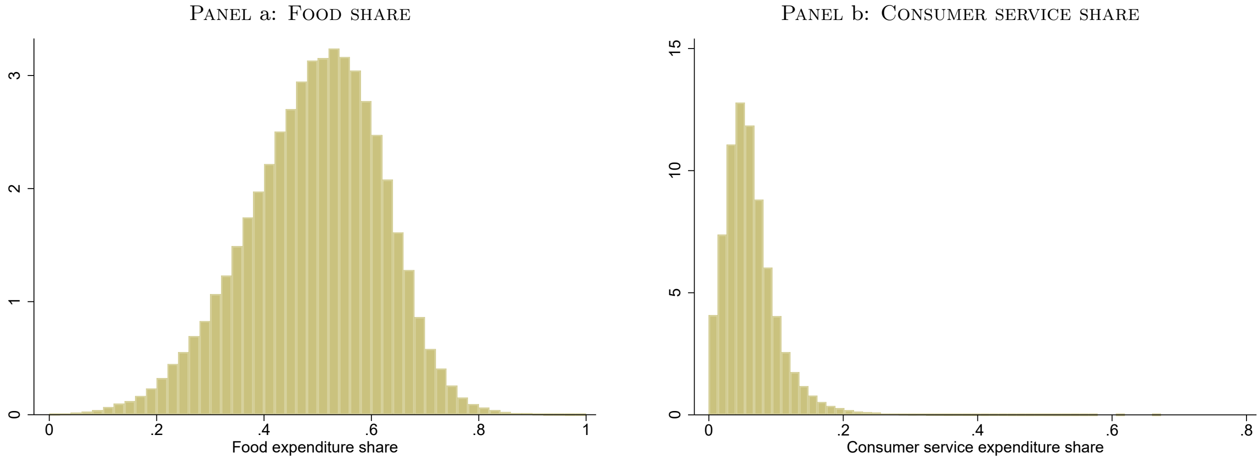


Figure B-1: Distributon of food and consumer service expenditure shares. The figure shows the unconditional distribution of the expenditure shares for food (left panel) and consumer services (right panel).

- the household's religion—Hinduism, Islam, Christianity, Sikhism, Jainism, Buddhism, Zoroastrianism, or other;
- the household's social group—scheduled tribe, scheduled case, backward class, and other.

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

For our analysis of regional food prices, we rely on expenditure and quantities of detailed food varieties. In Table B-9 we report the cumulative expenditure share on the top ten food varieties in the expenditure survey.

| **1987** | Cumulative Share | **2011** | Cumulative Share |
|---|---|---|---|
| Rice | 18.2 | Cereal: s.t. | 9.1 |
| Milk (liquid) | 29.0 | Fuel and light: s.t. | 16.9 |
| Atta | 37.3 | Milk & milk products | 24.7 |
| Fire-wood and chips | 41.9 | Milk: liquid (litre) | 31.7 |
| Sugar (crystal) | 44.7 | Rice: o.s. | 36.4 |
| Mustard oil | 47.2 | Vegetables: s.t. | 40.2 |
| Ground nut oil | 49.5 | Edible oil: s.t. | 43.3 |
| Arhar (tur) | 51.6 | Egg, fish & meat: s.t. | 46.2 |
| Cooked meals | 53.3 | Served processed food: s.t. | 49.1 |
| Potato | 54.9 | Wheat/atta: o.s. | 51.9 |

Table B-9: NSS expenditure survey: expenditure shares of the ten most important food varieties. The table reports the cumulative expenditure shares on the ten most important food categories.

## B-2 Geography: Harmonizing Regional Borders

In this section we describe our procedure to harmonize the geographical boundaries to construct a consistent panel of time-invariant localities. This need arises because the borders of numerous Indian districts have changed between 1987 and 2011. This is seen in the left panel of Figure B-2 that plots the districts' boundaries in 2001 and 2011. The purple line represents the boundaries in 2001, and the red line represents the boundaries in 2011.

The most common type of regional re-districting is a *partition* in which one district has been separated into several districts in the subsequent years. The second type is a *border move* in which the shared border between two districts has been changed. The third is a *merge* in which two districts were merged into a single district.

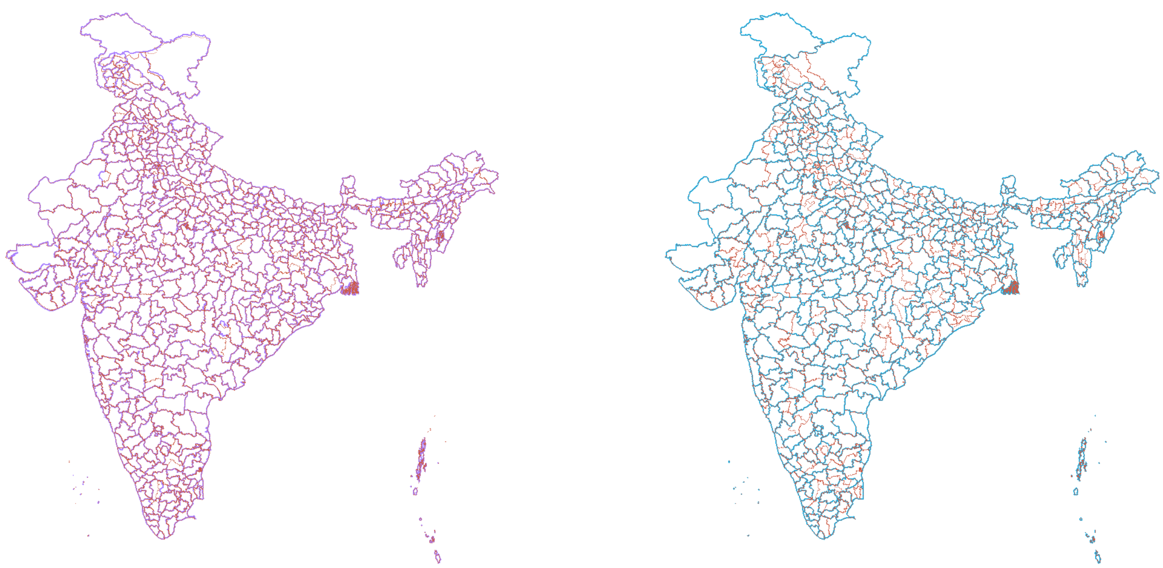

Figure B-2: District Borders in India 1987–2011. The left figure plots the districts' boundaries in 1987 and 2011. The purple line represents the boundaries in 1987 and the dashed red line represents the boundaries in 2011. The right figure shows the official Indian districts in the year 2011 (dashed red lines) and the time-invariant geographical units we construct (solid blue lines) upon which our analysis is based.

To carry out the analysis on a panel of districts with a consistent geography, we construct regions that have consistent borders in 1987 and 2011. To keep the number of regions as large as possible, a region is always the smallest area that covers a single district or a set of districts with consistent borders over time. For instance, in the case of a partition, the region is constructed as the district in the pre-partition year. In the case of a border move, a region is constructed as the union of two districts. We construct a regional map with consistent borders from 1987 to 2011. The right panel of Figure B-2 shows the official Indian districts in the year 2011 (dashed red lines) and the time-invariant geographical units, that we for simplicity also refer to as districts (solid blue lines). We exclude from the analysis two small districts that did not exist in 1987 but did in 2011. Furthermore, because our methodology requires us to calculate sectoral employment shares at the district level, we exclude districts with less than 50 observations as these do not allow us to credibly estimate such shares.

## B-3 Classification of Industries

At the heart of our analysis is the sectoral composition of regional employment. In our theory we distinguish between four sectors: agriculture, manufacturing, consumer services and producer services. To map these concepts to sectors in the data, we first construct six broad industries (see Section B-3.1). In a second step we then attribute employment in services and construction to consumer and producer services respectively; see Section B-3.2.

### B-3.1 Broad Industry Classification

We initially divide economic activities into six industries:

1. Agriculture

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

To do so we rely on India's official classification system, the National Industrial Classification (NIC). We report our classification of industries in Table B-10.

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

Table B-10: Industrial Classification. The table reports the industrial classifications into six broad sectors.

Because the NIC classification system changes over time, we construct a concordance table between 2-digit industries of different versions of the NIC based on official NIC documents and detailed sector descriptions. This concordance system allows us to compare sectoral employment patterns over time. Our crosswalk is reported in Table B-11.

### B-3.2 Attributing Employment to Producer and Consumer Services

Our theory highlights the difference between PS, which are inputs in the production of goods, and CS, which are bought directly by consumers and are luxuries. In terms of the data, financial and insurance activities (NIC codes 64–66) are examples of the former while retail trade (NIC codes 45–47) is an example of the latter (see Table B-10).

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

Ideally, we would calculate the employment share of PS firms in each subsector of the service sectors and in each region. The regional variation is important because our theory stresses that CS and PS productivity varies at

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

Table B-11: Concordance between 2-digit industry Classes. The table reports the classification of NIC codes in different years to the broad sectoral categories of Table B-10.

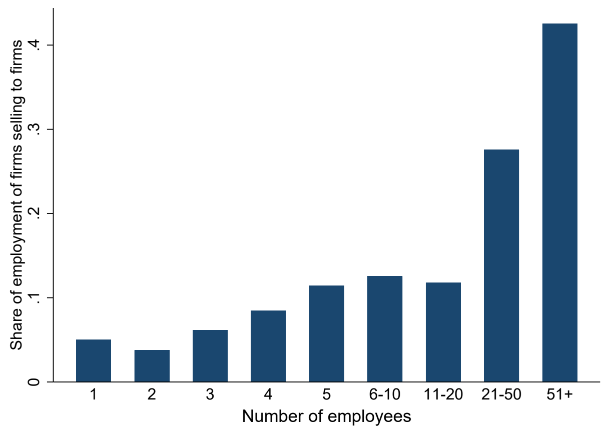


Figure B-3: PRODUCER SERVICE SHARE BY FIRM SIZE. The figure shows the share of service firms whose main customers are other firms (as opposed to private individuals) with a breakdown by firm size.

the regional level. Given the large number of regions and subsectors, the sample size of the Service Survey is not sufficiently large to estimate these averages precisely.

We therefore generate the regional variation in employment shares by using regional variation in the firm-size distribution and differences in the employment share of PS firms by firm size. Empirically, large firms are – within their subsector – much more likely to sell to firms. To see this, consider Figure B-3, where we depict the employment share of PS firms as a function of firm size in the raw data. In Table B-12 we show that the same pattern is present within 2- and 3-digit industries regardless of whether we use sampling weights. In particular, we regress a dummy variable for whether the firm sells mainly to other firms on different firm size dummies. The coefficients are generally positive and increasing.

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

1. For each 2-digit subsector $k$ within the service sector listed in Table B-10 and size bin $b$ we calculate the employment share of PS firms as
$$\omega_{kb}^{PS} = \frac{\sum_{f \in (k,b)} 1\{f \in PS\} l_f}{\sum_{f \in (k,b)} l_f}.$$
Here, $f$ denotes a firm, $1\{f \in PS\}$ is an indicator that takes the value 1 if firm $f$ is a PS firm and $l_f$ denotes firm employment. In practice we take three size bins, namely "1 or 2 employees," "3–20 employees," and "more than 20" employees. We always weigh observations with the sampling weights provided in the Service Survey.[9]

2. We then use the Economic Census (see Section B-1.2) and calculate the share of employment of firms in size bin $b$ in subsector $k$ in region $r$ as
$$\ell_{kbr} = \frac{\sum_{f \in (k,b,r)} l_f}{\sum_{f \in (k,r)} l_f}.$$

3. We then combine these two objects to calculate the share of employment of PS firms in region $r$ in subsector $k$ as
$$s_{rk}^{PS} = \sum_b \ell_{kbr} \omega_{kb}^{PS}.$$

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

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

Table B-12: Corporate Customers and Firm Size. Columns 1 and 2 (3 and 4) control for 2 (3) 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

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

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

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

Five subsectors within the service sector are not covered by the Service Survey. Table B-13 reports our approach to attribute the employment in these subsectors to the PS or CS sector respectively.

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

Table B-13: Imputation of PS employment. This table reports our imputation of PS and CS employment for subsectors that are not covered by the service survey.

### B-3.3 Construction and Utilities

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

From the description of the National Industry Classification, some subsectors are clearly for public purposes. We therefore classify 5-digit level industries within the construction sector into public and private. The results are reported in Table B-14.

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

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

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

In Table B-15 we report the relative employment shares of public employment (as classified in Table B-14), CS, and PS in the construction sector as a whole. The share of public employment is around 10% with a slight bump in

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

Table B-14: Classification of the construction sector. The table reports how we classify different subsectors in the construction sector as either public or private sectors.

2009, presumably a consequence of the financial crisis in 2008. Among the private subsectors, 12.9% of employment is associated with the provision of producer services.

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

Table B-15: Composition of the construction sector. The table shows the relative employment shares of PS, CS, and public employment in the construction sector in different years. We associate public employment to sectors classified as "public" in Table B-14. The classification of employment in the private subsectors to CS and PS is explained in the main text. The last row reports the relative employment share of PS within the private subsectors.

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

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

Note that the regional variation in PS and CS shares within the construction sector only arises because regions differ in the relative size of the different private subsectors listed in Table B-14.

## B-4 The Sectoral Composition of Human Capital

In Table 2 in the main text, we reported the distribution of human capital across sectors of production. In Table B-16 we report the same composition when we classify PS and CS workers according to the NIC classification, that is, we allocate workers in wholesale, retail, hotel, restaurants, health, and community services to CS, and workers in financial and business services, transport, and ICT to PS. This classification increases the skill content of workers in CS and PS, mostly because it implies that construction workers are not assigned as service workers. However, qualitatively, it is still the case that PS and CS workers are more educated than workers in the manufacturing sector or in agriculture.

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

Table B-16: Educational Attainment. The table shows the distribution of educational attainment. Wholesale, retail, hotel, restaurants, health, and community service are classified as CS. Financial, business, transport, and ICT services are classified as PS. The breakdown of rural and urban districts is chosen in a way that approximately half of the population lives in rural and urban districts.

## B-5 Urbanization and Spatial Structural Change

For some of our analysis we choose urbanization as our measure of spatial heterogeneity. We do so as a descriptive device and interpret urbanization as a broad proxy for regional economic development. Figure B-4 shows that there is a strong positive correlation between urbanization and expenditure per capita in the NSS data in 2011.

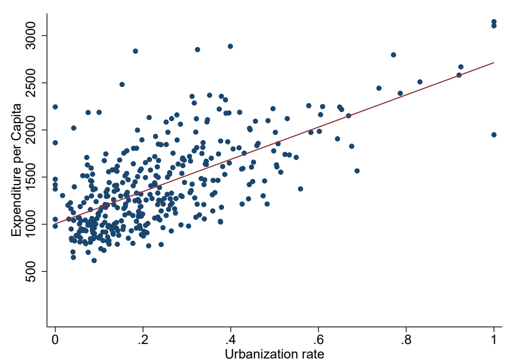


Figure B-4: Expenditure per capita versus Urbanization. The figure shows a scatter plot of the average expenditure per capita in the NSS data across district-level urbanization rates in 2011.

In Figure 4 in the main text we report sectoral employment shares as a function of the urbanization rate. In Figure B-5 we report sectoral income shares by urbanization quintiles in 1987 (Panel a) and in 2011 (Panel b). If anything, the patterns we describe in Figure 4 are more pronounced because earnings are higher in service industries and in cities.

Panel a: Sectoral Income by Urbanization (1987)

Panel b: Sectoral Income by Urbanization (2011)

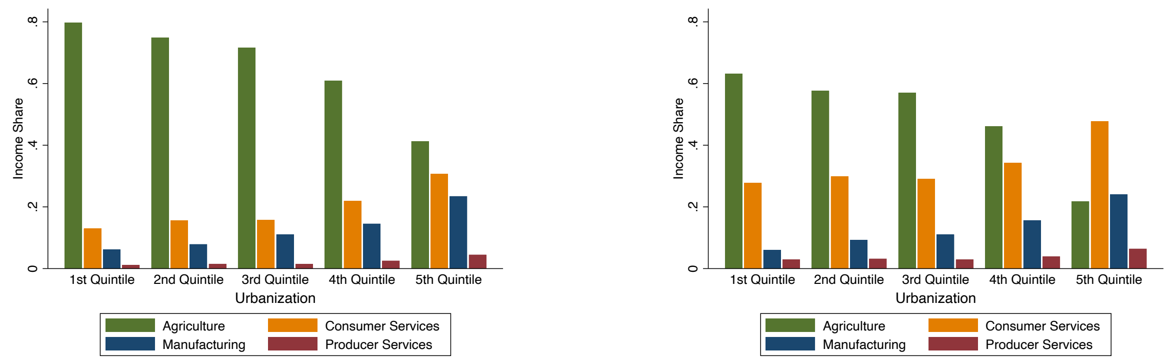


Figure B-5: Spatial Structural Change in India. The figure plots the sectoral income shares by urbanization quintile in 1987 and 2011.

In Figure B-6 we report the time-series change in the urbanization rate (Panel a) and in income per capita (Panel b). The urbanization rate is the share of the population living in urban areas according to the definition of the NSS. The NSS defines an urban location in the following way: (i) all locations with a municipality, corporation or cantonment and locations defined as a town area, (ii) all other locations that satisfy the following criteria: (a) a minimum population of 5,000, (b) at least 75% of the male population is employed outside of agriculture, and (c) a density of population of at least 1,000 per square mile. This share increased from around 22% in 1987 to 29% in 2010. Income per capita, shown in the right panel, stems from data by the World Bank. Between 1987 and 2010, income per capita increased by a factor of almost three.

Panel a: Urbanization

Panel b: Economic Growth

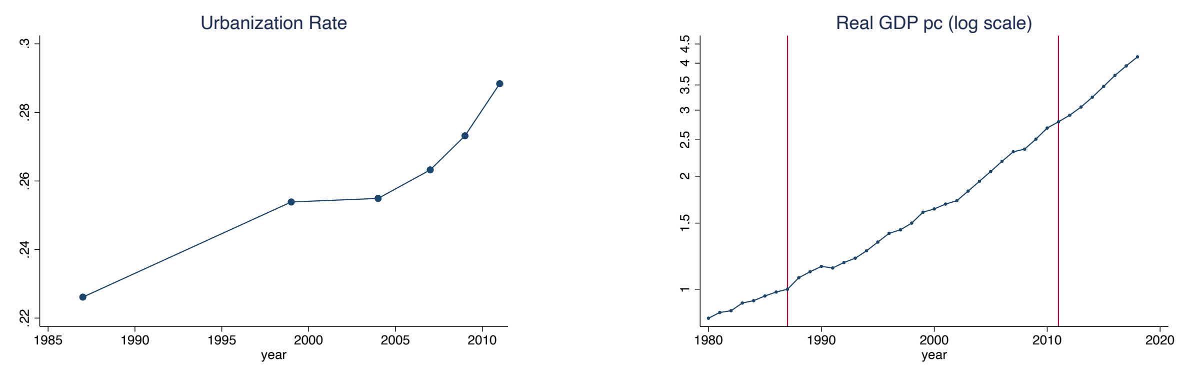


Figure B-6: Economic Growth in India 1987 – 2011. This figure shows the evolution of the urbanization rate (Panel a) and income per capita (Panel b). The urbanization rate is the share of population living in urban areas according to the definition of the NSS. Income per capita stems from World Bank data.

# APPENDIX C: ESTIMATION

In this section, we report additional details of the estimation.

## C-1 Estimating the Shape of the Human Capital Distribution ($\zeta$)

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

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

This implies that

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

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

Table C-1 contains two results. First, the estimated tail parameter for the aggregate economy is slightly below 3, is stable across years, and does not depend on the exact measure of earnings. Second, the estimated tail parameter is declining in the urbanization rate indicating that urban locations have higher inequality. Our estimates also indicate that inequality was lower in 2011 than in 1987. For our quantitative model, we set $\zeta$ to an average value of 3. In Section 7 we show that our results are robust to a variety of choices for $\zeta$. Hence, for simplicity, we abstract from the heterogeneity in $\zeta$ across urbanization quantiles.

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

Table C-1: Identification of $\zeta$. The table reports the estimate of $\zeta$ based on (C-1). In the first columns we report the estimates for the years 1987 and 2011. In the remaining columns we perform our estimation separately for different quantiles of the urbanization distribution.

## C-2 The Relative Price of Agricultural Goods

Our estimation uses the relative price of agricultural goods (relative to manufacturing goods) to identify the relative productivity in the agricultural sector (relative to manufacturing). The Ministry of Planning and Program Implementation (MOSPI) of the Government of India reports value added by 2-digit sectors at current prices and constant prices from 1950–2013[10] We then construct the sectoral price index by

$$p_i = \frac{\text{GDP at current price}_i}{\text{GDP at constant price}_i} \tag{C-2}$$

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

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

$$p_{relative} = \frac{p_{agri}}{p_{manu}}. \tag{C-3}$$

To check the validity of our results, we also use two additional data sources to calculate the relative price. The first is the GGDC 10-Sector Database[11], which provides long-run data on sectoral productivity performance in Africa, Asia, and Latin America. This dataset reports the annual series of value added at current national prices and value added at constant 2005 national prices. We follow the same procedures to calculate the relative price.

The second is the Wholesale Price Index (WPI) from the Office of the Economic Advisor.[12] The WPI tracks ex-factory prices for manufactured products and market prices 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 though 2009. The second one is the series with the base year 2004, which is available from 2005 though 2016. Again, we use the same method to calculate the relative prices, and normalize the relative price in the year 2005 to 1.

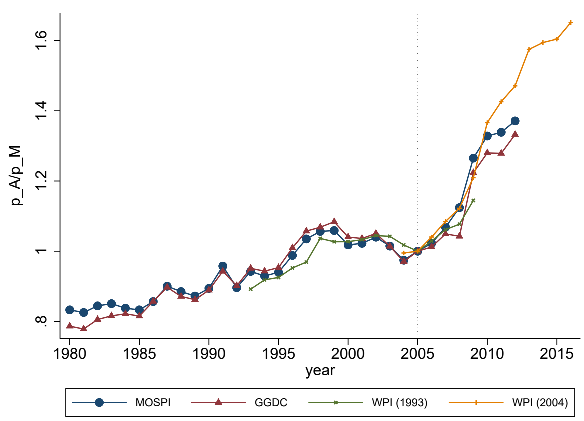


Figure C-1: RELATIVE PRICE OF AGRICULTURAL TO MANUFACTURING GOODS. The figure shows the relative prices of agricultural products as calculated in (C-2) and (C-3) from the different sources mentioned in the main text. "MOSPI" refers to the data from the Indian Government that is used in our analysis. "GGDC" stems from the GGDC 10-Sector Database. "WPI (1993)" and "WPI (2004)" are based on the Wholesale Price Index with a 1993 base year and a 2004 base year respectively.

In Figure C-1 we plot the relative price of agricultural goods to manufacturing goods. Since the pattern from the different data sources is very similar, we use the results based on MOPSI in our analysis.

## C-3 Productivity Growth and Urbanization

In Section 5.2 we showed: (i) CS productivity is systematically higher in urbanized locations (see Figure 6), and (ii) productivity growth is spatially dispersed (see Table 5). In Table C-2 we regress sectoral productivity growth in region $r$, that is, $\ln A_{rs2011} - \ln A_{rs1987}$, on the 1987 urbanization rate in region $r$. Urban locations experienced higher productivity growth in CS and the Industrial Sector (which, recall, includes some business services). Agricultural productivity growth is uncorrelated with the urbanization rate in 1987.

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

[12] The data are available at `https://eaindustry.nic.in/`

| | Productivity Growth | | |
|---|---|---|---|
| | Agriculture | Industry | Cons. Serv. |
| 1987 urbanization | 0.220** | 0.493*** | 1.676*** |
| | (0.078) | (0.092) | (0.504) |
| Weight (1987 Pop) | ✓ | ✓ | ✓ |
| N | 360 | 360 | 360 |
| $R^2$ | 0.022 | 0.074 | 0.030 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C-2: Productivity Growth and Urbanization. The table reports the results of univariate regressions of sectoral productivity growth, $\ln(A_{rs2011}/A_{rs1987})$, on the urbanization rate in 1987. We weigh all regressions by the population size in 1987.

## C-4 Non-targeted Moments: Additional Results

In this section we present additional details on the analysis of non-targeted moments reported in Section 5.3.

**Alternative Estimates of Sectoral Productivity Growth:**

In Figure 7 we reported productivity growth for the three broad sectors agriculture, manufacturing and services in the GGDC data. In Table C-3 we report productivity growth at a finer level of disaggregation. Within the service sector, business services like finance or real estate experienced particularly fast productivity growth of around 10% annually. In our classification, such services are partly allocated to the industrial and partly to the CS sector. However, even services like trade, restaurants and hotels, that are more traditionally thought to be consumer services as in our model, experienced fast productivity growth according to GGDC. Government services and community services show relatively little productivity growth. Recall that such services are excluded from our analysis, which could explain why our model shows slightly faster productivity growth in services compared to the GGDC (see Figure 7).

| Sector | Productivity growth |
|---|---|
| Agriculture | 0.98 |
| Manufacturing | 5.63 |
| Mining | 3.42 |
| Construction | 6.44 |
| Utilities | 5.68 |
| All services | 7.90 |
| Finance/insurance/ real estate/business services | 10.22 |
| Trade/restaurants/hotels | 7.22 |
| Transport/storage/communication | 7.89 |
| Community/social/personal services | 4.97 |
| Government services | 5.08 |

Table C-3: Sectoral Value Added Growth: The table reports sectoral productivity (value added per worker) growth from the GGDC data for 1987–2011.

**Analysis of Consumer Expenditure Data:**

We also directly use micro data on the CS expenditure (see Tables B-6 and B-7). In particular, we estimate a regression of the form

Panel a: $A_{rCS}$ and Fixed Effects of CS Spending. Panel b: Urbanization and Fixed Effects of CS Spending.

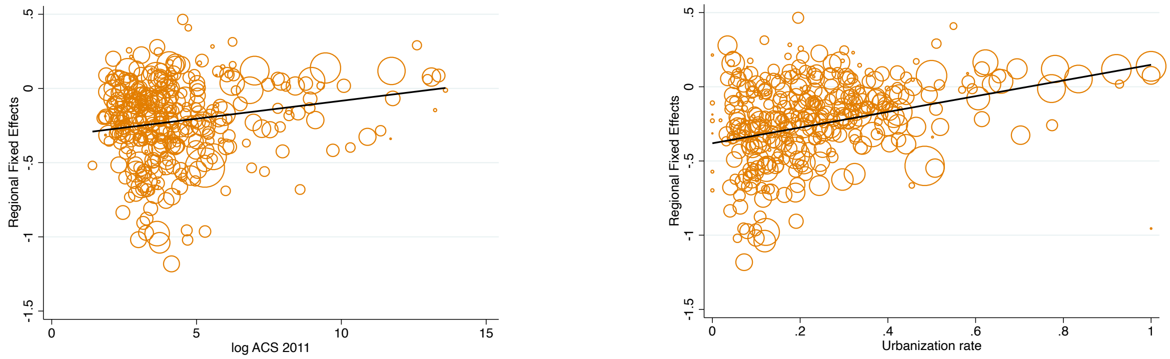


Figure C-2: Regional Variation in Consumer Spending. In the left (right) panel we display the correlation of the region fixed effect of a regression of log CS expenditure on individual income against our estimates of consumer service productivity (against the urbanization rate).

$$\ln \vartheta_{CS}^{h} = \delta_r + \gamma \times \ln e_h + x_h' \psi + u_{rh}, \tag{C-4}$$

where $\vartheta_{CS}^{h}$ denotes the CS expenditure share for household $h$. Note that this is the same specification as for the case of food (see (22)). However, the empirical elasticity $\gamma$ does *not* coincide with $\varepsilon$, because CS are luxuries and hence have a positive asymptotic expenditure share. Equation (C-4) thus just describes the empirical relationship between CS spending shares and household income.

According to our model, conditional on a level of spending $e$, CS spending shares are large if CS prices are low, that is, if CS productivity $A_{rCSt}$ is large relative to the wage. This suggests that the regional fixed effects $\delta_r$ in (C-4) should be positively correlated with $A_{rCSt}$.

In Figure C-2 we depict this correlation. In the left panel we show a scatter plot between $\hat{\delta}_r$ and our estimates $\ln A_{rCSt}$. There is a robust positive relationship; that is, in regions that we estimate to be productive in the CS sector, consumers spend a large fraction of their income on CS holing income constant. Similarly, as seen in the right panel, there is a positive correlation between $\hat{\delta}_r$ and the urbanization rate.

**Elasticities of Substitution:**

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

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

where $e(p,V)$ denotes the expenditure function. As we show in Section A-3 in the Appendix, our preference specification implies that

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

In the left panel of Figure C-3 we report the implied elasticities of substitution as a function of the regional urbanization.[13] The substitution elasticities are relatively close to unity. Goods and consumer services are complements, in particular in poor, rural districts. Food and consumer services are slightly more substitutable than implied by a Cobb-Douglas utility function. In the right panel we depict the elasticity of sectoral expenditure shares with respect

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

to income. In our model, this elasticity if given by

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

Quantitatively, our estimated model predicts that the expenditure elasticity for agricultural products is close to –0.34. This is expected because $\varepsilon \approx 0.34$. The expenditure elasticities on goods and consumer services are both positive and between 0.2 and 0.5. The consumer service elasticity is particularly large in rural regions, that are on average poor and unproductive in consumer services.

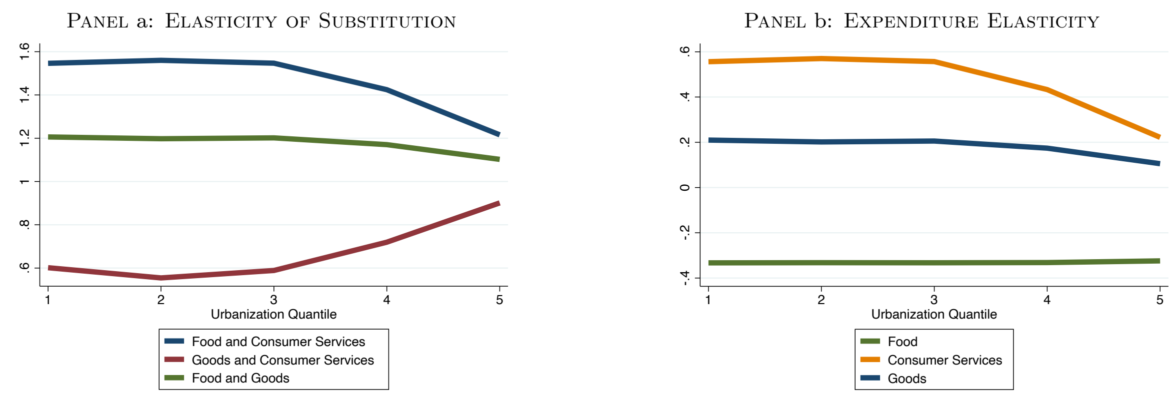


Figure C-3: Elasticities of Substitution and Expenditure Elasticities. The figure plots the elasticity of the substitution between the three goods (left panel) and the elasticity of expenditure shares with respect to expenditure (right panel) by urbanization quintile in 2011.

**Analysis of Food Prices:**

The expenditure survey reports both total expenditure and the total quantity bought for a variety of food items. We thus compute the price of product $n$ in region $r$, $p_{nr}$, as the ratio between total expenditure and total quantity. We then run the regression

$$\ln p_{nr} = \delta_r + \delta_n + u_{nr}, \tag{C-5}$$

where $\delta_r$ and $\delta_n$ are region and product fixed effects. The estimated fixed effect $\hat{\delta}_r$ thus describes the average food price in region $r$.

In Figure C-4 we show the correlation between the estimated $\hat{\delta_r}$ and the regional price of agricultural goods in the model, that is $\ln p_{rFt}$. The two measures are strongly positively correlated, even though we do not use the data on local food prices as targets of our estimation. In the model, the variation in local food prices reflects local agricultural productivity, local wages, and food prices of close-by locations (which have low transport costs).

## C-5 Outliers in Quantitative Analysis

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

This is seen Table C-4, where we report the upper and lower quantiles of the regional distribution of welfare changes for the different counterfactuals. Consider for example the agricultural sector. If agricultural productivity had not grown since 1987, the most adversely affected region would have seen its welfare decline by 65.6% in terms of an equivalent variation. Conversely, some regions would have seen their welfare increase. The region benefitting

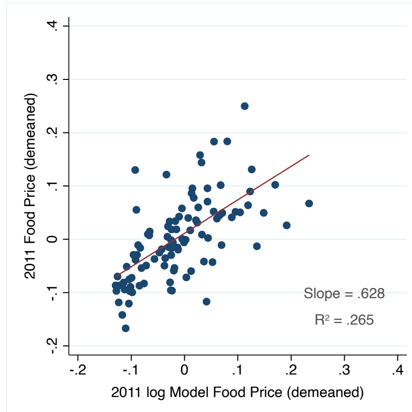


Figure C-4: Regional food prices—Data versus Model. The figure shows a binscatter plot of regional log food prices in the model ($\ln p_{rF}$) and the data ($\hat{\delta}_r$ from (C-5))

the most would have seen an increase in welfare by 54.8%. The last row of Table C-4 shows that some regions would have seen very large gains if CS productivity had not grown. These are regions where CS productivity *declined* between 1978 and 2011. As explained above, this pattern is entirely driven by a few districts being close to the theoretical threshold of $\omega_{CS}$. For comparison, in the last row we also report the estimated distribution of the welfare effects in our baseline analysis, where we truncate the productivity growth distribution at the top and bottom 3%. This has large effects on the distribution of welfare effects in the right tail of the distribution.

| | Regional Welfare Changes (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Min | 1% | 2% | 3% | 5% | 95% | 97% | 98% | 99% | Max |
| Agriculture | -57.5 | -47.4 | -46.4 | -45.2 | -42.8 | -0.7 | 5.9 | 11.2 | 14.6 | 41.0 |
| Industry | -35.0 | -28.2 | -27.3 | -25.8 | -24.2 | -6.4 | -3.7 | -3.4 | 1.6 | 26.9 |
| Cons. Serv. | -98.9 | -97.9 | -95.5 | -93.7 | -85.7 | 23.0 | 61.4 | 272.1 | 2523.8 | $6.5 \times 10^4$ |
| Cons. Serv. (Baseline) | -97.0 | -96.7 | -94.8 | -93.5 | -85.7 | 23.0 | 50.2 | 61.4 | 117.7 | 151.2 |

Table C-4: Distribution of Welfare Losses. The table reports the lower and upper percentiles of the regional distributions of sectoral welfare losses.

These extreme values at the bottom of the regional productivity growth distribution have aggregate effects. For our baseline analysis we trim the top and bottom 3% of the productivity growth distribution and set regional productivity growth in such regions to the 3% and 97% quantile respectively. In Table C-5 we report the change in aggregate in the absence of CS productivity growth as a function of this trimming cutoff. Without any trimming, the aggregate effect is 32%, that is, is positive due to the extreme outliers reported in Table C-5. Once such outliers are truncated, we recover our baseline results of a welfare loss of about −26%. In the last row of Table C-5 we report the aggregate employment share of the affected districts. The changes in the aggregate effects of CS growth are not driven by few large districts but by a small number of small districts with very large changes in CS productivity.

## C-6 The Bootstrap Procedure

In this section we describe the implementation of our bootstrap procedure. We rely on a non-parametric bootstrap, which treats the observed empirical distribution of the data as the population (see, for example, Horowitz (2019)). We implement this procedure in the following way:

| | | Trimming cutoff | | | | |
|---|---|---|---|---|---|---|
| | No trimming | 1% | 2% | 3% | 4% | 5% |
| Welfare Loss | 31.9% | -6.3% | -21.9% | -26.4% | -27.1% | -27.6% |
| Employment Share | 0 | 1.2% | 1.4% | 3.2% | 4.2% | 6.7% |

Table C-5: Welfare Losses with Different Trimming Cutoffs. The table reports the aggregate welfare effects of productivity growth in the CS sector for different trimming rules. A trimming cutoff $x\%$ means that we set the $x\%$ highest and lowest productivity growth rates to $x\%$ and $1-x\%$ respectively.

1. From the underlying micro data of the NSS, we draw households randomly with replacement and we sample, within each district, the same number of households as the current dataset.[14]
2. Given this bootstrap sample, we recalculate all statistics used in our accounting procedure, that is, sectoral employment shares, sectoral income shares, and the supply of human capital at the district level.
3. We then redo our entire analysis on this bootstrap sample:
   (a) We re-estimate the structural parameters that rely on this data, that is, the income elasticity $\varepsilon$ (by targeting the estimated income elasticity of the expenditure of food reported in Table 3) and the preference parameters $\nu_F$ and $\omega_{CS}$ (as explained in Section 5),
   (b) We re-estimate the productivity fundamentals $\mathbf{A_t}$, and
   (c) We calculate our counterfactuals by setting sectoral productivity growth between 1987 and 2011 to zero.
4. This procedure provides us with alternative estimates of the welfare effects and the impact on the structural transformation. Let $\Delta\varpi_r^{q(b)}$, $\Delta\overline{\varpi}_r^{(b)}$ and $\Delta\overline{\varpi}^{(b)}$ denote the individual, regional, and aggregate welfare impact from bootstrap iteration $b$. Similarly, let $L_{s2011}^{CF_F,(b)}$, $L_{s2011}^{CF_CS,(b)}$ and $L_{s2011}^{CF_I,(b)}$ denote counterfactual employment share in sector $s$ in bootstrap iteration $(b)$ in 2011 if productivity in agriculture $(F)$, CS, and Industry $(I)$ had not grown since 1987. We always use the same choices to treat outliers as in our baseline analysis (see Section C-5).
5. We replicate this procedure $B$ times and hence arrive at the vector

$$\left\{\Delta\varpi_r^{q(b)}, \Delta\overline{\varpi}_r^{(b)}, \Delta\overline{\varpi}^{(b)}, L_{s2011}^{CF_F,(b)}, L_{s2011}^{CF_CS,(b)}, L_{s2011}^{CF_I,(b)}\right\}_{b=1}^{B}. \tag{C-6}$$

   In practice we take $B=200$.
6. From C-6 we can estimate the distribution of the statistics of interest. For example, the $\tau$th quantile of the distribution of aggregate welfare gains, $m^{\tau}_{\Delta\overline{\varpi}}$, can be estimated from the empirical distribution

$$\frac{1}{B}\sum_{b=1}^{B} 1\left[\Delta\overline{\varpi}^{(b)} \leq m^{\tau}_{\Delta\overline{\varpi}}\right] \leq \tau.$$

   The quantiles for the other objects of interest are calculated similarly.
7. In the box plots in Figures 9, 10, and 11 we plot the 5%, 25%, 50%, 75% and 95% quantiles of the respective distribution.

[14] We decided to sample individuals *within* districts for two reasons. First, we wanted to ensure the regional population shares (which we take as exogenous in our theory) are relatively constant across bootstrap iterations. They are not exactly constant because different households have different sampling weights. Second, some districts are small. By fixing the number of sampled households within each districts we ensure a comparable sample size with our baseline analysis.

Note that, for simplicity, this procedure only captures the sampling variation stemming from the NSS micro data. Hence, we do not, for example, resample firms in the Economic Census or the firm survey to re-estimate the relative weights of PS versus CS employment within the different subsectors of the service sector (see Section B-3).

In Figure C-5 we show the bootstrap distribution of the aggregate sectoral employment shares in 1987 (left panel) and 2011 (right panel). Expectedly, the sampling variation in these aggregate statistics is very small and the distribution is close to the value of our baseline analysis, which is shown as a dashed vertical line.

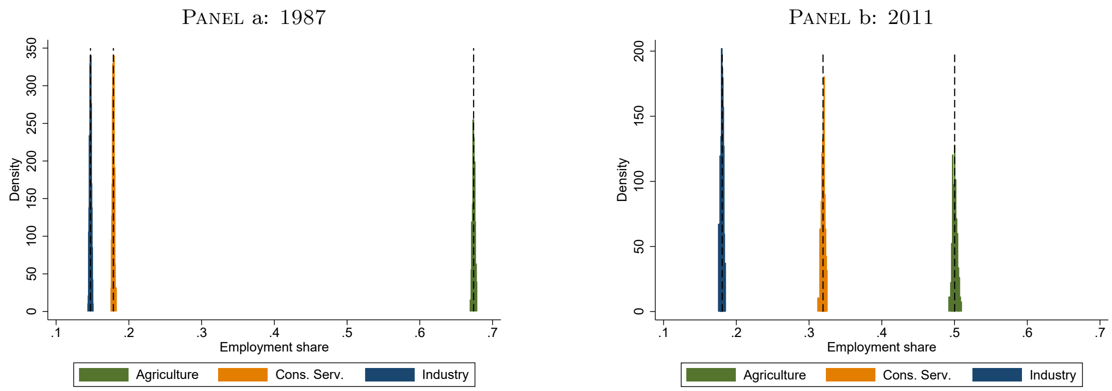


Figure C-5: Bootstrap Distribution of Aggregate Employment Shares. The figure shows the bootstrap distribution of the aggregate sectoral employment share in 1987 (left panel) and 2011 (right panel). The vertical dashed line corresponds to the empirically observed value.

In Figure C-6 we show the estimated distribution of the welfare losses depicted in Figures 9 and 10. We show the losses attributable to productivity growth in agriculture (Panel a), in CS (Panel b), and in the industrial sector (Panel c). For each case we depict the aggregate welfare losses and the losses for the first and fifth urbanization quintile on the left and for different quantiles of the income distribution on the right. The distributions are well-behaved and do not seem to be driven by extreme outliers.

# C-7 Details of Robustness Analysis (Section 7)

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

## C-7.1 Sensitivity to Structural Parameters

In Figure C-7 we show the robustness of our results with respect to the elasticity of substitution across traded varieties $\sigma$ (left panel) and the trade elasticity $\eta$ used in the open economy extension of our theory (right panel). The structure of the graphs is the same as in Figure 12 in the main text.

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

In Figure C-8 we report the results of our analysis discussed in Section 7, where we allow for heterogeneity in the Engel elasticity $\varepsilon$. In the left panel of Figure C-8, we assume $\varepsilon = 0.363$ in highly urbanized Delhi and $\varepsilon = 0.32$ in rural Bankura as suggested by column 7 of Table 3. Doing so yields a mild reduction in spatial inequality but the quantitative effect is small. In the right panel, we allow for heterogeneous $\varepsilon$ across the income ladder. In particular, again motivated by the results reported in Table 3, we assume that individuals above (below) the median have an elasticity of 0.418 and 0.265 respectively. Figure C-8 highlights that this *amplifies* the differential welfare impact of service-led growth between rich and poor households.

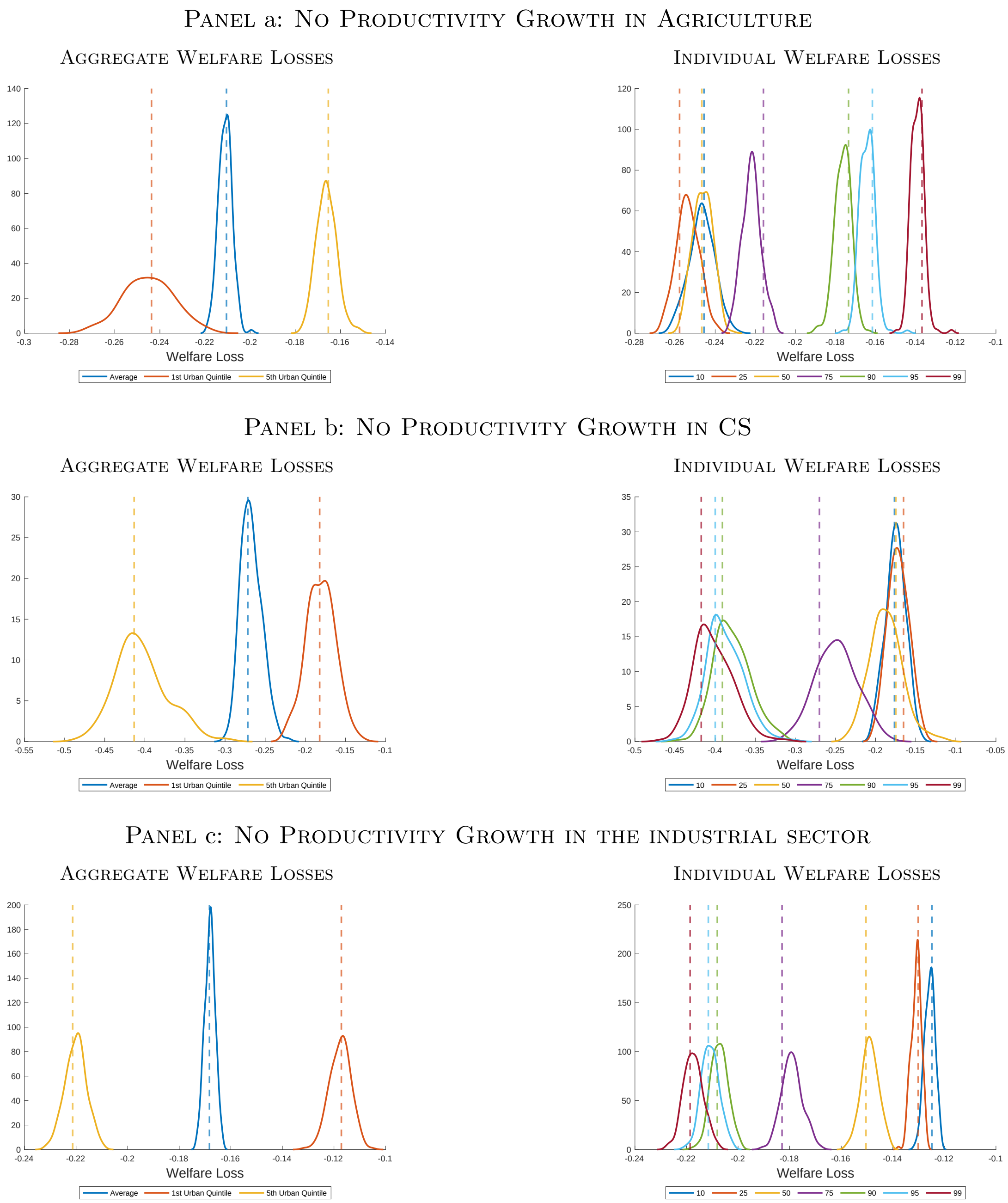


Figure C-6: Bootstrap Distribution of Welfare Losses. The figure shows the bootstrap distribution of the welfare losses when we counterfactually set sectoral productivity in 2011 to its level in 1987. In panel (a) we shut down productivity growth in agriculture, in panel (b) we shut down productivity growth in CS and in panel (c) we shut down productivity growth in the industrial sector. Within each panel, on the left we show the aggregate welfare losses and the losses for the first and fifth urbanization quintile. On the right we show the losses for the different quantiles of the income distribution.

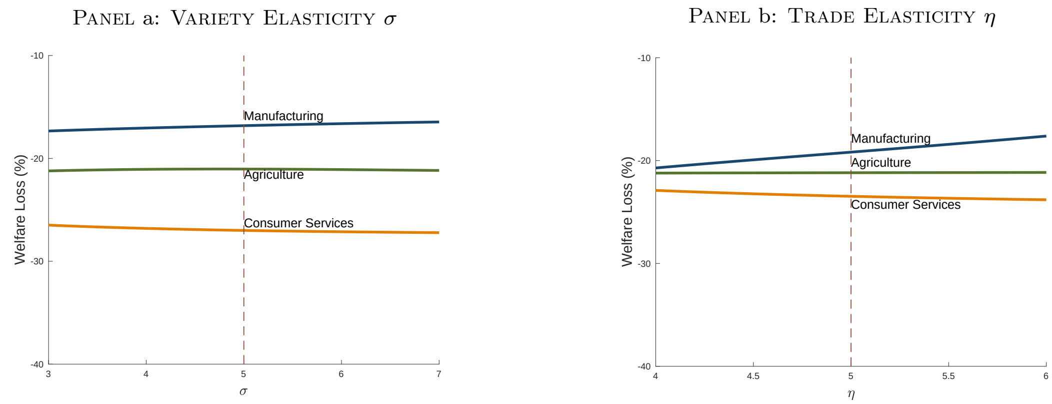


Figure C-7: Robustness Analysis. Panels (a) and (b) show the welfare effects as a function of the variety elasticity $\sigma$ and the trade elasticity $\eta$. The vertical dashed line corresponds to the parameter value in our benchmark analysis.

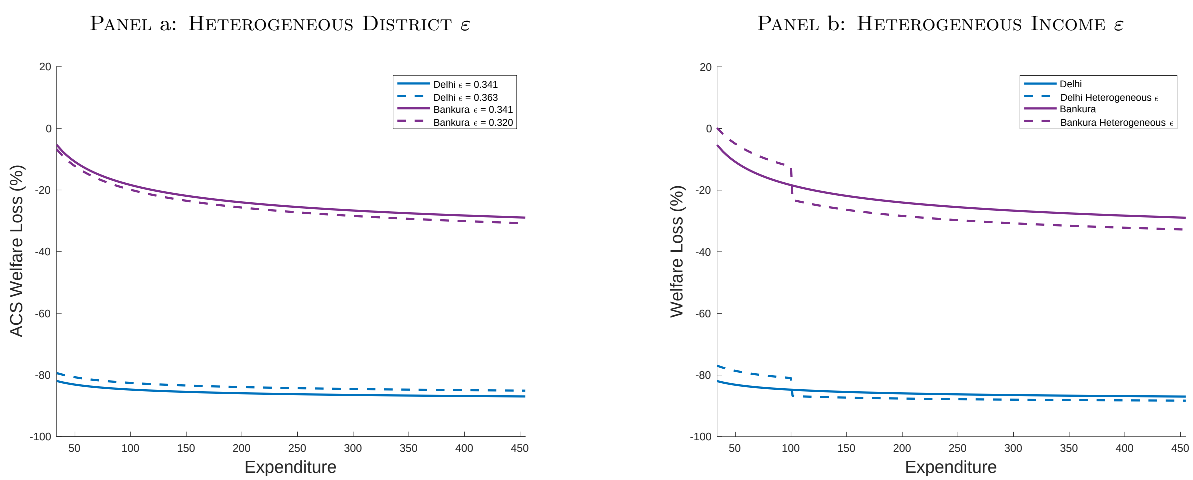


Figure C-8: Heterogeneous Engel Elasticities. In the left panel we allow for heterogeneous $\varepsilon$ across locations. We assume that $\varepsilon$ of individuals in Delhi (Bankura) is 0.363 (0.320), which is in line with the results reported in Table 3. In the right panel we allow for different $\varepsilon$ across individuals. In line with Table 3, we assume that individuals above (below) the median income have $\varepsilon$ of 0.418 (0.265).