Jobless Modernity

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Abstract

Emerging economies grow without creating many modern jobs, and display large formal/informal average income gaps. We show that distortions in the labor market play a key role to explain these phenomenaWe study this jobless modernity in a general-equilibrium occupational-choice model with modern and traditional/informal production, incorporating labor market distortions (productivity-correlated payroll taxes and minimum wage) as well as other wedges. The model is disciplined with historical Colombian household and firm microdata to adequately capture the features of technology and demand, the observed distribution of payroll taxes, and the distributions of human capital, productivity and productivity-correlated wedges. Distortions raise the gap between the share of modernity in income vs. employment during the Colombian industrialization peak from 23.4 to 60.0 percentage points. Because the selection of high productivity workers into formality is key to explain jobless modernity, the minimum wage plays a more significant role than firm level-wedges (77% vs 23%). Within the wedge bundle, payroll taxes are the main margin depressing modern jobs, while revenue distortions drive most of the aggregate output loss. With selection, human capital improvements only expand modern jobs if they compress the human capital distribution.

Keywords: Informality, Employment, Distortions, Technology, Human Capital, Modernity.

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1 Introduction

A stark and systematic pattern of "jobless modernity" emerges in developing economies where, unlike their richer counterparts, the expansion of modern production fails to translate into broad-based modern employment gains. This raises first-order concerns about growth, from how inclusive it is to whether an excessive allocation of resources to traditional, mostly informal, keeps it depressed, potentially helping explain low aggregate income levels in these countries.

Table 1 illustrates the joblessness of modern production in emerging economies. It compares the contribution of modern firms, defined as those employing at least 10 workers, to aggregate value vs. employment, in countries at different stages of development. For a group of nine developing countries, including India and several Latin American countries, modern activities generate roughly half of total labor income while employing only about one-third of the workforce. By contrast, in advanced economies such as the United States and Europe, the shares of income and employment are closely aligned. Similar statements applied when comparing Colombia in the 1970s with the U.S. at the same point in time.

Table 1: Contribution of modern firms to aggregate employment vs. value (shares)

	Modern = 10+ workers		Modern = 25+ workers	
	High-income 2019	Middle-income 2019	US 1970s	Colombia 1970s
to labor income	0.69	0.43	0.71	0.37
to employment	0.63	0.26	0.70	0.18

Sources: The table documents the share of modern firms in total labor income and employment. Middle-Income: India, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Peru, using household income data. High-income- 6: Denmark, France, Italy, Spain, Sweden, US, using data from Eurostat for European countries and CPS for the US.

In this paper, we investigate the role of productivity-correlated distortions–both in the labor market and other margins–to explain jobless modernity, as well as its implications for aggregate income and for income gaps between formal and informal workers. We do so through a model of occupational choice that features both modern and traditional occupations, where modern firms are subject to distortions from regulation that traditional producers do not face. The model is calibrated using detailed microdata for Colombia at the peak of its industrialization process and then used to study the effect of different margins of distortion, including labor market regulations and revenue wedges, and their interactions with the distribution of human capital and with technology. Rich historical

microdata is key for an appropriate measurement of the distributions of productivity and human capital, and consequently to estimate distortions and assess their effects.

Our analysis introduces a general equilibrium model of constrained occupational choice in which modern and traditional businesses emerge endogenously given the available technologies and the underlying distributions of human capital and distortions. The model features a continuum of agents who select among three occupations: entrepreneurship in the modern sector (which employs labor and other inputs), wage employment, or self-employment using a traditional technology. Agents are heterogeneous along two dimensions: embodied human capital, which augments earnings in all occupations, and sector-specific entrepreneurial ability. Although the modern and traditional sectors both operate within the same economy, sectors differ in their intensity of modern-technology use. Occupational choice is distorted by a minimum wage that constrains entry into wage employment, and correlated wedges across modern producers that differentially distort revenue, capital, and labor allocations.

Combined, these elements of the model reproduce key features of under-development illustrated by our data: low average income and a large informal/traditional segment, where all low-income employment is generated. We explore the role of four potential rationales to explain the low employment generation in the segment of modern firms: i) Human capital concentrated below the threshold of productivity necessary to integrate to modern production. ii) Partial segmentation induced by a minimum wage requirement that modern firms must abide by, so that low-productivity workers go to an informal sector that uses traditional technologies, leading to small size iii) Distortions within the modern segment such that the highest productivity firms remain smaller than optimal, not generating enough jobs and limiting their contribution to aggregate productivity. iv) The adoption of labor-saving technologies–available to late industrializing economies–in the modern sector.

We inform the quantification of the model with detailed microdata representative of both modern (formal) and traditional (informal) businesses for Colombia, at the peak of its industrialization, in the seventies. These data allow us to estimate the distributions of different dimensions of productive talent in Colombia's working population, technology and demand parameters in the modern segment, and the distribution of firm-level distortions, separately identifying labor market wedges from residual distortions to firm size. We complement. We complement this analysis with more recent data from the 2010s.

Our empirical strategy combines two sources. First, we use household and employment surveys to estimate the distribution of human capital and track occupational sorting across formal and informal workers and entrepreneurs, including their income lev-

els and the types of businesses in which they operate. Second, we combine these data with Colombia's Annual Manufacturing Survey—a census of all modern manufacturing firms—which records output quantities and values, input use, and the costs associated with specific labor regulations. Crucially, firms report payroll taxes separately from wage payments, allowing us to isolate payroll tax distortions from residual revenue wedges and other factor-biased distortions. Together, these sources allow us to discipline both the household and firm sides of the model simultaneously, an approach that, to our knowledge, is novel in the misallocation literature. We follow Eslava et al. (2023) joint estimation method of production and demand firms.

Results from the micro-estimation indicate that payroll taxes, capital-biased wedges, revenue wedges were all productivity correlated across modern Colombian firms in the 1970s. While revenue wedges and payroll taxes in our data are most taxing for high productivity firms, capital wedges in fact tend to affect low productivity producers the most negatively. The household survey micro-data, in turn, shows that modern sector workers earn significantly more on average than those in traditional businesses, although high-earning workers are also found in the traditional sector, and very few modern entrepreneurs are at the very top of the income distribution. Our calibration reproduces these features of the data, as well as the gap between the contribution of the modern segment to income vs. employment.

Quantitatively, distortions generate large aggregate and allocative losses. Relative to an undistorted benchmark, they reduce aggregate income by approximately 31 percent and lower the share of modern employment from 72.6 percent to 24.0 percent, while the modern sector continues to account for a disproportionately large share of value added. This divergence sharply increases the gap between the modern sector's contribution to income and employment—from about 15 percentage points in the undistorted allocation to more than 50 percentage points in the baseline economy.

Our results show that the roots of jobless modernity in emerging economies lie in the interaction between strong labor market segmentation, driven by the minimum earnings constraint, and productivity-correlated distortions that compress the scale of modern firms. The minimum earnings rule accounts for most (77%) of the disconnect between modern value added and modern employment by excluding low–human capital workers from formal jobs and pushing them into traditional activities, although it does not reduce the share of total income contributed by modern firms. Revenue and labor wedges on their own also induce jobless modernity, moreover, reducing the income weight of the modern sector. The job's effect of payroll taxes is more substantial than that of revenue wedges.

Simulated human capital interventions further reveal that broad improvements in worker capabilities concentrated in the lower half of the ability distribution are uniquely powerful in expanding modern employment, reducing segmentation, and compressing earnings gaps. By contrast, raising talent only at the top or improving product appeal increases value added but leaves joblessness largely unchanged. Labor-saving technological change raises output without generating additional modern job losses or reducing jobless modernity. Together, the results indicate that escaping jobless modernity requires combining regulatory reforms that reduce segmentation with policies that lift human capital precisely where it most expands access to modern production, since neither technology nor wedge reductions alone deliver massively inclusive modernization.

Related Literature. This paper contributes to several strands of the literature. Most directly, it relates to work on misallocation and firm-level distortions in developing economies. A large body of research documents that firm-specific wedges between actual and optimal scale generate substantial aggregate productivity losses (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). We extend this literature in two ways. First, we map residual distortions to specific labor and product market institutions—minimum wages, payroll taxes, and revenue wedges—and quantify their separate effects while accounting for remaining distortions. The richness of our microdata allows us to link measured wedges to concrete regulations. Second, we study these distortions in an environment with an undistorted informal sector. This distinction is central, as the distortions we identify apply only to formal firms, which account for a small share of employment in poorer economies. Together, these contributions highlight the role of labor market distortions in generating segmentation and sustaining high levels of informality. Related work includes Atkin et al. (2025) and Restuccia (2025), which also decompose residual distortions, though with a different focus on margins and outcomes.

A central feature of our framework is the coexistence of a productive modern sector and a large traditional, informal sector. The tension between these segments has been central to the development literature since Lewis (1954) and Harris and Todaro (1970). Subsequent work has characterized informality as a competitive fringe (Rauch, 1991), a refuge for low-productivity workers (La Porta and Shleifer, 2014), or a constraint on monopsony power in labor markets (Amodio et al., 2022). We contribute by showing that misallocation away from high-productivity firms is a key force behind the persistence of informality, and by highlighting self-employment as an important adjustment margin often abstracted from in quantitative models. Dix-Carneiro et al. (2021) study how labor market institutions shape sorting between formal and informal jobs through trade; we instead abstract from trade and focus on the joint role of labor, capital, and product market dis-

tortions and their interaction with human capital and technology. Engbom et al. (2025) emphasize skill shortages as a constraint on the expansion of large, skill-intensive firms. In contrast, we focus on the informal sector—particularly self-employment, which they largely abstract from—and on how labor market institutions interact with the modern-informal divide to generate misallocation.

Our focus on differential firm entry across modern and traditional segments also relates to the literature on firm size in developing versus high-income economies (Tybout, 2000; Hopenhayn, 2016; Bento and Restuccia, 2017, 2021; Eslava et al., 2026; Eslava, 2026). This literature documents that firms are significantly smaller in poorer economies, largely due to the prevalence of micro-establishments and non-employers—what we label as traditional producers—which absorb most workers despite their limited contribution to aggregate output (Eslava et al., 2026). We contribute by jointly analyzing multiple margins of distortion, including labor market regulations, together with the roles of human capital and dual technologies. While these mechanisms have typically been studied in isolation—particularly in the context of informality (Ulyssea, 2018)—we provide a unified framework linking them to both informality and income gaps between formal and informal workers. In our setting, minimum earnings constraints induce sorting between modern and traditional sectors, generating "jobless modernity." Related work has emphasized sorting driven by human capital requirements or financial frictions limiting entry into modern firms (Midrigan and Xu, 2014; D'Erasmo and Moscoso Boedo, 2012); we instead highlight the role of labor market institutions in shaping entry and sectoral allocation.

A methodological contribution of the paper is the use of matched firm and household microdata covering both formal and informal activity. Most of the misallocation literature relies on data from formal firms alone, omitting the self-employed and small informal producers that account for a large share of employment and value added in developing economies (Lewis, 1979; Huneeus and Rogerson, 2020). By combining these sources, we separately identify revenue distortions, payroll taxes, and capital wedges at the firm level while simultaneously tracking occupational sorting across the income distribution. To our knowledge, this joint identification is novel in the literature. As in Ulyssea (2018) and Dix-Carneiro et al. (2021), we integrate firm and household data to study both formal and informal activity. Our setting, however, emphasizes cross-firm heterogeneity within each segment—not only in productivity but also in distortions and regulatory exposure. We show that productivity-correlated distortions within the modern sector interact with regulations that apply differentially across formal and informal firms, with important implications for allocation and sectoral sorting.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model that underpins our quantitative analysis. Sections 3 and 4 focus on the empirical quantification. In Section 3, we estimate key parameters and moments for modern manufacturing, leveraging detailed historical microdata from Colombia. Section 4 calibrates the model and conducts counterfactual exercises to assess the impact of product and labor market distortions on employment generation. The final section concludes.

2 Framework

We develop a model that captures the salient features of emerging economies—such as Colombia—documented above. The model provides a unified framework for measurement, including production function estimation, as well as for calibration and counterfactual analysis.

The economy features four sources of heterogeneity. First, on the production side, we allow for the coexistence of self-employment and modern technologies. Modern technologies are operated by entrepreneurs and combine labor, capital, and intermediate inputs. Second, the economy comprises three sectors that differ in their reliance on self-employment and modern technologies; for instance, manufacturing is more intensive in modern technologies than agriculture. Third, agents are heterogeneous in ability and endogenously sort into self-employment, wage work in modern firms, or entrepreneurship. Fourth, distortions affect production technologies asymmetrically. Self-employment is largely exempt from these distortions, whereas modern firms face idiosyncratic wedges that vary across firm types. In particular, modern firms hire labor subject to minimum wage constraints and face size-dependent distortions to revenue, labor, and capital, which we estimate jointly with the production function.

2.1 Preferences

Consumers' preferences are defined over three types of sectoral goods—agriculture (A), industry (I), and services (S)—given by the CES aggregator:

$$U = \left(\sum_{i \in A,I,S} \lambda_i^{1/\epsilon} C_i^{(\epsilon-1)/\epsilon} \right)^{\epsilon/(\epsilon-1)},$$

where $0 < \epsilon < 1$, $\lambda_i > 0$ for all i, and we normalize $\sum_{i \in A,I,S} \lambda_i = 1$.

In turn, the production of sectoral goods is itself a CES composite of modern (M) and traditional (T) production:

$$C_i = \left(\phi_{i,M}^{1/\rho} C_{i,M}^{(\rho-1)/\rho} + (1-\phi_{i,M})^{1/\rho} C_{i,T}^{(\rho-1)/\rho}\right)^{\rho/(\rho-1)},$$

where $\phi_{i,M} \in (0,1)$ for all i and $\rho > 0$. Modern varieties are differentiated and aggregated through a CES index, while traditional production is homogeneous:

$$C_{i,M} = \left(\sum_{j \in N_{i,M}} d_{i,j}^{1/\sigma} c_{i,j}^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}, \qquad C_{i,T} = \sum_{j \in N_{i,T}} q_{i,j},$$

where $\sigma > 1$, j indexes firms, and $N_{i,M}$ and $N_{i,T}$ denote the sets of modern and traditional producers in sector i, respectively. The weights $d_{i,j}$ capture quality or taste shifters across modern varieties. This nested CES structure delivers standard demand systems at the sectoral, segment (modern versus traditional), and variety levels.

A modern firm j in sector i faces demand:

$$c_{i,j} = \frac{E_{i,M}}{P_{i,M}^{1-\sigma}} d_{i,j} p_{i,j}^{-\sigma} = d_{i,j} \left(\frac{p_{i,j}}{P_{i,M}}\right)^{-\sigma} \left(\frac{P_{i,M}}{P_i}\right)^{-\rho} \left(\frac{P_i}{P}\right)^{-\epsilon} \frac{\phi_{i,M} \lambda_i E}{P} \tag{2}$$

where $P_{i,M} = \left(\sum_{j \in N_{i,M}} d_{i,j} p_{i,j}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is an aggregate price index of the modern segment in sector i. The last equality uses the expenditure system derived in Appendix A.2, along with the corresponding price indexes.

2.2 Technologies

Agents operate a single production technology—either modern or traditional—in one sector of their choice. Entrepreneurs bring embodied ability a to the firm. Modern producers hire labor (l) and combine it with capital (k) and modern intermediate inputs (m). Traditional producers use only their own embodied ability together with an idiosyncratic self-employment productivity shock s. In particular, an agent j operating one of these technologies in sector i generates output according to:

$$j \in N_{i,M} : q_{i,j} = a_j l_{i,j}^{\gamma_l} k_{i,j}^{\gamma_k} m_{i,j}^{\gamma_m} \tag{3}$$

$$j \in N_{i,T} : q_{i,j} = s_j a_j \tag{4}$$

where $\gamma_l + \gamma_k + \gamma_m = 1$ and s_j is relevant only in traditional self-employment. Within each segment (modern or traditional), production technologies are identical across sectors. Accordingly, all sectoral heterogeneity is captured through preferences, which sharpens the interpretation of the model.[1]

Traditional production is used exclusively for final consumption, whereas modern production is used for both final and intermediate purposes. Total intermediate input use aggregates inputs produced by modern firms j across all sectors.

$$\mathrm{Y}_m = \left(\sum_{i \in \{A,I,S\}} \sum_{j \in N_{i,M}} d_{i,j}^{1/\sigma} v_{i,j}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}$$

The resulting demand for intermediates faced by producer j in sector i is given by:

$$v_{i,j} = d_{i,j} \left(\frac{p_{i,j}}{p_m} \right)^{-\sigma} \mathrm{Y}_m, \tag{5}$$

where Y_m denotes the aggregate quantity of intermediate inputs and total expenditure on intermediates is given by $p_m \mathrm{Y}_m$. The aggregate price index for intermediate inputs is:

$$p_m = \left(\sum_{i \in A,I,S} \sum_{j \in N_{i,M}} d_{i,j} p_{i,j}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{6}$$

with $\sigma > 1$. As we argue below, we can normalize the price of the traditional sector to one in all sectors without loss of generality. The value of (gross) total output in the economy is therefore given by:

$$\begin{aligned} \sum_{i \in A,I,S} \left(\sum_{j \in N_{i,T}} q_{i,j} + \sum_{j \in N_{i,M}} p_{i,j} q_{i,j} \right) &= \sum_{i \in A,I,S} \left(\sum_{j \in N_{i,T}} q_{i,j} + \sum_{j \in N_{i,M}} p_{i,j} \left(c_{i,j} + v_{i,j} \right) \right) \\ &= E + p_m \mathrm{Y}_m. \end{aligned} \tag{7}$$

where prices $p_{i,j}$ are allowed to vary across modern producers j, reflecting firm-level heterogeneity. Each producer, however, charges a single price for its variety, independent of whether output is used for final or intermediate consumption.

[1] There is limited empirical guidance on technological differences across sectors within modern and traditional segments. Norris Keiller et al. (2024) document similar production elasticities across service sectors (e.g., restaurants and retail) and manufacturing (electronics).

2.3 Occupational Choice

The economy consists of a unit mass of agents with heterogeneous abilities. Each agent is endowed with one unit of time, which can be allocated to modern entrepreneurship, traditional self-employment, or wage work. To avoid confusion with the sector index i, we index agents by n and denote their characteristics by $(a_n, d_n, s_n, \Gamma_n)$. Agent n chooses among the following occupations:

- Supply a_n efficiency units of labor to a modern firm at wage w, earning labor income wa_n;
- Operate a traditional technology in any sector, producing $s_n a_n$ units of output according to (4), and earning $s_n a_n$ as the traditional goods price is normalized to one;
- Operate a modern firm in any sector, with productivity a_n in (3), quality shifter d_n in demand, facing distortions Γ_n, and earning after-tax profits.

Agents choose the occupation that yields the highest income. The distribution of embodied ability, $f_a(a)$, is estimated non-parametrically from micro data and truncated on $[a_{\min}, a_{\max}]$. The entrepreneurial quality shifter d and the self-employment productivity shock s follow truncated Pareto distributions with densities $f_d(d)$ and $f_s(s)$, respectively. Although (a, d, s) are independently drawn, selection into occupations induces ex post correlation between a and d among modern firms. Distortions Γ are drawn from distributions that may correlate with a and d, and are estimated from firm-level data.

2.4 Markets and Distortions

We assume that all modern firms, regardless of sector, hire labor, rent capital, and purchase intermediate inputs in integrated modern input markets. Accordingly, equilibrium input prices are common across modern firms. We allow for firm-specific distortions to revenue, capital, and labor, but not to materials.

Labor market. Only modern firms hire wage labor. Firm j employing a worker of ability a_j must satisfy the minimum-earnings constraint $wa_j \geq e_{\min}$. In addition, firm j faces a labor wedge τ_j^l, so the cost per efficiency unit of labor is $(1 + \tau_j^l)w$.

Capital market. The economy is endowed with a fixed aggregate capital stock that modern firms rent at rate r. Access to capital may differ across firms, implying that firm j faces an effective rental rate $(1 + \tau_j^k)r$.

Materials market. Modern firms in all sectors purchase intermediate inputs from other modern firms. We assume no distortions in the use of materials, consistent with standard production-function and markup estimation. Supporting this assumption, Eslava et al. (2023) show that in Colombian data the relevant dispersion in input prices is driven mainly by wages rather than by materials prices.

Goods market. Output produced in the modern segment is subject to a firm-specific revenue distortion τ_j^R, which may be correlated with firm characteristics (a_j, d_j). Traditional producers are not subject to this distortion.

We assume that all tax revenues are rebated lump-sum to households. A modern firm j therefore faces the distortion vector $\Gamma_j = \{\tau_j^R, \tau_j^l, \tau_j^k\}$. While we refer to τ^R, τ^l, and τ^k as *taxes*, they more generally capture distortions to revenue and input use. In the quantitative implementation, τ_j^l is disciplined by employers' mandatory social-security contributions, while τ_j^R and τ_j^k capture residual scale and capital distortions. Because only modern firms are subject to minimum wage requirements and these distortions, we use "modern" and "formal" interchangeably, as well as "traditional," "informal," and "self-employed."[2]

2.4.1 Factor Demand in the Modern Sector

The profit maximization problem of a modern firm operating in sector i is:

$$\max_{\{l_{i,j}, k_{i,j}, m_{i,j}\}} (1 - \tau_j^R) p_{i,j} q_{i,j} - w(1 + \tau_j^l) l_{i,j} - r(1 + \tau_j^k) k_{i,j} - p_m m_{i,j}$$

subject to the demand system implied by (2) and (5). Appendix A.2 collects the corresponding demand equation, input demands, and revenue expression.

We focus on monopolistic competition with constant markups.[3] Appendix A.2 derives the firm's first-order conditions for labor, capital, and materials, together with the implied input ratios, labor demand, and revenue. Those optimality conditions imply the following profit expression:

[2]While stylized, this distinction reflects the higher prevalence of informality in traditional segments of less developed economies. In the data, we classify firms with fewer than 10 employees (including the self-employed) as traditional. Using data from 11 Latin American countries, Eslava et al. (2023) report that labor informality—defined as not contributing to a pension system—affects 75% of workers in this segment, compared to 12% among modern firms (those with 10 or more employees).

[3]We relax this assumption in the Appendix and use the more general specification in the estimation.

$$\pi_{i,j} = \left(1 - \frac{1}{\mu}\right) \underbrace{D_{i,M}}_{\text{market access}} \left[\frac{\overbrace{a_j d_j^{1/(\sigma-1)}}^{\Delta_j:\text{ firm capability}}}{\mu c} \underbrace{\frac{(1-\tau_j^R)^{\sigma/(\sigma-1)}}{(1+\tau_j^l)^{\gamma_l}(1+\tau_j^k)^{\gamma_k}}}_{\Omega_j:\text{ wedges}} \right]^{\sigma-1}, \tag{12}$$

where $\mu \equiv \frac{\sigma}{\sigma-1}$ is the constant markup, $D_{i,M}$ is the sector-specific demand shifter for modern goods, and $c \equiv \left(\frac{w}{\gamma_l}\right)^{\gamma_l} \left(\frac{r}{\gamma_k}\right)^{\gamma_k} \left(\frac{p_m}{\gamma_m}\right)^{\gamma_m}$ is the common pre-tax unit cost index. The expression makes the economics transparent. Profits rise with market access $D_{i,M}$, with firm capability $\Delta_j \equiv a_j d_j^{1/(\sigma-1)}$, and with a favorable wedge term Ω_j, which summarizes the combined effect of revenue, labor, and capital distortions. Appendix A.2 reports the intermediate algebra and equivalent revenue expression used in the quantification.

2.5 Equilibrium

A competitive equilibrium is a set of wages, firm prices, and sectoral modern price indexes such that agents choose occupations optimally, effective labor supplied by workers equals labor demanded by modern firms, goods markets clear once intermediate demand is taken into account, and all distortion revenues are rebated lump-sum to households. Appendix A.2 states these equilibrium conditions formally.

We now characterize the equilibrium. To determine the income of a modern entrepreneur, and hence occupational choice as a function of (a, d), we first solve the firm's problem and then characterize sorting across occupations. For expositional simplicity, we present the solution for the case $s = 1$ for all agents, and reintroduce heterogeneity in s in the quantitative analysis.

Under Inada conditions, all segments are consumed in equilibrium provided $0 < \phi_{i,M} < 1$ and $\lambda_i > 0$ for all i. As a result, an agent with characteristics (a, d, s, Γ) who selects a given occupation must be indifferent across sectors. Appendix A.2 shows that this implies a symmetry property: the shares of modern expenditure, modern labor demand, and modern entrepreneurship coincide across sectors. The intuition is that entrepreneurs are indifferent across sectors and the distribution of firm characteristics is common across sectors, so each modern segment has the same distribution of prices and firm sizes up to a sectoral scale term. Sectoral indifference then equalizes the demand shifter $D_{i,M}$ across sectors for a given type. The symmetry property allows us to solve the model sequentially: first across occupations, and then across sectors through expenditure shares

implied by relative demand.

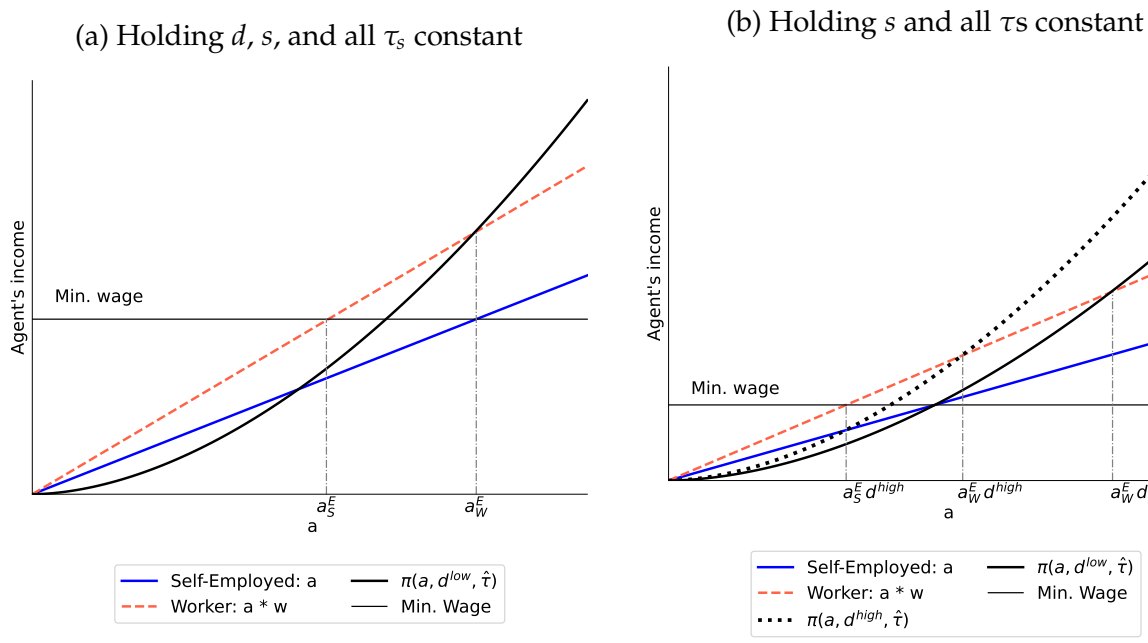
2.5.1 Occupational Choice in Modern and Traditional Sectors

An agent with characteristics (a, d, s, Γ) chooses the occupation that maximizes income:

$$\max\{sa, wa, \pi(a, d, \Gamma)\}. \tag{13}$$

The left panel of Figure 1 illustrates these schedules holding (d, s, Γ) fixed. Wage work and self-employment are linear in embodied ability a, with slopes w and s, whereas profits in the modern sector are convex in a by (12). For a given (d, s, Γ), there is therefore a threshold above which modern entrepreneurship becomes optimal. In the special case without self-employment heterogeneity and distortions, the model nests the occupational choice logic of Lucas (1978).

Figure 1: **Income as a function of an unconstrained agent's occupation and human capital** a

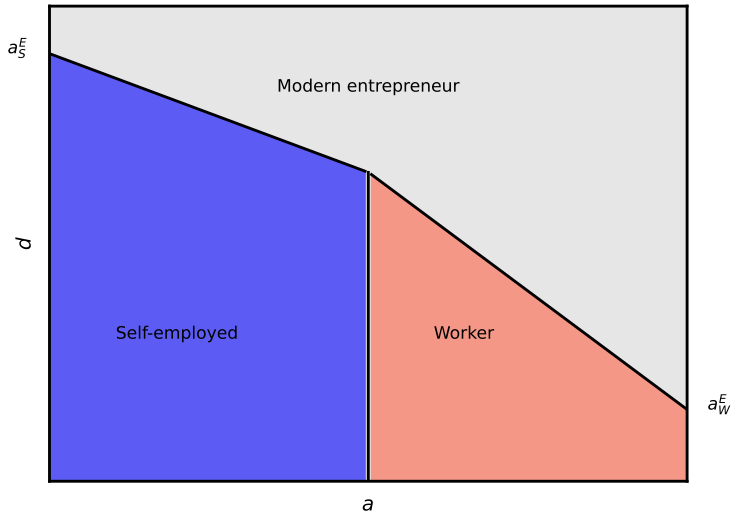


The self-employment shock s matters because it allows some agents with high embodied ability to remain traditional producers rather than becoming wage workers or modern entrepreneurs. The minimum-earnings requirement further restricts wage work: employment in the modern sector is feasible only if $wa \geq e_{\min}$, so low-ability agents with $a < e_{\min}/w$ are rationed out of wage employment. Among unconstrained non-

entrepreneurs, the choice between wage work and self-employment depends on whether wage earnings wa dominate self-employment earnings sa.

The right panel of Figure 1 illustrates the role of heterogeneity in d holding s and distortions fixed. A higher d shifts up the profit schedule for modern entrepreneurship, increasing the range of a for which entrepreneurship is optimal. Figure 2 characterizes the resulting occupational allocation in (a, d) space for a given value of s. Agents with sufficiently high a or d select into modern entrepreneurship; among the remaining agents, those with high s or with $a < e_{\min}/w$ select into self-employment, while the rest work for wages.

Figure 2: Occupational choice given a draw of a and d, holding s fixed.



In the quantitative implementation, the distribution of s helps match the fact that self-employment and informality are concentrated among low-income individuals but remain present throughout the income distribution.

3 Quantification: Firm Level Estimation and Calibration Strategy

Quantification proceeds in three steps. First, we estimate the modern firm's technology and demand system using establishment-level manufacturing data. Second, we use the resulting firm-level residuals to recover the joint distribution of entrepreneurial ability, product appeal, and distortions in the modern sector. Third, we calibrate the remaining preference, traditional-sector, and occupational-choice parameters to match moments

from 1970s Colombia. This structure makes transparent which objects are estimated directly from the data and which are pinned down in equilibrium.

Historical Micro Data We combine two complementary sources produced by DANE. The Household Surveys provide economy-wide information on occupation, sector, firm size, and labor income, including the 1971 wave that records establishment size together with earnings and occupation. These data allow us to measure the employment and income shares of modern versus traditional production and to recover the earnings distributions relevant for workers and the self-employed.

The Annual Manufacturing Survey covers establishments with at least ten employees and reports revenue, payroll, capital, material inputs, and product-level information. We use the 1974–1989 waves to estimate the modern-sector production and demand system and to measure the joint distribution of firm types and distortions. Appendix A.1 provides additional construction details.

3.1 Firm Level Estimation

In light of the model, we use the income distributions from the household surveys to estimate the ex-post distribution of a for salaried and own-account workers. In particular, we use the Annual Manufacturing survey to estimate the parameters of technology and demand $\{\gamma_l, \gamma_k, \gamma_m, \sigma\}$, and subsequently obtain measures of $a, d, \tau_l, \tau_k, \tau_r$ for each manufacturing establishment. These correspond to the ex-post distribution of each of these dimensions of talent among those who self-select as entrepreneurs. We now explain the estimation in detail.

The manufacturing data directly report, for each unit, revenue (pq), total salary payments (wl), capital stocks (k), value of material inputs used ($p_m m$). We build, based on our theory for product demand, plant level deflators for output, p, and materials, p_m, which we use to deflate revenue and value of materials to obtain y and m. Effective labor l is measured from the idiosyncratic variation in total salary payments, given an equilibrium wage w homogeneous across production units. In the data, the empirical analog of our theoretical modern firms is the manufacturing establishment, but we will continue to use the language "firm" for consistency.[4] The data allows us to accurately measure, for the estimation period, technological parameters that are crucial for simulations in the model. We can also re-estimate them for later periods, shedding light on reasonable patterns of

[4]Over 90% of firms are uni-establishment in the data.

Table 2: **Factor and demand elasticities**

Year	γ_l	γ_k	γ_m	σ
1974 - 1989	0.374	0.105	0.542	2.391
2000 - 2012	0.227	0.113	0.674	2.793

evolution over relatively long periods that we later use to assess the role of factor-biased technology changes.

We let both technology and demand parameters vary across 29 manufacturing sectors for the historical sample and the first decade of the twenty-first century. Details of that estimation are presented in the appendix. Table 2 reports the corresponding averages across manufacturing sectors.

Table 2 highlights two patterns that matter for the counterfactuals. First, labor intensity falls sharply between 1974–1989 and 2000–2012, from 0.374 to 0.227, while materials intensity rises from 0.542 to 0.674, consistent with labor-saving technical change in modern production. Second, the elasticity of substitution across modern varieties rises only moderately, from 2.391 to 2.793. We use the early-period estimates to calibrate the baseline economy and the later-period estimates to discipline the technology counterfactuals.

Having estimated the parameters of the firm problem, we obtain a for each firm as the idiosyncratic residual of the production function (3) and d as the idiosyncratic residual of demand function (30). We work only with the idiosyncratic part of firm-level a and d by taking the log difference vs. the mean of logs in the respective sector and year.

We subsequently estimate idiosyncratic firm-level distortions. We directly measure $\tau^l = \frac{\text{payroll tax}}{wl}$ for each establishment, taking advantage of reports in the data about the payroll taxes paid by each establishment. Using only the idiosyncratic component of τ_l and of k and l in the capital-labor ratio, we obtain (the idiosyncratic component of) $1 + \tau^k = \frac{l}{k}(1 + \tau^l)$. We then solve for $(1 - \tau^R)$ re-writing equation 38 as:

$$(1 - \tau^R) = \frac{\mu(1 + \tau^l)^{\gamma_l}(1 + \tau^k)^{\gamma_k}(pq)^{\frac{1}{(\sigma-1)}}}{D_{i,M} a d^{\frac{1}{\sigma-1}}} \tag{14}$$

Since all firm-level variables and parameters in the right-hand side of this equation have been measured at this point, we can estimate the idiosyncratic variation in $(1 - \tau^R)$ up to $D_{i,M}$.

Table 3 reports correlation coefficients across these moments. Two facts stand out. Rev-

Table 3: **Correlation matrix for establishment attributes**

	Δ	a	d	pq	τ^R	τ^k	τ^l	$\frac{1-\tau^R}{(1+\tau^k)^{\gamma_k}(1+\tau^l)^{\gamma_l}}$
	1974-1989							
Δ	1,00							
a	0,17	1,00						
d	0,96	-0,09	1,00					
R	0,98	0,09	0,97	1,00				
τ^R	0,22	0,36	0,12	0,09	1,00			
τ^k	-0,01	0,08	-0,04	-0,03	-0,02	1,00		
τ^l	0,48	0.08	0,47	0,49	-0,07	0,00	1,00	
$\frac{1-\tau^R}{(1+\tau^k)^{\gamma_k}(1+\tau^l)^{\gamma_l}}$	-0,26	-0,48	-0,14	-0,10	-0,84	-0,11	-0,04	1,00
	2010-2019							
Δ	1,00							
a	0,25	1,00						
d	0,80	-0,24	1,00					
R	0,84	0,00	0,90	1,00				
τ^R	0,28	0,42	0,07	0,02	1,00			
τ^k	-0,04	0,05	-0,08	-0,08	-0,01	1,00		
τ^l	0,01	0.01	0,01	0,01	0,00	-0,01	1,00	
$\frac{1-\tau^R}{(1+\tau^k)^{\gamma_k}(1+\tau^l)^{\gamma_l}}$	-0,32	-0,55	-0,04	0,02	-0,79	-0,09	-0,01	1,00

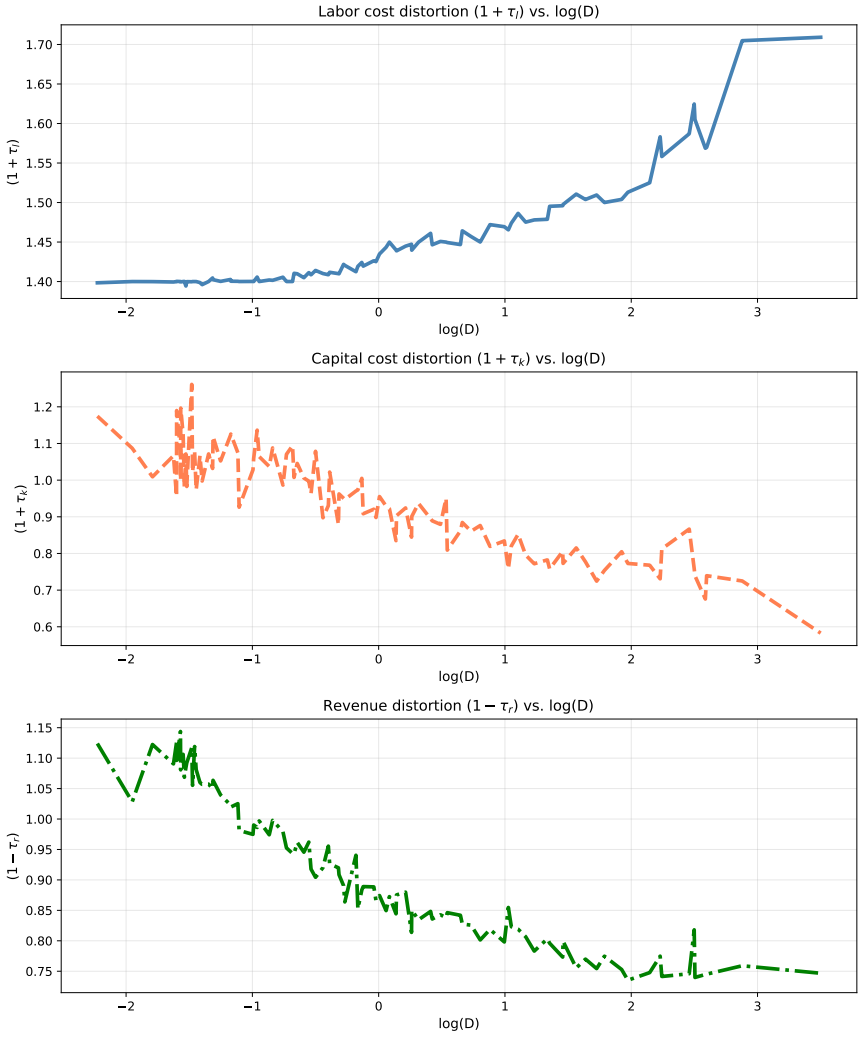
enue and quality-adjusted productivity are strongly positively correlated in both periods, with correlations of 0.98 in 1974–1989 and 0.84 in 2010–2019. At the same time, the composite distortion term that compresses firm scale is negatively correlated with productivity, with correlations of -0.48 and -0.55 with a across the two periods, and revenue distortions are positively associated with productivity. In the data, the firms with the highest underlying productivity do not expand proportionally because they face stronger wedges, especially through revenue distortions.

The fact that the most highly productive firms are most taxed by revenue distortions and payroll taxes τ^L, while the opposite is true of capital distortions, is also shown in Figure 3, which displays the distortions observed in the data as a function of quality-adjusted productivity, $\Delta = ad^{\frac{1}{\sigma-1}}$. This empirical pattern is a central input into our policy experiments.

3.2 Estimation of underlying type distributions f_a and f_d

To estimate the distributions f_a and f_d used for calibrating the model, we use the estimates of a and d for manufacturing model firms, the overall income distribution reported in the household survey, and insights from the model. The distribution of income for workers and the self-employed directly gives us the distribution of a for this set of

Figure 3: **Distortions vs quality-adjusted productivity,** $\Delta = ad^{\frac{1}{\sigma-1}}$



individuals. For modern entrepreneurs, we have the idiosyncratic distribution of a.

These two distributions are then put together to obtain the overall f_a. This poses two challenges: 1) the techniques employed in our firm estimation only allow us to estimate idiosyncratic attributes of firms so that by construction, our firm estimates of a are centered around $a = 1$, while the income reports in the household survey are in monetary units; 2) there is apparent measurement error in the left tail of income reports in the household surveys, with a mass of zeroes for a fraction of, mainly, the self-employed.

We deal with these problems by taking advantage of the optimal occupational choice, which implies that the range of a that the ex-post selects into entrepreneurship is the same range of the ex-ante distribution f_a. We thus take a_{max} to correspond to the maximum income of workers in the Household Survey and obtain a_{min} by requiring the range to

replicate the range of a in the manufacturing firm data.[5] Our calibration uses the non-parametric distribution of $f(a)$ thus obtained.

The optimal occupational choice also implies that modern entrepreneurs (firms) with large enough a should display a distribution of d similar to that in the population. With this in mind, we estimate parameters for a Pareto distribution for d using the d distribution observed among the top decile of the a distribution among manufacturing firms.

3.3 Calibration Strategy

Having estimated the firm-side parameters, we calibrate the remaining equilibrium parameters. The baseline targets 1970s Colombia, combining the 1971 Household Survey with manufacturing estimates from 1974–1989. We parameterize the modern production function with the early-period estimates, set $(\gamma_k, \gamma_l, \sigma) = (0.105, 0.374, 2.391)$, impose exact constant returns to scale by adjusting the materials share from 0.542 to 0.521, and feed the estimated non-parametric objects for (a, d) and the distortion schedules into the simulated economy.

The remaining parameters fall into two groups. Internally, we calibrate the taste shifters that govern modern expenditure, the minimum-earnings threshold, and the distribution of self-employment utility shocks to match the modern employment share and the main earnings moments in the household data. Externally, we set the broad-sector and modern-traditional elasticities to $\epsilon = 0.15$ and $\rho = 1.5$, while maintaining the restriction that modern varieties are at least as substitutable with one another as with traditional production. Table 4 summarizes the estimated, calibrated, and externally imposed parameters.

Distortions As explained above, our firm-level estimation delivers a firm-specific estimate of idiosyncratic revenue, capital, and labor distortions (see section 3). Given a type (a, d) we compute the average distortion for these types $\tau^R(a, d)$, $\tau^k(a, d)$, and $\tau^l(a, d)$ and fit each distortion non-parametrically through splines. This gives us the profile of distortions faced by a type (a, d) in the model. Because, at this point, we have only considered idiosyncratic variation across firms, we scale each of the distortions (τ^R, τ^l, τ^k) by an intercept. For τ_l, directly measured in the data, the intercept is simply the average level of contributions paid per unit of wage, which stands at $\tau_l = 0.47$. For τ^R and τ_k, we fix intercepts that approximate tax rates of corporate income and dividends, respec-

[5] We estimate the range and distribution in log terms.

Table 4: **Model Parameters: Estimated from the Microdata, Internally Calibrated or Exogenously Set**

Parameter	Value	Target or Empirical Counterpart
	Parameters Estimated from Firm-level Data	
γ_k	0.105	Capital intensity
γ_l	0.374	Labor intensity
γ_m	0.521	Materials intensity
σ	2.391	Elasticity Substitution between modern varieties
Average τ_l	0.47	Avg. $\frac{\text{Contributions on workers}}{\text{Wage Payments}}$
	Distributions Estimated from Firm-level Data	
Density (a, d)	$[\cdot]_{122\times30}$	Talent a and product appeal d joint distribution
$\tau^R(a, d)$	$[\cdot]_{122\times30}$	Revenue distortions matrix, Non-parametric fit
$\tau^l(a, d)$	$[\cdot]_{122\times30}$	Labor distortion matrix, Non-parametric fit
$\tau^k(a, d)$	$[\cdot]_{122\times30}$	Capital distortion matrix, Non-parametric fit
	Parameters Internally Calibrated	
λ_I	0.40	Preference weight industry
λ_S	0.58	Preference weight services
$\phi_{A,M}$	0.04	Preference weight modern in agriculture
$\phi_{I,M}$	0.67	Preference weight modern in industry
$\phi_{S,M}$	0.49	Preference weight modern in services
e_{min}	0.0006	Regulatory minimum earnings
Pareto tail s	0.444	Tail par. self-employment shocks distribution
Lower bound s	0.072	Lower bound self-employment shocks
Upper bound s	1.163	Upper bound self-employment shocks
$\bar{d}$	5.227	Average value of d shocks
ρ	1.5	Elasticity substitution Modern-Traditional
	Parameters Set Exogenously from the Model	
ϵ	0.15	Elasticity substitution broad sectors (Herrendorf et al., 2014)
Average τ^R	0.20	Corporate income tax rate
Average τ^k	0	Dividends tax rate

tively. We set $\tau^R = 0.2$ and $\tau^k = 0$, taken from historical accounts on Colombian tax reforms (Cardenas and Perry, 1986). Lastly, we calibrate the minimum earnings requirement e_{min} and the distribution of s to match the modern sectors' employment share and the likelihood of agents above and below the median income to be self-employed.[6]

[6]Specifically, we assume that s follows a truncated Pareto, with a minimum value equal to 1. We then calibrate the tail parameter and the upper bound of the distribution.

Table 5: **Internal Calibration: Targets, Fit, and Parameter Values**

Moment	Data	Baseline	Parameter	Value
N_M/N	23.4	23.9	ϕ_M	0.459*
$(N_{entrep}/N) * 100$	1.2	1.2	$\bar{d}$	5.227
$\bar{e}_{worker}/\bar{e}_{self}$ (earnings)	2.29	2.35	e_{min}	0.0006
e_{P50}/e_{P5}	38.1	39.3	s_-	0.072
e_{P50}/e_{P10}	2.90	2.71	s^+	1.163
$\frac{\|\|e>e_{p50}\Omega Self\|\|}{\|\|e>e_{p50}\|\|}$	59.7	62.3	Pareto tail s	0.444

*Average across sectors, weighted by sectoral expenditure shares.

Model Solution Given the draws in (a, d, s), our calibration strategy computes the occupational choice for each agent conditional on its draw and the distortions should the agent choose to become an entrepreneur. We conjecture values for the aggregate demand shifter D_{im}, the price of the intermediates, and the wage in the modern manufacturing labor market w and compute a *tâtonnement* process until we find market clearance.

Calibration Results The calibration is designed to account quantitatively for the modern employment share and the main earnings moments that characterize jobless modernity in 1970s Colombia.

Table 5 reports the internally calibrated moments, their fit in the model, and the corresponding parameter values taken from the final calibration tables. The model matches the modern employment share closely, reproduces the entrepreneur share, and fits the average earnings gap between workers and the self-employed. It also captures the dispersion in the earnings distribution through the 50–5 and 50–10 ratios and the share of above-median earners who are self-employed.

4 Counterfactual policy experiments

We next use the baseline calibration to quantify which mechanisms are most important for the small and jobless modern segment emphasized in the introduction. Throughout, we focus on three margins: the overall size of modern vs. total production; the gap between the modern share of aggregate income (value added) and the modern share of employment; and the earnings gap between workers in the modern and the traditional segments. A mechanism that raises modern value added without raising modern jobs

increases aggregate income but also makes modernity more jobless.

These exercises are tightly linked to the firm-level evidence from Section 3. Table 3 shows that the highest-productivity modern firms face stronger scale-compressing wedges, especially through revenue distortions. We examine the effects of the different distortions through counterfactual exercises turning them on one by one or in groups, after having tightly disciplined the distortions' cross-firm distribution with the data. We then turn to counterfactual exercises that alter features of technology or the distribution of productivity/human capital. In one of the we simulate the effect of the large decline in labor intensity between the 1970s and the 2000s documented in Table 2. Because the baseline calibration in Table 5 matches the observed modern employment share and the main earnings moments, our counterfactual exercises are aimed at decomposing the mechanisms behind jobless modernity, rather than compensating for a poor fit of the baseline.

4.1 Distortions, segmentation, and modern job creation

We first examine the effects of the different margins of distortions incorporated in our framework: τ_j^R, τ_j^l, τ_j^k, and the minimum earnings constraint. Distortions in the model apply to the modern segment only, so that all of them affect the allocation between modern and traditional production/employment. Moreover, productivity-correlated distortions across firms within modernity (the different τ's) further impact the allocation of resources.

Table 6 presents three sets of counterfactual exercises alternatively turning on and off the minimum earnings constraints and the τ's, to be compared to the baseline calibration where all are present, presented in column (4). Relative to a hypothetical scenario without any of these distortions (column (1)) the baseline case reduces aggregate income by 31 percentage points, and reduces the share represented by the modern segment from 87.3% to 76.4%. The effect of distortions is strongest on the contribution of modernity to job creation, which falls from 72.6% in the undistorted world to 24% in the baseline case. That is, distortions generate exactly the kind of jobless modernity that motivates the paper: the gap between the share of modernity in aggregate income vs. jobs increases from 14,7 percentage points in the hypothetical undistorted world to 52,4 in the baseline economy. Finally, the share of jobs contributed by the modern segment is inversely proportional to average business size, given the minimal operating scale in traditional production: the average business engages 3.5 people in the world without distortions but only 1.3 in the baseline case.

Table 6 also separates the effect of the minimum earnings constraint from that of the firm-

Table 6: **Effect of distortions: min wage vs. proportional distortions / taxes**

	Undistorted (1)	Min earn only (2)	τ's only (3)	Min earn+τ's (baseline) (4)
Aggregate income	1.00	0.99	0.69	0.69
Average business size	3.5	1.6	1.8	1.3
Modern income (%)	87.3	87.3	76.4	76.4
Modern jobs (%)	72.6	37.4	45.5	24.0
Modern % in income-jobs	14,7	50,0	30,9	52,4
Average real earnings				
Self-employed	1.00	0.43	0.43	0.30
Formal workers	0.86	1.68	0.37	0.71
Entrepreneurs	105.2	103.6	44.6	44.3
Formal work / self-emp	0.86	3.88	0.86	2.34
Entrep / formal work	122.8	61.7	121.4	62.2
Entrep / self-emp	105.1	239.0	104.8	145.8

level wedges in modern production, which were disciplined to match the correlation with productivity in the data. The contrast between columns (2) and (3) is sharp. The minimum earnings constraint is the main source of labor-market segmentation and of the employment-value added divorce: when it operates on its own, modern jobs fall from 72.6% in the undistorted allocation to 37.4%, even though total value added is almost unchanged at 0.99 and the modern share of value added remains at 87.3%. By contrast, the τ distortions are the main source of aggregate income losses: with τ's only, total value added falls to 0.69 and the modern value-added share to 76.4%, but modern employment remains higher than in the min-earnings-only economy.

Measured as the gap between the modern value-added share and the modern employment share, joblessness rises from 14,7 points in the undistorted allocation to 30,9 points in the world with only τs (column (3) and 50 points in that with a minimum earnings restriction alone. If we compute each distortion's contribution by averaging over whether it is introduced first or second, 28.4 of the 37.7-point increase is attributable to the minimum earnings constraint and 9.3 points to the τ wedges. Thus, 75.3% of the increase in joblessness generated by distortions comes from minimum earnings and 24.7% from the τ bundle. The same calculation applied to the shortfall in modern jobs relative to the undistorted allocation assigns 58.4% of missing modern jobs to the minimum earnings constraint and 41.6% to the τ's.

The table also illustrate distributional effects of distortions across workers in different

occupations/segments. The minimum earnings constraint creates a large formal-sector premium by excluding low-productivity workers from modern salaried jobs, that is, via selection on the reasons why a workers ends up in the traditional or modern sector. Relative to the undistorted allocation, it raises the formal-worker to self-employed earnings ratio 4.5-fold, from 0.86 to 3.88, and the entrepreneur to self-employed earnings ratio 2.3-fold, from 105.1 to 239. The τ bundle acts very different: because it does not induce selection per se, it keeps the formal-worker to self-employed earnings ratio at 0.86 and has little effect on other cross-occupation earnings gaps. However, it lowers real earnings in all occupations by roughly the same amount, around 57–58%, while reducing modern jobs by 27.1 percentage points and total value added by 31%. The baseline combines these two forces: the minimum earnings rule generates segmentation, while the τ wedges compress earnings and activity inside modernity.

Table 7 decomposes the effects of the different firm-level wedges (τs). Revenue distortions are the most harmful for aggregate value added: without the minimum earnings constraint, adding only τ_R lowers total value added from 1.00 to 0.74 and modern value added from 87.0% to 81.6%. This is consistent with the firm-level evidence in Table 3, where revenue distortions are precisely the wedges most strongly associated with the most productive establishments.

Table 7: **Specific margins of distortion and allocation**

	No minimum earnings constraint present				
	Undistorted	+ τ_R	+ τ_l	+ τ_K	+ all τ's
Aggregate income	1.00	0.74	0.93	1.05	0.69
Average business size	3.5	2.4	2.1	3.3	1.8
Modern income (%)	87.3	81.6	84.7	85.6	76.4
Modern jobs (%)	72.6	59.3	54.4	70.6	45.5
	Minimum earnings constraint present				
	no τ's	+ τ_R	+ τ_l	+ τ_K	Baseline (all)
Aggregate income	0.99	0.73	0.92	1.04	0.69
Average business size	1.6	1.5	1.4	1.5	1.3
Modern income (%)	87.4	81.5	84.7	85.6	76.4
Modern jobs (%)	37.4	33.2	32.1	33.5	24.0

Labor distortions, in turn, are the most damaging for job creation within modernity, reducing modern employment to 54.4% without the minimum earnings constraint and to 32.1% when the constraint is present. Under the minimum earnings constraint, the drop

in modern jobs relative to the no-τ benchmark is 5.3 percentage points for τ_l, compared with 4.2 for τ_R and 3.9 for τ_K, so τ_l is the most important margin for modern job creation within the τ bundle. For aggregate value added, however, τ_R is by far the dominant wedge: with minimum earnings in place, total value added falls from 0.99 to 0.73 under τ_R, to 0.92 under τ_l, and it rises to 1.04 under τ_K. Because the capital wedge is positively correlated with productivity (i.e. it subsidizes the most productive firms relative to unproductive ones, as shown in Table 3), its effects are different from the others: it slightly raises total value added, to 1.05 without the minimum earnings constraint and 1.04 with it, although it still reduces modern employment and keeps business size small. The picture is therefore not that every distortion works through the same channel. Revenue wedges mostly depress productivity and scale, labor wedges mostly choke off modern job creation, and the capital wedge mainly biases the composition of modern production away from labor absorption. Keep also in mind that aggregate capital supply is infinitely elastic in the model, and as a result capital-labor substitution effects are magnified despite the capital-labor complementarity.

The earnings table confirms these distinct channels. Table 8 shows that revenue and labor wedges lower the real earnings of all occupations, with especially strong effects on formal workers and entrepreneurs. Starting from the economy with minimum earnings but no firm-level wedges, adding τ_R cuts average formal-worker earnings from 1.68 to 0.93 and entrepreneur earnings from 103.58 to 50.66; adding τ_l yields similarly large declines. The capital wedge again looks different: under the minimum earnings constraint it raises formal-worker earnings to 1.97 and entrepreneur earnings to 114.07, while self-employed earnings remain low at 0.52. Combined with Table 7, this suggests that the capital wedge helps sustain measured output and incomes at the top but does not generate the broad-based increase in modern employment that would make modernization less jobless.

The previous subsection isolates the role of segmentation and firm-level wedges while holding technology and the distributions of productive capabilities fixed. The introduction, however, emphasizes two broader forces behind jobless modernity: the labor-saving nature of modern production and the possibility that too few workers are near the margin of entering modern jobs. We therefore turn next to experiments that modify technology and the distributions of a and d, asking whether the modern sector becomes less jobless because more agents can access it or only because the firms already inside it become more productive.

Table 8: **Specific margins of distortion and earnings**

No minimum earnings constraint present					
	Undistorted	$+\tau_R$	$+\tau_l$	$+\tau_K$	+ all τ's
Self-employed	1.00	0.51	0.59	1.19	0.43
Formal workers	0.86	0.52	0.63	0.93	0.37
Entrepreneurs	105.15	51.66	82.14	116.19	44.59
Minimum earnings constraint present					
	no τ's	$+\tau_R$	$+\tau_l$	$+\tau_K$	Baseline (all)
Self-employed	0.43	0.31	0.40	0.52	0.30
Formal workers	1.68	0.93	1.07	1.97	0.71
Entrepreneurs	103.58	50.66	80.19	114.07	44.30

4.2 Technology, productivity, and human capital counterfactuals

Table 9 evaluates changes in technology and in the underlying talent distributions. The technology experiment is disciplined by the fall in γ_l from 0.374 in 1974–1989 to 0.227 in 2000–2012 documented in Table 2. Two results stand out. First, labor-saving technological change is powerful for aggregate output but not for modern job creation. Lowering γ_l to its 2000s level raises total value added from 1.00 to 1.89, by far the largest gain in the table, yet modern employment remains stuck at 24.0%. In other words, technology can make modernity much more productive while leaving its employment capacity unchanged. This is jobless modernization in the literal sense.

Second, the interventions that reduce joblessness are those that relax the human-capital constraint for workers near the margin of entering modern production. A uniform 13% increase in a raises total value added by 45% and modern employment from 24.0% to 27.8%, while lowering the formal worker/self-employed income gap from 2.34 to 2.01. The strongest inclusive gains come from shifting the bottom half of the a distribution: modern employment rises to 34.3%, average business size increases to 1.49, and the formal worker/self-employed gap falls to 1.46. By contrast, boosting the top 5% of a or raising product appeal d leaves modern employment unchanged at 24.0% while increasing inequality. In those cases, aggregate value added rises, but the gains accrue disproportionately to those already best positioned to benefit from modern production.

These counterfactuals reinforce the paper's main message. The minimum earnings constraint is central for explaining why modern production absorbs so little labor; revenue and labor wedges are central for explaining low aggregate productivity within moder-

Table 9: **Technology/productivity/human capital interventions**

	Baseline (1)	$\downarrow \gamma_l$ to 2000s (2)	$\uparrow$ 13% a (3)	$\uparrow$ 42% a bottom 50 (4)	$\uparrow$ 17% a top 5 (5)	$\uparrow$ 28.5% d (6)
VA						
Total income	1.00	1.89	1.45	1.49	1.46	1.47
Modern income%	76.4	78.6	77.3	77.1	77.4	77.8
Jobs						
Modern Jobs %	24.0	24.0	27.8	34.3	24.0	24.0
Av. business size	1.29	1.29	1.36	1.49	1.29	1.29
Average real earnings						
Self-employed	1.00	1.70	1.46	1.66	1.38	1.38
Formal workers	2.35	4.23	2.94	2.43	3.44	3.50
Entrepreneurs	145.8	273.0	210.4	182.0	223.0	213.6
Earnings gaps						
formal work / self-emp	2.34	2.49	2.01	1.46	2.48	2.53
entrep / formal work	62.16	64.41	71.56	75.11	65.03	61.05
entrep / self-emp	145.84	160.54	143.80	109.90	161.61	154.80

nity; and broad improvements in embodied human capital, especially toward the lower half of the distribution, are the most effective way to reduce jobless modernity. Technology alone raises output dramatically, but without complementary improvements in worker capabilities, it does not create more modern jobs.

4.3 Distortions interact with technology / human capital

Tables 10 and 11 examine how the effects of technology and human capital interventions depend on the distortion environment. The main message is that distortions and technology/human capital are largely complementary in their effects on value added, but interact in subtle ways on modern employment and inequality, in particular depending on their combined effects on the selection of particular types of workers into modernity. Notice that all interventions have proportional effects on total income and the fraction of income in the modern segment of similar magnitude to those reported in Table 9. Their modern job creation power is quite muted in the absence of a minimum earnings restriction, given the lack of forced selection into informality. But to the extent that such selection exists, their job creation effects differ across interventions depending on the extent to which they compress the human capital distribution, especially from the left. Conversely, the reduction in modern jobs caused by the minimum earnings constraint is much more muted in an environment with a more compressed human capital distribution.

Table 10: **Distortions interact with technology / human capital on allocation**

	Baseline (1)	$\downarrow \gamma_l$ to 2000s (2)	$\uparrow$ 13% a (3)	$\uparrow$ 42% a bottom 50 (4)	$\uparrow$ 17% a top 5 (5)	$\uparrow$ 28.5% d (6)
			Baseline			
Total income	1.00	1.89	1.45	1.49	1.46	1.47
Modern income%	76.4	78.6	77.3	77.1	77.4	77.8
Modern Jobs %	24.0	24.0	27.8	34.3	24.0	24.0
			No min. wage (τ's only)			
Total income	1.00	1.90	1.45	1.49	1.46	1.48
Modern income%	76.4	78.6	77.3	77.1	77.4	77.8
Modern Jobs %	45.5	48.5	48.4	46.8	49.2	49.6
			No τ's (min. wage only)			
Total income	1.44	2.79	2.08	2.14	2.08	2.09
Modern income%	87.4	88.9	88.1	87.9	88.1	88.1
Modern Jobs %	37.4	39.7	41.9	50.1	38.2	38.9
			Undistorted			
Total income	1.45	2.81	2.09	2.15	2.10	2.12
Modern income%	87.3	89.0	88.1	87.9	88.2	88.4
Modern Jobs %	72.6	72.6	72.6	72.7	72.6	72.6

In terms of particular interventions, Column (2) of Table 10 shows that the output gains from labor-saving technology ($\downarrow \gamma_l$) are roughly proportional across distortion regimes: total value added approximately doubles whether distortions are present or absent, rising from 1.00 to 1.89 in the baseline and from 1.45 to 2.81 in the undistorted economy. However, the employment implications differ starkly. In the baseline, lowering γ_l to its 2000s level leaves modern employment completely unchanged at 24.0%, and the same is true in the undistorted world, where modern jobs remain at 72.6%. Labor-saving technology therefore raises aggregate output regardless of the distortion environment, but its employment neutrality is equally robust across all four regimes.

A key insight from comparing rows within Table 10 is that the employment gains from human capital improvements depend critically on whether labor-market segmentation is present. Raising the bottom half of the aa a distribution by 42% increases modern employment from 24.0% to 34.3% in the baseline, but pushes it all the way to 50.1% when the τ wedges are removed. By contrast, in the fully undistorted economy the same intervention leaves modern employment essentially unchanged at 72.7%, because without the minimum earnings constraint workers near the margin are already absorbed into modern production. This asymmetry points to a complementarity between relaxing the minimum earnings constraint and investing in human capital at the bottom: the two re-

Table 11: **Distortions interact with technology / human capital on earnings**

	Baseline (1)	$\downarrow \gamma_l$ to 2000s (2)	$\uparrow$ 13% a (3)	$\uparrow$ 42% a bottom 50 (4)	$\uparrow$ 17% a top 5 (5)	$\uparrow$ 28.5% d (6)
			Baseline			
Cross occupation income gaps						
formal work / self-emp	2.34	2.49	2.01	1.46	2.48	2.53
entrep / formal work	62.2	64.4	71.6	75.1	65.0	61.1
entrep / self-emp	145.8	160.5	143.8	109.9	161.6	155.4
			No min. wage (τ's only)			
formal work / self-emp	0.86	0.81	0.80	0.86	0.79	0.79
entrep / formal work	121.36	134.45	127.41	104.09	137.66	130.34
entrep / self-emp	104.79	109.26	103.12	89.23	108.28	103.53
			No τ's (min. wage only)			
formal work / self-emp	3.88	3.82	3.4	2.41	4.0	3.89
entrep / formal work	61.66	67.77	68.84	70.05	66.00	63.28
entrep / self-emp	239.04	259.08	234.12	168.78	264.17	245.94
			Undistorted			
formal work / self-emp	0.86	0.94	0.92	0.90	0.92	0.95
entrep / formal work	122.78	126.93	121.71	102.91	129.25	121.31
entrep / self-emp	105.13	119.72	111.72	92.59	119.14	114.89

inforce each other precisely because the constraint binds most tightly for workers whose capabilities are close to the entry threshold of modern production. Boosting the top 5% of a or raising product appeal d, on the other hand, has negligible effects on modern employment across all distortion regimes, confirming that the extensive margin of modern job creation depends on conditions at the bottom of the capability distribution.

Turning to earnings gaps in Table 11, the interaction between distortions and human capital interventions is most visible in the formal-worker to self-employed earnings ratio. In the baseline, the bottom-50% human capital upgrade compresses this ratio from 2.34 to 1.46, as more workers become productive enough to access modern jobs and arbitrage away the segmentation premium. In the no-τs world, where the minimum earnings constraint operates alone and the segmentation premium is highest at 3.88, the same intervention compresses the ratio to 2.41—a large reduction, but one that still leaves a substantial premium because the constraint continues to exclude a significant share of workers. In the undistorted economy, where the formal-worker to self-employed ratio is already close to one, the same upgrade has little additional equalizing effect. The capital wedge's anomalous character persists across all scenarios: it consistently raises formal-worker and entrepreneur earnings relative to the self-employed, regardless of the distortion environment.

Taken together, these tables underscore the central conclusion that removing distortions raises both output and modern employment, but the gains are not substitutes for human capital investment. Conversely, improving worker capabilities—especially at the bottom of the distribution—generates the largest employment and distributional gains precisely when the minimum earnings constraint is also relaxed, pointing to a complementarity between structural reform and broad-based human capital policy as the most effective pathway out of jobless modernity.

5 Conclusions

This paper studies why many developing economies modernize in value added without modernizing in employment. Using Colombian historical microdata and a general-equilibrium model of occupational choice, we show that jobless modernity is generated by two distinct mechanisms. The first is segmentation: a minimum-earnings constraint excludes low-ability workers from salaried modern jobs and pushes them into self-employment. The second is within-modern misallocation: firm-level wedges compress the scale of productive firms and limit their labor demand.

Quantitatively, the decomposition is clear. Relative to the undistorted allocation, the gap between the modern share of value added and the modern share of employment rises from 23.4 to 60.0 percentage points. Averaging over the order in which distortions are introduced, 77.5% of this increase in joblessness is due to the minimum-earnings constraint and 22.5% to firm-level wedges. Measured instead as the shortfall in modern jobs relative to the undistorted benchmark, 58.3% of missing modern jobs is due to the minimum-earnings constraint and 41.7% to the wedge bundle. Thus, all distortions matter, but they do not matter through the same margin, and the main source of jobless modernity is labor-market segmentation.

The decomposition within firm-level wedges is equally sharp. Revenue distortions account for most of the aggregate income loss, while labor distortions are the most important firm-level force depressing modern job creation. Capital distortions, by contrast, do little to expand inclusive modern employment. Distortions therefore do not simply reduce efficiency in a generic sense: some mainly reduce output, others mainly reduce jobs, and those differences are central for understanding the development path of emerging economies.

The counterfactuals reinforce this message. Labor-saving technological change can sharply raise output while leaving modern employment unchanged. Broad improvements in

embodied human capital, especially among workers near the margin of entering modern wage work, are more effective at expanding modern jobs and compressing inequality. The broader implication is that employment-rich development depends not only on raising productivity, but on relaxing the barriers that keep workers out of modern employment in the first place.

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APPENDIX

A Data Construction

A.1 Modern firm's problem

The modern firm solves

$$Max_{\{k,l\}} \left(1-\tau^R\right) py - \left(1+\tau^l\right) wl - \left(1+\tau^K\right) rk - p_m m \tag{15}$$

subject to 30. Revenue $R = py$ is given by,

$$R = D^{\frac{1}{\sigma}} d^{\frac{1}{\sigma}} y^{1-\frac{1}{\sigma}} \tag{16}$$

The first order condition for any factor $x = \{k, l\}$ with price p^x is thus given by

$$\begin{aligned} \left(1+\tau^x\right) p^x &= \left(1-\tau^R\right)\left[p\frac{\partial y}{\partial x} + y\left(\frac{\partial p}{\partial y} + \frac{\partial p}{\partial P}\frac{\partial P}{\partial y}\right)\frac{\partial y}{\partial x}\right] \\ &= \left(1-\tau^R\right) p\left(\frac{\sigma-1}{\sigma}\right)(1-s)\frac{\partial y}{\partial x} \end{aligned} \tag{17}$$

where s is the firm's revenue share in the market, and the last line uses Shepard's lemma ($\frac{\partial P}{\partial y}\frac{y}{P} = -s$), and the facts that $\frac{\partial p}{\partial y}\frac{y}{p} = -\frac{1}{\sigma}$ and $\frac{\partial p}{\partial P}\frac{P}{p} = \frac{\sigma-1}{\sigma}$.

Moreover, the markup is given by:[1]

$$\mu^{-1} = \left(\frac{\sigma-1}{\sigma}\right)(1-s) \tag{18}$$

Thus, optimal k is given by $\left(1+\tau^k\right) rk = \left(1-\tau^R\right)\mu^{-1}\alpha\gamma R$, and the optimal capital-labor ratio is given by

$$l = \frac{(1-\alpha-\phi)\, r\left(1+\tau^k\right)}{\alpha w\left(1+\tau^l\right)} k \equiv \theta k \tag{19}$$

whilst the optimal capital-materials ratio is

[1] See Hottman, Redding and Weinstein, 2016, and Eslava, Haltiwanger and Urdaneta, 2022.

$$m = \frac{\phi r\left(1+\tau^k\right)}{\alpha p_m} k \equiv \theta_m k \tag{20}$$

Using these FOCs, profits are given by:

$$\begin{aligned} \pi &= \left(1-\tau^R\right) R - \left[\left(1+\tau^l\right) w\theta k + \left(1+\tau^k\right) rk + p_m\theta_m k\right] \\ &= \left(1-\tau^R\right) R\left(1-\mu^{-1}\gamma\right) \end{aligned} \tag{21}$$

Further, plugging (19), (20) and (18) into the FOC for capital and replacing p using (30), we obtain optimal capital

$$k^{1-\gamma\left(1-\frac{1}{\sigma}\right)} = \frac{\left(1-\tau^R\right)\mu^{-1}\Delta^{\frac{\sigma-1}{\sigma}}\alpha\gamma\theta^{(1-\alpha-\phi)\gamma\frac{\sigma-1}{\sigma}}\theta_m^{\phi\gamma\frac{\sigma-1}{\sigma}}}{\left(1+\tau^k\right) r} \tag{22}$$

$$= \left(1-\tau^R\right)\mu^{-1}\Delta^{\frac{\sigma-1}{\sigma}}\gamma\left(\frac{\alpha}{r(1+\tau^k)}\right)^{1-(1-\alpha)\gamma\frac{\sigma-1}{\sigma}}\left(\frac{1-\alpha-\phi}{w(1+\tau^l)}\right)^{(1-\alpha-\phi)\gamma\frac{\sigma-1}{\sigma}}\left(\frac{\phi}{p_m}\right)^{\phi\gamma\frac{\sigma-1}{\sigma}} \tag{23}$$

where we have denoted quality-adjusted physical productivity by $\Delta = D^{\frac{1}{\sigma-1}} d^{\frac{1}{\sigma-1}} a$.

For future reference, plugging (22) into (19), labor demand is

$$l^{1-\gamma\left(1-\frac{1}{\sigma}\right)} = \left(1-\tau^R\right)\mu^{-1}\Delta^{\frac{\sigma-1}{\sigma}}\gamma\left(\frac{\alpha}{r\left(1+\tau^k\right)}\right)^{\alpha\gamma\left(\frac{\sigma-1}{\sigma}\right)}\left(\frac{1-\alpha-\phi}{w\left(1+\tau^l\right)}\right)^{\left(1-(\alpha+\phi)\gamma\left(\frac{\sigma-1}{\sigma}\right)\right)}\left(\frac{\phi}{p_m}\right)^{\phi\gamma\frac{\sigma-1}{\sigma}} \tag{24}$$

Because $y = a(k\theta^{(1-\alpha-\phi)}\theta_m^{\phi})^{\gamma}$ and $R = py = D^{\frac{1}{\sigma}} d^{\frac{1}{\sigma}} y^{\frac{\sigma-1}{\sigma}}$, we obtain

$$R = \left[\Delta^{\frac{1}{\gamma}}\frac{\left(1-\tau^R\right)}{\left(1+\tau^k\right)^{\alpha}\left(1+\tau^l\right)^{1-\alpha-\phi}}\mu^{-1}\gamma\left(\frac{\alpha}{r}\right)^{\alpha}\left(\frac{1-\alpha-\phi}{w}\right)^{1-\alpha-\phi}\left(\frac{\phi}{p_m}\right)^{\phi}\right]^{\frac{\gamma(\sigma-1)}{\sigma-\gamma(\sigma-1)}} \tag{25}$$

One could thus write revenue (and profits, using (21)) as a the function of quality-adjusted quantity productivity, distortions in product and labor markets (τ^R, τ^l and τ^k), markups and a set of parameters and equilibrium input prices that are constant across firms (of

the same sector).

$$R = \left(\Delta \mu^{-\gamma} \frac{\left(1-\tau^R\right)^{\gamma}}{\left(1+\tau^k\right)^{\alpha\gamma}\left(1+\tau^l\right)^{\gamma(1-\alpha-\phi)}} \Theta \right)^{\frac{(\sigma-1)}{\sigma-\gamma(\sigma-1)}} \tag{26}$$

$$\pi = \left(\Delta \left(1-\mu^{-1}\gamma\right)^{\frac{\sigma-\gamma(\sigma-1)}{(\sigma-1)}} \mu^{-\gamma} \frac{\left(1-\tau^R\right)^{\frac{\sigma}{\sigma-1}}}{\left(1+\tau^k\right)^{\alpha\gamma}\left(1+\tau^l\right)^{\gamma(1-\alpha-\phi)}} \Theta \right)^{\frac{(\sigma-1)}{\sigma-\gamma(\sigma-1)}} \tag{27}$$

where $\Theta = \gamma^{\gamma}(\frac{\alpha}{r})^{\gamma\alpha}\left(\frac{1-\alpha-\phi}{w}\right)^{\gamma(1-\alpha-\phi)}(\frac{\phi}{p_m})^{\phi\gamma}$. Revenue and profits are convex in a and in quality-adjusted quantity productivity Δ whenever $\frac{(\sigma-1)}{\sigma-\gamma(\sigma-1)} > 1$ and concave otherwise.

Aggregation of modern sector As shown in Appendix C, modern manufacturing productivity is given by

$$TFP_{MF} = \frac{C_{MF}}{K^{\alpha}L^{(1-\alpha)}} = D^{-\frac{1}{\sigma-1}} \left(\sum_I \left[\left(\frac{\Delta}{tfpr^{\gamma}} \right)^{\frac{1}{\sigma\left(1-\gamma\left(1-\frac{1}{\sigma}\right)\right)}} TFPR_{MF} \right]^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{28}$$

where $tfpr \equiv \frac{py}{k^{\alpha}l^{(1-\alpha)}} = \frac{\left(\frac{\alpha}{\left(1+\tau^k\right)r}\right)^{\alpha}\left(\frac{1-\alpha-\phi}{w\left(1+\tau^l\right)}\right)^{1-\alpha-\phi}(\frac{\phi}{p_m})^{\phi}\mu}{\gamma(1-\tau^R)}$ is a modern firm's revenue productivity (see Appendix C) and $TFPR_{MF} \equiv \frac{E_{MF}}{K^{\alpha}L^{1-\alpha}}$ is aggregate revenue productivity in manufacturing.

A.2 Additional derivations for the three-sector framework

The nested CES structure in Section 2 implies the expenditure shares and price indexes

$$\begin{aligned} &\frac{E_i}{E} = \lambda_i \left(\frac{P_i}{P}\right)^{1-\epsilon}, \qquad \frac{E_{i,M}}{E_i} = \phi_{i,M}\left(\frac{P_{i,M}}{P_i}\right)^{1-\rho}, \qquad \frac{E_{i,T}}{E_i} = (1-\phi_{i,M})\left(\frac{P_{i,T}}{P_i}\right)^{1-\rho}, \\ &P_i = \left(\phi_{i,M}P_{i,M}^{1-\rho} + (1-\phi_{i,M})P_{i,T}^{1-\rho}\right)^{\frac{1}{1-\rho}}, \qquad P = \left(\sum_{i\in A,I,S}\lambda_i P_i^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}, \end{aligned} \tag{29}$$

where $P_{i,T}$ denotes the price of traditional goods in sector i, and expenditures satisfy $E_i = P_i C_i$, $E_{i,M} = P_{i,M}C_{i,M}$, and $E_{i,T} = P_{i,T}C_{i,T}$.

Combining final demand (2) and intermediate demand (5) yields the firm-level demand shifter

$$D_{i,M} \equiv \frac{E_{i,M}}{P_{i,M}^{1-\sigma}} + \frac{p_m \Upsilon_m}{p_m^{1-\sigma}}, \qquad p_{i,j} = D_{i,M}^{1/\sigma} d_{i,j}^{1/\sigma} q_{i,j}^{-1/\sigma}. \tag{30}$$

The modern firm's first-order conditions are

$$(1-\tau_j^R)\frac{p_{i,j}q_{i,j}}{l_{i,j}}\gamma_l\frac{\sigma-1}{\sigma} = w(1+\tau_j^l), \tag{31}$$

$$(1-\tau_j^R)\frac{p_{i,j}q_{i,j}}{k_{i,j}}\gamma_k\frac{\sigma-1}{\sigma} = (1+\tau_j^k)r, \tag{32}$$

$$(1-\tau_j^R)\frac{p_{i,j}q_{i,j}}{m_{i,j}}\gamma_m\frac{\sigma-1}{\sigma} = p_m. \tag{33}$$

These conditions imply that profits are proportional to after-tax revenue:

$$\pi_{i,j} = (1-\tau_j^R)p_{i,j}q_{i,j}\left(1-\frac{1}{\mu}\right). \tag{34}$$

These conditions imply the input ratios

$$\frac{k_{i,j}}{l_{i,j}} = \frac{\gamma_k}{\gamma_l}\frac{w(1+\tau_j^l)}{r(1+\tau_j^k)}, \qquad \frac{m_{i,j}}{l_{i,j}} = \frac{\gamma_m}{\gamma_l}\frac{w(1+\tau_j^l)}{p_m}. \tag{35}$$

Substituting these ratios into (31), together with (3) and (30), yields optimal labor demand:

$$l_{i,j} = \frac{D_{i,M}}{\mu^\sigma}\left(\frac{(a_j d_j^{1/(\sigma-1)})^{\sigma-1}(1-\tau_j^R)}{c^{\sigma-1}\hat{\tau}_j^{\sigma-1}}\right)\left(\frac{\gamma_l}{w(1+\tau_j^l)}\right). \tag{36}$$

Define the common unit-cost index and the composite distortion by

$$c = \left(\frac{w}{\gamma_l}\right)^{\gamma_l}\left(\frac{r}{\gamma_k}\right)^{\gamma_k}\left(\frac{p_m}{\gamma_m}\right)^{\gamma_m}, \qquad \hat{\tau}_j = \frac{(1+\tau_j^l)^{\gamma_l}(1+\tau_j^k)^{\gamma_k}}{1-\tau_j^R}. \tag{37}$$

Using optimal labor demand, pre-tax revenue can be written as

$$p_{i,j}q_{i,j} = D_{i,M}\left(\frac{a_j d_j^{1/(\sigma-1)}}{\mu c\hat{\tau}_j}\right)^{\sigma-1}. \tag{38}$$

Combining (38) with (34) delivers the profit expression reported in Section 2.4.1.

Because entrepreneurs are indifferent across sectors and the distribution of (a, d, s, Γ) is common across sectors, equilibrium pricing implies

$$p_{i,j} = \frac{\mu c \hat{\tau}_j}{a_j}. \tag{39}$$

Therefore,

$$P_{i,M}^{1-\sigma} = \sum_{j \in N_{i,M}} d_j p_j^{1-\sigma} = \frac{N_{i,M}}{N_M} \sum_{i \in \{A,I,S\}} \sum_{j \in N_{i,M}} d_j p_j^{1-\sigma} = \frac{N_{i,M}}{N_M} \sum_{i \in \{A,I,S\}} P_{i,M}^{1-\sigma}, \tag{40}$$

which implies that sectoral expenditure shares, modern employment shares, and entrepreneur shares satisfy

$$\alpha_{i,M} \equiv \frac{E_{i,M}}{E_M} = \frac{P_{i,M}^{1-\sigma}}{\sum_{i \in A,I,S} P_{i,M}^{1-\sigma}} = \frac{L_{i,M}}{L_M} = \frac{N_{i,M}}{N_M}. \tag{41}$$

An analogous argument applies to labor demand because firm-level labor demand depends on firm characteristics, whose equilibrium distribution is the same across sectors.

The equilibrium conditions summarized in Section 2.5 can be written as follows. Given prices $(w, \{p_{i,j}\}_{i,j}, \{P_{i,M}\}_{i \in \{A,I,S\}})$, agents choose occupations to maximize (13), the labor market clears,

$$\sum_{i \in A,I,S} \sum_{j \in \mathcal{W}_i} a_{i,j} = \sum_{i \in A,I,S} \sum_{j \in N_{i,M}} l_{i,j}, \tag{42}$$

goods markets satisfy

$$\begin{aligned} E &= \sum_{i \in A,I,S} \left(\sum_{j \in N_{i,T}} q_{i,j} + \sum_{j \in N_{i,M}} c_{i,j} \right) \\ &= \sum_{i \in A,I,S} \left(\sum_{j \in N_{i,T}} a_j + \sum_{j \in N_{i,M}} (\pi_{i,j} + w l_{i,j} + r k_{i,j}) \right) + \hat{T}, \end{aligned} \tag{43}$$

and total distortion revenues rebated to households are

$$\hat{T} = \sum_{i \in A,I,S} \sum_{j \in N_{i,M}} \left(\tau_j^R p_{i,j} q_{i,j} + \tau_j^l w l_{i,j} + \tau_j^k r k_{i,j} \right). \tag{44}$$

B Estimation of parameters of production and demand functions in modern manufacturing

We follow the structural value-added approach to the estimation of the establishment's production function (Ackerberg et al., 2015, Gandhi et al. 2017). An establishment indexed by i produces y_{it} using labor l_{it} and capital k_{it}, with technology

$$y_{it} = a_{it} l_{it}^{1-\alpha} k_{it}^{\alpha} \tag{45}$$

The underlying assumption is that production is Leontieff, $y_{it} = \min(l_{it}^{1-\alpha} k_{it}^{\alpha} a_{it}, m_{it})$. At the optimum, thus, (45) is satisfied and $m_{it} = l_{it}^{1-\alpha} k_{it}^{\alpha} a_{it}$.

Following Ackerberg, Caves, and Frazer (2015, ACF henceforth), we use material inputs to proxy for productivity. The Leontieff assumption implies the optimal choice of material inputs can be written as:

$$\ln m_{it} = h\left(\ln a_{it}, \ln k_{it}, \ln l_{it}\right)$$

Inverting, we obtain

$$\ln a_{it} = h^{-1}\left(\ln m_{it}, \ln l_{it}, \ln k_{it}\right) \equiv h^{-1}\left(\overrightarrow{W_{it}}\right)$$

Incorporating this expression, recognizing that y_{it} is subject to measurement error and other shocks not observed by either the econometrician or the firm at the time of making input choices, and denoting by $\widehat{y_{it}} = y_{it} e^{\varepsilon_{it}}$ measured y_{ft}, we write:

$$\ln \widehat{y_{it}} = \alpha\gamma \ln k_{it} + (1-\alpha)\gamma \ln l_{it} + h^{-1}\left(\overrightarrow{W_{it}}\right) + \varepsilon_{it} \tag{46}$$

y_{it} is a CES composite of varieties produced by i. We follow Eslava et al. (2022) to jointly estimate 46 and the demand function implied by preferences in our setting:

$$R_{it} = D_t + d_{it} + p_{it}^{1-\sigma} \tag{47}$$

where $R_{it} = p_{it} y_{it}$ is $i's$ revenue. CES preferences across varieties produced within i imply (see Eslava et al. (2023)) $p_{it} = \overline{P_{ft}^{*}} P_{fB} \left(\Lambda_{ft}^{Q}\right)^{\frac{1}{\sigma-1}}$ where $s_{ijt} = \frac{p_{ijt} y_{ijt}}{R_{it}}$; $\Omega_{t,t-1}^{i}$ is the set of products that i produces in both t and $t-1$ and s_{ijt}^{*} is the share that product j

represents in the revenue that i obtains in t from products in $\Omega^i_{t,t-1}$; $\lambda^{QF}_{it} = \frac{\sum_{\Omega^i_{t,t-1}} s_{ijt}}{\sum_{\Omega^i_{t,t-1}} s_{ijt-1}}$; and $\lambda^{QRW}_{it} = \prod_{\Omega^i_{t,t-1}} \left(\frac{s^*_{ijt}}{s^*_{ijt-1,\Omega^i_{t,t-1}}} \right)^{\frac{1}{\left\| \Omega^i_{t,t-1} \right\|}}$.

Since $y_{it} = \frac{R_{it}}{p_{it}}$ and $p_{it} = \overline{P^*_{it}} P_{iB} \left(\Lambda^Q_{it} \right)^{\frac{1}{\sigma-1}}$, σ is necessary to measure prices and thus y_{it}. An estimate of σ is not available at the stage of estimating 46 and 47, so we estimate a modified version of 46:

$$\ln \widehat{y^*_{it}} = \ln \left(\frac{R_{it}}{\overline{P^*_{ft}}} \right) = \alpha\gamma \ln k_{it} + (1-\alpha)\,\gamma \ln l_{it} + h^{-1}\left(\overrightarrow{W_{it}} \right) + \frac{1}{1-\sigma} \Lambda^Q_{ft} + \widehat{\varepsilon}_{it} \tag{48}$$

Following Eslava et al. (2023) and the proxy-methods literature on production function estimation, we estimate 48 in two stages. The first stage purges measurement error $\widehat{\varepsilon}_{it}$, while the second stage, jointly estimated with 47 via GMM, estimates (α, γ, σ). Assuming that a_{it} and d_{it} follow flexible AR1 processes:

$$\begin{aligned} \ln a_{it} &= \pi^a_0 + \pi^a_1 \ln a_{it-1} + \pi^A_2 \ln a^2_{it-1} + \pi^A_3 \ln a^3_{it-1} + \xi^A_{it} \\ \ln a_{it} &= \pi^D_0 + \pi^D_1 \ln D_{it-1} + \pi^A_2 \ln D^2_{it-1} + \pi^A_3 \ln D^3_{it-1} + \xi^D_{it} \end{aligned}$$

we use the following moment conditions for identification based on those proposed by Eslava et al. (2022):

$$E \begin{bmatrix} \ln L_{it} \times \xi^A_{it} \\ \ln K_{it} \times \xi^A_{it} \\ \ln D_{it-1} \times \xi^A_{it} \\ \ln A_{it-1} \times \xi^D_{it} \\ \ln A_{it} \\ \ln D_{it} \end{bmatrix} = 0 \tag{49}$$

Table 12 presents the detailed results.

Table 12: Factor and demand elasticities by sector (pooling years)

Sector	$1-\alpha$	α	γ	σ_w	σ	$\gamma\left(\frac{1}{1-\sigma}\right)$
311	0,646	0,354	1,052	8,110	4,073	0,794
313	0,674	0,326	1,042	5,531	4,303	0,799
321	0,546	0,454	0,885	4,776	4,036	0,666
322	0,594	0,406	0,679	6,287	4,019	0,510
323	0,539	0,461	0,946	5,268	4,081	0,714
324	0,640	0,360	0,865	5,975	3,957	0,647
331	0,758	0,242	0,887	4,785	3,828	0,655
332	0,580	0,420	0,884	3,616	4,003	0,663
341	0,588	0,412	0,961	2,570	4,058	0,724
342	0,775	0,225	1,053	2,012	4,057	0,794
351	0,657	0,343	1,127	8,042	4,162	0,857
352	0,563	0,437	0,979	6,171	4,174	0,744
355	0,736	0,264	0,975	4,028	4,176	0,741
356	0,703	0,297	1,050	3,467	4,022	0,789
362	0,685	0,315	1,092	3,745	4,031	0,821
369	0,603	0,397	1,019	6,880	4,078	0,770
371	0,685	0,315	1,249	4,856	4,155	0,949
381	0,659	0,341	0,946	1,912	3,955	0,707
382	0,709	0,291	0,959	3,401	4,011	0,720
383	0,688	0,312	1,056	4,447	4,051	0,795
384	0,748	0,252	1,132	7,526	3,990	0,848
385	0,640	0,360	1,002	4,260	3,901	0,745
390	0,741	0,259	0,971	2,009	4,004	0,729
Average	0,659	0,341	0,992	4,768	4,049	0,747
Min	0,539	0,225	0,679	1,912	3,828	0,510
Max	0,775	0,461	1,249	8,110	4,303	0,949

C TFP

Modern manufacturing productivity is given by

$$TFP_{MF} = \frac{C_{MF}}{K^{\alpha}L^{(1-\alpha)}} = \frac{E_{MF}}{K^{\alpha}L(1-\alpha)}\frac{1}{P_{MF}} = \frac{TFPR_{MF}}{P_{MF}} \tag{50}$$

where E_{MF} is total expenditure in manufacturing, and $TFPR_{MF} \equiv \frac{E_{MF}}{K^{\alpha}L^{1-\alpha}}$ is aggregate revenue productivity in manufacturing.

Define also $tfpr = \frac{py}{k^{\alpha}l^{(1-\alpha)}} = \frac{D^{\frac{1}{\sigma}}d^{\frac{1}{\sigma}}y^{1-\frac{1}{\sigma}}}{\left(k^{\alpha}l^{1-\alpha}\right)} = \frac{D^{\frac{1}{\sigma}}d^{\frac{1}{\sigma}}a^{1-\frac{1}{\sigma}}}{\left(k^{\alpha}l^{1-\alpha}\right)^{1-\gamma\left(1-\frac{1}{\sigma}\right)}}$. Moreover, from the optimal

revenue expression above it is apparent that, at the optimum:

$$k^{\alpha}l^{(1-\alpha)} = \left(\frac{\Delta^{\frac{\sigma-1}{\sigma}}\gamma}{\mu c\left(1-\tau^{R}\right)^{-1}}\right)^{\frac{1}{1-\gamma\left(1-\frac{1}{\sigma}\right)}}. \tag{51}$$

Replacing this into $tfpr$, we obtain:

$$tfpr = \frac{c\mu}{\gamma\left(1-\tau^{R}\right)} \tag{52}$$

where $c = \left(\frac{\alpha}{\left(1+\tau^{k}\right)r}\right)^{\alpha}\left(\frac{1-\alpha}{w\left(1+\tau^{l}\right)}\right)^{1-\alpha}$. As a result, we can also write $k^{\alpha}l^{(1-\alpha)} = \left(\frac{\Delta^{\frac{\sigma-1}{\sigma}}}{tfpr}\right)^{\frac{1}{1-\gamma\left(1-\frac{1}{\sigma}\right)}}$. Replacing this into $tfpr$ we obtain $tfpr = pa\left(k^{\alpha}l^{1-\alpha}\right)^{\gamma-1} = pa\left(\frac{\Delta^{\frac{\sigma-1}{\sigma}}}{tfpr}\right)^{\frac{\gamma-1}{1-\gamma\left(1-\frac{1}{\sigma}\right)}}$, so that after some manipulation

$$tfpr^{\frac{\gamma}{\sigma(1-\gamma\frac{\sigma-1}{\sigma})}} = pa\left(\Delta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\gamma-1}{1-\gamma\left(1-\frac{1}{\sigma}\right)}} \tag{53}$$

Using 53 in 50

$$\begin{aligned}
TFP_{MF} &= TFPR_{MF}\left(\sum_{I} dp^{1-\sigma}\right)^{\frac{1}{\sigma-1}} \\
&= TFPR_{MF}\left(\sum_{I}\left(d^{\frac{1}{\sigma-1}}\frac{a\left(\Delta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\gamma-1}{1-\gamma\left(1-\frac{1}{\sigma}\right)}}}{tfpr^{\frac{\gamma}{\sigma(1-\gamma\frac{\sigma-1}{\sigma})}}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \\
&= D^{-\frac{1}{\sigma-1}}\left(\sum_{I}\left[\left(\frac{\Delta}{tfpr^{\gamma}}\right)^{\frac{1}{\sigma\left(1-\gamma\left(1-\frac{1}{\sigma}\right)\right)}}TFPR_{MF}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}}
\end{aligned} \tag{54}$$

where we have used the fact that $\Delta = D^{\frac{1}{\sigma-1}}d^{\frac{1}{\sigma-1}}a$ and $1+\left(\frac{\sigma-1}{\sigma}\right)\frac{(\gamma-1)}{\left(1-\gamma\left(\frac{\sigma-1}{\sigma}\right)\right)} = \frac{1}{\sigma\left(1-\gamma\left(\frac{\sigma-1}{\sigma}\right)\right)}$.

D Data and Additional Results

D.1 Historical Data Sets

The study utilizes long-time series of individual and firm microdata from Colombia. The Colombian data, generally unavailable for other countries, is unparalleled in scope and detail in most of developing countries and provides microdata level information for over 50 years. In particular, we have recovered and use microdata from two official historical sources produced by the Colombian Statistics Bureau, DANE: The Annual Manufacturing Survey available and the Household Survey.

The Household Surveys are the source of official statistics on employment and the distribution of income and are thus representative of the whole economy, formal and informal, in all sectors. For all respondents that take part in production, the survey records whether they are salaried workers, own-account workers without employees or employers, and the size of the business where their activity takes place in broad categories. This provides a comprehensive picture of income and employment in the whole economy, their allocation across sectors and different types of firms, and the distribution of earnings in the economy and within each of these segments. Although there have been methodological changes over time, the Household Surveys go back in time several decades. Unlike other waves for years close to the peak of industrialization, the digital records of the 1971 wave contain the individual responses on the size of the business to which the worker is affiliated, besides income and occupational category. For this reason, we use the household survey information from 1971.

The Annual Manufacturing Survey is a census of all manufacturing establishments with at least 10 employees. We use data for 1974-1989.[2] It records detailed information at the establishment level on the value of output and input use (capital, labor, intermediates consumed), including quantities and values for all individual products and all individual material inputs produced by the establishments plus payroll. A firm in the model corresponds to an establishment (plant) in the data. The within-plant product level information is used to estimate establishment-level prices that are comparable across es-

[2]The data has been collected annually since 1974, but there is a gap in the electronic records in 1977-1982: for this set of years, the information on individual products and material inputs is missing. Thus, although the peak occurred at the end of the 1970s, we use the available data for the full 1974-1989 period to represent the peak of industrialization. We do not use solely 1974-1976 because we have less assurance of the quality of the data for the earliest years, especially at the detailed product-input level. Since the methods we use to separately measure quantities and prices rely on chained firm-level prices, we take advantage of the robust data for the 1980s to improve the quality of our price measurement in the early years.

tablishments of the manufacturing sector, even for multiproduct plants. Plant prices are then used to measure plant output for uni- and multi-product plants with differentiated products and to subsequently estimate the plant production and demand functions 3 and 30 with the methodology proposed by (Eslava et al. (2023)).

In the data, we define the modern segment to correspond to establishments with 10 or more employees. The traditional segment is the complementary set of all establishments with less than 10 employees, including own-account individuals. Since the household surveys classify workers by sector and firm size category and into self-employed/salaried workers/employers, we can construct the share of employment and income (i.e., value-added) represented by modernity in each sector. We also have the detailed distribution of income overall, by sector, and by segment (modern/traditional) within each sector. A common concern when aggregating income data from household surveys is that individuals at the very top of the income distribution are likely under-represented, implying that value-added may be underestimated. We address this concern by scaling income in each sector to reflect the aggregate reported in GGDC data.

The Annual Manufacturing Survey then provides us with a detailed picture of the distribution of productivity and distortions across firms of the modern segment and, consequently, for modern entrepreneurs. Modern manufacturing is the main modern activity during the episode we study. For this reason, the lack of equally detailed data on modern services or modern agriculture, and the difficulties inherent to measuring firm productivity and distortions in services and agriculture in a comparable way to manufacturing, we assume that the distributions we observe in manufacturing also represent the distributions in the modern segments of services and agriculture.

D.2 Additional Data

Using data on establishments (i.e., salaried employment) and focusing on a subset of late industrializers in Latin America, Table 13 shows that micro establishments are much more prevalent in these countries as compared to advanced economies, dominated by early industrializers, especially in terms of their weight in employment. Although this holds in all sectors, the weight of micro establishments is lesser in manufacturing than in basic services (including retail). Moreover, there is a tight link between the prevalence of microestablishments and that of informality in these late industrializers. Even among salaried workers, the vast majority of informal employment, i.e., employment that does not abide by labor regulations, concentrates on micro-employers (Table 14. The

proportion grows to almost 100% of informal workers if self-employment is included. The weight of microestablishments in formal employment is much lower, especially in manufacturing, where it does not reach above 10%.

Table 13: **Establishments under 10 Employees as a % of all (Economic Censuses, circa 2005)**

	Unweighted			Employment-weighted		
	Advanced Economies	Latin America	Colombia	Advanced Economies	Latin America	Colombia
Manufacturing	71,1%	91,6%	87,2%	11,5%	30,3%	31,7%
Wholesale-Retail	85,0%	96,9%	96,0%	27,4%	65,8%	61,4%
Accom-Restaur.			95,7%			69,9%
Other Services	88,1%	91,0%	87,8%	25,7%	34,3%	34,0%

Table 14: **Workers in Establishments of at most 10 Employees as a % of all workers in the category: Formal or Informal. Excludes self-employment**

	Latin America		Colombia		
	Formal workers	Informal workers	Formal workers	Informal workers	US
Manufacturing	10%	69%	8%	71%	4%
Wholesale-Retail	28%	82%	24%	88%	11%
Services	15%	60%	11%	73%	13%
Accom-Restaur.	29%	78%	33%	88%	31%

Latin America: average of Argentina, Bolivia, Colombia, El Salvador, Guatemala, Honduras, Mexico, Paraguay, Peru, and Uruguay. Formal workers: contributing to a pension. Pooled data from 2011 to 2015. Latin America from household surveys, the US from Business Dynamics Statistics. Source: Eslava (2018).

Table 15: **Distribution of Colombian workers across employer size classes by sector and formality status: 2012**

Employer size	Manufacturing		Non-manufacturing		All
	Formal workers (45%)	Informal workers (55%)	Formal workers (35%)	Informal workers (65%)	
$\leq$ 10 workers (incl. Self-employed)	0.9%	7.5%	9.1%	53.7%	71.1%
11-50 workers	1.2%	0.6%	4.1%	1.8%	7.6%
51-100 workers	0.6%	0.1%	1.5%	0.2%	2.3%
101+ workers	3.3%	0.2%	14.6%	0.9%	19.0%
Total	6.0%	8.2%	29.2%	56.6%	100%

Source: Colombian Household's Survey. Urban and rural coverage.