Economic Development According to Chandler*

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Abstract

Chandler (1977) shows that large firms require hierarchies of white-collar workers to coordinate complex production. We document that this insight continues to hold globally today, and we show that low education levels in developing countries limit the supply of white-collar workers and constrain firm size. We extend the occupational choice model of Lucas (1978) to allow entrepreneurs to reorganize their firms by allocating administrative tasks to hired professionals, which brings the firm closer to constant returns to scale. We calibrate the model to be consistent with cross-sectional microdata and validate it using quasi-experimental and experimental evidence on the effects of educational expansions and management training interventions. Skills explain two-thirds of the reorganization of production into large firms with economic development, while structural transformation and reductions in barriers are needed to explain the remaining shift.

Keywords: skills, white-collar workers, returns to scale, firm size, endogenous duality

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1 Introduction

In a seminal contribution, Chandler (1977) explores the transformation of American businesses during the Second Industrial Revolution. The defining technologies of this era leveraged economies of scale and scope to achieve productivity gains. As firms adopted these technologies and grew large, they encountered new logistical challenges: sourcing a steady supply of inputs, coordinating mass production across product lines and establishments, and marketing and selling large volumes of output. The firms that successfully met these challenges recruited and organized a hierarchy of white-collar workers such as managers, accountants, purchasing agents, and clerks. Firms and countries that failed to invest in this hierarchy did not benefit fully from new technologies and lost ground to competitors that did (Chandler, 1977, 1990).

This paper shows that Chandler's thesis – that white-collar workers are important for large firms – remains true today, and that this link has important implications for contemporary economic development. Using census and labor force survey data from nearly one hundred countries, we document two motivating facts. First, large firms consistently employ a higher share of white-collar workers. Second, economic development is associated with a shift toward white-collar employment, especially in manufacturing and low-skill services, consistent with Chandler's historical work.

We then document a new fact: differences in educational attainment account for nearly all of the gap in white-collar employment shares between developing and developed countries. Globally, the share of white-collar workers rises sharply with education—from about 10 percent among workers with no schooling to about 90 percent among those with tertiary education. Conditional on education, however, white-collar employment rates are similar across countries. Education appears to be a necessary ingredient for a large white-collar workforce, which Chandler showed was important for scaling up firms and profitably adopting modern technologies.

These facts motivate us to develop a model of the endogenous reorganization of production into larger firms that use white-collar labor intensively. Following Lucas (1978), the model features a continuum of individuals with exogenous skills who choose between entrepreneurship and wage work. We enrich the model in two ways. First, there are two types of workers: blue-collar laborers who perform production tasks and white-collar professionals who perform administrative tasks. Second, the entrepreneur chooses both how much to produce and how to organize production. A continuum of administrative tasks needs to be accomplished in order for the firm to produce. For each task, the entrepreneur decides whether to do it herself or to hire professionals to do it for her. The essential tradeoff is that professionals have to be paid, but they are a variable input, whereas the entrepreneur can provide a fixed supply of tasks.

We provide conditions under which the full task assignment problem is equivalent to a simplified one in which the entrepreneur operates a decreasing returns Cobb-Douglas production function with laborers and professionals as inputs.[1] The entrepreneur chooses the amount of each type of labor to hire and the share of tasks to professionalize. The share of tasks she professionalizes determines the organization of her firm: a higher share increases the factor share of white-collar workers, allows the firm to produce with less severe decreasing returns to scale, and leads the firm to become larger.

We impose assumptions on the skill intensity of occupations such that occupational choices can be characterized by two cutoff skill levels. Low-skill workers are indifferent between entrepreneurship and working as laborers; intermediate-skill workers become professionals; and high-skill workers become entrepreneurs. Low-skill and high-skill workers both choose to be entrepreneurs, but they operate very different types of firms. Low-skill entrepreneurs operate small firms and professionalize few tasks, while high-skill entrepreneurs run large firms and professionalize a large share of tasks. Thus, the model generates an endogenous dual economy with traditional and modern firms coexisting.

Under simplifying assumptions, the analytical model yields sharp characterizations of the forces that shape the organization of production. The main comparative static shows that an exogenous increase in the aggregate supply of skills raises the share of white-collar workers through a pure composition effect, consistent with our empirical accounting results. The underlying mechanism is that more skilled workers both supply professional labor and become entrepreneurs of modern firms, increasing the demand for professional labor. The assumptions imply that this *skill-biased organizational change* exactly offsets the increase in supply, leaving the skill premium constant. The growth in the modern sector also pulls less-skilled workers from traditional entrepreneurship into large firms as laborers.

We then develop a richer quantitative model to assess the importance of skills, barriers, and structural transformation in the reorganization of production. The model relaxes the simplifying assumptions of the analytical model and incorporates four sectors, each with its own technology and potential productivity gain from professionalizing administrative tasks. We close the model using the structural transformation preferences from Comin, Lashkari and Mestieri (2021).

We calibrate the model to fit a rich set of cross-sectional moments that build on our motivating facts about the relationships among education, occupational choice, sec-

[1]This equivalence builds on a similar result by Acemoglu and Restrepo (2018), but our aggregation yields endogenously decreasing returns to scale as in Akcigit, Alp and Peters (2021).

toral choice, and the organization of production. We focus on middle-income countries because they feature the coexistence of modern and traditional firms. Although overidentified, the model provides a good fit to these moments. We then recalibrate a limited set of parameters governing skills, structural transformation, and the organization of production so that the economy is consistent with the average low-income country.

Because the model is calibrated using cross-sectional moments, we assess its causal mechanisms by comparing its predictions with evidence from exogenous expansions in schooling and exposure to management training (Cox, 2025; Bloom et al., 2013; Giorcelli, 2019). The model matches the direction and magnitude of these effects, typically producing conservative estimates.

We use the model as a laboratory to understand the reorganization of production from self-employment to large firms. Our counterfactuals yield two main insights. First, reorganization is not a mechanical consequence of structural transformation. Giving the low-income economy the sectoral prices, productivities, and distortions of the middle-income economy produces an increase in the employment share at medium and large firms that is at most one-quarter of the actual difference between the two groups of countries in the data. The shortage of skills limits the supply of white-collar labor and prevents a reorganization of production.[2]

Second, increasing skills alone can generate only two-thirds of the observed growth in employment in medium and large firms. The bottleneck is that higher skills by themselves generate almost no structural transformation. Agriculture remains the dominant sector – but it is also the sector that benefits least from a reorganization of production into large firms staffed by white-collar workers. Matching the full shift therefore requires exogenous shifts that reallocate activity out of agriculture and into sectors where white-collar labor is more productive.

Our paper owes an obvious debt to Chandler's work. We combine his historical, narrative work with detailed cross-country evidence to show the broad importance of skilled, white-collar workers for the reorganization of production. Besides his work, our paper is most closely related to two existing literatures. First, we touch on the literature that links the supply of skills to the organization of production.[3] Second, we touch on a recent body of work that allows firms to choose their returns to scale and estimates the outcome or models the consequences.[4]

[2]This is consistent with the evidence that management quality is lower in developing countries (Bloom and Van Reenen, 2007), that raising management quality in developing countries raises profits (Bloom et al., 2013), and that high-quality management in developing countries is expensive (Hjort, Malmberg and Schoellman, 2025).

[3]See Murphy, Shleifer and Vishny (1991), Garicano and Rossi-Hansberg (2006), Porzio (2017), Gomes and Kuehn (2017), and Gottlieb, Poschke and Tueting (2025).

[4]See Hubmer et al. (2025), Tamkoç (2024), Argente et al. (2025), and Kopytov, Taschereau-

We are particularly closely related to three recent papers that combine elements of these literatures in the context of development. Akcigit, Alp and Peters (2021) formulate a model in which entrepreneurs choose how many tasks to delegate in response to contract enforcement, generating endogenous returns to scale through a different mechanism than ours. Amaral and Rivera-Padilla (2025) generate a dual economy through an extensive-margin technology choice, whereas in our model duality arises despite all entrepreneurs having access to a common technology. Their work also differs in connecting to data on technology adoption rather than the organization of production. Finally, Cox (2025) provides novel empirical evidence on the causal effects of expanding schooling and develops a model with non-homothetic production functions that captures that non-agriculture uses college-educated workers more intensively. He focuses on the consequences of building colleges in Brazil, whereas we bring to bear rich cross-country data. Our model provides a microfoundation for the non-homothetic production function that also generates endogenous duality, which is key for our results.

2 Motivating Evidence

This section documents several facts that motivate our analysis. Using representative data sets drawing on nearly one hundred countries around the world to show the relevance of Chandler's insights today. We then provide new evidence on the role of skills in the reorganization of production into large firms. We summarize the data and main results here and provide additional details in Appendix A.

2.1 White-Collar Labor and Production

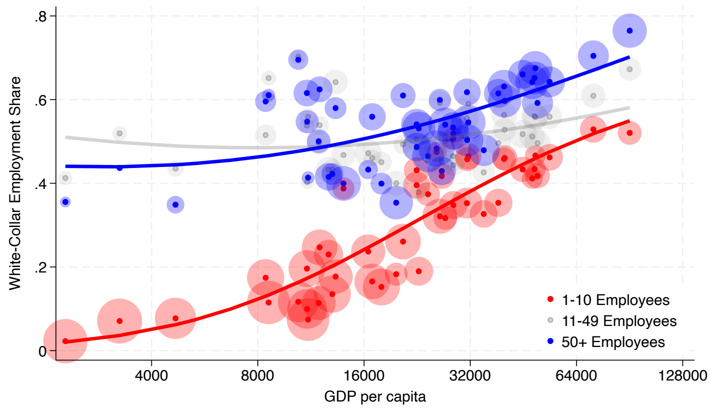
As discussed in the introduction, we build on two essential insights of Chandler's historical work. The first is that as firms adopted new technologies and became large, they encountered logistical challenges that required hierarchies of white-collar workers[5] We document the systematic importance of white-collar workers for large firms using the labor force survey database of Donovan, Lu and Schoellman (2023). Occupations are harmonized at the International Standard Classification of Occupations (ISCO) 1-digit level. We define white-collar workers as codes 1-4 (managers, professionals, technicians and associate professionals, and clerks); we define blue-collar workers as codes

Dumouchel and Xu (2025).

[5] In his words, administrative coordination "became the central function of modern business enterprise"; without it, firms were little more than "federations of autonomous offices" that "could not lower costs through increased productivity" (Chandler, 1977, pp. 7–8).

5-9. The database also groups firms into three size categories: small (1-10 employees), medium (11-49), and large (50+).

Figure 1: White-Collar Employment Share and Firm Size



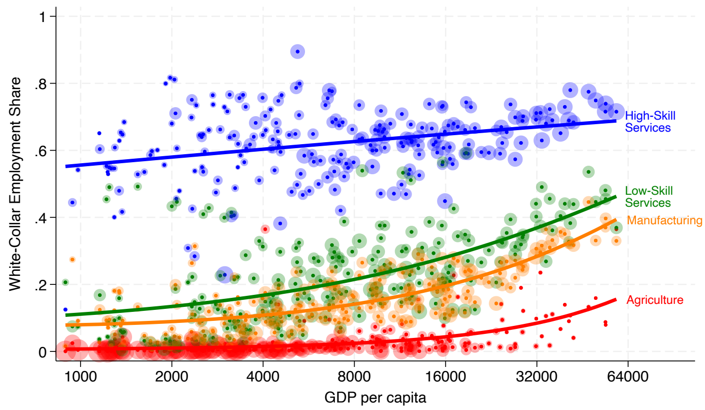
Notes: Each marker corresponds to a country × firm size group observation. The bubbles around the markers are proportional to the employment share of the firm size group within each country. The lines show the fits of multinomial logistic regressions on a quadratic in log GDP per capita.

Figure 1 plots the share of white-collar workers by firm size category in each country against the country's PPP GDP per capita, taken from Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015). Each marker in this figure captures a country × firm size category, with the three firm size categories plotted using different colors. In this and subsequent figures, we scale the size of each marker in proportion to the employment share of the relevant category in the country as a whole and include the fit of a logit regression with a quadratic in log GDP per capita for reference. The main feature of this figure is that there are large differences in the employment share of white-collar workers across firm size categories; medium and large firms systematically use a higher share of white-collar labor than small firms.

Chandler's second insight is that the effect of new technologies and the reorganization of production was uneven across industries. Manufacturing, transportation, and wholesale and retail trade were reshaped dramatically, while changes were smaller or non-existent in other industries.[6] We use the census microdata from Ruggles et al. (2025) to document the relative importance of white-collar workers by sector and country. We define white-collar workers as in the labor force survey database. We use industry codes to divide workers into four broad sectors following Herrendorf and Schoellman (2018): agriculture, manufacturing, low-skill services, and high-skill services.

[6] Again in Chandler's words, "...modern business enterprise first appeared, grew, and continued to flourish in those sectors and industries characterized by new and advancing technology and expanding markets." Elsewhere, "administrative coordination was rarely more profitable than market coordination." (Chandler, 1977, p. 8).

FIGURE 2: SECTORS AND WHITE-COLLAR LABOR



Notes: Each marker corresponds to a country × year × sector observation. The bubbles around the markers are proportional to the employment share of the sector within each country × year. The lines show the fits of multinomial logistic regressions on a quadratic in log GDP per capita.

Figure 2 plots the share of white-collar workers by sector in each country against the country's PPP GDP per capita. Each marker in this figure captures a country × year × sector, with the four sectors plotted using different colors. Two patterns stand out. First, there are large level differences in the white-collar intensity of the sectors. High-skill services use white-collar labor intensively in all countries, whereas agriculture uses almost no white-collar labor in any country; low-skill services and manufacturing have intermediate shares of white-collar workers. Second, development is associated with a transformation of manufacturing and low-skill services (which includes transportation and wholesale and retail trade) towards more white-collar-intensive production, exactly as Chandler (1977) documented for U.S. history. Results for more detailed industries are available in Appendix A.

2.2 Skills and the Organization of Production

Our perspective on contemporary development differs from Chandler's historical work in one important dimension. Chandler takes the view that new technologies and expanding markets led to the growth in firm size, which then led to the adoption of a hierarchy of white-collar workers.[7] We seek instead to understand why these technologies and production in large firms have not been adopted in developing countries today, more than a century after they were invented. Our view is that low educational attainment limits the size of the potential white-collar workforce and slows the reorganization of firms and adoption of new technologies. Consistent with this, we show in Appendix

[7] Ferraro, Iacopetta and Peretto (2024) offer a theory closer to this spirit, where growing market size induces a switch from owner-managed to professionally managed firms.

A.4 that the typical developing country has only recently acquired secondary completion rates comparable to what the United States had at the onset of the Second Industrial Revolution; more than half still have secondary completion rates lower than what the United States had at the end of the Second Industrial Revolution.

There is substantial variation in the share of white-collar workers, ranging from 10 percent of the workforce in the poorest countries to 60 percent in the richest countries (Figure A.1). Our first empirical contribution is to document that this variation is almost entirely accounted for by differences in human capital. We use international census data and measure human capital as educational attainment in four broad bins: less than primary completed, primary completed, secondary completed, and tertiary completed. Figure 3a plots the share of white-collar workers at the country $\times$ year $\times$ education level against PPP GDP per capita, with the four education levels plotted using different colors.[8] The striking finding is that the white-collar employment share conditional on education is essentially uncorrelated with development. For example, 50–60 percent of secondary-educated workers engage in white-collar work in the poorest as well as in the richest countries in our sample.

This fact turns out to be extremely robust. Appendix A.3 shows that it holds in both the time series and the cross section; if we use alternative measures of skills such as test scores; and if we explore excluding some white-collar occupations that are less relevant to modern businesses. Across all these alternative specifications, a shift-share accounting exercise shows that human capital accounts for 70–104 percent of the aggregate cross-country variation in the share of white-collar workers.[9] Overall, the strength and consistency of these results motivate us to model a link between a worker's skills and their occupational choices.

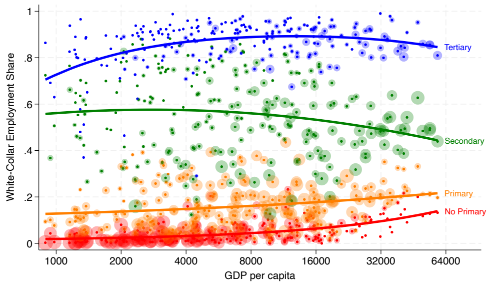
This result foreshadows that education will have an important composition effect in our model: countries with higher aggregate educational attainment have a larger pool of white-collar workers, which makes it more profitable to reorganize production into large firms. However, this composition effect is not the entire story. We document how the organization of production varies by educational attainment and development. Figure 3b plots the share of workers employed in medium and large firms against development, while Figure 3c plots the share of workers who are own-account self employed against development (constructed using labor force survey data and international census data, respectively). Each marker captures a country $\times$ education level, with the four education levels plotted using different colors.

[8] Gottlieb, Grobovšek and Monge-Naranjo (2025) also use cross-country data to document large differences in occupational choices by educational attainment.

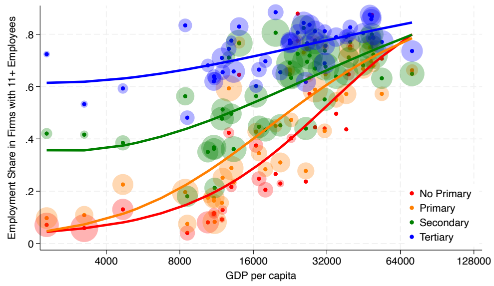
[9] An implication of our findings is that large firms also use educated workers more intensively around the world, which is consistent with contemporaneous work by Gottlieb, Poschke and Tueting (2025).

Figure 3: Education and the Organization of Production

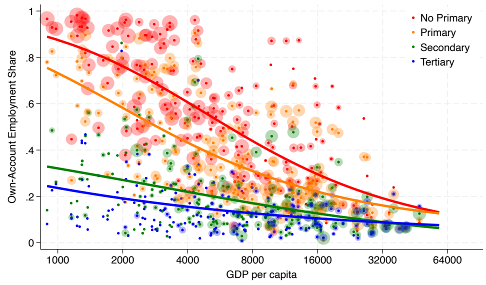
(a) White-Collar Employment Share



(b) Medium/Large Firm Employment Share



(c) Own-Account Employment Share



Notes: Each marker corresponds to a country × education (× year for panels (a) and (c)) observation. The bubbles around the markers are proportional to the employment share of the education within each country (× year for panels (a) and (c)). Medium/Large firms are those with 11+ employees. The lines show the fits of multinomial logistic regressions on a quadratic in log GDP per capita.

This figure shows that education accounts for a much smaller share of cross-country variation in the organization of production. For example, workers with a primary education rarely engage in white-collar work – roughly twenty percent do so globally. Despite this fact, development leads to a large change in where they work: in the poorest countries, more than half of them are engaged in own-account self-employment; in the richest, roughly three-quarters of them work for medium and large firms. These findings hint at an equilibrium force. We now turn to our model, which explains this shift as a natural consequence of the reorganization of production.

3 Model

These motivating facts lead us to develop a model that captures the link between skills, the organization of production, and development. The model features a continuum of individuals with heterogeneous skills who make occupational choices. Individuals who become entrepreneurs also choose how to organize production, which we model as a decision about whether to hire professional white-collar workers to perform administrative tasks.[10] This section presents a simplified, one-sector version of the model. In Section 4 we characterize optimal choices for this model and provide analytical results that build intuition for key mechanisms. We enrich the model and take it to the data in Section 5. Proofs for this section and the next are in Appendix B.

3.1 Environment

We model the long-run (static) equilibrium of an economy where labor is the only factor of production. The economy is inhabited by a unit mass of heterogeneous individuals who differ in their skill z, which is continuously distributed on a support $(0, \infty)$ according to a CDF $G(z)$. Individuals maximize their income.

The core element of our model is the entrepreneur's problem, which integrates a task assignment model in the spirit of Acemoglu and Restrepo (2018) or Akcigit, Alp and Peters (2021) into the Lucas (1978) span-of-control model. The production process uses two task inputs. First, there is a single production task that is accomplished by hiring efficiency units of laborers, denoted by n_ℓ (e.g., machine operators who work the assembly line).

Second, there is a unit continuum of administrative tasks that are inputs to the production process. For each task, the entrepreneur chooses whether to *professionalize* the task, meaning hire dedicated professionals to perform it. If she professionalizes task i and hires $n_p(i)$ efficiency units of professional labor, then she receives $a(i)n_p(i)$ units of task output. The term $a(i)$ captures the relative productivity of professionalizing task i. If she does not professionalize task i, then she receives a fixed, baseline task output of 1, which captures the output from the task being performed in a residual or ad hoc manner. For example, Bloom et al. (2013) show that many important administrative functions such as performance monitoring, inventory control, or sequencing of orders are not done in any planned or formal way in Indian manufacturing firms.

The continuum of administrative task inputs is aggregated with an unweighted Cobb-Douglas function. The total administrative and production inputs are then aggregated with a further Cobb-Douglas production function with output elasticities γ_p and γ_ℓ. Finally, we assume that entrepreneurs face a distortion $\tilde{\tau}(\{n_p(i)\})$ that is an increasing function of how intensively professionals are used in production. This wedge captures the many legal restrictions, tax laws, barriers, and other non-labor cost factors that inhibit setting up large, formal firms.

[10] Managers are an important part of the white-collar professionals, so we deviate from Lucas and call the founder and residual claimant of the firm the entrepreneur.

Formally, an entrepreneur with skill z solves

$$\pi(z) = \max_{\{n_p(i)\}_{i\in[0,1]},n_\ell} \tilde{\tau}(\{n_p(i)\}) \Big\{ zA \exp\left(\int_0^1 \log \tilde{n}(i)^{\gamma_p} di\right) n_\ell^{\gamma_\ell} \\ -w_p \int_0^1 n_p(i)di - w_\ell n_\ell \Big\} \tag{1}$$

s.t.

$$\tilde{n}(i) = \max\{1, a(i)n_p(i)\}$$
$$n_p(i) \geqslant 0 \quad \text{for} \quad i \in [0,1] \qquad \text{and} \qquad n_\ell \geqslant 0.$$

The choice of optimal technology

Without loss of generality, we order tasks in descending order by their relative productivity $a(i)$. We also assume a convenient functional form for the distortion.

ASSUMPTION 1. *The wedge $\tilde{\tau}(\{n_p(i)\})$ takes the following functional form: $\tilde{\tau}(\{n_p(i)\}) = \exp\left(\int_0^1 \log \tilde{n}(i)^{-\tau\gamma_p} di\right)$.*

Under these assumptions, Lemma 1 shows that the multi-dimensional problem (1) can be simplified to the choice of the share q of tasks to professionalize and how many professionals and laborers to hire.

LEMMA 1 (Equivalence Result)**.** *The problem of the entrepreneur (1) is equivalent to the following simplified problem, where q is the share of professionalized tasks and n_p is the professional labor input per task:*

$$\pi(z) = \max_{q\in[0,1],n_p\geqslant 0,n_\ell\geqslant 0} \Big\{ z\tilde{A}(q) \left[n_p^{\alpha(q)} n_\ell^{1-\alpha(q)} \right]^{\eta(q)} - qw_p n_p - w_\ell n_\ell \Big\}, \tag{2}$$

where

$$\begin{aligned} \tilde{A}(q) &\equiv A \times \left(\exp \frac{1}{q} \int_0^q \log a(i)^{\gamma_p(1-\tau)} di \right)^q \\ \eta(q) &\equiv q\gamma_p(1-\tau) + \gamma_\ell \\ \alpha(q) &\equiv \frac{q\gamma_p(1-\tau)}{\eta(q)}. \end{aligned}$$

The main implication is that the entrepreneur's problem can be reduced to a standard maximization of profits given a Cobb-Douglas production function over two types of labor, with one additional twist: the entrepreneur also chooses the share of tasks to professionalize. We refer to this choice as determining the organization of the firm because it implicitly determines the firm's productivity $\tilde{A}(q)$, the factor share of professionals $\alpha(q)$, and the returns to scale in production $\eta(q)$. The last property plays a central role in our results. Intuitively, professionalizing a task allows the entrepreneur to switch from using a fixed to a variable input, leading to less decreasing returns to scale in production. We return to this point when we characterize the optimal choices of q for different types of entrepreneurs in Section 4.1. We define $y(z)$ to be output that solves problem 2 for an entrepreneur with skill z.

Note from the expressions for $\alpha(q)$ and $\eta(q)$ that the functional form for τ implies that distortions affect the organization of the firm for all entrepreneurs who choose $q > 0$ as long as $\tau > 0$. In this sense it functions as a correlated distortion as in Hopenhayn (2014). If we instead modeled the distortion as a more standard proportional tax on revenue or profits, it would only affect the organization of the firm for marginal entrepreneurs.

Occupational Choice

Each individual chooses an occupation, which can be starting a firm (entrepreneurship) or working for a firm as a professional or a laborer. A worker with skill z earns income $\pi(z)$ as an entrepreneur, $w_p z^\rho$ as a professional, and $w_\ell z^\chi$ as a laborer, where w_p and w_ℓ are the equilibrium wages per efficiency unit. ρ and χ are parameters that modulate the intensity with which professionals and laborers use skills in the respective occupations.

Each worker chooses the occupation that maximizes income:

$$\phi(z) = \max \left\{ \underbrace{w_\ell z^\chi}_{\text{Laborer}}, \underbrace{w_p z^\rho}_{\text{Professional}}, \underbrace{\pi(z)}_{\text{Entrepreneur}} \right\}. \tag{3}$$

The occupational choice yields shares of workers with skill level z that choose to be entrepreneurs, professionals, and laborers $\omega_\pi(z), \omega_p(z)$, and $\omega_\ell(z)$, respectively.

3.2 Equilibrium

We define an equilibrium in our setting, which requires that agents' occupational choices maximize their objectives and that all labor markets clear.

Definition of Competitive Equilibrium *The competitive equilibrium is given by: i. wages per efficiency unit for laborers and professionals, (w_p, w_ℓ); ii. the share of tasks to professionalize, hired labor input of professionals and laborers, and profits for each* *entrepreneur z, ($q(z)$, $n_p(z)$, $n_\ell(z)$, $\pi(z)$); iii. shares of individuals in each occupation ($\omega_\pi(z)$, $\omega_p(z)$, $\omega_\ell(z)$) such that:*

1. *entrepreneurs maximize firm profits solving (1);*

2. *$\omega_\pi(z)$, $\omega_p(z)$, $\omega_\ell(z)$ satisfy the occupational choice (3), that is,*

$$\begin{aligned}\omega_\pi(z) > 0 \quad &\textit{only if} \quad \phi(z) = \pi(z)\\ \omega_p(z) > 0 \quad &\textit{only if} \quad \phi(z) = w_p z^\rho\\ \omega_\ell(z) > 0 \quad &\textit{only if} \quad \phi(z) = w_\ell z^\chi;\end{aligned}$$

3. *the markets for professionals and laborers clear:*

$$\begin{aligned}\int q(z)n_p(z)\omega_\pi(z)dG(z) &= \int z^\rho \omega_p(z)dG(z)\\ \int n_\ell(z)\omega_\pi(z)dG(z) &= \int z^\chi \omega_\ell(z)dG(z);\end{aligned}$$

4 Characterization and Analytical Results

We now characterize the optimal organization of production, occupational choices, and sectoral choices. With these properties in hand, we provide analytical results to build intuition for the interaction between skills and the organization of production.

4.1 Characterization

For the remainder of the paper we restrict attention to a parametric function for $a(i)$ that yields convenient analytical solutions.

ASSUMPTION 2. *The relative productivity of professionalizing task i is a decreasing function of i: $a(i) = \beta^{1/\gamma_p}(1-i)^{\theta/\gamma_p}$.*

Intuitively, β controls the overall level of productivity of professionalizing tasks, while θ controls the dispersion of productivity of professionalizing tasks. This function implies that log productivity is a decreasing, concave function of i with $\lim_{i\to 1}\log(a(i)) = -\infty$ when $\theta > 0$. Under this assumption, the endogenous productivity term becomes

$$\begin{aligned}\tilde{A}(q) &= A \times \left(\exp\left(\frac{1-\tau}{q}\int_0^q (\log\beta + \theta\log(1-i))\,di\right)\right)^q\\ &= Ae^{-q\theta(1-\tau)}\beta^{(1-\tau)q}(1-q)^{-\theta(1-\tau)(1-q)}\end{aligned}$$

Note that $\lim_{q\to 0} \tilde{A}(q) = A$ while $\lim_{q\to 1} \tilde{A}_j(q) = A\beta^{1-\tau}e^{-\theta(1-\tau)}$.

Entrepreneurial Decisions

We start by characterizing the decisions for an individual with skill level z conditional on choosing entrepreneurship. These decisions and the resulting profits are inputs to the equilibrium occupational choice, which we discuss next. An entrepreneur takes wages as given and chooses the share of administrative tasks to professionalize q and the efficiency units of laborers n_ℓ and professionals n_p to hire to maximize profits. Using the representation of Lemma 1 and the properties of the Cobb-Douglas production function, we can solve for the profits as a function of parameters, the skill z, and the (endogenous) organization of production q:

$$\tilde{\pi}(z;q) = (1-\eta(q))z\tilde{A}(q)\left[\tilde{n}_p(z;q)^{\alpha(q)}\tilde{n}_\ell(z;q)^{1-\alpha(q)}\right]^{\eta(q)}, \tag{4}$$

where $\tilde{n}_p(z;q)$ and $\tilde{n}_\ell(z;q)$ are the optimal labor inputs of entrepreneur z if she uses technology q. We can in turn solve for the total labor input in the standard way to find

$$\tilde{n}_p(z;q)^{\alpha(q)}\tilde{n}_\ell(z;q)^{1-\alpha(q)} = \left[z\tilde{A}(q)\left(\frac{(1-\tau)\gamma_p}{w_p}\right)^{\alpha(q)}\left(\frac{\gamma_\ell}{w_l}\right)^{1-\alpha(q)}\right]^{\frac{1}{1-\eta(q)}}. \tag{5}$$

Equations (4) and (5) show that the expressions for labor utilization and profits are similar to their counterparts in standard span of control models (Lucas, 1978). The main novel feature is that several elements on the right-hand side of these expressions depend on the share of tasks that are professionalized, q. These include the productivity term $\tilde{A}(q)$, the factor share of professionals $\alpha(q)$, the returns to scale $\eta(q)$, and the return to entrepreneurial skills z.

We use equations (4) and (5) to characterize the optimal organization of production, which encompasses both the share of tasks that are professionalized q and the scale of production. Lemma 2 establishes that when there is sufficient heterogeneity in the cost of professionalizing different tasks (θ is sufficiently large), then the optimal organization of production is a smooth and well-behaved function of the entrepreneur's skill. The reason is that when θ is large enough, the entrepreneurial problem is a quasi-concave function of q.[11]

Lemma 2 (Optimal Organization of Production). *Let $\theta > \frac{\gamma_p^2(1-\tau)}{1-\gamma_\ell}$. The entrepreneur's*

[11] Conversely, if θ is zero, the entrepreneur's problem instead is convex in q and has the feature that entrepreneurs either professionalize no tasks or all of them. We use this feature to help derive analytical results in Section 4.2.

optimal organizational choice, $q(z)$, is governed by a cutoff skill level $\hat{z}_q$: for $z \leqslant \hat{z}_q$, the firm does not professionalize any tasks ($q(z) = 0$), while for $z > \hat{z}_q$, the degree of professionalization $q(z)$ is a strictly increasing and differentiable function of skill that converges to full professionalization for large z, $\lim_{z\to\infty} q(z) = 1$. The value of the cutoff is given by

$$\log \hat{z}_q = (1-\gamma_\ell)\left[1 - \underbrace{\log(1-\tau)}_{\textit{Distortions}} + \underbrace{\log \frac{w_p/\gamma_p}{w_\ell/\gamma_\ell}}_{\textit{Skill premium}} - \underbrace{\frac{1}{\gamma_p}\log\beta}_{\textit{Scalability}}\right] + \underbrace{\log \frac{w_\ell/\gamma_\ell}{A}}_{\textit{Labor cost level}}, \tag{6}$$

and the firm's optimal output as a function of the entrepreneur's skill satisfies:

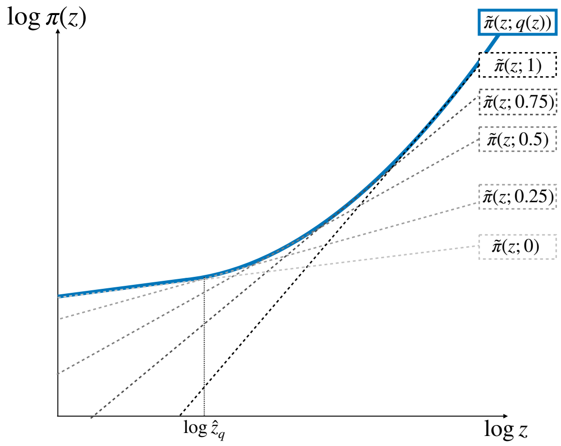
$$\frac{\partial \log y(z)}{\partial \log z} = \begin{cases} \frac{1}{1-\gamma_\ell} & \textit{if } z \leqslant \hat{z}_q \\ \frac{1+\gamma_p(1-\tau)\frac{dq(z)}{d\log z}}{1-\eta(q(z))} & \textit{if } z > \hat{z}_q. \end{cases}$$

The cutoff $\hat{z}_q$ in the lemma serves as an index for how attractive professionalization is, with a higher cutoff meaning fewer firms will professionalize. Equation (6) shows that the cutoff increases with the relative cost of professional labor (w_p/w_ℓ) and the distortion (τ), while it decreases with the scalability parameter (β). The final "Labor cost level" term indicates that professionalization is also less attractive when wages are high relative to productivity A, since this lowers the desired scale of production. In equilibrium, however, this mechanism is not relevant, as we will show below that wages scale with A.

Figure 4 provides a graphical representation of the results of Lemma 2. Each gray line shows log-profits as a function of the log of the entrepreneur's skill for a given choice of q (e.g., $\tilde{\pi}(z,q)$). A higher q implies a higher elasticity of profits with respect to skill. This reflects that a higher q reduces the degree of diminishing returns, disproportionately benefiting more skilled entrepreneurs. The blue line is the upper envelope of the gray curves. It represents the resulting profits of entrepreneurs, taking into account the optimal choice of the organization of production.

Lemma 2 and Figure 4 feature two very different types of entrepreneurs. Entrepreneurs with sufficiently low z find it optimal to choose $q = 0$ and hire only laborers. They face steeply decreasing returns (since $\eta(0) = \gamma_\ell$) and therefore operate small firms in equilibrium. The elasticity of output with respect to skill is $\frac{1}{1-\gamma_\ell}$, which is the familiar expression from Lucas (1978). We interpret these entrepreneurs as representing traditional production—own-account workers or small firms with little labor specialization, as in Bassi et al. (2025), and refer to these entrepreneurs as traditional

FIGURE 4: ORGANIZATION OF PRODUCTION AND FIRM PROFITS



entrepreneurs.

Entrepreneurs with sufficiently high z professionalize at least some tasks. The share of tasks they professionalize rises with their own skill, implying that the white-collar employment share also increases with the entrepreneur's skill. The elasticity of output with respect to the entrepreneur's skill is larger than the standard $\frac{1}{1-\gamma_\ell}$. It is also increasing in q, which is consistent with recent evidence from Quieró (2022) that the thickness of the firm size distribution tail is increasing in the entrepreneur's education level. We refer to firms that professionalize administrative tasks as modern business enterprises, and to their owners as modern entrepreneurs.[12]

Thus, individuals with different levels of skill z operate very different types of firms if they become entrepreneurs. We now solve for occupational choices, which inform us about who chooses entrepreneurship in equilibrium.

Occupational Choice, Equilibrium, and Duality

We describe the equilibrium occupational choice and the wages and profits that support it. The occupational choices depend on the equilibrium returns to skills in the various occupations. In the previous section, we characterized equilibrium profits as a function of skills for traditional and modern entrepreneurs and showed that the elasticity of profits with respect to skill is higher for modern entrepreneurs. Assumption 3 completes the ordering of the elasticity of income with respect to skill across all four occupations.

[12] Banerjee and Newman (1993) also develop a model of the endogenous allocation of workers to different types of firms, although the underlying mechanism is different than ours.

ASSUMPTION 3. *The parameters χ and ρ satisfy*

$$\underbrace{\chi}_{\textit{Laborers}} = \underbrace{\frac{1}{1-\gamma_\ell}}_{\textit{Traditional Entrepreneurs}} < \underbrace{\rho}_{\textit{Professionals}} < \underbrace{\frac{1}{1-\gamma_p(1-\tau)-\gamma_\ell}}_{\textit{Modern Entrepreneurs}}.$$

Note that the elasticity for modern entrepreneurs applies for a hypothetical entrepreneur who professionalizes all administrative tasks.

The ordering in Assumption 3 implies that low-skill workers have a comparative advantage as laborers or traditional entrepreneurs, while high-skill workers have a comparative advantage as professionals or modern entrepreneurs. This comparative advantage drives occupational sorting, as described in the following Lemma.

LEMMA 3 (Occupational Choice)**.** *Given Assumption 3, the equilibrium satisfies the following properties*

1. *there exists cutoffs $\hat{z}_0 \leqslant \hat{z}_1 < \hat{z}_2$ such that individuals with $z \leqslant \hat{z}_0$ are laborers or traditional entrepreneurs, those with $z \in (\hat{z}_1, \hat{z}_2)$ are professionals, while those with $z \in [\hat{z}_0, \hat{z}_1]$ or $z \geqslant \hat{z}_2$ are modern entrepreneurs;*

2. *the equilibrium incomes satisfy*

   - *$w_\ell z^\chi \geqslant \tilde{\pi}(z, 0)$ with equality on the support of traditional entrepreneurs, i.e., for those $z \leqslant \hat{z}_0$ with $\omega_\pi(z) > 0$.*
   - *if $\hat{z}_0 = \hat{z}_1 : w_\ell \hat{z}_0^\chi = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;*
   - *if $\hat{z}_0 < \hat{z}_1 : w_\ell \hat{z}_0^\chi = \pi(\hat{z}_0)$, $\pi(\hat{z}_1) = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;*

3. *there are traditional entrepreneurs – i.e. $\int_{\underline{z}}^{\hat{z}_0} \omega_\pi(x) dG(x) > 0$ – if and only if:*

$$\int_{\underline{z}}^{\hat{z}_0} z^\chi dG(z) > \int_{\hat{z}_0}^{\infty} n_\ell(x)\omega_\pi(z) dG(x).$$

Lemma 3 shows that the equilibrium can take one of two possible structures. Figure 5 shows the simpler case where $\hat{z}_0 = \hat{z}_1$, which implies that all modern entrepreneurs are more skilled than all professionals; Figure B.10 in the Appendix shows the case where $\hat{z}_0 < \hat{z}_1$. Figure 5a shows the incomes that each worker would make (given equilibrium prices) for each occupation as a function of their skill level z. The red line is the wage for laborers, which is identical to the profit of traditional entrepreneurs (in an equilibrium with some traditional entrepreneurs). The green line is the wage of professionals, which is increasing in z, with elasticity modulated by ρ. Finally, the blue line shows the profit of entrepreneurs (both traditional and modern), which takes into account the optimal choice of technology q.

FIGURE 5: OCCUPATIONAL CHOICE AND ENDOGENOUS DUALITY

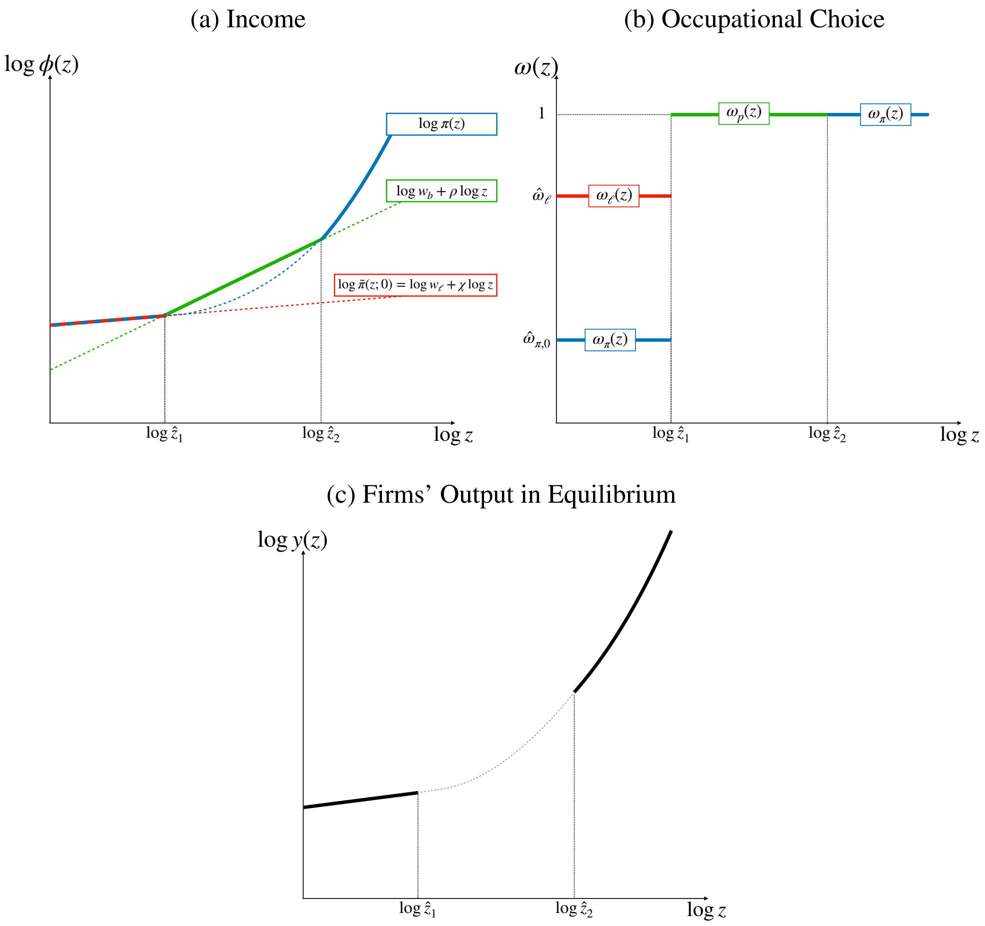


Figure 5b shows the resulting occupational choice. Workers with low skill levels are indifferent between becoming traditional entrepreneurs or laborers. Workers with intermediate levels of skills earn the most as professionals and consequently choose that occupation. Workers with the highest levels of skills choose the most skill-intensive occupation, which is modern entrepreneurship.

Finally, Figure 5c illustrates a key implication of Lemma 3: equilibrium in this model can feature duality. If there are a sufficiently large number of modern entrepreneurs, then they hire all low-skilled workers as laborers. If there are not, then the surplus low-skilled workers turn to traditional entrepreneurship. In this equilibrium, both the most- and least-skilled individuals become entrepreneurs – but of distinct types of firms with very different productivity levels.

DEFINITION 1. *An equilibrium features* duality *if there is a positive mass of traditional* *entrepreneurs, that is, if* $\int_{\underline{z}}^{\hat{z}_0} \omega_\pi(x)dG(x) > 0$.

Our empirical results in Section 2 focus on the share of workers in blue-collar versus white-collar occupations. When taking the model to the data, we treat laborers and traditional entrepreneurs as blue-collar workers, and professionals and modern entrepreneurs as white-collar workers.

4.2 Analytical Results: the Reorganization of Production

In this section, we explore how an increase in the aggregate supply of skills can generate a reorganization of production. We introduce a simplified version of the model that can be solved analytically. A proposition builds intuition for the quantitative results in Section 5 and show how the model can be consistent with the motivating facts documented in Section 2.

The results rely on two simplifying assumptions.

ASSUMPTION 4. *The productivity of professionals does not vary across tasks:* $\theta = 0$.

ASSUMPTION 5. *The income of professionals is as skill-sensitive as the profits of a modern entrepreneur,* $\rho = \frac{1}{1-\gamma_\ell-\gamma_p(1-\tau)}$.

ASSUMPTION 6. *The value of* $\beta^{1-\tau}(1-\gamma_\ell-(1-\tau)\gamma_p)^{1-\gamma_\ell-(1-\tau)\gamma_p}$ *is decreasing in* τ.

Assumption 4 implies that the entrepreneurial profits are convex in q, and thus there are only two types of entrepreneurs: traditional entrepreneurs who choose $q = 0$ and modern entrepreneurs who choose $q = 1$. Assumption 5 implies that high-skilled workers are indifferent between modern entrepreneurship and working as a professional. Last, Assumption 6 ensures β is sufficiently large to ensure that modern firms become less profitable as the wedge τ increases, despite a larger profit share $1 - \gamma_\ell - (1-\tau)\gamma_p$ becomes larger.

Increase in the Supply of Skills

We now show that an increase in the supply of skills can lead to a reorganization of production.

PROPOSITION 1 (Impact of an Increased Skill Supply)**.** *Start from an equilibrium featuring duality. Consider a uniform increase in the supply of skills that shifts up each individual by a factor of* $\kappa > 1$*, implying a new distribution function,* $\tilde{G}(z) = G(z/\kappa)$.

There exists a threshold $\hat{\kappa}$ such that for any $\kappa < \hat{\kappa}$, an increase in κ yields:

1. ***Constant wages and cutoff rules.*** *The wages for both type of workers and the occupational cutoff $\hat{z}$ remain constant. Consequently, occupational choices are unchanged conditional on skill level z.*

2. ***Reorganization of production.*** *There is an increase in the share of white-collar workers and average firm size, and a decline in the share of traditional entrepreneurs.*

The proof of Proposition 1 is provided in the Appendix. The key step is to recognize that, as long as duality persists, wages (per efficiency unit of labor) remain unchanged in response to shifts in the supply of skills. To build intuition for this result, we explain each wage in turn.

An increase in the supply of skills increases the share of individuals who choose to work as professionals or become modern entrepreneurs. The increase in the share of professionals tends to push the wage of professionals down. However, the increase in the share of modern entrepreneurs increases the demand for professionals to staff the growing number of large firms. This *skill-biased organizational change* pushes the wage for professionals up. Generically it is not possible to sign the overall effect on wages. In this special case, the fact that skilled workers are indifferent between working as professionals or modern entrepreneurs ensures that the supply and demand forces exactly offset, leaving professional wages unchanged.

A different mechanism keeps the wages of laborers constant. The increase in skills both reduces the supply of laborers and increases the demand for laborers (to work in the larger number of modern firms). However, low-skilled workers are indifferent between being laborers or traditional entrepreneurs, and we begin in an equilibrium with duality. The traditional entrepreneurs act as a reserve supply of laborers who step in to meet the increased demand. As a result, laborer wages remain fixed until this reserve is exhausted.

The property that wages are invariant to the supply of skills relies on simplifying assumptions specific to this analytical model. However, two key mechanisms carry over to the general framework: first, skilled workers contribute to both the supply of and demand for professional labor; and second, traditional entrepreneurs act as a reserve labor supply for laborers. These features help explain why the model generally produces muted movements in the relative wages. These same features are also important when taking the model to the data, as available evidence shows that developing and developed countries exhibit broadly similar relative wages despite vastly different supplies of skilled workers (Banerjee and Duflo, 2005; Rossi, 2022).

Given that wages are invariant to the supply of skills, the rest of the results can be naturally understood as arising through composition effects. The increase in the aggregate supply of skills leads to more modern entrepreneurs and an increase in the size of firms. The growth in the modern sector pulls workers from traditional entrepreneurship into working as laborers in large, modern firms.

These properties are consistent with the motivating facts outlined in Section 2. The fact that occupational choices depend only on the worker's skill level z and not the aggregate skill level is consistent with the findings about occupational choice by education level shown in Figure 3a. The resulting growth in large, white-collar-intensive firms is consistent with Figure 1. The fact that equilibrium reorganization pulls blue-collar workers out of traditional entrepreneurship and into large firms is consistent with Figure 3b.

We conclude the analysis of changes in the supply of skills by considering what happens when an increase in skill supply is large enough to fully exhaust the reserve of traditional entrepreneurs. In this case, the equilibrium no longer features duality and the economy's behavior is very different, as shown in the following corollary.

COROLLARY 1. *An increase of skills by $\kappa = \hat{\kappa}$ implies an end to duality: no entrepreneurs choose $q = 0$. Any increase in skills beyond $\hat{\kappa}$ yields the following:*

1. *the cutoff type $\hat{z}(\kappa)$ satisfies $\log \hat{z}(\kappa) = \log(\kappa/\hat{\kappa}) + \log \hat{z}$, where $\log \hat{z}$ is the cutoff in the economy with duality;*
2. *the share of white-collar workers is constant;*
3. *average firm size is constant;*
4. *the relative wage of professionals to laborers declines;*
5. *the probability of choosing white-collar work conditional on skill level z declines.*

It is worth highlighting the second and third parts of the corollary: both firm size and the labor force composition in terms of white- and blue-collar workers remain constant. Thus, an increase in skills only leads to a reorganization of production if the initial equilibrium features duality. A straightforward but important implication is that an increase in skills does not generate a reorganization of production in the Lucas (1978) model.

Summing up, Proposition 1 shows that an increase in skills can generate a reorganization of production consistent with the data. At the same time, Lemma 2 shows that a number of other forces affect an entrepreneur's organization of production even in this simple analytical economy, including distortions and relative wages. Our next goal is to study the quantitative importance of various driving forces in a richer calibrated model that relaxes the simplifying assumptions that permit these propositions.

5 Quantitative Model and Calibration

We now turn to a quantitative model, which enriches the analytical model in three dimensions. First, we extend the model to include multiple sectors, so that it can speak to the relationship between structural transformation and the reorganization of production. Second, we introduce parameters necessary for bringing the model to the data, such as those governing the mapping between schooling in the data and skills in the model. Third, we allow for preference shocks that smooth the relationship between comparative advantage and occupational choice, enabling the model to replicate the empirical occupational choice patterns.

Our calibration strategy is to choose parameters so that the model is consistent with a rich set of cross-sectional facts for the average middle-income country in our dataset. We define middle-income countries as those with a GDP per capita between 10 and 50 percent of the United States. We focus on these middle-income countries because they feature a dual economy with coexistence of sizable traditional and modern sectors. We then recalibrate a limited set of driving forces to replicate select moments for the average low-income country with GDP per capita less than 10 percent of the United States. We use these calibrated economies to study the sources of reorganization of production and to conduct counterfactuals in Section 6.

5.1 Extensions and Mapping to the Data

This section enriches the analytical model so that it can be taken to the data.

Education and Skills. We assume that the four education groups that we observe consistently in the cross-country data—no primary, primary complete, secondary complete, tertiary complete—proxy for unobserved skills. We assume that skills z of education group i are lognormally distributed with mean $z_{\mu,i}$ and a common standard deviation z_σ. We normalize $z_{\mu,\text{No Primary}} = 0$.

Sectors. We extend the analytical model to include the four sectors discussed in Section 2: agriculture, manufacturing, low-skill services, and high-skill services. Each sector j produces a differentiated good that trades at price p_j. Sectors differ in their technologies, which include both the TFPQ, A_j, and the curvature parameters in the two types of labor, $\gamma_{p,j}$ and $\gamma_{\ell,j}$. This flexibility allows for differences in both firm size by sector (through the sum $\gamma_{\ell,j} + \gamma_{p,j}$) and the extent to which a sector can benefit from a reorganization of production around white-collar workers (through $\gamma_{p,j}$).

Sectors also differ in the intensity with which they use skills. We impose $\chi_j = (1 - \gamma_{\ell,j})^{-1}$ so that traditional entrepreneurship and working as a laborer are equally skill-intensive within each sector, consistent with the case that we analyzed in the analytical model. To further reduce dimensionality, we impose that the skill sensitivity of professionals is the mid-point of the skill sensitivity of traditional entrepreneurs (and hence blue-collar workers) and the modern entrepreneurs who adopt $q = 1$:

$$\rho_j \quad = \quad \frac{1}{2}\left(\frac{1}{1-\gamma_{\ell,j}} \quad + \quad \frac{1}{1-\gamma_{p,j}(1-\tau)-\gamma_{\ell,j}} \right).$$

The sectors are affected equally by the distortion τ.

Preference Shocks. In our analytical model, workers maximize income, leading to sharp occupational choice cutoffs (see Figure 5b). In the quantitative model we allow workers to have idiosyncratic taste shocks over both occupations and sectors. Working backwards, workers who have chosen sector j receive idiosyncratic preference shocks for the three occupations that are i.i.d. draws from a type-I extreme value distribution with shape parameter ξ. Hence, the fraction of workers within sector j who choose to be laborers is:

$$\omega_{i,j}(z) \quad = \quad \frac{\left(w_{\ell,j} z^{\chi_j}\right)^{\xi}}{\left(w_{\ell,j} z^{\chi_j}\right)^{\xi} + \left(w_{p,j} z^{\rho_j}\right)^{\xi} + \left(\pi_j(z)\right)^{\xi}}. \tag{7}$$

Similar expressions give the share who choose to be professionals and entrepreneurs. We amend the definition of traditional entrepreneurship to be entrepreneurs who would earn more working as laborers than as professionals (rather than those who are indifferent to working as laborers, as we did in the analytical model).

Workers are forward-looking and anticipate these draws when making sectoral choices. Hence, up to sector-wide factors that we discuss further below, the maximum expected income a worker derives from choosing sector j is:

$$\phi_j(z) \quad \propto \quad \left(\left(w_{\ell,j} z^{\chi_j}\right)^{\xi} + \left(w_{p,j} z^{\rho_j}\right)^{\xi} + \left(\pi_j(z)\right)^{\xi}\right)^{\frac{1}{\xi}}. \tag{8}$$

Workers also receive idiosyncratic preference shocks for the four sectors that are i.i.d. draws from a type-I extreme value distribution with shape parameter ν. Similarly, these shocks imply that the share of workers with skills z who choose sector j depends on their expected earnings in j relative to the other sectors. However, a substantial literature documents a divergence between sectoral employment shares and relative sectoral wages. For example, the large literature on the agricultural productivity gap shows that most workers in developing countries work in agriculture despite agriculture offering lower wages than other sectors, particularly for skilled workers (Gollin, Lagakos and Waugh, 2014; Herrendorf and Schoellman, 2018). We follow this literature by modeling a sectoral distortion that acts as a tax, leaving a worker with skill level z who chooses sector j with a share $\delta_j z^{\varphi_j}$ of their paid income. The term δ_j captures the distortion that is common to all workers, while z^{φ_j} allows for a correlated distortion that affects skilled workers differentially. As is standard, this distortion stands in for factors such as geography, information frictions, or labor market distortions that reduce the effective income from entering or switching to a sector. The share of workers with skill level z that choose sector j is then given by:

$$\sigma_j(z) \quad = \quad \frac{\left(\delta_j z^{\varphi_j} \phi_j(z)\right)^{\nu}}{\sum_{k \in J} \left(\delta_k z^{\varphi_k} \phi_k(z)\right)^{\nu}}. \tag{9}$$

Markets. We close the model by assuming a fictitious representative consumer with the average income of all workers who chooses sectoral consumption to maximize a non-homothetic CES utility function as in Comin, Lashkari and Mestieri (2021). Utility U is implicitly defined by

$$\sum_{j \in \{\text{ag,mfg,hs,ls}\}} \Upsilon_j^{\frac{1}{\sigma}} \left(\frac{C_j}{U^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}} = 1. \tag{10}$$

This approach allows us to capture consumption responses to changing prices and rising (average) incomes without requiring us to solve for and aggregate the expenditures of the entire distribution of workers.

5.2 Targeted Moments, Identification, and Model Fit

We now describe how we calibrate the model to match the relevant empirical moments for a middle-income country, discuss how the data identify model parameters, and show that the calibrated model provides a good fit to key empirical patterns.

Externally Calibrated Parameters. We divide the calibration procedure into two parts. We begin with a set of parameters that are fixed exogenously, either through a

TABLE 1: EXTERNALLY CALIBRATED PARAMETERS

Parameter		Value				Source
Panel A. Education-specific		No primary	Primary	Secondary	Tertiary	
υ	Employment share	0.16	0.38	0.32	0.14	Ruggles et al. (2025)
Panel B. Aggregate						
ξ	Occup. preferences	8.00				Dix-Carneiro (2014); Ashournia (2018)
ν	Sectoral preferences	8.00				Dix-Carneiro (2014); Ashournia (2018)
σ	Aggregate elasticity	0.43				Comin, Lashkari and Mestieri (2021)
η_{mfg}	Returns to scale in Mfg	0.80				Buera, Kaboski and Shin (2011)
τ	Firm size wedge	0.00				Normalization
Panel C. Sector-specific		Agri.	Manu.	Ser (HS)	Ser (LS)	
ϵ	Sector elasticity	0.25	1.00	1.88	1.12	Comin, Lashkari and Mestieri (2021)
$\frac{\gamma_{p,j}}{\gamma_{p,j}+\gamma_{\ell,j}}$	Factor share of prof.	0.27	0.55	0.90	0.66	Own calculation

direct correspondence with an empirical moment or based on existing estimates in the literature. Table 1 summarizes these parameters.

Panel A reports the share of workers in each education group, υ_i, in the average middle-income country, which we compute from international census data (Ruggles et al., 2025). Panel B reports five aggregate parameters taken from the literature. The parameters ξ and ν govern the dispersion of taste shocks across occupations and sectors. We take these from the trade literature, focusing on studies that explicitly estimate long-run responses to trade shocks. Our central estimate is $\xi = \nu = 8$, consistent with Dix-Carneiro (2014) and Ashournia (2018); we show results for values in the range of 4–16 in Section 6.3.[13] We estimate the elasticity of substitution in demand across sectoral outputs to 0.43 following Comin, Lashkari and Mestieri (2021), using their replication files and code but splitting services into low-skill and high-skill services. We fix the returns to scale of a fully modernized firm ($q = 1$) in manufacturing at 0.80, a value broadly consistent with the literature—for example, Buera, Kaboski and Shin (2011) use 0.79. Finally, we normalize $\tau = 0$ for the middle-income country.

Panel C reports two sector-specific parameters that we calibrate externally. First, we estimate the income elasticity of demand by sector again following Comin, Lashkari and Mestieri (2021). Second, the ratio $\gamma_{p,j}/(\gamma_{p,j} + \gamma_{\ell,j})$ determines the compensation share of professionals in fully modernized firms. We calibrate this to match the observed compensation share of professionals in large firms, which we calculate using labor force survey data for middle-income countries. In the next section we describe how we internally calibrate $\gamma_{p,j} + \gamma_{\ell,j}$; with this value in hand, we can recover the

[13]Both papers provide estimates of the long-run sectoral elasticity, ν. Revenga (1992) estimates that the five-year sectoral elasticity is 4. Artuç and McLaren (2015) estimate the long-run elasticity across sectors and occupations, finding similar magnitudes and values as large as 20.

underlying structural parameters $\gamma_{p,j}$ and $\gamma_{\ell,j}$.

Internally Calibrated Parameters. We next turn to the vector of internally calibrated parameters, shown in Table 2.

A useful property of the model is that sectoral choices depend only on the product $\delta_j p_j A_j$, but not on the individual terms. This follows from equation (9) and the fact that wages, profits, and hence ϕ_j are all homogeneous of degree one in $p_j A_j$. The individual's sectoral choice thus depends only on the relative value of $\delta_j p_j A_j$ across sectors, while occupational choice and the optimal organization of production within sector are independent of these terms.

This property implies that it is sufficient to calibrate the joint product $\delta_j p_j A_j$ for three sectors, normalizing $p_{\text{mfg}} A_{\text{mfg}} \delta_{\text{mfg}} \equiv 1$. To further reduce dimensionality, we normalize the distortion correlated with skills for manufacturing and low-skilled services to be the same ($\varphi_{\text{mfg}} = \varphi_{\text{ls}} = 0$) because they have similar skill composition and we impose $\varphi_{\text{ag}} = -\varphi_{\text{hs}}$. This leaves us with a vector of 13 parameters:

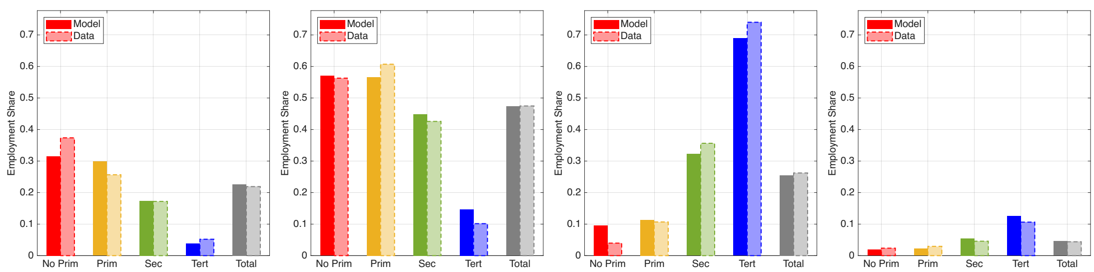
$$\mathbf{p} \;=\; \Big[\, z_{\mu,2}\ ,\ z_{\mu,3}\ ,\ z_{\mu,4}\ ,\ z_{\sigma}\ ,\ \beta\ ,\ \theta\ ,\ \varphi_{\text{hs}}\ ,\ \{\eta_j\}_{j\in\{\text{ag,hs,ls}\}}\ ,\ \{\delta_j A_j p_j\}_{j\in\{\text{ag,hs,ls}\}} \Big].$$

We select the parameter vector to minimize the weighted sum of squared deviations between moments in the model and moments in the data.

Targeted Moments and Model Fit. This section uses figures to summarize the targeted moments and the model fit. Appendix C.1 contains tables providing the exact values for model and data as well as the weight assigned to each moment while computing the likelihood function. Broadly, we want the model to replicate the motivating empirical patterns described in Section 2, which cover the distribution of labor across occupations, sectors, and firm sizes, as well as how these distributions vary with educational attainment. We now describe more specifically the moments we target.

FIGURE 6: OCCUPATIONAL SHARES

(a) Traditional Entr. (b) Blue-Collar Workers (c) White-Collar Workers (d) Modern Entr.



We first target aggregate occupational choices and occupational choices by education. The model allows for four occupational choices: traditional entrepreneurs, laborers, professionals, and modern entrepreneurs. We map wage workers in the data to the employee categories and self-employment to the entrepreneur categories. We use occupation codes to subdivide each category: workers with blue-collar occupations are laborers, while the self-employed with blue-collar occupations are traditional entrepreneurs.[14] Figure 6 shows these moments in the data and in the model. We also target the distribution of labor across sectors at the aggregate and within each education level (Figure 7). Finally, we target the distribution of educational shares within a sector (Figure 8.) While these moments are simply renormalized versions of those in Figure 7, our model is highly overidentified and in practice we find it useful to include both to ensure that our model delivers a good fit along this dimension as well.

FIGURE 7: SECTORAL SHARES

(a) Agriculture (b) Manufacturing (c) Services (LS) (d) Services (HS)

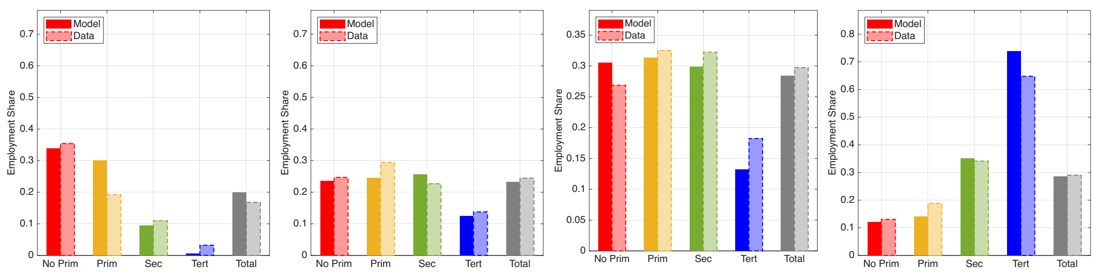
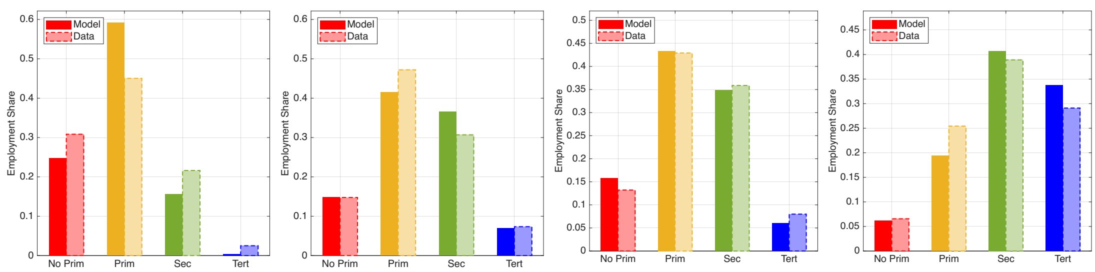


FIGURE 8: EDUCATIONAL SHARES, WITHIN SECTOR

(a) Agriculture (b) Manufacturing (c) Services (LS) (d) Services (HS)



Importantly, we want the model to capture sectoral differences in the organization of production. For example, high-skill services are characterized by many large firms, while roughly half of individuals in agriculture are traditional entrepreneurs. Accord-

[14] We include unpaid family workers with the self-employed; given their occupations, they are then largely counted as traditional entrepreneurs.

ingly, we target occupational shares, average firm size, and the shares of employment in firms with more than 10 and more than 50 employees for each sector (Figures 9–10).

FIGURE 9: DIFFERENCES IN WITHIN-SECTOR ORGANIZATION

(a) Traditional Entr. (b) Blue-Collar Workers (c) White-Collar Workers (d) Modern Entr.

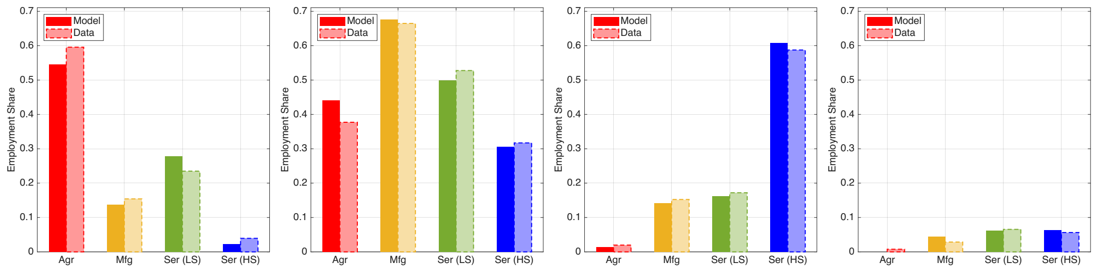
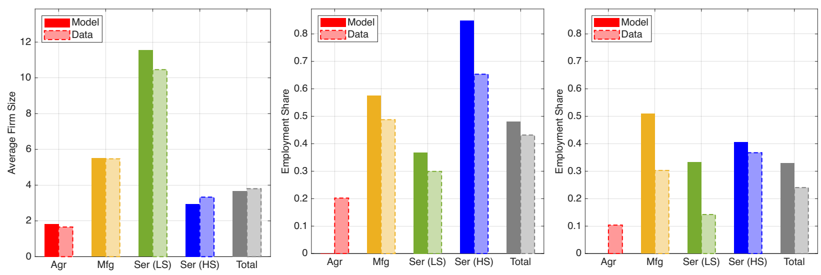


FIGURE 10: DISTRIBUTION OF FIRM SIZES

(a) Avg. Firm Size (b) Empl. in 10+ Firms (c) Empl. in 50+ Firms



One of our key motivating facts, consistent with Chandler's narrative, is that larger firms employ a higher share of white-collar workers. We therefore target the share of white-collar employment within each sector for firms smaller and larger than 10 employees, as well as the relationship between firm size and the relative white-collar share, estimated via a cubic regression with sector fixed effects using a subset of LFS countries with more detailed firm size categories (Figure 11).

Finally, we target wage outcomes. Specifically, we match the residual wage gaps across education groups and the residual wage dispersion within education groups (Figure 12). We residualize wages for the estimated effect of potential experience, gender, and location (*geolevel1*) fixed effects, removing variation associated with factors absent from our model.[15]

In total, we target 125 moments. Although some are collinear by construction (e.g., employment shares sum to one), the model remains overidentified. Nonetheless, it fits

[15]These moments are computed using 11 IPUMS cross-sections and 23 LFS countries with available wage information. See Appendices A and C.1 for details on the construction and aggregation of the country-specific estimates.

Figure 11: White-Collar Employment Share by Firm Size

(a) Firms 1-10 (by Sec) (b) Firms 11+ (by Sec) (c) by Firm Size (w/i Sec)

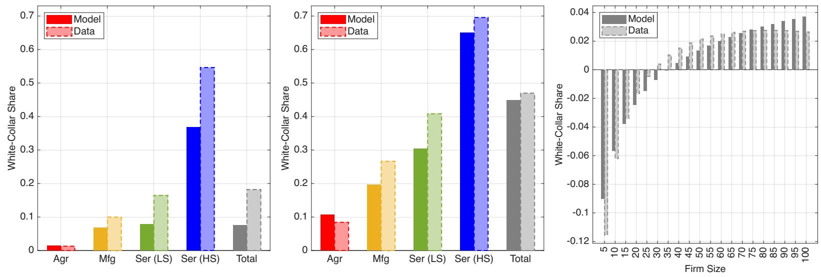
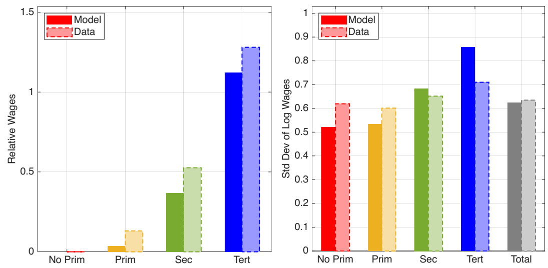


Figure 12: Wage Gaps Between and Within Education Groups

(a) Wage Premia (b) Wage Dispersion



the empirical patterns well.

Identification. All parameters are jointly identified. Appendix C.2 provides results developed through simulation showing that the parameters are locally and globally well-identified as well as documenting which moments are most informative for each parameter. Here, we provide an overview of the identification that builds on these results.

The parameters z_μ and z_σ govern the distribution of unobserved skill z within and between schooling groups. In the model, more skilled workers are more likely to choose skill-intensive occupations and also have higher earnings. The parameters z_μ and z_σ can thus be pinned down by heterogeneity in occupational choices and earnings within and between school groups. For example, the model requires a sizable gap $\mu_4 - \mu_2$ relative to σ_z to be consistent with the fact that most college-educated individuals choose white-collar occupations but few primary-educated individuals do so.

The productivity of professionalizing tasks, β, determines how easily firms can adopt modern technologies. A higher β lowers the relative cost of professionalization, increasing the share of white-collar workers and modern entrepreneurs at the expense of blue-collar workers and traditional entrepreneurs.

While β governs the average cost of professionalizing tasks, the parameter θ modulates heterogeneity in the cost of professionalizing tasks and thus heterogeneity in the organization of production. As discussed in Section 4.2, a low value of θ implies that entrepreneurs choose to professionalize either no tasks or all of them, which in turn makes the profit schedule highly sensitive to the entrepreneur's skill. Conversely, when θ is high, some tasks remain costly to professionalize even for highly skilled entrepreneurs and profits are less sensitive to the entrepreneur's skill. The extent to which skilled individuals sort into modern entrepreneurship is therefore informative about θ.

The sector-specific returns to scale of a fully modernized firm, $\gamma_{p,j} + \gamma_{\ell,j}$, are disciplined by firm size distributions: all else equal, sectors with higher $\gamma_{p,j} + \gamma_{\ell,j}$ have larger firms in equilibrium.

The correlated amenity parameter, φ, helps match the strong observed sorting of skilled workers into high-skill services and away from agriculture. While cross-sector wage profiles already generate some sorting—since high-skill services are more skill-intensive than agriculture—matching the magnitude observed in the data requires a positive value of φ.

Finally, the combination of parameters $\delta_j p_j A_j$ are identified from sectoral employment shares: larger values lead to a greater fraction of workers in sector j.

Parameter estimates. Table 2 summarizes our internally calibrated parameter values. As expected, more educated workers are on average more skilled (Panel A). For instance, $z_{\mu,\text{Tertiary}} = 1.11$ implies that college educated workers are three times as productive as workers without primary education.

Panel B summarizes our estimates of the economy-wide parameters. The standard deviation of dispersion in skills within education groups is roughly equal to the mean difference in skills between high-school and no primary degrees. That is, we estimate a non-trivial overlap in the distribution of skills across education groups. Combined with our estimates of $\gamma_{p,j}$ and $\gamma_{l,j}$, our estimate $\theta = 1.09$ implies that the restriction $\theta > \gamma_{p,j}^2(1-\tau)/(1-\gamma_{\ell,j})$ holds in all sectors.

Panel C shows the parameters that vary by sector. The total curvature in labor $\gamma_{p,j} + \gamma_{\ell,j}$ is modestly lower in services than in manufacturing and much lower in agriculture. The values of $\delta_j p_j A_j$ are hard to interpret in isolation; we return to these further when we discuss the cross-country calibration. The correlated distortion is significant, indicating that more skilled workers sort away from agriculture and towards high-skill services to a greater extent than can be explained by wages alone.

Finally, Panel (d) shows the parameters that are implied by our other estimates. There are large differences across sectors in the potential factor intensity for professionals $\gamma_{p,j}$ as well as the skill intensity for laborers and professionals. These parameters

TABLE 2: INTERNALLY CALIBRATED PARAMETERS

Parameter	Interpretation	Value			
Panel A. Education-specific		No primary	Primary	Secondary	Tertiary
z_μ	Average skills relative to previous level		0.06	0.48	1.11
Panel B. Aggregate					
z_σ	St.d. of skills cond. on education	0.49			
β	Productivity of hired professional, intercept	1.67			
θ	Productivity of hired professional, slope	1.09			
Panel C. Sector-specific		Agriculture	Manufacturing	Ser (HS)	Ser (LS)
$\gamma_{p,j} + \gamma_{\ell,j}$	Decreasing returns to scale of $q = 1$ firm	0.59	0.80	0.73	0.79
$\delta_j p_j A_j$	Sectoral labor supply shifter	0.73	1.00	0.60	1.16
φ_j	Skill-sensitivity of sector	-1.52	0.00	1.52	0.00
Panel D. Implied parameters		Agriculture	Manufacturing	Ser (HS)	Ser (LS)
χ_j	Skill-sensitivity of laborers	1.75	1.56	1.08	1.37
ρ_j	Skill-sensitivity of professionals	2.08	3.28	2.40	3.11
$\gamma_{p,j}$	Curvature in professionals	0.16	0.44	0.66	0.53
$\gamma_{l,j}$	Curvature in laborers	0.43	0.36	0.07	0.27

play an important role in shaping the organization of production.

5.3 Cross-Country Calibration

One of our main goals is to understand the sources of the reorganization of production that takes place as a country develops. To this end, we recalibrate the model to be consistent with the average low-income country. These two model economies are useful for benchmarking our model to causal evidence drawn from countries with widely varying income levels; for decomposing the differences between low-income and middle-income economies; and for conducting counterfactuals.

Our recalibration allows a limited number of driving forces to vary and fits a limited set of moments. We allow educational attainment to vary and take the shares of workers at each education level v_i) directly from the data (Ruggles et al., 2025).[16] We allow the product $\delta_j p_j A_j$ to vary and use it to fit sectoral employment shares exactly, normalizing $p_{\text{mfg}} A_{\text{mfg}} \delta_{\text{mfg}} \equiv 1$ within each country. Accounting for the fact that shares sum to 1, this gives us six parameters and six moments. We also let the distortion τ vary and use it to fit the share of employment in medium and large firms.

[16]This choice is conservative, since the evidence indicates that education quality and life-cycle human capital formation are lower in developing countries (Schoellman, 2012; Lagakos et al., 2018).

TABLE 3: CALIBRATED CROSS-COUNTRY PARAMETERS

Parameter	Value		Target
	Low-Income	Middle-Income	
Sectoral labor supply shifter			Sectoral employment share
Agriculture	1.359	0.733	
Manufacturing	1.000	1.000	
High-skilled services	0.602	0.604	
Low-skilled services	1.217	1.164	
Share with no primary degree	0.511	0.157	Share of no primary degree workers
Share with primary degree	0.292	0.379	Share of primary degree workers
Share with secondary degree	0.150	0.319	Share of secondary degree workers
Share with tertiary degree	0.047	0.144	Share of tertiary degree workers
Firm size wedge	0.003	0.000	Employment share of 10+ firms
Agriculture size wedge	0.301	0.000	Self-employment share in agr.

Finally, we introduce a distortion, λ, that lowers the effective curvature of agricultural production with respect to laborers to $\gamma_{\ell,agr} - \lambda$ in the low-income economy (λ is normalized to 0 in the middle-income economy). This parameter aims to fit the reorganization of production within agriculture between poor and middle-income countries, specifically the shift from a sector dominated by traditional entrepreneurs, i.e., owner-operated farms, to one with a significant share of hired laborers (Figure 9).

Targeting this transition is important because agriculture contains much of the reserve labor force that could be drawn into employment in manufacturing and low-skill services. However, this reorganization does not involve an expansion of white-collar labor and so falls outside the scope of our main model. We therefore treat λ as a reduced-form friction that captures barriers to the emergence of large farms in poor countries—such as size-dependent distortions or frictions in land and labor markets that limit renting land or hiring in labor (e.g., Ayerst, Brandt and Restuccia, 2023; Chen, Restuccia and Santaeulàlia-Llopis, 2023; Foster and Rosenzweig, 2022).

This recalibration involves choosing eight parameters to fit eight moments exactly. Table 3 shows the resulting parameters in the low-income economy. Low-income countries have much lower educational attainment, with more than half of workers reporting no primary degree. The sectoral labor supply shifter for agriculture is much higher relative to the other sectors in the low-income economy, consistent with the view that distortions reduce the effective income for workers who switch from agriculture to non-agriculture in low-income countries. Further, the value of λ implies that the effective curvature for laborers in agriculture is much lower, at 0.13, broadly consistent with conventional estimates of the land share in agriculture. Finally, the value of τ is somewhat larger in low-income economies.

5.4 Benchmarking with Causal Evidence

Our calibrated model is consistent with a rich set of cross-sectional facts on the relationship among education, occupations, sectors, and the organization of firms for low-income and middle-income countries. In this section we show that it is also consistent with experimental and quasi-experimental evidence on the effect of expanding schooling and providing management training on the reorganization of production, which relates to the key mechanisms in the model. Details for this section are available in Appendix D.

Educational Expansions. There is a growing literature on the effects of plausibly exogenous expansions of educational attainment. Among this literature, Cox (2025) is the most useful for our purposes because he studies the effects of a plausibly exogenous expansion of college availability on college attainment as well as sectoral employment choices and several measures of the organization of production in affected regions.[17] To approximate Cox's experiment in our model, we start from the calibrated middle-income economy. We give it the educational attainment distribution that prevailed in Brazil in 2000. We exogenously shift a share of workers from secondary to tertiary education that is consistent with Cox's IV estimates on the effect on college attainment.

We then compare our model results to Cox's IV estimates for a range of other outcomes of interest, shown in Panel A of Table 4. Our model results are qualitatively aligned with Cox's estimates, but quantitatively on the conservative side. For example, we get just over half of the rise in the white-collar employment share and 90 percent of the rise in the employment share at large firms (which we measure as the share of employment at firms with more than six workers, as he does). The most notable discrepancy is that Cox finds a substantially larger effect of the expansion of college attainment on exit from agricultural employment and self-employment. A likely contributor to this discrepancy is changes in regions' comparative advantage for nonagricultural tradable goods, which we abstract from in our framework but Cox (2025) finds to be significant in the Brazilian context.

We also benchmark our model to evidence on the effect of an exogenous expansion of education in a low-income country. We use the individual-level effects of the INPRES primary school construction program in Indonesia (Duflo, 2001). Following

[17] See also Porzio, Rossi and Santangelo (2022), Russell, Yu and Andrews (2024), Coelli et al. (2023), Vu (2024), and Verma (2025), who study a narrower range of outcomes. Nimier-David (2023) also provides estimates for a wider range of outcomes for France, a developed country.

Table 4: Causal Evidence on Educational Expansions

	White Collar	Agri	LS Serv	HS Serv	Self-Emp Share	Emp Share Large Firms
Panel A. Cox (2025)						
Data	0.830	-1.800	1.940	0.980	-1.440	0.730
	(0.270)	(0.320)	(0.630)	(0.260)	(0.310)	(0.270)
Model	0.441	-0.149	-0.438	0.772	-0.284	0.654
Panel B. Duflo (2001)						
Data	0.021	-0.056	-0.018	0.019	-0.059	
	(0.022)	(0.029)	(0.032)	(0.023)	(0.034)	
Model	0.044	-0.050	0.004	0.038	-0.047	

Notes: The "Data" rows report the estimated coefficients from Cox (2025) and our adaptation of Duflo (2001), with standard errors in parentheses. The "Model" rows report the model-based coefficients. See Appendix D for more details on the implementation of the two exercises.

Porzio, Rossi and Santangelo (2022), we adopt the empirical specification in Duflo (2001), but focus on sectoral and occupational outcome variables. In the model, we approximate the experiment as a partial equilibrium exercise where we shift the educational distribution consistent with the first-stage results, keeping all prices and wages fixed (see Appendix D for more details on the empirical implementation). Panel B of Table 4 shows that the model generates a shift towards white-collar employment that is now larger than what the data suggest. The model also predicts a shift out of agriculture and self-employment that is consistent with the data, but again slightly smaller than the IV estimates suggest.

Management Training. To further explore the model mechanism, we turn to evidence from studies that offer management training to firms in low-income and middle-income countries. While a number of papers show that this training has positive effects on outcomes such as firm profitability or sales, two recent papers also provide evidence that speak to the response of the internal organization of the firm that are useful for benchmarking our model.

Giorcelli (2019) studies the effects of a quasi-experimental intervention that exposed managers of randomly chosen Italian firms to American-style management practices during the recovery from World War II. She evaluates the effect of this treatment on firm employment and productivity, but also on the ratio of managers per employee. Bloom et al. (2013) evaluates a randomized intervention that uses a consulting firm to provide management training to the owners of textile plants in India. Again, their intervention not only raised productivity, but also led the firm owners to professionalize a wider range of management tasks. For example, the intervention increased the share of firms that perform routine maintenance on machinery, track inventory, or set clear job descriptions and performance incentives for workers.

We replicate these experiments in the calibrated middle-income and low-income economy, respectively. We model the experiment as an information intervention that reduces τ and thus increases q for the treated firms. This approach is consistent with the historical evidence that the diffusion of management best practices started within the United States during World War II and diffused internationally afterwards, including to Italy. Bloom et al. (2013) also find information to be an important barrier in India: managers often either were unaware of important practices, or believed that they would not be profitable for their firm. We simulate a drop in τ such that our model produces the same change in TFPR as is reported in the original studies.

We study the implied effects of this change on other outcomes of interest. Giorcelli (2019) reports the change in employment and managers per worker. The first row in Table 5 shows that we get results again qualitatively consistent with hers. In terms of magnitudes, we get a growth in overall employment that is 2.5 times larger than her estimates but a growth in managers per worker that is about one-third of what she finds.

TABLE 5: CAUSAL EVIDENCE ON MANAGEMENT IMPROVEMENTS

		TFPR		Managers/workers		Log size		Management	
Study	τ	Data	Model	Data	Model	Data	Model	Data	Model
Giorcelli (2019)	-0.044	0.401	0.400	0.099	0.039	0.300	1.007		
Bloom et al. (2013)	-0.013	0.154	0.153					50.0	12.5

Notes: TFPR computed as $\log(y) - 0.6\log(\text{employment})$ in the model, where employment is constructed by dividing efficiency units hired by the firm by average efficiency units per worker. Managers/workers ratio and log employment constructed in a similar fashion. Management is computed as the shift in the share of management practices adopted in the data or q in the model, reported as $100\times$ the change in the pre-treatment CDF. See Appendix D for more details on the implementation of the two exercises.

Bloom et al. (2013) reports the change in the adoption of a range of management practices. Because q in our model does not have meaningful units, we convert the treatment effect to the percentile change it induces in the pre-treatment distribution. Our model generates a smaller reorganization of production equivalent to a 12.5 percentage point change in the baseline distribution of q. Again, the key causal forces in our model are conservative relative to the best evidence.

6 Counterfactual Experiments

In the last section we showed that a calibrated version of our quantitative model is consistent with a rich set of cross-sectional moments on the relationships among skills, sectors, and the organization of production. It is also broadly consistent with – and in many cases conservative relative to – causal evidence from experimental and quasi-experimental evaluations of the effects of changing skills or improving the management of firms. In this section, we use the model as a tool to understand why development is associated with a reorganization of production.

6.1 Structural Transformation and the Organization of Production

We start by assessing whether the reorganization of production is simply a consequence of structural transformation. To do so, we start from our calibrated low-income economy and replace each group of parameters with those of the middle-income economy sequentially. The results are summarized in Table 6. Each value in this table is the difference between the counterfactual economy and the baseline low-income economy. Panel A contains all of the moments targeted in the cross-country calibration, while Panel B shows other moments that are useful in understanding our results. Finally, the three rows show the results from changing parameter values sequentially, starting with changing only those that drive structural transformation, then adding frictions, and finally adding also skills. Note that the third row is equivalent to the calibrated middle-income economy. For the calibration targets, the differences shown in this third row are equal to the differences in the data in these targets.

We start with the structural transformation only experiment. This experiment replaces the calibrated product $\delta_j p_j A_j$ for each sector with the value of the middle-income economy, holding all other parameters fixed. This product encompasses the traditional forces that generate structural transformation: changes in the relative productivity with which outputs in different sectors can be produced or changes in the distortions that workers face when choosing or switching sectors. In our model, this product is the direct force that shifts the sectoral allocation of labor. Changing these parameters generates a large reallocation of labor: the employment share in agriculture declines by 21.1 percentage points, with labor shifting roughly equally to manufacturing and low-skill services. Comparing these values to the third row, we can see that changing $\delta_j p_j A_j$ already generates most of the structural transformation in the data.

However, this experiment generates almost no reorganization of production. The employment share in medium and large firms rises by just 3.1 percentage points, as

TABLE 6: UNDERSTANDING THE REORGANIZATION OF PRODUCTION

Panel A. Calibration Targets

	Sectoral employment shares					
	Agr	Mfg	Ser (HS)	Ser (LS)	10+ share	SE (agr.)
ST only	-0.211	0.099	0.007	0.105	0.031	0.007
ST + frictions	-0.220	0.104	0.007	0.110	0.069	-0.283
ST + frictions + skills	-0.311	0.100	0.143	0.069	0.291	-0.283

Panel B. Other Moments

	10+ share by sector			
	Mfg	Ser (HS)	Ser (LS)	Traditional Entrepreneur
ST only	-0.040	0.008	-0.075	-0.082
ST + frictions	0.033	0.030	-0.026	-0.181
ST + frictions + skills	0.260	0.083	0.170	-0.288
	White collar employment share			
	Secondary	Tertiary	Aggregate	$\log w_p/w_\ell$
ST only	0.006	0.006	0.000	0.040
ST + frictions	0.017	0.021	0.006	0.028
ST + frictions + skills	0.009	0.041	0.099	-0.018

Notes: Each value is the moment for a counterfactual low-income economy minus the value for the baseline, calibrated low-income economy. The "ST" row changes $\delta_j p_j A_j$, while the "ST + frictions" row also changes λ and τ. Finally, the "ST + frictions + skills" row also changes skills υ_i, which is equivalent to studying the calibrated middle-income economy.

opposed to 29.1 percentage points in the data, and the share of workers in agriculture who are self-employed actually rises. Panel B contains a number of moments that help understand this result. Agriculture is the sector with the lowest employment share at large firms (Figure 10). Structural transformation thus implies a push towards sectors with more large firms and an increase in demand for white-collar labor, which increases the relative wage of professionals by 4 log points. However, we find very little switching of labor towards white-collar employment within education groups, consistent with our motivating facts (Figure 3a in the data, which the model successfully replicates in Figure 6). The only way for the model to square rising demand for skilled labor with an unchanged supply of skilled labor is through a decline in large firms within sectors. This decline particularly affects low-skill services and manufacturing, the two sectors that have the largest growth in large firms with development in the data. We conclude that the reorganization of production is not a simple consequence of structural transformation.

The second row of Table 6 shows the effect of also reducing the frictions τ and λ. The results for the sectoral reallocation of labor are very similar to the first experiment. The model now generates a large decline in self-employment in agriculture, which allows it to match about two-thirds of the overall decline in traditional entrepreneurship. However, it still generates only a modest rise in the aggregate employment share in large firms and the employment share at medium and large firms within the low-skill service sector still declines. In short, a lack of skills constrains the reorganization of production.

6.2 The Equilibrium Effects of Expanding Education

The last section showed that the economy cannot generate a full reorganization of production without an increase in skills. In this section we ask whether an increase in skills alone is sufficient to generate a reorganization. To do so, we take the low-income economy and give it the educational attainment of the middle-income economy, while holding all other parameters fixed. We conduct these experiments in general equilibrium, which means that we solve for the new sectoral prices p_j that clear the output markets given consumer demand as described in equation (10).

The results are shown in Table 7, which has the same structure as Table 6. The first row gives the value of each moment for the calibrated middle-income economy minus the calibrated low-income economy, for reference; this is the same as the last row of Table 6. The "Counterfactual: Skills" heading organizes several rows showing the effects of comparing a low-income economy with middle-income education levels to the calibrated low-income economy. For now we focus on the Baseline case, $\xi = 8$.

This experiment achieves a sizable reorganization of production. For example, the growth in the employment share at medium and large firms within the manufacturing and low-skill service sectors is actually larger than in the baseline calibrated economies. However, at the aggregate, the model generates only about two-thirds of the growth in employment at medium and large firms (18 percentage points in the model versus 29.1 percentage points in the data). It generates a little less than one-third of the decline in traditional entrepreneurship as compared to the baseline calibrated economy.

The key obstacle that prevents the model from achieving a full reorganization of production is that we hold $\delta_j A_j$ and λ fixed. The increase in the supply of skills benefits the manufacturing and low-skill service sectors most because they have the most scope to reorganize production into large firms. However, the estimated elasticity of substitution between the output of different sectors in the structural transformation literature is well below 1. This estimate implies that there are large declines in the relative price of manufacturing and low-skill service outputs. Thus, without an exogenous shift in $\delta_j A_j$, the economy achieves little structural transformation, and employment remains dominated by the agricultural sector, where skilled workers are of little use. One symptom of

TABLE 7: THE EQUILIBRIUM EFFECTS OF EXPANDING SCHOOLING

	Sectoral employment shares					
	Agr	Mfg	Ser (HS)	Ser (LS)	10+ share	SE (agr.)
Calibrated	-0.311	0.100	0.143	0.069	0.291	-0.283
Counterfactual: Skills						
Inelastic Labor ($\xi = 4$)	-0.086	0.005	0.071	0.009	0.161	-0.009
Baseline ($\xi = 8$)	-0.022	-0.011	0.057	-0.025	0.180	-0.004
Elastic Labor ($\xi = 16$)	-0.035	0.004	0.044	-0.013	0.245	0.000
No reserve labor	-0.004	-0.022	0.044	-0.018	0.092	0.083

	10+ share by sector			
	Mfg	Ser (HS)	Ser (LS)	Traditional Entrepreneur
Calibrated	0.260	0.083	0.170	-0.288
Counterfactual: Skills				
Inelastic Labor ($\xi = 4$)	0.305	-0.002	0.280	-0.107
Baseline ($\xi = 8$)	0.405	0.060	0.454	-0.084
Elastic Labor ($\xi = 16$)	0.505	0.141	0.595	-0.102
No reserve labor	0.205	0.008	0.238	-0.000

	White collar employment share			
	Secondary	Tertiary	Aggregate	$\log w_p/w_\ell$
Calibrated	0.009	0.041	0.099	-0.018
Counterfactual: Skills				
Inelastic Labor ($\xi = 4$)	-0.037	-0.038	0.081	-0.151
Baseline ($\xi = 8$)	-0.041	-0.007	0.067	-0.165
Elastic Labor ($\xi = 16$)	-0.044	0.033	0.068	-0.105
No reserve labor	0.031	0.050	0.117	-1.085

Notes: Each value is the moment for a counterfactual economy minus the value for the baseline calibrated low-income economy. The "Calibrated" row shows the calibrated middle-income economy, while the "Counterfactual: Skills" rows shows the low-income economy with middle-income skill levels for the case of inelastic, baseline, and elastic labor supply across occupations, as well as the case where the reserve labor supply effect is entirely shut down.

this is that the relative wage of professionals to laborers (averaged across sectors) falls substantially (16.5 log points, 15 percent).

Holding λ fixed further implies that a large share of workers who remain in agriculture also choose traditional entrepreneurship. This further reinforces the fact that the model cannot generate a large aggregate decline in traditional entrepreneurship. Finally, holding τ fixed acts to reduce the growth in firm size. Overall, these results show that increasing skills is not sufficient to generate a full reorganization of production on its own.

6.3 Endogenous Duality as a Model Mechanism

We stressed in our analytical section the importance of endogenous duality. This model feature is important because it leads to a large mass of traditional entrepreneurs who are effectively a reserve labor force that can be pulled into wage work, allowing the model to generate a large reorganization of production in response to an aggregate increase in the supply of skills, without large movements in relative wages. In this section we conduct two sets of counterfactuals to show the quantitative importance of this mechanism in our model. Each counterfactual considers again the effects of giving the low-income economy the educational attainment of the middle-income economy.

First, we consider the effect of increasing educational attainment in economies that vary in the value of ξ, which governs the dispersion of taste shocks across occupations and hence the elasticity of labor supply across occupations. Larger values of ξ imply that workers are more responsive to wage differentials (equation (8)). As ξ becomes larger the quantitative model approaches the analytical model in the sense that workers become more likely to choose the highest-paying occupation. On the other hand, smaller values of ξ imply that workers are less responsive to wages and hence less willing to switch from traditional entrepreneurship to working as a laborer (among other margins).

Table 7 shows the results of expanding schooling with values of ξ ranging from 4 to 16, motivated by the range of parameter estimates in the trade literature. We have organized the rows so that the move from the inelastic to the baseline to the elastic cases. Since the underlying experiment in terms of expanding schooling is the same in all three cases, the rows can be compared to get a sense of the importance of ξ and endogenous duality.

In many ways these three counterfactuals look similar. All three generate a muted structural transformation and no change in the share of agricultural workers who are traditional entrepreneurs. Because of this, all three generate roughly one-third of the decline in traditional entrepreneurship that we see in the baseline calibrated economies. The main difference is in the employment share at medium large firms. When $\xi = 8$ (the benchmark), the model gets 18/29.1 = 62 percent of the overall growth in the employment share at medium and large firms in response to a change in skills. If workers were more elastic ($\xi = 16$), this result would be yet larger, at 84 percent, because the higher labor supply elasticity makes workers more willing to switch occupations and so accommodates the growth in large firms. On the other hand, for the case where workers are less elastic it the same result is just 55 percent.

An alternative approach to exploring the role of endogenous duality is to shut down the reserve labor force effect entirely. To accomplish this, we introduce into the economy a proportional tax on the wages paid to laborers that is thrown into the ocean. We again give the low-income economy the skill level of the middle-income economy, but now we adjust the tax on laborers such that the aggregate traditional entrepreneurship rate remains unchanged. Conceptually, the difference between these economies shows how structural transformation and reorganization would proceed without endogenous duality and the reserve labor force of traditional entrepreneurs.

The results of this experiment are shown in the last row of Table 7. Increasing skills generate only about one-half of the growth in the employment share at medium and large firms that it did in the original counterfactual (9.2 versus 18.0 percentage points). The main reason for this smaller reorganization is the scarcity of laborers. The table reports the gross (pre-distortion) relative cost that entrepreneurs face to hire professionals relative to laborers, which falls to one-third of its original level. Low-skill services and manufacturing use laborers intensively, so this price rise discourages the expansion of medium and large firms in these sectors – the employment share growth of medium and large firms in these sectors is roughly half of the original counterfactual. The model also generates a large *rise* in the share of traditional entrepreneurs in agriculture, which is another way to economize on the use of laborers. Altogether, these findings reinforce that endogenous duality and the idea that traditional entrepreneurs are a reserve labor force that aids the reorganization of production is quantitatively important for our results.

7 Conclusion

Chandler (1977) explores the transformation of American businesses during the Second Industrial Revolution. The defining technologies of this era leveraged economies of scale and scope to achieve productivity gains. As firms adopted these technologies and grew large, they found it necessary to recruit and organize a hierarchy of white-collar workers to solve the logistical challenges of production at scale.

We show that these same forces remain relevant today. We develop a theory of occupational choice that extends the classic work of Lucas (1978) by allowing entrepreneurs to decide both how much to produce and how to organize production. In equilibrium, the least and most skilled workers become entrepreneurs, but they organize production very differently. We calibrate the model to rich cross-sectional data and show that it is also consistent with experimental and quasi-experimental evidence on the effect of expanding education or providing management training. The model shows that expanding education is a necessary ingredient for the reorganization of production – structural transformation and reducing barriers generates less than half of the reorganization observed in the data. At the same time, expanding education is not sufficient – an expansion of education without structural transformation generates only two-thirds of the reorganization of production.

Our work abstracts from a number of features to focus on the link from skills to occupational choice and the organization of production. We treat skills as exogenous, but in the long run the supply of skills may itself be endogenous to the skill-biased organizational change that we study. We also abstract from physical capital and electrification, which we view as important but already well-understood in the literature (e.g., Buera, Kaboski and Shin, 2011; Fried and Lagakos, 2023). Finally, we focus on the role of skills in enabling a reorganization of production in manufacturing and low-skill services, consistent with Chandler's historical work. For today's developed countries, the educated, white-collar workforce is increasingly devoted to the high-skill service sector, which is arguably shaped by different forces. These are all exciting avenues for future research.

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Online Appendices

A Data Appendix

This appendix provides details on the data and further results related to the motivating facts established in Section 2.

A.1 Data Construction

IPUMS International. We use all cross-sections with available information on educational attainment, occupation, and sector. This gives us 218 cross-sections from 74 countries, spanning the global income distribution between Mali and the United States. Within each cross-section, we restrict the sample to the employed in the 16-65 age range. For the construction of wage moments, we focus on 11 cross-sections with available wage information: Brazil 2010, Canada 2001, India 1999, Indonesia 1995, Jamaica 2001, Mexico 2010, Panama 2010, Trinidad and Tobago 2000, United States 2015, Uruguay 2006, Venezuela 2001. We use hourly wages whenever available and restrict the sample to wage workers with high levels of labor market attachment (35+ weekly hours worked or full-time status, if available). We follow Rossi (2022) in implementing a number of country-specific adjustments, and we refer the reader to Appendix A in that paper for the details.

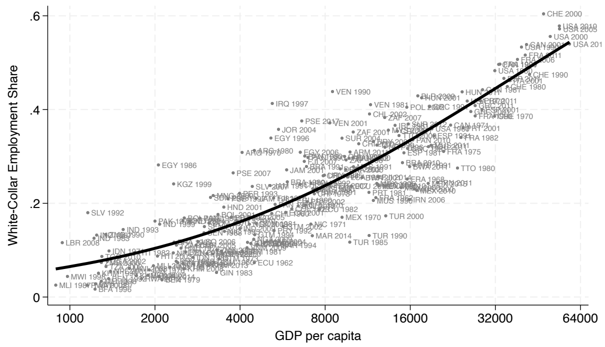
LFS. We use all surveys from Donovan, Lu and Schoellman (2023) with available information on firm size. We pool all available years within a country and use the country-level average. This gives us 44 countries, spanning the global income distribution between Rwanda and Switzerland. We again restrict the sample to the employed in the 16-65 age range. For the construction of wage moments, we focus on a partially overlapping sample of 23 countries with available wage information. We again use hourly wages and restrict the sample to wage workers with high levels of labor market attachment.

GDP per capita. We construct real GDP per capita in PPP (*rgdpo/pop*) from from Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015). We extrapolate to the years after 2019 applying the growth rate of GDP per capita in PPP from the World Development Indicators (World Bank, 2022).

A.2 Further Results: White-Collar Employment

An important feature of the data is the large cross-country differences in the share of white-collar workers. Figure A.1 draws on census data from Ruggles et al. (2025) to show that this varies from 10 percent in the poorest countries to 60 percent in the richest.

FIGURE A.1: WHITE-COLLAR EMPLOYMENT AND DEVELOPMENT



Notes: Each marker corresponds to a country × year observation. The line shows the fit of a logistic regressions on a quadratic in log GDP per capita.

Some of the shift towards white-collar workers is due to the growth of occupations such as doctors or teachers that are not involved in the administrative coordination of firms. Our baseline analysis deals with this by grouping most such workers into a high-skill service sector that plays little role in our analysis. As a complementary analysis, we also explore excluding such workers entirely. Figure A.2 shows the results of two such analyses. Figure A.2a shows the results when we exclude all workers employed in the education, health, and public administration sectors. Figure A.2b shows the results where we exclude all workers in the public sector and focus solely on the private sector.[18] Each shows a strong, positive correlation between the white-collar employment share and development.

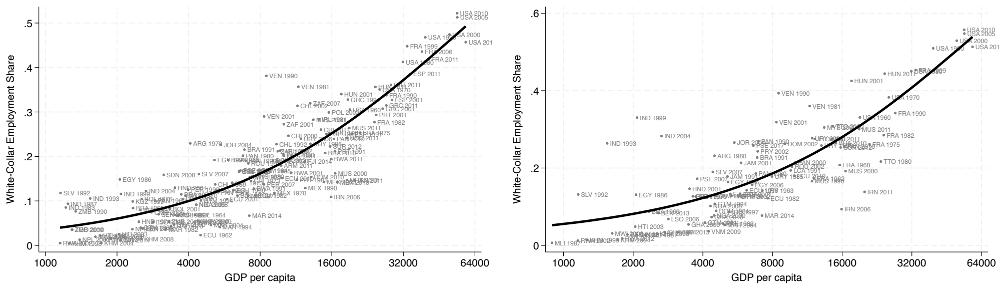
In Section 2.1 we document two facts that build on Chandler's insight about the role white-collar labor plays in production. The first fact, shown in Figure 1, is that large firms use white-collar labor more intensively. Although this fact is partly reflects structural transformation, we show here that the same pattern holds if we control for sector or industry.

Both IPUMS and labor force survey data are harmonized to a common industry variable with fifteen codes. For most of the paper, we further aggregate industries into four broad sectors. High-skill services consist of industries whose workers have at least 13 years of schooling in the United States, which includes education; financial services

[18] This exercise uses data from 41 countries and 97 cross sections where we know whether the worker is employed in the private or public sector.

FIGURE A.2: WHITE-COLLAR EMPLOYMENT AND DEVELOPMENT: CORE SECTORS

(a) Exclude Education, Health, Public Admin (b) Private Sector Only



Notes: Each marker corresponds to a country $\times$ year observation. The lines show the fits of logistic regressions on quadratic polynomials in log GDP per capita.

TABLE A.1: WHITE-COLLAR EMPLOYMENT AND FIRM SIZE

	White-Collar Employment Share		
	(1)	(2)	(3)
Medium	0.212***	0.136***	0.106***
	(0.001)	(0.001)	(0.001)
Large	0.250***	0.175***	0.142***
	(0.001)	(0.001)	(0.001)
Fixed Effects	Country	Country + Sector	Country + Industry
R-squared	0.131	0.261	0.284
Sample Size (m)	31.8	31.8	31.8

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

and insurance; health; public administration; other services; and real estate and business services. Low-skill services consist of hotels and restaurants; private household services; communication and transportation; and wholesale and retail trade. Manufacturing includes also construction, mining, and utilities. Agriculture is its own code.

We use the microdata from the labor force survey database to estimate the probability that a worker has a white-collar occupation as a function of firm size. We use a linear probability model for ease of interpretation; results from a logit are similar. Table A.1, column (1) reports the effect of estimating this probability while controlling for country fixed effects. In this case we find that workers in medium and large firms are 20–25 percentage points more likely to have white-collar occupations, consistent with Figure 1. In column (2) we control also for broad sector fixed effects, while in column (3) we control instead for industry fixed effects. Doing so reduces the point estimates by about half. However, even within the same sector or industry it remains the case that workers in medium and large firms are 10–14 percentage points more likely to have white-collar occupations.

The second fact about the role white-collar labor plays in production, shown in Figure 2, is that development is associated with a growing white-collar employment share in some sectors. We now decompose broad sectors into the underlying detailed industry codes (where such codes are available) in Figure A.3. Each of the four panels covers one of the four broad sectors; within the panel, we display the data for the detailed industries within that broad sector. The observations are at the country $\times$ year $\times$ detailed industry level.[19] The figure shows that the main detailed industries affected by a reorganization of production are manufacturing, wholesale and retail trade, and transportation, which experience increases of approximately 30 percentage points, 35 percentage points, and 40 percentage points in the employment share of white-collar workers when comparing the poorest to the richest economies. These are precisely the industries emphasized most by Chandler (1977).

A.3 Further Results: Skills and White-Collar Employment

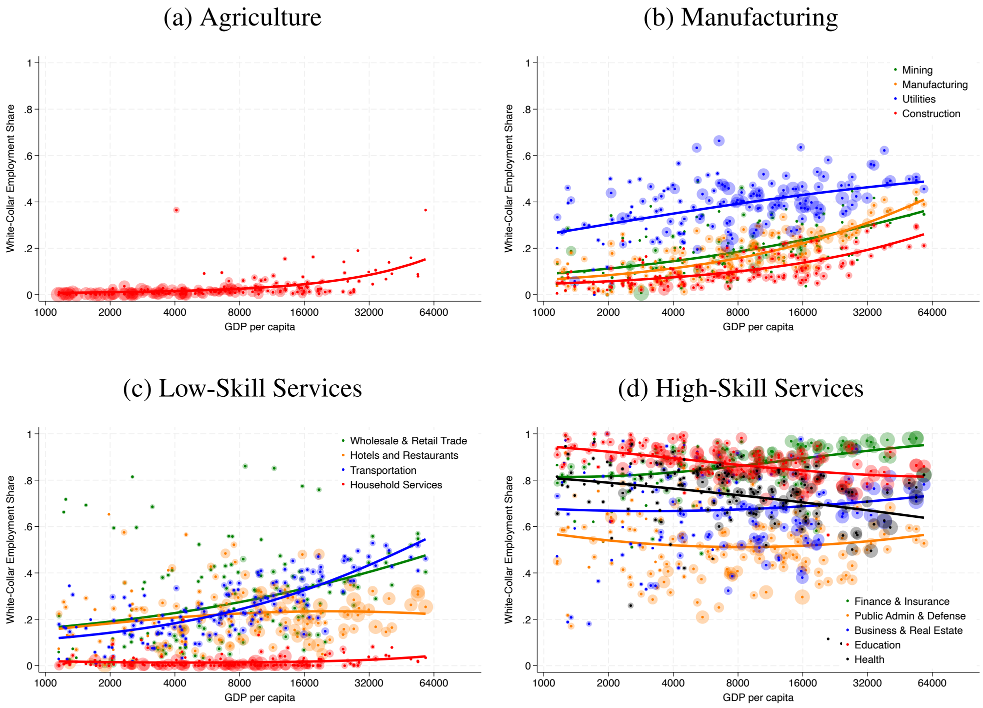
Our main new empirical result is that most of the cross-country differences in the employment share of white-collar workers can be accounted for by differences in skills. In the main text we use educational attainment as our proxy for human capital and show the results using cross-country data. We consider several alternative measures of skills here.

A.3.1 Alternative Measures of Skills: Adult Test Scores

In addition to educational attainment, we can study trends in white-collar employment shares as a function of adult test scores for a large number of countries around the world. For this analysis we use data from the Organisation for Economic Co-operation and Development (OECD)'s PIAAC Survey of Adult Skills and the World Bank's STEP Skills Measurement Program. The OECD PIAAC surveyed roughly 5,000 adults aged 15–65 in more than 40 countries. Its tests measure skills in literacy, numeracy, and problem solving. The World Bank STEP program builds on and expands the scope of PIAAC by surveying 2,000–4,000 adults aged 16-65 in 12 poorer countries/regions. They measure literacy and socioemotional skills. We combine the two datasets and

[19] We focus on a subsample of 54 countries (153 cross-sections) where we observe separately all the 14 industries listed in Figure A.3. We do not use the "Other Services" category that might include different industries across countries.

FIGURE A.3: DETAILED SECTORS AND WHITE-COLLAR EMPLOYMENT



Notes: Each marker corresponds to a country × year × sector observation. The bubbles around the markers are proportional to the employment share of the sector within each country × year. The lines show the fits of multinomial logistic regressions on quadratic polynomials in log GDP per capita.

focus on literacy skills, which are measured in both, as done elsewhere in the literature (Caunedo, Keller and Shin, 2023). Our final sample includes 43 countries spanning the income distribution between Kenya and Norway.

Figure A.4 presents results using adult literacy scores instead of education. The same patterns apply: workers with higher test scores are much more likely to engage in white-collar work; cross-country differences in white-collar employment shares conditional on test scores are small.

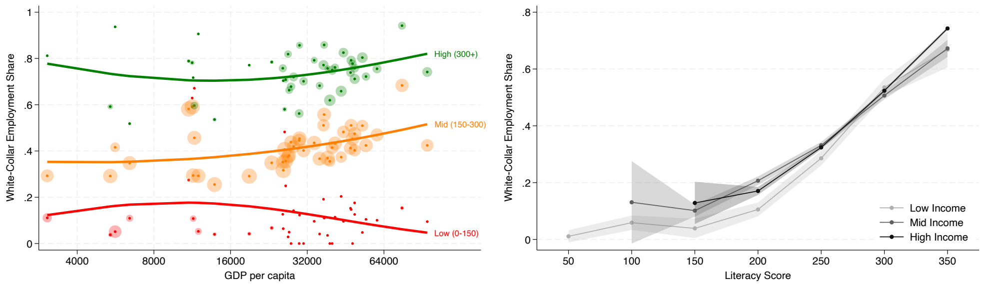
A.3.2 Alternative Measures of Skills: Childhood Test Scores

The advantage of adult test scores is that they measure the skills workers have (rather than how long they sat in a classroom). However, they are plausibly endogenous, in the sense that workers' skills may in part be caused by practicing and using those skills more in the course of performing their occupation. As an alternative approach, we also explore the relationship between occupational choices and childhood test scores.

To do so, we use data from the Longitudinal Survey of Australian Youths (LSAY), which builds off of the administration of the Programme for International Student As-

Figure A.4: White-Collar Employment Share and Literacy Scores

(a) Share by Literacy Score Group (b) Propensities by Income Group



Notes: Each marker in Panel (a) corresponds to a country × year × literacy score bin observation. The bubbles around the markers are proportional to the employment share of the literacy score bin within each country × year. The lines show the fits of multinomial logistic regressions on quadratic polynomials in log GDP per capita. Panel (b) displays estimates (and shaded 95% confidence intervals) from individual-level regressions of white collar status on 7 literacy score bin fixed effects (0-49, 50-99, ..., 250-299, 300+), controlling for age group (16-20, 21-25,...,61-65) and gender fixed effects. Observations re-weighted so that each country contributes equally to the regressions.

sessment (PISA) in Australia. It tracks a subset of test-takers into early adulthood, as late as age 25, and hence allows us to link the test scores of Australian students with their subsequent occupational choices. We combine the 2003, 2006 and 2009 waves of the data. We use the last reported occupation for each worker, disregarding occupations reported before age 21. Occupations are recorded using a modified version of ISCO codes, which permits us to classify workers into blue- versus white-collar categories as we do elsewhere in the paper.

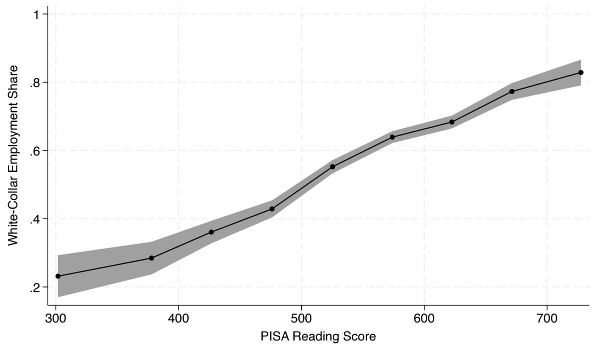
Figure A.5 plots the propensity of being a white-collar worker as a function of the PISA score in Australia. The relationship is strongly increasing. PISA scores are normalized so that a 500 represents the OECD average and 100 the OECD standard deviation. A score of 300 is thus two standard deviations below the OECD mean and is comparable to the average test scores from the poorest countries that participated in a pilot program seeking to extend PISA to low- and middle-income countries (Organization for Economic Development, 2018).[20] About 20 percent of workers with such scores enter white-collar occupations, consistent with the results from adult test scores in Figure A.4.

A.3.3 Time-Series Results

The analysis in Section 2 combines the cross-sectional and time-series variation by pooling all available surveys. This appendix illustrates the results when focusing on the

[20] For example, the mean reading score in Senegal was 306 and in Zambia was 275.

FIGURE A.5: WHITE-COLLAR OCCUPATIONS AND CHILDHOOD SKILLS



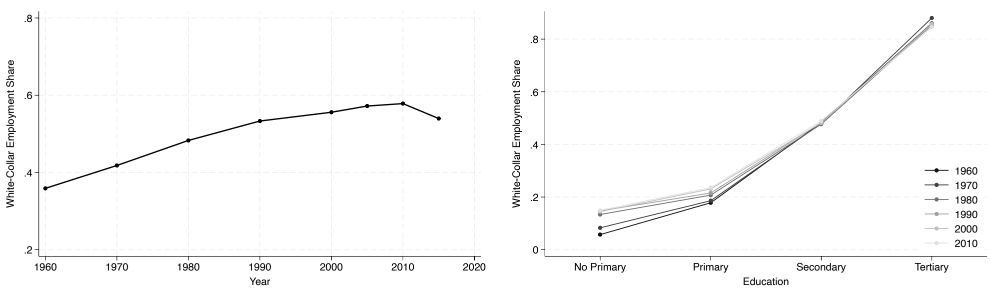
Notes: The Figure plots the average white-collar share (with shaded 95% confidence interval) against the average reading score across 9 bins of the reading score distribution (0-349, 350-499,...,650-699, 700+).

time series alone. Figure A.6 starts by focusing on the United States, the country with the longest available time series. Figure A.6a shows that the white-collar share of employment increased by more than 20 percentage points between 1960 and 2015. Figure A.6b shows that the share of workers choosing a white-collar occupation conditional on education is remarkably constant across decades, implying that virtually all the aggregate increase in Figure A.6a can be accounted for by changes in the educational composition over time.

FIGURE A.6: WHITE-COLLAR SHARE OVER TIME – UNITED STATES

(a) White-Collar Share Over Time

(b) Propensities by Decade



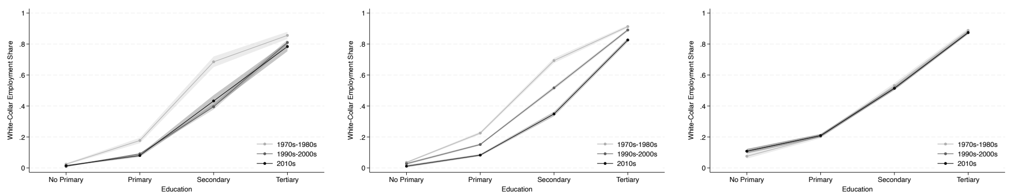
Notes: Panel (a) plots the average white-collar employment share for each year. Panel (b) displays estimates from individual-level regressions of white collar status on the 4 education dummies, controlling for age group (16-20, 21-25,...,61-65) and gender fixed effects (confidence intervals omitted for visual clarity).

Figure A.7 shows the share of workers choosing a white-collar occupation conditional on education for all countries in the sample. Figures A.7a, A.7b, and A.7c show results for low-income, middle-income, and high-income countries, while the lines within each figure capture the estimated share for different time periods.

The share of workers choosing white-collar occupations is very stable in high-

FIGURE A.7: WHITE-COLLAR SHARE OVER TIME – ALL COUNTRIES

(a) Low Income (b) Middle Income (c) High Income



Notes: The Panels display estimates (and shaded 95% confidence intervals) from individual-level regressions of white collar status on the 4 education dummies, controlling for age group (16-20, 21-25,...,61-65) and gender fixed effects. Observations re-weighted so that each country contributes equally to the regressions.

income countries. For low- and middle-income countries there is a decline in the white-collar share of primary- and secondary-educated workers. One possible explanation for this declining share is that the years 1970–2010 correspond to a period of massive educational expansion in these countries. Recent work suggests that this expansion may have lowered education quality, which would imply that educational attainment does not map into skills in a consistent way over time (Le Nestour, Moscoviz and Sandefur, 2023). Nevertheless, differences across education groups remain large in all periods, and changes in the education composition can account for most of the variation in the white-collar employment share over time.

A.3.4 Restrict to Core Sectors

Figure A.8 displays the white-collar employment share by education using only core sectors and excluding education, health, and public administration (Figure A.8a) or excluding all public-sector workers (Figure A.8b). Broadly similar results carry through.

A.3.5 Detailed Occupations

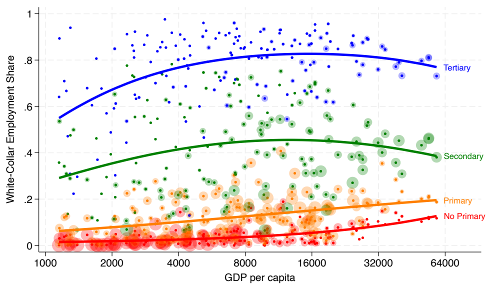
Figure A.9 shows the results separately for the four white-collar occupations. The share of managers and professionals monotonically increases with education, with profiles quite comparable across countries. For associate professionals and clerks, the gradient is quite strong at lower levels of education, though the educational profile flattens out or even decreases between the secondary and tertiary levels.

A.3.6 Summary Accounting Results

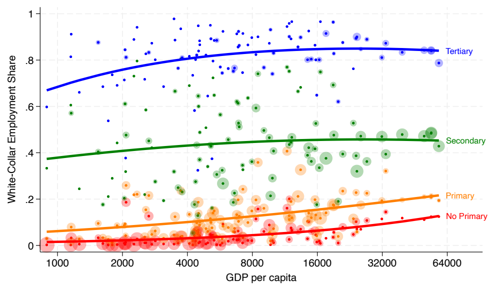
In Section 2.2 we document that human capital accounts for a substantial share of cross-country differences in the share of white-collar workers. This appendix formalizes this

FIGURE A.8: ALTERNATIVE SUBSAMPLES OF WORKERS, BY EDUCATION

(a) No Education, Health, Public Admin



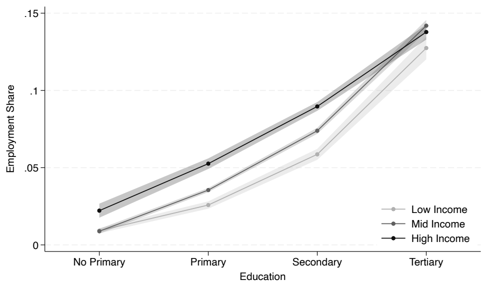
(b) Private Sector Only



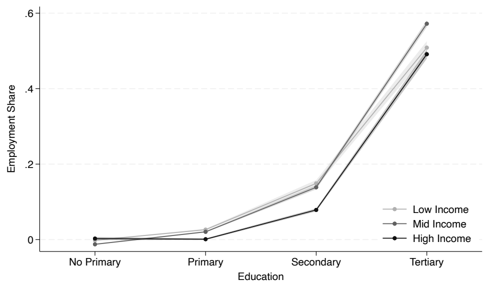
Notes: Each marker corresponds to a country × education × year observation. The bubbles around the markers are proportional to the employment share of the education within each country × year. The lines show the fits of multinomial logistic regressions on a quadratic in log GDP per capita.

FIGURE A.9: DETAILED WHITE COLLAR OCCUPATIONS AND EDUCATION

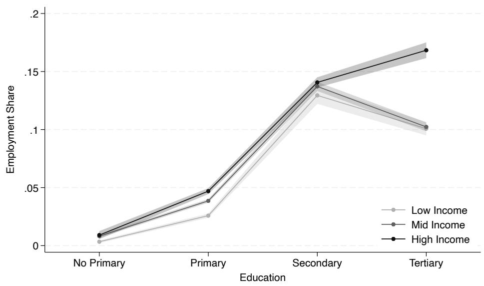
(a) Managers



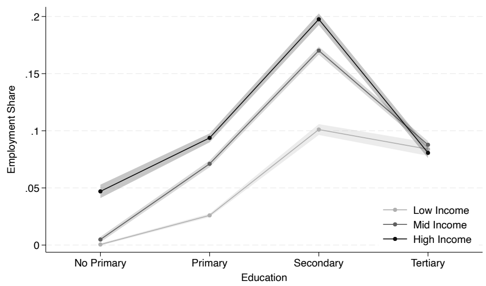
(b) Professionals



(c) Technicians and Associate Professionals



(d) Clerks



Notes: The Panels display estimates (and shaded 95% confidence intervals) from individual-level regressions of occupational dummies on the 4 education dummies, controlling for age group (16-20, 21-25,...,61-65) and gender fixed effects. Observations re-weighted so that each country contributes equally to the regressions.

idea as a shift-share accounting result. We collapse the Ruggles et al. (2025) data to the white-collar employment share at the country × year × education × 5-year age group × gender level. We run a weighted regression of the white-collar employment share on log GDP per capita, with the weights being given by the cells' employment shares within each cross section (so that all cross sections are weighted equally). We include dummies for gender and age groups. We refer to the estimated coefficient on log GDP per capita as the unconditional elasticity of white-collar employment with respect to development. We then re-estimate the same specification while also including dummies to control for educational attainment. We refer to the estimated coefficient on log GDP per capita in this case as the conditional elasticity.

We measure the share of the relationship between the white-collar employment shares and development that is accounted for by skills as:

$$\text{Accounting Share} = 1 - \frac{\text{Conditional Elasticity}}{\text{Unconditional Elasticity}}.$$

TABLE A.2: ACCOUNTING RESULTS: ROBUSTNESS

	Unconditional Elasticity	Conditional Elasticity	Accounting Share
(1) Baseline	0.112	0.015	0.865
	(0.001)	(0.001)	
(2) Within Sector	0.050	0.001	0.986
	(0.001)	(0.001)	
(3) Country and Decade FE	0.038	0.001	0.968
	(0.005)	(0.003)	
(4) Men	0.082	0.003	0.966
	(0.001)	(0.001)	
(5) Women	0.160	0.029	0.817
	(0.002)	(0.001)	
(6) Literacy Score	0.120	0.004	0.968
	(0.002)	(0.002)	
(7) No Education, Health, Public Admin	0.102	0.033	0.679
	(0.001)	(0.001)	
(8) Private Sector Only	0.114	0.027	0.765
	(0.001)	(0.001)	

Notes: The Table shows the results of the accounting exercises described in the text. Rows 1-5 and 7-8 use data from IPUMS International, while Row 6 uses data from PIAAC and STEP.

Table A.2 displays the results. In the baseline case, the unconditional elasticity (shown in Figure A.1) is 0.112, while the conditional one is 0.015. This implies that variation in the aggregate supply of skills accounts for 87 percent of the cross-country correlation between white-collar employment share and development. Rows (2)–(8) show that the large accounting role of human capital is confirmed when focusing on variation within sectors, within countries over time, by gender, when measuring skills as literacy scores (as discussed in Appendix A.3.1), and when focusing on core sectors (as in Figures A.2 and A.8).

A.4 Educational Attainment in Developing Countries

This appendix shows that educational attainment in many developing countries today is low relative to the levels that prevailed in the United States during the Second Industrial Revolution. It follows that a low aggregate supply of skills may be a larger impediment to the growth of medium and large firms in developing countries today.

The U.S. Second Industrial Revolution is conventionally dated to 1870–1914. We measure the educational attainment of workers by birth cohort using the full count 1940 U.S. Census, the first to collect such data nationally (Ruggles et al., 2025*b*). Among those who would have been 15–24 years old in 1870, the average secondary completion rate was 11 percent; among those who would have been 15–24 years old in 1914, the secondary completion rate had risen to 22 percent.[21]

We compare this to contemporary educational attainment data from Barro and Lee (2013). We focus on educational attainment of 15–24 years old; older workers generally have lower educational attainment. We also focus on countries with a 2019 GDP per capita (rgdpe/pop) of less than $5,000 in the Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015). Among the 33 countries below this threshold with education data, 8 have secondary completion rates among young workers below 11 percent and 20 have secondary completion rates below 22 percent. The median country in this set achieved an 11 percent secondary completion rate only in 2010, and has not yet achieved a secondary completion rate of 22 percent.

[21] Using responses from older workers in the census introduces some survivorship bias, but is unavoidable given the lack of earlier data on educational attainment.

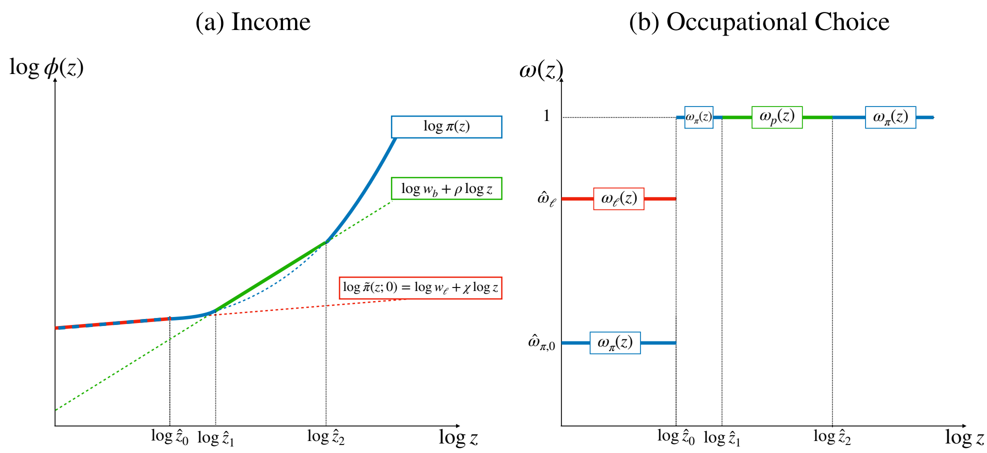
B Model Appendix

This section contains additional results referred to in the text as well as proofs of select results.

B.1 Visualizations of Alternative Occupational Choice Rules

Lemma 3 provides a general characterization of occupational choices. Figure 5b visualizes one possible income schedule and choice rule with the feature that $\hat{z}_0 = \hat{z}_1$. In this case, all modern entrepreneurs are more skilled than all professionals. An alternative case that can arise in equilibrium features $\hat{z}_0 < \hat{z}_1$, such that some modern entrepreneurs are less skilled than all professionals. Figure B.10 shows the income schedule and occupational choices for this case.

FIGURE B.10: ALTERNATIVE OCCUPATIONAL CHOICE RULES



B.2 Proofs of Select Results

Proof of Lemma 1.

Substituting in the expression for $\tilde{\tau}$ from Assumption 1, the profit maximization problem of an entrepreneur with skill z is given by

$$\max_{\{n_p(i)\}_{i\in[0,1]},\, n_\ell \geqslant 0} \; zA\exp\Big(\int_0^1 \log \tilde{n}(i)^{(1-\tau)\gamma_p}\, di\Big) n_\ell^{\gamma_\ell} \;-\; w_p \int_0^1 n_p(i)\, di \;-\; w_\ell n_\ell. \tag{B.1}$$

We note that the optimal allocation $\{n_p(i)\}$ must satisfy a cutoff rule, with a uniform choice $n_p(i) = n_p$ for $i \leqslant q$ and $n_p(i) = 0$ otherwise. The equal allocation follows from the concavity of the aggregator, and since $a(i)$ is decreasing in i, the firm optimally chooses to professionalize the highest-productivity tasks, which corresponds to the interval $[0, q]$.

Substituting this expression for $n(i)$ into the objective function means that we obtain a choice over q, n_p, and n_ℓ:

$$\max_{q\in[0,1],\, n_p\geqslant 0,\, n_\ell\geqslant 0} \; zA\exp\Big(\int_0^q \log a(i)^{(1-\tau)\gamma_p}\, di\Big)\, n_p^{(1-\tau)\gamma_p q}\, n_\ell^{\gamma_\ell} \;-\; qw_p n_p \;-\; w_\ell n_\ell.$$

This can be reparameterized into:

$$\max_{q\in[0,1],\, n_p\geqslant 0,\, n_\ell\geqslant 0} \; z\tilde{A}(q)\Big[n_p^{\alpha(q)} n_\ell^{1-\alpha(q)}\Big]^{\eta(q)} \;-\; qw_p n_p \;-\; w_\ell n_\ell,$$

with $\tilde{A}(q) = A\exp\Big(\int_0^q \log a(i)^{(1-\tau)\gamma_p}\, di\Big)$, $\alpha(q) = \frac{(1-\tau)\gamma_p q}{\eta(q)}$ and $\eta(q) = (1-\tau)\gamma_p q + \gamma_\ell$.

Proof of Lemma 2.

The expressions (4) and (5) imply that total profits satisfy

$$\pi(q,z) = (1-\eta(q))\left[z\tilde{A}(q)\right]^{\frac{1}{1-\eta(q)}}\left[\left(\frac{\gamma_p(1-\tau)}{w_p}\right)^{\alpha(q)}\left(\frac{\gamma_\ell}{w_\ell}\right)^{1-\alpha(q)}\right]^{\frac{\eta(q)}{1-\eta(q)}}.$$

For each z, the entrepreneur chooses q to maximize this function, and we write

$$f(q,z) \equiv \log \pi(q,z)$$

for the log profit function, which is twice-differentiable whenever $q < 1$.[22] The properties of the solution can be derived from properties of the first and second derivatives of $f(q,z)$. We start by establishing these derivatives, and then use our findings to establish the properties of the optimal solution.

1. Properties of derivatives of f. The profit expression can be written as

$$f(q,z) \equiv \log\pi(q,z) = \log[1-\eta(q)] + \frac{1}{1-\eta(q)}\left[\log z + \Phi(q)\right],$$

[22]For $q = 0$, we define the derivatives of f as right-derivatives.

where $\eta(q) = \gamma_\ell + q(1-\tau)\gamma_p$ and

$$\Phi(q) = \log \tilde{A}(q) - \eta(q)\log(w_\ell/\gamma_\ell) - q(1-\tau)\gamma_p \log \frac{w_p/[(1-\tau)\gamma_p]}{w_\ell/\gamma_\ell}$$

Using that we have $\eta''(q) = 0$, we can derive

$$f_q(q,z) = \frac{1}{1-\eta(q)}\left[-\eta'(q) + \frac{\eta'(q)}{1-\eta(q)}\left[\log z + \Phi(q)\right] + \Phi'(q)\right] \tag{B.2}$$

$$f_{qq}(q,z) = \frac{1}{1-\eta(q)}\left[\Phi''(q) + \frac{\eta'(q)^2}{1-\eta(q)} + 2\eta'(q) f_q(q,z)\right], \tag{B.3}$$

$$f_{qz}(q,z) = \frac{\eta'(q)}{(1-\eta(q))^2}\frac{1}{z}. \tag{B.4}$$

In addition, one critical property is that given our assumption on θ, f does not have any local minima. In particular, for all z and $q \in [0,1)$,

$$f_q(q,z) = 0 \quad \Longrightarrow \quad f_{qq}(q,z) < 0. \tag{B.5}$$

That is, if there is any stationary point of f, it has to be a local maximum.[23]

2. Existence of a cutoff $\hat{z}_q$. To establish the existence of a cutoff, we first note from (B.2) that for $q = 0$, the partial derivative is $f_q(0,z)$ is strictly increasing in z, going from $-\infty$ to $+\infty$, which means that there is a unique value $\hat{z}_q$ such that

$$f_q(0,\hat{z}_q) = 0.$$

The value $\hat{z}_q$ our candidate cutoff point. To verify this, consider the firm's choice of q.

For any $z \leqslant \hat{z}_q$, we have that $f_q(0,z) \leqslant 0$. This means that at $q = 0$, the profit function is either decreasing (for $z < \hat{z}_q$) or is momentarily flat before decreasing (for $z = \hat{z}_q$, since the second derivative is negative by (B.5)). Since (B.5) also implies that there are no interior local minima where the function could turn back to achieve a higher value, the profit $f(q,z)$ for any $q > 0$ cannot exceed its value at the origin. Therefore,

[23] To derive this, we note that

$$f_{qq}(q^*,z) < 0 \quad \Longleftrightarrow \quad \frac{(1-\tau)^2\gamma_p^2}{1-q(1-\tau)\gamma_p-\gamma_\ell} < \frac{\theta(1-\tau)}{1-q} \Longleftrightarrow \frac{1-q}{1-q\frac{(1-\tau)\gamma_p}{1-\gamma_\ell}}\frac{(1-\tau)\gamma_p^2}{1-\gamma_\ell} < \theta,$$

where we use that $\Phi''(q) = (\log\tilde{A})''(q) = -\frac{\theta(1-\tau)}{1-q}$. Since $(1-\tau)\gamma_p + \gamma_\ell < 1$, the factor $(1-\tau)\gamma_p/(1-\gamma_\ell) < 1$, and the left-hand side is maximized at $q = 0$. Hence, $f_{qq} < 0$ under our assumption that $\theta > (1-\tau)\gamma_p^2/(1-\gamma_\ell)$.

the optimal choice must be the corner solution $q(z) = 0$.

Conversely, for any $z > \hat{z}_q$, we have $f_q(0, z) > 0$. A strictly positive derivative at $q = 0$ means that profits can be increased by choosing a small positive q. Thus, $q = 0$ is no longer optimal, and the firm will choose an interior solution $q(z) > 0$. Hence, $\hat{z}_q$ has the desired properties.

3. Organizational choice $q(z)$ is monotonic in z. We now show that the optimal choice $q(z)$ is increasing in skill z. The result is immediate when comparing any $z_1 \leqslant \hat{z}_q$ with any $z_2 > \hat{z}_q$. The non-trivial case is to show that $q(z)$ is strictly increasing for all $z > \hat{z}_q$.

To establish this, we first use that (B.2) that implies an Inada condition at $q = 1$: the marginal profit tends to minus infinity as we approach the upper bound of professionalization: $\lim_{q \to 1} f_q(q, z) = -\infty$. In particular, in that expression, we have

$$\Phi'(q) = (1 - \tau)\theta \log(1 - q) + C_\Phi,$$

where C_Φ is a constant independent of q. Since $\log(1 - q) \to -\infty$ as $q \to 1$ and all other terms in the derivative are bounded, the overall derivative tends to $-\infty$.

This Inada condition ensures that the solution is never at the corner $q = 1$. Therefore, for any $z > \hat{z}_q$, we have a strictly interior solution, $q(z) \in (0, 1)$. This interior optimum must satisfy the first-order condition:

$$f_q(q(z), z) = 0,$$

and since (B.5) rules out interior local minima, any point satisfying the first-order condition is the unique global maximum. Totally differentiating the first-order condition with respect to z, we obtain:

$$f_{qq}(q, z) \cdot q'(z) + f_{qz}(q, z) = 0 \implies q'(z) = \frac{f_{qz}(q, z)}{-f_{qq}(q, z)}.$$

We know from (B.5) that $f_{qq} < 0$. Together with the complementarity between q and z, $f_{qz} > 0$, from (B.4), we have $q'(z) > 0$.[24] Hence $q(z)$ is strictly monotonic for $z > \hat{z}_q$.

[24] We assume here that $q(z)$ is differentiable. The result that $q(z)$ is non-decreasing follows more generally from the supermodularity of f, which does not require differentiability.

4. Solution $q(z)$ tends to $q = 1$ as $z \to \infty$. To establish the limiting behavior of the organizational choice, we note the following property of the derivative $f_q(q, z)$ in (B.2):

$$\lim_{z \to \infty} f_q(q, z) = \infty. \tag{B.6}$$

This property says fixed organizational structure $q < 1$, the marginal profit of improving it becomes arbitrarily large as skill increases.

To see why this implies $\lim_{z\to\infty} q(z) = 1$, consider any small $\epsilon > 0$. From (B.6), there must exist some skill level $\bar{z}$ such that for all $z > \bar{z}$, the marginal profit is positive even at $q = 1 - \epsilon$; that is, $f_q(1 - \epsilon, z) > 0$. Since we established that the profit function has a single peak, a positive slope at $1 - \epsilon$ implies the optimal choice $q(z)$ must lie to the right of this point. Hence, for any arbitrarily small $\epsilon > 0$, we can find a $\bar{z}$ such that for all $z > \bar{z}$, we have $q(z) > 1 - \epsilon$, which is the formal definition of $\lim_{z\to\infty} q(z) = 1$.

5. Value of cut-off point $\hat{z}_q$. The cut-off point $\hat{z}_q$ solves the following equation

$$f_q(0, \hat{z}_q) = 0 \Longleftrightarrow 0 = \left[-\eta'(0) + \frac{\eta'(0)}{1 - \eta(0)} [\log \hat{z}_q + \Phi(0)] + \Phi'(0) \right].$$

Using that $\eta(0) = \gamma_\ell$ and $\eta'(0) = (1 - \tau)\gamma_p$, as well as

$$\begin{aligned}
\Phi(0) &= \log A - \gamma_\ell \log(w_\ell/\gamma_\ell), \\
\Phi'(0) &= (1 - \tau) \log \beta - (1 - \tau)\gamma_p \log w_\ell/\gamma_\ell - (1 - \tau)\gamma_p \log \left(\frac{w_p/[(1 - \tau)\gamma_p]}{w_\ell/\gamma_\ell} \right),
\end{aligned}$$

we can manipulate the equation to arrive at

$$\log \hat{z}_q = (1 - \gamma_\ell) \left[1 - \log(1 - \tau) + \log \frac{w_p/\gamma_p}{w_\ell/\gamma_\ell} - \frac{1}{\gamma_p} \log \beta \right] + \log \frac{w_\ell/\gamma_\ell}{A}$$

as desired.

6. Elasticity of output with respect to z. For $z \leqslant \hat{z}_q$, we can explicitly solve for $y(z)$:

$$y(z) = z^{\frac{1}{1-\gamma_\ell}} A^{\frac{1}{1-\gamma_\ell}} \left(\frac{w_\ell}{\gamma_\ell} \right)^{-\gamma_\ell/(1-\gamma_\ell)},$$

which yields $\partial \log y(z)/\partial \log z = 1/(1 - \gamma_\ell)$ as in the Lemma.

For $z > \hat{z}_q$, we have an interior solution, and the Cobb-Douglas production function implies that

$$\pi(q(z), z) = (1 - \eta(q(z)))y(q(z), z). \tag{B.7}$$

Furthermore, the envelope theorem and the optimality of $q(z)$ implies[25]

$$\frac{\partial \pi(q(z), z)}{\partial z} = \frac{y(q(z), z)}{z}, \qquad \frac{\partial \pi(q(z), z)}{\partial q} = 0.$$

Thus, differentiating (B.7) with respect to z yields

$$\frac{y}{z} = -(1-\tau)\gamma_p y \frac{dq}{dz} + (1-\eta)\frac{dy}{dz} \quad \Longrightarrow \quad \frac{d\log y}{d\log z} = \frac{1 + (1-\tau)\gamma_p \frac{dq}{d\log z}}{1 - \gamma_\ell - \gamma_p (1-\tau) q(z)},$$

where we use $\eta(q) = 1 - \gamma_\ell - q\gamma_p(1-\tau)$, divide both sides with y/z, and re-arrange.

Proof of Lemma 3

I. Cutoff Result. We normalize the payoffs for professionals and entrepreneurs relative to the blue-collar worker's payoff. The relative payoffs are

$$\begin{aligned} \tilde{P}(\log z) &:= (\alpha_p - \alpha_w) + (\rho - \chi)\log z \\ \tilde{E}(\log z) &:= \log \pi(z) - (\alpha_w + \chi \log z) \end{aligned}$$

An agent with ability z chooses the occupation corresponding to $\max\{0, \tilde{P}(\log z), \tilde{E}(\log z)\}$.

Below, we document a number of facts about the curves $\tilde{P}$ and $\tilde{E}$ and the restrictions that need to hold in equilibrium, which we then use to derive the result.

1. **Shape of the curves $\tilde{P}$ and $\tilde{E}$.** The professional payoff is simply a linear curve with slope $\rho - \chi$. For $\tilde{E}$, 2 implies a slope $1/(1-\gamma_\ell - (1-\tau)\gamma_p q) - \chi$. Since $1/(1-\gamma_\ell) = \chi$, the slope is zero for $z < \hat{z}_q$ where $q = 0$. For $z > \hat{z}_q$, the slope is positive and strictly increasing, with an asymptotic slope of $1/(1-\gamma_\ell - (1-\tau)\gamma_p) - \chi$ which is steeper than the slope of the professional curve $\rho - \chi$. We write $\hat{z}_{e,\ell}$ for the largest z for which $\tilde{E}(\log z) \leqslant 0$.

2. **Positive supply of both laborers and professionals.** In equilibrium, there is a positive measure of modern entrepreneurs, since for sufficiently large z, we are above the cutoff $\hat{z}_q$ and $\tilde{E}$ grows faster than $\tilde{P}$, implying that modern entrepreneurship is the preferred choice. Since modern firms demand both professionals and laborers, labor market clearing requires these are in positive supply in equilibrium.

[25] For the envelope theorem, note that we can write $\pi(z, q) = \max_{n_l, n_p}[zf(n_l, n_p, q) - w_\ell n_\ell - qw_p n_p]$, and use that the first-order effect of changing z is simply $f(n_l^*, n_p^*, q^*) = y/z$.

3. **No traditional firms with $\tilde{E}(\log z^*) > 0$.** Since the profit elasticity with respect to ability is the same for traditional entrepreneurs and laborers, the payoff of traditional entrepreneurship relative to blue-collar work is constant. If this constant was positive, all individuals would strictly prefer traditional entrepreneurship to being a laborer, implying zero supply of laborers, which violates market clearing.

4. **Almost all modern firms have $\tilde{E}(\log z) > 0$.** First, there are no modern firms where $E(\log z) < 0$, since this would be dominated by being a blue-collar worker. Second, a modern firm needs to have $\log z > \log \hat{z}_q$, and since the entrepreneur's payoff function $\tilde{E}$ is steeper than χ when $\log z > \log \hat{z}_q$, there can at most be a point where $\tilde{E}(\log z) = 0$, so almost all modern firms have $\tilde{E}(\log z) > 0$.

5. **Single Intersection $\hat{z}_{p,\ell}$ of Professional and Laborer Payoffs.** The professional's relative payoff, $\tilde{P}(\log z)$, is an upward-sloping line, as the condition $\rho > \chi$ ensures that professional wages grow faster with ability than those of laborers. We write $\hat{z}_{p,\ell}$ for the unique intersection of $\tilde{P}$ with the horizontal line, giving the point of indifference between being a professional and a laborer.

6. **Exactly Two Intersections $\hat{z}^1_{p,e}, \hat{z}^2_{p,e}$ of Professional and Entrepreneurial Payoffs.** The professional line $\tilde{P}$ starts out steeper than the entrepreneurial curve $\tilde{E}$ for small $\log z$, since $\rho > 1/(1-\gamma_\ell)$, but ends up less steep at large $\log z$, since $\rho < \frac{1}{1-\gamma_\ell-\gamma_p}$. Hence, the professional payoff line begins and ends below the entrepreneurial payoff curve. This configuration allows for zero, one (tangency), or two intersections.[26] However, for the professional labor market to clear, a positive measure of individuals must choose this occupation. This equilibrium condition rules out the zero- and one-crossing cases, as they would leave no region where becoming a professional is the optimal choice. We therefore conclude that the two curves intersect exactly twice, at points we denote $\hat{z}^1_{p,e} < \hat{z}^2_{p,e}$.

7. **Payoff at Second Intersection $\hat{z}^2_{p,e}$ Strictly Dominates Laborer Payoff 0.** The payoff at the second intersection of the professional and entrepreneurial curves has to satisfy $\tilde{E}(\log \hat{z}^2_{p,e}) = \tilde{P}(\log \hat{z}^2_{p,e}) > 0$ to ensure that some z choose to be professionals. Otherwise, being professional would be dominated by laborers for $z \leqslant \hat{z}^2_{p,e}$, and would be dominated by entrepreneurship for $z > \hat{z}^2_{p,e}$.

The sorting cutoffs can now be constructed. We set the highest cutoff at $\hat{z}_2 = \hat{z}^2_{p,e}$. For all $z \geqslant \hat{z}_2$, entrepreneurship is the optimal choice, and it needs to be modern since

[26] To see that there can be at most two crossings, we note that the difference between the two functions, $\tilde{P}(\log z) - \tilde{E}(\log z)$, is strictly concave. To have more than two crossings would require a local minimum, which is not possible for a strictly concave function.

since payoffs exceed 0. The other cutoffs, $\hat{z}_0$ and $\hat{z}_1$, depend on the ordering of the remaining intersection points. Two cases arise:

1. **Case 1:** $\hat{z}^1_{p,e} \leqslant \hat{z}_{p,\ell}$. The professional line intersects the entrepreneur line at or before it intersects the zero line. We set $\hat{z}_0 = \hat{z}_1 = \hat{z}_{p,\ell}$. In this case, individuals with $z \in (\hat{z}_1, \hat{z}_2)$ choose to be professionals, while individuals with $z \leqslant \hat{z}_0$ choose to be either laborers or traditional entrepreneurs.[27]

2. **Case 2:** $\hat{z}_{p,\ell} < \hat{z}^1_{p,e}$. The professional line crosses the zero line strictly before its first intersection with the entrepreneur's line. Since the professional line has to be strictly below the entrepeneur's line when it crosses zero, the entrepreneur line has to be strictly above 0 at $\hat{z}_{p,\ell}$, which implies that the entrepreneur left 0 at $\hat{z}_{e,\ell} < \hat{z}_{p,\ell}$. We set $\hat{z}_0 = \hat{z}_{e,\ell}$ and $\hat{z}_1 = \hat{z}^1_{p,e}$. As before, those with $z \leqslant \hat{z}_0$ are laborers or traditional entrepreneurs. However, for $z \in (\hat{z}_0, \hat{z}_1]$, individuals choose to be modern entrepreneurs, since $\tilde{E}(\log z) > 0$ and $\tilde{E}(\log z) > \tilde{P}(\log z)$ in this interval.

This construction confirms that there exist cutoffs $\hat{z}_0 \leqslant \hat{z}_1 < \hat{z}_2$ such that individuals with $z \leqslant \hat{z}_0$ are laborers or traditional entrepreneurs, those with $z \in (\hat{z}_1, \hat{z}_2)$ are professionals, and those with $z \in (\hat{z}_0, \hat{z}_1]$ or $z \geqslant \hat{z}_2$ are modern entrepreneurs, proving the result.

II. Equilibrium Incomes

- To ensure there are any blue-collar workers, traditional entrepreneurship cannot have a higher payoff than blue-collar work Hence, $\pi(z, 0) \leqslant w_\ell z^\chi$. Furthermore, if $\omega_\pi(z)\mathbb{I}_{z \leqslant \hat{z}_q} > 0$, at least one z chooses traditional entrepreneurship, in which case we get equality.

- **Case 1:** $\hat{z}_0 = \hat{z}_1$.
  This case corresponds to the scenario where the set of modern entrepreneurs is fully above the set of professionals. The first occupational transition, occurring at $\hat{z}_0$, is directly from worker to professional. At this margin, an agent must be indifferent between the two, yielding the condition:

$$w_\ell \hat{z}_0^\chi = w_p \hat{z}_0^\rho.$$

[27] Modern entrepreneurship is precluded since $\tilde{E}(\log z) \leqslant 0$ in this interval. This follows since $\tilde{E}(\hat{z}_0) \leqslant 0$ and $\tilde{E}$ is weakly increasing.

The second cutoff, $\hat{z}_2$, is defined by the point where professionals and modern entrepreneurs yield the same payoff, hence:

$$w_p \hat{z}_2^{\rho} = \pi(\hat{z}_2).$$

- **Case 2: $\hat{z}_0 < \hat{z}_1$.**
  In this case, the optimal choice as z increases is to first switch from blue-collar work to modern entrepreneurship, then to professional, and subsequently back to modern entrepreneurship.
  - At the first cutoff, $\hat{z}_0$, individuals are indifferent between working and becoming a modern entrepreneur. This gives the equality: $w_\ell \hat{z}_0^{\chi} = \pi(\hat{z}_0)$.
  - At the second cutoff, $\hat{z}_1$, the marginal individual is indifferent between being an entrepreneur and becoming a professional, leading to $\pi(\hat{z}_1) = w_p \hat{z}_1^{\rho}$.
  - Finally, at the highest cutoff, $\hat{z}_2$, the choice is again between professional and entrepreneur roles, with high-ability entrepreneurs dominating. The indifference condition is: $w_p \hat{z}_2^{\rho} = \pi(\hat{z}_2)$.

III: Existence of traditional entrepreneurs. The market-clearing condition for blue-collar workers is given by:

$$\int_{\underline{z}}^{\hat{z}_0} \omega_L(z) z^{\chi} dG(z) = \int_{\underline{z}}^{\infty} n_\ell(z) \omega_\pi(z) dG(z),$$

where $n_\ell(z)$ is the labor demand from a firm of type z. The integral for labor supply (left-hand side) is capped at $\hat{z}_0$ because we have that $\omega_L(z) = 0$ for $z \geqslant \hat{z}_0$. By substituting $\omega_L(z) = 1 - \omega_\pi(z)$ for $z \leqslant \hat{z}_0$, we can rearrange the market-clearing condition as follows:

$$\int_{\underline{z}}^{\hat{z}_0} z^{\chi} dG(z) = \int_{\underline{z}}^{\hat{z}_0} \omega_\pi(z)[z^{\chi} + n_\ell(z)] dG(z) + \int_{\hat{z}_0}^{\infty} n_\ell(z) \omega_\pi(z) dG(z),$$

where the left-hand side is the total supply of efficiency units for $z \leqslant \hat{z}_0$, and the right-hand side is the total demand for such individuals, which comes from traditional entrepreneurs and their labor demand, as well as the labor demand from modern entrepreneurs.

From this, we observe that $\omega_\pi(z) > 0$ on the interval $[\underline{z}, \hat{z}_0)$ is equivalent to

$$\int_{\underline{z}}^{\hat{z}_0} z^{\chi} dG(z) > \int_{[\hat{z}_0, \hat{z}_1) \cup [\hat{z}_2, \infty)} n_\ell(z) \omega_\pi(z) dG(z)$$

where we use that, for $z \geqslant \hat{z}_0$, $\omega_\pi(z)$ is only positive on $[\hat{z}_0, \hat{z}_1) \cup [\hat{z}_2, \infty)$, which is the result.

Proof of Proposition 1

Our proof strategy is to do a guess-and-verify approach where we propose an equilibrium for a given κ, where cutoffs and wages are independent of κ, and then verify that it is an equilibrium if κ is sufficiently small. We then show that comparative statics with respect to κ have the desired form, and that there exists a $\hat{\kappa}$ such that duality disappears.

Production and profit functions. With $\theta = 0$, the optimal organizational choice is either fully traditional ($q = 0$) or fully modern ($q = 1$), since there is no heterogeneity in how easy tasks are to professionalize. Substituting in $q = 0$ and $q = 1$ into the expressions for $\alpha(q), \eta(q)$, and $\tilde{A}(q)$, we obtain the following two production functions for modern and traditional entrepreneurs:

$$y_0(n_\ell; z) = Azn_\ell l^{\gamma_\ell}, \qquad y_1(n_\ell, n_p; z) = A\beta^{1-\tau} z n_\ell^{\gamma_\ell} n_p^{\gamma_p(1-\tau)}.$$

Standard profit maximization with Cobb-Douglas production functions yields:

$$\pi(z, q = 0) = z^{\frac{1}{1-\gamma_\ell}}(1-\gamma_\ell)A^{\frac{1}{1-\gamma_\ell}}\left(\frac{w_\ell}{\gamma_\ell}\right)^{-\gamma_\ell/(1-\gamma_\ell)},$$

$$\pi(z; q = 1) = (1-\gamma_\ell-(1-\tau)\gamma_p)\left[zA\beta^{1-\tau}\left(\frac{w_\ell}{\gamma_\ell}\right)^{\gamma_\ell}\left(\frac{w_p}{\gamma_p}\right)^{(1-\tau)\gamma_p}\right]^{\frac{1}{1-\gamma_\ell-(1-\tau)\gamma_p}}.$$

Indifference conditions. In our posited equilibrium, there is a single skill cutoff, $\hat{z}$. This candidate equilibrium requires that for all individuals with $z \leqslant \hat{z}$, the returns to being a laborer and a traditional entrepreneur are equal, and for all individuals with $z > \hat{z}$, the returns to being a professional and a modern entrepreneur are equal. At the cutoff, individuals are indifferent between all four occupations. This yields three indifference conditions:

$$\begin{aligned} w_\ell z^\chi &= \pi(z, q = 0) \quad z \leqslant \hat{z}. \\ w_p z^\rho &= \pi(z, q = 1) \quad z > \hat{z}, \\ w_\ell \hat{z}^\chi &= w_p \hat{z}^\rho. \end{aligned}$$

Substituting in the profit expressions, using that $\chi = 1/(1-\gamma_\ell)$ and $\rho = 1/(1-\gamma_\ell-(1-\tau)\gamma_p)$, we obtain the following expressions for the wages and the productivity cutoff

$$
\begin{aligned}
w_\ell &= A(1-\gamma_\ell)^{1-\gamma_\ell}\gamma_\ell^{\gamma_\ell}, &\text{(B.8)}\\
w_p^{1-\gamma_\ell} w_\ell^{\gamma_\ell} &= A\beta^{1-\tau}(1-\gamma_\ell-(1-\tau)\gamma_p)^{1-\gamma_\ell-(1-\tau)\gamma_p}\gamma_\ell^{\gamma_\ell}\gamma_p^{\gamma_p}, &\text{(B.9)}\\
\hat{z} &= \left(\frac{w_p}{w_\ell}\right)^{-\frac{1}{\rho-\chi}}. &\text{(B.10)}
\end{aligned}
$$

By substituting (B.8) into (B.9), we can solve for w_p and thus w_p/w_ℓ purely in terms of the production parameters $A, \gamma_\ell, \gamma_p, \beta, \tau$, which also lets us calculate $\hat{z}$ from (B.10). Note that the skill distribution does not show up in any of these expressions.

Market clearing. The previous derivations established wages and a cutoff, $\hat{z}$, such that individuals optimally choose their occupations. To finalize the equilibrium, we must allocate individuals on either side of this cutoff to wage work or entrepreneurship and verify that markets clear.

To this end, let Z_{occ} denote the aggregate skill-weighted units in each occupation (e.g., $Z_{e,m}$ for modern entrepreneurs, Z_p for professionals). An individual's contribution is z^ρ if they are in a high-skill role ($z > \hat{z}$) and z^χ if they are in a low-skill role ($z \leqslant \hat{z}$). The market clearing conditions for the total supply of these units are:

$$
\begin{aligned}
Z_{e,m} + Z_p &= \int_{\hat{z}}^{\infty} z^\rho dG_\kappa(z) &\text{(B.11)}\\
Z_{\ell,m} + (Z_{e,t} + Z_{\ell,t}) &= \int_0^{\hat{z}} z^\chi dG_\kappa(z), &\text{(B.12)}
\end{aligned}
$$

where $Z_{\ell,m}$ and $Z_{\ell,t}$ denote blue-collar workers in modern and traditional firms respectively, and $Z_{e,t}$ denotes traditional entrepreneurs.

Since profits in modern entrepreneurship scale with z^ρ, we define profits per efficiency unit as $\tilde{\pi}_m \equiv \pi(z)/z^\rho$. Similarly, for traditional entrepreneurship, $\tilde{\pi}_t \equiv \pi(z)/z^\chi$ for $z \leqslant \hat{z}$. Both $\tilde{\pi}_m$ and $\tilde{\pi}_t$ are constant for all z within their respective domains. Given the Cobb-Douglas production functions, the following ratios of total payments hold:

$$
\begin{aligned}
\frac{Z_{e,m}\tilde{\pi}_m}{Z_p w_p} &= \frac{1-\gamma_\ell-(1-\tau)\gamma_p}{\gamma_p(1-\tau)}\\
\frac{Z_{e,m}\tilde{\pi}_m}{Z_{\ell,m} w_\ell} &= \frac{1-\gamma_\ell-(1-\tau)\gamma_p}{\gamma_\ell}\\
\frac{Z_{e,t}\tilde{\pi}_t}{Z_{\ell,t} w_\ell} &= \frac{1-\gamma_\ell}{\gamma_\ell}.
\end{aligned}
$$

The indifference conditions ($\tilde{\pi}_m = w_p$ and $\tilde{\pi}_t = w_\ell$) simplify these expressions. For the high-skilled group, this directly determines the allocation of efficiency units:

$$Z_{e,m} = \left(\frac{1-\gamma_\ell-(1-\tau)\gamma_p}{1-\gamma_\ell}\right)\int_{\hat{z}}^{\infty} z^\rho dG_\kappa(z), \tag{B.13}$$

$$Z_p = \left(\frac{\gamma_p(1-\tau)}{1-\gamma_\ell}\right)\int_{\hat{z}}^{\infty} z^\rho dG_\kappa(z), \tag{B.14}$$

showing that the aggregate units in modern entrepreneurship and professional work are fixed shares of the total high-skill supply. For the low-skilled individuals, the demand for laborers from modern firms, $Z_{\ell,m}$, is pinned down by $Z_{e,m}$:

$$Z_{\ell,m} = Z_{e,m}\frac{\gamma_\ell}{1-\gamma_\ell-(1-\tau)\gamma_p}\left(\frac{w_p}{w_\ell}\right),$$

where we recall that the wage ratio w_p/w_ℓ is fully pinned down by primitives in (B.8)-(B.9). The remaining low-skilled units form the traditional sector, which exists as long as the residual supply of low-skilled workers is positive. These units are split between traditional entrepreneurs and laborers in proportion to their income shares:

$$Z_{e,t} = (1-\gamma_\ell)\left[\int_0^{\hat{z}} z^\chi dG_\kappa(z) - Z_{\ell,m}\right]$$

$$Z_{\ell,t} = \gamma_\ell\left[\int_0^{\hat{z}} z^\chi dG_\kappa(z) - Z_{\ell,m}\right]$$

Duality exists if and only if the term in the brackets is positive, which happens for a sufficiently low κ, which we assume obtain in our case. This concludes the equilibrium construction.

Effect of increasing in $\hat{\kappa}$. The skill distribution parameter κ only enters through the integrals that determine the total supply of skill-weighted units; it does not affect wages or the cutoff $\hat{z}$ provided duality still exists. An increase in κ instead raises the total units of modern entrepreneurs ($Z_{e,m}$) and thus the laborers they demand ($Z_{\ell,m}$). This shrinks the residual supply for the traditional sector, implying there is a threshold $\hat{\kappa}$ above which duality disappears.

Proof of corollary 1

In the regime where $\kappa > \hat{\kappa}$ so that there is no duality, there are two changes in the equilibrium conditions. First, we remove the requirement (B.8) that low-skill individuals are indifferent between traditional entrepreneurship and blue-collar work. Second, we require that the blue-collar employment of modern firms equal the supply of unskilled workers, i.e., setting $Z_{\ell,t} + Z_{e,t} = 0$ in (B.12).

New equilibrium conditions. To pin down the skilled wage premium $\frac{w_p}{w_\ell}(\kappa)$ and the cut-off $\hat{z}(\kappa)$ as functions of κ, we use the following equilibrium equations

$$\frac{w_p}{w_\ell}(\kappa) = \hat{z}(\kappa)^{-(\rho-\chi)} \tag{B.15}$$

$$Z_{e,m} = \left(\frac{1-\gamma_\ell-(1-\tau)\gamma_p}{1-\gamma_\ell}\right)\int_{\hat{z}(\kappa)}^{\infty} z^\rho dG_\kappa(z), \tag{B.16}$$

$$\int_0^{\hat{z}(\kappa)} z^\chi dG_\kappa(z) = Z_{e,m}\left[\frac{\gamma_\ell}{1-\gamma_\ell-(1-\tau)\gamma_p}\frac{w_p}{w_\ell}(\kappa)\right] \tag{B.17}$$

$$\tag{B.18}$$

The two first equations are the same as in the dual economy equilibrium: indifference between blue-collar work and professional work and an expression of the measure of modern entrepreneurs in terms of primitives and the supply of high-skilled workers. The last equation is new, stating that blue-collar employment in modern firms equal the low-skilled supply.

Constructing and verifying equilibrium. To solve the system, we first note that at the boundary $\kappa = \hat{\kappa}$, the solution must be the one from the dual economy, which we denote $\hat{z}_{dual}$ and $(w_p/w_\ell)_{dual}$. This follows from the definition of $\hat{\kappa}$ as the precise skill level at which the blue-collar labor market clears at the dual-economy prices without a traditional sector.

For $\kappa > \hat{\kappa}$, we guess and verify that the equilibrium is a simple scaling of this solution:

$$\log \hat{z}(\kappa) = \log \hat{z}_{dual} + \log(\kappa/\hat{\kappa})$$
$$\log(w_p/w_\ell)(\kappa) = \log(w_p/w_\ell)_{dual} - (\rho-\chi)\log(\kappa/\hat{\kappa})$$

It is immediate that this solution respects the indifference between blue-collar work and professional work at the cut-off. For the market clearing condition, we use the structure of the skill distribution, $G_\kappa(z) = G(z/\kappa)$. Specifically, a change of variables ($u = z/\kappa$) shows that for any power ξ, the aggregate skill supply integral scales directly with κ:

$$\int_a^\infty z^\xi dG_\kappa(z) = \int_a^\infty z^\xi \frac{1}{\kappa} g\left(\frac{z}{\kappa}\right) dz = \kappa^\xi \int_{a/\kappa}^\infty u^\xi dG(u).$$

Under our proposed solution, the rescaled cutoff $\hat{z}(\kappa)/\kappa$ is constant and equal to $\hat{z}_{dual}/\hat{\kappa}$. Consequently, the high-skill supply integral scales with κ^{ρ}, the low-skill supply integral scales with κ^{χ}. When these terms are substituted into the new market-clearing condition (B.17), we obtain a power κ^{χ} on the left-hand side and a power κ^{ρ} on the right-hand side, which perfectly cancels the $-(\rho - \chi)$ power coming from the wage premium.

Last, given solutions for the cut-off and the skilled wage premium, we can recover the wage levels w_p, w_ℓ from the indifference condition between professional work and entrepreneurship (B.9) and the measure of professionals Z_p from (B.14), since both of these conditions hold in the economy without duality.

Properties of equilibrium. From the definition of the equilibrium, we immediately see that the cut-off type satisfies $\log \hat{z}(\kappa/\hat{\kappa}) = \log(\kappa/\hat{\kappa}) + \log \hat{z}$ as stated in the corollary, as well as the skilled wage premium being decreasing with κ. Furthermore, since the cut-off scales proportionally with the probability distribution, the share of workers above the threshold is constant, meaning that the share of white-collar workers is constant even though the conditional probability declines conditional on a skill level z. Last, the share of individuals who are entrepreneurs stays constant, since this is only pinned down by the share of individuals above the threshold and production parameters, both of which are fixed. Thus, average firm size stays the same.

C Estimation Appendix

This section provides details on how we estimate the quantitative model.

C.1 Moments, Weighting, and Model Fit

In Section 5.2 we use figures to display the targets and model fit. Here, we provide further details on the construction of these moments. We also describe how we weight the various moments.

At a high level, we target 125 moments in total: 20 moments on occupational shares by education and at the aggregate (Figure 6 and Table C.3); 20 moments on sectoral shares by education and at the aggregate (Figure 7 and Table C.4); 16 moments on educational shares by sector (Figure 8 and Table C.5); 16 moments on occupational shares within sector (Figure 9 and Table C.6); 15 moments on the distribution of firm size by sector (Figure 10 and Table C.7)[28]; 30 moments on white-collar employment share by firm size (Figure 11 and Table C.8) and 8 moments on wage gaps between and within education groups (Figure 12 and Table C.9).

Sources and Samples. The moments are constructed using a combination of the census data from IPUMS International and the labor force survey database. All moments that do not involve firm size are constructed using the census data, taking the latest available year for each country. All moments involving firm size are constructed using the LFS data. Since LFS samples are generally smaller, we pool all available years within a country and study the country-level average. Wage moments are based on the combination of 11 cross-sections from IPUMS International and 23 countries from the LFS with the necessary wage data (we use IPUMS International for countries covered in both).

Aggregation. We construct an internally consistent set of moments for our fictional "average" middle-income country as follows. We use the IPUMS International data to fit multinomial logistic regressions of (i) the employment share in each education $\times$ white collar status $\times$ sector cell, and (ii) the self-employment share conditional on education $\times$ white collar status $\times$ sector on a quadratic polynomial of log GDP per capita. We compute the fits from these regressions for the average GDP per capita among middle-income countries in the IPUMS International sample and construct all

[28]Table C.7 reports unconditional moments—for example, the total share of employees in firms with 11 or more workers—whereas Figure 10 shows conditional moments, such as the share of employees in firms with 11 or more workers within each sector, to facilitate cross-sector comparisons.

the moments in Tables C.3-C.6 (as well as the education shares in Table 1) by aggregating them up at the required level. The wage moments in Table C.9 are computed as quadratic fits on log GDP per capita, again evaluated at the average GDP per capita across middle-income countries in the whole IPUMS International sample.

For Table C.7, we compute two different measures of the distribution of firm size. For average firm size, we compute the inverse of the average sector-level self-employment rate for each country in the IPUMS International sample. We use logistic regressions and compute the fit as we did for other census moments. We compute the share of workers at medium and large firms in each country with the necessary data in the LFS database. We fit a logistic regression of these moments on a quadratic polynomial of log GDP per capita. We compute the fits from these regressions for the average GDP per capita among middle-income countries in the IPUMS International sample (so that we hold the definition of a middle-income country fixed).

Finally, Table C.8 again mixes two types of moments. For Panels A and B, we use the LFS data and fit multinomial logistic regressions of the employment share in each firm size group (1-10, 11-49, 50+) conditional on education $\times$ white collar status $\times$ sector on a quadratic polynomial of log GDP per capita. We apply these conditional probabilities to the education $\times$ white-collar status $\times$ sector distribution computed from the IPUMS International sample and aggregate them up at the required level. The moments in Panel C are instead constructed by pooling all countries in the LFS with more detailed firm size categories, regressing the white collar share within each firm size group on firm size and sector fixed effects, and computing predicted values on the displayed firm size grid.

Weighting and Fit. As noted above, Tables C.3-C.9 display the exact moments, data value, and model value for the moments used in our calibration. As is standard, we minimize a weighted sum of squared errors. Conceptually, we would like our measure of the error to be the percentage error in fitting each moment. However, we face the usual practical problem that for moments whose data value is close to 0, this percentage error is not well-defined. To avoid this, we instead use a moment-specific deflator, which is generally the average of all data values within a category. For example, in Table C.3, Panel A, we assign the deflator of 0.214 to all of the first four moments; this is simply the average of the data for these first four moments, which avoids assigning excess weight to the (low) value of the share of traditional entrepreneurs with tertiary education.

We also weight moments to ensure that different economic concepts contribute comparably to the overall fit. For instance, we want our estimation to give similar importance to matching the relationship between white-collar employment and firm size (Panel C of Table C.8) and to matching the wage premium for tertiary-educated workers (row 3 of Panel A of Table C.9). Yet the former concept is represented by about twenty separate moments, while the latter corresponds to just one. To balance this, we assign each moment in Panel C a weight of 0.05, so that the entire group sums to one. This logic guides our broader weighting scheme: we group moments by economic concept and allocate equal total weight across groups, based on our assessment of their relevance for the model's overall fit.

While some arbitrariness is unavoidable—since the model is overidentified and not all moments can be matched perfectly—most choices are straightforward. The only departure from equal weighting across groups is that we assign greater overall weight to patterns involving tertiary-educated individuals. For example, in Table C.4, we treat "employment shares across sectors by education" as one concept (implying a per-moment weight of 0.062, since $16 \times 0.062 = 1$), and we treat "employment shares across sectors for tertiary-educated individuals" as an additional concept, which raises the weight for the tertiary-educated rows to 0.312 (= 0.250 + 0.062). The final two columns of each table report the deflator and the corresponding weight applied to each moment.

TABLE C.3: OCCUPATIONAL SHARES

Moment	Model	Data	Deflator	Weight
Panel A. Traditional Entrepreneurs				
Traditional Entrepreneurs (No Primary)	0.315	0.374	0.214	0.250
Traditional Entrepreneurs (Primary)	0.299	0.257	0.214	0.250
Traditional Entrepreneurs (Secondary)	0.174	0.172	0.214	0.250
Traditional Entrepreneurs (Tertiary)	0.039	0.052	0.214	1.250
Traditional Entrepreneurs (Overall)	0.226	0.219	0.219	1.000
Panel B. Blue-Collar Workers				
Blue-Collar Workers (No Primary)	0.570	0.563	0.424	0.250
Blue-Collar Workers (Primary)	0.566	0.607	0.424	0.250
Blue-Collar Workers (Secondary)	0.449	0.426	0.424	0.250
Blue-Collar Workers (Tertiary)	0.147	0.101	0.424	1.250
Blue-Collar Workers (Overall)	0.473	0.475	0.475	1.000
Panel C. White-Collar Workers				
White-Collar Workers (No Primary)	0.095	0.040	0.311	0.250
White-Collar Workers (Primary)	0.113	0.107	0.311	0.250
White-Collar Workers (Secondary)	0.322	0.356	0.311	0.250
White-Collar Workers (Tertiary)	0.689	0.740	0.311	1.250
White-Collar Workers (Overall)	0.255	0.262	0.262	1.000
Panel D. Modern Entrepreneurs				
Modern Entrepreneurs (No Primary)	0.019	0.024	0.051	0.250
Modern Entrepreneurs (Primary)	0.022	0.029	0.051	0.250
Modern Entrepreneurs (Secondary)	0.055	0.046	0.051	0.250
Modern Entrepreneurs (Tertiary)	0.125	0.106	0.051	1.250
Modern Entrepreneurs (Overall)	0.046	0.044	0.044	1.000

Table C.4: Sectoral Shares

Moment	Model	Data	Deflator	Weight
Panel A. Agriculture				
Employment Share in Agriculture (No Primary)	0.338	0.354	0.250	0.062
Employment Share in Agriculture (Primary)	0.301	0.193	0.250	0.062
Employment Share in Agriculture (Secondary)	0.094	0.110	0.250	0.062
Employment Share in Agriculture (Tertiary)	0.006	0.032	0.250	0.312
Employment Share in Agriculture (Overall)	0.199	0.168	0.250	1.000
Panel B. Manufacturing				
Employment Share in Manufacturing (No Primary)	0.235	0.247	0.250	0.062
Employment Share in Manufacturing (Primary)	0.245	0.294	0.250	0.062
Employment Share in Manufacturing (Secondary)	0.256	0.227	0.250	0.062
Employment Share in Manufacturing (Tertiary)	0.124	0.138	0.250	0.312
Employment Share in Manufacturing (Overall)	0.231	0.244	0.250	1.000
Panel C. Low-Skilled Services				
Employment Share in Low-Skilled Services (No Primary)	0.305	0.269	0.250	0.062
Employment Share in Low-Skilled Services (Primary)	0.313	0.325	0.250	0.062
Employment Share in Low-Skilled Services (Secondary)	0.299	0.322	0.250	0.062
Employment Share in Low-Skilled Services (Tertiary)	0.132	0.182	0.250	0.312
Employment Share in Low-Skilled Services (Overall)	0.284	0.297	0.250	1.000
Panel D. High-Skilled Services				
Employment Share in High-Skilled Services (No Primary)	0.121	0.130	0.250	0.062
Employment Share in High-Skilled Services (Primary)	0.141	0.188	0.250	0.062
Employment Share in High-Skilled Services (Secondary)	0.351	0.341	0.250	0.062
Employment Share in High-Skilled Services (Tertiary)	0.738	0.648	0.250	0.312
Employment Share in High-Skilled Services (Overall)	0.285	0.290	0.250	1.000

TABLE C.5: EDUCATIONAL SHARES, WITHIN SECTOR

Moment	Model	Data	Deflator	Weight
Panel A. Agriculture				
Share of No-Primary Educated in Agriculture	0.248	0.308	0.250	0.062
Share of Primary Educated in Agriculture	0.592	0.450	0.250	0.062
Share of Secondary Educated in Agriculture	0.156	0.216	0.250	0.062
Share of Tertiary Educated in Agriculture	0.004	0.025	0.250	0.062
Panel B. Manufacturing				
Share of No-Primary Educated in Manufacturing	0.149	0.148	0.250	0.062
Share of Primary Educated in Manufacturing	0.415	0.472	0.250	0.062
Share of Secondary Educated in Manufacturing	0.366	0.307	0.250	0.062
Share of Tertiary Educated in Manufacturing	0.070	0.073	0.250	0.062
Panel C. Low-Skilled Services				
Share of No-Primary Educated in Low-Skilled Services	0.157	0.132	0.250	0.062
Share of Primary Educated in Low-Skilled Services	0.433	0.429	0.250	0.062
Share of Secondary Educated in Low-Skilled Services	0.349	0.359	0.250	0.062
Share of Tertiary Educated in Low-Skilled Services	0.061	0.080	0.250	0.062
Panel D. High-Skilled Services				
Share of No-Primary Educated in High-Skilled Services	0.062	0.066	0.250	0.062
Share of Primary Educated in High-Skilled Services	0.194	0.254	0.250	0.062
Share of Secondary Educated in High-Skilled Services	0.407	0.389	0.250	0.062
Share of Tertiary Educated in High-Skilled Services	0.337	0.291	0.250	0.062

TABLE C.6: DIFFERENCES IN WITHIN-SECTOR ORGANIZATION

Moment	Model	Data	Deflator	Weight
Panel A. Traditional Entrepreneurs				
Traditional Entrepreneurs in Agriculture	0.545	0.596	0.256	0.250
Traditional Entrepreneurs in Manufacturing	0.137	0.154	0.256	0.250
Traditional Entrepreneurs in Low-Skilled Services	0.279	0.235	0.256	0.250
Traditional Entrepreneurs in High-Skilled Services	0.023	0.039	0.256	0.250
Panel B. Blue-Collar Workers				
Blue-Collar Workers in Agriculture	0.441	0.377	0.472	0.250
Blue-Collar Workers in Manufacturing	0.677	0.665	0.472	0.250
Blue-Collar Workers in Low-Skilled Services	0.498	0.528	0.472	0.250
Blue-Collar Workers in High-Skilled Services	0.306	0.317	0.472	0.250
Panel C. White-Collar Workers				
White-Collar Workers in Agriculture	0.014	0.020	0.233	0.250
White-Collar Workers in Manufacturing	0.142	0.152	0.233	0.250
White-Collar Workers in Low-Skilled Services	0.162	0.172	0.233	0.250
White-Collar Workers in High-Skilled Services	0.608	0.587	0.233	0.250
Panel D. Modern Entrepreneurs				
Modern Entrepreneurs in Agriculture	3.75e-09	0.008	0.039	0.250
Modern Entrepreneurs in Manufacturing	0.045	0.029	0.039	0.250
Modern Entrepreneurs in Low-Skilled Services	0.062	0.065	0.039	0.250
Modern Entrepreneurs in High-Skilled Services	0.064	0.056	0.039	0.250

TABLE C.7: DISTRIBUTION OF FIRM SIZES

Moment	Model	Data	Deflator	Weight
Panel A. Average Firm Size				
Average Firm Size (Agriculture)	1.835	1.658	5.230	1.000
Average Firm Size (Manufacturing)	5.502	5.472	5.230	1.000
Average Firm Size (Low-Skilled Services)	2.940	3.329	5.230	1.000
Average Firm Size (High-Skilled Services)	11.542	10.460	5.230	1.000
Average Firm Size (Overall)	3.677	3.802	3.802	1.000
Panel B. Medium+ Firms				
Employment in 11+ Firms (Agriculture)	0.000	0.034	0.084	0.125
Employment in 11+ Firms (Manufacturing)	0.133	0.119	0.084	0.125
Employment in 11+ Firms (Low-Skilled Services)	0.104	0.089	0.084	0.125
Employment in 11+ Firms (High-Skilled Services)	0.242	0.190	0.084	0.125
Employment in 11+ Firms (Overall)	0.480	0.432	0.336	0.500
Panel C. Large Firms				
Employment in 51+ Firms (Agriculture)	0.000	0.017	0.084	0.125
Employment in 51+ Firms (Manufacturing)	0.118	0.074	0.084	0.125
Employment in 51+ Firms (Low-Skilled Services)	0.095	0.042	0.084	0.125
Employment in 51+ Firms (High-Skilled Services)	0.116	0.107	0.084	0.125
Employment in 51+ Firms (Overall)	0.328	0.240	0.336	0.500

TABLE C.8: WHITE-COLLAR EMPLOYMENT SHARE BY FIRM SIZE

Moment	Model	Data	Deflator	Weight
Panel A. Firms 1–10				
White-Collar Share Firms 1–10 (Agriculture)	0.014	0.013	0.206	0.250
White-Collar Share Firms 1–10 (Manufacturing)	0.068	0.100	0.206	0.250
White-Collar Share Firms 1–10 (Low-Skilled Services)	0.079	0.164	0.206	0.250
White-Collar Share Firms 1–10 (High-Skilled Services)	0.368	0.546	0.206	0.250
White-Collar Share Firms 1–10 (Overall)	0.076	0.182	0.326	0.500
Panel B. Firms 11+				
White-Collar Share Firms 11+ (Agriculture)	0.107	0.084	0.364	0.250
White-Collar Share Firms 11+ (Manufacturing)	0.196	0.266	0.364	0.250
White-Collar Share Firms 11+ (Low-Skilled Services)	0.303	0.408	0.364	0.250
White-Collar Share Firms 11+ (High-Skilled Services)	0.651	0.695	0.364	0.250
White-Collar Share Firms 11+ (Overall)	0.449	0.470	0.326	0.500
Panel C. Predicted Share by Firm Size				
White-Collar Share (Firm Size 5)	-0.090	-0.116	0.028	0.050
White-Collar Share (Firm Size 10)	-0.057	-0.062	0.028	0.050
White-Collar Share (Firm Size 15)	-0.038	-0.034	0.028	0.050
White-Collar Share (Firm Size 20)	-0.025	-0.017	0.028	0.050
White-Collar Share (Firm Size 25)	-0.015	-0.005	0.028	0.050
White-Collar Share (Firm Size 30)	-0.007	0.004	0.028	0.050
White-Collar Share (Firm Size 35)	-0.001	0.010	0.028	0.050
White-Collar Share (Firm Size 40)	0.005	0.015	0.028	0.050
White-Collar Share (Firm Size 45)	0.009	0.019	0.028	0.050
White-Collar Share (Firm Size 50)	0.013	0.022	0.028	0.050
White-Collar Share (Firm Size 55)	0.017	0.024	0.028	0.050
White-Collar Share (Firm Size 60)	0.020	0.025	0.028	0.050
White-Collar Share (Firm Size 65)	0.023	0.026	0.028	0.050
White-Collar Share (Firm Size 70)	0.026	0.027	0.028	0.050
White-Collar Share (Firm Size 75)	0.028	0.027	0.028	0.050
White-Collar Share (Firm Size 80)	0.030	0.028	0.028	0.050
White-Collar Share (Firm Size 85)	0.032	0.027	0.028	0.050
White-Collar Share (Firm Size 90)	0.034	0.027	0.028	0.050
White-Collar Share (Firm Size 95)	0.036	0.027	0.028	0.050
White-Collar Share (Firm Size 100)	0.037	0.026	0.028	0.050

TABLE C.9: WAGE PREMIA AND DISPERSION

Moment	Model	Data	Deflator	Weight
Panel A. Wage Premia				
Wage Premium (Primary)	0.035	0.131	0.646	1.000
Wage Premium (Secondary)	0.366	0.526	0.646	1.000
Wage Premium (Tertiary)	1.122	1.280	0.646	1.000
Panel B. Wage Dispersion				
St. Dev. Log Wages (No Primary)	0.521	0.619	0.619	0.250
St. Dev. Log Wages (Primary)	0.532	0.601	0.601	0.250
St. Dev. Log Wages (Secondary)	0.684	0.651	0.651	0.250
St. Dev. Log Wages (Tertiary)	0.857	0.710	0.710	0.250
St. Dev. Log Wages (Overall)	0.623	0.635	0.635	1.000

C.2 Identification

This section reports two exercises that provide evidence on the identification of the model and the moments most informative for each parameter.

Single-Peaked Minimum Distance Function. We first examine the shape of the minimum distance function to verify that our calibration corresponds to both a local and global minimum. We first vary one parameter at a time while holding all others fixed to assess local identification, and then vary all parameters jointly over a broad support to assess global identification. In practice, for this second exercise, we draw 4,000,000 parameter vectors spanning a wide range around our estimates.[29]

Figure C.11 summarizes the results. Each panel corresponds to one parameter. The x-axis reports alternative parameter values, and the y-axis reports the model fit at that value, relative to the best fit. The weights of the minimum distance function are normalized so that the vertical distance can be interpreted as the increase in the average squared percentage deviation of the moments from their targets (e.g., a value of one corresponds to a 1% increase in squared deviation, or a 10% increase in the average percentage deviation).

Within each panel, the blue line shows the model fit when varying only the chosen parameter, thus testing for a local optimum. The red line shows the fit when all parameters are allowed to vary simultaneously, thus testing for a global optimum. The figure shows that all parameters are well identified both locally and globally: each curve exhibits a clear minimum at the calibrated value, and the fit deteriorates as we move away from it. As expected, the global fit is always better (i.e., closer to the best fit) than the local one, since allowing all parameters to adjust improves the overall fit.

Jacobian Matrix. While Figure C.11 confirms that parameters are well identified, it does not reveal which moments are most informative for each parameter. To explore this mapping, Figure C.12 presents a normalized Jacobian matrix summarizing how each parameter affects each targeted economic concept. For each parameter, we select the moment that, according to our heuristic mapping discussed in the main text, should be most directly related to it.

Moments and parameters are ordered in the matrix so that the moment in the first row corresponds to the parameter in the first column, the second to the second, and so on.

[29] Given the high dimensionality of the parameter space, even 4,000,000 draws cannot fully cover it. To increase precision, we draw more densely near the estimated values.

Most moments are self-explanatory. The only two requiring clarification are the sorting variables. The variable sorting into modern entrepreneurship measures the relative propensity of individuals with secondary or higher education to enter modern entrepreneurship and of individuals with primary or less education to enter traditional entrepreneurship.[30] The variable sorting into high-skill services is defined analogously, focusing on employment in high-skill services rather than agriculture.

We use the 4,000,000 model evaluations described above to compute all targeted moments for each parameter vector. For each pair of moment and parameter, we then run a simple univariate regression and store the resulting slope, which captures the sensitivity of that moment to the parameter. All slopes are normalized so that the absolute values sum to one along both rows and columns, using a Sinkhorn balancing algorithm. The resulting normalized matrix is displayed in Figure C.12.

In interpreting the magnitudes in Figure C.12, note that in a hypothetical case where each parameter affects only its corresponding moment, the diagonal elements of the matrix would all equal one.Conversely, if all parameters affected all moments equally, every cell would equal $1/13 \approx 0.077$. In practice, we find that diagonal entries are substantially higher than off-diagonal ones and reach the maximum for each parameter, indicating that the targeted moment is indeed the one most closely associated with that parameter. A similar pattern holds across rows: for nearly every moment, the parameter identified heuristically as its key determinant is also the most influential empirically. The only notable exception is sorting into high-skill services, which is also strongly affected—unsurprisingly—by the relative utility parameters for agriculture and services.

Overall, this exercise validates the heuristic mapping between parameters and moments described in the main text.

[30] Formally, we compute the difference between the share of individuals with secondary or higher education who are modern entrepreneurs and the share of individuals with primary or less education who are modern entrepreneurs, plus the difference between the share of individuals with secondary or higher education who are traditional entrepreneurs and the share of those with less than primary education who are traditional entrepreneurs.

Figure C.11: Identification Checks

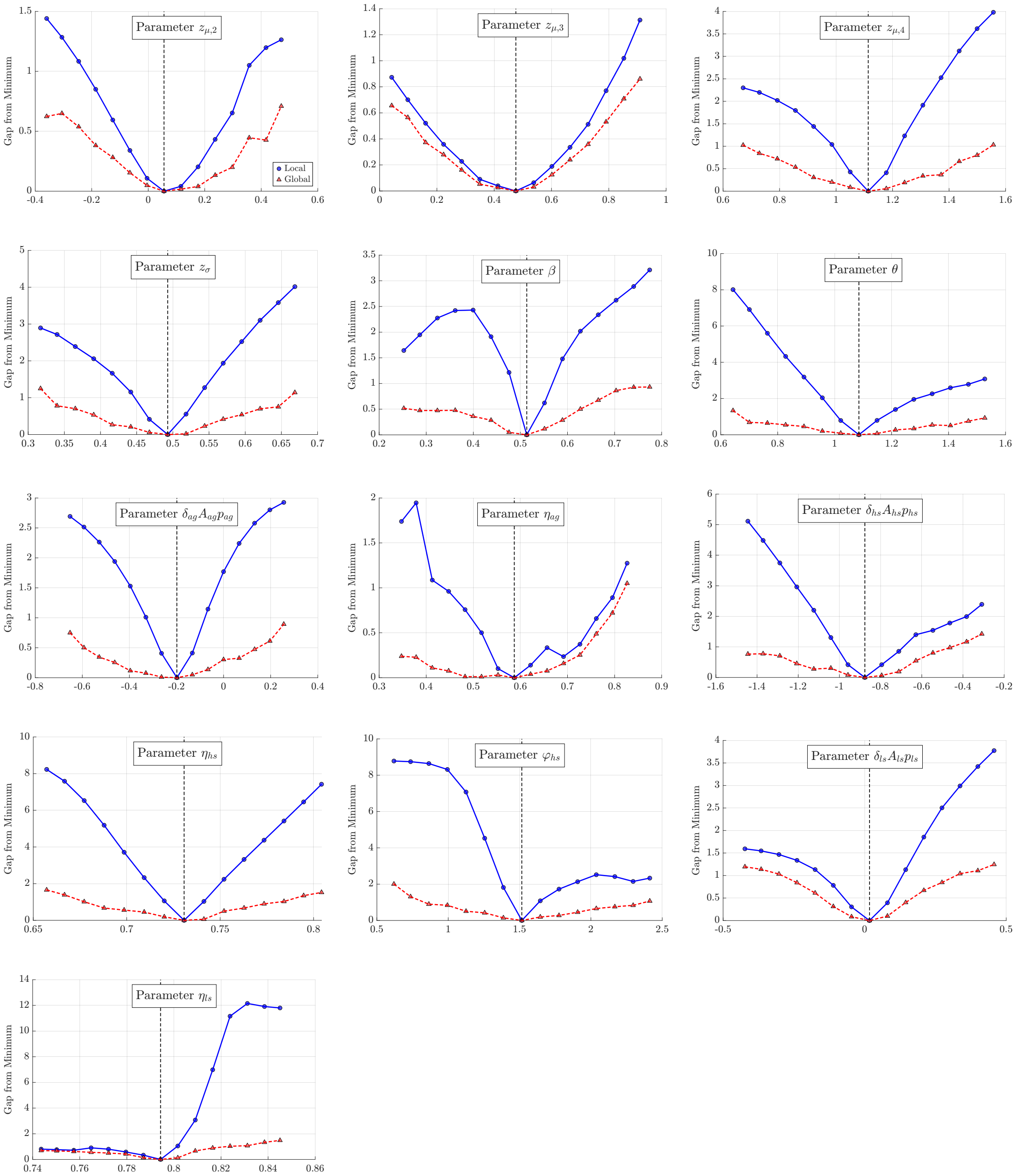
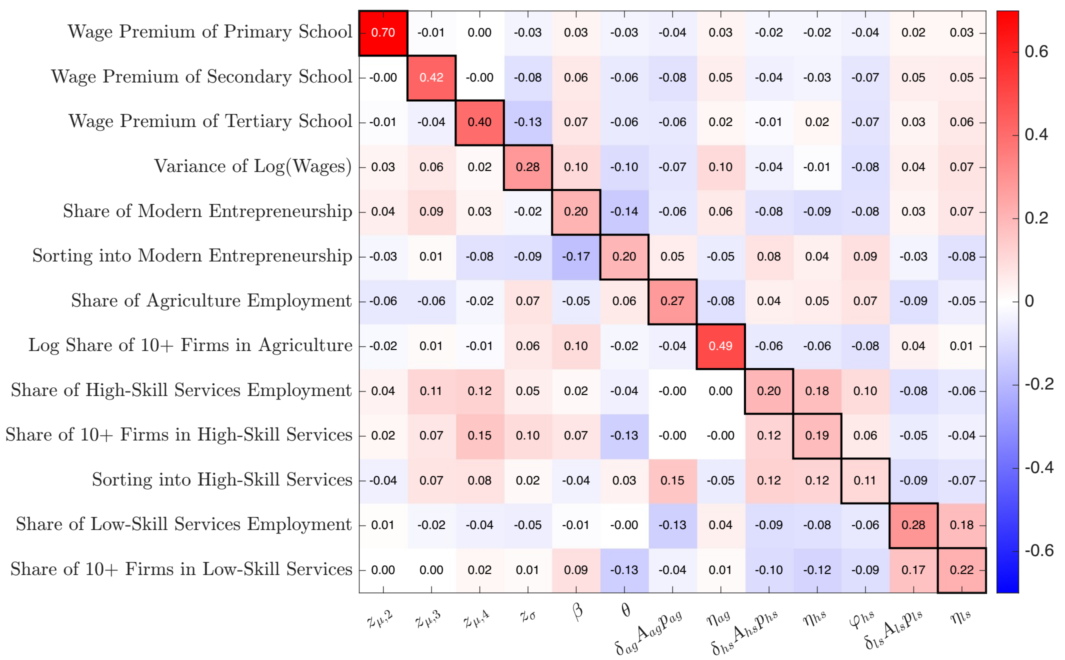


FIGURE C.12: JACOBIAN MATRIX TO VERIFY IDENTIFICATION ARGUMENT



D Benchmarking Against Causal Evidence

This section provides details on how we replicate the design of the quasi-experimental and experimental evidence on school expansions and management training interventions in our model.

D.1 Brazilian College Expansion

To approximate Cox (2025)'s experiment in the model, we simulate an increase of 3.5 percentage points of the tertiary share and a corresponding decline of the secondary share, based on the decline in the college cost inferred by Cox in his structural model. Given that Cox's design uses regional variation, we hold all sectoral prices fixed, effectively treating Brazilian regions as small open economies. Cox reports the effects of changes in the college share among the 25-34 age group on outcomes measured either for the same age group or the overall population. We use the former when available, and rescale the model-based coefficient by multiplying it by the 25-34 share in Brazil 2000 within the 25-59 sample when only the aggregate results are reported (this applies to the self-employment and large firms' employment share outcomes in Table 4).

D.2 INPRES School Construction Program

We use data from the 1995 Intercensus Population Survey from Ruggles et al. (2025), and impose the same sample restrictions as in the rest of the paper. Following Duflo (2001) and Porzio, Rossi and Santangelo (2022), we take individuals born in 1962-1968 as the control group and individuals born in 1968-1972 as the treatment group. We consider the specification

$$y_{icd} = \alpha_c + \alpha_d + \beta \text{Sch}_{icd} + \sum_k \left(X_d I_i^k \right) \Gamma_k + \varepsilon_{icd}$$

where y_{icd} denotes outcomes for individual i in cohort c and district d, α_c and α_d are cohort and district fixed effects, Sch_{icd} is years of schooling, and $\sum_k \left(X_d I_i^k \right) \Gamma_k$ denotes interactions between cohort fixed effects and a vector of district-level outcomes in 1971 (enrollment rate and the age 5-14 population). We then instrument Sch_{icd} with the interaction between a treated group dummy and the intensity of the program (number of schools built per 1000 children) in district d. We refer the reader to Duflo (2001) for more details on the context and the identification strategy.

Column (1) of Table D.10 shows the first-stage results - an additional school per 1000 students leads to 0.16 years of schooling for the treated cohorts. Columns (2)-(5)

show that this increase in schooling is due to a decline in the share without primary education and an increase across all other education groups, secondary in particular. To compare the model's predictions with the IV results in Table 4, we consider changes in the educational shares given by the coefficients in columns (2)-(5) divided by the coefficient in column (1), so that the variation corresponds to an additional year of schooling, and compute the resulting changes across the different outcomes. Given that the empirical exercise consists of a cross-cohort comparison within a district, we keep all prices and wages fixed.

TABLE D.10: FIRST STAGE RESULTS

	(1) Yrs School	(2) No Primary	(3) Primary	(4) Secondary	(5) Tertiary
Treated x Intensity	0.162	-0.017	0.003	0.010	0.004
	(0.040)	(0.004)	(0.006)	(0.005)	(0.002)
N	44160	44160	44160	44160	44160
F Stat	16.26	14.57	0.29	3.93	3.57
Cohort FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes

Notes: The Table shows estimates from regressions of either years of schooling (column 1) or dummies for educational attainment (columns 2-5) on the interaction between a treated group dummy (born in 1968-1972) and the number of schools built per 1000 children in the district. All specifications control for cohort fixed effects, district fixed effects and interactions between cohort fixed effects and a vector of district-level outcomes in 1971 (enrollment rate and the age 5-14 population). Robust standard errors in parentheses.

D.3 Italian Management Training

Giorcelli (2019) provides evidence from a management training intervention in post-World War II Italy. We use the calibrated middle-income economy to simulate this intervention. We focus on firms with at least 10 employees, consistent with the design of the original training program. We simulate a drop in τ that induces an increase in TFPR consistent with Giorcelli (2019)'s estimates. To compute TFPR, we map efficiency units in the model into employment in the data emp by dividing efficiency units by the average efficiency units per worker. We then compute $TFPR = \log y(z) - 0.6 \log emp(z)$. Our main outcome in this case is managers per worker, which we measure by dividing the efficiency units of each type of labor in each firm by the economy-wide average efficiency units per worker of each type of labor.

D.4 Indian Management Training

Bloom et al. (2013) provide evidence from an experimental management training program in India. We use the calibrated low-income economy to simulate this intervention. We focus on firms with at least 100 employees, consistent with the design of the experiment. We simulate a drop in τ that induces an increase in TFPR consistent with Bloom et al. (2013)'s estimates. We measure TFPR as we did for the Italian intervention; it turns out that the two studies use very similar labor shares.

The main outcome of interest is the causal effect of the management training intervention on the unweighted share of a range of 38 management practices that a firm had adopted. Conceptually, we compare this to the change in the share of tasks professionalized q in order to induce the necessary TFPR increase in the model.

The main challenge is that share of management practices and q do not necessarily have a comparable underlying scale or distribution. Our approach is to report each effect in terms of how far it moves treated firms within the baseline (pre-treatment or calibrated) CDF. While Bloom et al. (2013) do not report the full baseline distribution, they do report the min, median, and max (Table I). We fit a triangular distribution to these statistics. We then evaluate the treatment effect in terms of how far in the CDF it moves the treated firms. In the model, we also report how far the change in q moves firms in the distribution, in this case among firms with more than 100 workers in the baseline, calibrated low-income economy.

Supplementary Materials Appendix

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