Economic Development According to Chandler*

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Abstract

Chandler (1977) documents that large, modern businesses require hierarchies of white-collar workers for coordination and administration. We show that low education levels in developing countries limit the white-collar workforce, thereby constraining the potential for large firms. We expand the occupational choice model of Lucas (1978) by allowing 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. Expansions of education and reductions in barriers to large firms are complementary in generating the endogenous reorganization of production.

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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 the large volume 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 fully benefit from new technologies and lost ground to their competitors that did (Chandler, 1977, 1990).

This paper shows that Chandler's insights about development remain relevant today. We start by documenting motivating facts using censuses and labor force surveys spanning nearly one hundred countries. Large firms use white-collar labor more intensively around the world. Development is associated with a shift towards white-collar employment that is most pronounced in the manufacturing and low-skill service sectors, consistent with Chandler's historical work.

We then document a new fact: the large differences in white-collar employment shares between developing and developed countries are almost entirely accounted for by differences in educational attainment. This pattern reflects that there are large differences in the share of white-collar workers across education levels, ranging from ten percent for workers without any education to ninety percent for workers with tertiary education. At the same time, the share of white-collar workers conditional on education level is similar in developing and developed 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. The model features a continuum of individuals with exogenous skills. As in Lucas (1978), individuals decide whether to become entrepreneurs or workers, but we distinguish between two types of workers: blue-collar laborers and white-collar professionals. Workers supply their labor in competitive markets. Entrepreneurs hire the workers, pay their wages, and receive firm profits as their income.

Laborers and professionals perform different tasks within the firm. Laborers perform production tasks that lead directly to output, fulfilling the same role as the homogeneous labor in the standard Lucas model. The main new feature of the model is

that firms also need to perform a continuum of administrative tasks in order to produce. For each task, the entrepreneur decides whether to do it herself or to hire professionals to do it for her. We provide conditions under which the full task assignment problem is equivalent to a simpler problem in which the entrepreneur operates a decreasing returns Cobb-Douglas production function with laborers and professionals as inputs.[1] In addition to choosing how much of each type of labor to hire, the entrepreneur also chooses the share of tasks to professionalize. This choice determines the organization of the firm: an increase in the share of tasks that are professionalized allows the firm to produce with less severe decreasing return to scale, increases the factor share of white-collar labor, and leads the firm to become larger.

Occupational choices can be characterized by two cutoff skill levels. Workers with the lowest levels of skills are indifferent between becoming entrepreneurs or working as laborers, those with intermediate levels of skills become professionals, and those with the highest levels of skills become entrepreneurs. While both the least-skilled and most-skilled workers are entrepreneurs, they operate very different types of firms. The least-skilled entrepreneurs run small firms and professionalize few or no tasks, whereas the most-skilled entrepreneurs run large firms and professionalize a larger share of the tasks. Thus, the model can endogenously generate a dual economy with co-existence of traditional and modern firms organized very differently.

Under simplifying assumptions, the analytical model yields sharp characterizations that are useful for building intuition about the relationship between skills, the organization of production, and development. Our main comparative static describes the effects of an exogenous increase in the aggregate supply of skills. This change leads to a higher share of white-collar workers that operates through a pure composition effect, consistent with our empirical accounting results. The mechanism for this result is that increasing the aggregate supply of skills leads to a higher share of workers who want to be both professionals and entrepreneurs of large firms. The former increases the supply of white-collar workers, but the growth in the modern sector increases the demand for white-collar workers. Under the simplifying assumptions we use, this *skill-biased organizational change* exactly offsets the increase in supply and leaves the skill premium constant. Because of the endogenous duality, the growth in the modern sector also pulls less-skilled workers out of traditional entrepreneurship and into large firms where they work as laborers. This mechanism is also consistent with new evidence that we document.

We then use a richer quantitative model to explore these forces further. The quantitative model relaxes many of the strong assumptions needed for analytical solutions.

[1] This equivalence is similar to Acemoglu and Restrepo (2018).

It includes four sectors, each with its own technology that allows for differential productivity gains from professionalizing administrative tasks. We close the model by imposing standard preferences from the literature on structural transformation (Comin, Lashkari and Mestieri, 2021). Combined, these elements allow the model to generate two-way interactions between structural transformation and the reorganization of production.

We calibrate the model to fit a rich set of cross-sectional moments characterizing the relationships among education, occupational choice, sectoral choice, and the organization of production for the average middle-income country in our data. We focus on middle-income countries because they feature co-existence of modern and traditional firms. Although the model is overidentified, it provides a good fit to the moments we consider. We then recalibrate a limited set of driving forces to generate model economies that are consistent with the average low-income and high-income countries from our data.

The model is calibrated purely to cross-sectional moments. To test the strength of the causal mechanisms embedded in the model, we replicate the direct effect of an exogenous expansion in schooling as well as exogenous exposure to management training and compare the model's performance to estimates in the relevant literature (Cox, 2025; Porzio, Rossi and Santangelo, 2022; Bloom et al., 2013; Giorcelli, 2019). We find that the model performs well on both dimensions and is, if anything, conservative in the magnitude of its effects.

We use the model as a laboratory to understand the determinants of the reorganization of production from small firms and self-employment to large firms. Our counterfactuals yield two main insights. First, reorganization of production and structural transformation are largely distinct phenomena. In our counterfactual, we take the calibrated low-income economy and give it the exogenous parameters traditionally associated with structural transformation of the middle-income economy. This counterfactual economy generates most of the structural transformation between low-income and middle-income countries, missing primarily the expansion of the high-skill service sector. However, it experiences almost no reorganization of production.

Second, we find that the reorganization of production is generated by a joint, complementary process of increasing skills and relaxing barriers to the growth of large firms. We provide several counterfactuals to help make this point. First, we again take the low-income economy, and now give it all the parameters of the middle-income economy except for its skills. We show that in this case, the economy experiences some reorganization of production, but only about one-fourth of that in the baseline economy. The wage for white-collar worker rises, inducing some workers to switch occupations.

Still, the economy has a limited supply of white-collar labor and so it cannot fully reorganize.[2]

In a second counterfactual, we do the opposite: we give the low-income economy only the skills of the middle-income economy. This economy achieves a little more than half of the total reorganization of production. In this case, the lack of demand for white-collar labor is the main barrier: the price of white-collar labor falls and skilled workers become less likely to take up white-collar labor. Our final counterfactual considers the most pessimistic case, where the low-income country has higher skills but also faces large firm size barriers that prevent any reorganization of production. We show that this economy features a low price for white-collar labor and substantial "underemployment" of educated workers in blue-collar occupations, consistent with the experience of some developing countries.

Our paper owes an obvious debt to Chandler's historical work. We seek to 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]

We are particularly closely related to three papers that combine elements of these literatures in the context of development. Akcigit, Alp and Peters (2021) formulate a model where firm owners reorganize production by choosing how many tasks to delegate in response to the quality of contract enforcement. Their model also features endogenous returns to scale, but uses a different driving mechanism. Amaral and Rivera-Padilla (2024) develop a model where entrepreneurs first make an extensive margin choice between a traditional and a modern technology, and then those who choose the modern technology also make an intensive margin adoption choice. Their paper differs in that they connect the model primarily to data about technology adoption rather than the organization of production. They also generate a dual economy through the assumption of an extensive margin technology choice; we generate duality despite all entrepreneurs having access to a common technology. Finally, Cox (2025) provides

[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 has large effects on 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), and Gottlieb, Poschke and Tueting (2025).

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

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 some of our results.

2 Motivating Evidence

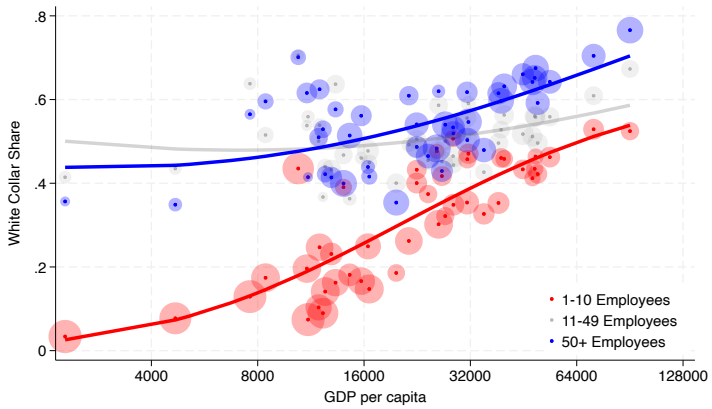
This section documents several facts that motivate our model and analysis. We use representative data sets drawing on nearly one hundred countries around the world to show the relevance of Chandler's insights today. We then provide new evidence on the role that skills play in the reorganization of production into large firms. To keep the exposition brief we describe the data and main results briefly, with additional discussion and results reserved for Appendix A.

As described in the Introduction, we build on two essential insights of Chandler's historical work covering the Second Industrial Revolution in the United States (Chandler, 1977). The first insight is that new technologies that leveraged economies of scale and scope greatly raised the productivity of operating a large modern business enterprise – but only for firms that developed a hierarchy of white-collar workers to administer and coordinate production.[5] We use the the database of labor force surveys from Donovan, Lu and Schoellman (2023) to document the systematic importance of white-collar workers for large firms. That database includes harmonized occupations at the International Standard Classification of Occupations (ISCO) 1-digit level. We define white-collar workers to include the 1-digit codes 1–4 (managers, professionals, technicians and associate professionals, and clerks) and blue-collar workers to include the 1-digit codes 5–9 (service and sales, agriculture, crafts and trades, plant and machine operators, and elementary occupations). The database also includes firm size grouped into three categories for a large number of countries: small firms with 1–10 employees, medium-sized firms with 11-49 employees, and large firms with 50 or more employees.

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 $\times$ firm size category, with the three firm size categories plotted using different colors. In

[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).

FIGURE 1: WHITE-COLLAR SHARE AND FIRM SIZE



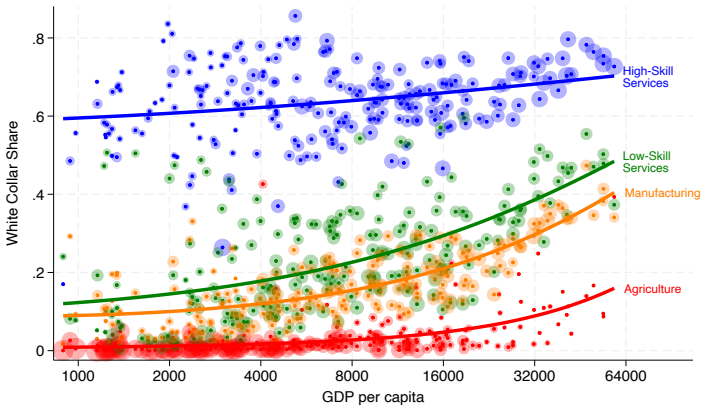
this and subsequent figures, we scale the size of each marker in proportion to the employment share of the relevant category in the country as a whole and include quadratic best fit lines for reference. There are large differences in the employment share of white-collar workers across firm size categories. These differences are particularly pronounced in developing countries, where there is a large gap between small as compared to medium or large firms. Medium and large firms have similar, high white-collar employment shares within most countries, so we pool them together for the remainder of the paper.

The second insight of Chandler that is relevant is that the productivity advantages conferred by new technologies and large firms organized around a hierarchy of white-collar workers varied substantially across industries. The advantages were concentrated in manufacturing, transportation, and wholesale and retail trade; they were smaller or non-existent in other industries.[6] We use the census microdata from Ruggles et al. (2025*a*) 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.

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 $\times$ year

[6]Again in Chandler's words, "The large industrial enterprise continued to flourish when it used capital-intensive, energy-consuming, continuous or large-batch production technology to produce for mass markets. It flourished when its markets were large enough and its consumers numerous enough and varied enough to require complex scheduling of high-volume flows and specialized storage and shipping facilities, or when the marketing of its products in volume required the specialized services of demonstration, installation, after-sales service and repair, and consumer credit." (Chandler, 1977, p. 347) These factors led primarily to "a relatively small number of large mass producing, large mass retailing, and large mass transportation enterprises" (Chandler, 1977, p. 11).

FIGURE 2: SECTORS AND WHITE-COLLAR LABOR



$\times$ sector, with the four sectors plotted using different colors. There are two main findings in this figure. 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 both transportation as well as 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.

2.1 Skills and the Organization of Production

Our perspective on contemporary development differs from Chandler's historical work in one important dimension. Chandler's study of U.S. history takes the view that innovation of new technologies and growth in 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 more than a century after they were invented. Our view is that developing countries today have low educational attainment that limits the size of the potential white-collar workforce, which inhibits the reorganization of firms and adoption of new technologies.

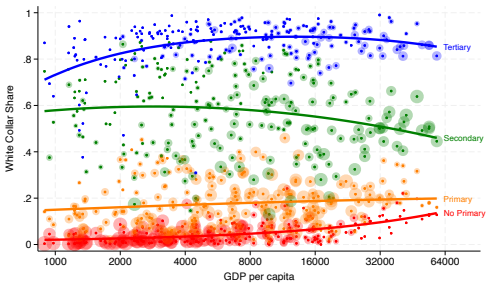
There are certainly large differences in the size of the white-collar workforce across countries, ranging from roughly 10 percent in the poorest countries to 60 percent in the richest (Figure A.1). Our first novel empirical contribution is to document that these

[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.

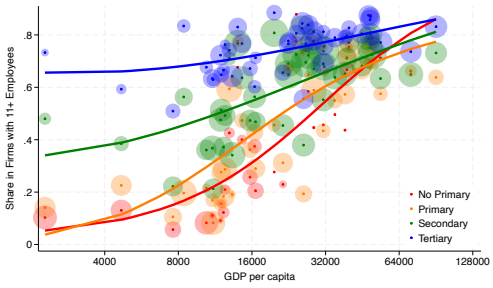
differences are entirely accounted for by differences in human capital. Using the international census data, we measure human capital as educational attainment in four broad bins: less than primary completed, primary completed, secondary completed, and tertiary completed. Figure 3a plots the share of white-collar workers at the country × year × education level against PPP GDP per capita, with the four education levels plotted using different colors.[8] The striking finding is that while there are large differences in the share of white-collar workers between education groups, there is essentially no relationship between the share of white-collar workers and development after conditioning on educational attainment. For example, roughly 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.

FIGURE 3: EDUCATION AND THE ORGANIZATION OF PRODUCTION

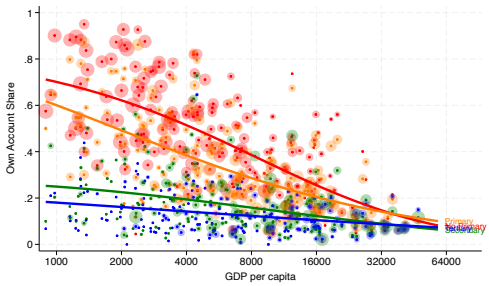
(a) White-Collar Share by Education



(b) Medium and Large Firm Share by Education



(c) Own Account Work by Education



This fact turns out to be extremely robust. Appendix A.2 shows that similar facts hold 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 variation in the share of white-collar workers.[9] Overall, the strength and consistency of

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

[9] An implication of our findings is that large firms also use educated workers more intensively around

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 return to the labor force surveys to document how firm size varies with 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. Each marker in this figure captures a country $\times$ education level, with the four education levels plotted using different colors.

This figure shows that education is much less able to account for cross-country variation in firm size. Instead, development is associated with a substantial transformation of the organization of production for less-educated workers. For example, workers with a primary education rarely engage in white-collar work – roughly twenty percent do so globally. Despite this fact, development is still associated with a substantial shift in their workplace. 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 reorganization of production, and development. The model features a continuum of individuals with heterogeneous skills who make occupational choices. Individuals who become entrepreneurs also choose the organization of their firm, which we model as a decision about whether to hire professional white-collar workers to perform administrative tasks. 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, including by adding multiple sectors, when we take it to the data in Section 5. Proofs for this section and the next are in Appendix B.

the world, which is consistent with contemporaneous work by Gottlieb, Poschke and Tueting (2025).

3.1 Environment

We model the long-run (static) equilibrium of an economy with one factor of production, labor, and many sectors. 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) model of span of control. The production process uses two task inputs. First, there is a single production task that can only be accomplished by hiring laborers, for example machine operators on an 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 size-dependent distortions, which we model as a wedge $\tilde{\tau}(\{n_p(i)\})$ that is an increasing function of how intensively professionals are used in production. This wedge stands in for the many legal restrictions, tax laws, barriers, and other cost factors (besides labor) that inhibit setting up larger firms in a country.

Formally, an entrepreneur with skill z solves

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

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 size-dependent distortions.

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

The parameter τ governs the extent of size-dependent distortions: when $\tau = 0$, there is no distortion; for $\tau > 0$, the returns to scaling up by hiring more white-collar workers are reduced.

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:

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

where

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

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 extent of decreasing returns to scale in production $\eta(q)$. We return to this point when we characterize the optimal choices of q for different types of entrepreneurs in Section 4.1. Note that the way we introduce τ has the effect that it reduces the incentive to professionalize tasks, the equilibrium firm size, and the equilibrium returns to scale for all entrepreneurs with $q > 0$. Finally, we define $y(z)$ to be the optimally chosen output by an entrepreneur with productivity z, which solves problem 2.

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. $\omega_{\pi,j}(z)$*,* $\omega_{p,j}(z)$*,* $\omega_{\ell,j}(z)$ *satisfy the occupational choice* (3)*, that is,*

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

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 several important properties of equilibrium in the model, with a focus on the optimal organization of production chosen by entrepreneurs, occupational choice, and sectoral choice. With these properties in hand, we provide analytical results to build intuition for the interaction between human capital and the reorganization 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 component of TFP becomes

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

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

We also define two objects that are central in the characterization of the equilibrium.

DEFINITION 1. The *skill premium* is defined as $\mathbb{W} \equiv \log \frac{w_p \gamma_\ell}{w_\ell \gamma_p}$.

DEFINITION 2. *Scalability* is defined as $\mathbb{A} \equiv \frac{1}{\gamma_p}\log\beta$.

The skill premium captures the relative price of efficiency units of professionals and laborers. Scalability is the potential productivity gains from professionalizing administrative tasks, which is informative about the benefits from adopting managerial capitalism. We now characterize the solutions to the worker's problem.

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 characterize next. An entrepreneur takes prices and 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:

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

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

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

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).[10] 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 firm productivity $\tilde{A}(q)$, the factor share of professionals $\alpha(q)$, the returns to scale $\eta(q)$, the distortion the entrepreneur faces $\tilde{\tau}(q)$, and the return to entrepreneurial skills z.

[10] One important distinction is that Lucas (1978) and much of the following literature refers to z as the ability of the manager. We prefer the term entrepreneur because some of the professionals hired to perform administrative tasks will themselves be managers.

We use equation (4) 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 concave function of q.[11]

LEMMA 2 (Optimal Organization of Production)**.** Let $\theta > \frac{\gamma_p^2}{1-\gamma_\ell}$. Then there exists a cutoff value $\log \hat{z}_q$ given by

$$\log \hat{z}_q = (1-\gamma_\ell)\left[1+\tau+\mathbb{W}-\mathbb{A}-\frac{\log\left(A\frac{\gamma_\ell}{w_\ell}\right)}{1-\gamma_\ell}\right].$$

The optimal choice of q is given by a monotonically increasing and differentiable function $g(\cdot)$ satisfying $g(0)=0$ and $\lim_{x\to\infty} g(x)=1$ such that

$$q(z) = \begin{cases} 0 & \text{if } z \leqslant \hat{z}_q \\ g\left(\log z - \log \hat{z}_q\right) & \text{if } z > \hat{z}_q. \end{cases}$$

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

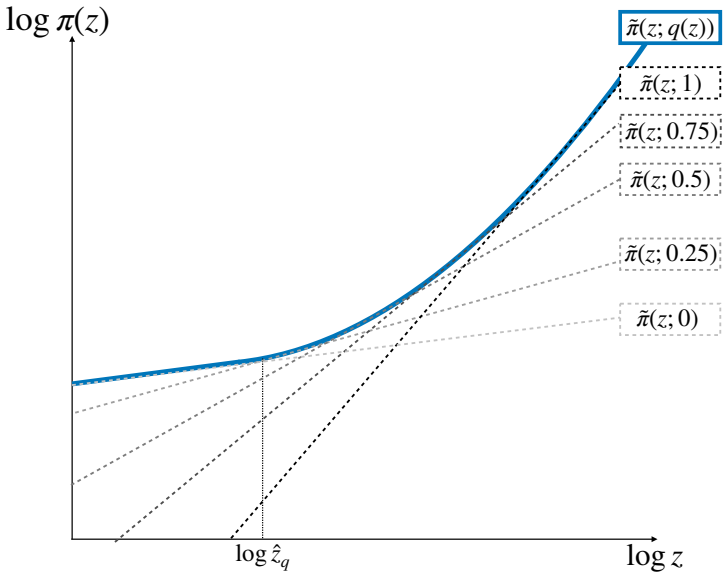
$$\frac{\partial \log y(z)}{\partial \log z} = \begin{cases} \frac{1}{1-\gamma_\ell} & \text{if } z \leqslant \hat{z}_q \\ \frac{1+\gamma_p \frac{dq(z)}{d\log z}}{1-\eta(q(z))} & \text{if } z > \hat{z}_q. \end{cases}$$

Figure 4 provides a graphical representation of the results of Lemma 2. Each gray line shows profits as a function of entrepreneurial skill z for a given choice of q (e.g., $\tilde{\pi}(z,q)$). As q increases, the profit functions become more convex in z. 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 for each level of z, 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 so operate small

[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.

FIGURE 4: TECHNOLOGY CHOICE AND FIRM PROFITS



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 think of this set of entrepreneurs as capturing the traditional organization of production, including own account work or work in small firms with little labor specialization as described in Bassi et al. (2025).

Entrepreneurs with sufficiently high z professionalize at least some tasks. The share of tasks that they professionalize is increasing in their own skill, which implies that white-collar employment share is increasing in the entrepreneur's skill as well.[12] The elasticity of output with respect to the entrepreneur's skill is larger than the standard $\frac{1}{1-\gamma_\ell}$ and is 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 think of these firms that professionalize some tasks as modern business enterprises and refer to the entrepreneurs of such firms as modern entrepreneurs.[13]

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 informs 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

[12] The share of tasks they professionalize also depends on external factors such as the skill premium and the production technology; see Appendix B.1 for a full characterization.

[13] 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.

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 skills across all four occupations.

ASSUMPTION 3. The parameters χ and ρ satisfy

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

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

The ordering in Assumption 3 implies that workers with low skill levels have a comparative advantage in working as a laborer or traditional entrepreneur, while workers with high skill levels have a comparative advantage in working as a professional or modern entrepreneur. 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 if and only if $\omega_\pi(z)\mathbb{I}_{z \leqslant \hat{z}_q} > 0$
   - if $\hat{z}_0 = \hat{z}_1 : w_\ell z^\chi = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;
   - if $\hat{z}_0 < \hat{z}_1 : w_\ell z^\chi = \pi(\hat{z}_0)$, $\pi(\hat{z}_1) = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;

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

$$G(\hat{z}_0) > \int_{\underline{z}}^{\hat{z}_{0,j}} n_\ell(x)\omega_\pi(x) dG(x) + \int_{\hat{z}_0}^{\hat{z}_1} n_\ell(x) dG(x) + \int_{\hat{z}_2}^{\infty} n_\ell(x) dG(x).$$

Lemma 3 shows that the equilibrium can take one of two possible equilibrium 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.11 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 take into account the optimal choice of technology q.

FIGURE 5: OCCUPATIONAL CHOICE AND ENDOGENOUS DUALITY

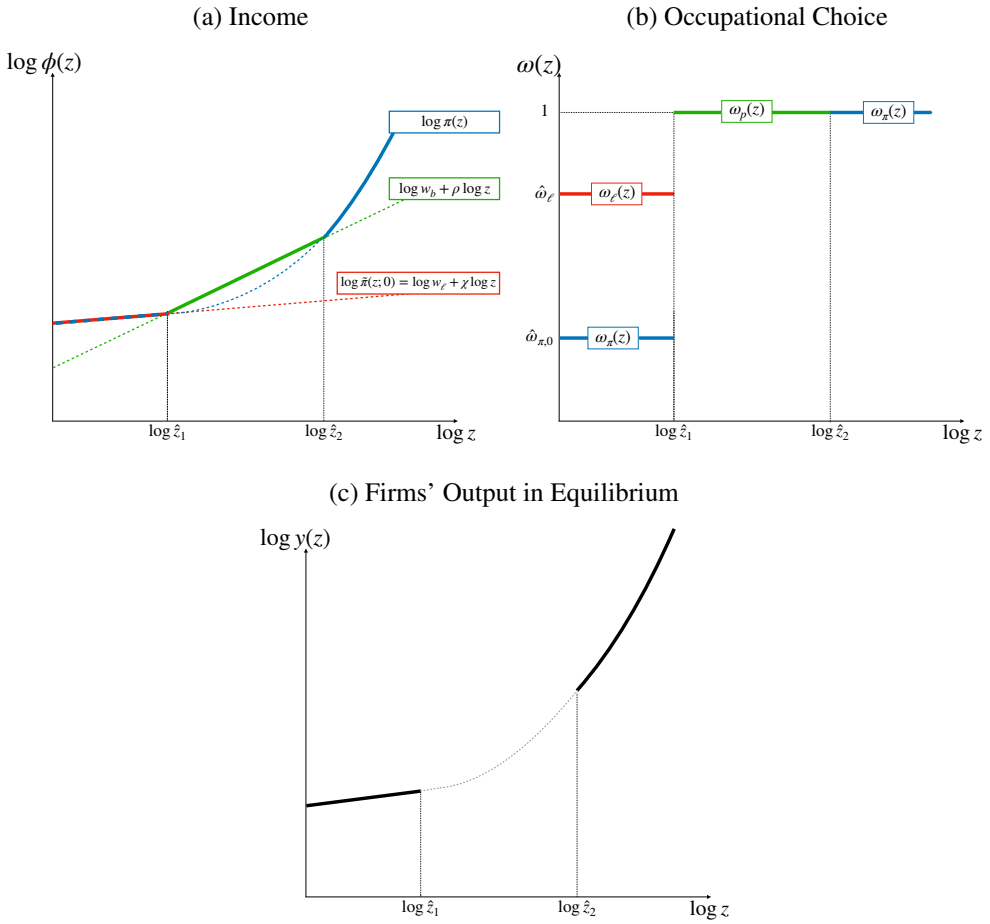


Figure 5b shows the resulting occupational choice. Workers with low skill levels are indifferent between becoming traditional entrepreneurs or laborers. Workers with intermediate levels of skills earn the most as professionals and consequently choose that occupation. Workers with the highest levels of 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 in very different ways, with distinct types of firms and productivity levels.

DEFINITION 3. An equilibrium features *duality* if there is a positive mass of traditional entrepreneurs, that is, if $\int_{\underline{z}}^{\hat{z}_0} \omega_\pi(x) dG(x) > 0$.

4.2 Analytical Results: the Reorganization of Production

In this section, we explore two forces that can generate a reorganization of production: changes in the aggregate supply of skills and changes in the size-dependent wedge. We introduce a simplified version of the model that can be solved analytically and use it to explore these two driving forces. These analytical results build intuition for the quantitative results in Section 5 and shows how the model can be consistent with the motivating facts documented in Section 2.

These analytical results rely on two simplifying assumptions.

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

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

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.

Increase in the Supply of Skills

We first consider how an increase in the supply of skills can lead to a reorganization of production.

PROPOSITION 1 (Shift in the Supply of Skills)**.** Start from an equilibrium featuring duality and consider an increase in the supply of skills from a distribution $G(z)$ to one $G'(z)$, such that $G'(\kappa z) = G(z)$ for a $\kappa > 1$.

There is a value $\hat{\kappa}$ such that for any $\kappa < \hat{\kappa}$ an increase in κ yields

1. a constant cutoff type $\hat{z}$, with

$$\log \hat{z} = -\frac{1}{1-\chi}\left(\mathbb{W} + \log \frac{\gamma_p}{\gamma_\ell}\right) \tag{6}$$

such that all workers with $z \leqslant \hat{z}$ are indifferent between being laborers or traditional entrepreneurs, while all those with $z > \hat{z}$ are indifferent between being professionals or modern entrepreneurs;

2. an increase in the share of white-collar workers and a decline in the share of traditional entrepreneurs;

3. an increase in average firm size;

4. a constant skill premium increasing in scalability $\mathbb{A}$ and decreasing in the distortion given by

$$\mathbb{W} = \frac{\gamma_p}{1-\gamma_\ell}\mathbb{A} - \tau \log\left(\frac{1-\gamma_\ell}{1-\gamma_\ell-\gamma_p}\right) + \Phi \tag{7}$$

where Φ is a constant defined as $\Phi \equiv -\log\left(\frac{1-\gamma_\ell}{\gamma_\ell}\right) - \frac{1-\eta}{1-\gamma_\ell}\log\left(\frac{1-\eta}{\gamma_p}\right)$.

5. no change in the occupational choices for workers conditional on skill level z.

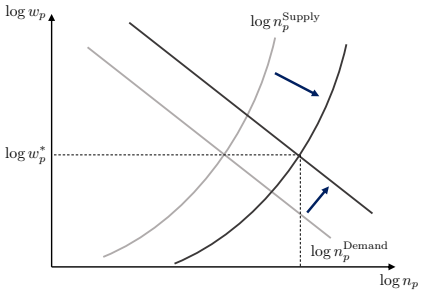
The proof of Proposition 1 is provided in the Appendix. The key step is to recognize that, as long as duality persists, the skill premium remains unchanged in response to shifts in the supply of skills. To build intuition for this result, we next explain why both professional and laborer wages remain constant.

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.

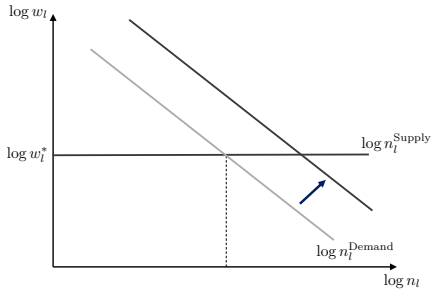
A different mechanism keeps the wages of laborers constant. The increase in skills both reduces the supply of laborers and increases the demand for laborers (to work in the larger number of modern firms). However, low-skilled workers are indifferent between being laborers or traditional entrepreneurs, 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. Figure 6 illustrates the resulting shifts in the labor markets.

FIGURE 6: AN INCREASE IN SKILL SUPPLY

(a) Professionals



(b) Laborers



The property that the skill premium is 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 serve as a reserve labor supply for laborers. These features help explain why the model generally produces muted movements in the skill premium. 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 the skill premium is 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 $\log \hat{z} = \log \kappa + \log \hat{z}$, where $\log \hat{z}$ is given by equation (6)
2. a constant share of white-collar workers;
3. no change in average firm size;
4. a decline in the skill premium;
5. the probability to work in a white collar occupation declines conditional on skill level z.

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 remains 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.

Declining Distortions

Next, we return to the role of declining distortions, which in our model stands in for other factors that may reduce the incentive to establish large, modern firms. Proposition 2 shows the effects of a reduction in distortions.

PROPOSITION 2 (Decline in Distortions)**.** Consider a decline in distortions – i.e. a decrease in τ. This change yields the following:

1. a decline in the cutoff type $\hat{z}(\kappa)$;
2. an increase in the share of white-collar workers and a decline in the share of traditional entrepreneurs;
3. an increase in average firm size;
4. an increase in the wage premium;
5. a (weak) increase in the propensity to be a white collar for each skill type z.

Proposition 2 shows that a decline in size-dependent distortions is also able to generate a growth in the white-collar workforce and a reorganization of production towards large firms. However, the underlying mechanism is different. It works through an increase in the wage premium, which implies that it alters the occupational choices of workers of a given skill level, contrary to the data.

Summing up, Propositions 1 and 2 show that even in the simple analytical model there are multiple mechanisms that can generate a reorganization of firms. They also show that the underlying mechanism through which they work can differ. However, they rely on simplifying assumptions and yield comparative statics. 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 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 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 focus on middle-income countries because they feature endogenous duality and a non-trivial traditional sector, unlike high-income countries. We then recalibrate a limited set of driving forces to replicate select moments for the average low-income country. 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 $z_{\mu,1} = 0$.

Sectors We expand the analytical model to include four sectors, corresponding to those shown 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 includes both the TFPQ, A_j, and the returns to scale 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. Further, 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 $q = 1$:

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

The sectors are affected equally by the firm size distortion τ.

Preferences We allow workers to have idiosyncratic preferences 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:

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

Similar expressions give the share who choose to be professionals and entrepreneurs.[14] These taste shocks affect the elasticity of labor supply across occupations within a sector. 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

[14] In the analytical model, we define traditional entrepreneurs as entrepreneurs who are indifferent between entrepreneurship and working as a laborer. With the introduction of taste shocks, this indifference condition is no longer well-defined. Instead, we use the closely related idea that they are entrepreneurs who would earn a higher income working as a laborer than as a professional.

expected income a worker derives from choosing sector j is:

$$\phi_j(z) \quad = \quad \left(\left(w_{\ell,j} z^{\chi_j} \right)^{\xi} + \left(w_{p,j} z^{\rho_j} \right)^{\xi} + \left(\pi_j(z) \right)^{\xi} \right)^{\frac{1}{\xi}}. \tag{9}$$

Workers also have direct preferences over the sector in which they work, consisting of two components. First, workers have idiosyncratic relative preference shocks for the four sectors that are i.i.d. draws from a type-I extreme value distribution with shape parameter ν_σ. Second, sectors also differ in the level of utility that they provide, $\nu_{\mu,j} z^{\varphi_j}$. In the absence of this term, our model predicts that patterns of worker sorting should be perfectly correlated with wages. Empirically, this is not the case, even conditional on education. The term $\nu_{\mu,j}$ acts like an amenity that makes some sectors more attractive to workers than wages would suggest, while z^{φ_j} is a correlated amenity that makes sector j particularly attractive to high-skilled workers. These assumptions imply that the share of workers with skill level z that choose sector j is given by:

$$\sigma_j(z) \quad = \quad \frac{\left(\nu_{\mu,j} z^{\varphi_j} \phi_j(z) \right)^{\nu_\sigma}}{\sum_{k \in J} \left(\nu_{\mu,k} z^{\varphi_k} \phi_k(z) \right)^{\nu_\sigma}}. \tag{10}$$

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

$$\sum_{j \in \{\text{ag,mfg,hs,ls}\}} \Upsilon_j^{\frac{1}{\sigma}} \left(\frac{C_j}{U^{\epsilon_j}} \right)^{\frac{\sigma-1}{\sigma}} = 1. \tag{11}$$

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 identifies 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

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*a*)
Panel B. Aggregate						
ξ	Occup. preferences	8.00				Dix-Carneiro (2014); Ashournia (2018)
ν_σ	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	Wedge	0.00				Normalization
Panel C. Sector-specific		Agri.	Manu.	HS	LS	
ϵ_j	Sector elasticity	0.25	1.00	1.88	1.12	Comin, Lashkari and Mestieri (2021)
α_j	Factor share of prof.	0.27	0.55	0.90	0.66	Own calculation

a 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. These correspond directly to the education shares in middle-income countries reported by Ruggles et al. (2025*a*).

Panel B reports four aggregate parameters taken from the literature, as well as $\tau = 0$, which we normalize for the middle-income country. The parameters ξ and ν_σ 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 $\xi = \nu_\sigma = 8$, consistent with Dix-Carneiro (2014) and Ashournia (2018), though we also explore values in the range of 4–12.[15] We set the elasticity of substitution in demand across sectoral outputs to 0.43, following Comin, Lashkari and Mestieri (2021). Finally, we fix the returns to scale in manufacturing at 0.80, a value broadly consistent with the literature—for example, Buera, Kaboski and Shin (2011) use 0.79.

Panel C reports two sector-specific parameters that we externally calibrate. First, we estimate the income elasticity of demand by sector following Comin, Lashkari and Mestieri (2021), using their replication files and code but splitting services in a way consistent with our classification. Second, the parameter $\alpha_j(1)$, which determines the compensation share of professionals in fully modernized firms, is calibrated to match the observed compensation share of professionals in large firms. In the next section we describe how we internally calibrate $\eta_j(1) = \gamma_{p,j} + \gamma_{\ell,j}$; with this value in hand, we

[15] Both papers provide estimates of the long-run sectoral elasticity, ν_σ. Revenga (1992) estimates that the five-year elasticity of labor across sectors is 4, which provides a useful lower bound. Artuç and McLaren (2015) estimate the long-run elasticity across sectors and occupations, finding similar magnitudes and values as large as 20.

can recover the 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 $p_j A_j \nu_{\mu,j}$, but not on the individual terms. This follows from equation (10) and the fact that wages, profits, and hence ϕ_j are all homogeneous of degree one in $p_j A_j$. Inspection shows that an individual's sectoral choice depends on the relative value of $p_j A_j \nu_{\mu,j}$ across sectors, while occupational choice and the optimal organization of production are independent of these terms.

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

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

As is standard, 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 The full set of targeted moments, along with their data values, model values, and weights, are reported in Appendix Tables C.3–C.8.[16] 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.

We first target the shares of individuals who are traditional entrepreneurs, blue-collar workers, white-collar workers, and modern entrepreneurs at the aggregate and within each education level (Figure 7).[17] Figure 7 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 8).[18]

[16] The same appendix also provides details on the minimization algorithm and the choice of weights. In brief, we use a standard Markov Chain Monte Carlo simulation, and we assign equal weight across economic concepts, as described below.

[17] In the data, we do not directly observe the type of entrepreneur. However, we observe whether an individual is self-employed and whether they are in a white- or blue-collar occupation. We define traditional entrepreneurs as self-employed blue-collar workers.

[18] In practice, we target both the employment shares across sectors by education group, and the em-

FIGURE 7: OCCUPATIONAL SHARES

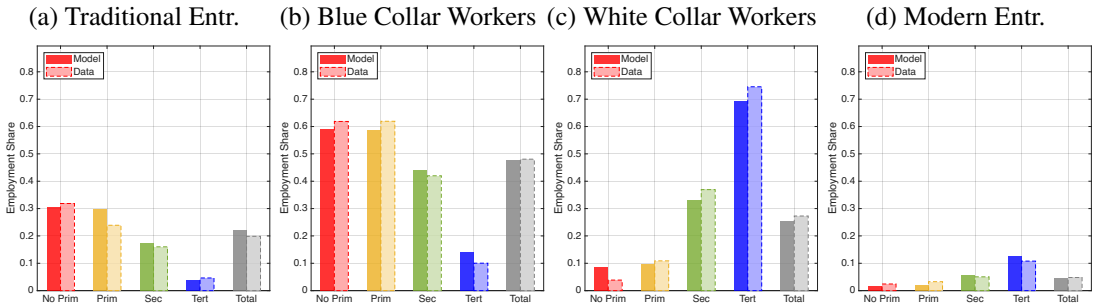
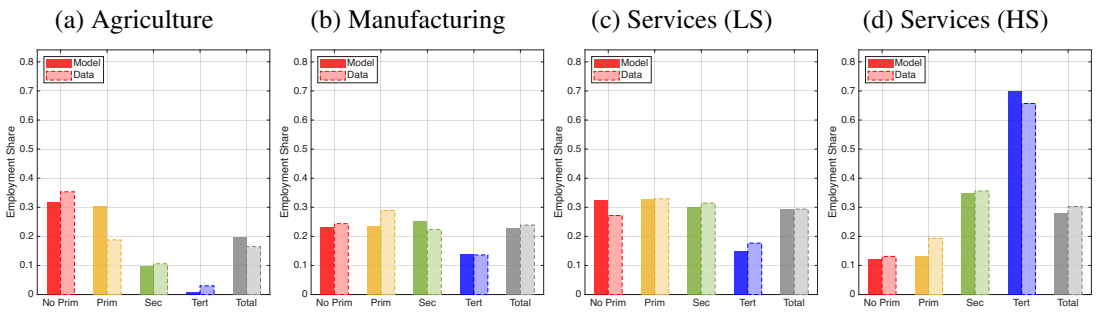


FIGURE 8: SECTORAL SHARES



We also want the model to capture sectoral differences in the organization of production. For example, high-skill services are characterized by many large and modern firms, while most individuals in agriculture are traditional entrepreneurs. Accordingly, we target occupational shares by sector, average firm size, and the shares of employment in firms with more than 10 and more than 50 employees (Figure 9).

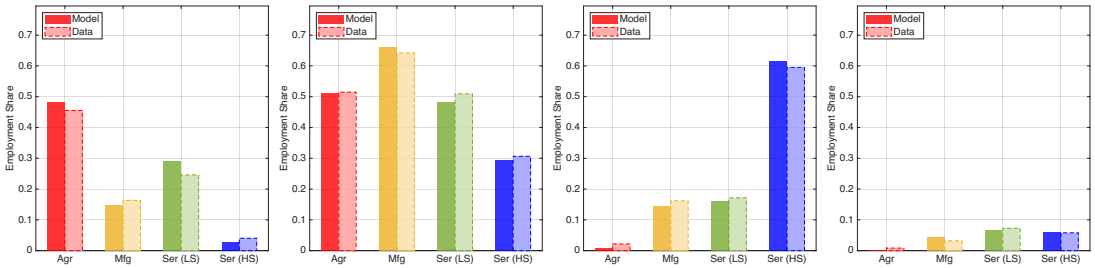
One of our key motivating facts, consistent with Chandler's narrative, is that larger firms employ a higher share of white-collar workers. We therefore target the share of white-collar employment within each sector for firms smaller and larger than 10 employees, as well as the relationship between firm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

Finally, we target wage outcomes. Specifically, we match the residual wage gaps across education groups and the residual wage dispersion within education groups (Figure 11). We residualize wages for the estimated effect of potential experience, gender, and location fixed effects, removing variation associated with factors absent from our model.

ployment shares across education groups by sector. These are equivalent moments expressed under different normalizations.

FIGURE 9: DIFFERENCES IN WITHIN-SECTOR ORGANIZATION

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



(e) Avg. Firm Size (f) Empl. in 10+ Firms (g) Empl. in 50+ Firms

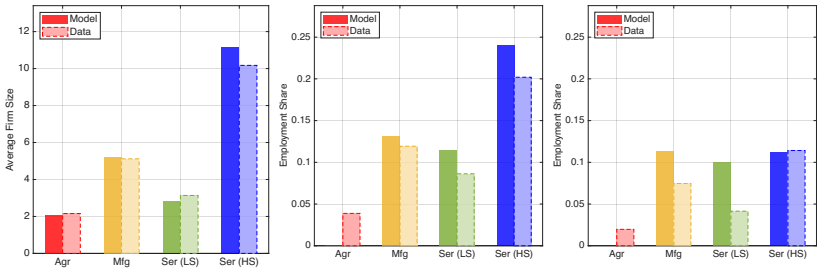


FIGURE 10: WHITE COLLAR SHARES BY FIRM SIZE

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

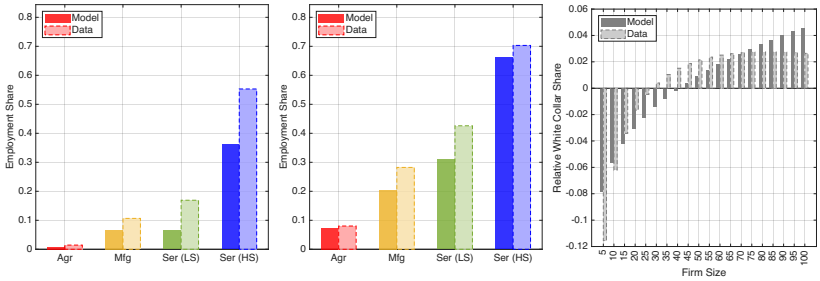
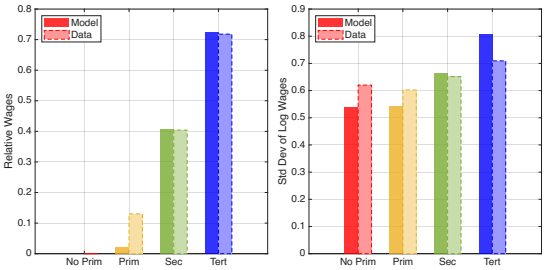


FIGURE 11: WAGE GAPS, BETWEEN AND WITHIN EDUCATION GROUPS

(a) Wage Premia (b) Wage Dispersion



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 the empirical patterns very well.

Identification All parameters are jointly identified. To build intuition, we provide a heuristic discussion—verified through model simulations—of which sets of moments are most informative for each parameter.

Parameter estimates Table 2 summarizes our internally calibrated parameter values. As expected, more educated workers are on average more skilled (panel A). For instance, college educated workers are approximately 100 log points, or 170% percent more productive than those without primary education, $z_{\mu,4} = 0.98$.

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 (panel B). 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 $\theta = 0.94$ implies that the restriction $\theta > \gamma_{p,j}^2/(1-\gamma_{\ell,j})$ 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 correlated amenity 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 play an important role in shaping the organization and reorganization of production. Finally, we take the calibrated values for $p_j A_j \nu_{\mu,j}$ and back out the underlying values as follows. First, we choose A_j so that the model is consistent with sectoral labor productivity from the Productivity Level Database (Inklaar, Marapin and Gräler, 2023). Second, we normalize prices $p_j \equiv 1$ for all sectors in the baseline economy (but not in counterfactuals). This normalization pins down the sectoral preference shifters Y_j that are needed to clear goods markets for each of the four sectors. Finally, $\nu_{\mu,j}$ is the residual. Given prices and preferences, we find that workers have a slight level preference for working in high-skill services or manufacturing relative to agriculture or low-skill services.

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		0.02	0.44	0.98
Panel B. Aggregate					
z_σ	St.d. of skills cond. on education	0.42			
β	Productivity of hired professional, intercept	1.48			
θ	Productivity of hired professional, slope	0.94			
Panel C. Sector-specific					
		Agriculture	Manufacturing	HS services	LS services
η_j	Decreasing returns to scale of $q = 1$ firm	0.69	0.80	0.75	0.79
φ_j	Correlated amenity of sector	-1.24	0.00	1.24	0.00
Panel D. Implied parameters					
		Agriculture	Manufacturing	HS services	LS services
χ_j	Skill intensity of laborers	2.01	1.56	1.08	1.37
ρ_j	Skill intensity of professionals	2.60	3.28	2.54	3.11
$\gamma_{p,j}$	Curvature in professionals	0.19	0.44	0.68	0.53
$\gamma_{l,j}$	Curvature in laborers	0.50	0.36	0.07	0.27
$\nu_{\mu,j}$	True preference shifter	0.92	1.00	1.01	0.91
A_j	Sectoral TFPQ	1.08	1.00	0.47	1.12

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 economy. 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 directly from the data (Ruggles et al., 2025*a*).[19] We allow the product $p_j A_j \nu_{\mu,j}$ to vary, which allows us to fit the sectoral employment shares in each country exactly. Finally, we let the distortion τ vary and use it to fit the share of employment in medium and large firms. Note that this process defines an exactly identified system, so we fit each moment exactly, by construction.

Table 3 shows the calibrated parameters that are allowed to vary between low-income and middle-income economies. All other parameters are held fixed at the calibrated values for the middle-income economy. Low-income countries have much lower

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

TABLE 3: CALIBRATED CROSS-COUNTRY PARAMETERS

	Value		
Parameter	Low-Income	Middle-Income	Target
Sectoral labor supply shifter, $\nu_{\mu,j} p_j A_j$			Sectoral employment share
Agriculture	1.303	0.994	
Manufacturing	1.000	1.000	
High-skilled services	0.476	0.477	
Low-skilled services	1.062	1.017	
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	0Share of tertiary degree workers
Wedge	0.005	0.000	Employment share of 10+ firms

educational attainment, with more than half of workers reporting no primary degree. The sectoral labor supply shifter for agriculture is much higher for low-income countries. Otherwise, the parameter values are fairly similar. The value of τ is only slightly higher in the low-income economy. To get a sense of the magnitude of this shift, note that for firms that have fully professionalized ($q = 1$), the elasticity of firm size with respect to z is given by $\frac{1}{1-\gamma_p(1-\tau)-\gamma_\ell}$. For the calibrated values in the manufacturing sector, this shift in τ implies that the elasticity is 4.95 in the low-income economy versus 5.0 in the middle-income economy.

5.4 Benchmarking with Causal Evidence

Our calibrated model is consistent with a rich set of cross-sectional facts on the relationship among education, sectors, and the organization of firms across the income distribution. 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 organization of production, which relates to the key mechanisms in the model.

There is a rapidly 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 an expansion of college attainment in Brazil on a wide variety of outcomes that are relevant for our model, including sectoral employment shares, the share of workers who are self-employed, and the share of large firms.[20]

We simulate an exogenous shift of 1.5 percentage points of the population from secondary to tertiary attainment in our calibrated middle-income economy, consistent

[20] 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: COMPARISON TO COX (2025)

	White Collar	Agri	LS Serv	HS Serv	Emp Share Large Firms	Self-Emp Share	Skill Premium
Cox	0.83	-1.80	1.94	0.98	0.73	-1.44	-4.72
	(0.27)	(0.32)	(0.63)	(0.26)	(0.27)	(0.31)	(1.87)
Model	0.42	-0.21	-0.35	0.70	0.52	-0.25	0.16

with the Cox's IV estimates of the effect of expanding colleges in Brazil. Table 4 compares his IV estimates of the effect of this shift for sectoral employment patterns and the organization of production with the response we generate in our model. Our model results are qualitatively aligned with Cox's empirical estimates, but our results are conservative relative to his estimates. For example, we get half of the rise in the white-collar employment share and around two-thirds of the rise in the employment share at medium and large firms. The most notable discrepancy is that Cox finds a large effect of the expansion of college attainment on exit from agricultural employment and self-employment, whereas in our model secondary-educated workers in middle-income countries already have low propensities to engage in these activities and so giving them instead tertiary education has a small effect on these outcomes.

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 comparing to 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 shows that the 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 who perform routine maintenance on machinery, track inventory, or set clear job descriptions and set performance incentives for workers.

We use the calibrated middle-income economy to simulate the quasi-experimental intervention in post-War Italy and the calibrated low-income economy to simulate the experimental intervention in India. We implement the intervention on Italian firms with

TABLE 5: IMPACT OF MANAGEMENT IMPROVEMENT

		TFPR		Managers/workers		Log size		Management	
Study	τ	Data	Model	Data	Model	Data	Model	Data	Model
Giorcelli (2019)	-0.042	0.401	0.401	0.099	0.036	0.300	1.019		
Bloom et al. (2013)	-0.013	0.154	0.154					50.0	17.8

Note: TFPR computed as $\log(y) - 0.6\log(emp)$ in the model, where employment is constructed using by dividing efficiency units hired by the firm by average efficiency units per worker. Managers per worker and log employment constructed in a similar fashion. Management is computed using the effect on q in the model and the share of management practices adopted in the data. Each is converted to the change in the pre-treatment percentile rank induced by the treatment. We fit a triangular distribution to the min, median, and max reported by Bloom et al.

at least 10 employees and Indian firms with at least 100 employees, consistent with the original program design and sample selection. We model the experiment as an information intervention that reduces τ and thus increased 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 and an increase in q such that our model produces the same change in TFPR as is reported in the original studies, where we compute $TFPR = \log(y(z)) - 0.6\log(emp(z)$, consistent with the original studies.[21] We map efficiency units in the model into employment emp in the data by dividing efficiency units by the average efficiency units per worker. 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 that are broadly consistent with hers: a growth in overall employment that is three times what she estimates and a reorganization of the firm to be more manager-intensive that is one-third of what she estimates.

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. We approximate the distribution from the moments the authors report and find that their treatment induced a shift of 50 percentage points. Our model generates a smaller reorganization of production equivalent to a 17 percentage point change in the baseline distribution of q. Again, the key causal forces in our model are conservative relative to the best evidence.

We model management interventions as a decrease in τ. A plausible alternative – in-

[21] They also data on capital when constructing TFPR, which is absent from our model.

deed, the only way to model them in a standard Lucas (1978) model – would be to treat them as an increase in the entrepreneur's productivity, z. This approach has the counterfactual implication that the predicted effect on employment should be much larger than the predicted effect on productivity. For example, a version of our model with no professional workers closely resembles the standard Lucas model. In this model, the optimal employment of laborers is given by $\log(n_\ell(z)) = \frac{1}{1-\gamma_\ell}\log(z)$. With typical calibrated values of $\gamma_\ell \in [0.6, 0.8]$, the employment effect should be 2.5–5 times larger than the productivity effect, whereas Giorcelli (2019) finds employment effects that are smaller than productivity effects, which is more consistent with our approach.[22]

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 professionalizing the management of firms. In this section, we use the model as a tool to understand the determinants of the reorganization of production with development.

6.1 Understanding the Reorganization of Production

Our first goal is to use the calibrated model as a tool to understand what forces generate the reorganization of production. To do so, we perform a series of counterfactuals where we take a low-income economy and give it calibrated parameters of a middle-income economy. Throughout this section, we treat sectoral prices as exogenous, because we want to be able to cleanly disentangle structural transformation forces from other forces. We provide counterfactuals where sectoral prices are allowed to adjust in Section 6.2.

We start by assessing the relationship between structural transformation and the organization of production. To do so, we take our calibrated low-income economy and replace the product $\nu_{\mu,j} p_j A_j$ for each sector with the value of the middle-income economy, holding all other parameters fixed. Recall that in our model, this product is the direct force that shifts the sectoral allocation of labor. Further, this product encompasses the traditional forces that affect structural change, particularly productivities and prices.

Table 6 summarizes our results. Each value in the table captures the difference in the corresponding moment between the middle-income and the low-income economy. The

[22] See also Bruhn, Karlan and Schoar (2018).

moments are organized into two panels: Panel A shows the moments that we targeted in the data, while Panel B summarizes key moments about the organization of production by sector and occupational choices by skill level. Each row corresponds to one of the experiments. The baseline row shows the differences in moments between the middle-income and low-income country in our baseline model where all the forces vary.

Turning to the "structural transformation only" experiment, we see that the model with shifts in $\nu_{\mu,j} p_j A_j$ alone generates most of the observed structural transformation, but very little reorganization of production. On the first point, note that it generates about two-thirds of the decline in agriculture and an even larger growth in low-skill services and manufacturing, but then fails to generate almost any increase in the high-skill service sector. On the latter point, it generates less than one-quarter of the increase in the share of workers employed at medium and large firms, and it fails entirely to generate a decline in traditional entrepreneurship.

Panel B contains a number of useful moments that help understand why the model cannot generate a reorganization of production. Agriculture is the sector with the lowest employment share at large firms (Figure 9g). Structural transformation thus implies a push towards sectors with more large firms and a consequent increase in demand for white-collar labor. To some extent, the economy can meet this rising demand by changing occupational choices of workers. However, this margin turns out to be limited, consistent with our accounting results that occupational choices conditional on education are remarkably stable across countries (Figure 3a in the data, which the model successfully replicates in Figure 9). Hence, even a 4 percent rise in the relative price of white collar to blue collar labor generates a modest increase in white collar employment shares. The only way for the model to square rising demand for skilled labor with a modest increase in supply is through a decline in large firms within sectors – particularly low-skill services.

Thus, the reorganization of production is largely distinct from structural transformation (and vice versa, as we show in the Section 6.2). We next study the relative importance of skills and τ in generating the reorganization of production. Here, our results echo the original insight of Chandler. He shows that during the Second Industrial Revolution, new technologies and growth in market size generated economies of scale. However, only firms that developed hierarchies of skilled, white-collar workers could fully realize the cost savings of such production; those that failed to do so lost market share to competing firms or countries.

A central insight of this paper is that a lack of skilled labor in developing countries may limit their ability to form the necessary hierarchy of white-collar workers, even if they experience structural transformation and reduce distortions to the adoption of

TABLE 6: UNDERSTANDING THE REORGANIZATION OF PRODUCTION

	Sectoral employment shares (targeted)					
	Agr	Mfg	HS	LS	10+ share (targeted)	
All three factors	-0.311	0.100	0.143	0.069	0.288	
ST only	-0.215	0.094	0.013	0.108	0.022	
No skills	-0.219	0.098	0.014	0.107	0.065	
No reserve labor	-0.359	0.021	0.195	0.143	0.170	
	10+ share by sector				Entrepreneurship rate	
	Agr	Mfg	HS	LS	Traditional	Modern
All three factors	0.000	0.239	0.087	0.174	-0.124	0.004
ST only	0.000	-0.069	-0.004	-0.083	0.010	0.009
No skills	0.000	0.013	0.030	-0.029	-0.007	0.003
No reserve labor	-0.000	-0.021	0.022	-0.059	0.000	0.030
	White collar share by education and in the aggregate					
	No primary	Primary	Secondary	Tertiary	Aggregate	WC/BC pay
All three factors	0.003	0.004	0.020	0.052	0.109	-0.017
ST only	0.003	0.003	0.010	0.007	0.004	0.042
No skills	0.009	0.010	0.026	0.029	0.013	0.037
No reserve labor	0.025	0.027	0.067	0.084	0.140	0.116

the relevant technologies and the development of large firms. Consistent with this, in Appendix A.3, we show 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.

To demonstrate the effects of a lack of skills in the model, we take the calibrated low-income economy and give it both the parameters associated with structural transformation ($\nu_{\mu,j} p_j A_j$) and modernization (τ) of the middle-income economy, while holding the level of skills fixed. Table 6 shows the results under the "no change in skills" label. Comparing this economy to the no structural change experiment is instructive. The results in terms of structural transformation are essentially unchanged, but the economy now achieves a muted reorganization of production as well. The aggregate growth in employment at medium and large firms is roughly one-quarter of the baseline; there is now growth in medium and large firms in manufacturing and high-skill services, although still not in low-skill services. The model still fails to generate a substantial decline in traditional entrepreneurship. As Chandler documents, a lack of skills constraints the growth of large firms.

Finally, an important property of our theory is that it generates a theory of endogenous duality where traditional entrepreneurs provide a reserve labor force that can be pulled into wage work. This property speeds the reorganization of production. To highlight the quantitative importance of this phenomenon, we compare again the low-

income economy to a middle-income economy that has a proportional tax on the wages paid to laborers that is thrown into the ocean. We adjust this tax until the economy has the same aggregate traditional entrepreneurship rate as the low-income economy. 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 effects of this experiment are shown in Table 6 for the rows “No reserve labor". They are very different from the structural transformation and reorganization with endogenous duality, shown in the baseline “all three factors" experiment. Again, the economy fails to generate much reorganization of production. The growth in employment at medium and large firms is a little more than half of the baseline case; further, the growth in employment at medium and large firms is actually negative within three of the sectors. Aggregate self-employment rises instead of falling; we hold the traditional entrepreneurship rate fixed, but the share of modern entrepreneurs is slightly larger in the middle-income economy. Finally, these shifts distort the process of structural transformation. While the economy still generates a large push out of agriculture, it generates a rise in manufacturing less than one-quarter of the baseline, consistent with the fact that manufacturing is the most laborer-intensive sector in the economy. The workers who traditional entrepreneurship in agriculture largely enter traditional entrepreneurship in other sectors, contrary to the data. We conclude that endogenous duality is an important feature of our model.

6.2 The Equilibrium Effects of Expanding Education

We now study the effect of expanding education in our model. In Section 5.4 we studied the partial equilibrium effect of small increases in educational attainment and showed that they were in line with the available evidence in the literature for low-income and middle-income countries. Our results here differ in that we consider large expansions of education: we take the low-income economy and give it the educational attainment of the middle-income economy, while holding all other factors 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 (11).

Table 7 shows the results using the same format as Table 6. The first row again shows the difference between the middle-income and the low-income economy in the baseline calibration. The second row, “Only change in skills", shows the effect of giving the low-income economy the middle-income country skills in general equilibrium. The

TABLE 7: THE EQUILIBRIUM EFFECTS OF EXPANDING SCHOOLING

	Sectoral employment shares				10+ share	
	Agr	Mfg	HS	LS		
Baseline	-0.311	0.100	0.143	0.069	0.288	
Only change in skills	-0.023	-0.006	0.051	-0.022	0.174	
Fixed modernization	-0.043	0.002	0.038	0.002	0.000	
	10+ share by sector				Entrepreneurship rate	
	Agr	Mfg	HS	LS	Traditional	Modern
Baseline	0.000	0.239	0.087	0.174	-0.124	0.004
Only change in skills	0.000	0.367	0.063	0.419	-0.094	-0.009
Fixed modernization	0.000	-0.034	-0.156	0.005	-0.046	0.020
	White collar share by education and in the aggregate					
	No primary	Primary	Secondary	Tertiary	Aggregate	WC/BC pay
Baseline	0.003	0.004	0.020	0.052	0.109	-0.017
Only change in skills	-0.019	-0.020	-0.044	-0.010	0.067	-0.154
Fixed modernization	-0.030	-0.033	-0.091	-0.102	0.032	-0.059

economy achieves a substantial reorganization. At the aggregate, it generates more than half of the observed shift in employment at medium and large firms as well as three-fourths of the decline in self-employment. Looking within sectors, it actually generates a larger reorganization in production within manufacturing and low-skill services than we see when comparing actual middle-income to low-income economies.

Yet the economy achieves little structural transformation. The underlying intuition is one that is familiar from the structural transformation literature. An increase in the supply of skills raises the relative productivity of manufacturing and low-skill services because they benefit most from the ability to reorganize production. However, standard preferences in the structural transformation literature have an elasticity of substitution between the output of different sectors below 1. The rise in productivity induces an offsetting change in sectoral prices: the relative price of manufacturing and low skill services decline substantially compared to agriculture. These price movements dull the incentive of workers to reallocate out of agriculture.[23] The other important mechanism is again the relative price of white-collar to blue-collar labor, which declines by 15 log points and somewhat dampens the overall increase in white-collar labor supply from this rise in educational attainment.

This first counterfactual reinforces the finding of the last section of complementarity. Increasing skills alone cannot generate a full reorganization of production without τ. Further, a reorganization of production cannot generate much structural transformation

[23]The biggest changes the model generates are the decline in agriculture and the rise in high-skill services, consistent with the existing empirical evidence that skills play a particularly important role in these two sectors (Buera et al., 2022; Porzio, Rossi and Santangelo, 2022).

given standard preferences.

Our final counterfactual considers the case in which an increase in skills does not even generate a reorganization of production. A common concern in policy circles is that some developing countries have high rates of unemployment among young, tertiary-educated workers. This raises the concern that large expansions of schooling may not be beneficial. We show in Appendix A.4 that high tertiary unemployment reflects persistent country-level factors rather than transitory responses to rapid increases in educational attainment. Within the model, we think about them as being generated by large and rising distortions τ that limit the reorganization of production and hence the opportunities for white-collar workers.

We take the calibrated low-income economy, give them again the skill level of the average middle-income country, but at the same time increase the level of τ so that the rise in skills generates no reorganization of production (measured using our baseline target, the employment share of workers employed at medium and large firms). These results are shown in Table 7 as “fixed modernization".

The results are consistent with the experience of countries such as Ghana. The pay for white-collar work declines, which leads to a large drop in the share of workers at each education level who choose white-collar occupations. For example, 10 percent fewer college graduates take up white-collar work; this would be captured by standard measures of underemployment. The economy generates little reorganization of production at the aggregate by design; the reorganization of production within sectors goes the wrong direction. Finally, despite having the education level of the average middle-income country, this counterfactual economy experiences almost no structural transformation, implying that agriculture is still the dominant sector in the economy.

7 Conclusion

Chandler (1977) documents that the rise of managerial capitalism was an important component of the Second Industrial Revolution. Innovation yielded new technologies in select industries that leveraged economies of scale and scope to raise productivity. Firms that adopted these technologies grew large and found it necessary to develop hierarchies of white-collar workers to solve the new challenges associated with high-velocity production and sales.

We show that these same forces remain relevant today. The reorganization of production between low-income and middle-income economies is explained by a joint process of lowering distortions to large firms and increasing the aggregate supply of skills. The increase in skills mechanically increases the white-collar employment share

through a composition effect, consistent with the data, but it also pulls less-educated workers out of traditional entrepreneurship and into the growing large firms. All of this process is largely distinct from structural transformation, which by itself generates little 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. For example, we abstract from physical capital and electrification, under the view that these two forces are well understood in the literature (e.g., Buera, Kaboski and Shin, 2011; Fried and Lagakos, 2023). Given our focus on comparing consistent moments across countries we define modern firms in terms of size, but it would be interesting to study other dimensions such as technology adoption and utilization, nature of the labor hierarchy, or number of establishments or products in a firm. Finally, our theory focuses on the forces and sectors that were emphasized by Chandler as being relevant for the U.S. at the turn of the 20th century and that we find to be important for developing countries today. 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. We view these as all profitable areas for future research.

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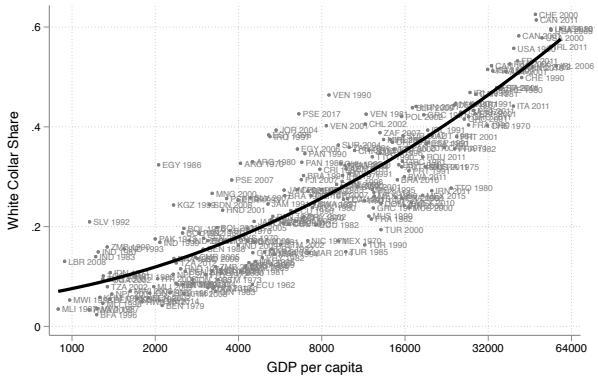
A Data Appendix

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

A.1 Further Results: White-Collar Work

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*a*) to show that this varies from 10 to 60 percent as we move from the poorest to richest countries in the world.

FIGURE A.1: WHITE-COLLAR WORK AND DEVELOPMENT



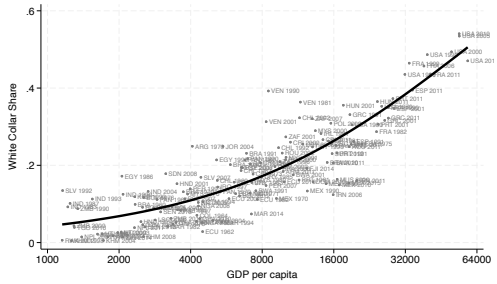
Some of the shift towards white-collar workers is due to the growth of occupations such as doctors or teachers that are not involved in administrative coordination of firms. Our baseline analysis deals with this by grouping most such workers into a high-skill service sector that plays little role in 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.[24] Each shows a strong, positive correlation between the white-collar employment share and development.

In the text, we classify economic activity 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 and insurance; health; public administration; other services; and real estate and business services. Low-skill services

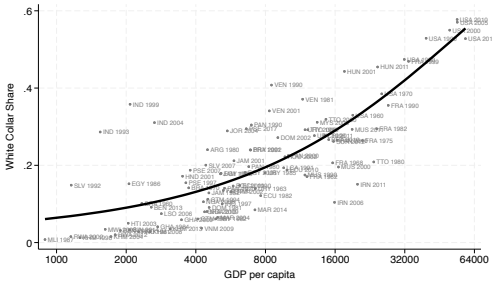
[24]This exercises uses 41 countries and 97 cross sections where we know whether the worker is employed in the private or public sector.

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

(a) Exclude Education, Health, Public Admin



(b) Private Sector Only



consist of hotels and restaurants; private household services; communication and transportation; and wholesale and retail trade. Manufacturing includes also construction, mining, and utilities.

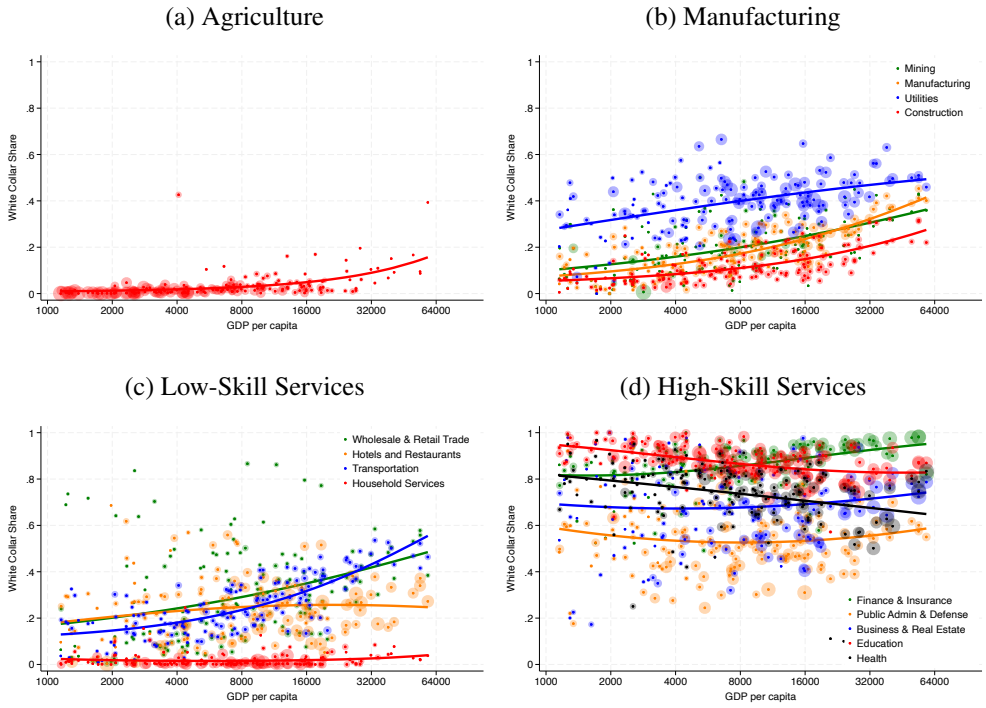
Figure A.3 plots the white-collar share of employment for the slightly more detailed industry code available in IPUMS (indgen). Each of the four panels covers one of the four broad sectors; within the panel, we display the data for the detailed industries within that broad sector. The observations are at the country $\times$ year $\times$ detailed industry level.[25] The figure reveals again that there are significant differences across industries both in the level of the white-collar employment share and how it varies with development. Some industries, such as agriculture, household services, or public administration experience essentially no reorganization of production. Others, such as hotels and restaurants or business services, experience only a muted reorganization, while education and health services see a decline in the white-collar share. The reorganization of production affects most 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.2 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

[25] 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 LABOR



the results using cross-country data. We consider a number of alternative choices here.

A.2.1 Alternative Measures of Skills: Adult Test Scores

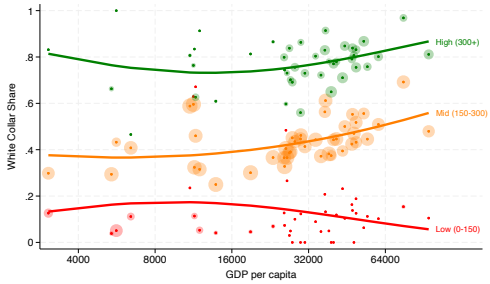
In addition to educational attainment, we can study trends in white-collar employment shares as a function of adult test scores for a large number of countries around the world. For this analysis we use data from the Organisation for Economic Co-operation and Development (OECD)'s PIAAC Survey of Adult Skills and the World Bank's STEP Skills Measurement Program. The OECD PIAAC surveyed roughly 5,000 adults age 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 age 16-65 in 12 poorer countries/regions. They measure literacy and socioemotional skills. We combine the two datasets and 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 (a direct measure of skills) in place 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 skills are small. Figure A.4b shows again that the

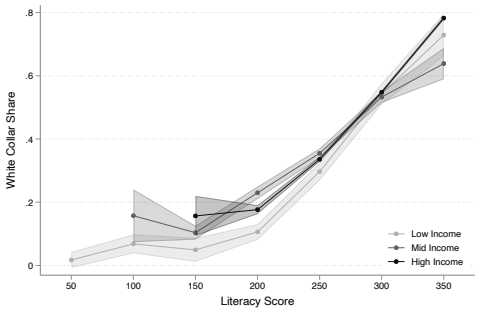
propensities are strongly increasing with adult test scores, in a nearly identical fashion across countries with vastly different income levels.[26]

FIGURE A.4: LITERACY AND WHITE-COLLAR OCCUPATIONS

(a) White-Collar Share by Literacy Score



(b) Estimated Propensities



A.2.2 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.

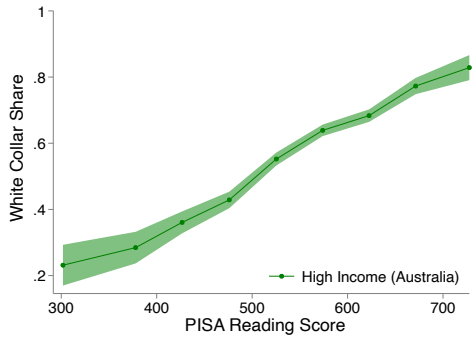
We source this data from two sources. First, we combine Programme for International Student Assessment (PISA) and Longitudinal Survey of Australian Youths (LSAY) data. The former measures literacy and mathematics proficiency of 15-year olds in countries around the world. The latter builds on the PISA in Australia. It tracks 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. This dataset has the advantage that it is directly linked to PISA. However, the sample size is relative small; after pooling waves we have test scores and occupational choices for 12,000 Australians. Given that Australians score relatively well on the PISA exam, this implies that we have a small sample of students with low test scores in terms of the global distribution. To help address this final concern, we turn to the Swedish microdata. We measure childhood skills using scores from the military conscription test given to all men at age 18. This allows us to link test scores to occupational choice for all Swedish men, providing a much larger sample of millions of men.

[26]For the purpose of this graph, we assign Ghana to the low-income group despite of its GDP p.c. in 2013 being marginally above the threshold for middle-income countries in order to have at least two countries per income group (the other low-income country being Kenya).

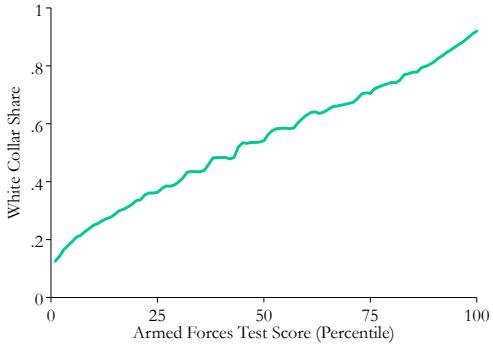
Figure A.5a plots the propensity of being a white-collar workers as a function of the PISA score in Australia. The relationship is strongly increasing. Figure A.5b replicates the same analysis on the Swedish data. Once again, workers with higher skills at age 18 are more likely to subsequently work in a white-collar occupation.

FIGURE A.5: WHITE COLLAR OCCUPATIONS AND ADULT SKILLS

(a) Childhood Test Scores (Australia)



(b) Armed Forces Score (Sweden)



A.2.3 Time-Series Results

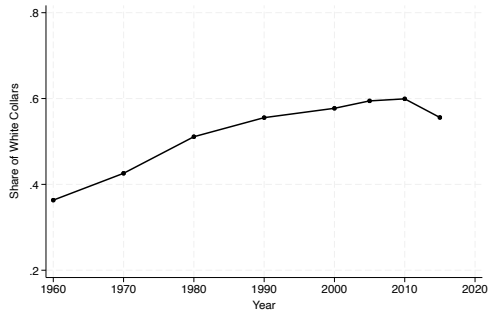
The analysis in Section 2 combines the cross-sectional and time-series variation by pooling all available surveys. This appendix illustrates the results when focusing on the time series alone. Figure A.6 starts by focusing on the United States, the country with the longest available time series. Figure 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.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-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

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

(a) White-Collar Share Over Time



(b) Propensities by Decade

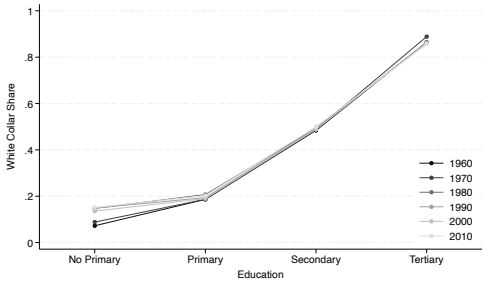
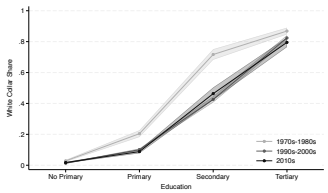
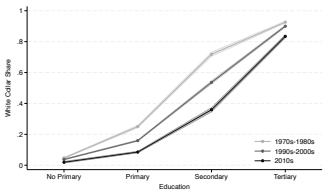


FIGURE A.7: WHITE-COLLAR SHARE OVER TIME – ALL COUNTRIES

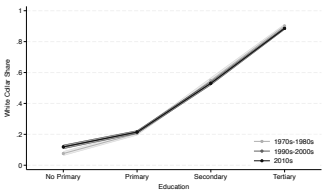
(a) Low Income



(b) Middle Income



(c) High Income



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 share over time.

A.2.4 Restrict to Core Sectors

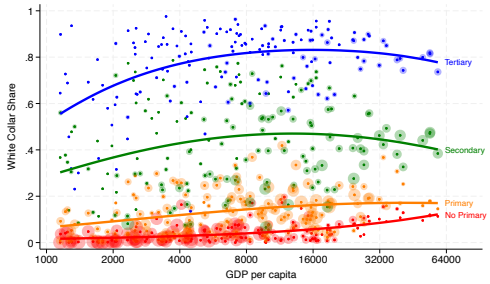
Figures A.8 displays the white-collar employment share by education using only core sectors and excluding education, health, and public administration (Figure A.8a) or excluding all public-sector workers (Figure A.8b). Broadly similar results carry over.

A.2.5 Detailed Occupations

Figure A.9 shows the results separately for the four white-collar occupations. The share of managers and professionals monotonically increase 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.

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

(a) No Education, Health, Public Admin



(b) Private Sector Only

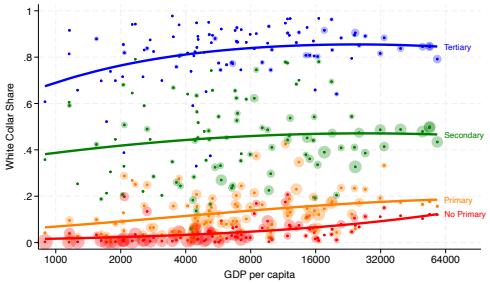
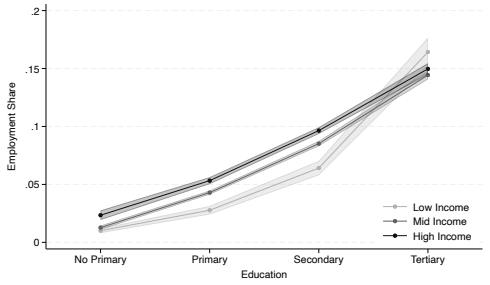
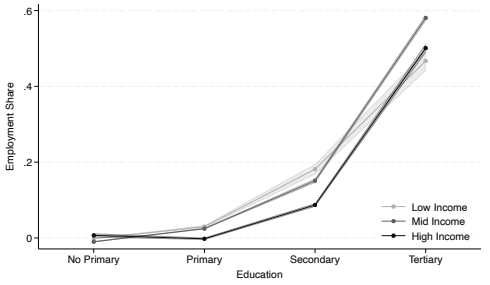


FIGURE A.9: DETAILED WHITE COLLAR OCCUPATIONS AND EDUCATION

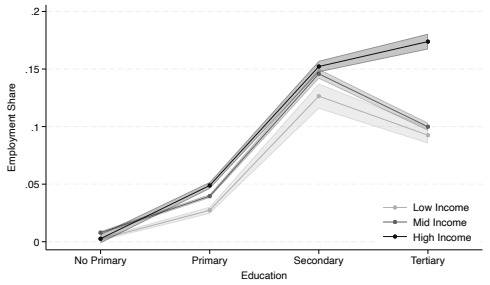
(a) Managers



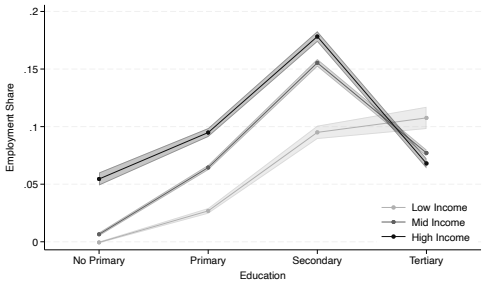
(b) Professionals



(c) Technicians and Associate Professionals



(d) Clerks



A.2.6 Summary Accounting Results

In Section 2.1 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 idea as a shift-share accounting result. We collapse the Ruggles et al. (2025*a*) 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 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 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.1: ACCOUNTING RESULTS: ROBUSTNESS

	Unconditional Elasticity	Conditional Elasticity	Accounting Share
(1) Baseline	0.117	0.013	0.889
	(0.001)	(0.001)	
(2) Sector FE	0.050	-0.001	1.021
	(0.001)	(0.001)	
(3) Country and Decade FE	0.036	-0.001	1.036
	(0.006)	(0.004)	
(4) Men	0.088	0.002	0.979
	(0.002)	(0.001)	
(5) Women	0.165	0.026	0.843
	(0.002)	(0.001)	
(6) Literacy Score	0.133	0.008	0.940
	(0.002)	(0.002)	
(7) No Edu, Health, Pub Admin	0.106	0.032	0.697
	(0.001)	(0.001)	
(8) Private Sector Only	0.119	0.026	0.784
	(0.002)	(0.001)	

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

Table A.1 displays the results. In the baseline case, the unconditional elasticity (shown in Figure A.1) is 0.117, while the conditional one is 0.013. This implies that variation in the aggregate supply of skills accounts for roughly 90 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 and by gender, as well as when

measuring skills as literacy scores (as discussed in Appendix A.2.1) and when focusing on core sectors (as in Figures A.2 and A.8).

A.3 Education Scarcity in Developing Countries

This section makes the case that many developing countries today have low supplies of human capital even relative to what the U.S. had during the period studied by Chandler (1977). The U.S. Second Industrial Revolution is conventionally dated to 1870–1914. We measure the educational attainment of workers by birth cohort in the full count 1940 U.S. Census, the first to collect such data nationally (Ruggles et al., 2025*b*). Among young workers entering the labor market in 1870, the average secondary completion rate was 11 percent; by 1914, young workers had an average secondary completion rate of 22 percent.[27]

We merge educational attainment data from Barro and Lee (2013). We focus on educational attainment of young people, meaning 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 data, 8 still have secondary completion rates among young workers below 11 percent – the level that prevailed in the U.S. in 1870. The median country crossed 11 percent only in 2010. Among these same countries, 20 still have secondary completion rates among young workers below 22 percent – the level that prevailed in the U.S. in 1914. Put differently, the median country has not yet reached the level of secondary completion that the U.S. had in 1914. We take from this that educational attainment is more likely to be a limiting factor in many developing countries today than it was in the United States.

A.4 Education and Unemployment

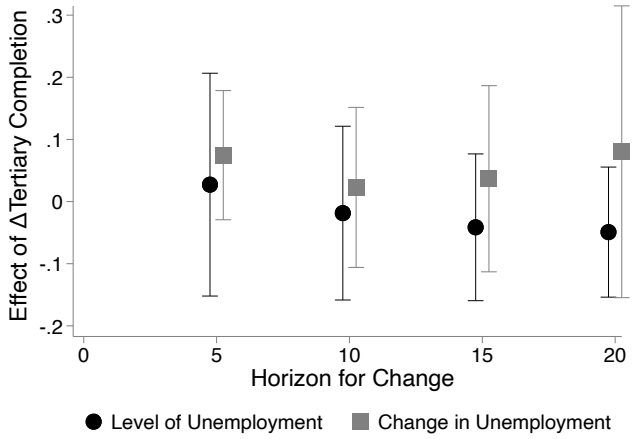
A common concern with expanding access to education in developing countries is that it might result in high levels of unemployment if new graduates cannot find suitable work, as opposed to the re-organization of production that we hypothesize here. The International Labour Organization publishes data on the unemployment rate by age and educational attainment for a wide range of countries that makes it possible to investigate this concern. Focusing on data from the year 2015, we find that college-educated

[27] Based on cohorts who would have been 15–24 years old the appropriate year, to align with the Barro-Lee data that we use across countries. Using responses from older workers in the Census introduces some survival bias, but is unavoidable given the lack of earlier data.

workers aged 25–34 have high unemployment rates in some countries, with one-tenth of countries reporting unemployment rates above 25 percent.[28]

An important question is whether high unemployment rates for young workers with tertiary education reflect persistent, structural factors in a country or a transitory response to rapid growth in the college-educated workforce. To help distinguish between these two classes of explanations, we merge on the newest edition of the Barro-Lee dataset, which builds on Barro and Lee (2013). When combined, the two datasets include information on unemployment among tertiary-educated workers and the share of workers with a tertiary education by ten-year age groups (25–34, 35–44, 45–54, and 55–64) for a large number of country-years. Note that the Barro-Lee data are available every five years until 2015, whereas the ILO unemployment draw on results from Labor Force Surveys and so the coverage varies widely by country.

FIGURE A.10: TERTIARY EXPANSIONS AND TERTIARY UNEMPLOYMENT



We start by investigating whether there is a relationship between expansions of tertiary education and unemployment among young tertiary-educated workers. Since Barro-Lee data are available only every five years, we construct for each country and year the change in the share of 25–34 year old workers who have completed tertiary education over a five-, ten-, fifteen-, and twenty-year window. We regress the level of the unemployment rate among tertiary-educated 25–34 year-olds on this change. We then measure the change in the unemployment rate over the same five-, ten-, fifteen-, and twenty-year window and regress the change in unemployment on the change in tertiary completion.

[28] Available from the Education and Mismatch Indicators, series id UNE_DEAP_SEX_AGE_EDU_RT_A. Downloaded from https://rshiny.ilo.org/dataexplorer3/ on May 9, 2025. They also report figures for 15–24 year olds, but this group has a small sample size.

Figure A.10 summarizes our results by showing the point estimates and 95 percent confidence intervals for each specification (level of unemployment or change in unemployment) and each horizon for constructing the change. The first, visually obvious takeaway is that we cannot reject zero in any of these specifications. Perhaps more importantly, all of the point estimates are small. Both the unemployment rate and the tertiary completion rate are measured in percents, so a coefficient of 0.1 indicates that a 10 percentage point expansion over a decade would be associated with just a 1 percentage point increase in the unemployment rate – a small effect relative to the high levels of the unemployment rate we set out to understand. This finding suggests that much of the unemployment is due to structural factors.

To make this point more systematically, we use the merged unemployment and education data to estimate a pooled regression with a large set of interaction terms,

$$u_{i,a,t} = d_{i,t} + d_{i,a} + \beta edu_{a,t} + \varepsilon_{i,a,t}.$$

Here $u_{i,a,t}$ is a measure of unemployment in country i among tertiary-educated workers in age group a in year t. On the right-hand side, $d_{i,t}$ is a full set of country-year interactions and $d_{i,a}$ is a full set of country-age interactions. The coefficient of interest β, captures whether higher tertiary educational attainment is associated with higher unemployment rates. Conceptually, the country-age interactions fully saturate the data for a given cross section. Hence, this regression is only identified off of countries with multiple cross sections of data on educational attainment and unemployment. The country-year interactions allow the entire schedule of unemployment by age to shift by a common factor across years for a country. The term β thus captures whether cohorts with unusually large levels of tertiary education have unusually high unemployment rates as they move through the labor force.

Table A.2 shows the results. We use two measures of unemployment, the log and the level of the unemployment rate, which differ in whether covariates are assumed to shift the proportion or the level of unemployment across years within a country. We also explore three measures of exposure to tertiary education: the share of workers who have completed tertiary education, the share with any exposure to tertiary education, and the average years of tertiary eduction. As was the case with Figure A.10, the resulting estimates are consistently small and typically statistically insignificant. For example, the marginally significant result in column (4) suggests that a cohort with an expansion of college attainment than is 10 percentage points larger than typical (for the relevant country) would experience a 0.7 percentage point increase in its unemployment rate. These results suggest to us that most cases of high tertiary unemployment are the result

TABLE A.2: TERTIARY COMPLETION AND UNEMPLOYMENT

	log(unemp.)			unemp. (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Tertiary Complete (%)	0.004			0.069*		
	(0.005)			(0.028)		
Some Tertiary (%)		-0.000			0.032	
		(0.004)			(0.020)	
Average Yrs. Tertiary			0.033			1.211*
			(0.113)			(0.595)
N	916	916	916	916	916	916

All specifications include country × year and country × age interaction terms.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of persistent, country-level factors rather than a transitory adjustment response. For example, the literature frequently discusses low education quality or a high public-sector wage that induces queuing for government jobs as structural sources of unemployment (Martellini, Schoellman and Sockin, 2024; Duflo, Dupas and Kremer, 2025). We view such factors as being captured by skills and the distortion τ in our model, respectively.

B Model Appendix

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

B.1 Characterization of Optimal Interior Technology Choice

This appendix provides an analytical characterization of the optimal technology choice for modern entrepreneurs (e.g., those with $z > \hat{z}_{q,j}$ in Lemma 2). In this case, the optimal share of tasks that the entrepreneur professionalizes $q_j(z)$ satisfies

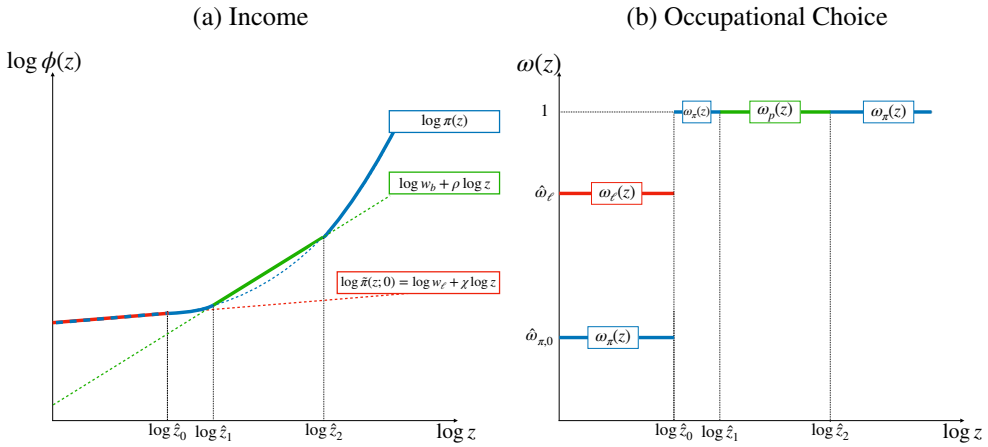
$$\underbrace{\eta_j'(q)\log\tilde{n}_j}_{\text{Returns to Scale}} + \underbrace{\gamma_p\lambda_j\log z}_{\text{Visible Hand}} = \underbrace{\alpha_j'(q)\eta_j(q)\mathbb{W}_j}_{\text{Relative Cost of Labor}} - \underbrace{\gamma_p\log a_j(q)}_{\text{Marginal Task}} + \underbrace{\eta_j'(q)}_{\text{Entr. Share}}. \tag{B.1}$$

Note that we suppress the arguments of the functions q in equation (B.1) to simplify notation. This equation highlights the trade-offs entrepreneurs face when professionalizing the marginal task. Each term has an intuitive interpretation given by the term in brackets. The left-hand side captures the benefits, which include a marginal increase in the returns to scale (which in turn interacts with firm size $\tilde{n}_j$) and a larger weight on the entrepreneur's ability (for $\lambda > 0$). The right-hand side summarizes the three costs. First, more professionalization increases the factor share of professionals, which is a cost if there is a wage premium $\mathbb{W}_j > 0$. Second, there is a decline in productivity as long as the relative productivity of the marginal task ($\gamma_p \log a(i)$) is smaller than the productivity of doing the task in an ad hoc fashion (normalized to 1). Third, more professionalization increases the returns to scale, which in turn reduces the share of profits retained by the entrepreneur.

B.2 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.11 shows the income schedule and occupational choices for this case.

FIGURE B.11: ALTERNATIVE OCCUPATIONAL CHOICE RULES



B.3 Proofs of Select Results

Proof of Lemma 1. The cost function for producing output y is

$$c[y, w_l, w_p] = \min_{n_l, \{n_{p,i}\}} w_l n_l + \int_0^1 n_p(i) w_p di$$

subject to

$$A \exp\left[\int_0^1 \log\left(\frac{\tilde{n}(i)}{\bar{\eta} - \gamma_l}\right) di\right]^{\bar{\eta}-\gamma_l} \left[\frac{z n_l}{A \gamma_1}\right]^{\gamma_l} \geqslant y$$

$$\tilde{n}(i) \leqslant \max\{\tilde{a}(i)(\bar{\eta} - \gamma_l)^{1/(\bar{\eta}-\gamma_l)}, \frac{z}{A} n_p(i)\}$$

$$n_p(i) \geqslant 0$$

First order conditions

$$w_l = \frac{\lambda_y \gamma_l}{y n_l}$$

$$\frac{\bar{\gamma}_p}{\tilde{n}(i)} \frac{\lambda_y}{y} = \lambda_{\tilde{n}}(i)$$

$$w_p \geqslant \lambda_{\tilde{n}}(i) \frac{\partial \max\{\tilde{a}(i)(\bar{\eta} - \gamma_l)^{1/(\bar{\eta}-\gamma_l)}, \frac{z}{A} n_p(i)\}}{\partial z} \qquad = \text{if } n_p(i) > 0$$

We can further simplify to

$$w_p \geqslant \begin{cases} 0 & \text{if } \frac{z}{A} n_p(i) < \tilde{a}(i)(\bar{\eta} - \gamma_l)^{1/(\bar{\eta}-\gamma_l)} \\ \frac{z}{A} \lambda_{\tilde{n}}(i) & \text{if } \frac{z}{A} n_p(i) \geqslant \tilde{a}(i)(\bar{\eta} - \gamma_l)^{1/(\bar{\eta}-\gamma_l)} \end{cases}$$

with equality if $n_p(i) > 0$. Note that if $n_p(i) > 0$, then $n_p(i) \geqslant \frac{1}{z}\tilde{a}(i)$. Now, assume that $\tilde{a}(i)$ is differentiable and strictly increasing in i. Then, there exist a unique cutoff $q \in [0, 1]$ such that $n_p(i) > 0$ for all $i \leqslant q$ and $n_p(i) = 0$ for all $i > q$. To establish this, we show that $n_p(i) > 0$ that implies that $n_p(i') > 0$ for all $i' < i$ and that $n_p(i) = 0$ implies $n_p(i') = 0$ for all $i' > i$. Let's start with case 1. Suppose that $n_p(i) > 0$. Now, $n_p(i) > 0$ implies $n_p(i) \geqslant \frac{1}{z}\frac{\tilde{a}(i)}{a(i)}$ and thus $\tilde{n}(i) \geqslant \tilde{a}(i)$, meaning that $\lambda_n(\tilde{i}) \leqslant \frac{\bar{\gamma}_p}{\tilde{a}(i)}\frac{1}{y}$. Now, suppose that there exists $i' < i$ such that $n_p(i') = 0$. Then, we have

$$\tilde{\lambda}_n(i') = \frac{\bar{\gamma}_p}{\tilde{a}(i')}\frac{1}{y}.$$

However, this means that we have

$$\begin{aligned}
\frac{z}{A}\lambda_{\tilde{n}}(i')a(i') &= \frac{z}{A}\frac{1}{\tilde{a}(i')}\bar{\gamma}_p\frac{1}{y} \\
&> \frac{z}{A}\frac{1}{\tilde{a}(i)}\bar{\gamma}_p\frac{1}{y} \\
&\geqslant \frac{z}{A}\frac{1}{\left(\frac{\bar{\gamma}_p}{\lambda_{\tilde{n}}(i)}\frac{1}{y}\right)}\bar{\gamma}_p\frac{1}{y} \\
&= \frac{z}{A}\lambda_{\bar{n}}(i) \\
&= w_p
\end{aligned}$$

which is a contradiction.

Conversely, suppse that $n_p(i) = 0$. Then we have

$$\lambda_{\tilde{n}}(i) = \frac{\bar{\gamma}_p}{\tilde{a}(i)}\frac{1}{y}$$

Suppose now that we have some $i' > i$ with $n_p(i) > 0$. Then we have at least output $\tilde{a}(i)$, so we have

$$\tilde{\lambda}_n(i) \leqslant \frac{\bar{\gamma}_p}{\tilde{a}(i)}\frac{1}{y}.$$

Now, we get

$$\begin{aligned}\frac{z}{A}\lambda_{\tilde{n}}(i')a(i') &\leqslant \frac{z}{A}\frac{\bar{\gamma}_p}{\tilde{a}(i')}\frac{1}{y}a(i') \\ &< \frac{z}{A}\bar{\gamma}_p\frac{1}{y}\frac{1}{\tilde{a}(i)} \\ &= \frac{z}{A}\bar{\gamma}_p\frac{1}{y}\frac{}{\frac{\bar{\gamma}_p}{\lambda_{\tilde{n}}(i)}\frac{1}{y}} \\ &= \frac{z}{A}\lambda_{\tilde{n}}(i) \\ &\leqslant w_p\end{aligned}$$

Contradicting that $\frac{z}{A}\lambda_n(i') = w_p$ when $n_p(i') > 0$.

Thus, we can define the problem in terms of choosing a cutoff q and then choosing optimally given the cutoff. Formally, defining a problem P_q with that property, we first note that $V[P_q] \leqslant V[P]$ for all q since the choice set is restricted. However, given an optimal solution, we know that there exists q^* so that the solution has the right form. Hence $V[P_{q^*}] = V[P]$, and

$$\min_q V[P_q] = V[P]$$

gives you the same minimum cost as the full problem. We obtain the problem

$$V_q = \min_{n_l>0, n_p(i)>0} w_l n_l + \int_0^q n_p(i)w_p$$

subject to

$$\begin{aligned}A\left(\frac{n_l}{A\gamma_1}\right)^{\gamma_1}\exp\left[\left(\int_0^q \log\left[\frac{z}{A}\frac{n_p(i)}{\bar{\eta}-\gamma_l}\right]di + \int_q^1 \log\tilde{a}(i)di\right)\right]^{\bar{\eta}-\gamma_l} &\geqslant y \\ n_p(i) &> 0 \quad \forall i \leqslant \bar{\eta} \\ n_l &> 0.\end{aligned}$$

Since profit maximization implies cost minimization, this means that a profit maximization problem that operates under this constraint will find the same optimum, which is the lemma.

Proof of Lemma 2 For a given output level y and technology choice q, profits are given by

$$\pi(y, q; z, w_p, w_l) = py - c(y, q; z, w_p, w_l)$$

where

$$c(y,q;z,w_p,w_l)=\min_{n_p\geqslant 0,n_l\geqslant 0} qn_pw_p+n_lw_l$$

subject to

$$z^{\mu+q\lambda\gamma_p}A\times\left(\exp\frac{1}{q}\int_0^q\log a\,(i)^{\gamma_p}\,di\right)^q\left[n_p^{\alpha(q)}n_\ell^{1-\alpha(q)}\right]^{\eta(q)}\geqslant y$$

and

$$\begin{aligned}\eta\,(q)&\equiv q\gamma_p+\gamma_\ell,\\ \alpha\,(q)&\equiv\frac{q\gamma_p}{\eta\,(q)}.\end{aligned}$$

Using that the cost function is that of a decreasing Cobb-Douglas production function with TFP given by $z^{\mu+q\lambda\gamma_p}A\times\left(\exp\frac{1}{q}\int_0^q\log a\,(i)^{\gamma_p}\,di\right)^q$ and prices given by qw_p and w_l, we obtain

$$\begin{aligned}c(y,q;z)&=\left[\frac{y}{z^{\mu+q\lambda\gamma_p}\tilde{A}(q)}\right]^{\frac{1}{\eta(q)}}\left(\frac{qw_p}{\eta(q)\alpha(q)}\right)^{\alpha(q)}\left(\frac{w_l}{\eta(q)(1-\alpha(q))}\right)^{1-\alpha(q)}\eta(q)\\&=\left[\frac{y}{z^{\mu+q\lambda\gamma_p}\tilde{A}(q)}\right]^{\frac{1}{\eta(q)}}\left(\frac{w_p}{\gamma_p}\right)^{\alpha(q)}\left(\frac{w_l}{\gamma_l}\right)^{1-\alpha(q)}\eta(q).\end{aligned}$$

The first-order condition of the entrepreneur for size implies

$$p=\frac{\partial c}{\partial y}=\frac{1}{\eta(q[z])}\frac{1}{y[z]}c[y(z),q(z);z].$$

Consider two cases: $z<\hat{z}$ and $z>\hat{z}$. For $z<\hat{z}$, we have $q(z)=0$ and $\eta[q(z)]=\gamma_l$. Totally differentiating the first-order condition with respect to z yields

$$\begin{aligned}0&=-\frac{d\log y}{d\log z}+\frac{\partial\log c}{\partial\log y}\frac{d\log y}{d\log z}+\frac{\partial\log y}{\partial\log q}\frac{d\log q}{d\log z}+\frac{\partial\log c}{\partial\log z}\\&=\left(\frac{1}{\gamma_l}-1\right)\frac{d\log y}{d\log z}-\frac{\mu}{\gamma_l}\end{aligned}$$

implying

$$\frac{d\log y}{d\log z}=\frac{\mu/\gamma_l}{1/\gamma_l-1}=\frac{\mu}{1-\gamma_l}.$$

For $z > \hat{z}$, we obtain

$$\begin{aligned} 0 &= -\frac{d\log\eta}{d\log z} - \frac{d\log y}{d\log z} + \frac{\partial\log c}{\partial\log y}\frac{d\log y}{d\log z} + \frac{\partial\log c}{\partial\log q}\frac{d\log q}{d\log z} + \frac{\partial\log c}{\partial\log z} \\ &= -\frac{d\log\eta}{d\log z} + \left(\frac{1}{\eta(q)} - 1\right)\frac{d\log y}{d\log z} - \frac{\mu + q(z)\lambda\gamma_p}{\eta(q)} \end{aligned}$$

Which implies

$$\begin{aligned} \frac{d\log y}{d\log z} &= \frac{\frac{d\log\eta}{d\log z} + \frac{\mu+q(z)\lambda\gamma_p}{\eta(q)}}{\frac{1}{\eta(q)} - 1} \\ &= \frac{\frac{d\eta}{d\log z} + (\mu + q(z)\lambda\gamma_p)}{1-\eta(q)} \\ &= \frac{\mu + \left[\gamma_p\frac{dq}{d\log z} + q(z)\lambda\gamma_p\right]}{1-\eta(q)} \end{aligned}$$

C Details on Quantitative Results

C.1 Estimating the Model

To solve the model in estimation, define the piece rates $\tilde{w}_{\ell,j}$ and $\tilde{w}_{p,j}$ relative to sectoral revenue productivity, $w_{l,j} = p_j A_j \tilde{w}_{l,j}$ and $w_{p,j} = p_j A_j \tilde{w}_{p,j}$. As a starting point, we need to solve for the optimal choice $q_i(z)$ in each sector. There are two cases of relevance:

1. Suppose that $\theta > \frac{\gamma_{p,j}^2}{1-\gamma_{\ell,j}}$ in sector j. Then the threshold $\widehat{z}_{q,j}$ is:

$$\widehat{z}_{q,j} = \beta_j^{-\frac{1-\gamma_{\ell,j}}{\gamma_{p,j}\varphi_j}} \exp\left(\frac{1-\gamma_{\ell,j}}{\varphi_j}\left(1+\tau_j+\log\frac{\tilde{w}_{p,j}\gamma_{\ell,j}}{\tilde{w}_{\ell,j}\gamma_{p,j}}+\frac{1}{1-\gamma_{\ell,j}}\log\frac{\tilde{w}_{\ell,j}}{\gamma_{\ell,j}}\right)\right).$$

   For $z > \widehat{z}_{q,j}$, the optimal $q_j(\tilde{z})$ is given by the first-order ordinary differential equation:

$$q_j'(z) = \frac{1}{z}\frac{\varphi_j\gamma_{p,j}\left(1-q_j(z)\right)}{\theta\left(1-\gamma_{\ell,j}-\gamma_{p,j}q_j(z)\right)-(1-\tau_j)\gamma_{p,j}^2\left(1-q_j(z)\right)}.$$

   We solve the initial value problem to obtain $q_j(z)$.

2. Suppose that $\theta < \frac{\gamma_{p,j}^2}{1-\gamma_{\ell,j}}$ in sector j. Then we approximate the optimal $q_i(z)$ as that which generates highest profits among potential q on a grid $\mathcal{Q}$:

$$\begin{aligned}
q_j(z) &= \arg\max_{q\in\mathcal{Q}}\left\{(1-\eta_j(q))\tilde{\tau}_j(q)z^{\varphi_j}\tilde{A}_j(q)n_j(z;q)^{\eta_j(q)}\right\},\\
n_j(z;q) &= \left(z^{\varphi_j}\tilde{A}_j(q)\left(\frac{\gamma_{p,j}}{\tilde{w}_{p.j}}\right)^{\alpha_j(q)}\left(\frac{\gamma_{\ell,j}}{\tilde{w}_{\ell,j}}\right)^{1-\alpha_j(q)}\right)^{\frac{1}{1-\eta_j(q)}},\\
\eta_j(q) &= q\gamma_{p,j}+\gamma_{\ell,j},\\
\alpha_j(q) &= \frac{q\gamma_{p,j}}{\eta_j(q)},\\
\tilde{A}_j(q) &= e^{-q\theta}\beta_j^q\left(1-q^{-\theta(1-q)}\right),\\
n_{p,j}(q) &= \frac{\alpha_j(q)\eta_j(q)}{q\tilde{w}_{p,j}}z^{\varphi_j}\tilde{A}_j(q)n_j^{\eta_j(q)},\\
n_{\ell,j}(q) &= \frac{(1-\alpha_j(q))\eta_j(q)}{\tilde{w}_{\ell,j}}z^{\varphi_j}\tilde{A}_j(q)n_j(z;q)^{\eta_j(q)}.
\end{aligned}$$

Given a solution $q_j(z)$, we recover maximized profits and firm labor demand:

$$\begin{aligned}
\pi_j(z) &= (1-\eta_j(z))\tilde{\tau}_j(z) z^{\varphi_j} \tilde{A}_j(z) n_j(z)^{\eta_j(z)}, \\
n_j(z) &= \left(z^{\varphi_j} \tilde{A}_j(z) \left(\frac{\gamma_{p,j}}{\tilde{w}_{p.j}} \right)^{\alpha_j(z)} \left(\frac{\gamma_{\ell,j}}{\tilde{w}_{\ell,j}} \right)^{1-\alpha_j(z)} \right)^{\frac{1}{1-\eta_j(z)}}, \\
\eta_j(z) &= q_j(z)\gamma_{p,j} + \gamma_{\ell,j} \\
\alpha_j(z) &= \frac{q_j(z)\gamma_{p,j}}{\eta_j(z)} \\
\tilde{A}_j(z) &= e^{-q_j(z)\theta} \beta_j^{q_j(z)} (1-q_j(z))^{-\theta(1-q_j(z))} \\
n_{p,j}(z) &= \frac{\alpha_j(z)\eta_j(z)}{q_j(z)\tilde{w}_{p,j}} z^{\varphi_j} \tilde{A}_j(z) n_j^{\eta_j(z)} \\
n_{\ell,j}(z) &= \frac{(1-\alpha_j(z))\eta_j(z)}{\tilde{w}_{\ell,j}} z^{\varphi_j} \tilde{A}_j(z) n_j(z)^{\eta_j(z)}
\end{aligned}$$

Define:

$$\begin{aligned}
x_{\ell,j}(z) &= \left(\tilde{w}_{\ell,j} z^{\varphi_j \chi_j} \right)^{\xi} \\
x_{p,j}(z) &= \left(\tilde{w}_{p,j} z^{\varphi_j \rho} \right)^{\xi} \\
x_{e,j}(z) &= \pi_j(z)^{\xi}
\end{aligned}$$

The share of workers in sector j with productivity z that opt to work in occupation $i = \{\ell, p, e\}$ is:

$$\frac{x_{i,j}(z)}{x_{\ell,j} + x_{p,j} + x_{e,j}}$$

The payoff from choosing sector j given productivity z is:

$$\phi_j(z) = \nu_{\mu,j} \left(\sum_i x_{i,j}(z) \right)^{\frac{1}{\xi}}$$

so that the share of workers with productivity z that opt to be in sector j is:

$$\sigma_j(z) = \frac{\phi_j(z)^{\nu_\sigma}}{\sum_{k \in J} \phi_k(z)^{\nu_\sigma}}.$$

Aggregate supply of blue and white collar labor in sector j is:

$$\begin{aligned} L_j^s &= \sum_{z \in \mathcal{Z}} \frac{x_{\ell,j}(z)}{x_{\ell,j} + x_{p,j} + x_{e,j}} \sigma_j(z) \\ P_j^s &= \sum_{z \in \mathcal{Z}} \frac{x_{p,j}(z)}{x_{\ell,j} + x_{p,j} + x_{e,j}} \sigma_j(z) \end{aligned}$$

Demand for laborers and professionals in sector j is:

$$\begin{aligned} L_j^d &= \sum_{z \in \mathcal{Z}} n_{\ell,j}(z) \frac{x_{e,j}(z)}{x_{\ell,j} + x_{p,j} + x_{e,j}} \sigma_j(x) \\ P_j^d &= \sum_{z \in \mathcal{Z}} n_{p,j}(z) \frac{x_{e,j}(z)}{x_{\ell,j} + x_{p,j} + x_{e,j}} \sigma_j(x) \end{aligned}$$

Let $\tilde{\mathbf{w}}$ be the matrix of prices:

$$\tilde{\mathbf{w}} = \begin{bmatrix} \tilde{w}_{\ell,\text{agg}} & \tilde{w}_{p,\text{agg}} \\ \tilde{w}_{\ell,\text{mfg}} & \tilde{w}_{p,\text{mfg}} \\ \tilde{w}_{\ell,\text{ls}} & \tilde{w}_{p,\text{ls}} \\ \tilde{w}_{\ell,\text{hs}} & \tilde{w}_{p,\text{hs}} \end{bmatrix}$$

and $\mathbf{ND}(\tilde{\mathbf{w}})$ the matrix of net labor demand:

$$\mathbf{ND}(\tilde{\mathbf{w}}) = \begin{bmatrix} L^d_{\text{agg}}(\tilde{\mathbf{w}}) - L^s_{\text{agg}}(\tilde{\mathbf{w}}) & P^d_{\text{agg}}(\tilde{\mathbf{w}}) - P^s_{\text{agg}}(\tilde{\mathbf{w}}) \\ L^d_{\text{mfg}}(\tilde{\mathbf{w}}) - L^s_{\text{mfg}}(\tilde{\mathbf{w}}) & P^d_{\text{mfg}}(\tilde{\mathbf{w}}) - P^s_{\text{mfg}}(\tilde{\mathbf{w}}) \\ L^d_{\text{hs}}(\tilde{\mathbf{w}}) - L^s_{\text{hs}}(\tilde{\mathbf{w}}) & P^d_{\text{hs}}(\tilde{\mathbf{w}}) - P^s_{\text{hs}}(\tilde{\mathbf{w}}) \\ L^d_{\text{ls}}(\tilde{\mathbf{w}}) - L^s_{\text{ls}}(\tilde{\mathbf{w}}) & P^d_{\text{ls}}(\tilde{\mathbf{w}}) - P^s_{\text{ls}}(\tilde{\mathbf{w}}) \end{bmatrix}$$

Since in equilibrium the supply of each type of labor has to equal demand, we use a non-linear equation solver to solve the system of equations:

$$\mathbf{ND}(\tilde{\mathbf{w}}) = \mathbf{0}.$$

C.2 Identification

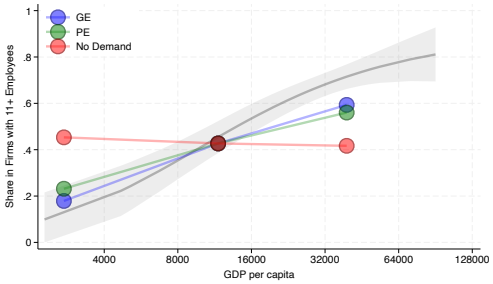
C.3 Counterfactuals

We consider two types of counterfactual exercises. In the first, we hold sectoral output prices fixed, which we refer to as open economy. In this case, we can proceed identically to how we estimate the model to solve for the equilibrium. In the second, we let sectoral

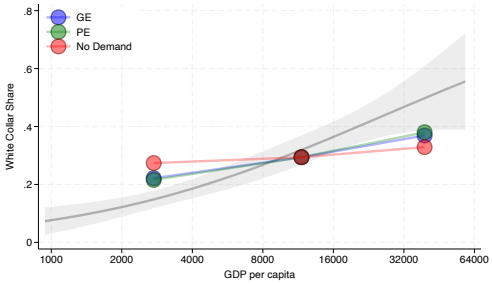
output prices adjust. To that end, we add an equilibrium loop over sectoral prices such that supply for the sectoral good equals demand under our assumed demand system.

FIGURE C.12: SKILLS COUNTERFACTUAL - PE VS GE VS NO DEMAND

(a) Share in 11+ Firms



(b) White Collar Share



(c) Self-Employment

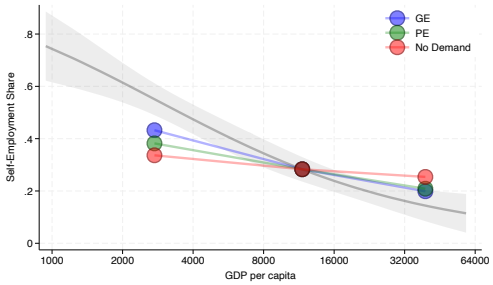


TABLE C.3: OCCUPATIONAL SHARES

Moment	Model	Data	Deflator	Weight
White Collar Workers – No Primary	8.68	3.86	31.56	0.25
Blue Collar Workers – No Primary	58.97	61.85	43.95	0.25
Modern Entrepreneurs – No Primary	1.81	2.43	5.39	0.25
Traditional Entrepreneurs – No Primary	30.54	31.86	19.10	0.25
White Collar Workers – Primary	9.53	10.89	31.56	0.25
Blue Collar Workers – Primary	58.63	61.92	43.95	0.25
Modern Entrepreneurs – Primary	1.97	3.28	5.39	0.25
Traditional Entrepreneurs – Primary	29.86	23.90	19.10	0.25
White Collar Workers – Secondary	32.92	36.93	31.56	0.25
Blue Collar Workers – Secondary	44.13	42.00	43.95	0.25
Modern Entrepreneurs – Secondary	5.66	5.05	5.39	0.25
Traditional Entrepreneurs – Secondary	17.29	16.02	19.10	0.25
White Collar Workers – Tertiary	69.44	74.54	31.56	1.25
Blue Collar Workers – Tertiary	14.01	10.04	43.95	1.25
Modern Entrepreneurs – Tertiary	12.67	10.79	5.39	1.25
Traditional Entrepreneurs – Tertiary	3.88	4.63	19.10	1.25
White Collar Workers – Overall	25.50	27.28	27.28	1.00
Blue Collar Workers – Overall	47.62	48.07	48.07	1.00
Modern Entrepreneurs – Overall	4.67	4.80	4.80	1.00
Traditional Entrepreneurs – Overall	22.21	19.86	19.86	1.00

TABLE C.4: EMPLOYMENT SHARE BY EDUCATION

Moment	Model	Data	Deflator	Weight
Employment Share by Education – No Primary – Agriculture	31.96	35.34	25.00	0.06
Employment Share by Education – Primary – Agriculture	30.33	18.79	25.00	0.06
Employment Share by Education – Secondary – Agriculture	9.81	10.60	25.00	0.06
Employment Share by Education – Tertiary – Agriculture	0.98	3.00	25.00	0.31
Employment Share by Education – No Primary – Manufacturing	23.20	24.39	25.00	0.06
Employment Share by Education – Primary – Manufacturing	23.65	28.89	25.00	0.06
Employment Share by Education – Secondary – Manufacturing	25.29	22.35	25.00	0.06
Employment Share by Education – Tertiary – Manufacturing	14.01	13.62	25.00	0.31
Employment Share by Education – No Primary – Services (HS)	12.20	13.10	25.00	0.06
Employment Share by Education – Primary – Services (HS)	13.12	19.39	25.00	0.06
Employment Share by Education – Secondary – Services (HS)	34.77	35.61	25.00	0.06
Employment Share by Education – Tertiary – Services (HS)	70.10	65.69	25.00	0.31
Employment Share by Education – No Primary – Services (LS)	32.64	27.17	25.00	0.06
Employment Share by Education – Primary – Services (LS)	32.89	32.93	25.00	0.06
Employment Share by Education – Secondary – Services (LS)	30.13	31.45	25.00	0.06
Employment Share by Education – Tertiary – Services (LS)	14.91	17.68	25.00	0.31

TABLE C.5: EDUCATIONAL SHARES BY SECTOR

Moment	Model	Data	Deflator	Weight
Sector Share by Education – No Primary – Agriculture	25.34	33.64	25.00	0.06
Sector Share by Education – Primary – Agriculture	58.12	43.22	25.00	0.06
Sector Share by Education – Secondary – Agriculture	15.83	20.52	25.00	0.06
Sector Share by Education – Tertiary – Agriculture	0.71	2.62	25.00	0.06
Sector Share by Education – No Primary – Manufacturing	16.04	16.03	25.00	0.06
Sector Share by Education – Primary – Manufacturing	39.51	45.87	25.00	0.06
Sector Share by Education – Secondary – Manufacturing	35.56	29.88	25.00	0.06
Sector Share by Education – Tertiary – Manufacturing	8.89	8.22	25.00	0.06
Sector Share by Education – No Primary – Services (HS)	6.82	6.80	25.00	0.06
Sector Share by Education – Primary – Services (HS)	17.71	24.31	25.00	0.06
Sector Share by Education – Secondary – Services (HS)	39.51	37.58	25.00	0.06
Sector Share by Education – Tertiary – Services (HS)	35.97	31.30	25.00	0.06
Sector Share by Education – No Primary – Services (LS)	17.45	14.54	25.00	0.06
Sector Share by Education – Primary – Services (LS)	42.48	42.56	25.00	0.06
Sector Share by Education – Secondary – Services (LS)	32.76	34.22	25.00	0.06
Sector Share by Education – Tertiary – Services (LS)	7.32	8.69	25.00	0.06

TABLE C.6: OCCUPATIONAL SHARES BY SECTOR

Moment	Model	Data	Deflator	Weight
White Collar Workers – Agriculture	0.69	2.16	23.77	0.25
Blue Collar Workers – Agriculture	51.09	51.48	49.33	0.25
Modern Entrepreneurs – Agriculture	0.00	0.83	4.28	0.25
Traditional Entrepreneurs – Agriculture	48.22	45.53	22.62	0.25
White Collar Workers – Manufacturing	14.58	16.21	23.77	0.25
Blue Collar Workers – Manufacturing	66.22	64.25	49.33	0.25
Modern Entrepreneurs – Manufacturing	4.49	3.21	4.28	0.25
Traditional Entrepreneurs – Manufacturing	14.70	16.33	22.62	0.25
White Collar Workers – Services (HS)	61.70	59.52	23.77	0.25
Blue Collar Workers – Services (HS)	29.35	30.65	49.33	0.25
Modern Entrepreneurs – Services (HS)	6.12	5.80	4.28	0.25
Traditional Entrepreneurs – Services (HS)	2.83	4.03	22.62	0.25
White Collar Workers – Services (LS)	16.04	17.18	23.77	0.25
Blue Collar Workers – Services (LS)	48.37	50.93	49.33	0.25
Modern Entrepreneurs – Services (LS)	6.56	7.28	4.28	0.25
Traditional Entrepreneurs – Services (LS)	29.02	24.61	22.62	0.25

TABLE C.7: FIRM SIZES BY SECTOR

Moment	Model	Data	Deflator	Weight
Average Firm Size – Agriculture	2.07	2.16	5.15	1.00
Firms 10+ – Agriculture	0.01	3.88	8.70	0.13
Firms 50+ – Agriculture	0.00	1.97	8.70	0.13
WC Share (<10 firms) – Agriculture	0.78	1.45	21.07	0.25
WC Share (10+ firms) – Agriculture	7.36	8.02	37.29	0.25
Average Firm Size – Manufacturing	5.21	5.12	5.15	1.00
Firms 10+ – Manufacturing	13.11	11.93	8.70	0.13
Firms 50+ – Manufacturing	11.27	7.46	8.70	0.13
WC Share (<10 firms) – Manufacturing	6.70	10.65	21.07	0.25
WC Share (10+ firms) – Manufacturing	20.36	28.23	37.29	0.25
Average Firm Size – Services (HS)	11.17	10.17	5.15	1.00
Firms 10+ – Services (HS)	23.98	20.20	8.70	0.13
Firms 50+ – Services (HS)	11.17	11.42	8.70	0.13
WC Share (<10 firms) – Services (HS)	36.07	55.29	21.07	0.25
WC Share (10+ firms) – Services (HS)	66.11	70.31	37.29	0.25
Average Firm Size – Services (LS)	2.81	3.14	5.15	1.00
Firms 10+ – Services (LS)	11.49	8.62	8.70	0.13
Firms 50+ – Services (LS)	10.00	4.14	8.70	0.13
WC Share (<10 firms) – Services (LS)	6.43	16.92	21.07	0.25
WC Share (10+ firms) – Services (LS)	31.01	42.60	37.29	0.25

TABLE C.8: WHITE COLLAR SHARES BY FIRM SIZE

Moment	Model	Data	Deflator	Weight
WC Share by Firm Size – Size 5	-7.87	-11.55	2.84	0.05
WC Share by Firm Size – Size 10	-5.62	-6.21	2.84	0.05
WC Share by Firm Size – Size 15	-4.19	-3.42	2.84	0.05
WC Share by Firm Size – Size 20	-3.10	-1.66	2.84	0.05
WC Share by Firm Size – Size 25	-2.20	-0.46	2.84	0.05
WC Share by Firm Size – Size 30	-1.44	0.40	2.84	0.05
WC Share by Firm Size – Size 35	-0.76	1.03	2.84	0.05
WC Share by Firm Size – Size 40	-0.16	1.51	2.84	0.05
WC Share by Firm Size – Size 45	0.39	1.88	2.84	0.05
WC Share by Firm Size – Size 50	0.90	2.15	2.84	0.05
WC Share by Firm Size – Size 55	1.37	2.36	2.84	0.05
WC Share by Firm Size – Size 60	1.80	2.51	2.84	0.05
WC Share by Firm Size – Size 65	2.22	2.62	2.84	0.05
WC Share by Firm Size – Size 70	2.60	2.69	2.84	0.05
WC Share by Firm Size – Size 75	2.97	2.73	2.84	0.05
WC Share by Firm Size – Size 80	3.32	2.75	2.84	0.05
WC Share by Firm Size – Size 85	3.66	2.75	2.84	0.05
WC Share by Firm Size – Size 90	3.98	2.73	2.84	0.05
WC Share by Firm Size – Size 95	4.29	2.69	2.84	0.05
WC Share by Firm Size – Size 100	4.58	2.64	2.84	0.05